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A Research Agenda for Skills and Inequality

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Elgar Research Agendas

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# Contents

List of contributors vii  
Preface ix  
Acknowledgements xi  

1 Skills and inequality - Introduction and overview 1  
*Michael Tåhlin*  

2 Skills, class and gender 19  
*Charlotta Magnusson and Michael Tåhlin*  

3 Culture, skills, job tasks and inequality 37  
*George Farkas*  

4 Skills and structural change 51  
*Johan Westerman and Edvin Syk*  

5 Skills and occupational sex segregation in Europe 65  
*Amanda Almstedt Valldor and Karin Halldén*  

6 Skills and adult educational choice: Gender (in)equality in a new form of Swedish vocational education 85  
*Margarita Chudnovskaya, Erik Nylander, and Rebecca Ye*  

7 Occupational skills and subjective social status 103  
*Anton B. Andersson and Arvid Lindh*  

8 Skill and job quality: Polarisation in a ‘liberal’ economy? 121  
*Duncan Gallie*
9 Occupational skills, ethnic stratification, and labor market assimilation across immigrant generations
Alice Skeie Hermansen, Jon Horgen Friberg, and Arntfinn H. Midtbøen

10 Can work protect against age-related decline of cognitive skills?: An empirical test of the use-it-or-lose-it hypothesis
Mark Levels and Rolf van der Velden

11 Reconceptualizing human capital
Paula England and Nancy Folbre

12 Parental education–occupation matching and offspring earnings
Dirk Witteveen

13 Skill and power at work: A Relational Inequality perspective
Dustin Avent-Holt and Donald Tomaskovic-Devey

14 The meaning of job-required education
Michael J. Handel

15 Skills and educational systems
Heike Solga and Herman G. van de Werfhorst

16 Skills and collective wage bargaining
Christian Kjellström and Irene Wennemo

17 Skills and macro-level economic inequality
Tomas Korpi, Michael Tåhlin and Johan Westerman

18 Skilled work and ethics: How can we expand opportunities for meaningful work?
Andrea Veltman

Index

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In the simplest conceivable terms, the link between skills and inequality is this: if you’re good at something, you’re likely to get more highly rewarded for doing it than someone less able at the same task. In not quite as simple terms, but still straightforward enough: doing something well that is difficult to accomplish is likely to be more highly rewarded than doing something that is easy. These statements are close to trivially true, supported by countless pieces of evidence of many different kinds. Yet their significance is rightfully contested: inequality in rewards depends on many things aside from skills and all purported skills are not real; sometimes (no one would seriously claim always) they’re just a deceptive façade.

The interesting question regarding how skills and inequality are linked is hence not if skills are important and real – the answer is obviously yes – but how important and real they are. My own view is that skills are more important for inequality than are any other immediate (a crucial proviso) determinants and that most of this importance is due to real rather than merely purported abilities and requirements. But these issues are highly controversial.

Much or even most of what sociology has to offer as explanations of inequality ignores or downplays skills, perhaps due to a belief that placing skills at center stage conceals (or supports) illegitimate power structures in society. In economics, by contrast, skills play a leading explanatory role, but typically with a strong individualistic emphasis and a corresponding neglect of social structure (including unequal access to skill development and recognition). Both disciplines evidently have much to learn from each other and from other areas in this field.

In tandem with the long-run development toward a knowledge society, skills are a growing global concern. The present volume brings together researchers who share an interest in examining links between skills and inequality, but usefully differ in their conceptions of how best to accomplish this as well as in their topical expertise. By reviewing existing knowledge, presenting novel findings and conceptual innovations, and outlining perspectives for future work,
the contributors to the book open vistas for new research in many directions. There is much of great interest to discover in this fertile and rapidly expanding field. So far, we have only begun to map out the terrain – welcome to join the exploration.

M.T.
In the spring of 2020, Daniel Mather at Edward Elgar Publishing approached me with the idea of producing an edited volume with the present title. All the way to publication just under three years later, things have been running very smoothly. Almost without exception, all contributors whom I invited to join the project not only quickly accepted but swiftly delivered manuscripts of high interest and quality. This is due, I think, not only to the authors’ high-level skills – with respect to both competence and diligence – but also to the nature of the topics to be covered: low-hanging fruit was (and still is) available to pick in this field, and doing so has been an enjoyable task. Given the strong links between skills and inequality, it’s quite remarkable that a book such as the present one wasn’t already available.

Aside from saluting all contributing authors, I would like to thank my colleagues in the All-Inclusive research program at the Swedish Institute for Social Research (SOFI) for productive and stimulating collaboration in bringing the book about, the team involved at Elgar – Sally Evans-Darby, Izzie Green, Daniel Mather and Phillip Thompson – who helped make the project easy and pleasant to complete, as well as the students at Stockholm University attending the course “Labour markets, economic growth and inequality” (fall term 2021) who read and provided comments on chapter drafts. Finally, financial support from the Swedish Research Council for Health, Working Life and Welfare (FORTE, grant no. 2019-01352) is gratefully acknowledged.

M.T.
Introduction

The links between skills and inequality have long been a central theme in analyses of social structure and economic development; in recent years both academic and political interest in this topic has grown rapidly. For more than half a century, human capital theory has been a cornerstone in analyses of economic development at both the individual and societal level. Despite its great importance, however, the traditional human capital model is incomplete in a number of crucial respects. It needs contributions from other disciplines in order to accurately account for broader inequalities within and across countries. The present volume provides an overview of recent advances in research on skills and inequality against the backdrop of established insights from related but separate fields of inquiry; mainly economics and sociology but also philosophy, human resource management, political science and psychology. By bringing these advances and insights together, we aim to build a new framework for research on how unequal living conditions are formed, persist and change in interplay with human skill formation and development.

In sociology, interest in skills in analyses of inequality has waxed and waned over time. According to an older, functionalist view, skills are tied to productivity, in line with economic theory. A positive correlation between skills and rewards, e.g., earnings, is then natural to expect. Over time, the view of skills as objectively visible and productive was gradually replaced by a more critical view of skills as socially constructed. Social and economic stratification was seen less as the outcome of skill-based differences in productivity and more as the result of unequal power relations along the lines of class, race and gender. This long-run shift from functionalist to more critical and radical reasoning – from efficiency to power as key concepts in explaining inequality – is now arguably approaching its endpoint. Much has been learned along the way, but much has also been lost. The time is ripe for a synthesis of the two perspectives.
In economics, skills have a long tradition as a central concept in analyses of economic development, with human capital models as the paramount example. In contrast to sociology, the issue has not been if skills are real and important but how best to conceive of and measure them. In recent years, the economic conception of skills has been considerably broadened. Non-cognitive capacities have begun to be taken seriously as a complement to cognitive skills in assessing the determinants of individual living conditions. In addition, job (or occupation) characteristics have entered the scene in assessments of how the structure of earnings in the labor markets of different countries has evolved. Such analyses of the nature of work tasks are essentially new to economics; much can be learned here from well-established sociological accounts.

In policy circles, skill formation is by now firmly established as a primary concern in all countries. Young students’ achievements are mapped in the PISA (Programme for International Student Assessment) studies and adult competencies are assessed in the PIAAC (Programme for the International Assessment of Adult Competencies) project, both organized as large-scale cross-nationally comparative studies by the Organisation for Economic Co-operation and Development (OECD). Cedefop, the European Union’s (EU’s) agency for advancing vocational education and training, regularly maps the evolution of educational attainment and occupational structures in member countries, and provides descriptions of skill supply, demand and mismatch as well as forecasts of change in these skill factors. The US Department of Labor assembles the highly ambitious Occupational Information Network (O*Net) with large amounts of data on the traits and requirements of jobs and occupations, with a focus on skill-related factors. These and other large-scale efforts reflect the strong conviction among policymakers around the world that the formation and development of skills are paramount in fostering economic and social advancement.

In the academic community, by contrast, a consensus concerning the value of a comprehensive skills-based approach is much less clear; indeed, skills continue to be a controversial concept in sociology, and in economics the conception of skills is still quite narrow and analytically limited. But a cross-disciplinary synthesis is emerging, slowly but steadily, carrying great potential. The present volume aims to increase the speed of this process. What is primarily needed at this point is a synthesis of the large number of analytical bits and pieces that have emerged over several decades in related but separate lines of study. Such a synthesis will not only benefit further research advances but also provide important input in the process of policy development.
Once the value of skills as a natural centerpiece of any reasonably comprehensive perspective on inequality is acknowledged, a wide array of analytical paths, insights and implications opens up. As shown by the chapters included in the present volume, a skills-based focus is highly relevant for a large number of different aspects of social structure and development. Apparently, there is low-hanging fruit to harvest here; it is quite remarkable that a general and extensive overview on the topic of skills and inequality has not already appeared in the research literature. We are very pleased that it has now arrived.

The remainder of this introductory chapter is organized as follows. We begin by reviewing research from several disciplines that converges on the conclusion that job complexity is the central dimension of work content. The review (partly adapted from Tåhlin 2011) shows that job complexity is essentially equivalent to the skill requirements of a job’s work tasks; these requirements determine non-pecuniary job rewards via the formation and use of cognitive capacity and monetary rewards via enhanced productivity. We then turn to measurement issues and describe the content and properties of job complexity indicators in large-scale survey data, and show some important empirical patterns revealed by them. Finally, the stage is set for the 17 chapters following this introduction. The wide variety of contributions together form a comprehensive agenda for future research in this highly fertile but still remarkably uncultivated field.

**Job complexity: the primary dimension of work**

Job complexity – the skill requirements of a job’s work tasks – is the primary dimension of the work activities carried out each day by individuals in work organizations around the world. A massive amount of empirical research, from several disciplines and fields across many decades, clearly shows that complexity is the most important characteristic of jobs, from workers’ and employers’ perspectives alike. Job complexity can be defined as the level of cognitive capacity needed in order to carry out the daily work tasks of a job in a satisfactory manner. It is a strong predictor of individual productivity (job performance) and therefore of wages. It is also the major determinant of learning at work, and hence of work-life careers as well as living conditions outside work that depend on cognitive capacity. Job complexity can be validly and reliably measured by asking workers about the educational and training requirements for the work they do. Such measurement has been successfully carried out for many years in national surveys and has also been extended into a standardized multi-country framework.
In analyses of skills it is important to distinguish conceptually between individuals and jobs, and to develop separate measures of job characteristics aside from individual characteristics. To begin with, the impact of individual characteristics on central outcomes (such as performance, wages and well-being) is mediated by job characteristics (such as occupation). Further, the impact of individual characteristics is strongly dependent on the character of the job; i.e., individual and job traits interact in producing outcomes. If there is no room to use a particular individual characteristic in a particular job, the individual characteristic will have no utility in that job. In addition, job characteristics feed back into – i.e., causally affect – individual characteristics; much or even most learning occurs on the job rather than in school. A positive learning environment on the job helps maintain previously acquired individual abilities, develop such abilities further and create new abilities; a negative learning environment has the opposite effects, potentially to the point of causing skill decline.

Three disciplines – economics, psychology and sociology – have made important contributions to understanding how work content is structured vertically and how it affects work-related outcomes such as wages, careers and well-being. Economics and sociology have mainly provided insights into how the larger social structure of work and labor markets is related to the general character of jobs, while psychology has provided detailed information on the inner traits and causal mechanisms that produce the larger structure. In economics, the main field of relevance in this context is human capital studies, which examine the connection between individuals’ investment in productive capacities – mainly education – and the monetary returns to these investments – mainly wages. In sociology, two lines of inquiry are relevant: analyses of occupational stratification (class, status and prestige) and studies of the reciprocal association between work and personality. Finally, industrial and organizational (I-O) psychology has conducted a vast number of detailed studies on how the character of work tasks is related to individual resources, such as cognitive ability, and how tasks and resources combine in producing important outcomes, such as job performance. An additional important contribution, at the intersection of psychology and human resource management, is job analysis, especially job evaluation, which shows how wages are actually set within firms and other work organizations. We give a brief overview of contributions from these perspectives below.

From research in the human capital tradition in economics (Becker 1962, 1964; Mincer 1974) we know, first, that wages are strongly tied to education at the micro (individual) level, a finding that is universal across a very large number of empirical studies in many countries from many time-points. The educa-
tional wage premium varies across time and place, but is always and everywhere large and systematic (for an overview, see, e.g., Harmon et al. 2003). A second conclusion from human capital studies is that productivity is likely to be the main driving mechanism behind the education-wage association. One crucial piece of evidence is macro-level studies showing that aggregate education in the population, and especially aggregate cognitive ability (which correlates imperfectly with aggregate education), is strongly associated with rates of economic growth (Hanushek and Woessmann 2008).

Human capital models tend to ignore the job side of skills and cognition, however. Sociological research on stratification, by contrast, has jobs—typically in the form of occupations—in focus. In essence, sociological status models (Duncan 1961; Stevens and Featherman 1981; Hauser and Warren 1997) complement human capital models by examining the job-level mediation of the link between education and earnings. A particularly clear case is Ganzeboom et al. (1992) who construct a scale of occupational status by estimating a latent occupational variable that maximizes the association between education and earnings. A second approach is to construct an occupational prestige scale by letting random samples of individuals rank occupations in terms of perceived social standing (Treiman 1977). Status and prestige estimated in these ways correlate very highly with each other, around 0.9. While the status and prestige scales are not explicitly framed in terms of job complexity, implicitly such a connection is clear. The latent status scale can be seen as indicating those attributes of occupations that act as transmitters of educational input to monetary output. This comes very close to being a latent scale of educational requirements of the job. Indeed, the correlation between status (or prestige) and manifest measures of educational requirements tends to be very high (le Grand and Tåhlin 2013).

In the I-O psychology (and human resource management) tradition of job analysis and evaluation (see, e.g., McCormick 1979; Fine and Cronshaw 1999; Brannick and Levine 2002; Landy and Conte 2010: ch. 4; Morgeson and Dierdorff 2011), the primary characteristic universally regarded as indicating job worth, and thus deserving monetary compensation, is job complexity. The strong link between job worth and complexity is apparently a general norm, held by both employers and workers, as shown by its widespread acceptance by management and unions alike in countries with very different labor market institutions and bargaining traditions. The highly general acceptance of job complexity as indicating job worth aligns well with the notion in functionalist sociological theory that the rank order of positions in modern societies is ultimately based on universally held social norms rather than being an outcome of power struggles between actors with conflicting interests (cf. England and
Dunn 1988). This normative order is also believed to underlie the ratings of occupational prestige that are close to invariant across time and social space (Treiman 1977). Successful performance of difficult tasks appears to command respect, probably more than any other factor (see, e.g., Algoe and Haidt 2009).

I-O psychology has also provided important clues in the case of reward determination at work: first, by showing what factors determine job performance, and second, how these factors vary across job categories (such as occupations). The first of these two contributions may be the most important. Productivity is crucial as a concept, especially in economic theory, but is difficult to measure. The psychological literature on job performance (see, e.g., Hunter and Hunter 1984; Schmidt and Hunter 2004) is therefore a vital piece of evidence to consider. Its findings clearly show that cognitive ability is a strong predictor of performance, especially in complex jobs, but to a substantial extent in other jobs as well. No other individual-level determinant of performance is as important as cognitive ability, at least not in complex jobs.

Performance measures can be broadly divided into two categories: ‘objective’ and ‘subjective’, with ‘objective’ meaning simple counts of easily perceived items (such as sales volume) and ‘subjective’ meaning some kind of rating (by supervisors, subordinates, peers, clients, etc.). A meta-analysis by Bommer et al. (1995) estimates the overall correlation between objectively and subjectively measured performance to be around 0.4, indicating substantial common variance but clearly imperfect substitutability. However, when limiting the estimation to a small subset of studies covering the same narrow dimension of performance as both objectively and subjectively assessed, the correlation is much higher, around 0.7. Further, research generally indicates that useful predictors of performance tend to be highly similar regardless of whether performance is measured objectively or subjectively (see, e.g., the meta-analysis by Nathan and Alexander 1988). It is also important to recognize that so-called objective measures are far from perfect indicators of performance or, indeed, completely non-subjective. Simple counts typically cover very narrow aspects of the tasks involved in a job. Furthermore, deciding what to count and how is rarely free of subjective considerations. In practice, most performance measures are based on ratings, often by supervisors, but also by peer examination of work samples or hands-on performance tests (see, e.g., Ree et al. 1994 and the reliability estimation in Viswesvaran et al. 1996).

A second contribution of psychology is the descriptive account of how factors important for the level of performance vary across jobs. The main finding, which is not surprising, is that cognitive ability is strongly correlated with job complexity (see, e.g., Schmidt and Hunter 2004). The causal interpretation
INTRODUCTION AND OVERVIEW

of this finding in psychology is that high-ability individuals are selected for complex jobs. In the sociological literature on work and personality (Kohn and Schooler 1983; Spenner 1988; Schooler et al. 2004), a more reciprocal interpretation is made: in addition to selection by ability, a causal effect running from complexity to ability is also important. Jobs requiring independent thinking and autonomous judgment – i.e., with high levels of ‘occupational self-direction’ (measured by indicators of substantive complexity, closeness of supervision and routinization) – tend to increase the intellectual flexibility of the job incumbents; i.e., their independent judgment and successful use of cognitive reasoning. Matching models (see further below and Handel 2003 for an overview) would appear to support the reciprocal interpretation.

Most empirical studies of job performance are based on within-job rather than between-job analyses. Therefore, there is little direct empirical evidence that job complexity affects productivity. However, the relation between job complexity and productivity can be grasped by considering the following stylized research findings in combination: (1) ability has a strong effect on job performance (Schmidt and Hunter 2004); (2) occupations are strongly graded by their incumbents’ ability (Cain and Treiman 1981; Gottfredson 1986; Schmidt and Hunter 2004); (3) occupations are strongly graded by complexity (ability requirements) (Cain and Treiman 1981; Gottfredson 1986; Tåhlin 2007a; le Grand and Tåhlin 2013); (4) occupations are strongly graded by prestige (Treiman 1977); (5) occupations are strongly graded by wages (Ganzeboom et al. 1992; le Grand and Tåhlin 2013); (6) the occupational gradients by ability, complexity, prestige and wages are strongly correlated with each other (Ganzeboom et al. 1992; le Grand and Tåhlin 2013); (7) in extensively used systems of job analysis and job evaluation, job complexity is the main determinant of job worth; i.e., job complexity is seen as the strongest legitimate determinant of wages, accepted by management and workers alike (McCormick 1979; England and Dunn 1988; Steinberg 1999; Brannick and Levine 2002; Landy and Conte 2010); (8) there is a strongly positive interaction effect between ability and complexity on performance (Hunter and Hunter 1984; Salgado et al. 2003; Hunter et al. 2006); (9) there is a strongly positive interaction (matching) effect between ability (education) and complexity (educational requirements) on wages (Duncan and Hoffman 1981; Rubb 2003; see further below); and (10) complexity has a strong effect on ability (Kohn and Schooler 1983; Schooler et al. 2004); i.e., the ability–complexity link is not only, or even mainly, due to occupational selection by ability but involves a causal impact of positional on individual traits. In sum, the combined evidence expressed by the stylized facts above would seem to clearly indicate that job complexity has a causal, positive and strong impact on productivity.
Table 1.1 Summary of conceptual and measurement components in five research fields

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<th>Individual capacity</th>
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<td>Human capital models</td>
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<td>Occupational status</td>
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<td>Job performance</td>
<td>manifest</td>
<td>manifest</td>
<td>manifest</td>
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</tbody>
</table>

Note: manifest = conceived and measured; latent = conceived but not directly measured; absent = unimportant or ignored; market = random samples; firm = organization-based samples.

Table 1.1 summarizes the contributions from the five fields of research considered in the discussion above. These contributions converge on, or are at least compatible with, the conclusion that job complexity is the main dimension of the vertical (hierarchical) division of labor. It is notable that cross-referencing between these five fields is very rare; it is close to non-existent. An important purpose of the foregoing review has been to indicate the usefulness of cross-fertilization in this regard.

We close this section by noting that the concept of occupation is currently receiving increased attention in several disciplines. It has always been strong in sociology, but weak in economics and fluctuating in level of interest in psychology. Occupation is the most central work-life manifestation of the more abstract concept of role or position. As an explicitly positional concept, occupation is tied to the notion of social structure, which is alien both to neoclassical economics and much of psychology with its traditional focus on individual traits. Recent economic research on work tasks, most clearly seen in the large literature on job and wage polarization (see, e.g., Autor 2013; Acemoglu and Autor 2011 provide a more general framing of these ideas), uses occupational data in empirical applications but lacks structural elements in formulating theory. Most economists still resist the idea that occupations have a causal impact on individuals, a crucial omission from the perspective outlined above of how job complexity determines work rewards via productivity.
But the recent interest in work tasks signifies an opening in this regard, which potentially can grow wider.

In psychological research on work-life issues, occupations were once seen as central categories, but the demand side of labor markets gradually became linked more to organizations; hence the subfield’s name tended to change from occupational to organizational psychology. More recently this trend has begun to reverse, partly due to the blurring of organizational boundaries along with rapid economic and technological change (Dierdorff 2019). Occupations tend to be more stable and consequential than organizations as contexts of individual working lives. In the field of personnel administration, currently known as human resource management, occupations never really fell out of fashion. Role analysis has always been important in management studies, with rewards tied to carefully defined positions rather than to personal traits. Role clarity with associated skill requirements is seen as fundamental for high organizational performance (McKinsey: ‘Think first about roles rather than people’; see Barriere et al. 2018). The situation is similar in applied policy work; the EU agency for vocational education and training, Cedefop, has recently (first edition 2017) developed a Handbook of European Skills, Competencies, Qualifications and Occupations: ESCO:

ESCO provides descriptions of 2942 occupations and 13485 skills linked to these occupations, published in 27 languages. The aim of ESCO is to support job mobility across Europe and therefore a more integrated and efficient labour market, by offering a ‘common language’ on occupations and skills that can be used by different stakeholders on employment and education and training topics. (European Commission 2020: 5)

Haupt and Ebner (2020) provide a recent and comprehensive sociological overview of how occupational traits are related to inequality, distinguishing between four main theoretical perspectives, with skills, tasks, institutions and culture, respectively, as lead concepts. Their account is useful as an initial guide to research on occupations, but is less clear in its discussion of concepts and mechanisms. Dierdorff (2019) is a valuable complement concerning the large psychological literature on occupations.

**Job complexity: measurement**

Having thus established the central importance of job complexity in understanding vertical differentiation at work, we now turn to how complexity can be measured. As spelled out in some detail below, measurement of skill
requirements is very well established. This fact has rarely been acknowledged in the more general research literature on skills and inequality. In the economic section of this field, the established practice in empirical analyses has been to infer change in skill demand from change in the skill supply (education) parameter in standard human capital wage equations, with upward (downward) shifts taken to indicate rising (falling) skill demand (Katz and Murphy 1992; Goldin and Katz 2008). This approach of course begs the question of how to properly measure skill at the job level – i.e., measuring skill demand independently from supply – and at any rate takes as axiomatic the orthodox economic model of how supply and demand determine wages in fully competitive markets; with this model, if supply and wages are known, demand can simply be inferred without any need of separate measurement.

But in sociology as well, measurement of skill requirements is often supposed to be poorly developed, even if – in contrast to common practice in economics – measurement issues on the demand side of labor markets are seen as important. For example, Liu and Grusky (2013) misleadingly claim that both economic and sociological research on earnings inequality has been plagued by a ‘spectacularly poor conceptualization and measurement of skill’ (p. 1332). Such remarks reveal a lack of familiarity with a highly useful literature, which has so far apparently not become sufficiently visible. Hopefully, the present volume will be helpful in broadening views and thereby stimulating both synthesis and analysis.

Job complexity can be defined as the level of cognitive capacity that a job’s tasks require in order for satisfactory performance of them to be achieved. This cognitive capacity may consist of innate abilities as well as acquired skills. Both of these components are strongly related to learning. Acquired skills are by definition learned. But how are innate abilities related to learning? First, most abilities, whether innate or acquired, need training in order to be maintained and developed. Indeed, this fact tends to undermine the very distinction between innate and acquired capacities. Second, in order for innate cognitive abilities to become useful job qualifications, the educational system typically works as a transmission mechanism. Individuals self-select into distinct educational paths partly on the basis of cognitive capacity. The resulting variation in educational credentials works as a signaling system of capacities, regardless of whether schooling as such has any causal impact on capacities (Spence 1973). Third, cognitive capacity is often defined as the capacity to learn, which would be true whether or not the learning capacities themselves are innate or acquired. Fourth, job knowledge appears to be the main mediating factor between cognitive ability and job performance (Schmidt and Hunter 2004).
A valid indicator of job complexity would therefore be the amount of learning required in order to perform the job tasks in a satisfactory manner. The process of learning – i.e., of skill formation – can be organized along a timeline, with different arenas in the forefront during different phases of the process. The timeline starts in childhood, with the first phase of learning taking place in the family of upbringing, well before first school entry. We abstract from this early phase of learning here (but see, e.g., Schooler 1984 and Farkas 2003 for evidence that job complexity is of central importance for intergenerational status transmission).

Abstracting from the pre-school phase, the skill formation process can be viewed as follows: first, to get a certain job, some kind of education is often required. This can be measured by asking how much – if any – schooling beyond the compulsory level is normally required of someone applying for the kind of job that the respondent holds. Such an indicator has been available in large-scale datasets for more than half a century, at least since the first waves of the US Panel Study of Income Dynamics (PSID) and the Swedish Level of Living Survey (LNU), both conducted in 1968; see further below. Second, after entering the job, some amount of training or learning may be necessary before the tasks can be carried out reasonably well. This can be measured by asking how long the initial training or learning typically takes from the point of job entry. Third, after the initial on-the-job training or learning period is completed, some amount of continuous learning is often required in order to perform at an acceptable level. There are established ways of asking about this component as well in standard surveys. The measurement of these three skill components is described in detail in the chapter’s online appendix, with examples from two surveys, one national Swedish survey (Level of Living Survey, LNU) and one multi-country European survey (European Social Survey, ESS).

The consequences of skill mismatch for labor market rewards are commonly analyzed in the framework of the ORU model (ORU = Over, Required, Under), originally designed by Duncan and Hoffman (1981) with an application to US data from the PSID. The research literature on wage determination using this model is by now very large; see the overview in Chapter 12 of the present volume. The ORU model uses the same basic form as Mincer (1974) but decomposes attained education (in years) into three parts defined in relation to the educational requirements of the job: matched education-occupation, excess education (above attained occupational skill level) and excess occupational skill level (above attained education). Table 1.2 shows estimates of these three parameters based on LNU survey data from 1974 to 2010.
Table 1.2 ORU models of wage attainment, Swedish Level of Living Survey (LNU), 1974–2010

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess educ. reqs</td>
<td>4.2</td>
<td>5.0</td>
<td>4.5</td>
<td>3.1</td>
<td>2.5</td>
</tr>
<tr>
<td>Matched education</td>
<td>9.0</td>
<td>6.9</td>
<td>6.9</td>
<td>7.3</td>
<td>7.9</td>
</tr>
<tr>
<td>Excess education</td>
<td>2.3</td>
<td>2.0</td>
<td>1.5</td>
<td>1.8</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Note: Economic returns (ln wage) are for three educational match components (measured in years). (Experience parameters and a sex dummy are included in the equations but estimates are not shown in the table.)

The pattern of results in Table 1.2 is typical for the empirical ORU literature. Matched education (middle line) – i.e., years of individual education corresponding to educational requirements of the job – gives much larger wage returns than both excess education (bottom line) and excess educational requirements (top line). The clearly smallest returns are for over-education, implying that education that is not used (not required) on the job is not well rewarded by the employer, presumably because excess education contributes little to productivity (job performance). A similar pattern (not shown in the table) is found if wages are replaced as the outcome variable with on-the-job learning or training: excess education is weakly or insignificantly tied to learning opportunities on the job, while matched education is strongly tied to job-related skill development (Korpi and Tåhlin 2021). This result underscores the importance of job complexity as a key factor in work-life inequality. Complex jobs are good learning environments while more simple jobs are not, in line with the set of findings discussed earlier in the chapter, thus improving worker productivity as well as cognitively related non-work outcomes. The value of individual education is seriously undercut if unsupported by beneficial learning conditions at work.

Table 1.3 shows results for five countries from regression analyses of log wages (per hour) on the three components of skill requirements, based on data from the second wave of the ESS (2004). Both educational requirements and on-the-job initial learning are measured in years, to get comparable scales. The third component, continuing learning on the job, is measured by ordinal index numbers rather than time, and so the point estimates are less comparable to the other two components.

As can be seen, job complexity and wages are strongly related in all countries in the table. (Similar results for a larger set of countries, 11 including the five in Table 1.3, are reported in le Grand and Tåhlin 2013; see also Tåhlin...
### Table 1.3: Wage regressions by job complexity in five countries, ESS 2004

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Germany</th>
<th>Spain</th>
<th>France</th>
<th>UK</th>
<th>Sweden</th>
</tr>
</thead>
<tbody>
<tr>
<td>Educational requirements</td>
<td>0.06</td>
<td>0.07</td>
<td>0.07</td>
<td>0.07</td>
<td>0.09</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>17.6</td>
<td>7.6</td>
<td>9.3</td>
<td>9.7</td>
<td>10.5</td>
<td>12.1</td>
</tr>
<tr>
<td>Initial job learning</td>
<td>0.05</td>
<td>0.05</td>
<td>0.03</td>
<td>0.05</td>
<td>0.11</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>5.6</td>
<td>2.6</td>
<td>1.4</td>
<td>3.9</td>
<td>6.1</td>
<td>4.2</td>
</tr>
<tr>
<td>Continuing job learning</td>
<td>0.04</td>
<td>0.05</td>
<td>0.10</td>
<td>0.01</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>3.8</td>
<td>1.9</td>
<td>5.0</td>
<td>0.4</td>
<td>1.5</td>
<td>2.1</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.39</td>
<td>0.18</td>
<td>0.27</td>
<td>0.21</td>
<td>0.30</td>
<td>0.28</td>
</tr>
<tr>
<td>n</td>
<td>2,826</td>
<td>595</td>
<td>278</td>
<td>554</td>
<td>522</td>
<td>877</td>
</tr>
</tbody>
</table>

**Note:** B coefficients (upper row) and t-values (lower row). Wages are logged, educational requirements and initial job learning are measured in years, and continuing learning is measured by a scale from 0 to 3. Pooled regression (column 1) includes country dummies.

2007b.) Especially educational requirements have a large economic impact, but also initial on-the-job learning has a strong effect on wages. The multiple correlation (R) between job complexity and wages is uniformly very high, between 0.4 and 0.6. We return to this pattern in several of the chapters below, beginning with Chapter 2, which contains an extensive discussion of social class inequality, concluding that class among employees is strongly tied to skill requirements.

In all countries except Britain, the wage increase of one additional year of required schooling is larger than the corresponding effect of one year of on-the-job initial learning. Britain has the highest economic payoff to both kinds of skill, but the difference in wage effects relative to other countries is twice as large in the case of firm-based skills as in the schooling case. Firm-based skill formation hence appears to be more important in Britain than elsewhere. With the exception of the Spanish labor market, the economic effects of continuing learning on the job seem small relative to the other two components of job complexity (educational requirements and initial on-the-job learning).

In sum, data from both the LNU and ESS surveys show clearly that job complexity is of paramount importance to understand vertical variation in work content. Evidently, given the very strong correlations involved as well as the high estimated reliabilities and tight connections between theoretical concep-
tion and measurement, the job complexity indicators are of high quality and utility. Still, there is obviously room for improvement, especially with regard to measuring continuing learning at work.

Conclusions

The main conclusions of the above discussion of conceptual and measurement issues related to the vertical differentiation of work tasks are as follows. First, job complexity is the main dimension of the vertical variation in work content. A large number of empirical studies in several disciplines converge on this conclusion. Productivity appears to be the driving mechanism of the tight link between job complexity and rewards. Second, time-based measures of job complexity (skill requirements) work well. By now there are well-established indicators of educational requirements and initial on-the-job learning, with good measurement properties. However, more work is needed on indicators of continuing on-the-job learning (both formal and informal).

Finally, aside from the vertical variation in work tasks examined here, horizontal variation in work content can be well captured by the distinction between working with things, data and people (TDP), as shown by research based on the US job classification systems DOT (Cain and Treiman 1981; Fine and Cronshaw 1999) and its successor O*NET (see, e.g., Handel 2016). Broad task indicators of TDP are included in several surveys, including LNU, ESS and the UK Skills and Employment Survey. Relations between vertical (job complexity) and horizontal (task variation within complexity levels) dimensions of work content are important issues to be examined in future research based on these and other data. Chapter 2 below develops a framework for understanding these relations by jointly considering the two arguably most fundamental dimensions of inequality: class and gender.

The book

The 17 chapters following this introduction each examine a specific but major aspect of the general topic of skills and inequality. The format differs across chapters, with some providing original empirical or conceptual analyses and others giving overviews of existing research. But regardless of format, all chapters are intended to open up vistas for new analyses of many kinds, together forming a comprehensive program and agenda for future research. As argued
above, the time is ripe for more systematically assessing the role of skills in the generation and reproduction of inequality, from a variety of different angles and for a wide array of economic and social outcomes. We hope that the present volume will contribute significantly to stimulating further development in this highly fertile field, both along the lines discussed here and in directions not yet envisaged.

References


Introduction

Class and gender are two core dimensions of stratification in the labor market. Arguably, they are the main axes in the structure of work-life conditions and rewards, perhaps corresponding to the twofold character of economic and social life: production and reproduction. Despite their fundamental importance in society, and their central place in research on inequality, the characteristics of work that underlie these two dimensions are still not well established.

The measurement of class and gender has serious shortcomings in the existing literature. Most fundamentally, measurement has suffered from strong tautological properties. Classes (among employees) have commonly been distinguished by grouping occupations into class categories without combining ex ante consideration of what characteristics that these occupational aggregates indicate with manifest measurement of those characteristics. Gender-typed (female or male) work has commonly been defined, in circular fashion, by grouping occupations based on the sex distribution of occupational incumbents. In contrast, the approach we develop below is based on job characteristics that are central for work-life inequality yet sharply distinct from standard categories of class and gender in their definition and measurement. Instead, class and gender emerge as outcomes of the latent dimensions that we distinguish empirically on the basis of explicit theoretical considerations. As will become clear, it is important to examine class and gender in a joint framework, since the structure of labor markets is indeed of a twofold character, reflecting both production and reproduction that depend on each other.

Gottfredson (1981) summarizes the universe of occupations in a figure with two dimensions: one vertical axis indicating ratings of prestige (from low to high, with strong links to class) and one horizontal axis indicating sex-type (from masculine to feminine). The ratings are based on subjective perceptions as revealed in population surveys. Gottfredson notes that these ratings of prestige and sex-type are remarkably accurate in that they correlate very strongly with actual inequality and differentiation (perceived prestige with real education...
tion and income, perceived sex-type with real proportions women and men in the occupations). She further observes that the ratings, despite their accuracy, are almost completely detached from descriptions of what the incumbents of these occupations actually do; i.e., of their daily work tasks. She concludes that most people do not know much “about job tasks and requirements, but they certainly possess a common general understanding of what it means socially and economically to have different jobs” (Gottfredson 1981: 551).

We attempt to bridge this gulf in research on work-life inequality between the well-established perceptions and measures of class and gender, on the one hand, and the hitherto vague, unsystematic impressions of work tasks and requirements that would appear to underlie the standard classifications, on the other. This detachment of major lines of research on social and economic inequality – using various indices of rank and other differentiation – from research on the detailed traits of different kinds of jobs – the kinds of tasks to be performed and the requirements for such performance – has long been evident. But little has been done to bring the two areas of inquiry together. We aim here to fill this gap.

The structure of work content: tasks and requirements for their completion

Our conceptual point of departure in assessing the structure of work content is the tradition of functional job analysis, originally developed by psychologist Sidney Fine (for overviews, see, e.g., Fine and Cronshaw 1999; Cronshaw 2012). Starting in the late 1940s, Fine prepared updates of the US Department of Labor’s Dictionary of Occupational Titles (DOT; first edition 1938, last revised 1991).

Fine (1955) suggested that all work is oriented toward three basic kinds of activities: dealing with things (physical entities), data (symbols) and people (interaction); TDP for short. This conceptualization was based on a massive data collection through on-site observations of a broad range of work activities and written descriptions of such observations. Factor analyses of highly detailed occupational traits as coded from these observational data support the TDP classification (see, e.g., Harvey 2004).

The fundamental unit of work is the task; jobs are collections of tasks, and occupations are collections of jobs. All jobs and occupations consist of some combination of tasks; single tasks are oriented toward things, data or people;
jobs and occupations consist of many tasks and are hence oriented toward things, data and people, although in different proportions. The specific mix of TDP indicates the basic task structure of each job or occupation.

In principle, variation in TDP across jobs and occupations is a horizontal dimension, expressing nominal rather than ordinal differences in work content. Fine further noted, however, that for each task orientation, different levels of complexity were involved in the work activities. Some tasks are easier than others to carry out; typically, the level of task difficulty corresponds to the amount of preparation and training required. A vertical dimension of complexity was therefore added to each of the three horizontally distinguished task types. This combination of horizontal and vertical dimensions produced a set of three scales: complexity in dealing with TDP, respectively. Each occupation in the DOT schema, around 12,000 titles in all, was assigned a value on these three scales (along with other information) in the revised edition designed by Fine, released in 1965.

During the 1990s, the US Labor Department came to the conclusion that further updates of DOT would be too costly and DOT was replaced with a new classification called the Occupational Information Network (O*NET; first edition 1998; see Handel 2016 for an overview and assessment).

The basic structures of the two classifications are very similar, however. Hence it seems safe to conclude that we are on solid ground when basing our mapping of the structure of work-life inequality on the insights from functional job analysis. Because of the strong patterning of work content along the dimensions outlined above, recent measurement in large-scale surveys rests upon the TDP classification in combination with work complexity. In the Swedish Level of Living Survey (LNU) 2010, each employed respondent was asked to describe her/his current job by reporting the extent to which the daily tasks are oriented toward TDP. The indicator on people-oriented work was split in two: (a) management tasks (workplace internal leadership) and (b) tasks involving interaction with people other than co-employees (such as customers, patients, pupils, etc.). For each of four task types – management, other people tasks, data and things – respondents were asked to report how large a part of their working time is spent on that kind of work. To these four items an indicator of work complexity was added: the educational requirements of the job currently held. As noted above, in the DOT classification work complexity is integrated into each task type, but we prefer to keep nominal task types and ordinal complexity levels separate for the purpose of analytic clarity.
These five indicators of work content are both necessary and sufficient in order to map the structure of work-life inequality as based on job traits. First, in line with functional job analysis, the trichotomy of work oriented toward TDP, respectively, needs to be taken into account, since omitting any one of them would evidently make the analysis incomplete. Second, a distinction needs to be made between two kinds of tasks oriented toward people, since internal management and interaction with non-employees are obviously distinct kinds of activities in the context of work-life inequality (see England 1992). Third, job complexity is a paramount feature of work content, as shown not only in functional job analysis but also more generally in several strands of work-life research in various disciplines (see Chapter 1 for an overview). Crucially, job complexity is the single most important characteristic tied to inequality in the labor market; for instance, as spelled out below, it is the main correlate of social class among employees (Tåhlin 2007; le Grand and Tåhlin 2013).

The division of labor by class

All class models – regardless of theoretical stripe – tend to place two job categories at the top of a vertical positional structure among employees: professionals and managers. Skills and authority are hence the two central dimensions of the hierarchical structure of labor market rewards. Different class theories can be sorted with respect to their explanations of why skill and authority determine rewards. There are two main types of such explanatory models: one emphasizing power, the other emphasizing efficiency.

Power-based class theories (e.g. Wright 1997; Goldthorpe 2000) use arguments tied to employment relations: professionals and managers have relations to their employers that fundamentally differ from those of other employee categories. Crucially, professionals and managers have a stronger bargaining position than other workers relative to the employer, and are therefore able to acquire relatively large rewards. In turn, this strong bargaining position is a result of two key vulnerabilities of employers: dependence on scarce skills and on uncertainty of work performance. Professionals’ and managers’ skills are in relatively short supply and their work tasks are relatively difficult to monitor by the employer. By exploiting these vulnerabilities, professionals and managers receive privileges from employers that other employees are unable to achieve. According to this kind of explanation, then, class distinctions among employees are rooted in labor quantities: relative supply of labor power (potential work) and relative supply of actual labor (delivered work). In order to ensure sufficient quantities of labor power and labor, employers offer mate-
rial rewards as incentives. The required level of such incentives is higher for professional and managerial jobs than for other jobs – hence class inequality in rewards.

In contrast, class models based on efficiency mechanisms are rooted in labor qualities: some kinds of work are more productive than others. Functionalist theories of stratification are examples of such models, although only some of them (e.g. Parsons 1949) are explicitly phrased in class terms; others speak more generally of stratification (e.g. Davis and Moore 1945), status (e.g. Ganzeboom et al. 1992) or prestige (e.g. Treiman 1977). Professionals and managers are able to achieve relatively large rewards because the work they do is of larger value to employers (or of larger importance for society) than other kinds of work; i.e., because professional and managerial work is more productive (yields a larger and/or better and/or more important output per time unit) than other work.

Theoretically, the efficiency line of explanation – based on labor qualities (rather than quantities) – is both simpler and more profound (fundamental) than the power line of explanation. It is simpler because it uses fewer and more straightforward mechanisms: work is simply rewarded in proportion to its productive value. While simplicity (all else equal) is a theoretically attractive trait, of larger importance is that the efficiency model is more fundamental. The power model is based on arguments tied to labor quantities. Professionals and managers are (believed to be) more able than other workers to extract large rewards from employers by threatening (explicitly or implicitly) to withhold their supply of skills and effort. In this context, the crucial question is why employers find it rational to pay such surplus rewards. If supply and effort in some kinds of jobs are not forthcoming at the level of rewards for other kinds of work, why not simply cut such demanding jobs from the work organization? In other words, why do employers create and keep (relatively) expensive jobs rather than filling their organizations exclusively with (relatively) cheap ones? For some reason, employers must believe that professionals and managers are worth hiring and keeping, despite the relatively high material cost for doing so. It is hard to see any other reason than the belief (correct or not) that the value of professional and managerial work is higher than the value of other work; i.e., that it is more productive than other work.

The theoretical conclusion is that the power model’s attempt to escape from the productivity mechanism fails: the escape consists in formulating a bargaining model with differential threat capacity across employee classes, rather than differential productive capacity. But it is hard to see any rational basis for superior threat capacity other than superior productivity.
Aside from these logical or conceptual considerations, there have also been empirical tests of the power-based class model (Tåhlin 2007; le Grand and Tåhlin 2013). These tests have clearly shown that the empirical basis of the power model is very weak. Class differences in scarce skills and in monitoring difficulties are simply far too small to affect class differences in rewards to any significant extent. Theoretical and empirical arguments taken together thus strongly indicate that power-based class models should be abandoned or at least extensively revised.

It is important to note, however, that power rather than efficiency is likely to be the main operative mechanism at the macro level. While efficiency determines the close to universal rank order of class rewards at the micro level, the distance between ranks is driven by institutional factors at the macro level with relative power resources of different classes as major causes. Institutional variation across time and place is large, with inequality rates hence differing markedly across periods and countries; see Chapter 17 below for an assessment of cross-country differences in this regard.

Aside from skill requirements and authority, there is a third clearly class-related job trait: manual versus non-manual work tasks. Manual tasks can be indicated by work oriented toward things, while non-manual tasks can be indicated by work oriented toward data or symbols. This distinction is empirically associated with skill requirements and authority, since the latter – for a variety of reasons – tend to be lower on average among manual than among non-manual workers. Yet, the manual/non-manual distinction is qualitatively different. Skill and authority are vertical job traits that can be clearly ranked on a scale from high to low, and are commonly accepted (e.g. by both employers and labor unions) reward criteria. The difference between manual and non-manual work is of another kind. Historically, white-collar occupations have tended to have a higher social status than manual worker occupations, reflected, for example, in the border between the office and the workshop. But there is no rational mechanism that can tie this distinction to productivity, aside from its empirical associations with skill and authority. Therefore differences in rewards between manual and non-manual employees, given complexity and authority, are apparently based on a pure social construction. The manual/non-manual distinction is hence a horizontal dimension with vertical consequences.

There are at least two causes of these vertical consequences. One is that manual jobs have come to be connected with low skill requirements (especially with regard to educational requirements in the sense of formal schooling) as well as with limited managerial responsibilities. Manual jobs might therefore be seen as less worthy of rewards, even if the manual/non-manual distinction is not in
itself viewed as a relevant determinant of rewards (i.e., is not seen as tied to productivity). To the extent that this explanation is valid, it can be assumed that the social construction consists of suppressing internal stratification within the category of manual workers, in wages and hierarchical divisions, either for ideological reasons – equality as an intrinsic value, or for more instrumental reasons – to maintain collective solidarity as a power device.

The other cause of the class relevance of the manual/non-manual divide is the traditionally higher status of mental than physical work. Of course, this is a very old if not ancient status distinction (see, e.g., Khan 2001 for an historical overview). Its foundation is linked to the strategies of elite groups in many different societies – from East to West, across cultural and religious traditions – to ensure that manual work, often physically demanding and socially demeaning, is carried out by relatively powerless groups. Conspicuous freedom from manual tasks has been a common indicator of high social status. This hierarchy of work has at least partly survived into modern times despite radical changes in social organization in other respects.

According to some contemporary class analysts (e.g. Wright 1985), the essentially horizontal character of the manual/non-manual distinction makes it less relevant in a class perspective than the vertical dimensions of skill and authority. In our view, by contrast, it is precisely the horizontal character of the distinction that makes its vertical consequences problematic in a normative perspective. For any given level of skill and authority, reward differences between manual and non-manual work to the latter’s benefit lack a legitimate basis. In this light, the issue of class becomes recoupled with power aside from efficiency.

The division of labor by gender

It is difficult to talk about a gendered labor market without a discussion of what gender actually is. Here we distinguish between gender and biological sex, or maybe more correctly specified, legal sex; the sex that is registered on one’s passport. The term sex has a reference to reproductive functions, the biological and hormonal differences between men and women. Gender is socially and culturally constructed, and is an achieved status (or role) based on culturally shared beliefs of masculinity and femininity (e.g. Rubin 1975).

The distinction between sex and gender is, however, not unproblematic and has been criticized. The most common critique may be that the division of sex
and gender may result in perceiving sex as something static, something that is beyond social and cultural change. But legal sex and the definition of biological sex is also a social construction (e.g. Butler [1990] 1999). In contrast, critics from fields outside social science (and the humanities) may assert that the term gender offers too much space for cultural influence, and argue that behavioral differences between men and women are primarily caused by biological and hormonal variation.

Regardless of how gender and sex are defined, it is clear that most societies – past as well as contemporary – have some kind of division of labor between males and females. But people differ in their view of the causes of these gender differences; i.e., to what extent they are biological, socially constructed or the outcome of biosocial processes (Wood and Eagly 2012).

Male and female tasks?

A common explanation of the gendered division of labor, where women largely perform work oriented toward people – relational work – and men work oriented toward things, is the above-mentioned formation of gender roles that constructs the settings for what types of activity are seen as suitable for girls and boys. According to Gottfredson (1981), children tend to aspire to occupations that fit with their self-concepts. The self-concept is defined as a person’s view of her/himself and consists of elements such as gender role (the most important component), abilities, social status and values. Gottfredson argues that all people share a common “cognitive map of occupations” (such as what kinds of people work in different occupations and the rewards they get). This map has a vertical dimension according to occupational prestige and a (mainly) horizontal dimension of gender: masculinity–femininity.

Historically, this division by gender is rooted in women’s childbirths and men’s larger physical strength and size compared with women (Wood and Eagly 2012). Today, women’s reproductive role is less consequential but women still spend much more time in unpaid labor taking care of family compared to men. Furthermore, while size and strength can vary both between and within biological sex, childbearing is – so far – only possible for biological women. Nevertheless, women are typically seen as nurturing and caring – performing relational work (cf. communion or expressiveness), while men are seen as assertive and powerful (cf. agency or instrumentality) (Bakan 1966; see Wood and Eagly 2012 for an overview). Thus, the division of labor could, simplified, be seen as existing of these two major dimensions – agency and communion – which are mutually dependent of each other (Bakan 1966).
The incumbents of these tasks (or roles) could, theoretically, be equally distributed between men and women (with the exception of childbearing) but the two dimensions of communion and agency are always present in all societies. The tendency to “gender” these dimensions, where expressive is seen as feminine and instrumental as masculine, has long been present in many disciplines (see, e.g., Freud 1927; de Beauvoir [1949] 1971; Parsons et al. 1954). In Parsons’ theory of the social system, instrumental (husband) actions and expressive (wife) actions are equally important for the system; both contain power, but different types of power (Parsons et al. 1954). Johnson et al. (1975) build on but modify Parsons’ theory and assert that both men and women, or all types of roles, contain both instrumental and expressive actions. They claim that expressiveness and instrumentality are two separate dimensions that do not stand in mutual opposition to each other. All kinds of combination between these two dimensions are, thus, possible as they are uncorrelated with each other, indicating that a person could score high (or low) on both expressiveness and instrumentality. Furthermore, and even more important here, Johnson and her colleagues claim that gender is related to expressiveness while instrumentality is not. “Femininity” might, in general, tend to be more expressive and “masculinity” to be less expressive, but expressiveness does not exclude instrumentality.

According to this line of reasoning, the gendered division of work is primarily related to communion while agency is a separate dimension not clearly connected to gender. From our point of view, communion is closely linked to relational work tasks, thus related to the horizontal dimension of the labor market where men and women (currently, on average) carry out different types of tasks: relational work, on one side, and work oriented toward things on the other. Agency is instead related to the vertical dimension (the class order) in the labor market and thus not tied to gender, at least not in contemporary societies where high-prestige occupations to a large extent are gender-integrated rather than male-dominated (Magnusson 2009). This does not imply that there is no gender bias in rewards tied to job traits. Such bias tends to exist both within jobs and between jobs. Furthermore, relational work tends to be less rewarded – regardless of the sex of the employee performing it (England et al. 2002). The gender wage gap is still persistent in all affluent countries and along the whole vertical order in the labor market, but today the gap tends to be largest in the upper part of the vertical distribution (Magnusson 2009; Blau and Kahn 2016). Vertical aspects are of course not irrelevant. In particular, authority (management tasks) tends to be tied to gender inequality.

Most of us would probably agree that gender roles are more flexible and less stereotyped today compared with the early 20th century. Occupations that
earlier were closed for women, such as physician or priest, now have many female incumbents. Since the 1970s the work-life of women has changed as they have increased their participation and time in paid labor and to a large extent entered high-skill occupations (e.g. Blau and Kahn 2017). In that sense, the vertical dimension of gender has become much weaker over time (see chapter 5 below on occupational sex segregation). This change has also influenced beliefs concerning gender relations. Many studies point out that differences by gender in personality and behavior have declined during the 1900s, much due to an increase in women’s “masculine” attributes, although the gender difference in feminine attributes has changed less (Twenge 1997; Wood and Eagly 2012). Accordingly, theoretical conceptions of male primacy were relevant when understanding the historical division of labor but have less explanatory value when understanding contemporary societies.

In contrast, the horizontal dimension remains strongly tied to gender. In line with Gottfredson (1981), we hypothesize gender to be clearly linked to the horizontal dimension of work-life differentiation but much less systematically to the vertical dimension. Thus, we expect that the “role” of communion in contemporary society is linked to gender while that of agency is not.

Despite these expectations, however, we do not yet have a sharp view of what gender-typed work actually is. Our contribution here is that we, unlike much prior research, do not base our conception of gender-typed work on the sex distribution of occupational incumbents. Thus, we do not force the gender dimension to be based on sex as a legal category. Moreover, in our model, in contrast to prior research (e.g. Charles and Grusky 2004; Levanon and Grusky 2016) we do not, in advance, firmly ascribe aspects of work content or skills as either masculine or feminine. While we, guided by previous research, formulate expectations of how the structure of work content might be linked to class and gender, we avoid preconceiving the dimensions to be examined. Lastly, we simultaneously consider class and gender as separate dimensions without forcing them to be related to each other in any particular manner.

**Empirical findings**

Our empirical analysis proceeds in three main steps. First, we examine how the five work content indicators are associated with each other, via factor analysis. Second, we test this interpretation by correlating the two work content factors with standard measures of class and gender. Third, while the work content dimensions of class and gender are linearly orthogonal (mutually uncorre-
lated) by construction, it is well known from earlier research (e.g. Magnusson 2009) that gender is related to vertical axes of labor market rewards (such as prestige and wages) in an inversely U-shaped pattern: rewards tend to be low in gender-typed positions, whether female or male, and high in gender-integrated positions. The main proximate reason for this pattern is that working-class jobs tend to be gender-typed, dominated by either women or men, while positions requiring relatively long education tend to be gender-integrated. This might be explained by the fact that complex jobs are gender neutral, in the sense that they are desired by both genders, and are not associated with the historical division of labor based on women’s childbearing and men’s larger physical strength (Wood and Eagly 2012).

Further, female-dominated occupations tend to be located relatively close to the middle of the class structure while male-dominated occupations tend to be found relatively close to either low or high class levels (with the low-level tendency slightly stronger than the high-level one). This relationship is closely related to a common critique against the measurement of skills. Critics assert that many skills in female labor are invisible, hence the sex bias in skill evaluation (see Steinberg 1990 for an overview). In particular, authority used in female-dominate occupations is clearly recognized, while authority used by women, such as coordinating the provision of service and care, is often invisible (Steinberg 1990). This sex bias is then incorporated in the coding of occupations that in turn underlies the construction of class schemas. Categories of female-typed work are hence lumped together with less differentiation according to authority and skill level than male-typed work. We examine these curvilinear properties of the class–gender associations further below.

In the factor analysis (principal components) of the five work content indicators – job complexity and tasks oriented toward management, data, things and people – two dominant and distinct factors emerge; see Table 2.1. The first is strongly and positively related to job complexity, management tasks and work oriented toward data, and strongly negatively related to work oriented toward things (manual tasks). The second factor is strongly and positively related to people-oriented tasks, moderately and negatively related to manual tasks (things), and weakly to moderately and negatively related to management tasks. These two factors together account for 80 percent of the full variation of the five indicators, 54 percent for the first factor and 26 percent for the second.

The covariation among the five indicators can thus be usefully reduced to two dimensions, the first one clearly (but not only) vertical and the second mainly (but not only) horizontal. Based on our discussion above, a straightforward
Table 2.1 Factor analysis of five work content indicators

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
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<tbody>
<tr>
<td>Job complexity</td>
<td>.88</td>
<td>.14</td>
</tr>
<tr>
<td>Management tasks</td>
<td>.73</td>
<td>-.34</td>
</tr>
<tr>
<td>Data-oriented tasks</td>
<td>.86</td>
<td>-.08</td>
</tr>
<tr>
<td>Things-oriented tasks</td>
<td>-.82</td>
<td>-.50</td>
</tr>
<tr>
<td>People-oriented tasks</td>
<td>-.02</td>
<td>.96</td>
</tr>
</tbody>
</table>

Note: Factor loadings (principal components, varimax rotation; i.e., constrained to be linearly uncorrelated). All indicators are cell means of individual responses (N=3,509) by two-digit ISCO occupation (25 categories). Job complexity is a factor-based index of three items, aggregated by occupation: self-reported educational requirements (years beyond compulsory school) of current job, initial learning time of current job and continuing learning in current job; see Chapter 1 above for details concerning these items. Management, Data, Things and People are self-reported work task orientations (expressed as proportions of total working time; these proportions may be overlapping; i.e., do not necessarily sum to unity) of the respondents’ current job.

The interpretation of this simple pattern is to associate the first factor with class and the second factor with gender.

Next we validate this interpretation by correlating the two factors based on work content with standard measures of class and gender. For class, we use location in the standard EGP schema (see, e.g., Erikson and Goldthorpe 1992) of the 25 occupations. Each occupation is assigned a class score based on the class distribution of their incumbents, using a schema with five EGP classes (among employees only: unskilled (VII, IIIb) and skilled (VI) workers, low- (IIIa), mid- (II) and high-level (I) salaried employees). A composite class score for each occupation is obtained through factor analysis (principal components, first rotated factor). For gender, we simply use the female share of each occupation.

The two class measures – one based on work content, the other based on the EGP schema – correlate .91 with each other. The two gender measures – one based on work content, the other based on occupational sex distributions – correlate .83 with each other. In a factor analysis (principal components, varimax rotation) of these four variables, the two class measures both correlate .98 with the first factor (“class”), while the two gender measures correlate .96 and .95, respectively, with the second factor (“gender”). We conclude that the work content measures of class and gender are close to perfect indicators of the standard variables while completely – and crucially – avoiding tautological (circular) elements (for details of these analyses, see the Online Appendix).
Lastly, we estimate associations between class and gender. By construction, the work content-based measures are orthogonal to (uncorrelated with) each other. This is actually not far from the unconstrained associations involved: the correlation between the standard measures of class (EGP) and gender (occupational sex distribution) is only .10; i.e., the standard dimensions have only a single percent (.10 squared) of their variation in common. But we know from earlier research (see above) that class and gender are strongly interrelated when curvilinear associations are taken into account. This is confirmed by correlating the work content-based measures of class and gender with their squared counterparts: the correlation between class and squared gender as well as the correlation between gender and squared class are strongly negative, hence producing the expected inverted U-shape in the class–gender relations. Mid-level gender (sex-integrated) occupations are high in class (the correlation is .46); mid-level class occupations are high (female-tilted) in gender (the correlation is .40) (for details, see the Online Appendix).

Explaining structural change

As shown above, the job structure of a society consists of a number of positions that can be vertically and horizontally ordered; we visualize this in Figure 2.1. Over time, the job structure has shifted in two directions: vertically upward – i.e., rising skill requirements (see arrow A in Figure 2.1) – and horizontally rightward – i.e., a growing share of jobs with people-oriented tasks (see arrow B in Figure 2.1). These structural shifts can be seen as skill upgrading and service expansion, respectively. Note that the figure drawn as a single triangle is a simplification of the empirical patterns revealed above. In line with the curvilinear associations estimated above, the right-hand side of Figure 2.1 should have an eastward tip at the diagonal line’s mid-point. Such a tip indicates the concentration of female-dominated occupations in the middle of the class structure, as a complement to the concentration of gender-integrated occupations in the top of the class structure. While both of these curvilinear associations are empirically real (with the latter stronger than the former), the dynamic features of Figure 2.1 are indicated within a single triangular form for the sake of visual clarity. To get a more realistic impression of the empirical patterns found above concerning how class and gender are related, imagine cutting off the smaller triangle indicated at the lower-right part of the figure from the larger triangle.

The two structural shifts – skill upgrading (A) and service expansion (B) – are mainly driven by technological change in combination with institutional
Factors. Technological development in manufacturing is the igniting force leading to rising skill requirements. First, productivity in the goods-producing sector grows due to improvements in technology. Second, this leads to rising wages in manufacturing. Third, the wage growth then spreads to other sectors of the economy (Baumol 1967), since wage differences across sectors tend toward zero due both to institutional (fairness norms and collective action) and market mechanisms (labor mobility). Fourth, the transmission of wage growth over the entire labor market raises the wage floor (the minimum level of accepted wages) in all industries, regardless of changes in their productivity. Fifth, since wages and productivity are tightly linked, employers’ requirements of labor productivity increase generally, which means that the least productive jobs – that typically have the lowest skill requirements – are gradually eliminated because they cannot carry (pay off for the employer) the raised minimum wage levels.

The outcome of this chain-reactive process is a general upward shift of the skill structure; i.e., a rising share of high-skill jobs and a falling share of low-skill jobs. This upgrading of the class structure has been the dominant tendency in all economically advanced societies in at least the most recent decades and probably in the last century (e.g. see Katz and Margo 2014 on the long-term development in the United States). Country-specific institutional traits have played a modifying role.

Technological development in manufacturing leads to a declining number of manual jobs (working with things), but the growth in productivity increases demand for other kinds of work throughout society. In recent decades, IT expansion has also led to elimination of many white-collar jobs, especially low-level clerical work. In contrast, people-oriented work tasks have so far not
been replaced by technology to any large extent, even if the currently rapid development of robots appears to provide new possibilities in this regard.

People-oriented work has expanded for a long time. A fundamental driver of this expansion has been the transformation of family life. When care for children and the elderly becomes organized collectively – by society – rather than within individual families, many work tasks move from the informal to the formal economy.

The structural movements over historical time along the vertical and horizontal axes – skill upgrading and service expansion, respectively – will be examined in more detail in Chapter 4 below. We close the present chapter with a concluding discussion of the dimensions of class and gender revealed by our analysis above.

**Divisions of labor: universal and eternal but socially variable**

We began the chapter by referring to the common observation that the material structure of human life is of a twofold character, with both production and reproduction as core features. As discussed above, at an even higher level of abstraction this duality can be seen as reflecting two fundamental “modalities” of human existence: agency and communion (Bakan 1966). They underlie a large number of related conceptual distinctions in patterns of human life, identified since antiquity (see, e.g., the overview in McAdams et al. 1996).

We suggest that class (agency) and gender (communion) can be seen as (con) temporary – and thus variable – manifestations of this eternal (constant) duality. The agency–communion duality is eternal and irreducible in human life, arguably corresponding to the likewise eternal and irreducible divisions by age and sex. Agency corresponds to age (the word age is indeed the first half of the word agency); communion corresponds to sex.

Age and sex are the two most central socially consequential dimensions in all societies, past and present. Human conception, birth, life and death are defined by them. No description of any human society, regardless of time and place, can do without them. Class is derivative of age; think, for instance, of education (requirements) as condensed experience (requirements) and experience as condensed age. Gender is derivative of sex. Divisions by class and gender are (close to) universal, but their forms and demarcations vary across societies,
and can – at least in principle – become abolished or redundant. We can and
do conceive of class-less and gender-less societies, typically as ideals, albeit
utopian. Age-less and sex-less human societies are (hardly) even conceivable.
All human divisions are profoundly contingent, except these two. While their
implications and consequences are of course highly variable, their existence
is constant. Women and men alike can in principle be located at any point
along these two dimensions, although in practice women have tended to be
more communal than men – hence the link between sex and gender – while
men have held more agentic positions than women – hence male class advan-
tage. Agency and communion are fundamental, eternal and universal traits
of human life – this is the point of using them as analytic concepts – but the
intersections between class and gender along the two underlying dimensions
are empirically fluid and thus historically variable; they are currently changing
rapidly.

Class is clearly less variable than gender in this regard. In contrast, sex/gender
is historically variable, with a decoupling of gender and agency almost com-
pleted in many contemporary societies, but with the communion–gender
link still strong. Still, even this link can obviously be broken, to the extent that
the association between sex and childbearing (including childcare through
infancy) can be cut off, as is currently being done at least for childcare, but
perhaps emerging for childbearing as well (through new social and technolog-
ical design).

Class and gender are arguably the two major dimensions of stratification in
the labor market. As we noted above, despite their fundamental importance,
the characteristics of jobs that underlie these two dimensions have so far not
been well established in the literature. Our aim in the present chapter has
been to advance understanding of this issue. Our analytic strategy has been to
bring together two major areas of inquiry: the study of social and economic
inequality and the study of work tasks and job requirements. On the basis of
a set of hypotheses on how the structure of tasks and requirements underlie
the major dimensions of inequality, we have used data from the LNU to
provide links between the world of work and the world of social and economic
stratification and differentiation. Hopefully, we have managed to bridge the
gulf that Gottfredson (1981) identified several decades ago: that between
well-established perceptions and measures of class and gender distinctions,
on the one hand, and vague, unsystematic impressions of the work tasks and
requirements underlying these distinctions, on the other.

This bridge can lead to several avenues of future research. We now have
explicit, non-tautological measures of class and gender. They can be applied to
all areas of social and economic life in which class and gender distinctions and interactions are important for the structure and change of living conditions. Hence, the potential domain of application is vast.

References


More than 40 years ago Blau and Duncan (1978), Jencks and colleagues (1979), and Bowles and Gintis (1976) set parameters for the study of social stratification and inequality that persist to this day. Every society has an occupational structure that is hierarchical in terms of the skill requirements and the associated prestige and compensation levels of jobs. Parent-to-child social mobility as well as social and economic inequality between sociodemographic groups can be measured by the skill, prestige and compensation levels of the jobs attained. Becker (1964) defined these skills as human capital, which is attained through schooling and on-the-job training. Hanushek and Woessmann (2015) showed that inequality in the relative prosperity of nations, and in the growth of this prosperity, can be explained by inequality in the human capital of their populations when this human capital is measured by cognitive skills assessed by test scores (but, crucially, not by years of schooling attained). Schooling, skills, occupational requirements, attainment and earnings are thus the concepts used by many sociologists and economists to describe and explain social and economic inequality.

One might suppose that this commonality of focus and terminology would have brought these two social scientific fields closely in tune with one another. Indeed, there is a synthesis of studies from each field that can provide an integrated and powerful perspective from which to address issues and improve our understanding of the distribution of skills and occupational attainment within and between nations. Yet this is not well known. Thus, the goal of this chapter is to present this synthesis, explaining how notions of cognitive and noncognitive skills, human and cultural capital and occupational job tasks have evolved to form an intellectual perspective that is rapidly increasing our understanding of these important issues.
Cognitive and noncognitive skills

The available private and public sector jobs, and the processes determining access to these jobs, constitute an economic and social structure of slots that can be occupied by workers, referred to as the demand side of the labor market. Each job has an employer who typically advertises the qualifications needed, often stated as “skill requirements.” On the supply side are workers, possessing varying skills and other characteristics, including the highest educational credential attained. One or more workers are hired, typically from among multiple applicants, with the total supply of and demand for workers constituting the labor market. Studies of inequality in this market have often focused on the distribution of skills, credentials and other worker characteristics among the population defined by parental social class background, gender and race/ethnicity or country of origin, and how these worker characteristics have typically been matched with the characteristics of the jobs available. Particular emphasis has been given by sociologists to searching for unfairness or bias in the determinants of worker skills and credentials, or in the hiring process matching workers to jobs. Such studies have been fundamentally defined by how worker skills and the skill demands of jobs have been measured.

Both Bowles and Gintis (1976) and Jencks et al. (1979) posited that cognitive skill, achieved via K-12 and higher-level schooling, and measured by standardized tests, is central to occupational attainment. They also believed that “forms of consciousness, interpersonal behavior, and personality” (Bowles and Gintis 1976, p. 9) as well as traits such as “ambition, good attitudes, high aspirations, and good judgment” (Jencks et al. 1979, p. 122), over and above cognitive skill, help determine labor market success. These individual traits have come to be referred to as noncognitive or socioemotional skills (Farkas 2003). As recently summarized by Heckman, Jagelka and Kautz (2019, p. 3):

Achievement tests do not adequately capture non-cognitive or socioemotional skills, a broad set of characteristics including preferences and personality. Examples include perseverance (sometimes called “grit”), conscientiousness (also called “grit”), self-control, trust, attentiveness, self-esteem and self-efficacy, resilience to adversity, openness to experience, empathy, humility, tolerance of diverse opinions, and the ability to engage productively in society, which are valued in the labor market, in school, and in society at large.

While there has been long-standing agreement that cognitive skills are adequately measured by test scores, much research attention has been given to noncognitive skills, addressing questions such as the following: which noncognitive skills are most important for inequality studies, and how should they be
measured? What determines within- and between-nation variation in noncognitive skills? What are the magnitudes of effect of different noncognitive skills on schooling, occupational and earnings outcomes at the individual level, and of economic growth at the national level? Which if any interventions are able to raise the noncognitive skills of disadvantaged individuals and nations?

Human and cultural capital

Farkas et al. (1990) and Farkas (1996, 2003, 2018) connected these questions to sociologist Pierre Bourdieu’s concept of cultural capital, which has come to be defined as long-lasting dispositions of the mind and body or as skills, habits and styles that individuals use to construct strategies of action. “Other names for these dispositions and skills include informal know-how, cultured capacities, practices, repertoires, orientations, tools, and procedural knowledge” (Farkas 2018, p. 5). The broad applicability of this concept to any and all activities that have an element of learning-by-doing is shown by Wacquant’s (2004, 2011, 2014) use of these ideas to describe how one learns to become a boxer. Farkas’ (2018, pp. 8–16) review of Wacquant’s work as well as that of others in this tradition demonstrates that such learning-by-doing, in which both cognitive and noncognitive skills are intertwined, is central to many if not most fields of human endeavor. Research into a particular activity requires understanding exactly which cognitive and noncognitive skills are central to the activity, how they interact and evolve over time, and how outcomes for individuals and nations are affected by the social and economic structures within which they occur.

Bourdieu invented the cultural capital concept so that sociologists could use it to explain the unequal academic success of children from different social classes (Bourdieu 1986, p. 243). Economists had already been employing the concept of human capital for the same purpose. As explained by Farkas (2003, 2018), when sociologists include cognitive skills within the cultural capital paradigm and economists include noncognitive skills within human capital, the two research traditions overlap. Because the two fields tend to begin with differing political stances, sociologists will likely continue to emphasize individual and societal bias and discrimination, while economists tend to emphasize individual choice and rationality and societal investment. Nevertheless, as long as each field is concerned with cognitive and noncognitive skills of individuals as well as each type of skill demands of jobs, sociologists and economists are essentially studying the same phenomena. Thus, for example, measuring noncognitive skills, both sociologists Jencks and colleagues (1979) and economists
Heckman, Jagelka and Kautz (2019) focused on similar personality characteristics defined by psychologists. In recent years researchers have focused on the “Big Five” – emotional stability, agreeableness, extraversion, conscientiousness and openness to experience. When each of these, as well as a measure of cognitive skill, are correlated with job performance, by far the highest correlation is with cognitive skill, with conscientiousness second (Heckman, Jagelka and Kautz 2019, figure 4). There is a large and growing literature investigating these and additional measures of noncognitive skills, as well as seeking to discover the extent to which cognitive and noncognitive skills predict success at school and work and account for class, race/ethnicity and gender differences in such success.

Bourdieu’s concepts of habitus and cultural capital attempt to add social and psychological reality to the economists’ notions of “rationally chosen” human capital investment. Quoting a variety of authors who have built on these concepts, Farkas (2018, pp. 8–12) explains that lower- and middle-class families, neighborhoods and peer groups socialize their children into different early habitual dispositions, skills and habits (see Lareau 2011), which in turn affect and determine the children’s strategies of action during the K-12 years (see Swidler 1986). These in turn interact with the larger external world. As summarized by Jenkins (1992, p. 78):

The habitus disposes actors to do certain things, it provides a basis for the generation of practices. Practices are produced in and by the encounter between the habitus and its dispositions, on the one hand, and the constraints, demands, and opportunities of the social field or market to which the habitus is appropriate or within which the actor is moving, on the other. This is achieved by a less than conscious process of adjustment of the habitus and practices of individuals to the objective and external constraints of the social world.

Wrong (1994, pp. 48–49) explained that such social interaction over time can generate norms of behavior that differ across social groups:

Instead of thinking of habit-expectation-norm as a seamless structural unity of simultaneously present elements or aspects, one might think of it as a sequence emerging in the course of time. Repeated interactions give rise to habits. They are perceived by the actors and become expectations in the sense of predictions or anticipations of behavior. Aware of what is expected by the other, each actor feels constrained to live up to the expectation, partly out of a feeling that the other will be irritated, offended, or disappointed if the expectation is not fulfilled. In short, interaction generates habits; perceived, they become reciprocal expectations; in addition to their purely predictive and anticipatory nature, sensitivity to them endows them with a constraining or even an obligatory character. This entire process is in no sense willed or even fully foreseen by either party. It is a *sui generis* resultant of their recurrent situated interaction. Whatever the needs, motives, and interests under-
lying this interaction, its continuation has precipitated mutually binding sets of expectations. Thus do norms grow in unplanned fashion out of ongoing interaction.

To take one example, low-income Black student underinvestment in education may become a norm if its interpretation as “acting White” becomes accepted within the adolescent peer group. In this case, special strategies of action may be required by Black students wishing to try hard at school while minimizing negative feedback from peers (Fordham and Ogbu 1986; see also Carter 2005).

Cultures and behavioral norms of national groups

Recently, economists have sought to measure cultural differences between national groups by computing the average values of particular noncognitive skills among individuals in each of these groups. Analyzing data from the Program of International Student Assessment (PISA), Figlio et al. (2019) focus on a variable previously studied by Hofstede (1991) and Hofstede, Hofstede and Minkov (2010, hereafter HH&M), referred to as Long-Term Orientation (LTO). This is described by HH&M as the cultural value that “stands for the fostering of virtues oriented toward future rewards, perseverance, and thrift.” (The principal survey item used is parental answers to the importance of thrift as a desirable trait for their children. See Figlio et al. (2019), footnote 16 on p. 282.) Figlio et al. (2019) describe this as a measure of the ability to defer gratification and exert self-control. This measure of the individual’s value of the trade-off between consumption and investment today enabling greater consumption in the future has long been a central feature of economists’ models of investment. This is particularly relevant for theories of human capital investment, since schooling investments require considerable patience before the return on investment is received. Using student-level data on immigrant children from different cultures (countries) in the same location, Figlio and colleagues find that, controlling a host of variables, children from those countries with a high average LTO score have better educational outcomes.

Related analyses are reported by Hanushek et al. (2020). Analyzing data from PISA and also from the Global Preference Survey (GPS), they focus on two cultural trait variables: patience and risk-taking. They consider the first of these synonymous with deferred gratification (like Figlio et al., measured by “thrift”), while the second measures a preference for risky outcomes over those that are certain. Risk aversion is important for human capital investment since it may reduce individuals’ chances of getting into trouble and thereby derailing their schooling investment. Undertaking analyses of migrant student
achievement similar to those of Figlio et al., Hanushek et al. (2020) find that among migrant students from different country-of-origin cultures observed in the same residence country, those from countries with higher average scores on patience and/or lower average scores on risk-taking show higher academic achievement, net of a host of control variables. The authors argue that the analyses are most definitive when both cultural measures are included simultaneously in the regressions, since they are substantially negatively correlated.

It is worth noting that this work by economists extends the field of “national character studies” originated by anthropologists Margaret Mead and Ruth Benedict (see, for example, Benedict 1946), which was subsequently “discredited” by Terracciano et al. (2005). This latter study used a very broad statistical brush to deny the existence of national character traits. By contrast, the economists’ studies have focused on one or two traits related to conscientiousness, and statistically demonstrated their relatedness to individual and national rates of educational investment and economic advancement.

**Noncognitive skills, deferred gratification and risk-taking**

How does the psychologists’ measurement of personality characteristics, as employed in research on noncognitive skills by sociologists (e.g. Jencks et al. 1979) and economists (e.g. Almlund et al. 2011; Heckman, Jagelka and Kautz 2019), relate to the recent work by economists (e.g. Figlio et al. 2019; Hanushek et al. 2020) on deferred gratification (time discount rate) and risk-taking? Estimating a model taking random components of decision-making into account, Jagelka (2020) finds that the two measurement approaches overlap substantially.

Up to 50% of the variation in risk aversion, discount rates, and in parameters governing individuals’ choice consistency can be explained by cognitive ability and personality traits. Conscientiousness is the trait with the highest overall explanatory power, in line with previous results on the predictive power of personality traits on real-world outcomes. It explains 33% of the cross-sectional variation in discount rates, 9% of the variation in risk aversion, and 23% of the variation in their individual-level stability. (Jagelka 2020, p. 46)

To summarize, as shown by Heckman, Jagelka and Kautz (2019) and Mendez and Zamarro (2018), cognitive skill and conscientious work habits are the strongest predictors of educational and occupational attainment as well as earnings. These are what employers want from their workers, and what are associated with the greatest labor market success of workers. These cognitive
and noncognitive skills explain significant portions of group differences in educational, occupational, employment and earnings outcomes.

**The demand side**

The supply of worker skills is only half the story. The other half involves employer demand for these skills, and how this demand varies over time across the jobs available in the occupational structure, which is determined by the work tasks involved in these jobs, the technology with which these tasks are accomplished and the earnings linked to these jobs. The central empirical trend here is the rising skill premium over the past three decades. During this time period the earnings gap between college and high school graduates has more than doubled in the United States (Autor 2014). This has been a major determinant of strongly rising earnings inequality over this time period. Economists (e.g. Autor, Levy and Murnane 2013, hereafter ALM; Goldin and Katz 2008) investigated such “skill biased technological change” by examining how computerization has affected the task composition of jobs. These authors distinguish between “routine” and “nonroutine” job tasks. The former involves tasks that are sufficiently well defined that they can be carried out by a computer program. These include repetitive production tasks, bookkeeping and clerical work. ALM’s distinction between routine and nonroutine tasks, and the effects of computerization on the share of these in the economy, has been summarized by Autor and Price (2013, pp. 2–3) who replicated and extended ALM’s findings:

ALM argue that as computers have taken over our routine tasks, they have boosted demand for workers who perform “nonroutine” tasks that are complementary to the automated activities. What are these nonroutine tasks? They can be roughly divided into two major categories that happen to lie on opposite ends of the occupational skill distribution. On one side are so-called “abstract” tasks, which require problem-solving, intuition, persuasion, and creativity. These tasks are characteristic of professional, managerial, technical and creative occupations, such as law, medicine, science, engineering, marketing and design. Workers who are most adept in these tasks typically have high levels of education and analytical capability, and they benefit from computers that facilitate the transmission, organization, and processing of information … On the other side of the occupational skill spectrum from abstract tasks are so-called “manual” tasks, which demand situational adaptability, visual and language recognition, and in-person interaction. Tasks like preparing a meal, driving a truck through city traffic, or cleaning a hotel room present mind-bogglingly complex challenges for software engineering. But from the human perspective, these manual tasks are straightforward, requiring primarily innate abilities like dexterity, sightedness, and language recognition, and perhaps a modest amount of training.
Thus, more powerful computers at decreasing prices have substituted for human workers in jobs with routine tasks, leading to fewer such jobs being available to workers. Economists have attributed the static or falling real wage rates of high-school-educated workers, and the rising real wage rates of college-educated workers, to the increasing automatization (computerization) of the workplace. This has increased the demand for and the wage rates of cognitively nonroutine jobs (e.g. professional and managerial), as well as manually and interpersonally nonroutine jobs (e.g. truck drivers, salespersons, personal trainers). At the same time, it has decreased the demand for manually routine (e.g. factory production) and cognitively routine (e.g. secretaries, bookkeepers, bank tellers) jobs. This has “hollowed out” or “polarized” the skill distribution of jobs, decreasing the employment share and relative wage rates of many white-collar jobs in the middle of the skill distribution that could be performed by workers with at most a high school degree, while increasing the employment share and relative wage rates of professional and managerial jobs above this skill level, as well as of service jobs below this skill level but unable to be automated. As stated by Autor and Dorn (2013, p. 1555):

As with employment growth, wage growth is strikingly U-shaped in skill percentiles, with the greatest gains in the upper tail, modest gains in the lower tail, and substantially smaller gains towards the median … The twisting of the lower tail of the employment and earnings distribution is substantially accounted for by rising employment and wages in a single broad category of employment: service occupations. (Emphasis in the original)

Thus, economists have attributed increasing earnings inequality primarily to the technical demands of production in a period of rapidly increasing computerization.

Sociologists, however, have emphasized a different set of forces driving the trend toward increasing inequality – power relations in the labor market, and the varying political economy of these relations across different nations. These sociologists (e.g. Kristal and Cohen 2017, hereafter K&C) see rising wage inequality over the past 30 years being driven by declines in union membership and power, declines in the real value of the minimum wage and the globalization of production, facilitating the outsourcing of jobs with routine tasks to lower-paid workers in less-developed countries. In this view, declines in the bargaining power of less-skilled workers have contributed more to their relative wage declines than have the lower cost and increasing reach of computerization. Indeed, K&C calculated that across 43 US industries between 1968 and 2021, declining unionization and the declining real value of the minimum wage explain about 50% of rising wage inequality, while computerization accounted for only about 25% of this rising inequality. In other words, increas-
ing earnings inequality may be more due to declines in the bargaining power of less-skilled workers and increases in the bargaining power of higher-skilled workers than to the increasing computerization of the workplace.

Support for this view comes from cross-national evidence that earnings inequality increased more strongly in the US than in many other rich countries. Kristal and Edler (2021) seek to explain this by building on a literature concerning the “varieties” of capitalism (Thelen 2014). Rich nations are divided into three groups, Liberal Market Economies (LMEs: Australia, Canada, Ireland, Israel, New Zealand, the United Kingdom and the USA), Continental Coordinated Market Economies (Continental CMEs: Austria, Belgium, France, Germany, Italy, Japan, Korea, the Netherlands and Spain) and Nordic Coordinated Market Economies (Nordic CMEs: Denmark, Finland, Norway and Sweden). In LMEs, importantly including the United States, wages are set primarily by markets in a very decentralized way, limiting the bargaining power of workers. By contrast, in the CMEs wages are coordinated more through non-market mechanisms involving sector- or nationwide bargaining by politically strong labor unions. These tend to enforce norms of equity that place a floor beneath the wages of low-skilled workers while limiting the pay raises of high-skilled workers. These norms of “equal pay for equal work” also tend to limit the pay of workers in the most profitable sectors or enterprises. The Continental CMEs, often led by conservative Christian Democratic political parties such as in Germany, illustrate this form of coordination. Nordic CMEs, such as Denmark, have been described as following a social democratic regime and are expected to have even stronger forms of nationwide coordination that collectivizes risk. These three national types also have accompanying educational systems – for LMEs these tend to be based on individuals’ own decision-making and self-funding, whereas in the CMEs there is greater government subsidization and educational policies designed to fill the needs of the economy as a whole.

To examine the relationship between these different varieties of capitalism and wage inequality, Kristal and Edler (2021) tested whether the wage premium for working with computers was highest for LMEs, lower for Continental CMEs and lowest for Nordic CMEs. This is exactly what they found. Their calculations, controlling a host of worker, occupational and industry variables, did not imply that workers using computers were highest paid in LMEs. In fact, they were highest paid in the Nordic CMEs. But the wage gap was largest in LMEs, particularly the United States, because of the relatively low wages of non-computer workers in these countries. In addition, these researchers found that higher levels of public spending on education and vocational training also reduced the computer wage premium, perhaps by increasing the supply...
of workers who use computers at work. Thus, Kristal and Edler explain how the structure of a nation’s political and economic institutions determines the relative bargaining power of employers and workers, as well as the existence of equity norms. Together, these determine the extent of wage inequality within nations. And yet, the greatest economic inequality is between nations. This is particularly strongly determined by national differences in political and economic institutions.

**Rich and poor nations**

Thus far the discussion has focused on the rich nations of the world – those with the highest per capita GNP. Yet the very much lower average earnings of workers in the poor nations of the world are a greater determinant of human misery than earnings inequalities within the rich nations. The reasons for intractable poverty in very many poor nations have been explored by Acemoglu and Robinson (2012; hereafter A&R).

These authors distinguish between inclusive and extractive national political and economic institutions. Inclusive institutions enable the great mass of people to make the economic choices they wish and that make best use of their skills. Such institutions include secure private property, an unbiased system of law and adequate public services, creating an economy in which individuals can safely exchange, invest and contract, and are incentivized to do so. They are typically created and supported by inclusive political institutions that are centralized and pluralistic – a strong central government distributes power broadly and subjects it to constraints. By contrast, extractive economic and political institutions concentrate power in the hands of a narrow elite, who then use this power to extract resources from the rest of the society. This leads to the impoverishment of the great mass of the population, who have little means or incentives to gain the skills that might raise their incomes. These differences in national institutions help create the cultural differences in cognitive and noncognitive skills of the immigrants from varying nations and national cultures studied by Figlio et al. (2019) and Hanushek et al. (2020). A&R provide many examples of nations exhibiting these institutional types, both worldwide and throughout history.
The macro to micro connection

Seeking to develop a general theory of action applicable to all social systems, Coleman (1992) began with Weber’s classic study of The Protestant Ethic and the Spirit of Capitalism ([1904] 1958). As diagrammed by Coleman (figure 1.2, p. 8), Weber’s theory is that Protestant religious doctrine (a society-wide or macro variable) leads to certain values held by individuals (particularly antitrivialism and duty to one’s calling), which lead to certain orientations to economic behavior by these individuals (micro variables), which in turn lead to or support capitalist economic organization (a macro variable). This is a causal sequence in which macrosocial variables (the cultural values espoused by the Protestant Reformation) led to microsocial habits and skills by individuals, which in turn affected the economic and employment-related behavior of these individuals, which in turn helped build the macrolevel institutions of capitalism and economic growth. A version of this causal sequence, generalized to the comparison of inclusive and extractive national political and economic institutions, is the theory of differential national wealth creation presented by Acemoglu and Robinson (2012). Doepke and Zilibotti (2008) make a similar argument, showing how the Industrial Revolution fostered an emphasis on skills, work ethic, patience and entrepreneurship in the rising middle class while at the same time the landed upper class, relying on stable income from their estates, cultivated refined tastes for leisure activities, guaranteeing their ultimate downward mobility. Other economic researchers have focused on other aspects of these micro–macro links. Galor and Ozak (2016) present evidence that nations and regions with the highest returns to agricultural investment (net crop yield) after the year 1500 developed populations with a stronger habit of patience. Hanushek and Woessmann (2015) showed that nations whose populations had the highest cognitive skills measured by test scores also showed the greatest economic growth. Falk et al. (2018) presented similar findings for nations whose population scored highest on patience. Acemoglu et al. (2019) showed that nations with democratic political systems showed the greatest economic growth. Kirkegaard and Karlin (2020) found that when cognitive skill as well as noncognitive skills of patience, trust, competitiveness and work ethic are used to predict national differences in economic growth, cognitive skills are the strongest predictor. This recent work on the relations among macro and micro variables of political and economic systems, the skills and habits of their populations, and the economic growth of nations has made a strong start on carrying out the micro–macro research agenda suggested by Coleman (1992).
Summary

A common language exists for sociologists and economists to understand earnings inequality. On the supply side, human and cultural capital include cognitive and noncognitive (social behavioral) skills. These are at least partly determined by parental social class status and the culture of the parents’ social or national group membership. As cognitive and noncognitive skills develop during K-12 education, they help determine the individual’s ultimate educational level and occupation-related skill set. Cognitive and noncognitive skills and completed education in turn determine the job tasks and thus occupations where the individual can be employed. In a poor country with extractive economic and political institutions, the great mass of the population has very limited opportunities available. In rich countries with inclusive political and economic institutions, these opportunities are more fully available. Further, rich countries vary according to the extent to which they facilitate the bargaining power of less-educated workers. As computerization has swept through these rich economies, nations such as the United States, where less-educated workers have relatively weak bargaining power, have seen the real wages of these workers stagnate over many decades. Meanwhile, workers with four-year college degrees have qualified for jobs where computerization has increased their productivity and bargaining power. Thus has earnings inequality increased within the rich nations, particularly the United States. In sum, human and cultural capital and the occupational job tasks they are matched to, which are conditioned by national political and economic institutions, determine the distribution of earnings within and between nations.

References


Introduction

Skill upgrading in the labor market is the growing share of tasks, jobs, and occupations that require complex problem-solving skills, active learning abilities, and tertiary education in order to be attained and properly conducted (Bell 1973; Goldin and Katz 1998; Krugman 1994; Solow 1957). Service sector expansion relates to the increasing presence of service-oriented tasks, jobs, and occupations in the labor market (Baumol 1967; Baumol et al. 1985; Clark 1940; Fisher 1935; Ngai and Pissarides 2007).

Figures 4.1\(^1\) and 4.2\(^2\) respectively show the shares of occupations demanding tertiary education and employment in service industries for several countries across five decades. The evident pattern is growing shares of jobs and occupations with high-skill and service content. These estimates are well in line with previous analyses of the same databases (Handel 2012; Kollmeyer 2009).

The pattern is also evident in analyses using alternative measures and data sources. The increase in self-reported numbers of jobs held to require a tertiary education grew from 20 percent to almost 40 percent between 1986 and 2017 in Britain (Henseke et al. 2018), and educational requirements counted in years rose from 1.8 to 3.1 on the average between 1974 and 2000 in Sweden (Korpi and Tåhlin 2009). The ‘data’ content in jobs – e.g., analysis and interpretation of work-related information – grew in the United States from at least the 1960s up to 2000 (Handel 2020). Oesch (2013) uses labor force survey data on occupational change and shows that high-skill analytical occupations grew between 1990 and 2008 in Denmark, Switzerland, Spain, Great Britain, and Germany, while mid-skill service occupations grew in all these countries except Germany where this group was stable.

Although high-quality data on these trends for obvious reasons are harder to recover further back in time, both skill upgrading and service expansion arguably extend back to at least the late 19th century (Cortada 2013). A trend toward the increasing presence of white-collar and technical professionals has
been documented from as early as the 1850s in the United States (Katz and Margo 2014). The service sector grew from about 24 to 38 percent between 1870 to 1920 in the United States (Browning and Singelmann 1975) and from 19 to 31 percent between 1890 and 1930 in Sweden (Schön 2014). Browning and Singelmann (1975) show that service expansion continued to rise during the period 1920 to 1970 in the United States, Canada, Great Britain, Germany, France, Italy, and Japan, although at a slower pace than in the European countries. From the 1970s onwards, the continued growth of the service sector occurred in parallel with a declining trend for manual work in the production industries (Handel 2012, 2020; Kollmeyer 2009). The parallel development of skill upgrading and service expansion over the 20th century, as described above, has led to numerous accounts of their possible relationship. Service expansion has been suggested to slow down the pace of skill upgrading, since many service-oriented jobs are reliant mainly on interpersonal skills, and thus have rather low formal skill requirements (Autor 2010). In contrast, service expansion in the skilled segments of the welfare sector or among service industries experiencing rapid digitalization...
has been suggested to amplify upgrading (Wren et al. 2013). Documenting trends in service expansion is thus crucial for understanding changes in skill requirements over historical time, as well as linked developments in inequalities between groups of contemporary labor markets (Appelbaum and Schettkat 1994, 1995; Esping-Andersen 1993; Oesch 2013; Oesch and Piccitto 2019).

This chapter will, in addition to providing new estimates of skill upgrading and the rise of the service sector, disentangle the interrelationship between these two processes. What is the direction of this association between skill upgrading and service expansion (positive or negative)? Does the relationship between the two differ depending on which type of definition of the service sector is used – industry or occupation? Is the association driven by compositional shifts between different service categories or rather by specific developments within certain service categories and/or the production sector? By utilizing the uniquely long-running Swedish Level-of-Living survey (LNU), we estimate trends of both skill upgrading and service expansion between 1968 and 2010 using both industry and occupational data on the individual level.
Definitions

The most common way of analyzing service expansion is to look at changes in the relative employment share of different industries. A basic idea is to divide industries based on their main function as either service, manufacturing, or agriculture. The Clark (1940) and Fisher (1935) three-sector model posits that labor markets consist of three sectors: (1) primary (agriculture, mining, fishing, and forestry); (2) secondary (manufacturing, utilities, and construction); and (3) tertiary (commerce, transport, services, and communication).

The service category in these early accounts consisted of basically all products that were not food or physical things, but there have also been numerous attempts to provide more exact definitions of what a ‘service’ constitutes. These attempts include abstract variants; e.g., that it is the production of ‘time’, ‘place’, ‘form’, or ‘psychological utilities’ (Murdick et al. 1990: 4). More concrete variants include lists of example tasks that are commonly considered services; e.g., ‘Provision of lodging … meals, snacks or beverages’ (OECD 2000: 39). Sometimes service tasks are equated to tasks demanding interpersonal skills, such as tasks conducted by flight attendees and waitresses (Hochschild 1983).

In a general but still concrete form, a service task can be understood as a work act that generates a product that the customer cannot return to the producer, or pass on to another consumer, without it losing a major part of its value. This is because a service product is either consumed immediately or highly adapted to the specific needs of a particular person or organization (cf. Cook et al. 1999).

Typically, services tend to either (a) create or preserve human capacity and energy (e.g. education and health), (b) maintain and allocate physical goods and monetary wealth (e.g. business services and logistics), or (c) provide convenience, amusement, or save time (e.g. repairs, sales, and assistance services). We label these variants of services: (a) human services, (b) market services, and (c) personal services.

The most common indicator of service expansion is industry. A problem with estimates based on industry classifications is that firms located within particular industries generally contain several different occupations. First, service personnel such as cleaners, caterers, etc. may either be employed in-house or provided by external service-oriented firms. These arrangements may change over time, which can lead to biased estimates. Second, administrative positions
in production industries, not directly working with the making, design, or development of products, are not included in industry-based estimates of service expansion. Third, staffing companies have expanded in many industrialized countries over recent decades. These firms are held to provide services (labor) but the work conducted by the hired personnel may have products as their output. Hence, these work acts should not be included in estimates of service expansion. Complementary occupation-based indicators are thus crucial for gaining thorough knowledge about trends in service expansion.

The substantive complexity of tasks is perhaps the central characteristic of jobs. Skill or occupational upgrading refers to a process in which the complexity of tasks increases in a given job over time or the general distribution of jobs on the labor market changes in favor of more high-skill jobs in general. The complexity of jobs is often conceptualized as the level of cognitive capacity that is required to carry out the task in a satisfactory manner. This type of capacity is captured well by self-reported education/training required to perform the task satisfactorily (see Chapter 1 or Tåhlin 2011).

The interrelationship between service expansion and skill upgrading

The interrelationship between service expansion and skill upgrading has generally been explained by two categories of explanations: consumer demand and labor supply explanations.

In demand explanations, consumer demand is expected to change over historical time, from basic commodities to luxury consumption. General economic development over time is the principal factor behind these changing preferences. From the earliest accounts of service expansion and onwards, luxury consumption has generally been associated with the consumption of labor-intensive personal services; e.g., visits to restaurants (Fisher 1935; Clark 1940; Appelbaum and Schettkat 1994; Kollmeyer 2009).

In supply explanations, the focus is on the trend toward rising productivity in the manufacturing industries. Machines and computers tend to replace routine tasks, usually present in manual labor. In contrast, demand for analytical tasks increases, with the effect of skill upgrading (Goldin and Katz 1998). Service sectors remain labor intense because of larger difficulties in raising productivity for tasks revolving around personal interaction, and thus expand in terms of employment relatively speaking (Baumol 1967; Baumol et al. 1985;
Ngai and Pissarides 2007). Both demand and supply explanations thus imply that the composition of service employment will be pushed toward low-growth personal services in which occupational upgrading is less pronounced.

A more recent critique of supply explanations states that easily routinized jobs are not mainly low-skilled, but rather encompass certain manual and clerical jobs in the mid-skill range. In several alternative accounts that have gained influence over recent decades, mid-level jobs are reduced because they can be substituted by technology, while interpersonal low-skill jobs remain stable because the impact of technology is marginal on these jobs (Autor et al. 2003; Manning 2003; Goos and Manning 2007). Replacement of mid-skill clerical jobs with low-skill interpersonal jobs implies skill downgrading within the category ‘personal services’ and a flattening out of the trend toward rising skill requirements in the aggregated economy.

During the last decades, the diffusion of communication and internet technology has increased productivity within market-oriented service industries such as business and financial services. Increasing skill requirements needed to carry out the tasks within these service sectors is thus expected to drive skill upgrading, while sectors that cannot benefit from this technology remain stable (Wren et al. 2013). Durable upgrading within the category ‘market services’ is therefore expected, which also has implications for aggregate upgrading.

Additional demand explanations of service expansion are derived from Leibenstein (1957), who argues that higher incomes for workers increase gains in (productive) human energy through better nutrition. This is generalizable to other core factors behind human energy and capacity, such as health and education. Human capital drives economic development, and excess wealth can be invested in sustaining this human capital as well as generating additional human capital (Mincer 1984; Acemoglu and Robinson 2012). Demand for human services thus expands with economic development.

Nevertheless, an expansion of human services can have a mixed impact on skill upgrading, depending, for instance, on how the assignment of different tasks between occupations in the health and education system varies between institutional contexts and over time (Esping-Andersen 1993, 1999; Oesch 2013), as well as on the empirical bearing of Baumol’s disease; i.e., the anticipation that growth is sluggish in all sectors reliant on interpersonal skills (including care and educational sectors) (Baumol 1967; Baumol et al. 1985).
Service expansion

Two trend estimates (based on industry and occupation) for the expansion of services in Sweden are provided in Figure 4.3, panels A and B. The general expansion of service is the sum of the service sub-categories. Point estimates and confidence intervals for all analyses can be found in the online appendix (Tables A4.1 and A4.2 in the appendix). The industry measure indicates that the expansion of services during the period is on average about 4 percentage points for each survey occasion. This increase is relatively stable over time; for the periods 1968–1981 and 1991–2000 the rate of change is slightly higher. In 2010 the proportion working in the service sector was 75 percent.

In contrast, the occupational definition (panel B) indicates that the service sector is larger in the early years and service expansion is less pronounced. The service sector already encompassed two-thirds of the employed in 1968, including administrative occupations and in-house service providers.

Both measures indicate that the growth in human services accounts for the whole expansion of services (from 17/12 percent to 43/35 percent). In contrast,
market services are stable at around 10/20 percent, while personal services first decline and then expand for the industry-coding (around 20 to 25 percent), but it declines steadily from around 30 to 20 percent for the occupational coding. The only viable explanation of an interrelationship between service expansion and skill upgrading in Sweden is thus related to the expansion of jobs within human services, mainly health and educational workers and governmental employees.

**Skill change in service expansion**

Figure 4.4, panels A and B, provides estimates of upgrading (increase in self-reported educational requirements of jobs) for industry- and occupation-based classifications of jobs. The general pattern suggests that service expansion is unlikely to be a major cause of skill change in the labor market. Skill upgrading occurs within major industry- and occupation-based categories.

More marginal differences are still obvious. Jobs within human services generally have high educational requirements, although in a slightly u-shaped
manner over time. The initial decline of educational requirements in this category between the years 1968 and 1981 coincides with the well-known expansion of this sector over this period. Presumably, this initial decrease corresponds to the expansion of many new low-skill jobs in the care sector in connection to the increased labor market entry of women (Gustafsson and Jacobsson 1985; Nermo 1996). Personal services experience less upgrading over the period if an occupation-based classification is used (panel B), compared to the industrial measure (panel A).

Beyond that, there are surprisingly few differences in the separate upgrading trends between the categories. The trends line up closely (although with large differences in level). Thus, the analysis does not provide evidence that secular changes in skill requirements within specific service categories drive aggregated changes in skill requirements in the labor market.

Conclusion

In line with the traditional supply and demand accounts of service expansion outlined above, the composition of employment has been pushed toward services that are largely dependent on interpersonal contact. The entire expansion of services can be attributed to the increasing size of the human services sector. In line with the expectations, the overall upgrading has been faster in production than in services. As the service sector constitutes a larger share of the labor market over time, the aggregate upgrading slows down.

This is, however, ameliorated by the fact that upgrading within human services is relatively high for the second half of the period. The mixed effect on upgrading from human services envisioned at the start of this chapter is clearly indicated in this pattern. After five decades of development, the skill requirements are back above the comparatively high average level it had at the outset, but with the sector now comprising around 35 percent of the employed.

The personal services category has continually had both the lowest skill average and rate of upgrading. The trend, however, shows upgrading over the period. The expectation of skill downgrading, based on that jobs in the mid-skill range – but not the low-skill range – are substituted by technology within this category (cf. Autor 2010), is thus not fulfilled.

Market services, on the other hand, is the service sector that has upgraded most quickly over the period. In line with the expectations in Wren et al. (2013), the
upgrading in this sector is more pronounced than in the other service sectors. In this sector, technological advancements over the past decades can be lever-aged to increase productivity more effectively. Increasing use of new technol-ogy also drives the need for more skilled personnel, which leads to higher levels of upgrading. However, developments within this sector seem to have little to do with aggregated upgrading, partly because this sector continues to comprise only a limited share of the service sector (especially if an occupational defi-nition is used), and in part because upgrading occurs across the whole labor market. The same holds for the personal service sector as well.

In sum, the results do not indicate any clear replacement effects between sectors nor interaction effects within sectors changing the skill composition of work in the labor market taken as a whole – except to some extent changes related to the category ‘human services’. The overarching relationship between service expansion and skill upgrading is quite similar over the period using both occupation- and industry-based measures. The latter, however, clearly fails to capture heterogeneity within categories, which is more clearly revealed if occupations are used to define service employment. In Sweden, the service expansion has primarily been driven by ‘human services’, which have relatively high skill requirements and upgrading rates (for the later decades). In countries where service expansion to a greater extent is driven by ‘personal services’, the relationship between service expansion and skill upgrading could be considerably different, since the composition of jobs would change toward jobs with a lower average skill and rate of upgrading.

Notes

1. The estimates in Figure 4.1 are based on data from OECD’s STAN database (Horvát and Webb 2020). They were created by taking the total number of indi-viduals employed in service (industry ‘D45T99’) divided by the total number of individuals in employment (EMPN in STAN), by country and year. The estimates show the percentage employed in service for each country and year.

2. The estimates in Figure 4.2 are based on data from the International Labour Organization (ILO). Jobs requiring tertiary education were defined as ISCO-08 1-digit categories 1, 2, and 3. Years coded in ISCO68/88 were extrapolated using growth rates for comparable categories (ISCO-88: 1, 2, and 3; ISCO-68: 1, 2). Some additional imputations and corrections of implausible growth rates were made during the process (see Tåhlin and Westerman 2021 for more details). The number of individuals employed in these categories were then divided by the total amount of employed individuals in the country that year.

3. The construction of the industry-based measure follows the common practice (e.g., Elfring 1989; Singelmann 1978) of using an industrial classification; in this
case, the Swedish Standard Industrial Classification (SNI) 1969 edition on the
two-digit level (SCB 1977). Values 61–96 are coded as service, which is close to
equivalent with values 45–99 in NACE; i.e., the groups G to U (see Eurostat 2008).
The sub-groups of service are coded as follows – production: 11–50; personal ser-
vant services: 61–63 and 83, 92, 94, 95; market services: 71–72 and 81–82; human services:
91, 93, and 96.
4. The occupational measure was constructed using ‘Nordisk Yrkesklassificering’
(NYK, SCB 1985). It distinguished occupations horizontally in terms of work character-
istics (but not vertically or based on industry or technology level). Thus,
it is an optimal categorization to disentangle a horizontal from a vertical dimen-
sion between occupations. The codebook for NYK (SCB 1985) contains a detailed
description for each occupation. Using this codebook, each occupation is coded
as either production (including food production) or service depending on what
terms are dominant in their descriptions. Terms like building, assembling, develop-
ing, inventing, constructing, designing, etc. (referring to products) are coded
as production, while terms like installing, repairing, transporting, caring for,
tend to, administer, give advice to, etc. are coded as service. Several occupations
traditionally carrying out equal amounts of service and production tasks are coded
as hybrid occupations (e.g., system scientists and some craft occupations). We
subsequently coded service occupations in accordance with their main function
being (a) human services, (b) market services, or (c) personal service. Full coding
schemes are available upon request.

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Skills and occupational sex segregation in Europe

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Introduction

Occupational sex segregation refers to the fact that men and women are not equally distributed across occupations. Women have been particularly over-represented in associate professional, clerical, service and sales occupations, and men have been predominant in managerial, agricultural and craft occupations and in operative and technical jobs (Charles & Grusky, 2004). From a societal perspective, occupational sex segregation is problematic as it may imply a misuse of human capital resources if norms rather than adaptivity sort individuals into jobs, leading to less than optimal economic growth (Woetzel et al., 2015). Moreover, sex segregation is tightly linked to other inequalities, such as the gender wage gap, since female-dominated occupations tend to have lower wages than male-dominated occupations (Blau & Kahn, 2017).

Nevertheless, there has been a trend towards decreased occupational sex segregation since the beginning of the 1970s (Halldén & Nermo, 2022; Elbers, 2021). The decrease in occupational sex segregation tends to be attributed to factors such as increased egalitarian views and antidiscrimination laws, less gender-stereotypical career choices and gender-stereotypical sorting into occupations by employers (Charles & Grusky, 2004; England, 2010). This development has coincided with women trumping men as regards educational attainment in the last decades (Charles & Bradley, 2009; Oesch, 2015), implying declined occupational sex segregation as women attain high-skilled professional positions and these occupations become more gender-integrated. The decrease in occupational sex segregation can also be due to changes on the margins, of which one important feature is the skill-upgrading in the labour market, where the more gender-integrated occupations of professionals have increased and the more gender-segregated occupations of production workers and clerks have decreased (Oesch, 2015). On the other hand, the female-dominated service sector has expanded, which may counteract gender integration. Also, increased female labour force participation across time could
imply more sex segregation, at least in the short run, as women that enter “on the margin” may sort into female-typed occupations that are symbolically and functionally more consistent with the female homemaker role (Charles, 2003).

This chapter examines levels and trends in the average rate of occupational sex segregation within Europe between 2000 and 2020. The aim is to map out average segregating and integrating forces in total and across nine major occupational groups. We use the Mutual Information (MI) index (see Elbers, 2021) to decompose the changes in sex segregation into “pure” (margins-free) changes, marginal changes in sex composition of labour supply and occupational composition, as well as emerging and disappearing occupations.

Theoretical framework

Explanations of occupational sex segregation can be theorized from a cultural-socialization perspective on the one hand and a rational-choice/economic perspective on the other (Polavieja, 2008). The socio-cultural theories highlight that our culture is permeated by gender essentialism, a belief that men and women are naturally and fundamentally different and thus suitable for different work tasks, which leads to persistent occupational sex segregation (Charles & Bradley, 2002, 2009; Charles & Grusky, 2004; Ridgeway, 2009). According to gender-essentialist beliefs, women are more suitable for nurturing and caring work and men are more suitable for working in physically demanding jobs (Charles & Grusky, 2004). There is a stark division between production work (male-typed) and service jobs (female-typed). Individuals are socialized into gender-stereotypical roles already at early ages and base their educational and subsequently occupational decisions on norms and societal expectations (Polachek & Siebert, 1993). Men to a higher extent than women tend to attain tertiary education in engineering, manufacturing, construction and ICT (information and communications technology), while women tend to attain tertiary education in education, health and welfare, arts and humanities, and social science (Eurostat, 2020). Individuals are also sorted by employers into gender-stereotypical occupations based on beliefs in sex-stereotypical traits and skills (Charles & Grusky, 2004; Correll, 2004; Levanon & Grusky, 2016).

The rational-choice/economic theories highlight that due to women’s larger household and childcare responsibility and higher expected labour market absence, women will have low incentives to invest in especially specific human capital, which leads to exclusion of women from certain occupa-
tions. Furthermore, employers may expect women to be more absent and statistically discriminate by not hiring women to jobs that require costly on-the-job-training investments or high presence and a large amount of overtime (Becker, 1971; Estévez-Abe, 2006; Mincer & Polachek, 1974; Polachek, 1981).

Variation in occupational sex segregation by skill

Most empirical findings indicate that high-skilled occupations are less gender-segregated (Blau et al., 2013; Grönlund & Magnusson, 2016). The integrating forces in high-skilled occupations are, for instance, more pervasive egalitarian and meritocratic pressures in higher non-manual occupations, as these occupations tend to be more publicly scrutinized and the hiring process more universalistic and based on formal credentials (Charles & Grusky, 2004). In addition, attributes that provide information about the applicant, such as tertiary education credentials, are expected to decrease the discrimination that is due to uncertainty about the applicant’s productivity (Goldin, 2014). A higher education might also signal commitment, making employers in high-skilled occupations less worried that their female employees will quit to care for children (Goldin, 2014). Also, high-skilled occupations generally involve less sex-typed job tasks compared to less skilled work.

Nevertheless, there are also some segregating forces in high-skilled occupations. Generally, on-the-job training is more prevalent and important (Iversen & Rosenbluth, 2012), and as employers are generally more reluctant to invest in on-the-job training for women, this might result in greater gender inequality and sorting in higher-skilled occupations (Grönlund & Magnusson, 2016; Mandel, 2012). In addition, women might be more discriminated against in higher-skilled occupations because the cost of employee absence is relatively larger and these occupations also tend to be more demanding in terms of overtime and thus more difficult to combine with family responsibilities (Boye et al., 2017).

Variation in occupational sex segregation across time and countries

Educational, economic, political and cultural institutions, and norms and laws, vary across countries and contexts. These factors shape how resources are distributed and how employees and employers will behave. Below we discuss how some of these often intertwined mechanisms are connected to cross-country and over-time variation at the level of occupational sex segregation.
Post-industrialism and change in the composition of occupations

Globalization, technical change and automation have induced changes in the labour market structure during the last decades (Carnevale et al., 2018). Employment in low- to medium-skilled manufacturing jobs dominated by men is declining, which has implied decreased occupational sex segregation (Charles & Grusky, 2004). On the other hand, employment in female-dominated jobs in the service sector has expanded during the transition from an industrial to a post-industrial economy, which probably has a segregating effect (Charles, 1992, 2003; Charles & Grusky, 2004; Goldin, 2006; Ngai & Petrongolo, 2017). However, the contraction of the manual blue-collar work industry may also force men into service jobs, which would then mitigate a potential trend towards increased occupational sex segregation. In the post-industrial knowledge society, work tasks have become more complex and there has been a skill-upgrading in the labour market (le Grand & Tåhlin, 2019). High-skilled occupations tend to be less gender-segregated and as these occupations expand it may have a decreasing effect on segregation.

Modernity and change in the sex composition of the labour force

In recent decades, more women have entered the labour force, but to a different extent and at different time points across countries. Increased female labour force participation is among other things due to the spread of gender-egalitarian norms, family policies that encouraged a dual breadwinner system and the expansion of “female-friendly” jobs in the public sector and in the service sector. It is sometimes argued that jobs in these sectors tend to be more consistent with the culturally ascribed female homemaker role and potentially also easier to combine with family responsibilities (e.g., Charles, 2003). Thus, women who enter the labour market “on the margin” are expected to enter these female-typed occupations. This tendency might, however, fade over time as women get increasingly integrated into the labour market and the dual breadwinner role becomes the norm in society, implying that labour market work, household responsibilities and childcare are shared within the household.

It is not clear how family-friendly policies, such as publicly subsidized childcare and generous parental leave, affect occupational sex segregation. On the one hand, it is easier for women to combine work and family in countries with such policies, which would increase female labour force participation. Hence, these policies might lead to higher segregation because they tend to increase the number of women in female-typed jobs and may increase employer discrimination due to anticipated family-related absence (Blau & Kahn,
However, high female labour force participation is not systematically connected to higher occupational sex segregation in recent research (Bettio & Verashchagina, 2009; Steinmetz, 2012). On the contrary, some studies indicate that an increase in women’s employment decreases segregation (Keane et al., 2017; Nermo, 2000). One interpretation is that an increase in female labour force participation initially increases occupational sex segregation, but this trend is time contingent and to be considered as a phase that passes when women’s participation in the labour market has matured.

**Data and methods**

**Data and sample**

The analyses are based on cross-sectional data from the EU Labour Force Survey (EU-LFS) for the 27 European countries that provided detailed occupational information in both 2000 and 2020 (see Online Appendix for a list of the countries included). Employees in the age group 22–62 are analysed.

**Variables**

Sex, occupation, country and year are the variables of interest. Occupation is measured both on a major group level (1-digit) as well as more detailed (3-digit) level and coded according to the International Standard Classification of Occupations (ISCO).

**Empirical strategy**

We use the MI index (Elbers, 2021) to study how variations in occupational sex segregation over time are linked to the marginal distribution of occupations and the sex composition of the labour force, as well as “pure” changes in sex segregation. The method also adjusts for appearing and disappearing occupations in the occupational structure. We estimate models for each country in the sample (using the yearly weighting factor) and then use the country figures to calculate the average European occupational sex segregation level in 2000 and 2020 and the five factors of the decomposition model:
The first term on the right-hand side applies to changes in the “pure” segregation. It measures the gender distribution over detailed occupational groups when every other change (such as the size of occupations and the share of women in the labour force) is held constant. The “pure” segregation is usually the main focus in previous studies on trends in occupational sex segregation and it is analogous to Charles and Grusky’s (2004) margins-free measurement A. Thus, a decrease in the “pure” segregation means that men and women become more equally distributed across occupations. The second term is the marginal change in occupational composition. For instance, if a country experiences a relative expansion of occupations that are more segregated than the average occupation, this term becomes positive and thus puts upward pressure on segregation. The third term is the marginal change in gender composition of the labour force. If the share of women in the workforce increases across time and tends to enter more female-typed occupations than average (as suggested by, e.g., Charles, 2003), this term becomes positive. The fourth and fifth terms are appearing and disappearing occupations. If appearing occupations are more segregated than already existing occupations, the term of appearing occupations becomes positive. If disappearing occupations are less segregated than in both periods’ existing occupations, the term becomes positive, since this implies more segregation. In the next step the decomposition is conducted separately for each major occupational group (1-digit level) within each country. One advantage with the method is that it makes it possible to discern integrating and segregating forces. In addition, in contrast to, for instance, the A index (Charles & Grusky, 2004), all occupations are automatically weighted according to their relative size. One disadvantage with the index is that it is not strictly confined to have a range between 0 and 1. Therefore, the commonly used Dissimilarity (D) index (Duncan & Duncan, 1955) as well as the H index are shown for comparison (see Elbers, 2021). These indexes range between 0 and 1, where 0 indicates full integration/no segregation and 1 indicates full segregation. The D index estimates the share of men (or women) that would need to change occupation for full labour market integration to be reached (adjusting for female labour force participation) (Elbers, 2021).
Results

The European trend in occupational sex segregation

We start the results section by examining the development of European women’s average employment rate. Across the time period studied, the share of employed women in the labour market (out of all employed) increased from, on average, 46.1% in 2000 to 48.5% in 2020 (see Table 5.1). A majority of the European countries in the sample had a fairly balanced sex composition among the employees in the labour market already in 2000 and did not undergo much change over time (see Online Appendix, Table 5A.1). However, in some countries the share of employees consisted of less than 45% women in 2000 (i.e., Austria, Belgium, Germany, Greece, Italy, Luxembourg, the Netherlands and Spain) and some of these countries subsequently experienced a more substantial increase in the female labour force employment rate. Only Romania had a female share of all employed that was below 45% in 2020 (due to a decrease in women’s employment in the last two decades).

Turning to sex segregation, it is clear that occupations on average have become more integrated across time (see Table 5.1). The H index fell from 0.37 in 2000 to 0.31 in 2020, indicating a moderate segregation rate (as the measure ranges between 0 and 1) and corresponds to a decline of about 16%. The D index on average decreased with over 10% across the European countries in the sample to 0.53 in 2020. This implies that 53% of all men or women would have to change occupation to reach full gender integration in the labour market.

All countries except Italy and Romania experienced a decrease in occupational sex segregation between 2000 and 2020 (see Online Appendix, Table 5A.1). In 2020, the variation in segregation rates across countries nevertheless remained substantial.

Decomposition of the trend in occupational sex segregation in Europe

Next, the average European trend in occupational sex segregation is decomposed into changes due to: additional occupations that existed in 2020 but not in 2000, disappearing occupations that existed in 2000 but not 2020, variation in the gender composition of the labour force and in the relative size of occupational categories, as well as changes in “pure” segregation (see Table 5.2). It is clear that the falling average rate in segregation across time is almost entirely driven by a decrease in “pure” segregation. That is, European women and men to a lower extent sort into and are sorted into different occupations in 2020
<table>
<thead>
<tr>
<th></th>
<th>2000</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share women of all</td>
<td></td>
<td></td>
</tr>
<tr>
<td>employed %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>0.37</td>
<td>0.31</td>
</tr>
<tr>
<td>D</td>
<td>0.59</td>
<td>0.53</td>
</tr>
<tr>
<td>MI</td>
<td>0.25</td>
<td>0.22</td>
</tr>
<tr>
<td>Nr occ groups</td>
<td>107.8</td>
<td>123.6</td>
</tr>
<tr>
<td>Share women of all</td>
<td></td>
<td></td>
</tr>
<tr>
<td>employed %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>H</td>
<td></td>
<td></td>
</tr>
<tr>
<td>D</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MI</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nr occ groups</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.1** Segregation indexes (H, D and MI), the share of women of all employed and the number of occupational categories as a mean value across European countries in 2000 and 2020.
than in 2000. Consequently, there are deep underlying forces towards less sex segregation in the labour market.

Besides changes in the “pure” segregation, segregating and integrating forces operated simultaneously. Appearing occupations were less segregated than already existing occupations, while the difference was minor for disappearing occupations, leading to a net integrating effect.

Changes in the relative size of existing occupations in both periods played only a very small role in the average decrease in sex segregation, while the overall increase of the female share of all employees implied higher occupational sex segregation on average.

In countries where female labour force participation increased substantially, such as in Spain, Luxembourg, Greece and Portugal, the change in sex composition had a segregating effect (see Online Appendix, Table 5A.1.), which points towards a correlation between increased female labour force participation and increased occupational sex segregation.

Thus, the change in the occupational structure had a modest net effect towards decreasing segregation, which was counteracted as increased female labour force participation had a modest effect towards more segregation.

Decomposition of the trend in occupational sex segregation in Europe across 9 major occupational groups

Next follows a detailed decomposition of the change in occupational sex segregation within each major occupational group as a European average. Table 5.3 presents descriptive statistics on skill levels, the average share of the workforce and women employed in each major occupational group across Europe in 2000 and 2020, while Table 5.4 shows the decomposition for each major occupational group (ISCO 1–9). To provide a full picture of the European average trend in occupational sex segregation, the descriptive statistics (Table 5.3) and the decomposition (Table 5.4) will be interpreted in conjunction. In the following section we will discuss the findings for each major occupational group one by one.

Starting with the major occupational group “1. Legislators, senior officials and managers”, this category consists of occupations that, except for some cases such as politicians, generally require high education. The share of employees within this major occupational group decreased very slightly between 2000 and 2020, while the share of women increased substantially (see Table
Table 5.2  Decomposition of the average change in occupational sex segregation in Europe, 2000–2020 (MI index)

<table>
<thead>
<tr>
<th></th>
<th>$MI_{2000}$</th>
<th>$MI_{2020}$</th>
<th>$\Delta MI_{2020-2000}$</th>
<th>Appearing</th>
<th>Disappearing</th>
<th>Group margin (sex)</th>
<th>Unit margin (occupation)</th>
<th>“Pure” segregation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.254</td>
<td>0.216</td>
<td>-0.038</td>
<td>-0.014</td>
<td>0.002</td>
<td>0.013</td>
<td>-0.002</td>
<td>-0.037</td>
</tr>
</tbody>
</table>
5.3). However, in 2020 European women remained underrepresented within the group on average, which is regarded as particularly problematic since employees within this occupational category exercise political and economic power. The sex segregation across the more detailed occupational groups within the major occupational group increased (see Table 5.4), which appears to be driven by appearing occupations that were more sex-segregated than existing ones and that the women that entered the group did not enter the male-dominated jobs to the expected degree. However, the men and women working in this major occupational group were relatively evenly distributed amongst the detailed occupations in this group, as indicated by the low levels of segregation according to the MI index.

Group “2. Professionals” is the category that has the highest skill requirement. Consistent with the fact that there has been occupational upskilling over time, this group grew substantially over the years 2000–2020. As women nowadays outperform men in attaining higher education (Charles & Bradley, 2002, 2009; Oesch, 2015), European women were on average overrepresented in this group already in 2000, and even more so in 2020. The group has a segregation rate that is close to the average in comparison to the other major occupational groups, which does not support the idea that a relative growth of high-skilled occupations is an integrative force. Over time, sex segregation within this major occupational category increased due to emerging occupations that were, on average, more segregated than the existing ones and segregated occupations grew in relative size as this major group expanded. However, “pure” segregation decreased the stratification of men and women, meaning that there was a tendency towards a more gender-balanced distribution among detailed professional occupations in 2020 (adjusted for the other factors).

Turning to group “3. Technicians and associate professionals”, employment in this occupational category require medium to high skills. The share of the European workforce that was employed in this group decreased very little between the two time points on average. It is an even balance of men and women that work within the group. However, men and women to a large extent work within different occupations within this major group, as is indicated by the relatively high level of segregation. Nevertheless, there is an integrating trend across time which was mostly driven by a decrease in “pure” segregation.

Group “4. Clerks” consists of occupations with medium skill requirements and this category has traditionally been dominated by women. It on average decreased in size in Europe and became slightly less female-dominated over time. There is also a trend towards somewhat less sex segregation. New occu-
Table 5.3 Descriptive statistics of the ISCO skill level, the share of employees and the share of female employees within each major occupational group as average values across European countries

<table>
<thead>
<tr>
<th>Occupational group</th>
<th>ISCO skill level</th>
<th>Share of all employed 2000</th>
<th>Share of all employed 2020</th>
<th>Share women of all employed 2000</th>
<th>Share women of all employed 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Legislators, senior officials and managers</td>
<td>3+4</td>
<td>5.6</td>
<td>5.2</td>
<td>29.6</td>
<td>37.6</td>
</tr>
<tr>
<td>2. Professionals</td>
<td>4</td>
<td>13.9</td>
<td>24.2</td>
<td>53.5</td>
<td>57.4</td>
</tr>
<tr>
<td>3. Technicians and associate professionals</td>
<td>3</td>
<td>16.0</td>
<td>15.8</td>
<td>53.1</td>
<td>50.0</td>
</tr>
<tr>
<td>4. Clerks</td>
<td>2</td>
<td>12.7</td>
<td>9.6</td>
<td>71.2</td>
<td>67.3</td>
</tr>
<tr>
<td>5. Service and sales</td>
<td>2</td>
<td>14.0</td>
<td>16.4</td>
<td>66.4</td>
<td>65.4</td>
</tr>
<tr>
<td>6. Agricultural</td>
<td>2</td>
<td>1.3</td>
<td>0.9</td>
<td>26.4</td>
<td>24.0</td>
</tr>
<tr>
<td>7. Craft</td>
<td>2</td>
<td>15.5</td>
<td>10.4</td>
<td>13.1</td>
<td>10.6</td>
</tr>
<tr>
<td>8. Plant, assembly and machinery</td>
<td>2</td>
<td>10.4</td>
<td>8.3</td>
<td>19.1</td>
<td>16.8</td>
</tr>
<tr>
<td>9. Elementary</td>
<td>1</td>
<td>10.0</td>
<td>8.6</td>
<td>55.2</td>
<td>55.0</td>
</tr>
</tbody>
</table>
Table 5.4  Decomposition of change in segregation within each major occupational groups as average values across European countries

<table>
<thead>
<tr>
<th>Group</th>
<th>MI_{2000}</th>
<th>MI_{2020}</th>
<th>ΔMI_{2000-2020}</th>
<th>Appearing</th>
<th>Disappearing</th>
<th>Group margin (sex)</th>
<th>Unit margin (occ.)</th>
<th>“Pure” segregation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1</td>
<td>0.022</td>
<td>0.061</td>
<td>0.039</td>
<td>0.035</td>
<td>-0.001</td>
<td>0.012</td>
<td>-0.006</td>
<td>-0.001</td>
</tr>
<tr>
<td>Group 2</td>
<td>0.118</td>
<td>0.133</td>
<td>0.015</td>
<td>0.029</td>
<td>-0.002</td>
<td>-0.004</td>
<td>0.019</td>
<td>-0.027</td>
</tr>
<tr>
<td>Group 3</td>
<td>0.183</td>
<td>0.159</td>
<td>-0.024</td>
<td>-0.014</td>
<td>-0.006</td>
<td>0.006</td>
<td>0.018</td>
<td>-0.028</td>
</tr>
<tr>
<td>Group 4</td>
<td>0.099</td>
<td>0.089</td>
<td>-0.010</td>
<td>0.061</td>
<td>0.014</td>
<td>-0.003</td>
<td>-0.057</td>
<td>-0.027</td>
</tr>
<tr>
<td>Group 5</td>
<td>0.133</td>
<td>0.127</td>
<td>-0.007</td>
<td>0.093</td>
<td>0.002</td>
<td>0.003</td>
<td>-0.047</td>
<td>-0.061</td>
</tr>
<tr>
<td>Group 6</td>
<td>0.078</td>
<td>0.056</td>
<td>-0.022</td>
<td>0.041</td>
<td>-0.050</td>
<td>0.001</td>
<td>0.008</td>
<td>-0.022</td>
</tr>
<tr>
<td>Group 7</td>
<td>0.159</td>
<td>0.122</td>
<td>-0.037</td>
<td>0.085</td>
<td>-0.087</td>
<td>-0.023</td>
<td>0.005</td>
<td>-0.017</td>
</tr>
<tr>
<td>Group 8</td>
<td>0.154</td>
<td>0.121</td>
<td>-0.043</td>
<td>0.002</td>
<td>-0.127</td>
<td>0.053</td>
<td>0.023</td>
<td>0.006</td>
</tr>
<tr>
<td>Group 9</td>
<td>0.248</td>
<td>0.223</td>
<td>-0.037</td>
<td>0.043</td>
<td>-0.148</td>
<td>0.034</td>
<td>0.033</td>
<td>0.006</td>
</tr>
</tbody>
</table>
pations within the group were more segregated than already existing ones (and vice versa for disappearing occupations), which counteracted the integrating unit marginal effect that segregated occupations within the group decreased in size. Also, the “pure” sex segregation decreased. Overall, the sex segregation in this major occupational category is rather low in comparison to the other occupational groups.

Next, we turn to the occupational group “5. Service and sales” that is a medium-skilled category that traditionally has been female-dominated. It increased slightly in size but the gender composition changed very little since there was only a small reduction in the share of female employees on average. There was close to zero decrease in gender segregation within this occupational group across time. However, examining the different factors of the decomposition, it is evident that the “pure” segregation decreased substantially and that segregated occupations within the group decreased in size, but these integrating trends were counteracted as emerging occupations in 2020 were more sex-segregated than occupations in 2000.

Group “6. Agricultural occupations” is a male-dominated medium-skilled category that employed a very small proportion of the workforce, and the group is declining across time. It developed towards less sex segregation, which was driven by a decrease in “pure” segregation. The effects of dis/appearing occupations counteracted each other, such that changes in occupational composition in total did not affect segregation much.

The next occupational category is “7. Craft” – a heavily male-dominated medium-skilled group that has decreased in share of employees of the total workforce during the years 2000–2020. Also, the share of women in the group decreased further from an initially very low level. The effect of emerging occupations and disappearing occupations on segregation counteracted each other, leading to a zero net effect of structural change. As the share of women decreased, the remaining women on the margin were allocated in less female-typed occupations than before, which perhaps paradoxically led to less segregation within this group. The “pure” segregation also decreased.

Group “8. Plant, assembly and machinery” is another heavily male-dominated medium-skilled occupational category that became even more male-dominated but decreased in size over time. There has been a trend towards less sex segregation, which was solely driven by the disappearance of heavily male-dominated detailed occupations. The few remaining women in the group 2020 were in more segregated occupations than expected by the change in sex composition in the major occupational group.
Finally, we examine occupational category “9. Elementary occupations” that consists of low-skilled occupations. This group has declined slightly in size over time. It was almost a similar share of women employed in this major occupational group in 2000 and 2020, but the high MI index value indicates that men and women worked in different types of elementary occupations and the sex segregation level was the highest among all the major occupational groups. This is consistent with previous research showing that low-skilled work tends to be more gender-stereotypical. There is nevertheless a trend towards less sex segregation, which was driven by disappearing occupations being more segregated than the remaining ones.

Discussion

The aim of this chapter was to examine average levels and trends in rates of occupational sex segregation within Europe between 2000 and 2020. Consistent with previous research, we found that female labour force participation has increased in general and that the average level of occupational sex segregation has decreased in Europe over time. Nevertheless, occupational sex segregation remains substantial (Elbers, 2021; Halldén & Nermo, 2022; Levanon & Grusky, 2016). Among the high-skilled groups men remain overrepresented in managerial occupations. Within the professional and associate professional groups men and women to a moderate to large extent work in different occupations. Among the medium-skilled occupations, women still crowd into “Clerks” and “Service and sales” and men into “Craft” and “Plant, assembly and machinery”. An even number of men and women work in low-skilled elementary occupations, but they tend to work in different types of low-skilled occupations.

Turning to the decomposition, the observed decline in segregation between 2000 and 2020 seemed mainly to be due to a decrease in “pure” (margins-free) segregation, implying that there are fundamental societal forces moving towards less sex segregation (Elbers, 2021). Such forces may be trends towards gender equity and less gender-essentialist beliefs, implying that women and men choose more similar career paths and are less sorted into gender-stereotypical tasks and occupations by employers (e.g., England, 2010; Levanon & Grusky, 2016). Also, more equally shared household responsibilities and care work (encouraged by policies such as “daddy months” in the parental leave insurance, with earmarked leave for each parent) could imply that women have more incentives to invest in their careers and that employers to a lower extent than before expect women to be absent due to family reasons,
leading to less discrimination (Becker, 1971; Estévez-Abe, 2006; Mincer & Polachek, 1974; Polachek, 1981). Further, we found that increased female labour force participation in Europe had a moderate segregating effect on average, which may be because women in countries that experience a sharp rise in female labour force participation across the time period studied entered on “the margin” and sorted into female-typed work that is arguably culturally and functionally more compatible with the homemaker role (e.g., Charles, 2003). Structural change in the occupational distribution played a moderate role towards less segregation, which was mainly driven by new occupations being less segregated than existing ones.

Moreover, as expected from previous research, there was occupational upskilling between the years 2000 and 2020 (Carnevale et al., 2018; le Grand & Tählin, 2019). We found that employment in low- to medium-skilled heavily male-dominated manufacturing occupations and in highly segregated elementary occupations declined, which implied decreased occupational sex segregation (see also Oesch, 2015). However, in contrast to what is predicted by previous research (e.g., Blau et al., 2013; Grönlund & Magnusson, 2016), we did not find consistent evidence indicating that the expansion of high-skilled occupations would have led to less sex segregation. Women still crowd into professional occupations and men into managerial occupations and the professional group is about averagely segregated in comparison to other major occupational groups. Moreover, the service sector expansion was expected to lead to more sex segregation as these occupations are female-dominated (Charles, 1992, 2003; Charles & Grusky, 2004; Goldin, 2006; Ngai & Petrongolo, 2017). We found no clear evidence supporting this view. Emerging service occupations were indeed sex-segregated but a decrease in “pure” segregation across service occupations counteracted this effect. Some of the discrepancies in relation to previous research could presumably be due to differences in countries and time points studied. For instance, the acceleration in service expansion mainly occurred before the 2000s and may have led to more sex segregation prior to 2000. Furthermore, the entering of women into higher education and subsequently into professional occupations probably initially had an integrative effect as the balance between women and men became more even (Charles & Bradley, 2009; Oesch, 2015), but as women now are overrepresented in these occupations, the entering of more women into these jobs currently has segregating effects. In total, our findings question some of the established theories about skills and occupational sex segregation, why future research should explore more detailed analyses of the association between level and type of skill and occupational sex segregation, as well as its connection to female labour force participation.
Notes

1. Bulgaria, Malta, Poland and Slovenia were not included in the analyses as these countries provided less detailed occupational information. Also, three of the countries included in the sample deviate in terms of the years selected for the analyses: the first time points for which Croatia and Romania provided detailed occupational information were 2002 and 2005, respectively. Also, 2019 is the last available time point for the UK.

2. The occupational category “0. Armed forces” was missing for Italy in 2000, for Switzerland in 2020, and for Iceland in both 2000 and 2020.

3. Since the occupational classification was updated (and given more detail) in 2020 compared to 2000, appearing (disappearing) occupations do not by necessity need to be new (old) occupations in the sense that they did not exist in 2000 (2020).


5. Within each major occupational group (ISCO categories 1–9 measured on a 1-digit level), there are more detailed occupational groups (measured on a 3-digit level). Since occupational category “0. Armed forces” generally did not contain subcategories measured on a 3-digit level, this category is excluded from the detailed decomposition.

6. This is to some extent related to the number of occupational categories within each major occupational group since more detailed occupational categories allow for more sex segregation.

References


Introduction

Men and women choose different fields of study – and these differences in study field lead to differences in labor market outcomes and pay (Charles and Bradley 2002; Gerber and Cheung 2008). These choices contribute to inequalities in the positions men and women occupy, the types of work they do, and the compensation they receive (Smyth and Steinmetz 2015; Barone 2011; van de Werfhorst 2017). Gender segregation in education and employment is a challenge to the social aim of empowering individuals and achieving greater gender equality in the labor market (Charles and Bradley 2009; Barone 2011).

In Sweden, the labor force participation of men and women is relatively equal: 69.7% of women and 76.4% of men aged 15–74 were in the labor force in 2021 (Statistics Sweden 2021). However, the gender equality in labor force participation is accompanied by substantial gender segregation. Men and women are employed in different industries (see Chapter 2 in this volume for the connection between gender and types of work), and hold different types of jobs within those industries (Gonäs et al. 2019; Nermo 2000). Unsurprisingly, the Swedish educational system also has a significant amount of gender inequality (UKÄ 2016). Gender segregation in Sweden follows a pattern seen internationally, where women tend to specialize more in care-oriented work (e.g., teaching, healthcare), whereas men tend to specialize more in product-oriented work (e.g., programming, industry).

This chapter explores gender differences in Higher Vocational Education (HVE, in Swedish, Yrkeshögskolan), an emerging form of Swedish...
post-secondary vocational education. HVE is an important and intriguing form of education for the study of gender inequality. It is short (1–2 years), requires upper-secondary education, and is publicly funded. The goal is to place graduates directly into jobs, and the curriculum is developed in tandem with industry actors to focus on giving graduates useful skills. This educational form is relatively new in Sweden and is expanding at a dramatic rate: from 15,000 participants in 2007 to 35,000 participants in 2020 (MYH 2021). HVE is especially interesting to study because one of its mandates is to alleviate gender segregation in the labor market by (re)training workers for work within gender-atypical occupations (Swedish Law 2009; MYH 2020).

This chapter evaluates gender inequality in field of study in this vocational educational form. The first contribution of this chapter is empirical: to document gender differences within HVE. Register data on every participant is used to show the overall level of gender segregation within HVE, comparing it to gender segregation in other forms of education in Sweden. The second contribution of this chapter is to show which participants are more likely to select into gender-(a)typical fields of study. Register data is used to study how socio-demographic variables including gender, age, and migration background are related to the probability of choosing a gender-(a)typical field of study, using a multinomial logistic regression model approach. Finally, we investigate whether previous enrollment in gender-atypical education or work in a gender-atypical industry corresponds to the probability of enrolling in gender-atypical HVE education. This study includes all HVE participants in years 2005–2019, a total of 278,107 observations.

National and institutional context

Gender segregation in the educational system and labor market is a major focus of social research and policy debate. In Sweden, there is significant difference in the types of jobs held by men and women, though gender segregation has slightly declined in the 2000s (Halldén and Härkönen 2015; Gonäs et al. 2019). Despite the gender inequality, the Swedish labor market is less segregated at the occupational level than many other European countries like Austria, Hungary, Slovenia, the Netherlands, and Finland (Smyth 2005).

Gender inequality in vocational education and training (VET) has been an important area of research in recent decades (Evans 2006; Webb et al. 2006; Orupabo 2018). Previous research has emphasized the importance of institutional factors for the processes of individual decision-making regarding field
of study (Charles and Bradley 2009; Imdorf et al. 2015; Smyth and Steinmetz 2015). Thus, it is worth situating HVE in the Swedish educational context.

As mentioned earlier, HVE is a relatively new form of education that has more than doubled in size since its experimentation phase to its formal establishment: from around 15,000 participants in 2007 to more than 35,000 participants in 2020 (MYH 2021). The system is a public and private hybrid. Programs are typically funded for a few years at a time and are designed in partnership with private actors. Funding for programs is conditional on effective training (including an internship component) and on the probability of job placement for program graduates. HVE is mid-skill education: participants learn more advanced material than what is taught at the upper-secondary vocational level. HVE seems relatively effective in facilitating education-to-work transitions: one year after graduation, more than 60% of graduates work in a job that requires skills they acquired in their HVE program (MYH 2020).

HVE has been designed to create effective (re)skilling within the Swedish labor market, and specifically to address issues of unemployment within groups with a precarious position in the labor market. Women, youths aged 18–25, and Swedish-born people are slightly over-represented in HVE compared to the overall population, but HVE also attracts foreign-born participants of all ages and individuals with a variety of educational backgrounds (Ye et al. 2022).

Factors relating to gender-(a)typical program choice

As discussed above, the topic of gender segregation and gendered choices in education is a major focus for sociological research. However, existing theories may not have complete relevance for study choice in the HVE system. Literature on the question of gender inequality has shown that institutional context has a strong impact on the decision-making processes of men and women. For example, parents’ occupation and education is often a variable of study when examining choices of youths in vocational education (Dryler 1998; Støren and Arnesen 2007; van de Werfhorst et al. 2003) – however, within the HVE context, where the majority of participants are over 25 years old, parental education seems less important than it does for children and youth.

Previous sociology of education literature has come up with two broad strands of explanation for gendered decision-making in education: cultural social explanations focusing on social influence and rational choice explanations focusing on individual risk and benefit calculations. This previous research
sees the choice of study field as a very important decision which defines individual identity, lifestyle, and finances – and a decision made based on assumptions about where different choices would lead (Erikson and Jonsson 1996; Breen et al. 2014).

The first explanation, of social influence, refers to direct interaction with parents, peers, teachers, and other community members who define the set of reasonable expectations for an individual (Charles and Bradley 2009; Kretschmer and Roth 2021). Men and women receive different messages from their surroundings about what is reasonable, possible, and desirable (Correll 2001). Previous research suggests that feedback on personal skills affects educational choices, and men and women receive different types of feedback (Holm et al. 2019). The second explanation is participants’ own perception of their ability and their likelihood to succeed in studies and eventually in the workplace (Breen et al. 2014). Men and women may have different expectations for the returns to their education, and these perceptions are based partially in previous educational performance and can vary by gender (Jonsson 1999; Støren and Arnesen 2007).

In practice, these two types of explanations are difficult to separate – individual “rational choice” explanations are affected by experiences of social norms. Additionally, it is hard to say how much gender weighs in the selection of study field: other factors like work–life balance or social prestige also matter, and these may be correlated with fields’ gender balance without gender being an explicit factor of consideration. In this chapter, we do not examine peer effects or level of ability directly, but rather we examine how gender-(a)typical choice in the field of study relates to individual socio-demographic variables and previous educational and work experience. Our aim is to understand who is more likely to participate in gender-balanced or opposite-gender-dominated programs compared to same-gender-dominant programs. Given the HVE goal of reducing gender segregation in training, institutionally desirable outcomes would include high enrollment in programs that are gender-balanced (have a similar number of men and women), a decline in the share of men/women studying same-gender-dominated programs, and an increase in participation in programs dominated by the opposite gender.

Socio-demographic variables

We start with participant socio-demographic variables. Previous research suggests that women are more likely to enter male-dominated fields, rather than vice versa (UKÄ 2016; Charles and Bradley 2009; England 2010). Official publications suggest that in recent years, women’s enrollment in some
male-dominated HVE fields of training (like building or IT) has grown somewhat faster than for men (MYH 2020). Thus, we expect that women would be more likely to enroll in gender-atypical education.

The second factor considered is age. Over the period of HVE expansion, the proportion of participants aged 18–25 has declined (from 51% in 2005 to 33% in 2019), while the share of those aged 26–45 has increased (from 45% to 59%) (Ye et al. 2022). Previous research on age in HVE program choice is scarce, but research on educational inequality suggests that youths are more likely to choose gender-typical fields of study, as they are more motivated by the ability to affirm their identity through choice of program (Imdorf et al. 2015). We thus expect that older participants are more likely to choose gender-atypical fields.

The third factor considered is migration background. Foreign-born participants make up about 15% of the total HVE student population, but previous literature does not offer sufficient theorizing to create a hypothesis on this variable. Finally, we also include a measure of individual education and income before HVE participation. These measures are to give context to individuals’ socioeconomic resources at the time of decision-making.

Previous education and employment in gender-balanced/atypical fields

Earlier research finds that students choose their study field in part with reference to their previous skills and experiences, which informs their probability of success in the chosen field of study (Jonsson 1999; van de Werfhorst et al. 2003; Tolsma et al. 2010; Gabay-Egozi et al. 2015).

Those who have already completed studies in a gender-atypical field may have more confidence in their ability to successfully complete the HVE program. They may have a gender-atypical skill profile, or may be more confident about their abilities to thrive in a gender-atypical environment. Likewise, those with experience working in a gender-atypical environment may have greater confidence in pursuing such vocational orientation.

We thus consider how previous education and employment in gender-balanced/atypical fields are related to the probability of enrolling in gender-balanced/atypical education at the HVE level. We use three measures of previous experience: field of study in previous education, previous occupation, and previous industry. Our hypothesis is that participants with previous experiences from gender-balanced/atypical education and work settings should have a higher
propensity of enrolling in HVE programs that are more equal in terms of gender or will choose to maintain a gender-atypical skills profile.

Limitations
The literature on individual educational choice acknowledges that explanations that refer to individual skills or experiences do not completely explain why men and women make different choices. However, through our register data we lack the ability to measure potentially significant variables such as individuals’ exposure to social norms or their individual beliefs and opinions about appropriate work (Barone 2011; Busch-Heizmann 2015; Gabay-Egozi et al. 2015). Our approach is also unable to take into account relationships between educational providers, social groups, and their participation in specific programs (Palme 2008). Given the limitations of this analysis, we acknowledge the possibilities for future avenues of research.

Data and method
This study is based on administrative register data from Sweden. Each individual has a personal national identifier, which makes it possible to identify them in the HVE enrollment registers and to connect them to other relevant national registers.

Enrollment in HVE is measured in the years 2005–2019. The first covariate in the study is Gender, which refers to the juridical sex registered at the time of enrollment. Age Group refers to the age of the individual in the year of enrollment, and is categorized into four groups (18–25, 26–35, 36–45, and 46–60). Country of Origin is based on an individual’s country of birth and categorized as Sweden, Organisation for Economic Co-operation and Development (OECD),¹ and non-OECD. This categorization is made to reflect (dis)similarities in the labor market between the individual’s country of origin and Sweden. Highest Level of Education is identified the year prior to the start of the HVE program, and categorized as Vocational Upper-Secondary, Academic Upper-Secondary, or Post-Secondary. Relative Income is identified the year prior to the start of the HVE program, using a disposable income measure from the registers.

Three covariates measure the gender composition of participants’ previous education and employment. First, their previous Field of Study. This is measured by calculating the percentage of men/women who hold each combination...
of level of education (e.g., upper-secondary three years) and three-digit coding of study field (e.g., chemistry, literature). This calculation is done among all men/women aged 18–60 in the year prior to the index person’s enrollment in HVE. The second variable is Previous Occupation. This variable is also measured by taking the percentage of men and women in each occupation in the year prior to the index person’s enrollment in HVE. Occupations are registered using the Swedish Occupational Classification (SSYK) format based on the ISCO-08 classification (114 occupations including, e.g., lawyer, flight attendant). The third variable captures the gender composition within participants’ Previous Industry of Work. In the registers, this variable is coded using the Swedish SNI categorization (766 industries, e.g., Driving School Activities, Pre-school Education). Each of the three variables are coded into same-sex dominant (0–33% same sex), balanced (34–66%), and opposite-sex dominant (67–100%).

The analysis in the study is conducted in three steps. The first step is to provide a description of gender segregation within HVE. For this, we calculate the percentage of men and women within each HVE field of study (using a three-digit program delineation, e.g., Journalism and Media) for each year. To show the segregation, we use the Duncan Dissimilarity Index, a measure that ranges from 0 to 1 and summarizes how many men/women would have to switch places to gain an equal distribution of men and women in each field of study (Duncan and Duncan 1955). A 1 in this measure means complete inequality (all women in only-women programs) and a 0 represents complete equality (each program is gender-balanced). To give context for this measure, we compare HVE to two other forms of education in Sweden: upper-secondary school and post-secondary school, where gender segregation is also measured at the program level. We also use a table to describe the top 10 study fields for men and for women to give context to this gender segregation (see Online Appendix), and a table that describes the gender distribution of participants’ previous education and work to their HVE choice.

The second stage of the analysis is a multinomial logistic regression model to study the probability that participants enroll in gender-atypical programs. The outcome of the model is a three-level variable: 1 (the reference level, enrollment in a same-sex-dominated program), 2 (enrollment in a balanced program), and 3 (enrollment in an opposite-sex-dominated program). Models are run separately for men and for women. The covariates included in the models are Age Group, Country of Origin, Highest Level of Education, Relative Income, and a control for the year of enrollment. The presented coefficients are interpreted as the relative to the likelihood of the reference outcome (enrollment in a same-sex-dominated program). In the final stage of analysis,
we perform the same multinomial logistic regression, but we also include the variables measuring previous education and work.

![Graph showing Duncan Dissimilarity Index (DI) for HVE compared to Swedish upper-secondary and post-secondary education.](image)

**Figure 6.1** Gender segregation in HVE by year, compared to upper-secondary and post-secondary education. Duncan Dissimilarity Index (DI) of study fields

### Results

Figure 6.1 shows the Duncan Dissimilarity Index (DI) for HVE compared to Swedish upper-secondary and post-secondary education. Overall, there is a slight positive trend in the DI over time, meaning that HVE is becoming slightly more sex-segregated. The DI ranges from 0.46 to 0.55: HVE is quite gender-segregated, given that 0 is the value where no gender segregation exists. This figure also shows that HVE is relatively more segregated than other forms of Swedish education (DI for gymnasium and college is around 0.36–0.4). For information on the different fields chosen by men and women, see the Online Appendix. There are three fields common among both men and women: “System development, programming”, “Graphic design, photography”, and “Purchasing, sales and distribution”. Otherwise, the gendered division in HVE follows broadly observed gendered patterns, men studying construction and technology whereas women are studying services and care.

Table 6.1 shows a descriptive overview of the study population. The study population includes 278,107 men and women enrolled in HVE from 2005 to 2019. The majority of participants are aged 18–35 and are born in Sweden. Among foreign-born participants, the majority are born outside of the OECD countries.
Table 6.1  Descriptive statistics for study population

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th></th>
<th>Women</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>%</td>
<td>N</td>
<td>%</td>
<td>N</td>
</tr>
<tr>
<td></td>
<td>129907</td>
<td>148200</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age Group</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18–25</td>
<td>47%</td>
<td>60649</td>
<td>35%</td>
<td>52241</td>
</tr>
<tr>
<td>26–35</td>
<td>34%</td>
<td>44300</td>
<td>35%</td>
<td>51361</td>
</tr>
<tr>
<td>36–45</td>
<td>14%</td>
<td>17925</td>
<td>21%</td>
<td>30447</td>
</tr>
<tr>
<td>46–60</td>
<td>5%</td>
<td>7033</td>
<td>10%</td>
<td>14151</td>
</tr>
<tr>
<td>Country Group</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sweden</td>
<td>83%</td>
<td>107304</td>
<td>84%</td>
<td>124551</td>
</tr>
<tr>
<td>OECD</td>
<td>4%</td>
<td>5084</td>
<td>4%</td>
<td>6666</td>
</tr>
<tr>
<td>Non-OECD</td>
<td>13%</td>
<td>17519</td>
<td>11%</td>
<td>16983</td>
</tr>
<tr>
<td>Relative Income</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 (lowest)</td>
<td>38%</td>
<td>49065</td>
<td>27%</td>
<td>39341</td>
</tr>
<tr>
<td>2</td>
<td>29%</td>
<td>37463</td>
<td>28%</td>
<td>40924</td>
</tr>
<tr>
<td>3</td>
<td>18%</td>
<td>23277</td>
<td>23%</td>
<td>34049</td>
</tr>
<tr>
<td>4</td>
<td>11%</td>
<td>13773</td>
<td>15%</td>
<td>21585</td>
</tr>
<tr>
<td>5 (highest)</td>
<td>4%</td>
<td>5220</td>
<td>8%</td>
<td>11183</td>
</tr>
<tr>
<td>Missing</td>
<td>1%</td>
<td>1109</td>
<td>1%</td>
<td>1118</td>
</tr>
<tr>
<td>Highest Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vocational Up-Sec</td>
<td>42%</td>
<td>54898</td>
<td>41%</td>
<td>60887</td>
</tr>
<tr>
<td>General Up-Sec</td>
<td>32%</td>
<td>42067</td>
<td>35%</td>
<td>52159</td>
</tr>
<tr>
<td>Post-Secondary</td>
<td>13%</td>
<td>17317</td>
<td>18%</td>
<td>26209</td>
</tr>
<tr>
<td>Missing</td>
<td>12%</td>
<td>15625</td>
<td>6%</td>
<td>8945</td>
</tr>
<tr>
<td>Previous Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>37%</td>
<td>48456</td>
<td>36%</td>
<td>53930</td>
</tr>
<tr>
<td>Balanced</td>
<td>54%</td>
<td>69510</td>
<td>57%</td>
<td>84927</td>
</tr>
<tr>
<td>Op-sex dominant</td>
<td>8%</td>
<td>10303</td>
<td>5%</td>
<td>7857</td>
</tr>
<tr>
<td>Missing</td>
<td>1%</td>
<td>1638</td>
<td>1%</td>
<td>1486</td>
</tr>
</tbody>
</table>
Most participants have a low income prior to enrolling in HVE, and almost half have a vocational upper-secondary degree. A minority of participants have previous experience in opposite-gender-dominated education (8% men and 5% women), occupation (13% men and 9% women), and industry (11% men and 12% women). Table 6.2 shows how previous education and income relate to HVE choice: those who have had experience of gender-atypical occupations and educations are most likely to make gender-atypical HVE choices.

Table 6.3 shows the results of the multinomial regression model. Results are presented in two columns for men and for women, with column A referring to the outcome “gender-balanced program” and column B referring to the outcome “opposite-gender-dominated program”, both in relation to the base outcome of “same-gender-dominated program”. Starting with the “opposite-gender-dominated” outcome and age, we can see that the relationship is different for men and women. Older male participants are more likely to enroll in gender-atypical programs, while older female participants are less likely to enroll. This is a mixed result to our hypothesis that older participants would be more likely to make gender-atypical choices.

Next, the opposite relationship continues for country group: among women, immigrants (especially from non-OECD countries) are more likely to make gender-atypical choices, while male immigrants differ. Those from non-OECD countries are less likely to enroll in a gender-atypical program, while those from OECD countries are more likely to enroll compared to Swedish-born participants.
Table 6.2 Percentage of HVE students by gender, previous education, industry, and occupation and the gender composition of their program

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th></th>
<th>Women</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mostly Men</td>
<td>Balanced</td>
<td>Mostly Women</td>
<td>Balanced</td>
</tr>
<tr>
<td>Previous Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>75</td>
<td>18</td>
<td>7</td>
<td>72</td>
</tr>
<tr>
<td>Balanced</td>
<td>51</td>
<td>32</td>
<td>17</td>
<td>59</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>42</td>
<td>32</td>
<td>26</td>
<td>36</td>
</tr>
<tr>
<td>Missing</td>
<td>51</td>
<td>34</td>
<td>15</td>
<td>47</td>
</tr>
<tr>
<td>Previous Job</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>68</td>
<td>23</td>
<td>9</td>
<td>72</td>
</tr>
<tr>
<td>Balanced</td>
<td>52</td>
<td>32</td>
<td>16</td>
<td>57</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>43</td>
<td>29</td>
<td>28</td>
<td>47</td>
</tr>
<tr>
<td>Missing</td>
<td>65</td>
<td>24</td>
<td>11</td>
<td>57</td>
</tr>
<tr>
<td>Previous Industry</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>67</td>
<td>23</td>
<td>10</td>
<td>72</td>
</tr>
<tr>
<td>Balanced</td>
<td>45</td>
<td>37</td>
<td>19</td>
<td>57</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>45</td>
<td>29</td>
<td>26</td>
<td>47</td>
</tr>
<tr>
<td>Missing</td>
<td>65</td>
<td>24</td>
<td>11</td>
<td>54</td>
</tr>
</tbody>
</table>

In terms of previous education, academic upper-secondary and college are related to a positive likelihood to choose gender-atypical education (compared to vocational upper-secondary). However, more education does not neatly relate to more gender-atypical choices: for men, those with an academic upper-secondary degree are those most likely to enroll in opposite-gender-dominated programs.

Finally, Table 6.4 presents the results of a second set of multinomial regression models, which additionally examine previous education, occupation, and industry. Columns 1A/2A show the probability of enrolling in gender-balanced programs (compared to a same-gender-dominant program). Columns 1B/2B show the probability of enrolling in opposite-gender-dominated programs.
### Table 6.3
Regression results: multinomial logistic regression coefficients with the outcome “enrolled in sex-balanced program” (1A, 2A) or “enrolled in opposite-sex-dominant program” (1B, 2B) – reference outcome is “enrolled in same-sex-dominant program”

<table>
<thead>
<tr>
<th></th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18–25 (Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>26–35</td>
<td>0.96</td>
<td>1.34</td>
</tr>
<tr>
<td>36–45</td>
<td>0.83</td>
<td>1.58</td>
</tr>
<tr>
<td>46–60</td>
<td>0.93</td>
<td>2.13</td>
</tr>
<tr>
<td>Country Group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sweden (Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>OECD</td>
<td>0.98</td>
<td>1.15</td>
</tr>
<tr>
<td>Non-OECD</td>
<td>0.69</td>
<td>0.90</td>
</tr>
<tr>
<td>Education Level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vocational Up-Sec (Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>Academic Up-Sec</td>
<td>1.70</td>
<td>1.54</td>
</tr>
<tr>
<td>Post-Secondary</td>
<td>1.49</td>
<td>1.26</td>
</tr>
<tr>
<td>Missing</td>
<td>0.79</td>
<td>0.80</td>
</tr>
</tbody>
</table>

**Note:** values with P>0.000 are in italics.

(compared to a same-gender-dominant program). Regarding the previous field of education, men and women who already hold opposite-gender-dominant education were more likely to enroll in an opposite-gender-dominant program in HVE, supporting the hypothesis that previous experience and skills relate to further gender-atypical choices.

With regard to previous occupation, the same pattern was observed. Men and women with an occupation that had a balanced or opposite-gender dominance were more likely to enroll in balanced or opposite-gender-dominant HVE educations. Similarly, those who worked in gender-balanced or opposite-gender-dominant industries were also more likely to enroll in gender-balanced or opposite-gender-dominant HVE programs.
# Table 6.4

Regression results: multinomial logistic regression coefficients with the outcome “enrolled in sex-balanced program” (1A, 2A) or “enrolled in opposite-sex-dominant program” (1B, 2B) - reference outcome is “enrolled in same-sex-dominant program”

<table>
<thead>
<tr>
<th></th>
<th>Men 1A</th>
<th>Men 2A</th>
<th>Women 2A</th>
<th>Women 2B</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Previous Field of Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>0.36</td>
<td>0.28</td>
<td>0.76</td>
<td>0.79</td>
</tr>
<tr>
<td>Balanced</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>1.02</td>
<td>1.26</td>
<td>1.61</td>
<td>4.00</td>
</tr>
<tr>
<td>Missing</td>
<td>2.23</td>
<td>1.77</td>
<td>1.45</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Previous Occupation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>0.59</td>
<td>0.55</td>
<td>0.58</td>
<td>0.84</td>
</tr>
<tr>
<td>Balanced</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>0.75</td>
<td>1.11</td>
<td>0.99</td>
<td>1.94</td>
</tr>
<tr>
<td>Missing</td>
<td>0.64</td>
<td>0.66</td>
<td>0.86</td>
<td>1.22</td>
</tr>
<tr>
<td><strong>Previous Industry</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Same-sex dominant</td>
<td>0.70</td>
<td>1.22</td>
<td>0.71</td>
<td>0.64</td>
</tr>
<tr>
<td>Balanced</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
<td>(Ref)</td>
</tr>
<tr>
<td>Opp-sex dominant</td>
<td>0.97</td>
<td>1.61</td>
<td>1.21</td>
<td>1.65</td>
</tr>
<tr>
<td>Missing</td>
<td>0.73</td>
<td>2.32</td>
<td>0.85</td>
<td>1.11</td>
</tr>
<tr>
<td><strong>Controls Included</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age Group</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Country Group</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Level of Edu</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Income Quintile</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Intercept</td>
<td>2.05</td>
<td>0.49</td>
<td>1.56</td>
<td>0.18</td>
</tr>
</tbody>
</table>

**Note:** values with P>0.000 are in italics.
Conclusion

The topic of gender segregation in education and work is significant in Sweden due to the stark differences between men and women’s choices and positions in the Swedish labor market (UKÄ 2016; Gonäs et al. 2019; Nermo 2000). Gender segregation in Sweden follows a pattern seen internationally, where women tend to specialize more in care-oriented work, whereas men tend to specialize more in product-oriented work (see Chapter 2 in this volume). This chapter has examined gender segregation in Swedish HVE: a rapidly expanding form of vocationally oriented, publicly funded, post-secondary education in Sweden. HVE has an institutional goal to reduce gender segregation in education and work, making the present research more salient.

In this chapter, we used Swedish administrative register data to identify all participants within the HVE system in the years 2005–2019. We first used the Duncan Index of Dissimilarity to study the overall gender segregation in the system. Our findings show that HVE is characterized by moderate gender segregation: around 0.5 on a scale of 0–1, meaning about half of all men and women would have to switch places to achieve gender inequality. We also showed that this segregation has increased slightly over time, and that it is more significant than gender segregation in other forms of Swedish education, such as upper-secondary and tertiary education. In Sweden, vocational education tends to be more gender-segregated at the upper-secondary level than academic education (Skolverket 2020), so this characteristic in HVE may be unsurprising.

In the second stage of the analysis, we performed a multinomial logistic regression to study the association between one’s field of study (choice of gender-balanced/atypical program compared to choice of gender-typical program) and one’s socio-demographic characteristics. The models were performed separately for men and for women and included age, country group of origin, previous education, and relative income. We found that associations differed for men and for women with regard to age and country of origin. We also found that previous educational level was positively related to gender-atypical choices.

Finally, we examined how previous education and work experiences related to field of study. We expected that previous experience of gender-atypical environments would facilitate gender-atypical choices in the HVE field of study. Our findings confirmed this expectation, showing that men and women who studied in gender-atypical fields, or worked in gender-atypical occupations or
industries, were more likely to choose gender-atypical programs in HVE. The relationship looked similar for men and for women, and previous educational experience had the strongest association with choice of HVE field. Those who already know that they can thrive in gender-atypical environments have a higher propensity to pursue a gender-atypical vocational program, with subsequent transition into work.

The findings in this chapter are congruent with earlier research that has shown that improving links between vocational education and work depends not only on educational provision or issues of labor supply but also on the structure of the labor market (Wheelahan and Moodie 2017). In contemporary times, higher-level vocational education is being celebrated by advocates for its effectiveness for labor market integration. With increasing public investments in this segment and growing interest and enrollment, further in-depth research into these participants’ experiences is needed. Broadening current conceptualizations of gendered vocational aspirations and education choices by incorporating examinations of how gender intersects with various key social dimensions to shape outcomes in transitions from HVE into work can be generative, and a possible direction for future research.

Note

1. Due to data issues, Mexico and Colombia cannot be identified separately from the greater Latin American region, and thus the small number of immigrants from these countries are classified as “non-OECD” in this study.

References


Introduction

How people view and situate themselves in society has long been a central area of inquiry in sociology (Evans and Kelley, 2004). Partly fuelled by Marxist theories of class consciousness and class formation (Marx, 1963 [1852]), for a long time a major focus was on how people place themselves in the economic order and how they self-identify in terms of class identity (Hodge and Treiman, 1968; Jackman and Jackman, 1973). However, in recent years there has been a surge of interest in subjective social status, which in theory is often said to probe individuals’ beliefs about their standing relative to others in chiefly social terms (e.g., Gidron and Hall, 2020). This growing literature argues that subjective social status is of relevance for a host of substantive outcomes, including health (Singh-Manoux et al., 2003; Miyakawa et al., 2012), life satisfaction (Schneider, 2019), reservation wages (Fuchs et al., 2022), and political orientations (Gidron and Hall, 2017; Kurer, 2020; Carella, 2021). While the psycho-social component of the concept is emphasized in theory, empirical studies suggest that subjective social status is related to actual socioeconomic conditions and inequalities. Subjective social status tends to be higher, on average, in more affluent countries (Lindemann and Saar, 2014) and among individuals who are in more advantageous socioeconomic positions within countries (Shaked et al., 2016).

Work can be a source of social recognition and esteem (Sandel, 2020). It has long been argued that the occupational structure is a central hub of status inequality, and that social prestige attaches onto occupations in a way that is highly similar across countries (Treiman, 1977; Hout and DiPrete, 2006). Yet the significance of occupations for the social status of individuals has scarcely been the subject of multivariate studies. While a few studies examine how subjective social status varies between a small number of ‘big’ occupational classes (Gidron and Hall, 2020; Oesch and Vigna, 2022; Nolan and Weisstanner, 2022), there is a lack of studies on how subjective social status varies in a larger...
set of more detailed occupational groups in relation to the type and level of skills required in different jobs.

The main purpose of this chapter is to examine the relationship between occupational skills and subjective social status in advanced knowledge economies. To this end, we study how subjective social status varies between individuals in different occupations within 25 countries, using multilevel modelling and data from the European Social Survey (ESS). We raise three main research questions:

1. To what degree is the subjective social status of individuals attached to their occupation?
2. To what extent is the occupational gradient in subjective social status accounted for by the educational requirements of jobs?
3. Does manual work convey lower subjective social status than non-manual work?

We also explore whether country differences in subjective social status may be accounted for by between-country variation in national skill regimes and levels of economic affluence.

**Theoretical background**

Following Max Weber (2009 [1922]), a fundamental conceptual distinction in sociology is that between class and status. Whereas the class concept is said to denote structural locations in production and labour markets, the status concept signifies inequalities inherent to hierarchical relations of superiority/inferiority in the social sphere of life (Weber, 2009 [1922]; Chan and Goldthorpe, 2004; Ridgeway, 2014). As crucial as this conceptual distinction is in theory, it is equally important to recognize that it can be a challenging task to distinguish these two axes of inequality in empirical analysis (e.g., Bihagen and Lambert, 2018). Partly (but not only) for this reason, there is a longstanding literature – especially in the United States – that instead uses the concept of socioeconomic status to refer to an overarching stratification order that synthesizes social *and* economic inequalities (e.g., Reiss, 1961).

In light of such theoretical heterogeneity within the broader research field, it is perhaps not surprising that the now standard scale of subjective social status
has been theorized in more than one way. The survey question that provides the basis for this scale reads as follows in the ESS:

There are people who tend to be towards the top of our society and people who tend to be towards the bottom. On this card there is a scale that runs from top to bottom. Where would you place yourself on this scale nowadays?

When first introduced in the US General Social Survey in the late 1970s, the main intention with the question was to augment existing measures of class identity (Smith, 1986). Still, some recent studies treat it as a tailored measure of social status in a Weberian sense (e.g., Gidron and Hall, 2020). A recent validation study of what the question actually captures, however, suggests that many people have economic factors (e.g., income, wealth) in mind when answering the question (Evans and Schaffner, 2022). This raises scepticism that the question measures social status stripped from class inequalities, which is why we instead treat it as a synthetic indicator of subjective socioeconomic status that encapsulates both social and economic conditions.2

**Occupational skills and subjective social status**

In sociology, it is common to make a theoretical distinction between structural positions in the division of labour (e.g., occupations) and the individuals who inhabit these positions at a given point in time. Three main methodological strategies have been used for grading occupations in terms of positional status inequality. The first is to scale occupations based on the level of social standing and prestige that survey respondents ascribe to them (e.g., Reiss, 1961; Treiman, 1977; Evans et al., 2022). The second is to identify social status based on differential social ties between incumbents of different occupations, focusing on social relations such as friendships, marriages, or cohabitations. This approach assumes that such ties confer information on equality in terms of status, implying that the larger the social distance between two occupations, the bigger the presumed status divide between them (e.g., Laumann, 1966; Stewart et al., 1980; Chan and Goldthorpe, 2004). The third is to scale occupations based on correlations with other socioeconomic indicators, chiefly the individual’s own educational attainment and income (Ganzeboom et al., 1992). Despite these differences in methodology, the empirical correlations between these different status scales tend to be high by conventional standards (Bihagen and Lambert, 2018).
Our analytical approach bears some resemblance to the first tradition described above, which builds on occupational prestige, in that our approach is based on people’s assessments of status. But rather than focusing on how people rate the prestige of different occupational positions, we study how individuals view their own social standing. The main advantage of this approach – compared to operationalizing status/prestige at the level of occupational positions – is that it permits multivariate analysis of the significance of occupational position for individual status (cf. Treiman, 1977: 228–229).

Why would we expect that skill requirements shape an occupational gradient in subjective social status? We take as a starting point that the exercise of skill in productive activities together with others is beneficial for one’s self-esteem and the perception of being valuable to society (Gomberg, 2016; Sandel, 2020). People also tend to admire and think highly of others who are skilful and display craftsmanship, expertise, or excellence (Algoe and Haidt, 2009). Skills may also be a source of power in the workplace, thus contributing to why occupations that require a higher degree of knowledge, training, or talent tend to be more prestigious (Treiman, 1977). Furthermore, there is a marked positive relationship between skill requirements and economic rewards at the occupational level (Tåhlin, 2011). Individuals in higher-skilled occupations thus enjoy a higher standard of living since they are more favourably rewarded at work, which could potentially lead to higher subjective social status compared to individuals in lower-skilled occupations who have a lower standard of living.

There is a tight link between the occupational structure and the formal educational system in advanced knowledge economies. Many jobs are highly complex and require skills that are difficult and costly to learn primarily through on-the-job training. This makes formal educational requirements a main indicator of the skill level in jobs (Tåhlin, 2011), although formal educational degrees and qualifications may in part also serve as a closure mechanism for restricting access to certain desirable occupations (Bol and Weeden, 2015). Even if educational degrees and qualifications may convey some status in their own right (Markovits, 2019), we posit that it is usually not until being put into practice in a matching occupation that individuals get the social standing associated with a certain craft or profession. Simply put, having the full social respect of being a medical doctor requires not only having a medical degree, but also practising the medical profession in paid work.

In addition to the level of skill and educational requirements, we also consider different types of skills that are closely related to the qualitative differentiation of work tasks. Some previous research argues that such qualitative variations in work tasks are of relevance for status, and that manual work and skills in
particular are socially devalued in advanced knowledge economies relative to non-manual skills. For example, Chan and Goldthorpe (2004) contrast a supposed old status order where skilled craftsmen ranked above typical service workers to the ‘relatively low positions of the skilled manual worker categories’ (p. 391) that they find in their empirical study of the present-day status hierarchy. Oesch and Vigna (2022), however, do not find any differences in subjective social status between service workers and production workers, but we suspect that status divides between manual and non-manual occupations may potentially be concealed in their study due to the heterogeneity of the service worker category they used and the exclusion of clerical workers in their analysis. In the following empirical analysis, we explore potential status divides between manual and non-manual occupations based on explicit information about the main type of work task performed in the job.

Data and methods

Data

Our main data source is the sixth round of the European Social Survey (ESS6) collected in 2012, which (to date) is the most recent ESS to include the standard scale of subjective social status. For data on work tasks and educational requirements, we draw on the ESS5 (2010) since the ESS6 does not include any detailed questions about this. The two ESS waves thus complement each other as each contains data on topics that the other does not. Our skill measures are thus constructed at the occupational level in ESS5 (n = 18,404) and then imputed to match the occupation of each respondent in ESS6. The following 25 countries that participated in both ESS rounds are included in our analysis: Belgium, Bulgaria, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Israel, Lithuania, the Netherlands, Norway, Poland, Portugal, Russia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, and the United Kingdom.

The ESS6 analytical sample (n = 23,283) is restricted to respondents who are currently active in a non-military occupation. We exclude those currently in unemployment, higher education, retirement, and so on because associations between occupational skills and subjective social status may be muddled by confounding factors among those who are not currently in paid employment.
Subjective social status

We use the standard question, asking respondents to place themselves on a scale from 0 to 10 where 0 represents ‘the bottom of society’ and 10 represents ‘the top of society’ (see previous section for full question wording). The scale shows sufficient variability (SD = 1.71), relatively few missing values (less than 2%), and an observed average score (5.71) that is close to the theoretical mean of the scale (5.5). (For more descriptive statistics, see Table 7A.1 in the Online Appendix.)

Occupational skills

We construct two skill measures at the occupational level using self-reported information in ESS5 which we aggregate to the ISCO 2-digit level and then match onto the occupations of respondents in ESS6. Since the occupational classification scheme differs between survey rounds (ESS5 uses ISCO88, and ESS6 uses ISCO08), we make a crosswalk based on the Stata ado-file ‘iscogen’ (Jann, 2019). We end up with 26 (ISCO88com sub-major) occupational categories for our main analysis after excluding a few residual occupational categories for which we cannot produce skill measures of sufficient reliability. As a robustness check, we also calculate our skill measures and re-run the multilevel analysis based on 384 detailed occupational categories (ISCO 4-digit level), which produces similar results (see Online Appendix, Table 7A.4).

Educational requirements: The measure is constructed by combining responses to the following two questions: ‘If someone was applying nowadays for the job you do now, would they need any education or vocational schooling beyond compulsory education?’ (Yes, No); if ‘Yes’: ‘About how many years of education or vocational schooling beyond compulsory education would they need?’ Eight ordinal-scale response options are provided for the second question, ranging from ‘less than one year’ to ‘10 years or more’. Following prior research, we recode responses into an approximate ratio scale with years as the scale unit and a top category of 11 years beyond compulsory education (Tåhlin, 2011).

Main type of work: To operationalize the distinction between manual and non-manual work, we rely on information about the main type of work task performed in the job (cf. Fine, 1955), using the following question: ‘In your main job, which one of the following tasks do you generally spend most time on?’. Possible responses are: ‘supervising personnel’ (which we label management); ‘working with people other than employees at your workplace’ (people); ‘text and/or numbers’ (data); ‘physical objects and/or other physical
material’ (things); and ‘animals and/or plants’ (nature). We treat the two last categories (things, nature) as mainly involving manual work, and the first three categories (management, people, data) as mainly involving non-manual work.

A standard assumption in sociological stratification research is that occupations are cross-nationally invariant on dimensions of interest. Against this background, we construct our two skill measures by aggregating responses to the occupational level for all 25 countries combined. We use the mean level of years for educational requirements and the modal response for main type of work. In our main analysis, each occupational category thus has the same data values on our skill measures in all 25 countries. However, we relax this assumption in additional robustness checks, where we calculate our skill measures individually for each country. These additional analyses confirm that the relative ranking of occupational categories in terms of educational requirements is very similar across countries, although average absolute scores vary (see Table 7A.3 in the Online Appendix).

Table 7.1 lists the 26 occupational categories distinguished in our main analysis, ordered by their level of educational requirements in number of years beyond compulsory education. Health professionals have the highest educational requirements with an average of 6.1 years, while elementary sales/service occupations show the lowest educational requirements with an average of 0.4 years. Listed is also the main type of work tasks in each occupational category, based on our distinction between work tasks oriented towards things (dominating in 10 occupational categories), people (8), data (3), management (3), or nature (2). Occupational categories with low educational requirements are more likely to be characterized by manual (things, nature) than non-manual work (data, management, people). Yet, educational requirements and main type of work are far from perfectly correlated. Most notably, occupations that mainly involve working with people are found both in the top and in the bottom half of the occupational ranking in terms of educational requirements. And although most occupations that mainly involve working with things are in the bottom half of the list, there are a couple of such occupations in the upper half as well.

Other covariates

Our regression models contain standard sociodemographic controls at the individual level, including gender (man/woman), age (in years), and immigration status (citizen of country; born in country; mother born in country). Additional models also include the respondent’s years of full-time education completed and household income (from all sources, reported in deciles cor-
### Table 7.1: Occupational categories by educational requirements and main type of work

<table>
<thead>
<tr>
<th>ISCO Code</th>
<th>Label</th>
<th>Educational requirements</th>
<th>Main type of work</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>22</td>
<td>Health professionals</td>
<td>6.1</td>
<td>People</td>
<td>609</td>
</tr>
<tr>
<td>23</td>
<td>Teaching professionals</td>
<td>5.4</td>
<td>People</td>
<td>1,586</td>
</tr>
<tr>
<td>21</td>
<td>Science/engineering professionals</td>
<td>5.0</td>
<td>Data</td>
<td>990</td>
</tr>
<tr>
<td>24</td>
<td>Other professionals</td>
<td>5.0</td>
<td>Data</td>
<td>1,557</td>
</tr>
<tr>
<td>12</td>
<td>Corporate managers</td>
<td>4.3</td>
<td>Management</td>
<td>1,691</td>
</tr>
<tr>
<td>11</td>
<td>Legislators/senior officials</td>
<td>4.2</td>
<td>Management</td>
<td>61</td>
</tr>
<tr>
<td>32</td>
<td>Health associate professionals</td>
<td>3.6</td>
<td>People</td>
<td>715</td>
</tr>
<tr>
<td>33</td>
<td>Teaching associate professionals</td>
<td>3.5</td>
<td>People</td>
<td>70</td>
</tr>
<tr>
<td>31</td>
<td>Science/engineering assoc. professionals</td>
<td>3.5</td>
<td>Things</td>
<td>732</td>
</tr>
<tr>
<td>13</td>
<td>Manager small enterprises</td>
<td>3.3</td>
<td>Management</td>
<td>862</td>
</tr>
<tr>
<td>34</td>
<td>Other associate professionals</td>
<td>3.1</td>
<td>People</td>
<td>2,075</td>
</tr>
<tr>
<td>73</td>
<td>Handicraft workers</td>
<td>2.3</td>
<td>Things</td>
<td>141</td>
</tr>
<tr>
<td>72</td>
<td>Metal/machinery workers</td>
<td>2.2</td>
<td>Things</td>
<td>974</td>
</tr>
<tr>
<td>41</td>
<td>Office clerks</td>
<td>2.1</td>
<td>Data</td>
<td>1,533</td>
</tr>
<tr>
<td>71</td>
<td>Extraction/building workers</td>
<td>1.5</td>
<td>Things</td>
<td>1,058</td>
</tr>
<tr>
<td>51</td>
<td>Personal/proective services workers</td>
<td>1.5</td>
<td>People</td>
<td>2,378</td>
</tr>
<tr>
<td>61</td>
<td>Skilled agricultural and fishery workers</td>
<td>1.4</td>
<td>Nature</td>
<td>492</td>
</tr>
<tr>
<td>74</td>
<td>Other craft workers</td>
<td>1.4</td>
<td>Things</td>
<td>421</td>
</tr>
<tr>
<td>42</td>
<td>Customer services clerks</td>
<td>1.3</td>
<td>People</td>
<td>501</td>
</tr>
<tr>
<td>81</td>
<td>Stationary plant operators</td>
<td>1.2</td>
<td>Things</td>
<td>169</td>
</tr>
<tr>
<td>83</td>
<td>Drivers/mobile plant operators</td>
<td>1.2</td>
<td>Things</td>
<td>1,110</td>
</tr>
<tr>
<td>52</td>
<td>Salespersons/demonstrators</td>
<td>0.9</td>
<td>People</td>
<td>1,197</td>
</tr>
<tr>
<td>82</td>
<td>Machine operators/assemblers</td>
<td>0.9</td>
<td>Things</td>
<td>699</td>
</tr>
<tr>
<td>92</td>
<td>Agricultural/fishery labourers</td>
<td>0.5</td>
<td>Nature</td>
<td>210</td>
</tr>
</tbody>
</table>
responding to the actual household income distribution of each country, as extracted from an external source).

We also provide an explorative account of country differences in subjective social status. We construct a country-level measure of how upskilled the national occupational structure is by looking at the average level of educational requirements by country (calculated based on our occupational measure of educational requirements). Using data from the Penn World Tables (Feenstra et al., 2015), we also include real GDP per capita since previous research suggests that subjective social status is higher in more affluent countries (Lindemann and Saar, 2014). These two macro variables are positively correlated (Pearson’s $R = 0.70$), and both are coded to vary between 0 and 1.

Analytical strategy and modelling

Individuals can be thought of as nested within both occupations and countries. To take this clustering into account, we estimate a three-level hierarchical linear model with random intercepts for country (level 3) and occupational categories nested in countries (level 2) (Snijders and Bosker, 2011). We thus estimate the following model to predict subjective social status:

$$Y_{coi} = \beta_0 + \beta_1 x_{coi} + \beta_2 x_{co} + \beta_3 x_c + v_c + u_{co} + r_{coi}$$

where $\beta_1 x_{coi}$ is a series of individual-level control variables and their coefficients, $\beta_2 x_{co}$ represents our focus variables that potentially vary between occupation-countries, and $\beta_3 x_c$ is our set of country-level variables. This means that respondent $i$ is nested both within countries $c$ (level 3) and in occupations within countries $co$ (level 2). A key aspect of this model is the group-level residuals for country $v_c$ and occupation-country $u_{co}$, which allows for the estimation of group-specific intercepts and the share of variance at each level. We calculate the share of residual variance at each level by dividing its variance component with the total variance, for example at level 2 (occupations within countries),

$$p = \frac{\tau^2}{\tau^2 + \varphi^2 + \sigma^2} \times 100$$
where \( \tau^2 = \text{var}(U_{oc}) \) denotes variance at the occupational level within countries, \( \phi^2 = \text{var}(V_c) \) variance at the country level, and \( \sigma^2 = \text{var}(R_{coi}) \) residual variance at the individual level. In addition, to assess how well our covariates account for variation in subjective social status at each level, we compare the residual variance of models that include a certain set of covariates \((m)\) with the empty model \((0)\) (i.e., that does not include any covariates). That is,

\[
a = 1 - \left( \frac{\tau^2_m}{\tau^2_0} \right)
\]

Lastly, we expect that occupational skills impact on subjective social status over and above own education and income, and we test this by introducing individual-level controls for years of completed education and household income in subsequent models. Still, it is important to keep in mind that income is partly a mediating variable that lies on the causal path between occupational skills and subjective social status. Moreover, given that not all three socioeconomic factors are measured with equal precision, we do not find it feasible to determine which of these factors matters the most for subjective social status.

**Main results**

Table 7.2 shows estimated subjective social status by occupational skills and other socioeconomic covariates across 25 European countries. We first ask what proportion of the variation can be allocated to different levels. The empty model (Model 0) suggests that a notable share (7%) of the variation in subjective social status is between occupations within countries (level 2). There is even more variation (17%) in subjective social status between countries (level 3). While comparative studies usually find that subjective beliefs vary significantly between countries, it is still somewhat unexpected to find this much between-country variation in subjective social status in our data, given that most theory and empirical research on social status focus exclusively on disparities within countries (although there are exceptions, e.g., Lindemann and Saar, 2014).

Model 1 introduces our sociodemographic controls at the individual level (see Online Appendix, Table 7A.4), which are found not to account for a sizable share of the variation in subjective social status at either level. In contrast, Model 2 shows a sturdy positive relationship between subjective social status and educational requirements at the occupational level: a one-year increase in educational requirements is associated with an increase in subjective social
status of 0.231 scale points. In addition, looking at the reduction in residual variance between Model 2 and Model 0, we find that this single measure of the level of skill requirements accounts for as much as 81\% (1−[0.038/0.202]) of the variation in subjective social status between occupations within countries.

Moreover, we hypothesized that main type of skill may be of relevance for subjective social status, also after taking the level of skill requirements into account. Model 3 shows that being in an occupation that mainly involves working with management \((b = 0.449)\), data \((b = 0.222)\), or people \((b = 0.233)\) is associated with significantly higher status than being in an occupation that mainly involves working with things (reference category) or nature \((b = −0.163)\). These results hence support the hypothesis that manual work (things, nature) conveys lower subjective social status than non-manual work (data, management, people), also after control for the level of skills required. Note also that the regression coefficient for educational requirements remains mostly intact after adding work tasks to the model. These two dimensions of job skills together account for about 90\% (1−[0.020/0.202]) of the variation in subjective social status across occupational categories.

Model 4 adds the individual’s number of years of full-time education and household income (in deciles), respectively. Both of these individual-level variables show expected results: having more individual resources – in terms of education and household income – is associated with higher subjective social status. These variables also increase explained variance at both the individual (level 1) and the occupational level (level 2).

The regression coefficients of our skills measures diminish in Model 4, although they still display significant direct associations with subjective social status. For instance, the coefficient for educational requirements goes down from 0.180 to 0.088. This suggests that an important reason for why some occupations convey higher subjective social status is that they are more favourably rewarded compared to other occupations (since income serves as a mediating variable between occupational skills and subjective social status). Yet, in line with our theoretical expectations, this result also suggests that there is a non-trivial ‘net’ status benefit to being in high-skilled and non-manual occupations that goes beyond economic rewards and individual educational attainment.

Models 5 and 6 attempt to account for between-country variation in subjective social status. Model 5 suggests that average subjective social status is higher in countries with a more upskilled occupational structure (scale 0–1) \((b = 2.064)\). This macro indicator accounts for about 60\% (1−[0.190/0.482]) of the
### Table 7.2

Subjective social status by occupational skills and other socioeconomic covariates across 25 European countries: multilevel random intercept linear regression

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
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<th>3</th>
<th>4</th>
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</thead>
<tbody>
<tr>
<td><strong>INDIVIDUAL</strong></td>
<td></td>
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<tr>
<td>Full-time education completed (years)</td>
<td>0.039***</td>
<td>0.039***</td>
<td>0.039***</td>
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</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td></td>
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</tr>
<tr>
<td>Household income (deciles)</td>
<td>0.131***</td>
<td>0.131***</td>
<td>0.131***</td>
<td></td>
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<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
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<tr>
<td><strong>OCCUPATIONAL SKILLS</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Educational requirements (years)</td>
<td>0.231***</td>
<td>0.180***</td>
<td>0.088***</td>
<td>0.088***</td>
<td>0.087***</td>
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<tr>
<td></td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td></td>
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</tr>
<tr>
<td>Main type of work (Ref cat: Things)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Management</td>
<td>0.449***</td>
<td>0.344***</td>
<td>0.345***</td>
<td>0.345***</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.052)</td>
<td>(0.047)</td>
<td>(0.047)</td>
<td>(0.047)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Data</td>
<td>0.222***</td>
<td>0.137**</td>
<td>0.137**</td>
<td>0.137**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.042)</td>
<td>(0.042)</td>
<td>(0.042)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>People</td>
<td>0.233***</td>
<td>0.178***</td>
<td>0.178***</td>
<td>0.177***</td>
<td></td>
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<tr>
<td></td>
<td>(0.037)</td>
<td>(0.033)</td>
<td>(0.033)</td>
<td>(0.033)</td>
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</tr>
<tr>
<td>Nature</td>
<td>-0.162*</td>
<td>-0.059</td>
<td>-0.060</td>
<td>-0.060</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Indicates significance level: *p < 0.1, **p < 0.05, ***p < 0.01, ****p < 0.001.
### COUNTRY

**Average educational requirements (0–1)**
- Constant: 5.650*** (0.141) 5.372*** (0.157) 4.799*** (0.153) 4.788*** (0.152) 3.709*** (0.155) 2.575*** (0.233) 2.407*** (0.200)
- Variance components:
  - Var level 1 (individual) $\sigma^2$: 2.234 2.227 2.228 2.229 2.123 2.123 2.123
  - Var level 2 (occupation-country) $\tau^2$: 0.202 0.202 0.038 0.020 0.009 0.009 0.009
  - Var level 3 (countries) $\phi^2$: 0.482 0.491 0.462 0.459 0.438 0.190 0.124
- BIC: 70724 70715 70271 70228 69248 69237 69236

**GDP per capita (0–1)**
- Constant: 5.372*** (0.157)
- Variance components:
  - Var level 1 (individual) $\sigma^2$: 2.064*** (0.364) 0.986* (0.422)
- Observations: 19,187
- BIC: 70715 69248

**Note:** Standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Based on linear multilevel models with 629 country–occupation units at level 2 and 25 country units at level 3.
variation in subjective social status between countries. Furthermore, Model 6 shows a positive relationship between economic affluence and subjective social status (scale 0–1) ($b = 1.534$), with real GDP per capita overtaking about half of the initial association between national skill regime and subjective social status. These two macro indicators combined account for about 74% (1−[0.124/0.482]) of the between-country variation in subjective social status in our data.

To summarize and visualize our main findings at the occupational level within countries, Figure 7.1 displays adjusted predicted values of subjective social status by the level of educational requirements for each of the 26 occupational categories distinguished in our main analysis (based on estimates in Model 3, Table 7.2). The predicted divide in subjective social status between occupations with the lowest and highest educational requirements is about 1.2 scale points (on full 0–10 scale, SD = 1.7). The figure also illustrates how manual
work (things, nature) is predicted to convey lower subjective social status than non-manual work (data, management, people), with the largest status premium for managerial occupations.

Discussion

The main purpose of this chapter has been to examine the relationship between occupational skills and subjective social status in advanced knowledge economies. While there are multiple ways to operationalize social status and analyse how it relates to occupations, we argued that an intriguing analytical feature of subjective social status is that it permits multivariate analysis of the determinants of individual status.

Our multilevel analysis of data from the European Social Survey, covering 25 countries, showed that a substantial share of the variation in subjective social status is between occupations within countries, although it is also clear from our analysis that occupational position tells far from the whole story of individuals’ social standing. We also found that the occupational gradient in status is tightly positively linked to the level of educational requirements in jobs, with additional status benefits for individuals in non-manual compared to those in manual occupations. In addition, our results showed that subjective social status tends to be higher, on average, in countries that are more affluent and have a more upskilled occupational structure. This all suggests that socioeconomic conditions have substantial bearing on subjective social status, and that a skill perspective is useful for understanding status inequality both within and between countries.

A burgeoning literature suggests that subjective social status is of relevance for a host of different outcomes. In this chapter, we have succeeded well in describing how the occupational gradient in subjective social status in Europe is closely linked to the skill requirements of different jobs. Parts of the broader literature alluded to above posit that not only absolute social status but also temporal shifts in relative social standing are consequential for ‘status anxiety’ and other outcomes, such as political preferences. There are a few recent studies on trends in social status among occupational groups over time that show mixed results (Gidron and Hall, 2017; Kurer, 2020; Oesch and Vigna, 2022; Nolan and Weissstanner, 2022). A promising area for future research would be to explicitly incorporate educational requirements and/or type of work (e.g., the manual/non-manual divide) into the analysis of ongoing shifts in status inequality in advanced knowledge economies and beyond.
Notes

1. This work was supported by the Swedish Research Council for Health, Working Life and Welfare (grant numbers 2017-00079, 2019-01352, and 2020-00963).
2. In the population health literature, it is common to use a slightly different version of this question, namely the so-called MacArthur Scale, which makes references to ‘money’, ‘education’, and ‘jobs’ as criteria of vertical differentiation (e.g., Singh-Manoux et al., 2003; Miyakawa et al., 2012). In the sociological literature, these factors are all core components of socioeconomic status, which suggests that this version of the question is even less likely to capture social status stripped from economic inequalities.
3. We use the mixed command in Stata and the model is fitted with a maximum likelihood procedure assuming an identity covariance matrix.

References

Carella, L. (2021), ‘The status of status: A review of contributions to the literature on social status in political science’, Unpublished manuscript.


Smith, T. W. (1986), 'Internationally comparable measurement of subjective social class', Presentation to the planning meeting of the International Social Survey Programme, April, Mannheim, Germany.
Skill and job quality: Polarisation in a ‘liberal’ economy?

Duncan Gallie

Concern with potential polarisation in employment conditions between different skill groups has been central to the research agenda on employment. The notion of polarisation, however, has been used to cover quite distinct issues. In particular, there have been differences in the skill groups of central concern. For much of the postwar period, the focus was on the diverging employment conditions of higher and lower-skilled workers. From the 2000s, however, the term increasingly came to be used in relation to the issue of whether technological change is increasing the loss of middle-class jobs, leading to a hollowing out of the job structure (Autor et al., 2003; Goos and Manning, 2007). While the intrinsic quality of work lay at the heart of the earlier tradition, the literature on polarisation involving intermediate skill groups has been primarily concerned with changes in the proportions employed, and consequently job insecurity. However, it could be expected that a decline in labour market security would lead to a more general deterioration in the quality of intermediate skill jobs, due to a reduction in employees’ market power.

Theses of skill polarisation tended to argue for relatively deterministic effects of technological change and market globalisation on the differential employment conditions of skill groups. But an alternative literature on varieties of capitalism has pointed rather to the significance of national institutional factors in shaping employment conditions (Hall and Soskice, 2001; Gallie, 2007). In particular, it is suggested that countries with ‘co-ordinated’ or ‘social-democratic’ regimes, characterised by greater involvement of labour organisations in decision-making and higher levels of institutional regulation of employment conditions, are associated with higher job quality than ‘liberal’ countries, which give primacy to the market as a system of regulation. By extension it leads to the expectation that trends to polarisation should be relatively limited in ‘co-ordinated’ countries and particularly severe in countries with ‘liberal’ regimes.
Investigation of these arguments requires good quality data over time, which is still far from common in European countries. Evidence, however, from the Finnish Quality of Work Life Survey for the period 1977–2013 has provided significant support for the view that there has been no significant polarisation of job quality in a country with strong institutional regulation; the pattern has been one of convergence rather than divergence in intrinsic job quality across the job structure (Mustosmäki et al., 2017). But is it the case that countries with a liberal regime have experienced sharp polarisation between skill groups? The UK is often regarded as an exemplar case of a liberal regime. It provides then a good test case of whether the underlying dynamics of technology and market competitiveness have tended to increase job quality polarisation, in a context of relatively weak state regulation. To explore this, we draw primarily upon the British Skills and Employment (SES) Surveys, which provide consistent national data on job quality between 1992 and 2017.

Skill levels and occupational groups

A first issue is the definition of skill groups. Some influential research on polarisation has taken the income level of occupations as an indicator of skill level (Goos and Manning, 2007). But this is problematic, given evidence on the implications of bargaining power and gender on relative income levels (Blanchflower et al., 2006; Olsen et al., 2010; ONS, 2019). An alternative approach is to examine how far rankings of occupational groups reflect differences in skill levels by more direct criteria. The UK’s Standard Occupational Classification (ONS, 2020) claims that it is based on criteria of ‘skill level’ (with further distinctions of ‘skill specialisation’ within skill levels). It explains that ‘skill levels are approximated by the length of time deemed necessary for a person to become fully competent in the performance of the tasks associated with a job. This, in turn, is a function of the time taken to gain necessary formal qualifications or the required amount of work-based training’.

How well do the ‘major groups’ of the classification correspond in practice with information about the overall learning time required to be able to do the job? The SES surveys provide two measures for approximating this. The first gives respondents’ reports of the general education currently required for the job in terms of the highest qualification required, while the second asks about the duration of subsequent work-based training with the question ‘How long did it take for you after you first started doing this type of job to learn to do it well?’. Responses about specific qualifications required have been converted into a measure of the number of years of education or training (since the
Table 8.1  Overall learning time (years since age 14) required for job by SOC 2000 major groups

<table>
<thead>
<tr>
<th>Number of Years Learning</th>
<th>Number of Years Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Managers</td>
<td>5.97</td>
</tr>
<tr>
<td>Professionals</td>
<td>8.38</td>
</tr>
<tr>
<td>Associate Professionals</td>
<td>6.27</td>
</tr>
<tr>
<td>Administrative/Secretarial</td>
<td>3.49</td>
</tr>
<tr>
<td>Skilled Trades</td>
<td>4.33</td>
</tr>
<tr>
<td>Personal Service Workers</td>
<td>3.02</td>
</tr>
<tr>
<td>Sales</td>
<td>1.52</td>
</tr>
<tr>
<td>Operatives</td>
<td>2.03</td>
</tr>
<tr>
<td>Elementary</td>
<td>1.02</td>
</tr>
</tbody>
</table>

Given the extended period the survey series covers, the data has been harmonised on the 2000 version of the classification. As Tåhlin (2007) has previously shown, learning requirements for jobs in the UK are generally relatively low compared to several other European countries, in particular due to low demands with respect to pre-entry education. It can be seen, moreover, from the first column in Table 8.1 that the official ranking has a rather imprecise relationship with the number of years of learning required. But there are three groups of occupations that stand out as forming a ‘learning time’ skill hierarchy in a relatively distinct way. The highest skilled (5.75 years or more learning required) are managers, professionals and associate professionals. An intermediate group (3 to 4.33 years) consists of administrative/secretarial, skilled trades and personal service workers, while a lower-skilled group (1.02 to 2.03 years of learning time required) includes those in sales, operative and elementary (non-skilled) occupations.

A potential problem with the measure is that employers may require qualification levels that are above the level really needed to carry out the work. We have
then used a question in the survey about how necessary employees thought the required qualifications were to do their job competently to create an adjusted measure, reducing by a year the learning time for those saying that they were neither essential nor fairly necessary. It can be seen from the second (adjusted) column that this leads to some reduction in the learning time estimates for all of the major occupational categories. Nonetheless, the relative skill rankings of the occupational categories remain the same. The three broad skill groups then are taken as the basis for the analysis of the relationship between job skill and job quality in the subsequent sections.

**Polarisation in the size of skill groups?**

The more recent literature on polarisation has focused heavily on changes in the structure of employment, developing a scenario of the ‘hollowing out’ of the intermediate categories of the workforce and the expansion of the higher and lower occupational categories. This contrasts with earlier scenarios, associated with theories of the knowledge society, of a trend towards an upgrading of the skill structure (OECD, 1996, 2001; Rodrigues, 2002).

Table 8.2 shows the changing size of the skill groups for the years of our surveys, drawing on the large-scale samples available from the Office of National Statistics. It is clear that the trend between 1992 and 2017 in the UK was closer to one of skill upgrading than of polarisation. Both the intermediate and lower-skilled groups declined (by 3 and 5 percentage points), while the higher-skilled increased (by 8 percentage points). The same broad pattern is evident for both men and women, although it was more pronounced in the case of women.

The most striking changes over time were the rise in the proportion of female higher-skilled and the decline in the proportion of women in lower-skilled work. There was no evidence of polarisation in the sense of a simultaneous growth of both higher- and lower-skilled work; rather, the divide was between the growth of higher-skilled and the decline in intermediate and lower-skilled jobs. The use of direct skill criteria leads then to a different picture of the pattern of change in the skill structure of the workforce than those provided by analyses (such as Goos and Manning, 2007) taking pay as a proxy for skill.

Given changes in the size of the intermediate and low-skilled categories and hence possibly their composition, it is important to see whether there were also changes in relative skill levels between the broad skill groups. To assess this, we
Table 8.2  Proportion of employment in different skill groups

<table>
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<tr>
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</thead>
<tbody>
<tr>
<td>All in Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>36.8</td>
<td>37.3</td>
<td>38.7</td>
<td>42.3</td>
<td>43.2</td>
<td>45.1</td>
</tr>
<tr>
<td>Intermediate</td>
<td>33.0</td>
<td>32.9</td>
<td>32.5</td>
<td>30.8</td>
<td>31.1</td>
<td>30.1</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>29.7</td>
<td>29.5</td>
<td>28.5</td>
<td>26.7</td>
<td>25.6</td>
<td>24.6</td>
</tr>
<tr>
<td>Men</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>42.0</td>
<td>42.3</td>
<td>43.4</td>
<td>45.4</td>
<td>46.2</td>
<td>47.0</td>
</tr>
<tr>
<td>Intermediate</td>
<td>28.2</td>
<td>27.8</td>
<td>27.0</td>
<td>25.9</td>
<td>26.3</td>
<td>25.9</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>29.2</td>
<td>29.5</td>
<td>29.4</td>
<td>28.5</td>
<td>27.6</td>
<td>26.7</td>
</tr>
<tr>
<td>Women</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>30.2</td>
<td>31.1</td>
<td>33.2</td>
<td>37.8</td>
<td>39.8</td>
<td>42.9</td>
</tr>
<tr>
<td>Intermediate</td>
<td>39.1</td>
<td>39.2</td>
<td>39.1</td>
<td>31.8</td>
<td>36.6</td>
<td>34.8</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>30.3</td>
<td>29.5</td>
<td>27.5</td>
<td>30.4</td>
<td>23.5</td>
<td>22.1</td>
</tr>
</tbody>
</table>

**Note:** Figures from Office for National Statistics Databases.²

Draw on data from the British Skills and Employment Surveys (SES). The SES surveys provide a picture of trends starting from the 1990s (depending on the specific indicator from either 1992 or 1997) to 2017. The analyses are restricted to differences between employees in the skill groups.

The SES data on mean levels of required learning time provides some support for the view that the relative skills levels of the three groups remained broadly similar across the 25-year period, although there was a small rise in the required learning time of higher and intermediate jobs, compared to a stable level for lower-skilled jobs (Figure 8.1). There was no significant change between 1992 and 2017 in relative skill levels between the higher and intermediate-skilled, but a deterioration in the relative skill level of the lower-skilled.

Further analysis showed that this polarisation in skill levels between the lower-skilled and the other skill groups was related to changes in the distribution of lower-skilled employees across industrial sectors. Over the period, there was a marked decline in the proportion of the lower-skilled who worked in manufacturing (where the learning requirements were relatively high even for the lower-skilled) and an increase in the proportion working in wholesale and the retail trade, or in hotels and restaurants, where learning requirements...
were relatively low. When change in industry structure is taken into account, the change in relative skill levels between the highest and lowest skill groups is non-significant.

**Polarisation in job quality?**

Job quality refers to the non-financial characteristics of jobs that affect workers’ psychological or physical health (OECD, 2017). Although there are a variety of typologies of the dimensions of job quality, there is considerable overlap between them and a relative consensus on the importance of a number of key factors. In particular, research has highlighted the importance of the opportunities for participation in decision-making and for skill development as positive factors for well-being and health, while high work intensity and job insecurity are negative factors. The relevance of these aspects of jobs for employee health has now been very widely demonstrated by both cross-sectional and longitudinal studies (for general overviews, see Marmot, 2010; OECD, 2017; Theorell, 2020; for the UK, Gallie et al., 2017).

The SES surveys include indicators of participation (discretion over the job task and influence in organisational decisions), the opportunities for skill development in terms of the on-going learning requirements of the job, work intensity and job insecurity. As can be seen in Table 8.3, which enters the items simultaneously, these relate in the expected way to psychological well-being as measured in a validated six-item scale of depression–enthusiasm (Warr, 1990; Green et al., 2016). All items have a highly significant relationship to psycho-
Table 8.3  

Job quality indicators and psychological well-being (enthusiasm–depression scale)

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>Task Discretion</td>
<td>0.14 ***</td>
</tr>
<tr>
<td>Influence over Work Organisation</td>
<td>0.20 ***</td>
</tr>
<tr>
<td>Job requires Learning New Things</td>
<td>0.13 ***</td>
</tr>
<tr>
<td>Work Intensity</td>
<td>-0.15 ***</td>
</tr>
<tr>
<td>Job Insecurity</td>
<td>-0.14 ***</td>
</tr>
</tbody>
</table>

It is notable, however, that influence over work organisation stands out as having a particularly strong relationship with well-being.

Participation: task discretion and influence over organisational decisions

The importance to worker well-being of the ability to influence decisions at work has been a central theme in both the psychological and sociological literature on work since the mid-20th century (Blauner, 1964; Hackman and Lawler, 1971; Gardell, 1977, 1991; Karasek and Theorell, 1990; Dobbin and Boychuk, 1999; Lopes et al., 2014). For some analysts this importance derives from basic psychological needs for self-determination (Ryan and Deci, 2018), while for others it is attributable to the emphasis on individualism and personal initiative embodied in the liberal cultures and educational systems of Western societies (Hofstede, 2001). In addition to its intrinsic benefits, participation provides the capacity to exercise control over major work task stressors, such as work intensity, and to influence the quality of other aspects of work conditions that affect well-being – for instance, skill development opportunities (Gallie et al., 2017).

There are two distinct dimensions of participation – task discretion (or the ability to take decisions about the immediate job task) and organisational participation (or voice). The early literature focused primarily on task discretion, but the significance of organisational participation for worker well-being has been increasingly documented in more recent research. Moreover, it has been shown that each make a distinct contribution to psychological health (Gallie et al., 2017).

A measure of task discretion is derived from four questions in the SES surveys asking people how much influence they personally had over how hard they
Table 8.4 Task discretion (mean scores)

<table>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>All Employees</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>2.63</td>
<td>2.49</td>
<td>2.37</td>
<td>2.35</td>
<td>2.33</td>
<td>2.31</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Intermediate</td>
<td>2.45</td>
<td>2.26</td>
<td>2.18</td>
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<td>1.88</td>
<td>1.99</td>
<td>1.92</td>
<td>n.s</td>
<td>n.s</td>
</tr>
</tbody>
</table>

Note: N=20,265. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1992. n.s.=not significant. Controls were: age, part-time work, industry, size of establishment and ownership (public/private).

worked; deciding what tasks they did; deciding how to do the tasks; and the quality standards to which they worked. Responses were on a four-point scale, ranging from a great deal of influence to no influence at all. Responses to the four items were averaged to create a summary index. The first three rows of Table 8.4 give the mean scores for each of the three skill groups for all survey years between 1992 and 2017, while the rows below show the responses for men and women separately.

Two points immediately stand out about the pattern across the years. The first is that, in every year, there was a clear skill gradient with the higher-skilled having the highest levels of decision-making influence over their immediate job tasks, followed by those with intermediate skills and lastly by the lower-skilled. Second, there was a substantial decline in task discretion across the years for each of the skill groups. The overall extent of decline between
1992 and 2017 was rather similar for the three broad skills groups, although there is somewhat more variation in the case of the sex-specific skill groups.

But was there evidence of polarisation by skill either between the highest and lowest skill categories or between the highest and intermediate categories? To examine this, the differences between skill groups in the earliest and latest year in the data were compared by taking the higher-skilled as the reference category and introducing an interaction term for both the intermediate and lower-skilled and year 2017. The analysis was first conducted including just the skill groups in the model and then subsequently a range of controls were added adjusting for age, part-time work, industry, workplace size and ownership sector (public/private).

As can be seen in the last two columns of Table 8.4, taking the skill groups overall, there was no evidence of a growing gap either between the higher and intermediate-skilled over the period, or between the higher and the lower-skilled. The same pattern of stability in task discretion differentials emerged from analysis of the sex-specific skill groups.

Turning to the second aspect of participation, the influence of employees over wider organisational decisions was assessed through a question focusing on the way organisational change was introduced by management. People were asked: ‘Suppose there was going to be some decision made at your place of work that changed the way you do your job. Do you think that you personally would have any say in the decision about the change or not?’ Those who responded that they would have some influence were then asked whether this would be ‘a great deal’, ‘quite a lot’ or ‘just a little say’. A scale of influence was then constructed ranging from 0 for those who had no say to 4 for those with ‘a great deal of say’.

As with task discretion, it is evident from Table 8.5 that there remained across the whole period a marked skill divide in the influence employees could exercise over organisational decisions. Similarly, in each skill group, there was a decline in organisational participation between 1992 and 2017. While there was no evidence of a change in the relative position of the lower-skilled, there was a divergence between female employees with intermediate skills and those with higher skills. More detailed analysis showed that it was an effect that was only significant in the private sector, in particular due to a marked decline in the influence in decision-making of women working in personal services.
### Table 8.5  Employee influence over decisions about work organisation (mean scores)

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<thead>
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<td>n.s.</td>
<td>n.s.</td>
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<tr>
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</tr>
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<td>1.25</td>
<td>n.s.</td>
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<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
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</tr>
<tr>
<td>Higher-Skilled</td>
<td>1.74</td>
<td>1.88</td>
<td>1.64</td>
<td>1.48</td>
<td>1.71</td>
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<tr>
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<td>-0.31</td>
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<td>Lower-Skilled</td>
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<td>1.04</td>
<td>0.94</td>
<td>0.91</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

**Note:** N=18,048. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1992. Controls, see Table 8.4. Figures in italics were significant at the 0.01 level, in regular font at the 0.05 level. n.s.=not significant.

In short, there was no evidence of polarisation with respect to task discretion, but there was a decline in the influence over organisational decisions of women with intermediate skills compared to those with higher skills.

### Skill development

The capacity for skill development in the job has been regarded as one of the conditions for worker well-being since the early days of Marxist theory (Marx, 1973; Wenger, 1998; Rainbird et al., 2004), arguably with roots traceable to Aristotle’s theory of human flourishing. Among psychologists, self-determination theorists postulate the fulfilment of the need to demonstrate and develop competence as one of the three basic motivational needs that underlie attitudes and behaviour at work (Ryan and Deci, 2018).
The measure in the SES surveys of the learning and self-development opportunities provided by the job asks people how much they agree that ‘My Job requires that I keep learning new things’. The response scale (reversed) ranges from 1 for strongly disagree to 4 for strongly agree. In sharp contrast to the pattern for influence over decision-making at work, the overall trend for learning opportunities between 1992 and 2017 was positive for each of the skill groups (Table 8.6).

There remained, however, for each of the survey years, a marked skill gradient – with learning opportunities greatest among the highest skilled, followed by those with intermediate skills, and lowest among the lower-skilled. But, since the increase in opportunities was particularly strong among those in intermediate and lower-skilled jobs, there was a degree of upward convergence in relation to the highest skilled. For employees with intermediate skills, this convergence was evident for both men and women. Moreover, further analysis

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<td>0.14</td>
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</tr>
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<td>3.09</td>
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<td>3.17</td>
<td>3.18</td>
<td>0.13</td>
<td>0.15</td>
</tr>
<tr>
<td>Lower-Skilled</td>
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<td>2.75</td>
<td>2.77</td>
<td>2.68</td>
<td>2.71</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
<td>Women</td>
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<td>2.68</td>
<td>2.81</td>
<td>0.19</td>
<td>0.13</td>
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</table>

Note: N=18,176. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1992. Controls, see Table 8.4. Figures in bold were significant at the 0.01 level, in regular font at the 0.05 level and in italics at the 0.10 level. n.s. = not significant.
showed that, within the intermediate skill group, it affected occupational categories with both relatively high and relatively low skill levels. It was most notable among those in skilled manual work (a category which declined in size over the period) and in personal services (a category which expanded). Among lower-skilled women, the relative improvement in skill development was only significant for women and was most marked for those in elementary occupations.

Work intensity and job strain

The major theories of psychosocial risks at work point to high levels of work intensity as the key source of psychological stress among employees (Karasek and Theorell, 1990; Siegrist and Wahrendorf, 2016). Although the severity of its effects may be offset to some degree by the level of employees’ control or rewards, there is little consistent evidence that these can eliminate its negative consequences. Research indicates that work intensity has been increasing in recent times in many European countries, although the rise was stronger in some periods than in others (Green and McIntosh, 2001; Gallie, 2005; Gallie and Zhou, 2013).

The measure of work intensity combined four questions. These captured whether or not the person worked under a great deal of tension; was required to work very hard; had to work at very high speed; and had to work extra time over and above the formal hours of the job to get through the work.

As can be seen in Table 8.7, the level of work intensity for employees in all of the skill groups was higher in 2017 than it had been in the early 1990s. The timing of the increases across the survey years was also similar for the three groups. Work intensity rose between 1992 and 2001, was stable (or in the case of the lower-skilled declined) between 2001 and 2006, rose again over the period of the global financial crisis between 2006 and 2012, and then remained stable between 2012 and 2017.

However, in contrast to the other dimensions of job quality, higher skill level was associated with disadvantage rather than advantage in work intensity. In each of the years, the most severe work intensity was experienced by employees in the higher skill group, followed by those with intermediate skills, with the lowest skilled having the lowest levels. Over the period as a whole, the differential between those with higher and intermediate skills grew somewhat greater (reflected in the negative interaction coefficient for intermediate skill workers). The growing gap between those with higher and those with intermediate skills
Table 8.7  Work intensity (mean scores)

<table>
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<tr>
<th>Skill Group</th>
<th>Year 2017 Interaction Coefficients re 1992</th>
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<td>2.09</td>
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<tr>
<td>Higher-Skilled</td>
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<td>1.97</td>
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Note: N=18,062. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1992. Controls, see Table 8.4. Figures in italics were significant at the 0.01 level, those in regular font at the 0.05 level. n.s. = not significant.

was only significant for female workers and largely reflected the particularly sharp rise in the work intensity experienced by women in higher-skilled jobs.

While work intensity is consistently associated negatively with psychological well-being, the evidence indicates that its consequences become particularly serious for physical health when combined with low levels of job control. These types of jobs, which have been termed ‘high-strain’ jobs, are associated with heightened blood pressure and increased risk of cardiovascular disease (Chandola, 2010).

We take workers in high-strain jobs to be those above the median level of work intensity and below the median level of task discretion in the combined data for all years. As can be seen in Table 8.8, as with work intensity, the proportion of employees in high-strain jobs rose in all skill groups between 1992 and 2017. There is, however, an important difference with respect to the pattern for work
### Table 8.8 Percentage of employees in high-strain jobs

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<tr>
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<td>10.0</td>
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<td>12.4</td>
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Note: N=17,956. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1992. Controls, see Table 8.4. Figures in italics were significant at the 0.01 level, in regular font at the 0.05 level. n.s. = not significant.

intensity. Whereas it was the higher-skilled that experienced the highest levels of work intensity, it was the lower-skilled that were most at risk of job strain. Moreover, the relative position of the lower-skilled deteriorated over the period as a whole, primarily due to the substantial increase in the proportion of lower-skilled men in high-strain jobs.

**Job insecurity**

Job insecurity has been shown to be a source of psychological stress comparable to that of unemployment (Burchell, 2011; De Witte, 1999). It varies with the state of the macro-economy, particularly in response to the level of unemployment. But since the 1990s, it has been suggested that new forms of structural insecurity are becoming increasingly prevalent, driven by the need for greater numerical flexibility for firms in an era of more rapid technological change and heightened global competition (Cappelli et al., 1997). It is thought...
that this has led to an increased reliance on temporary contracts that has heightened the precarity of work particularly among the lower-skilled.

The SES surveys measure job insecurity by asking people first whether they thought ‘there is any chance at all of you losing your job and becoming unemployed in the next 12 months’ and, if this was the case, how likely this was to happen (with responses from ‘very likely’ to ‘very unlikely’). A six-point scale was constructed ranging from those who had no concern about losing their job to those who thought it was very likely they would lose it.

It can be seen in Table 8.9 that there was no clear trend over time in job insecurity for any of the skill groups. It was particularly high in 2012 in the aftermath of the global financial crisis, but by 2017 had subsided to a level that was lower than in 2001. There has also been a varying differential between the skill groups. While the lower-skilled were indeed the most precarious in the early and mid-2000, this was no longer the case in the period 2012 to 2017, when there were very similar levels of insecurity in the highest and lowest skill groups. Overall tests of change in relative insecurity over the period 1992 to 2017 show no significant evidence of either polarisation or convergence.

It is notable that despite arguments that the jobs of those with intermediate skills were the most vulnerable to technological developments, this skill group had the lowest job insecurity scores in each year. However, the pattern of change was very different among male and female workers with intermediate skills. Between 1997 and 2006, men with intermediate skills had higher job insecurity than women, but there was a marked rise in women’s insecurity between 2006 and 2012, leading to a substantial convergence between men and women within this skill level. By 2017 the pattern of the 1990s and early 2000s had been reversed, with women showing higher levels of insecurity than men.

This was accompanied by contrasting changes in the differentials of the sex-specific intermediate and higher-skilled groups. Whereas in 1997 men with intermediate skills were less secure than those who were more highly skilled, by 2017 they had become more secure. Conversely, whereas women with intermediate skills had been more secure in 1997 than higher-skilled women, by 2017 they had become less secure. There was then a significant increase in the differential security of women with higher and intermediate skills. However, the principal factor affecting this was the marked increase in the job security of women with higher-skilled jobs between 2012 and 2017 (the period of recovery from the global financial crisis).
### Table 8.9  
Job insecurity (mean scores)

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<td></td>
<td></td>
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<td></td>
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<td>0.58</td>
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<td>0.50</td>
<td>0.55</td>
<td>0.75</td>
<td>0.39</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>0.71</td>
<td>0.62</td>
<td>0.61</td>
<td>0.77</td>
<td>0.41</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
<td>Men</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>0.76</td>
<td>0.62</td>
<td>0.62</td>
<td>0.77</td>
<td>0.50</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0.88</td>
<td>0.54</td>
<td>0.72</td>
<td>0.79</td>
<td>0.29</td>
<td>-0.33</td>
<td>-0.38</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>0.76</td>
<td>0.79</td>
<td>0.75</td>
<td>0.93</td>
<td>0.42</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
<tr>
<td>Women</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>0.70</td>
<td>0.42</td>
<td>0.52</td>
<td>0.77</td>
<td>0.28</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Intermediate</td>
<td>0.52</td>
<td>0.46</td>
<td>0.43</td>
<td>0.71</td>
<td>0.46</td>
<td>0.36</td>
<td>0.37</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>0.67</td>
<td>0.44</td>
<td>0.45</td>
<td>0.59</td>
<td>0.40</td>
<td>n.s.</td>
<td>n.s.</td>
</tr>
</tbody>
</table>

**Note:** N=19,683. The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 1997. Controls, see Table 8.4. Figures in italics were significant at the 0.01 level. n.s. = not significant.

### Overall job quality

An overall index provides a summary measure of the four key dimensions of job quality that affect psychosocial health. The items on work intensity and job insecurity were reverse scaled so that higher scores indicated better job quality. All of the indicators were standardised to a 0–10 scale and then aggregated with weights proportional to the strength of their association with psychological well-being (see Table 8.3). Since the full range of items is only available in the surveys since 2001, the analysis of trends is restricted to the period 2001 to 2017.

It can be seen in Table 8.10 that in each year there was a clear skill hierarchy in overall job quality with the higher-skilled having the highest job quality, followed by those in intermediate and lower-skilled jobs. The ranking was consistent across all of the years and held for both men and women. The level of job quality varied across the years: it declined in the overall period between
Table 8.10  Trends in overall job quality index (0–10 where higher scores=higher job quality)

<table>
<thead>
<tr>
<th>Skill Group</th>
<th>Year 2017 Interaction Coefficients re 2001</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2001</td>
</tr>
<tr>
<td>All Employees</td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>6.11</td>
</tr>
<tr>
<td>Intermediate</td>
<td>5.72</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>5.05</td>
</tr>
<tr>
<td>Men</td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>6.20</td>
</tr>
<tr>
<td>Intermediate</td>
<td>5.62</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>5.01</td>
</tr>
<tr>
<td>Women</td>
<td></td>
</tr>
<tr>
<td>Higher-Skilled</td>
<td>5.98</td>
</tr>
<tr>
<td>Intermediate</td>
<td>5.80</td>
</tr>
<tr>
<td>Lower-Skilled</td>
<td>5.11</td>
</tr>
</tbody>
</table>

Note: N=13,985 (reflecting the reduced period covered). The last two columns present the significance of coefficients for year* skill group interaction tests comparing 2017 with 2001. Controls, see Table 8.4. n.s.=not significant.

2001 and 2017, although it was at its lowest in 2012 – the first survey that followed the financial crash of 2008. However, these trends were common to all of the three skill groups. A test of change in the relative job quality of the intermediate and lower skill groups compared to the higher-skilled, showed no significant change for either the intermediary or the lower skill group relatively to the higher-skilled. Skill differentials in job quality appear then to have been highly stable over the first two decades of the 2000s.

Conclusion

Given theories of capitalist diversity in employment relations, the theoretical expectation was that the UK, as a generally accepted version of a ‘liberal’ regime, would have experienced a significant trend towards polarisation. However, the
long-term evidence for the UK is not consistent with this. Although changes in the composition of the workforce involved a decline in the relative shares of both intermediate and lower-skilled employees, differentials in job quality mostly remained very stable across time and there was no general pattern of polarisation between the skill groups for any of the dimensions of job quality. This was the case both for differentials between the higher- and lower-skilled and for those between the higher- and intermediate-skilled, contradicting both versions of the polarisation thesis.

There were three instances where there was evidence of a widening of the skill differential in job quality – but these were restricted to employees of a specific sex. Compared to the early 1990s, women in intermediate-skilled jobs in 2017 were less likely to be able to influence organisational decisions compared to higher-skilled women and were more likely to feel insecure in their jobs. The former reflected a particularly sharp loss of influence among women with intermediate skills, but the latter resulted primarily from a more marked increase in the security of higher-skilled women. In general, differentials for male employees were very stable, but there was one important exception – the greater exposure to high-strain jobs of lower-skilled male workers, compared to higher-skilled workers, grew worse over the period. The sex-specificity of these cases suggests that the rather general arguments of theorists of polarisation about the implications of technological change or market globalisation for the vulnerability of different skill groups need to be replaced with more precise arguments about their risks for specific types of work in a gender-segregated economy.

In contrast to these sex-specific instances of polarisation, there was one aspect of job quality – skill development opportunities – where the pattern was the reverse of the predictions of polarisation theories. The gap between the higher-skilled, on the one hand, and both intermediate and lower skilled employees, on the other, was reduced. This was particularly clear for intermediate-skilled employees, both male and female. Among lower-skilled workers, however, relative improvement in learning opportunities was only evident for women.

While tendencies to convergence in job quality between skill groups were less evident than in the case of Finland, skill differentials in the liberal regime of the UK showed remarkable stability across time, rather than any marked tendency for polarisation. What can account for the fact that theories of polarisation offer little explanation of the trends even in the liberal regime of the UK? Theories of the employment relationship (Goldthorpe, 2000) have stressed the importance of efficiency factors that may underlie the differences in job
quality of those in different occupational classes. Employers are concerned to ensure high commitment and performance of employees who are in jobs for which it is not possible to control behaviour through strong contractual rules. These are employees whose work is difficult to monitor in a continuous and detailed way or involves specific skills or knowledge whose productive value would pose a serious loss if transferred to another employer. Arguably both of these arguments point to the relatively stable significance of skill differences in structuring employment relationships, since the level of skill in work is likely to determine how difficult it is to monitor and the cost of replacement to the employer.

The pattern of a clear skill hierarchy in job quality with limited change across time is also consistent, however, with the view that skill is constitutive of employees’ power in the employment relationship, which is likely to affect job quality. Indeed, the ‘efficiency’ argument, with its emphasis on the variations in the potential cost to the employer of employees quitting their jobs, is implicitly premised on an argument about skill-derived power.

It has been seen that there was little change in the relative skill levels of the different skill groups, implying that the skill leverage over job quality remained similar over time. While this may help to account for the stability of skill rankings in the case of participation, skill development and job strain, it cannot explain the decline in the relative security of higher-skilled men. Arguably, when organisations face serious financial difficulty, as has been increasingly the case in traditional male-dominated industries, it is often the organisation as a whole that is at risk and higher skill is less protective.

Polarisation arguments have tended to point to new types of technological change that will undermine the value of the skills of particular groups, making them more vulnerable to a deterioration in their employment conditions. But the implementation of technical change tends to be relatively slow and its implications for organisational and job structure correspondingly piecemeal. As the OECD (2020) has shown, the displacement of middle-class jobs in recent decades has not taken the form of mass redundancies for particular categories of employee, but rather has taken place through cohort replacement. Its negative effect on the work conditions and security of existing employees is likely then to be limited and, indeed, may lead to a need to update their skills to offset diminishing numbers.

The assumptions underlying the expectation from theories of varieties of capitalism that the culture of liberal regimes is likely to lead to particularly pronounced negative effects of change may also be problematic. The essential
principle of a liberal regime is that employer behaviour more directly responds to the opportunities of the market rather than to politically devised rules. But responsiveness to the market does not necessarily mean that employers are unconstrained. A notable feature of the UK labour market over most of the period considered is that, in comparative terms, it was relatively tight. From the early 1990s the employment rate was significantly higher than the average for the OECD (73% compared with 61% in 1990; 76% compared with 69% in 2019). At the same time, the unemployment rate has been relatively low (6.9% compared with the OECD average of 8.0% in 1990; 4% compared with 5.6% in 2019). While British workers were less protected institutionally than in many other countries, a tighter labour market reduces the opportunities for employers to degrade the work conditions of substantial sectors of the workforce in a way that might change the relative job quality of specific skill groups.

A second factor that tends to be neglected in the discussion of employer behaviour in liberal regimes is that, although employers are less constrained by the norms imposed by formal institutional rules, this does not mean that they are not exposed to normative influences. Arguably a characteristic of the long-term historical development of liberal societies is the value centrality they give to individualism, which is reflected in respect for personal autonomy. Comparative studies of values provide some support for this view. Hofstede (2001), who measured individualism with indicators relating to work, placed the UK in third place with respect to individualism (following two other liberal societies – the United States and Australia) in a ranking of 53 countries. Later approaches to the study of individualistic values, focusing on a wider range of social attitudes, depict the UK as part of a wider group of Northern European and Anglo-Saxon countries that place a particularly strong emphasis on individualistic values (Minkov and Kaasa, 2021).

The norms about treatment that flow from such broader values can be influential not only because they affect the expectations of employees, but also because they can inform employers’ own conceptions of appropriate practice. This may help to account inter alia for the relatively high position of the UK with respect to employee task discretion and its stability across time, found in cross-national studies in the 2000s (Gallie and Zhou, 2013, 2020).

Notes

1. The categories were 0 ‘<3 months’; 1 ‘3–12 months’; 2 ‘1–2 years’; 3 ‘2 years +’. 
2. Although the SOC classification changed in 2001 from SOC90 to SOC00, a comparison of the proportions in the different skill groups using the two classifications for 2001 shows that figures were the same within two decimal points.

3. Employees who spontaneously responded ‘it depends’ were given a score of 1.

4. For further analysis of the British pattern of work intensity, based on the 2017 survey, showing the same pattern at the level of more differentiated occupational groups, see Green et al. (2018). A broadly similar ranking by occupational class also appears in analyses of the work conditions of employees in a wider set of countries in the European Union (Scherer and Steiber, 2007; Gallie and Zhou, 2013), although work intensity was found to be particularly high in ‘Liberal’ countries.

5. Green et al. (2000) showed that the marked convergence in job insecurity across occupational classes came between the mid-1980s and 1997, with rising insecurity particularly among professionals and a decrease in insecurity among manual workers. This was the period that followed the Thatcher administration’s offensive against the protected status of professions. However, a similar pattern of convergence has also been found in the trend data for Finland in more recent decades (Mustosmaki et al., 2017).

References


9 Occupational skills, ethnic stratification, and labor market assimilation across immigrant generations

Are Skeie Hermansen, Jon Horgen Friberg, and Arnfinn H. Midtbøen

Introduction

Recent decades have seen a secular trend toward upskilling in the workforce in modern, advanced economies, where formal education and occupational skills have become increasingly important for successful employment (Acemoglu and Autor 2011). As educational attainment has steadily risen, low-skilled occupational segments have declined in relative size in many labor markets (Oesch 2013). In the context of increasing immigration—especially from low-income origin countries—the interplay between increased occupational skill requirements and the sorting of immigrants into low-wage manual work is a salient feature of contemporary labor markets in many rich countries, where immigrant workers are increasingly overrepresented in the bottom rungs of the occupational class structure (Heath and Cheung 2007). The extent to which this pattern is reproduced across immigrant generations is a question with large implications for the future ethnic stratification of immigrant-receiving societies.

In this chapter, we assess the importance of skills for the occupational sorting of immigrants and their native-born descendants in the labor market. Our empirical point of departure is Norway, a ‘social democratic’ welfare state characterized by a labor market context with high bars for labor market success among low-skilled immigrants, but also by a comprehensive educational system that may equalize opportunities for socioeconomic progress among children of immigrants (Bratsberg, Raaum, and Røed 2010; Hermansen 2017a; Midtbøen and Nadim 2021). Focusing on the Norwegian case, Figure 9.1a shows how the occupational skill structure has changed across recent decades. Low-skill
occupations—defined as occupations where more than half of all native workers have less than full upper-secondary schooling—made up about four of ten workers in the mid-1990s, but fewer than one out of ten workers by the late 2010s. High-skilled occupational segments—with which more than half of all native workers had completed a short university degree or more—almost doubled from about one-fifth to about two-fifths of the workforce during the same period. Simultaneously, the share of immigrant-background workers in the labor force grew rapidly—from about 4% to about 17%. However, as shown in Figure 9.1b, this growth was much stronger in low-skilled occupations. By the end of the 2010s, almost 40% of all workers in the lowest skilled occupations had an immigrant background.

Over the course of the past few decades, we have consequently witnessed a rapid ‘ethnicization’ of low-skill segments of the Norwegian labor market. The key question we address in this chapter is whether this pattern is reproduced across immigrant generations or, rather, primarily applies to populations who themselves have migrated. This question taps into an overarching debate about the long-term consequences of immigration on receiving societies. To some, ethnic disparities are expected to be reduced across immigrant generations, as native-born children of immigrants can gain access to resources not accessible to their parents and are less vulnerable to discrimination (Alba and Nee 2003). To others, descendants of immigrants are expected to assimilate into different segments of society, including permanent positions in the lower classes, depending on their human capital acquisition and the persistence of discrimination (Portes and Rumbaut 2001). The original contribution of this chapter is to examine such long-term prospects through an analysis of generational skill profiles. In categorizing different occupations, we distinguish between five types of skills: the formal educational requirements and the analytical, communicative, socioemotional, and manual skill requirements in each occupation. Analyzing the distribution of skill requirements in the occupations held by immigrants and native-born children immigrants provides a novel glimpse into how immigration changes the occupational landscape of European societies in the twenty-first century.

The chapter proceeds as follows. In the first two sections, we discuss why the unequal distribution of skills is likely to result in occupational sorting of immigrant-origin workers. From a supply-side perspective, the human capital that immigrants bring with them to the host country may have limited transferability across national contexts and contribute to labor market disadvantage (Chiswick 1978). From a demand-side perspective, the occupational skill profiles and labor market sorting among immigrant-origin workers are likely to occur both through discrimination and channeling mechanisms, leading
Note: Panel A shows the share of workers in low-, medium-, and high-skill occupations, 1997–2018. Panel B shows the total share of immigrant-background workers in the labor force and separately within low, medium, and high occupational segments, 1997–2018. To construct the occupational skill segments, we calculate the educational attainment among all native majority workers in a given occupation separately for each year. The median educational attainment level of native majority workers in low-skill occupations was below upper-secondary schooling, in medium-skill occupations between completed upper-secondary and less than a short university degree, and in high-skill occupations completed short university degrees or higher. For further information, please see the Online Appendix.

Source: Norwegian administrative data. Authors’ own calculations.

Figure 9.1 Occupational skill segments and immigrant shares within occupational skill segments in the Norwegian labor market, 1997–2018
to the formation of immigrant niches in low-wage labor markets (Waldinger 1994; Friberg and Midtbøen 2019). In the third section, we argue why many of the skill-related explanations for differences in occupational sorting should be less relevant for descendants of immigrants who were born and raised in their parents’ country of destination. In the fourth section, we present empirical results documenting changes in the occupational skill profiles between immigrants and their descendants by linking information on occupational attainment by immigrant background to data with information job tasks and skill requirements within each occupation. In the final section, we summarize our findings and discuss how a focus on occupational skill profiles can broaden our understanding of intergenerational assimilation within immigrant minorities.

**Theoretical perspectives on immigrants’ occupational skills**

According to human capital theory, variation in labor market success is a function of individuals’ productivity-related skills (Becker 1964). However, some aspects of human capital, such as language or cultural know-how, is not easily transferable across borders; instead these skills are more or less specific to the country where they were acquired (Chiswick 1978). Because language skills constitute a basic form of human capital, immigrants who are not fluent in the host-country language tend to be severely disadvantaged compared to natives (Chiswick and Miller 1992). Linguistic skills raise productivity by facilitating the creation of opportunities and by increasing returns from future skill investments and in the labor market. However, investments for acquiring language fluency are costly in the sense that they require time and other resources. According to Chiswick and Miller’s (2001, 1995) general model of language learning among immigrants, host-country language acquisition is a function of efficiency (the degree to which language exposure translates into linguistic fluency, depending for example on their age, cognitive skills, and education), incentives (motivations for and costs of language learning), and exposure (how much they encounter the new language in their daily life). Numerous studies have reported a clear relationship between language skills and labor market outcomes among immigrants. For example, Bacolod and Rangel (2017) show that immigrants arriving in the United States from origin countries where the dominant language is distant from English tend to work in jobs that require more physical skills and less communicative, analytical, and socioemotional skills, and that this is particularly the case among those who arrive at older ages. In the Netherlands, Van Tubergen and Van De Werfhorst (2007) show that immigrants arriving from former colonies—Surinam and the Dutch
Antilles—are more likely to invest in post-migration education, which they attribute to more similar educational systems and better Dutch linguistic skills.

Differences in education may also explain why immigrants are sorted into jobs with different skill profiles than natives. Especially if they arrive as adults, they will have acquired most or all their education in their country of origin, and if they come from less-developed regions both their educational opportunities as well as the quality of their schooling may have been lower (Bratsberg and Terrell 2002; Wils and Goujon 1998; World Bank 2017). Moreover, even high-quality educations from countries of origin often have limited transferability to the labor market in the destination country due to linguistic barriers or differences between national systems of certification (Chiswick and Miller 2009; Friedberg 2000). Educational degrees function as formal requirements for gaining access to many well-paid and secure occupations (Collins 1979). If such access is limited to native degrees, immigrants with degrees acquired abroad will have less access to occupations congruent with their (foreign) qualifications (Drange and Helland 2019; Lancee and Bol 2017).

Whereas human capital theory focuses on the supply side, other perspectives focus on demand-side explanations for why immigrants often face labor market disadvantages in receiving societies. Employers often have limited information about applicants, and many types of skills are rather vague and may refer to different kinds of knowledge, characteristics, and competencies that are not easily conceptualized or measured (Arrow 1973; Spence 1973; Piore 1979; Moss and Tilly 2001). This is particularly the case when dealing with the type of ‘soft skills’ often required in the lower tiers of the labor market. Such soft skills may refer to physical strength, endurance, or handiness, or to one’s compliance and willingness to submit to discipline and workplace control—often boiling down to exploitability due to limited options (Wills et al. 2009; Ruhs and Anderson 2010). And because immigrants often tend to compare their own situation to friends and neighbors back home rather than co-workers in the host country—sometimes referred to as a ‘dual frame of reference’—they may be less sensitive to host society status hierarchies and more willing to take on low-status jobs (Waldinger and Lichter 2003). While this hardly constitutes a ‘skill’ in the strict sense of the term, it is often understood as such by employers looking for docile labor (Friberg and Midtbøen 2018).

Because soft skills include personal traits, features such as accent, style, and physical appearance will often influence employers’ gut feelings about which workers ‘look and sound right’ for a particular job (Moss and Tilly 2001; Warhurst and Nickson 2007). Rather than formal criteria for selection and hiring, employers often build their hiring decisions on approximations and
general ‘rules of thumb’ (Moss and Tilly 2001; Pager and Karafin 2009; Shih 2002). Finally, because employers are uncertain about the abilities and trustworthiness of new applicants, the actual recruitment and allocation of workers may often rely on informal networks whereby existing staff members vouch for newcomers, facilitate their training, and ensure their satisfactory performance (Friberg and Midtbøen 2019; Waldinger and Lichter 2003). In sum, these dynamics often work to channel immigrants and ethnic minorities into low-status and menial jobs.

In the paragraphs above, we have identified both supply-side and demand-side sources of skill differentials and task divisions between immigrants and natives. Yet, a question with large implications for the future ethnic stratification of immigrant-receiving societies is whether this pattern is reproduced over time and across generations. To the extent that immigrant labor market disadvantage and concentration in manual occupations is primarily a result of non-transferability of the immigrant generations’ educational, cultural, and linguistic skills, we should expect disparities relative to the majority to be reduced with time of residency, early age of arrival, and for native-born children of immigrants. Alternatively, disadvantages may be reproduced across generations to the extent that the second generation will also be overrepresented in manual occupations.

The assimilation literature proposes two different accounts of how the second generation will fare compared to their immigrant parents. On the one hand, both classical and contemporary versions of assimilation theory predict a gradual process through which ethnic disparities are reduced over time and across generations (Alba and Nee 2003). Although immigrants may arrive at the bottom of the host societies’ class structure and face discrimination and economic hardship, their native-born children learn the language and acculturate to the habits and orientations of the country in which they are born. By progressing through the educational system, they furthermore gain access to a variety of resources that were not accessible to their parents and become less vulnerable to discrimination, resulting in economic profiles that gradually come to resemble that of the native population (Alba and Nee 2003; Gordon 1964). Segmented assimilation theory, on the other hand, argues that children of immigrants assimilate into different segments of an established (American) racial and class hierarchy (Portes and Rumbaut 2001). Whereas some groups have the resources to move into middle-class status, others—facing a polarized labor market and entrenched racial discrimination—stagnate in the marginal working class or risk ‘downward assimilation’.
This chapter investigates the merit of these different propositions. If the optimistic scenario is most correct, the distribution of analytical, communicative, socioemotional, and manual skill requirements in the occupations held by the native-born children of all immigrant groups will resemble those of the native population rather than those of the immigrant generation. If the situation is more akin to that described by segmented assimilation theory, we should on the contrary expect that the distribution of skill requirements in the occupations held by the immigrant generation will be reproduced in the next generation—at least for the most disadvantaged groups.

**Intergenerational assimilation in occupational skill profiles: Norwegian evidence**

In the following, we compare the distribution of occupational skill profiles among immigrants and native-born children of immigrants in Norway. We focus on five occupational skill dimensions. This includes a measure of formal educational requirements (Levels, van der Velden, and Allen 2014) and the occupational requirements for analytical (e.g., problem solving, math, and abstract reasoning), communicative (e.g., reading, writing, and oral comprehension), socioemotional (e.g., coordinating and persuasion of others and the ability to work under stress), and manual (e.g., stamina, dexterity, and muscle strength) skills in each occupation (Bacolod and Rangel 2017).

We begin by describing variation in occupational skill profiles by immigrant generation, length of stay, and region of origin. To capture differences in the length of exposure to Norwegian society, we differentiate between immigrants who arrived less than ten years ago, immigrants who have stayed in Norway for ten or more years, childhood immigrants, and native-born descendants of immigrants. Furthermore, we differentiate between three broad origin regions: Western Europe and North America; Eastern Europe; and all remaining countries of origin outside Europe, which primarily consist of countries in Asia, the Middle East, and Africa.

Figure 9.2 shows estimated gaps in job skills relative to natives for different groups of immigrant-background workers. Within each region of origin, there is a quite consistent pattern across all skill dimensions. For immigrants and their descendants from Western European and North American origin countries, we see that recently arrived immigrants work in occupations that have lower educational requirements and lower analytical, communicative,
Note: Gaps estimated relative to non-migrant natives (vertical dark lines) using OLS regression, with controls for gender, age, and age squared. All occupational skill measures are z-standardized (mean = 0, std. dev. = 1).

Source: Norwegian administrative data. Authors’ own calculations.

Figure 9.2 Estimated mean gaps relative to non-migrant natives in educational requirements and analytical, communicative, socioemotional, and manual skill requirements in occupation for immigrants by years since migration, childhood immigrants, and immigrants’ native-born descendants by region of origin.
and socioemotional skill requirements. For all other immigrant-background workers of Western origin, the educational requirement gaps are also small.

For immigrant-background workers from Eastern Europe, the figure shows that both recently arrived immigrants and those who have been in the country for more than 10 years have a considerably higher concentration in occupations that require less education and fewer analytical, communicative, and socioemotional skills, but more manual skills. The gaps relative to natives are largest among those with the shortest length of stay in Norway. A large share of adult immigrants arriving from Eastern Europe arrived as migrant workers who were hired to work within manual industries, which is likely to explain why they are concentrated in occupations with high manual job skill requirements, but less need for analytical, communicative, and socioemotional skills. Childhood immigrants and the native-born descendants with Eastern European background are found in occupations with skill profiles that in large part resemble those of native Norwegians.

For immigrant-background workers from non-European origin countries, we observe clear gradients in occupational skill profiles by length of stay and immigrant generation. The largest gaps are found for occupations’ educational requirements and analytical skills, where there are sizeable gaps for both recent and more established immigrants but smaller gaps for childhood immigrants and no gap for immigrants’ native-born descendants. Although the estimated gaps for communicative and socioemotional job skills are smaller, the overall differences by years since migration and immigrant generation are similar. For manual job skills, the gaps are, perhaps surprisingly, smaller than for the other skill dimensions gaps. For the native-born descendants of non-European origins, there is either no gap or even a small advantage relative to natives for all the skill dimensions. Overall, this pattern indicates a gradual pattern of skill assimilation, where immigrant generation and the length of exposure to the Norwegian labor market and broader society is important for access to occupations with skill profiles that are more like those held by natives.

Finally, we explore whether and to what degree immigrant–native differences in occupational skill profiles reflect differences in individuals’ educational qualifications or labor market sorting across different industries, workplaces, and broad occupational categories. To simplify the main patterns, we do not differentiate between immigrant-origin workers’ regions of origin. Figure 9.2 presents estimated native–immigrant gaps in occupational skills before and after we assess differences between immigrant-origin and native workers within the same educational field, industry, workplace, and a broad division between professional-managerial occupations versus all other occupations.4
**Note:** Estimated immigrant–native gaps in skill dimensions from multivariate OLS regressions where the bars represent gaps relative to the non-migrant natives (vertical dark lines). All occupational skill measures are z-standardized (mean = 0, std. dev. = 1). All models control for gender, age, and age squared. The education model adds fixed effects for detailed educational fields of study, which capture both vertical and horizontal differences between educational degrees. The three subsequent models additionally adjust for fixed effects for either industry, workplaces, or broad occupational categories (professional-managerial occupations versus all other occupations).

**Source:** Norwegian administrative data. Authors’ own calculations.

**Figure 9.3** Estimated gaps in educational requirements and analytical, communicative, socioemotional, and manual skill requirements in occupation among immigrant-background workers before and after adjustment for detailed educational qualifications and sorting by industry, workplace, and occupation.
Figure 9.3 shows a similar baseline gradient in immigrant–native skill gaps as documented above for adult immigrants, childhood immigrants, and native-born descendants of immigrants. For immigrants, adjusting for formal educational qualifications only accounts for a small fraction of the skills differentials. Although additional adjustment for sorting into industries, workplaces, and professional-managerial occupations account for slightly more of the gaps observed among immigrants, about half or more of the total gaps remain. For childhood immigrants and native-born immigrant descendants, the patterns are quite different. To begin with, the overall gaps are much smaller, especially for native-born descendants. However, differences in educational qualifications account for a large share of the immigrant–native skill gaps for both groups, while adjustment sorting across industries, workplaces, and occupations matters comparatively less.

These findings suggest that formal human capital has limited influence on the sorting of immigrants into lower-skilled occupations and that immigrants to a considerable extent are found in lower-skilled occupations also when compared to native workers with similar formal educational qualifications within the same industry, workplace, and occupational category. Whether these differences reflect unobserved ethnic employer discrimination, stereotype-driven occupational sorting, or country-specific human and social capital—perhaps most importantly lack of language proficiency—is hard to disentangle. Interestingly, however, for childhood immigrants and immigrant descendants—which in large part share ‘visible minority’ statuses with co-ethnic adult immigrants of the same ancestry—differences in educational qualifications account for most of the immigrant–native skill gaps found within these groups. This may indicate that differences in country-specific human and social capital, as well as employers’ desire to hire workers who are willing to submit to discipline and workplace control, are more important drivers of occupational skill sorting among immigrants than ethnic discrimination.

Concluding discussion

Studying the role of skill profiles for the occupational sorting of immigrants in the Norwegian labor market, we find a distinct pattern. Whereas the skill profiles of immigrants from Western Europe do not differ much at all from those of natives, we find that non-European immigrants are substantially underrepresented in jobs with high requirements for formal education and analytical, communicative, and socioemotional skills. This pattern—which
persists almost irrespectively of how long they have resided in Norway—is even more pronounced for immigrants from Eastern Europe (including more recent EU member states like Poland and Lithuania), who are strikingly over-represented in jobs that require manual skills. Taking duration of residence into account, our findings suggest that immigrants from Western Europe do not experience any significant disadvantage in the labor market once they have become accustomed to life in Norway. However, the disadvantages experienced by non-European and Eastern European immigrants—which are only vaguely related to their formal skills or even to the types of industries and establishments where they work or access to professional-managerial occupations—are long-lasting.

However, for native-born descendants of immigrants and, to a lesser degree, childhood immigrants of Eastern European and non-European ancestry, the pattern is strikingly different. In contrast to the immigrant generation, their skill profiles are largely identical to those of native background, irrespective of their origins. This suggests that the disadvantages experienced by immigrants from outside Western Europe are not transmitted and reproduced across generations. This is broadly consistent with prior research from Norway that has shown considerable upward mobility in education and labor market attainments among descendants of immigrants from low-income origin countries (Hermansen 2016, 2017a; Midtbøen and Nadim 2021).

Our analyses thus provide additional evidence that the most pessimistic propositions about the long-term prospects of integration in immigration receiving societies do not apply to Norway. Despite striking differences in the skill profiles of different groups of immigrants, our analyses demonstrate that a pathway to integration remains open to their Norwegian-born descendants. This suggests that the ongoing ‘ethnicization’ of low-skill segments of the Norwegian labor market is more of a transitory phenomenon primarily driven by the inflow of migrant workers, and less as a durable process that is reproduced across immigrant generations.

Although striking intergenerational progress has previously been demonstrated in terms of educational attainment, employment, and earnings in Norway (Hermansen 2016), we establish that this pattern also applies to the actual occupational skill sets and work tasks that immigrants and immigrants’ descendants perform in the labor market. It should be noted, however, that our analyses are limited to persons in gainful employment and that we will, at best, only indirectly capture any disparities due to ethnic discrimination at the point of hire (Quillian and Midtbøen 2021). Nevertheless, we believe that our findings provide important insights for broader discussions about the
long-term consequences of immigration on receiving societies, as well as the specific context of the Norwegian welfare state.

Notes

1. For details about the empirical measures and our analytical approach, see the Online Appendix.
2. Childhood immigrants include those who arrived in Norway before turning 18, while native-born descendants of immigrants refer to individuals who were born in Norway with two immigrant parents.
3. See the Online Appendix for a brief description of the Norwegian context of immigration.
4. Although the magnitude of the immigrant–native gaps varies by world region of origin, the overall pattern when adjusting for covariates is similar. Furthermore, the pattern is also similar by gender, but the overall gaps tend to be larger among men.

References


Can work protect against age-related decline of cognitive skills?: An empirical test of the use-it-or-lose-it hypothesis

Mark Levels and Rolf van der Velden

So Nature deals with us, and takes away Our playthings one by one (Henry Wadsworth Longfellow)

Introduction

A considerable body of research demonstrates that in general, cognitive skills of adults depreciate later in life (Pfeiffer and Reuss, 2008; Lustig et al., 2009; Smith and DeFrates-Densch, 2008; Salthouse, 2011). But this is not necessarily universally true: a significant part of the oldest share of population shows no observable cognitive decline, and the depreciation of skills differs strongly between individuals (Hertzog et al., 2007; Kliegel, Moor and Rott, 2004; Yaffe et al., 2009). This chapter seeks to empirically explore an often-hypothesized explanation for differences in depreciation of cognitive skills: the assumption that depreciation of skills can be mitigated or even averted by remaining active on the labor market, or, as it is more popularly known, the “use-it-or-lose-it” hypothesis (Mincer and Ofek, 1982; Krahn and Lowe, 1998).

Why is this important? Skills’ accumulation and depreciation in adults have not been a scientific priority in the past decades. The economic literature on skills formation during the life cycle mostly focuses on the acquisition of cognitive and non-cognitive skills during the early stages of life (Cunha and Heckman, 2007, 2008). This is for two reasons. First, the economic returns to investment in human capital are higher when the investments are made earlier in life (Cunha and Heckman, 2007, 2008). Second, socio-economic
skills disparities later in life can largely be traced back to differences early in the life cycle (Heckman, 2006). Carneiro and Heckman (2003: p. 63) conclude that investment in older workers skills “is often not economically efficient”. However, as the population of many developed countries steadily ages (United Nations, 2002), it is increasingly important to understand skills accumulation and decline in adults as well. Given the increased share of older workers, improving the quality of the human capital of the older contingent of the work force by retraining might be an important strategy to keep the stock of skills in an economy up to date. The success of this strategy largely depends on the cognitive abilities of the older workers. Studies strongly suggest that (certain types of) cognitive skills generally decline over the life-course (Toga and Thompson, 2005; Drag and Bieliauskas, 2009), which hampers, for example, learning abilities and reduces cognitive functioning in older workers (Smith and DeFrates-Densch, 2008; Lindenberger, 2014).

Population aging and the growing share of older workers make understanding cognitive decline and how to counter it an important field of study. This chapter thus seeks to explore the extent to which the processes of accumulation and depreciation of key information processing skills in older people can be affected by remaining active. To answer this question, large surveys containing longitudinal data using identical skills measures on various time-points during people’s entire life-time would be ideal. However, such elaborate data sets hardly exist or have limitations in terms of number of observations or explanatory variables. The Programme for the International Assessment of Adult Competencies (PIAAC: OECD, 2013a) is an interesting data source for this research question, given the detailed information available in the data about different factors affecting the acquisition and depreciation of key information processing skills over the life-course. PIAAC is a large cross-national adult literacy survey of individuals aged 16 to 65 in over 40 countries. PIAAC psychometrically measures respondents’ proficiency in literacy and numeracy – two types of cognitive skills essential for the development of higher-order cognitive skills as well as required for gaining access to and understanding knowledge domains (OECD, 2013a). Although there is debate about the use of cross-sectional data to analyze age-related differences in skills (see Schooler, 2007; Abrams, 2009; Schaie, 2009), such data sets can be used to bear on hypotheses about processes of accumulation and depreciation, particularly if the samples are sufficiently large (Salthouse, 2006, 2007). We analyze these data with propensity score matching techniques, comparing workers over 40 who stopped working only recently before the survey with comparable adults who remained active. Our findings support the use-it-or-lose-it hypothesis.
Use it or lose it?

It is a well-established factoid that cognitive skills change with age. Skills generally increase in the first part of the life-course, then stay stable and after a certain age start to decline. The cognitive aging literature suggests that normal aging is accompanied by a progressive decline of cognitive abilities. Review studies identify several physiological causes of normal aging (Drag and Bieliauskas, 2009; Toga and Thompson, 2005). After a certain age, the aging brain declines in volume, most notably affecting the frontal cortex, but also, albeit slower, the temporal, parietal and occipital cortices (Haug, 1983; Haug and Eggers, 1991). Also, normal aging involves hippocampal atrophy, associated with decreasing memory performance (Morrison and Hof, 1997; Raz et al., 1998; Head et al., 2008; Persson et al., 2006). Studies further suggest that aging is related to increased bilateral prefrontal activation, which has also been shown to affect memory functioning (Cabeza et al., 1997; Reuter-Lorenz et al., 2000), and a shift in activity from the occipital and temporal lobes of the cerebral hemisphere to the frontal lobes (Davis et al., 2008), which has been explained as signs that the brain engages alternate brain areas to compensate for neurocognitive decline in other regions (Cabeza et al., 1997). Some evidence suggests that older people perform less well on tasks that rely on executive functioning power of the brain (Rodriguez-Aranda and Sundet, 2006). The decline of brains’ executive powers with normal aging has been linked to declining working memory (Babcock and Salthouse, 1990; Bopp and Verhaeghen, 2005).

Normal aging generally develops gradually, with declines in overall cognitive functioning beginning from age 20, progressively continuing with individuals’ age and accelerating after the age of 50. But different trajectories have been observed for different types of skills. Cattell’s (1971, 1987) distinction between fluid intelligence and crystallized intelligence is particularly helpful for illustrating the distinction. In this theory, fluid intelligence is associated with learning new things, inductive reasoning, concept formation, visual conceptualization, effectiveness in problem-solving and memory (Horn, 1988). Crystallized intelligence refers to a reservoir of skills and wisdom that individuals collect during their lives, including problem definition, verbal knowledge, the ability to follow instructions, and the accumulated body of knowledge about culture and the humanities, as well as the social and physical sciences. Theory predicts and empirical studies show that both types of intelligence increase in the early phases of the life span, crystallized intelligence keeps increasing and starts to decline only later in adulthood, and fluid intelligence
starts to decline already in early adulthood (Horn and Cattell, 1967; Baltes and Mayer, 1999; Schaie, 2009).

The abilities to perform well on tests measuring numeracy and literacy partly depend on fluid intelligence. As such, it is often observed that numeracy and literacy generally increase with age, and then progressively decline (cf. Hertzog et al., 2007). The process of cognitive decline and the extent to which it affects key information processing skills differs widely between individuals (Hertzog et al., 2007). The degree to which individuals experience normal cognitive aging depends on the complex interplay of biological and environmental parameters, on social influences and on individual behavior (Cunha and Heckman, 2007, 2008). Research suggests that training the mind helps to slow down cognitive decline (Salthouse, 2006). This implies skills acquisition can be fostered, and cognitive decline can be slowed down by regularly engaging in activities that require using the brain. This has become known as the “use-it-or-lose-it” hypothesis (Mincer and Ofek, 1982; Krahn and Lowe, 1998). One important way in which the brain may be activated and trained is by working. This suggests that older adults who stop working experience cognitive decline and as a result have lower cognitive skills than adults who are comparable but who remain working. It is this hypothesis that we will test.

Data

To test our hypothesis, we use cross-sectional data from the PIAAC survey, collected by the OECD (2013a) in over 40 countries. PIAAC samples adults between the age of 16 and 65 – the sampling procedure achieved a minimum of some 5000 respondents per country. We excluded the data for Australia for privacy reasons and data from the Russian Federation for technical-administrative reasons. Using a combination of computer-based assessment paper-and-pencil data collection strategies, respondents conducted tests that directly assess their numeracy and literacy skills. Given time restrictions, respondents took a subset of all items (adaptive testing) and item response techniques were used to calculate 10 plausible values on literacy, as well as 10 plausible values on numeracy. Together, these plausible values provide an unbiased estimate of the “real” score if the respondent would have taken all the literacy- and numeracy-related items (OECD, 2013b). The numeracy scale has a range from 0 to 500 with an OECD international average of 273; the literacy scale has an OECD average of 270. Respondents were further interviewed on non-cognitive skills, key demographic and socio-economic characteristics, as well as the extent to which they
use key information processing skills in the workplace or at home. The survey is designed to be cross-culturally and cross-nationally valid.

**Measurements**

Descriptive statistics of all measures we use for matching are available in Table 10.1.

- **Gender** indicating whether respondents identified as *male* (1) or *female* (0).
- **Age** is counted in years and added linearly.
- **Level of education**: three dummies distinguishing low (ISCED 1 or 2; the reference group), medium (ISCED 3 or 4) or a high level of education (ISCED 5 or 6).
- **Parental education**: based on a variable that indicates the level of the highest-educated parent. We distinguish whether the highest-educated parent was higher educated, medium educated or lower educated. Lower education is the reference category. We also add a dummy for missing values.
- As a second indicator of parental SES, we add dummies for *number of books in the household at age 16*: 11–25, 26–100, 101–200, 201–500, more than 500 (10 or fewer is the reference category) and a missing value dummy.
- **Immigration status**: distinguishing first-generation immigrants (both parents and respondent were foreign born), 1.5-generation immigrants (respondent and one parent foreign born), second-generation immigrants (both parents foreign born, respondent born in test country), 2.5-generation immigrant (respondent and one parent born in test country, one parent foreign born) and remigrants (i.e. respondent foreign born, both parents non-foreign born). People without migration background are the reference category.
- **Self-rated health**: based on the self-rated health question: “In general, would you say your health is excellent, very good, good, fair or poor?” We constructed a dummy distinguishing “poor health” (1) from the rest (0).
- **Work experience**: measured in years. Those without work experience score zero and an additional dummy “never worked” is added.
- **The number of years since leaving education**: indicates potential depreciation of key information processing skills accumulated in education. It is calculated by subtracting the age at leaving education from the age at the time of interview.
- **Use skills at home or at work**: the following indices have been taken up. (1) Use of literacy skills at home and (2) at work; (3) use of numeracy skills at home and (4) at work. The indices are based on the simple average scores on all literacy or numeracy skill use-related items in the questionnaire.
Table 10.1  Descriptive statistics of used variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Numeracy</td>
<td>0</td>
<td>467</td>
<td>268</td>
<td>53</td>
</tr>
<tr>
<td>Literacy</td>
<td>24</td>
<td>447</td>
<td>272</td>
<td>48</td>
</tr>
<tr>
<td>Parents’ education medium</td>
<td>0</td>
<td>1</td>
<td>0.362</td>
<td>0.481</td>
</tr>
<tr>
<td>Parents’ education high</td>
<td>0</td>
<td>1</td>
<td>0.248</td>
<td>0.432</td>
</tr>
<tr>
<td>11–25 books at home</td>
<td>0</td>
<td>1</td>
<td>0.155</td>
<td>0.362</td>
</tr>
<tr>
<td>26–100 books at home</td>
<td>0</td>
<td>1</td>
<td>0.319</td>
<td>0.466</td>
</tr>
<tr>
<td>101–200 books at home</td>
<td>0</td>
<td>1</td>
<td>0.169</td>
<td>0.375</td>
</tr>
<tr>
<td>201–500 books at home</td>
<td>0</td>
<td>1</td>
<td>0.132</td>
<td>0.338</td>
</tr>
<tr>
<td>&gt; 500 books at home</td>
<td>0</td>
<td>1</td>
<td>0.070</td>
<td>0.256</td>
</tr>
<tr>
<td>1st-generation immigrants</td>
<td>0</td>
<td>1</td>
<td>0.093</td>
<td>0.290</td>
</tr>
<tr>
<td>1.5-generation immigrants</td>
<td>0</td>
<td>1</td>
<td>0.009</td>
<td>0.092</td>
</tr>
<tr>
<td>2nd-generation immigrants</td>
<td>0</td>
<td>1</td>
<td>0.025</td>
<td>0.155</td>
</tr>
<tr>
<td>2.5-generation immigrants</td>
<td>0</td>
<td>1</td>
<td>0.052</td>
<td>0.222</td>
</tr>
<tr>
<td>Remigrants</td>
<td>0</td>
<td>1</td>
<td>0.008</td>
<td>0.091</td>
</tr>
<tr>
<td>Male</td>
<td>0</td>
<td>1</td>
<td>0.475</td>
<td>0.499</td>
</tr>
<tr>
<td>Age</td>
<td>16</td>
<td>65</td>
<td>40.217</td>
<td>14.371</td>
</tr>
<tr>
<td>Poor health</td>
<td>0</td>
<td>1</td>
<td>0.039</td>
<td>0.194</td>
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<tr>
<td>Education medium</td>
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<td>1</td>
<td>0.450</td>
<td>0.498</td>
</tr>
<tr>
<td>Education high</td>
<td>0</td>
<td>1</td>
<td>0.338</td>
<td>0.473</td>
</tr>
<tr>
<td>Total work experience</td>
<td>0</td>
<td>55</td>
<td>17.066</td>
<td>13.502</td>
</tr>
<tr>
<td>Total time out of formal education (years)</td>
<td>0</td>
<td>61</td>
<td>17.123</td>
<td>14.972</td>
</tr>
<tr>
<td>Not worked for 12 months or more last year</td>
<td>0</td>
<td>1</td>
<td>0.245</td>
<td>0.430</td>
</tr>
<tr>
<td>Using literacy skills at home</td>
<td>0</td>
<td>4</td>
<td>1.633</td>
<td>0.662</td>
</tr>
<tr>
<td>Using numeracy skills at home</td>
<td>0</td>
<td>4</td>
<td>1.124</td>
<td>0.825</td>
</tr>
</tbody>
</table>

Note: N=150,585.

Source: PIAAC (OECD, 2013a).
People who did not work were given the lowest scores possible on the indices reflecting skills use at work, and dummies were added to indicate this.

- **Motivation to learn**: Likert scale of six items on learning styles and motivations, including statements like “I like to get to the bottom of difficult things” and “I like learning new things”.

**Analyses and results**

**Descriptive analyses**

We start by showing the bivariate relation between age and key information processing skills. Figure 10.1 displays the age-skills profile for literacy and numeracy. For both types of skills, we see a sharp increase of proficiency scores between age 16 and 28. In the case of literacy from 270 to 285 and in the case of numeracy from 260 to 280. Then the stock of skills remains more or less constant until the age of 40, followed by a gradual decline from the age of 40 to 251 and 248 at age 65 for literacy and numeracy respectively. Since we use cross-sectional data, these observed trends partly reflect cohort differences; longitudinal studies (that do not conflate age and cohort effects) generally suggest that cognitive decline starts at a later age (Rönnlund et al., 2005).
Propensity score matching

In this section, we shed more light on the consequences of stopping with work for the skills of people over 40 years old. We focus on differences in numeracy skills between people who are currently working, and those who have only very recently stopped working. The intuition is that people who just stopped working are likely more similar to those who are still working on unobserved characteristics than people who have stopped working a longer time ago; this also allows us to hold constant for cohort effects. We select people older than 40, who reported to have been working in the 12 months before the date of their interview and identify two sub-groups: people who were no longer employed when they were interviewed for PIAAC (treatment group), and people who were still employed at the time of the interview (control group). We then use propensity score matching (PSM, cf. Rosenbaum and Rubin, 1983) to compare the numerical skills of the treatment and the control group. The raw data have N=52260 respondents who are still working and N=4045 respondents who have recently stopped.

PSM uses the propensity score of each respondent in the treatment group and matches it to the one respondent from the control group with a propensity score closest to that score. The true propensity score is unknown and has to be estimated. The goal of this estimation exercise is not to estimate the true propensity score as accurately as possible, but to find an estimate of the propensity score that statistically balances the covariates between treated and control groups. If overlap is sufficient, the estimated propensity score achieves more precise estimates than the true score (Rubin and Thomas, 1992), so achieving sufficient overlap is key. To estimate the propensity score, we use variables that are expected to be associated with whether or not people work and their skills level, either by theory or by previous literature, and are unaffected by whether or not people work. More specifically, we use dummies on respondents’ education level, the education level of their parents, the number of books in their home, their migrant status, age, health, total work experience, the time they are out of formal education, their motivation to learn new things and the extent to which they use skills at home. In addition, we use country dummies to estimate the propensity score, to deal with the effects of unobserved heterogeneity between countries. These variables are then linked to a propensity score for each respondent with a logit link. The propensity scores signify the propensity that individuals have stopped working within the last 12 months before the interview.

Using the propensity score, respondents from the treatment group are then matched to respondents from the control group. We used one-to-one,
Table 10.2  Balance of covariates after matching

<table>
<thead>
<tr>
<th>Variable</th>
<th>Treated</th>
<th>Control</th>
<th>t</th>
<th>%bias</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>0.018</td>
<td>0.016</td>
<td>0.60</td>
<td>1.1</td>
</tr>
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<td>Canada</td>
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<td>0.244</td>
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<td>-0.4</td>
</tr>
<tr>
<td>Cyprus</td>
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<td>0.037</td>
<td>-0.36</td>
<td>-0.9</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>0.044</td>
<td>0.052</td>
<td>-1.61</td>
<td>-4.1</td>
</tr>
<tr>
<td>Denmark</td>
<td>0.060</td>
<td>0.060</td>
<td>0.09</td>
<td>0.2</td>
</tr>
<tr>
<td>Estonia</td>
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<td>0.045</td>
<td>0.58</td>
<td>1.2</td>
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<td>0.037</td>
<td>0.23</td>
<td>0.5</td>
</tr>
<tr>
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<td>0.021</td>
<td>0.020</td>
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<td>0.6</td>
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<td>0.037</td>
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<td>Korea</td>
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<td>0.041</td>
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<td>0.6</td>
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<td>Netherlands</td>
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<td>0.024</td>
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<td>0.019</td>
<td>0.78</td>
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<td>Poland</td>
<td>0.025</td>
<td>0.021</td>
<td>1.41</td>
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</tr>
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<td>Slovenia</td>
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<td>0.028</td>
<td>0.025</td>
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<td>2.1</td>
</tr>
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<td>United Kingdom</td>
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<td>0.050</td>
<td>0.25</td>
<td>0.6</td>
</tr>
<tr>
<td>United States of America</td>
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<td>0.036</td>
<td>0.06</td>
<td>0.1</td>
</tr>
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<td>France</td>
<td>0.043</td>
<td>0.048</td>
<td>-1.12</td>
<td>-2.5</td>
</tr>
<tr>
<td>Parents’ education medium</td>
<td>0.280</td>
<td>0.275</td>
<td>0.47</td>
<td>1.0</td>
</tr>
<tr>
<td>Parents’ education high</td>
<td>0.131</td>
<td>0.128</td>
<td>0.46</td>
<td>1.0</td>
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<td>11-25 books at home</td>
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<td>0.186</td>
<td>0.20</td>
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<td>26-100 books at home</td>
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<td>0.297</td>
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<td>101-200 books at home</td>
<td>0.134</td>
<td>0.119</td>
<td>1.91</td>
<td>4.0</td>
</tr>
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<td>201-500 books at home</td>
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<td>0.094</td>
<td>-0.15</td>
<td>-0.3</td>
</tr>
<tr>
<td>Variable</td>
<td>Treated</td>
<td>Control</td>
<td>t</td>
<td>%bias</td>
</tr>
<tr>
<td>--------------------------------------</td>
<td>---------</td>
<td>---------</td>
<td>-----</td>
<td>-------</td>
</tr>
<tr>
<td>&gt; 500 books at home</td>
<td>0.047</td>
<td>0.050</td>
<td>-0.62</td>
<td>-1.3</td>
</tr>
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<td>1st-generation immigrants</td>
<td>0.101</td>
<td>0.103</td>
<td>-0.26</td>
<td>-0.6</td>
</tr>
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<td>1.5-generation immigrants</td>
<td>0.007</td>
<td>0.008</td>
<td>-0.50</td>
<td>-1.2</td>
</tr>
<tr>
<td>2nd-generation immigrants</td>
<td>0.020</td>
<td>0.018</td>
<td>0.81</td>
<td>1.7</td>
</tr>
<tr>
<td>2.5-generation immigrants</td>
<td>0.049</td>
<td>0.048</td>
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<td>0.7</td>
</tr>
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<td>0.011</td>
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<td>-0.5</td>
</tr>
<tr>
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<td>0.476</td>
<td>0.491</td>
<td>-1.33</td>
<td>-3.0</td>
</tr>
<tr>
<td>Age</td>
<td>54.143</td>
<td>54.280</td>
<td>-0.89</td>
<td>-2.0</td>
</tr>
<tr>
<td>Poor health</td>
<td>0.072</td>
<td>0.067</td>
<td>0.92</td>
<td>2.4</td>
</tr>
<tr>
<td>Education medium</td>
<td>0.450</td>
<td>0.446</td>
<td>0.38</td>
<td>0.8</td>
</tr>
<tr>
<td>Education high</td>
<td>0.273</td>
<td>0.278</td>
<td>-0.47</td>
<td>-1.0</td>
</tr>
<tr>
<td>Total work experience</td>
<td>28.526</td>
<td>28.831</td>
<td>-1.19</td>
<td>-2.8</td>
</tr>
<tr>
<td>Total time out of formal education</td>
<td>29.599</td>
<td>30.013</td>
<td>-1.48</td>
<td>-3.4</td>
</tr>
<tr>
<td>(years)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Using literacy skills at home</td>
<td>0.936</td>
<td>0.955</td>
<td>-1.20</td>
<td>-2.7</td>
</tr>
<tr>
<td>Motivation to learn</td>
<td>3.546</td>
<td>3.576</td>
<td>-1.69</td>
<td>-3.9</td>
</tr>
</tbody>
</table>

Notes: Balance after one-to-one nearest-neighbor matching. P-values of t-test on mean differences ***: p<0.001; **: p<0.01; *: p<0.05.

Source: PIAAC (OECD, 2013a).

nearest-neighbor matching with replacement, so, while cases from the treatment group are used only once, cases from the control group can be used multiple times if their propensity score is the nearest match for multiple different cases from the treatment group. The matching procedure thus creates a new analytic sample, containing all the original cases from the treatment group (N_T=4045), and only those cases from the control group that are used as matches (N_C=3688). Note that some of the matching cases are found more than once in the analytic sample because we match with replacement.

We use the psmatch2 procedure (Leuven and Sianesi, 2003) and Stata12 (StataCorp, 2011) to perform the PSM, and to estimate the average treatment effects for the treated (ATT). Before turning to this effect, two important requirements of PSM need to be discussed. First, for the results to be informative, the matching procedure must achieve balance of the covariates; that is, the means of the important covariates must not differ between treatment and...
control group. Table 10.2 shows that after matching, no significant differences between the treatment and control groups can be observed. It also shows that the standardized bias is less than 5%. Thus, matching succeeded in creating a good control group. The second requirement is sufficient common support, to assure that we have enough overlap between the treatment and control groups to make reasonable comparisons. To assess the degree of common support, consider Figure 10.2 in which the density functions of the propensity scores of both the control group and the treatment group are depicted in the left-hand panel. The panel shows that the distributions are not exactly similar, and that very few cases from treatment and control groups have propensities to have stopped working over .4. On close inspection, the histogram in the right-hand panel in Figure 10.2 reveals that cases from the control group span the full range of propensity scores, ensuring common support. However, there are very few cases from the control group with high propensities. As we match with replacement, this means that the control cases with higher propensity scores must be used multiple times to be matched to treated cases. Still, Table 10.3 shows that the number of cases from the control group used more than once is reasonable. Most cases from the control group are used only once, and only four respondents from the control group are matched to more than three members of the treatment group.

In Table 10.4, the results of our PSM analyses are presented. Before matching, the difference in predicted numeracy skills between the people who are still working (270,047) and those who have stopped (250,275) was almost 20 points on the numeracy scale. The ATT shows that after matching, the difference is
Table 10.3  Number of times cases are used to achieve matching

<table>
<thead>
<tr>
<th># used</th>
<th>Treatment: recently stopped working</th>
<th>Control: still working</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4045</td>
<td>3379</td>
</tr>
<tr>
<td>2</td>
<td>267</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4045</td>
<td>3688</td>
</tr>
</tbody>
</table>

Table 10.4  Propensity score matching results

<table>
<thead>
<tr>
<th>Sample</th>
<th>Mean scores on numeracy skills</th>
<th>Difference between treatment and control</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated: recently stopped working</td>
<td>Controls: still working</td>
</tr>
<tr>
<td>Unmatched</td>
<td>250.275</td>
<td>270.047</td>
</tr>
<tr>
<td>ATT</td>
<td>250.275</td>
<td>255.669</td>
</tr>
</tbody>
</table>

Source: PIAAC (OECD, 2013a).
Notes: Results after one-to-one nearest-neighbor matching on country fixed effects, respondents’ education level, the education level of their parents, the number of books in their home, their migrant status, age, health, total work experience, the time they are out of formal education, their motivation to learn new things and the extent to which they use skills at home.

much smaller. People who have stopped working in the past 12 months on average score 5.4 points lower on the numeracy scale than matched individuals who are still employed. This is in line with the use-it-or-lose-it hypothesis on cognitive decline.

Conclusions and discussion

The analyses in this chapter suggest that people’s skills decline after they stop working. We reach this conclusion based on propensity score matching.
analyses comparing skills of adults over 40 who were still working a year before the survey but had stopped working in the meantime, with those of comparable peers who are still working. We found that those who just stopped working had a slightly lower numeracy score on the PIAAC test than those who still worked. We may cautiously interpret this as evidence of the expectation that people who stop using specific skills experience a decline in these skills. Moreover, since the time that the people in our treatment group had been inactive was rather short by design, the effects we report are likely lower bounds.

Compared to OLS regression methods, PSM analyses provide a stricter test of our use-it-or-lose-it hypothesis. In addition, PSM has two main advantages over OLS. First, PSM does not require that the relationship between outcome and control variables follow a specific functional form. Second, and more importantly in the context of this chapter, PSM uses the matched sub-samples for estimation purposes, which reduces the estimation bias. PSM estimators are generally less sensitive to model misspecifications (Conniffe, Gash and O’Connell, 2000; Rubin and Thomas, 2000). However, we stress that our conclusions must nonetheless be accompanied with an important caveat. PSM techniques can yield an unbiased estimator of the treatment effect of not working on cognitive abilities, but it is important to note that they do so only under the assumption of unconfoundedness; that is, when there are no unobserved covariates plausibly affecting both whether or not people have stopped working and their observed skills. This assumption is intrinsically untestable, but we cannot exclude the possibility that we could not use all relevant covariates for matching. Although we test for the most common explanatory variables and compare people who only just stopped working with those who are still working, our findings may reflect that the matching is not perfect. Therefore, we caution against interpreting our results as proof of the causal effect of stopping to work and cognitive decline. For such conclusions, quasi-experimental analyses can provide more convincing identification strategies. However, these caveats notwithstanding and under reasonable assumptions, our analyses on high-quality cross-sectional data do suggest that working significantly mitigates cognitive decline in older adults.

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Introduction

When humans develop the health, skills, and motivation that allow them to engage in activities that contribute to the well-being of themselves or others, they have developed what we will call “capabilities”. Focusing more narrowly on investment in health or skills that increase earnings, neoclassical economists have developed a theory of human capital that has become influential across academic disciplines and in policy circles. Some economists, such as Gary Becker (1991), have broadened the concept of human capital somewhat to include skills useful in the “household production” that is the focus of the neoclassical “new home economics”. We want to broaden the conceptualization of human capital even further along several dimensions, with a result that undercuts several neoclassical formulations, including some of Becker’s views. Since the resulting view of “human capital” differs substantially from the orthodox view, we use a distinct term, “capabilities”, to remind readers of these differences. We borrow this term from Amartya Sen (see Sen 1993 and his past work cited there). We think our formulation is somewhat in the spirit of Sen’s. However, no strict equation of our view with his is implied by the choice of term; our formulation and Sen’s address somewhat different issues.

In this chapter, we work toward the development of a theory of human capabilities in the following steps: first we identify some of the basic capabilities that humans need. We discuss four overlapping categories: capabilities for physical functioning, cognitive functioning, self-regulation, and caring. We then ask what we know about how capabilities are developed. Comparisons of aspects of our broadened view to orthodox versions of neoclassical theory of human capital are made throughout the chapter, and we close by explicitly discussing differences in how the two views conceptualize basic issues and exploring a few implications of these differences.
What basic capabilities do humans need?

How do we decide which capabilities are of basic importance to humans? To answer this, we first need to define the term “capability”. A capability is a state (involving some combination of motivation, skill, and/or health) that requires some effort to develop, and that, when developed, enables one to function in ways that contribute to the well-being^{2} of oneself or others. That which the resulting functionings allow one to “produce” to contribute to well-being may be either a good or a service, with “service” broadly construed to include, for example, emotional support. The functioning that the capability enables may be carried out as part of a job for which one is paid, in the household, or elsewhere.

As we define capabilities, the person who benefits from the exercise of the capability need not be the same person who has and uses the capability. This has important implications. When we say that all the categories of capabilities we call basic here are beneficial for humans to develop, we don’t require it to be true that an individual will be better off if he or she develops each capability. Our claims that the capabilities are beneficial for human well-being are at the collective level. Thus, while it may be that individuals will themselves be better off if they develop at least a minimum of all these capabilities, the claim we are making is rather that humans, collectively, benefit from having these basic capabilities developed.

But this broad notion could lead to a list of thousands of specific detailed capabilities – being able to read, synthesize information, do math problems, repair machines, grow food, prepare meals, defend against physical attacks, feed babies, comfort the sad, and defuse conflicts, to name a few. All these are capabilities. However, for our purposes here, we want to identify and discuss a few categories of capability that are relatively basic. A capability may be basic because it is useful in many situations. This may be true simply because it is a broad category that groups many specific capabilities in it, or because the functionings it enables people to do fulfill widely shared needs or wants (of those doing the functioning or others). A capability may also be basic because it is a building block for many other capabilities. A criterion for something being on the short list presented below is that a capability is basic in one of these senses. We group capabilities by the type of function they allow people to carry out. The categories of capability discussed below are not mutually exclusive; we find them useful, nonetheless, in pointing to themes. We make no claim that some crucial capability has not been omitted. We do claim that all four of the types of capabilities we discuss are of basic importance to peo-
people's lives. We discuss capabilities that allow physical functioning, cognitive functioning, self-regulation, and caring.

Capabilities for physical functioning
We start with something exceptionally basic, physical functioning. This capability entails having the health, skills, and motivation for such functionings. Who would dispute their importance to many kinds of work in the household or market, and to many leisure activities? Physical skills are necessary to meet many human needs to work on the farm or in many factory jobs, to care for self and others, to drive a vehicle, and for many other functions. Literature on human capital investment in poor nations, where many people do not have basic inputs to health such as safe water, adequate nutrition, and antibiotics for infections, has always included a focus on physical health. Health and skills are related in that lack of health makes it harder to develop physical skills, causes them to atrophy, or saps the energy and motivation for exercising them. Yet, overall, the broad family of physical capabilities is little discussed in social science literature, except in applied literatures on disabilities. This neglect may be a legacy of metaphysical dualism in Western thought, that sees “bodies” and “minds” as entirely separate and deprecates the body as being “part of nature”. This deprecation also harmonizes well with the classical liberal view that rationality (seen as mental, and juxtaposed to “nature” and the body) is what is valuable about humans and the basis of their rights (Jaggar 1988, chapter 3). In distinguishing between physical and cognitive functionings, we do not want to reinforce such metaphysical dualism. We see the distinction as only a matter of emphasis since, of course, the brain (itself a part of the body) is always in use in physical movement, and there are motor skills entailed in many tasks we think of as “cognitive”, such as speaking or using a computer. Thus, when the use of the body is obvious and primary to carrying out a function, we call it physical. When the importance of language, reasoning, or calculation is the emphasized aspect, we call it cognitive. We recognize, however, that most activities are both cognitive and physical.

Capabilities for cognitive functioning
Cognitive functionings using language, reasoning, or calculation to solve problems are well recognized by economists and others as inputs into production. Few would dispute their importance. Unlike physical functionings, they are much discussed in social science research. There is a whole industry that draws upon psychometric research to devise tests to measure them. Cognitive skills are what formal education is supposed to be teaching. Education, a key type of measured human capital in social science research, has been shown to affect
earnings, presumably at least in part because of the cognitive skills imparted in school. Studies have shown effects of cognitive skills, as measured by test scores, on earnings, even net of years of educational attainment (Farkas et al. 1997).4

The benefits of cognitive skills, however, are not limited to allowing one to do market work for money, though such benefits are of huge importance. Cognitive skills also affect the well-being one can achieve for oneself and others through other life activities, such as dealing with household finances, doing home repairs, managing voluntary organizations, teaching one’s children problem-solving skills, and seeing evidence of cause-and-effect sequences in one’s personal life and using that to change behavior in ways that have desired outcomes.

Cognitive functioning also requires some aspects of what would more commonly be called “mental health”, those aspects that entail being relatively free from delusion, which obviously affects one’s ability to process information and reach conclusions that help solve everyday problems. But, not all of what we commonly call “mental health” is cognitive. Capabilities that might be labeled “emotional” are also important.

Capabilities for self-regulation

A key aspect of what journalist Daniel Goleman (1995) has called “emotional intelligence” is self-discipline. Different terms are used for what are basically variations of a single concept – the ability to make oneself do something one doesn’t want to do or keep oneself from doing something one has the urge to do. People may call it self-discipline, self-control, will power, impulse control, attention, restraint, or the ability to defer gratification. Parents seem to instinctively know that it is important to develop this in children. Every grade school teacher will tell you that children who don’t have it are in trouble (and a real pain to deal with). Kids whose parents have little self-regulation developed are really in trouble, since children routinely enrage parents, and great restraint is sometimes needed just to abstain from violence. In 12-step programs such as Alcoholics Anonymous people seek the help of a support group and a spiritual practice to increase their self-regulating capability around particular addictions. Self-regulation may be a good part of what employers are looking for when they talk about responsibility, attitude, or work ethic being as or more important than whether you have specific credentials, cognitive skills, or experience at this job.5 Criminologists Gottfredson and Hirschi (1990) argue that the psychological characteristic that best predicts committing crime is
lack of self-control. All this suggests that there is something fundamental and important here.

Self-regulation is basic and important because the goals that it serves are multiple. Sometimes it is a matter of forgoing immediate gratification to invest in something that provides gratification to the self later. The restraint it takes to work long hours now may provide rewards later. The discomfort of opening up old emotional wounds in psychotherapy is endured in the hope of greater happiness later. What economists call “investing” in human capital (or anything else) also requires self-regulation – one may need to restrain oneself from watching television in favor of studying, even if one likes television better, in order to get the degree that leads to the higher-paying job. In this case, in our terms, the capability of self-regulation is needed to be able to develop another capability. Self-regulation is sometimes needed to be an altruist or to do what one sees as one’s duty; for example, an exhausted parent is tempted to ignore a child the fourth time she cries in the middle of the night, but gets up to care for her nonetheless. As the examples above show, self-regulation can be in the interest of pecuniary or non-pecuniary goals, and it may be in the service of selfish, moralistic, or altruistic goals. The capability is relevant to achieving all these types of goals. We see self-regulation as basic enough to be included as a fundamental capability because the achievement of many of individuals’ goals necessitates regulating the self, orienting one’s behavior to what contributes to achieving these goals even when other behavior would be more gratifying in the moment.

Why is self-regulation not usually discussed by economists as a form of human capital? Perhaps it is because its meaning is very close to the economic concept of the discount rate, how one values present versus future utility. Other instances of self-regulation sound like the economic concept of risk-aversion; for example, when a teen forgoes the excitement of driving 100 miles per hour to avoid the risk of a crash, or the pleasure of sex because of the risk of AIDS, self-regulation has been exercised. But neoclassical economists think of one’s degree of risk-aversion (or risk-seeking) and one’s discount rate as preferences (or tastes – we use the terms synonymously), not as skills or health. By usual neoclassical assumption, preferences are seen as exogenous and unchanging. They aren’t something to invest in – they are taken as given. Recent theoretical work by Gary Becker (1996) has sought to endogenize preferences, and we applaud this move. But, in the case of self-regulation, even this is not adequate for understanding it as a capability. An adequate understanding requires recognizing how skill and preference are intertwined in capabilities.
The extent to which we have a preference for something is a statement of how much we like or want it vis-à-vis other things (that is, how much it contributes to our utility). To be sure, self-regulation has this “preference” aspect – we can be interested in how much one values the lowered risk or later gratification that comes from regulating oneself so as to abstain from certain behavior. Presumably, the more a person values it, the more likely s/he is to avoid the behavior, just as one will buy more chocolate ice cream if one likes it more. But there is another aspect to self-regulation that is missed in the “preference” formulation, an aspect that psychologists – and ordinary people – understand. To some extent a person’s propensity to self-regulate is a developed capability. It is like a muscle that some people have well developed and others do not. We find the metaphor of a “muscle” apt for capabilities in general, including self-regulation. The potential for strength inherent in muscles must be developed, and when it has not been developed, there is a very real sense in which one is not able to do the function it allows. Likewise, when one has developed self-regulation very little, one is less able to restrain oneself from behaviors that are risky or otherwise negative in the long run. It is not only a matter of one person differing from another in getting more utility from the tempting behavior, more disutility from the “good” behavior, or less utility from the long-term goal, although this may be true as well. We conclude that self-regulation entails both a preference and a skill.7

More generally, we think that skills and preferences for exercising the skill virtually always develop together. Thus most if not all capabilities are best conceptualized to have a skill and a taste aspect intertwined. This joint production of skills and tastes for exercising the skill occurs because the two acquisitions (skill and preference) have a positive causal effect on each other; on the one hand, when one gets better at something this tends to increase enjoyment at doing it, and on the other, when one enjoys doing something, it makes it less onerous to practice the task and get better at it. It makes sense to see a capability as more deeply developed if one has internalized both the “skill” or “muscle” aspect and the relevant preference. One reason for this is that people who have developed the preference as well as the skill can be relied upon more to exercise the skill even under loose or no surveillance.

Capabilities for caring

Let us define caring capabilities as those useful in providing what Folbre and Weisskopf (1998) have called “care services”. These are services provided with personal contact between the provider and recipient.8 This work may be performed by family members or others who are not paid for it, as when a parent takes care of a child, or one spouse provides another with emotional support,
or one friend helps another move into a new apartment. Care services may also be work done for a wage. Child care, teaching, psychotherapy, and nursing are examples of paid jobs in which the worker provides care services.

Why is caring so important? Specifically, why do we think that the capabilities relevant to caring are basic enough for us to say that humans need to develop them? For one thing, had someone not developed these capabilities enough to nurture each of us when we were children, we would all be dead, or at least so anti-social as to be locked up. The broader point is that one’s need to receive care from someone other than oneself flows from the fact that we are all sometimes unable to provide needed care for ourselves. Despite the glorification of autonomy in classical liberal theory, there are inevitable dependencies in human life. We all start out helpless, needing others to feed and protect us. As adults, most of us will be ill enough sometime to need medical care from others, and will have a period of illness or frailty in old age when we need others’ care. Even when we are strong, healthy, and “fully trained”, some services are difficult or impossible to self-provide; it is hard to give oneself a back massage or to teach oneself a new skill. Moreover, there may be a basic human need to feel loved by others. If any of these needs or wants for others’ care are to be met for “ego”, some “alter” has to develop the capability to provide care services.

What capabilities are needed to provide caring services? Often certain physical skills are relevant – one may need to know how to give an inoculation or bandage a wound, for example. Cognitive skills are also relevant; nursing requires knowledge of biology, the teacher needs to know how to read to teach reading, and so forth. Thus, caring capabilities overlap with our categories of physical and cognitive capabilities.

Caring capabilities also include certain motives or emotional states – whether one brings altruism, affection, warmth, or tenderness to the encounter. Let us call this a “caring attitude”. When caring services are provided with this attitude of caring (in common-sense terms, when the care giver “really cares” about the person receiving the service), Folbre and Weisskopf (1998) call the work “caring labor”. They argue that, in most cases, caring services contribute more to the recipient’s well-being if they are imbued with this attitude of caring. One reason for this is that most people are happier when they know someone really cares about them. Also, the care provider will be more conscientious if s/he really cares about the recipient. Including physical and cognitive skills and caring attitudes as all relevant to care is true to the ways we use the term “care” in everyday discourse. When we say, “Mary lives with her elderly mother and takes care of her” we refer to concrete activities such as bathing, feeding, and
whatever physical skill and cognitive knowledge it takes to do them. But when we say “Mary really cares about her mother” we refer to the emotional qualities brought to the interaction.

Some developmental psychologists have recognized the importance to children’s development of parents’ bringing an attitude of warmth or caring. For example, pre-school children’s cognitive skills (as assessed by test scores) have been shown to be affected by their mothers’ degree of warmth, net of her educational attainment, cognitive test scores, and many socio-demographic variables (Klebanov et al. 1994). An extreme example of the consequences for the development of one’s own capability of caring of not having been cared for is seen among children who have what is called “attachment disorder”. This sometimes occurs for unknown physiological reasons even with “normal” parenting. But it is disproportionate among children reared in orphanages with no consistent caretaker who regularly hugged them and really cared about them. Adoptive parents are frustrated by how hard it is to get these children to have the basic level of trust and trustworthiness needed for everyday life. Some of the children grow into genuine socio-paths – not caring at all if their actions harm others.10 If children’s emotional and cognitive development requires warm adult caretakers, then developing the capacity for this warmth in the children – who will be the next generation of caretakers – is a crucial developmental task. Yet serious attention to how care is developed in children is a relatively new area of developmental psychology (Chase-Lansdale et al. 1995).11 Even fewer economists have recognized caring as an important form of human capital.

The benefits to oneself, including pecuniary benefits, of developing physical, cognitive, and self-regulative capabilities are a sufficient reason to think every human needs to develop them, so we emphasized these benefits in our discussion of the consequences of these capabilities. But the reader may have noticed an asymmetry in our discussion of the effects of caring versus other categories of capabilities. With caring capabilities, what we have emphasized is how it is important for each person that someone else have caring capabilities. While all kinds of capabilities may benefit the self or others, we think there is an asymmetry in the ratio of benefits to self (narrowly construed to exclude being happy because another is happy) and other between caring and other capabilities. What is different about caring capabilities is that it is definitional to the kind of functionings they permit that they meet others’ needs and wants. Also, it is definitional to a caring attitude, which we have identified as one part of caring capability, that it entails altruism, which, by definition, orients one toward others’ well-being.
What are the consequences for the self of developing caring capabilities? To the extent that developing an attitude of warmth toward others encourages one to take such an attitude toward oneself (and we think it does), there are gains for the self from developing this capability. Also, to the extent that part of what is entailed in developing the capability is developing altruism, the acts done for others out of this altruism will bring some satisfaction to the self as well – this is inherent in the definition of altruism. Thus, the non-pecuniary gains to the self are clear.

What about pecuniary rewards? Caring labor is badly rewarded where money is concerned. Children, the sick, and the elderly are often cared for without a wage or salary by family members, usually women. It is not only that mothers aren’t paid for staying home to care for children, and forgo the pay they would have earned if they spent this time in a paid job, but also that their earnings (and pension rights) from any future employment are adversely affected by having less job experience (Waldfogel 1997). It is sometimes tempting to think of husbands’ financial support of wives as a wage for rearing their children, but this is quite misleading since mothers generally care for the children even if the husband leaves and provides little or no money, a common scenario in the United States in cases of nonmarital births or divorces.

Some caring work is done for pay through jobs procured in a labor market. So in one sense, caring skills are like any other skills in that they can be exchanged on a labor market for earnings. But there is evidence that jobs involving caring services pay less than other kinds of jobs, net of educational investments required, cognitive skill demands, physical skill demands, and a number of measures of physical disamenities (England 1992; England et al. 1994; Kilbourne et al. 1994). Thus, the development of caring capabilities would not seem a wise investment where earnings is the payoff of interest. The work is often done without pay or for a lower wage than commensurate other characteristics of the job.

Why has the capability of caring not been recognized by economists as a form of human capital? It is probably at least in part because caring labor is often exercised outside formal markets, and economists have focused mostly on human capital with payoffs of earnings in formal markets. One reason for economists’ focus on production in markets rather than in households, we believe, is the same sexism that has characterized all academic disciplines. Scholars have tended to see those activities women have traditionally done as unimportant, not requiring skill, natural, part of nature, and outside important analysis. But if care is an important part of what is done at home, one might think that it would at least have been discussed in the new home economics,
which has not ignored women’s traditional tasks. While Becker (1991) has made some references to human capital for home production, he has not explicitly discussed care as a form of human capital. His work on the family does, however, discuss altruism, which is very overlapping in meaning to what we are calling an attitude of caring. We suspect that one reason that Becker doesn’t think of it as a form of human capital is that, as with self-control, the concept bears similarity to something viewed as a preference. In the neoclassical view, altruism is a preference. But, as with self-regulation, while we recognize a preference aspect to caring capabilities, we believe that there is also a “muscle” or skill aspect as well. For example, effective altruism requires empathy, the cognitive/emotional skill of being able to put oneself in the other’s situation to discern what would be most helpful. It may also entail the “muscle” aspect of self-regulation. For example, when the urge is to hit a child, a caring attitude requires one to refrain from the behavior the momentary reaction inclines one toward.

Our more general point, as argued above with respect to self-regulation, is that the preference and skill aspects of all capabilities are intertwined; because the relevant skill and preference encourage each other’s development, they tend to be coproduced.

How are capabilities developed?

How do people develop their capabilities? Since the advent of human capital theory, economists’ answer has been through “self-investment”. First, let us examine why economists chose the term “capital” in “human capital”. The underlying metaphor is a parallel to the physical capital of machinery in a factory, which had long been called “capital” by economists, to distinguish it from labor. Capital is a stock, not a flow. That is, it is a durable asset, not something you use up in every short period (as you do monthly income). It is more like principal than interest. All this suggests that human capital acquisition is some long-lasting (if not entirely permanent) transformation of the human. We agree with this part of the conventional view. The next important thing to notice about human capital theory is the centrality of the notion of “investment”. Investment in anything (whether human capital, real estate, or factories) entails a present cost for a later benefit. Since learning the productive skills that economists think of as human capital has a cost in money or time (which itself has monetary opportunity costs), to acquire human capital someone must invest. The standard examples of the costs of obtaining human capital are tuition and books for schooling (direct costs), and the earnings
forgone by being in school (an opportunity cost). When on-the-job training is the type of human capital investment at issue, neoclassical theory posits that employers offer lower starting wages in jobs where they will provide training, to make the employee share in the costs of training. The reasoning is that the employee is motivated to invest by accepting this lower wage (in comparison to that offered in jobs equivalent except not offering the training) because of the steeper wage increases with seniority in such jobs. The underlying model is one in which self-interested individuals invest in their own human capital because of its later pecuniary returns. Individuals will differ in how much they invest in themselves, then, either because their genetic endowments (which affect how quickly they learn various skills) affect what investments are worthwhile, or because of differences in their discount rates – how much they value present versus future utility.

We suggest that an adequate theory of how human capabilities are developed needs to broaden this view in several ways. Developmental psychologists claim that early environments are very important determinants of basic capabilities, in part because some things are learned more easily at an early age. This makes it clear that the optimal time and setting for much learning is at a much earlier age than that at which the individual could possibly understand the benefits of self-investment! An optimal timing for learning will necessarily rely on someone else guiding the child, which conflicts with the imagery of an autonomous adult making self-interested investment decisions.

In some ways, the “new home economics” has addressed these inadequacies of the traditional economic view. One can see, for example, in Becker’s (1991) work on the family the recognition that it is often parents who invest in their children’s education, that parents may invest in children by teaching them things as well as by sending them to school, and that what parents teach children may be skills for household as well as market production. These broadenings were important, but despite them, the underlying imagery of human capital theory remains a theory of self-investment, with the “self” redefined as the dynasty, rather than the individual. Families choose how much to invest in themselves and their descendants, and this choice determines their economic position.

We see deficiencies in this view, even as amended and improved by the economics of the family. First, we prefer the more inclusive concept of “inputs” to the concept of “investment”. While some things parents do for their children are well described as deliberate “investments,” many of the behavioral inputs parents make to the development of their children’s capabilities do not have costs to them and are not undertaken because of their salutary effects on chil-
We define “inputs” to include deliberate investments, but to also include any actions that affect the development of capabilities, whether they have costs or not, and whether they were undertaken deliberately for their effects on children’s capabilities. Quite often, inputs that increase human capital are costless positive externalities of behavior that parents would undertake even if it did not benefit the child. Consider, for example, some of the behavior of well-educated, upper-middle-class parents that contributes to the development of their children’s cognitive capabilities. Over and over, their children are likely to hear good grammar and diverse vocabulary as their parents speak to each other, and they are likely to hear logical reasoning chains as their parents make plans with each other. These inputs are bound to affect the children’s skills. But in these examples, the parents have not incurred any cost or had the conversations in order to develop their children’s capabilities – they would have had these or similar discussions even if the children were absent. We would not deny that parents make many deliberate investments in their children’s capabilities that have costs of time or money to them – many read books to children, take them to the doctor, show them how to do physical and cognitive tasks, and give them feedback when they try, pay for college, and so forth. Our point is that many crucial inputs are not investments. This is not only true for inputs to cognitive capabilities, but applies to all the types of capabilities we have discussed here. We suspect that the variance across families explained by differences in parents’ level of deliberate investments is smaller than that explained by differences in their behavior that reflect their capabilities and resources rather than decisions about how much to contribute to children’s capabilities. Thus, many inputs are externalities, not investments.

This general logic of externalities can be extended into adulthood and to multiple sites, including neighborhood, community, social networks, and work groups on the job. The point, put most broadly, is that externalities are more pervasive in the development of capabilities than in some other areas because learning is a largely social process in which the capabilities of those with whom one interacts affects what one learns. This flows from the fact that one input to learning is to see or hear the function one is trying to learn done over and over again, and the fact that, insofar as capabilities have a preference or value aspect, surrounding oneself with those who have the capability better developed leads it to be positively reinforced. Thus, it is not just family background that is an input to capabilities, but social networks more broadly. To put it in the language of sociological theorists, we might say that the formation of capabilities is “socially embedded” (Granovetter 1985) or that “social capital” affects capabilities (Coleman 1988). By not looking at this, economists have missed the role of externalities. The relative explanatory power of deliberate investments with costs versus externalities is an empirical question that deserves research.
Our conceptual point is that the pervasive nature of externalities in learning limits the usefulness of the traditional imagery of “self-investment” underlying human capital theory.

Another problem in the orthodox economic view, even as amended by the new home economics, is that it underestimates the social and political nature of decisions that affect which children will have their capabilities developed the most. While few economists would dispute the political nature of state finance of public education, they have recognized little else that is social or political in investment decisions. But the actions of many people other than a child’s parents affect the development of their capabilities.

For example, as children get older, the influences of peers, schools, and neighborhoods on their development become increasingly important. The status attainment tradition in sociology has long shown effects of the class background of one’s school and neighborhood on one’s own education, net of family characteristics. In one sense this can be reconciled with the investment model by pointing out that when parents spend to buy a house in a “better school district”, this is an investment in their children, where what makes it a better school district is not merely expenditures per pupil or quality of instruction (although these may certainly be important), but also peers for their children who are advantaged in how much their home and other environments have enhanced their capabilities. This is true as far as it goes, but what is missed is again the role of externalities – the way that the actions of adults other than a child’s parents affect the development of his or her capabilities, even though the actions were not undertaken for that effect. For example, if we believe that parents’ education and class background is correlated with their own capabilities, and that being surrounded by other children whose capabilities are better developed helps develop any given child’s capabilities, then it is clear that the housing-market decisions of upper-middle-class white parents to live in homogeneously affluent and white areas have positive effects on the development of the capabilities of the children in their race and class, and negative effects on other children. Even if the negative effects on poorer children are not intended, they are negative externalities of intentional decisions in housing markets. Moreover, political actions taken outside of markets by advantaged parents to keep school financing local, and to keep district lines drawn so as to exclude more disadvantaged children also affect the capabilities of the students segregated with others sharing some of their initial disadvantages. Such effects are pervasive on capabilities precisely because one person’s development is so affected by access to information, role models, reinforcements, and opportunities to practice the skill that are afforded by interacting with others who have the capability.
Whether we are talking about externalities or deliberate investments, the role of resource constraints should not be ignored. At first glance it seems strange that economists would have ignored economic constraints; one might have thought economics would be the discipline most attuned to the role of individual differences in how much money parents have to invest in their children! One reason early human capital theorists did not see financial constraints as an important source of differences in investments (by self or parents) is because, if information is perfect and capital markets are competitive, neoclassical theory implies that loans will be available for investments that will pay off. But, an obvious implication of the new information economics is that non-collateralized loans, such as those for human capital investment, are subject to information and enforcement problems that will make capital markets for such loans imperfect. What is farther from any version of economic theory (although not in principle inconsistent with it) is the notion that parents’ own capabilities (which can be thought of as a resource) are a constraint on their ability to augment their children’s capabilities. This is true both for intentional investments and inputs through externalities. In the first case, the point is that you can’t teach a child to do something you haven’t learned how to do yourself, and you probably can’t teach anyone anything (except through the externalities from modeling how to do it) unless you have developed capabilities of caring and self-regulation. As regards learning by externality, just as positive externalities flow effortlessly from the interactions advantaged parents have with their children, negative externalities of children’s observation of their disadvantaged parents’ behavioral repertoires flow unintended from their conduct in day-to-day life. The myriad of ways in which resources of and decisions by one group affect the capabilities of another need to be examined to fully understand the social structure and political economy of capability development.

Conclusion: inadequacies of the neoclassical view

We started with the claim that an adequate theory of human capabilities needs to change or broaden the neoclassical theory of human capital along several dimensions. Although we noted some of our departures from orthodox economists’ views as we proceeded, we conclude with a more explicit examination of some of the ways our view challenges the economic theory of human capital and some implications often drawn from it.

Viewing cognitive skills as important capabilities that are differentially developed across individuals poses a challenge to the rationality assumption.
Neoclassical economic theory assumes rational agents. Moreover, this is the core assumption shared by economists, sociologists, and political scientists whose work is under the more generic umbrella of “rational choice” theories. Part of what is meant by “rationality” in all these theories is that agents make inferences in a logically correct way. Even the “new information economics”, which takes the effects of imperfect and costly information seriously, retains a strict rationality assumption. In this view, people operate rationally with the information they have, and decide whether to invest in more information using the same rational optimizing logic applied to other investment decisions. Consider, however, the implications of the fact that one part of learning cognitive skills is learning to make logical inferences from information. Thus, being a rational agent requires cognitive skills. It follows then that people are differentially able to function as rational actors when they differ how much their cognitive capabilities have been developed. This doesn’t deny that all humans have some rational powers and that these are important for social theory. But differences in cognitive capabilities may be important as well. Human capital theory has recognized the implications of differences in education (or other kinds of learning) for earnings, but ignored their implications for actors’ likelihood of behaving as the theory predicts!

A second problem we identified with the neoclassical theory of human capital is the claim that investment is the crucial determinant of human capital. We argued that, because of the social nature of the learning process, many of the inputs to the development of capabilities are positive externalities of actions taken for reasons other than to develop capabilities. Thus, we suggest a focus on all inputs, not just investments, in the study of capability formation.

A third way that our view departs from a strict neoclassical view is in its claim that any strict distinction between skills and preferences cannot be sustained because they tend to encourage each other’s production. We argued that the capability of self-regulation is both a matter of having developed a preference for rewards in the future relative to the present and a matter of having developed the “muscle” of being able to forgo behavior that is attractive in the moment for a later reward. We spoke of the capability of care as involving both an “attitude of caring”, which implies a preference for altruism, and the skills involved in delivering the personal service. While we did not discuss the intertwining of skills and preferences in our discussion of cognitive or physical capabilities, the principle undoubtedly applies to them too. Indeed, we believe that developing a skill virtually always coincides with coming to like doing the function the skill allows, so that all capabilities have a skill and a taste aspect intertwined. This joint production occurs because the two acquisitions (skill and preference) have a positive causal effect on each other; on the one hand,
when one gets better at something this tends to increase enjoyment at doing it, and on the other, when one enjoys doing something, it makes it less onerous to practice the task and get better at it. This empirical tendency for joint production of the related skill and preference is a particular claim about the endogeneity of preferences. In sum, our claim about the intertwining of skills and preferences in capabilities challenges standard neoclassical views that see skills and preferences as separate, and that formally assumes, more generally, that preferences are exogenous to the dynamics discussed in the model (such as decisions to invest in human capital).

The co-occurrence of preferences and skills in capabilities has implications for the theory of compensating differentials in labor markets. This has a special relevance to understanding the low pay accorded to caring labor. When neoclassical economists start from the low wages in jobs involving caring as the thing to be explained, see that this cannot be explained by measured forms of human capital such as education, and notice the relevance of altruism to choosing the jobs, these facts combine with their theoretical assumptions to produce a certain conclusion. Because they see altruism as a preference rather than as part of a capability of caring, applying the theory of compensating differentials, they generally conclude that the low wage must be explained by the job with the “amenity” of allowing indulgence of this preference. But if one accepts our view that most skill development entails the development of a taste for exercising the skill, then we would no more assume that the preference for caring among those with well-developed caring capabilities would lead to a lower wage for caring labor than we would assume that the preference for cognitively interesting work among the highly educated would lead to jobs requiring more education to pay less than those requiring less education. All jobs disproportionately self-select people who have the skills to do the job and like the kind of work involved. This is true of work requiring caring, math skills, physical agility, and any other capability. Thus, accepting our view of capabilities as combining skills and preferences that covary, one would search for other explanations of why caring labor pays less.

Including caring as a category of capability differentiates our approach from most economic discussions. Seeing caring as a capability led us to examine a number of issues. Under current arrangements, “investing in” or otherwise developing this capability probably will not benefit an individual in a pecuniary sense. It will develop the altruism that makes doing the caring labor more intrinsically enjoyable. But we have argued above that it is true of every capability that the skill acquisition process tends also to develop a taste for exercising the skill, so this doesn’t differentiate it from other capabilities. What is different about caring labor is that both the relevant preferences (altruism, warmth,
sympathy, etc.) and the work definitionally entail benefits (services) to others. Thus, our claim that caring is a fundamental capability, necessary for human life, is a claim made at a social not individual level, based not on the benefits to the person developing the capability, but on the necessity for all humans of receiving care at various points in their lives. If our underlying imagery of human capital investment is of self-investment by pecuniarily self-interested autonomous adults, we would miss this capability. But people do develop their caring capabilities, some more than others. This makes clear that the imagery of “self-investment by selfish autonomous adults” is a limitation.

Looking at the positive externalities or public goods created by caring capabilities leads to policy questions generally ignored by economists. While economists’ bias is toward reliance on markets because of their efficiency properties, a standard exception to this is advocacy of governmental funding and provision of public goods. Public goods are defined as goods for which consumption cannot be limited to those who pay for their provision. Sometimes state finance of education is justified this way, on the argument that we all benefit from more educated fellow citizens. Our analysis highlights how caring capabilities contribute to public goods provision. First, a major type of caring labor is the rearing of children to transform them into well-behaved adults. Living in a society with well-behaved adults benefits many people. We are all better off if our fellow citizens obey laws, if among them are people who make good spouses and friends, and if the next generation is economically productive enough to support us through the social security system (or some analogous mechanism). Well-behaved adults are public goods, created in large part by the labor of mothers and other caring laborers. Yet markets provide no way that those who offer this caring labor can demand compensation from those who benefit. How is a mother to collect a fee from the employer who benefits from her adult child’s cognitive skills and self-regulation, or from the person her child marries who enjoys the fruits of the mother’s contributions to the spouse’s caring capabilities? A second way that the development of caring capabilities creates a public good is more general than mothering, more direct, but more subtle. To develop the caring capability is, in part, we have argued, to develop a preference for and the muscle to effectively exercise altruism. The addition of a number of altruists in our midst, by the very nature of what altruists do, creates benefits for the rest of us (regardless of our level of altruism). In game-theoretic terms, there is a coordination problem here. The social dilemma is how to encourage the caring capabilities and caring labor that benefit all of us. If we each free ride, a suboptimal amount of care will result, but there are incentives to free ride. One collective strategy would be to use the state to tax ourselves to somehow compensate those who rear children. Another would be comparable worth policies that saw to it that jobs involving
caring did not carry a wage penalty. These policy proposals raise many thorny issues but deserve serious consideration. Policies that ensure an adequate supply of care and ensure equity by shifting the costs of caring from those who now bear them – parents (especially mothers) and those in badly paid caring labor jobs – to those who receive the public benefits may only come about if more altruism toward both the recipients who need care and those who give the care is developed. Economic theory seems little help in understanding how this capability might be developed.

Note


References


Parental education–occupation matching and offspring earnings

Dirk Witteveen

Introduction

A dominant stream of labor market stratification research is oriented toward job allocation because of its implications for educational expansion and labor market policies. Analyses of overeducation and undereducation, in particular, measure the extent to which earnings variation is attributable to education–occupation “matching” of individuals. Pioneering work by Duncan and Hoffman (1981) revealed that 42 percent of US workers hold more education than is required for their jobs. In later years, scholars reported overeducation rates between 11 percent (Groot 1996) and 31 percent in various high-income countries (Sloane et al. 1999), while a meta-analysis across similar countries estimated the overeducation rate to be 23 percent (Groot and Maassen van den Brink 2000). Importantly, Duncan and Hoffman (1981) and subsequent studies demonstrated that overeducation – also called “surplus education” – yields an earnings advantage over and above the required level of education for one’s job. The surplus education coefficient (O) is typically lower than the required education coefficient (R), which means that overeducated workers earn less than equally educated workers in “matched” jobs. “Surplus occupation” (U) also boosts earnings compared to equally educated workers but is associated with an earnings disadvantage relative to workers in the same jobs who hold exactly the right amount of education. The model is named after its key parameters – overeducation, required education, and undereducation (ORU) – in a joint wage function.

The ORU model is a dominant framework in the economics of education. It is an appealing model because it improves on the Mincer wage function (which ignores matching), is easy to interpret, and elegantly specifies the joint and separate impact of two highly correlated predictors of earnings, namely the job’s education requirement and the worker’s level of education. While
the empirical validity of ORU models is uncontested, scholarship debates its (non-mutually exclusive) theoretical interpretations (Levels et al. 2014). Several economists are concerned with the extent to which overeducation and undereducation indicate “true” skill gaps, skill shortages, and skill mismatches (Cappelli 2015). Conversely, sociologists emphasize why credentials do not always (have to) align with job requirements to generate earnings payoffs, as well as the consequences of both over- and undereducation for job allocation dynamics and various socio-economic outcomes.

This chapter explores the intergenerational dimensions of the ORU model, asking: what is the association between parental over- and undereducation and offspring earnings? Specifically, we measure the effects of parental “surplus education” (O parameter), parental “surplus occupation” (U parameter), and parental “education–occupation match” on one’s earnings – terms preferred in our own analysis but used interchangeably in the literature discussion. Our exercise combines ORU wage-setting mechanisms with scholarship on intergenerational transmission of socio-economic standing: the origin-education-destination (OED) framework. We argue that if forms of education–occupation matching produce relative advantages for the socio-economic wellbeing of individuals and families, they must also give the next generation a leg up in their educational outcomes and labor market position. This dynamic bears similarities with the transmission of socio-economic status within families and between generations (Blau and Duncan 1967; Breen and Müller 2020; Featherman and Hauser 1978). To be sure, if surplus education (O) and surplus occupation (U) reflect relatively smaller economic advantages, as shown in conventional ORU models, these parental statuses should be associated with smaller relative boosts for educational attainment and earnings of offspring. We further expand this “intergenerational ORU model” with offspring’s own ORU in order to measure the net intergenerational effect of education–occupation matching on earnings.

Our intergenerational ORU model is applied to US longitudinal data. The earnings of offspring are measured during occupational maturity (mid-1990s). The Online Appendix includes a full replication of the study with UK data from mid-2010s interviews, displaying similar results. The Online Appendix further unpacks gender differences in the parental generation (i.e., both father’s and mother’s education–occupation matching) and the offspring generation (i.e., both men’s and women’s earnings) in both countries.
Literature

The standard ORU model

The ORU model is an expansion of the Mincer equation (Mincer 1974), in which earnings are modeled as a function of individuals’ attained level of education (in years) and experience (in years, plus a quadratic term). In their original application of the ORU model, Duncan and Hoffman (1981) found that overeducation yields higher earnings relative to individuals in comparable jobs, yet lower earnings compared to similarly educated workers in jobs with education requirements that exactly match their qualifications. Using US Panel Study of Income Dynamics data, they estimated that one year of surplus education (O) is associated with 3 to 5 percent higher earnings. These findings have been replicated in various countries with remarkably similar effect sizes (e.g., Alba-Ramirez 1993; Daly et al. 2000; Hartog and Oosterbeek 1988; Kiker et al. 1997; Korpi and Tåhlin 2009; Sloane 2003; Sloane et al. 1999), including the United States (Cohn and Khan 1995; Rumberger 1987; Sicherman 1991; Tsang et al. 1991). Researchers also reported comparable ORU estimates in subsamples of college graduates (Tsai 2010).

While evidence from ORU models is by no means controversial, scholarship has contested its theoretical implications (Hartog 2000). Duncan and Hoffman (1981) debunked the job competition model (Berg 1970; Freeman 1976; Thurow 1975) and the screening model (Arrow 1973; Spence 1973). The former explicitly stated that surplus education cannot be absorbed by the labor market and that wage setting is solely dependent on job characteristics – not the individual. The ORU model demonstrated that wages are a function of the occupation, its educational requirements, and their match with the individual. Some have argued that this is because firms slowly adapt to (new) skills and credentials, which restricts skill-use in individuals’ first jobs. Thus, surplus education reflects a temporary disequilibrium as overeducated workers are allocated to positions more appropriate to their education later on (Sicherman and Galor 1990). Scholars have cast doubt on this interpretation. Overeducation is indeed much less prevalent among older workers (Alba-Ramirez 1993; Hartog 2000; Sicherman 1991), but overeducated workers also tend to remain overeducated while still enjoying earnings advantages compared to their colleagues (Mendes de Oliveira et al. 2000).

As evidence mounted in favor of surplus education being a stable labor market position, scholarship sought for alternative explanations for its advantage. Most popular among ORU researchers is the assignment model (Sattinger 1993), which stands in the middle between human capital theory and job
competition theory. It states that higher educational requirements raise firms’ productivity (including wages), which is simultaneously realized by matching the worker’s educational level with the job level. This implies that overeducated workers indeed underutilize their skills, but that undereducated workers raise the market’s productivity ceiling because they are more productive than they would have been in lower-ranked jobs. Raising educational requirements is optimal as long as workers are top-down allocated according to their skills: “most skilled” workers assigned to the most complex jobs (experiencing surplus education) and “least skilled” workers assigned to the least complex jobs (Teulings 1995). Individuals would continue to invest in education because the returns to surplus education remain positive. This is consistent with persistence of overeducation across careers (Meroni and Vera-Toscano 2017) and with the positive association between overeducation and firm productivity (Kampelmann and Rycx 2012).

Crucially, ORU models allow for an empirical examination of job characteristics, educational requirements, and education–occupation “(mis)matching.” This may pick up “skill mismatches,” although the connection between both forms of mismatch remains ambiguous. One could be overeducated and still provide a perfect match with regard to demanded and supplied skills on the job. Furthermore, someone with fewer skills than required may be formally matched on the basis of their education and someone whose education matches the job requirement may possess more skills (Kracke et al. 2018). Studies have shown that educational mismatches and skill mismatches correlate only weakly (Flisi et al. 2017; Green and McIntosh 2007). For these reasons, the ORU estimates in models presented should be interpreted in a straightforward manner: deviations from the educational level as required on the job (see Leuven and Oosterbeek’s [2011] discussion). This strict definition of overqualification – rather than skill mismatch per se – is important for our intergenerational perspective on parental ORU.

Consequences of education–occupation matching

The observed ORU effects have given rise to research on the implications for socio-economic inequalities. Do different forms of education–occupation matching lead to long-term desirable and undesirable outcomes for society and individuals across their work lives? For example, it is paramount to examine consequences of surplus education because overeducated workers are evidently not becoming less educated over time – mid-career education level typically remains unchanged. Yet they are likely becoming more educated (or skilled) through on-the-job training or job-specific credentials. The long-term consequences of surplus education hinge on two possible underlying dynam-
ics: workers may either (intentionally) move from one overeducated position to another, or workers simply fail to make progress within their (current) overeducated position (Sloane et al. 1999). In other words, surplus education yields continuous payoffs that are sought-after, or it reflects workers who are potentially stuck in a secondary sector from which they cannot escape. These possibilities are not mutually exclusive and also apply to surplus occupation (U).

On the one hand, one may assume forms of accumulating disadvantages from the fact that being overeducated is associated with lower job satisfaction and lower job retention (Tsang et al. 1991). These could be non-trivial indicators of adverse effects for future employment positions as well as personal and family life. Some scholars also argue that overeducation is associated with a net earnings penalty and reduced employment opportunities later on (Baert et al. 2013), such that the societal investments made in surplus education workers could be perceived as “a waste of resources” (Caroleo and Pastore 2018). Research also suggests that historically disadvantaged groups are at higher risk of attaining a surplus education position, as well as workers who have had labor market interruptions, such as women with children (Groot and Maassen van den Brink 1996).

On the other hand, evidence points to overeducation being a desirable labor market status. In line with the assignment model, surplus education appears more prevalent among younger workers (Groot 1993, 1996) – which can be attributed to less experience and less on-the-job training – and overeducated workers change jobs more frequently (Sicherman 1991). Overeducated workers who switch jobs are more likely to change occupation, while undereducated workers are more likely to move to a different firm within the same occupation (Alba-Ramirez 1993). Furthermore, early-career overeducated workers are more likely to be overeducated later on (Meroni and Vera-Toscano 2017) and have significantly steeper earnings progression (Mendes de Oliveira et al. 2000). These mobility patterns suggest that many overeducated workers “choose” to be overqualified, while experiencing relative labor market advantages. It also implies that overeducated workers are not necessarily in a position of frustration about “unfulfilled skill-use.”

Taken together, it is paramount to examine the long-lasting advantages and disadvantages of education–occupation matching for individuals and households. The extension proposed in this study asks whether matching (R), surplus education (O), and surplus occupation (U) are associated with the earnings of offspring (who grew up in the same household). We therefore derive hypotheses from intergenerational mobility research.
The intergenerational ORU model

The cornerstone of intergenerational mechanisms of socio-economic inequality is the occupation-education-destination (OED) framework as originally proposed by Blau and Duncan (1967). It spurred a wide body of research on the relationship between parental occupation (“origin”) and offspring labor market outcomes (“destination”). This relationship is twofold – it contains one indirect path via offspring education (E) into destination and another direct path toward destination. It uncovers the extent to which ascriptive features of individuals (i.e., parental class) impact their socio-economic destination and, simultaneously, how much of this relationship is moderated or mediated by offspring’s own attained education. The paths of the OED framework have been well established in subsequent empirical work in the United States and many other high-income countries (Breen and Müller 2020).

Many social stratification researchers treat the O and D parameters as indicators of socio-economic standing in both generations, which allows measurement of intergenerational inequality. While many studies rely on class or occupation (SEI), recent studies have explored a variety of socio-economic indicators to understand intergenerational mechanisms – most prominently the parent–offspring correlations in educational attainment, family income, and individual earnings (Blanden 2013; Corak 2004). The results underscore the plurality of transmission of economic, social, and cultural advantages and inequalities across generations. Thus far, the role of parental education–occupation matching has not been considered in an intergenerational mobility or inequality framework.

The current intergenerational ORU exercise contains several non-mutually exclusive implications for OED research. The degree of perfect parental “education–occupation” (R) may carry the largest intergenerationally transmissible socio-economic advantage. In addition, a positive association between parental surplus education (O) and offspring earnings, or a positive association between parental surplus occupation (U) and offspring earnings, would indicate that deviating from a “perfect education–occupation match” also yields advantages for the next generation. Some of these advantages may operate via offspring education (E), such that the effects of parental ORU on offspring earnings are moderated by offspring education. The different parental ORU components could point to the specific elements of parents’ relative labor market position that are relevant for intergenerational advantages. These parameters could, for instance, indicate whether growing up in a household in which parents are bringing more (or less) education to their jobs than required...
may carry economic advantages or (unconsciously) set examples for one’s initial school-to-work transition and subsequent labor market integration.

**Analytical approach and research design**

We concentrate on two interrelated questions about the intergenerational associations between parental education–occupation matching and offspring educational and labor market outcomes, as well as whether the earnings effects are moderated by offspring’s earnings own educational pathway. First, focusing on offspring education and labor market location, we ask: (1a) What is the association between parental ORU on offspring years of education? (1b) And what is the association between parental ORU on offspring required years of education for their current occupation? Second, addressing the intergenerational effects of parental education–occupation matching, we ask: (2a) What is the association between parental ORU and offspring earnings? (2b) And to what extent are these pathways absorbed by individuals’ own educational destinations?

Data are drawn from the 1996 wave of the National Longitudinal Survey of Youth 1979 (NLSY79) (Bureau of Labor Statistics 2019), when most respondents had reached occupational maturity (ages 31–38). The NLSY79 records the father’s and mother’s occupation in three-digit 1970 census codes, which we converted to the Standard Occupational Classification (SOC). The SOC can subsequently be matched with occupations’ education requirements in the Occupational Information Network (O*NET) (National Center for O*NET Development 2022).

From this sample, individuals are selected if they are not enrolled in education, are employed, and report positive annual earnings in the interview year. We also only select respondents for whom intergenerational linkages can be observed based on parent(s), stepparent(s), or adoption parent(s). Parental data should include (a) their highest educational credential and (b) a valid occupation code for the main job when respondents were in high school. Finally, we drop cases for whom (c) the parental SOC cannot be matched with the O*NET data because of inevitable data limitations. For example, some jobs are only classified in the broadest possible category (e.g., “miscellaneous teachers”), which cannot be linked to any particular SOC code. A similar problem arises for occupational titles that have disappeared (e.g., “molder apprentice”). Military occupational titles are not covered in O*NET. These steps reduce the analytical sample by about 25 percent (remaining N = 4,556).
One straightforward way to transform the original ORU model into an intergenerational ORU model would be to regress offspring’s logged annual earnings ($\ln E_i$) on parental overeducation ($E^{po}_i$), parental required education ($E^{fr}_i$), and parental undereducation ($E^{pu}_i$), while controlling for respondent’s work experience (i.e., age) and residence in an urban area [1]:

$$\ln E_i = \beta + \delta_{po} E^{po}_i + \delta_{fr} E^{fr}_i + \delta_{pu} E^{pu}_i + \gamma AGE + \alpha URBAN + \varepsilon_i$$  \[1\]

This equation deviates slightly from Duncan and Hoffman’s (1981) model because no squared age term is necessary for our mid-career study sample and city size and residence in the South are replaced with a dummy variable for urbanicity. Following Korpi and Tåhlin (2021), we employ another modification to improve the interpretability of the ORU parameters. We use years of matched education–occupation ($\delta_{pm}$) instead of years of required education (R). This implies that the parental overeducation and undereducation parameters can be interpreted as years of “surplus education” ($\delta_{se}$) and years of “surplus occupation” ($\delta_{so}$), respectively, while the R parameter reflects both matched occupation and matched education since these have identical (matched) values. We further add dummies for the respondent’s gender, part-time employment, and self-employment:

$$\ln E = \beta + \delta_{E} E^- + \delta_{E^*} E^{*} + \delta_{E^*} E^- + \gamma AGE + \alpha URBAN + \omega GENDER + \lambda PTIME + \psi SELFEMP + \varepsilon_i$$  \[2\]

We assess the extent to which the intergenerational associations of ORU are moderated through respondent’s own education and job attainment by expanding equation [2]. In order to (first) establish whether a relationship exists between parental ORU and offspring initial educational and labor market destinations, we fit the parental ORU parameters on [3] offspring years of education ($D_i$) and [4] offspring required years of education in their current job ($R_i$):

$$D_i = \beta + \delta_{E} E^- + \delta_{E^*} E^{*} + \delta_{E^*} E^- + \gamma AGE + \alpha URBAN + \omega GENDER + \varepsilon_i$$  \[3\]

$$R_i = \beta + \delta_{E} E^- + \delta_{E^*} E^{*} + \delta_{E^*} E^- + \gamma AGE + \alpha URBAN + \omega GENDER + \varepsilon_i$$  \[4\]
Components of the parental ORU

The ORU variables can be derived using a variety of different approaches (Capsada-Munsech 2019). These include “worker self-assessment” (WA), which was employed by Duncan and Hoffman (1981). One disadvantage of this measure is the likely upward bias of overeducation because workers could interpret a question about the level of education as referring to qualifications to get the job rather than to perform job tasks (Hartog 2000). This question is unavailable in the NLSY79. Second, proposed by Verdugo and Verdugo (1989), one can use “realized matches” (RA) in the labor market to derive either the mean or the mode for the educational credentials in the respondent’s occupations (see also Groot and Maassen van den Brink 1996). Although this technique produces similar results (Cohn and Khan 1995), it is not preferred because it treats job allocation as endogenous (Hartog 2000). Third, a “job analysis” (JA) approach makes use of a systematic evaluation by professional job analysts of the required level of education for all jobs titles in an occupational classification (e.g., Rumberger 1987). This measure is most sensitive to the role of technological change in occupations’ skill requirements and has shown to produce the most reliable estimates of over- and undereducation, both over time and across countries (Groot and Maassen van den Brink 2000; Hartog 2000).

In this study, the JA approach is used to measure the required years of education of each parental job and respondent job. We derive the modal education level required for each SOC codes using the occupational information in O*NET. The modal credential required for the occupation is converted into years of education using the following conversions: less than high school (10 years), high school (12 years), some college (13 years), associate’s degree (14 years), bachelor’s degree (16 years), and postgraduate degree (17 years). The number of matched education–occupation years (R) and its deviations (O and U) are calculated by comparing the education years required with education years attained. We apply the same approach for offspring’s ORU variables. Parental ORU variables are calculated for fathers and mothers separately. However, we opt for a dominance approach in the analysis, whereby the ORU variables of the parent with the highest ranking ISEI (International Socio-Economic Index of Occupational Status) are included in the model.
Results

Offspring education and required years of education

The first exercise examines the relationship between, on the one hand, parental over- and undereducation and, on the other hand, offspring education attained and labor market position. Table 12.1 presents the parental ORU coefficients in a regression on the attained number of years of education of respondents. Having parents with more matched education–occupation years yields higher levels of education attained, as shown in the baseline model (1) as well as the full model which contains all socio-demographic controls (2): $\beta = 0.476$ and $\beta = 0.471$, respectively. Furthermore, concentrating on model 2, we find that parental surplus education is associated with higher educational attainment ($\beta = 0.245$), while parental surplus occupation also increases the number of years of education ($\beta = 0.164$). Hence, parental ORU is associated with individuals’ educational attainment in a similar way as in the standard ORU model. Furthermore, in agreement with research on the O-E pathways from inter-generational inequality research, offspring from families in which parental education and occupation were matched attain more education, followed by those with surplus education parents and surplus occupation parents. In practice, these individuals overlap rather than being distinct as many have one “matched” part and one “mismatched” part of their link between education and occupation. However, by definition, no individual has positive values all three ORU components.

Table 12.2 contains the parental ORU estimates of offspring required years of education of their occupation. The coefficients from the baseline model 1 indicate that matched education–occupation years of parents yields a significantly higher required level of education of offspring’s job ($\beta = 0.271$). Parental surplus education is associated with significantly higher educational requirements of one’s job: one year of parental overeducation increases offspring required years of education with 0.207 years. Each year of parental surplus occupation is associated with 0.153 more years of required years of education for offspring jobs. Controls for socio-demographics, which are added in model 2, do not change these coefficients. Model 3 indicates that the effects of parental ORU on offspring required years of education are moderated by offspring’s own educational attainment in both countries, which accords with research on OED pathways.
Table 12.1 Effects of parental ORU on offspring years of education

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parental matched education–occupation (years)</td>
<td>.476*** (0.017)</td>
</tr>
<tr>
<td>Parental surplus education (years)</td>
<td>.258*** (0.047)</td>
</tr>
<tr>
<td>Parental surplus occupation (years)</td>
<td>.163*** (0.023)</td>
</tr>
<tr>
<td>Age</td>
<td>-.003 (0.015)</td>
</tr>
<tr>
<td>Gender (woman)</td>
<td>.287*** (0.063)</td>
</tr>
<tr>
<td>Urban area</td>
<td>.468*** (0.079)</td>
</tr>
<tr>
<td>Intercept</td>
<td>7.464 (0.222)</td>
</tr>
<tr>
<td>R-sq</td>
<td>.191</td>
</tr>
<tr>
<td>N</td>
<td>4,556</td>
</tr>
</tbody>
</table>

**Notes:** Ages 31–38. P-values: * = <.05, ** = < .01, *** = < .001 (two-sided). Standard errors in parentheses.

**Source:** NLSY79 (offspring observed in 1996).

Intergenerational ORU

The main results from the intergenerational ORU are presented in model 1 of Table 12.3. This specification replicates the original ORU as introduced by Duncan and Hoffman (1981). Parental matched education–occupation years (R) is associated with about 9.9 percent higher offspring earnings. Surplus education (O) in the parents’ generation has no statistically significant impact on offspring earnings. However, parental surplus occupation (U) increases offspring earnings. Each year of parents being short of the educational requirement of their occupation increases offspring earnings with about 4.0 percent. Model 3 adds additional controls for part-time work and self-employment.
## Table 12.2 Effects of parental ORU on required years of education of offspring occupation

<table>
<thead>
<tr>
<th></th>
<th>model 1</th>
<th>model 2</th>
<th>model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>parental matched education–occupation (years)</td>
<td>.271***</td>
<td>.270***</td>
<td>.093***</td>
</tr>
<tr>
<td></td>
<td>(.016)</td>
<td>(.016)</td>
<td>(.016)</td>
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<tr>
<td>parental surplus education (years)</td>
<td>.207***</td>
<td>.199***</td>
<td>.094*</td>
</tr>
<tr>
<td></td>
<td>(.045)</td>
<td>(.045)</td>
<td>(.041)</td>
</tr>
<tr>
<td>parental surplus occupation (years)</td>
<td>.153***</td>
<td>.152***</td>
<td>.092***</td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.021)</td>
<td>(.019)</td>
</tr>
<tr>
<td>offspring education (years)</td>
<td></td>
<td>.378***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.013)</td>
<td></td>
</tr>
<tr>
<td>age</td>
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<td>-.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.014)</td>
<td>(.013)</td>
<td></td>
</tr>
<tr>
<td>gender (woman)</td>
<td>.398***</td>
<td>.272***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.061)</td>
<td>(.055)</td>
<td></td>
</tr>
<tr>
<td>urban area</td>
<td>.127</td>
<td>-.049</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.074)</td>
<td>(.067)</td>
<td></td>
</tr>
<tr>
<td>intercept</td>
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<td>9.481</td>
<td>6.810</td>
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<td></td>
<td>(.212)</td>
<td>(.545)</td>
<td>(.499)</td>
</tr>
<tr>
<td>R-sq</td>
<td>.083</td>
<td>.094</td>
<td>.265</td>
</tr>
<tr>
<td>N</td>
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<td>3,713</td>
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</tr>
</tbody>
</table>

**Notes:** Ages 31–38. P-values: * = <.05, ** = < .01, *** = < .001 (two-sided). Standard errors in parentheses. **Source:** NLSY79 (observed in 1996).

to the original ORU specification, which leads to parental surplus education becoming statistically significant (+3.9%).

We next add offspring’s own years of education to the baseline specification (model 2) and the expanded specification (model 4) of the intergenerational ORU. This additional control, which mimics an OED framework, moderates the parental R and U effects on earnings. The coefficients of parental education–occupation matching and parental surplus occupation are reduced by about half.
Table 12.3  Intergenerational ORU model applied to offspring logged annual earnings

<table>
<thead>
<tr>
<th></th>
<th>model 1</th>
<th>model 2</th>
<th>model 3</th>
<th>model 4</th>
</tr>
</thead>
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<tr>
<td>parental matched education–occupation (years)</td>
<td>.099***</td>
<td>.041***</td>
<td>.103***</td>
<td>.045***</td>
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<td></td>
<td>(.007)</td>
<td>(.007)</td>
<td>(.007)</td>
<td>(.007)</td>
</tr>
<tr>
<td>parental surplus education (years)</td>
<td>.036</td>
<td>.006</td>
<td>.039*</td>
<td>.009</td>
</tr>
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<td></td>
<td>(.020)</td>
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<tr>
<td>parental surplus occupation (years)</td>
<td>.040***</td>
<td>.020*</td>
<td>.041***</td>
<td>.021*</td>
</tr>
<tr>
<td></td>
<td>(.010)</td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.007)</td>
</tr>
<tr>
<td>offspring education (years)</td>
<td>.124***</td>
<td></td>
<td>.122***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td></td>
<td>(.006)</td>
<td></td>
</tr>
<tr>
<td>age</td>
<td>.008</td>
<td>.009</td>
<td>.010</td>
<td>.010</td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.006)</td>
<td>(.006)</td>
<td>(.006)</td>
</tr>
<tr>
<td>gender (woman)</td>
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<td>-.569***</td>
<td>-.449***</td>
<td>-.485***</td>
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<tr>
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<td>(.027)</td>
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<td>(.026)</td>
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<td>urban area</td>
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<td>.164***</td>
<td>.107**</td>
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<td></td>
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<td>(.033)</td>
<td>(.033)</td>
<td>(.032)</td>
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<tr>
<td>part-time</td>
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<td>-.915***</td>
<td>-.901***</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(.052)</td>
<td>(.050)</td>
<td></td>
</tr>
<tr>
<td>self-employed</td>
<td>-.123**</td>
<td>-.100*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.047)</td>
<td>(.045)</td>
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<td></td>
</tr>
<tr>
<td>intercept</td>
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<td>8.198</td>
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<tr>
<td></td>
<td>(.246)</td>
<td>(.239)</td>
<td>(.238)</td>
<td>(.231)</td>
</tr>
<tr>
<td>R-sq</td>
<td>.126</td>
<td>.198</td>
<td>.183</td>
<td>.253</td>
</tr>
<tr>
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<td>4,556</td>
<td>4,556</td>
<td>4,556</td>
</tr>
</tbody>
</table>

Notes: Part-time defined as 30 hours or less. Ages 31–38. P-values: * = < .05, ** = < .01, *** = < .001 (two-sided). Standard errors in parentheses.
Source: NLSY79 (observed in 1996).

Combined generations ORU

Presented in Table 12.4, we fit a standard ORU specification for respondents (model 2) and a combined standard and intergenerational ORU specification (model 3), which can be compared to the intergenerational ORU (model 1).
Table 12.4  Combined standard and intergenerational ORU model applied to offspring logged annual earnings

<table>
<thead>
<tr>
<th></th>
<th>model 1</th>
<th>model 2</th>
<th>model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.103***</td>
<td>.035***</td>
<td></td>
</tr>
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<td></td>
<td>(.007)</td>
<td>(.008)</td>
<td></td>
</tr>
<tr>
<td>parental matched education–occupation (years)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>parental surplus education (years)</td>
<td>.039*</td>
<td>.007</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.020)</td>
<td>(.020)</td>
<td></td>
</tr>
<tr>
<td>parental surplus occupation (years)</td>
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<td>.017</td>
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</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.009)</td>
<td></td>
</tr>
<tr>
<td>offspring matched education–occupation (years)</td>
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<td>.186***</td>
<td></td>
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<tr>
<td></td>
<td>(.008)</td>
<td>(.008)</td>
<td></td>
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<tr>
<td>offspring surplus education (years)</td>
<td>.094***</td>
<td>.082***</td>
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</tr>
<tr>
<td></td>
<td>(.013)</td>
<td>(.013)</td>
<td></td>
</tr>
<tr>
<td>offspring surplus occupation (years)</td>
<td>.063***</td>
<td>.060***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.011)</td>
<td>(.011)</td>
<td></td>
</tr>
<tr>
<td>age</td>
<td>.010</td>
<td>.018**</td>
<td>.018**</td>
</tr>
<tr>
<td></td>
<td>(.006)</td>
<td>(.006)</td>
<td>(.006)</td>
</tr>
<tr>
<td>gender (woman)</td>
<td>-.449***</td>
<td>-.484***</td>
<td>-.478***</td>
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<td>(.027)</td>
<td>(.027)</td>
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<tr>
<td>urban area</td>
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<td>.120***</td>
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<td>(.033)</td>
<td>(.033)</td>
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<tr>
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<td>-.899***</td>
</tr>
<tr>
<td></td>
<td>(.052)</td>
<td>(.054)</td>
<td>(.054)</td>
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<tr>
<td>self-employed</td>
<td>-.123**</td>
<td>.021</td>
<td>.008</td>
</tr>
<tr>
<td></td>
<td>(.047)</td>
<td>(.051)</td>
<td>(.051)</td>
</tr>
<tr>
<td>intercept</td>
<td>8.895</td>
<td>7.323</td>
<td>7.104</td>
</tr>
<tr>
<td></td>
<td>(.238)</td>
<td>(.243)</td>
<td>(.249)</td>
</tr>
<tr>
<td>R-sq</td>
<td>.183</td>
<td>.272</td>
<td>.277</td>
</tr>
<tr>
<td>N</td>
<td>4,556</td>
<td>3,713</td>
<td>3,713</td>
</tr>
</tbody>
</table>

Notes: Part-time defined as 30 hours or less. Ages 31–38. P-values: * = <.05, ** = < .01, *** = < .001 (two-sided). Standard errors in parentheses.

Source: NLSY79 (observed in 1996).
We find that the standard ORU yields estimates that are in line with the literature. Respondent’s surplus education is associated with higher earnings compared to workers in the same jobs (+9.4%, model 2). However, this positive effect is smaller compared to the earnings advantage from (perfect) matching education–occupation: +20.1%, model 2. Respondent’s surplus occupation is associated with the smallest positive effect: +6.3% (model 2). As expected, the coefficients of the standard ORU are much stronger than the intergenerational (parental) ORU coefficients (model 1).

The results from model 3, which adds parental ORU variables, indicate that the respondent’s ORU associations with their own earnings remain virtually unchanged compared to model 2. The parental ORU coefficients are reduced in the combined standard and intergenerational compared to model 1. Importantly, after accounting for respondent’s ORU effects, parental years of matched education–occupation (still) increase earnings by about 3.5 percent. However, parental surplus occupation is no longer statistically significant (comparing models 1 and 3). In other words, (perfect) parental education–occupation matching affects offspring’s earnings in a similar fashion as in the standard ORU relationships with earnings, over and above the impact of offspring’s own degree of over- and undereducation.

Conclusion

The ORU framework continues to influence the economics of education and social stratification scholarship because higher education continues to expand, and a substantial share of the workforce remains overeducated. This study is the first to examine the long-term intergenerational consequences of ORU by measuring the association between parental over- and undereducation and offspring earnings. This approach contributes to our understanding of the long-term advantages and disadvantages of educational matching, as well as the extent to which educational matching in “O” (origin), has something to say about the “E” (education) and “D” (destination), analogous to the OED framework for intergenerational mobility research.

The empirical results from the intergenerational ORU are straightforward. Parents’ levels of education–occupation matching (R parameter), as measured in years, increase earnings by 10.3 percent. We find a positive association between parents’ surplus education and offspring earnings (+3.9%). Importantly, a parent’s surplus occupation (or “undereducation”) also yields a positive earnings effect of about 4 percent. These intergenerational ORU
estimates are remarkably similar to the standard ORU model. Hence, all three parental skill components have significant positive payoffs, with matched education–occupation providing the strongest impact. Note that ORU coefficients do not reflect exact counterfactuals: in practice, many individuals have parents with positive values on both matched education–occupation and either surplus education or surplus occupation, while having positive values on all three ORU indicators is not possible.

How should we understand the findings from an intergenerational ORU? First, it is important to note that parental ORU impacts both offspring’s educational and occupational attainment (see Tables 12.1 and 12.2). Second, we found that the positive earnings effects of parental education–occupation matching (R) and parental surplus occupation (U) persist after additionally controlling for respondents’ own educational attainment. This is also the case for the positive effect of parental education–occupation matching (O) when accounting for respondent’s own ORU. This suggests that the type and strength of educational matching in the childhood home have considerable direct impact on one’s earnings level. Specifically, surplus occupation boosts the earnings of individuals, but it also positively affects the earnings of the next generation, regardless of their offspring’s education. It implies that surplus education and surplus occupation reflect socio-economic advantages with far-reaching consequences. Future research should therefore address the ways in which young individuals experience the educational matching of their parents, and how these relative advantages in turn boost earnings.

Furthermore, our findings have implications for intergenerational mobility research. The ORU estimates indicate intergenerational effects on earnings that bear conceptual similarities with the ways in which parental occupation have shown to affect offspring occupational attainment (Blau and Duncan 1967) and offspring earnings (Corak 2004). Future research should therefore address the ways in which young individuals experience the educational matching of their parents while in school and transitioning to the labor market. Integrating the OED and ORU frameworks, one may consider “origin occupation” as containing intergenerationally transmissible relative advantages that are located in parental job, as well as the embedded parental education–occupation matching. The intergenerational ORU demonstrates that the origin component in the O-D pathway is multifaceted: advantages are not only located in the vertical occupational positioning of parents, but also in the ways in which parents’ education is matched with the occupation’s requirements. Different types of parental occupation match absorb a considerable component of the intergenerational effect of O on both E and D.
Additional exercises available in the Online Appendix demonstrate that, among workers with two working parents during childhood, components of the ORU of the father and the mother can jointly affect offspring earnings – with slightly larger effect sizes being for fathers. These results should be interpreted with some caution given the smaller sample sizes of the selected subgroup of two-parent working families. Finally, we find virtually the same effect sizes for the parental ORU parameters for offspring’s attained education and offspring’s occupational attainment, and only small differences between the United States and the United Kingdom.

**References**


Skill and power at work: A Relational Inequality perspective

Dustin Avent-Holt and Donald Tomaskovic-Devey

In this chapter, we examine the basic idea of skill, and its close cousin and certifier education, from the viewpoint of Relational Inequality Theory (RIT) (Tomaskovic-Devey and Avent-Holt 2019). We developed RIT as an explicit alternative to occupational status models in sociology (e.g. Treiman 1977) and to human capital models in labor economics (e.g. Mincer 1974). In these approaches, skill is typically unobserved, but inferred from indicators such as education, experience, and occupational position.

Both approaches share an understanding of skill as a self-evidently legitimate basis of distinction. Merit-based processes and societies are normatively attractive, they erode invidious distinctions based on ascription, and they seem consistent with stories of technological innovation driving rising standards of living, reduced privation, and less human suffering. In the technological progress view the skilled, particularly the educated technologist, is the hero of history.

We strongly believe that sociologists should be critically examining the very notion of skill, and its associated normative commitment to merit. We should ask questions such as: what exactly is skill and how do perceived skill differences produce particular socio-economic outcomes? That is, we need to explore the mechanisms through which skill is defined and translated into incomes, jobs, status, and other outcomes rather than merely assuming that skill is reflective of merit. Rising education-linked inequalities that accompany unreflective endorsements of educational signals of merit suggest that if we achieve the meritocratic dream society we will simply enter a new era of “unjust meritocracy” as prophesized by Daniel Bell a half-century ago (1972).

RIT offers an alternative, we believe scientifically sounder, approach to thinking about skills, education, and power. We begin with a short introduction
to RIT, follow with an examination of each of its key assumptions and mechanisms as they relate to skill and education as claims-making statuses, and then outline the ways in which technical skills and technological progress are typically subsumed by the goals and agenda of more powerful organizational actors.

**Relational Inequality Theory**


RIT asserts that to understand the processes that generate inequalities we need to focus on relationships between people, positions, and organizations. RIT rejects social science approaches that rely on individual or societal explanations, at the expense of interaction, social organization, and the relative power of actors to extract resources from their interactions with others. From an RIT perspective individual skill is a basis on which actors make claims on organizational resources, and education, gender, race, perhaps even height and physical beauty are signals of potential skill. Skill as productive capacity exists, not in people as isolated individuals, but in relation to the task complexity of jobs as they are linked to other jobs in organizational divisions of labor.

The starting premise of RIT is that the causally most powerful locations in social life are proximate networks of social relationships. People interact meaningfully and consequentially in social relationships, and the categories of our social world – including the categorization of skill – are produced in those relationships.

The second central premise of RIT is that it is almost always within and between organizations that the influential relationships that generate and distribute resources emerge and a local social order develops. In organizations actors develop and enact production, but also hierarchies of power and status, typically around categorical distinctions between roles, jobs, and people. We negotiate local organizational inequality regimes, importing meaning, status, and power from the environment, reacting to both local and global cultural
and material constraints on meaning and action. The same processes happen between organizations in the negotiation over who has access to organizational roles, exchange opportunities, and opportunities to exploit or cooperate in markets. There is no direct line from culture or social structure or markets to human behavior, as all actions are produced in local social contexts. It is organizations that make both cultural and material production possible.

From the RIT perspective human beings use socially produced categories to generate status distinctions, which in turn are the bases for claims over resources. Skill is a very general, even primordial, basis of status expectations. In practice skill is often inferred based on other more visible status distinctions such as job titles and educational credentials as well as cultural signals associated with merit. These can include class, gender, race, and other signals that may not even be associated with the ability to do good work, but are culturally translated as signals of merit.

Among the most fundamental human attributes is our cognitive tendency to understand the world around us by packaging social objects into distinct categories (Stewart, Brown, and Chater 2005). At the same time inferring task competence – skill – is fundamental to human status attributions. People infer competence from socially salient categories (Ridgeway 2011). Status expectations that people in high-status jobs, or who are educated, white, men, or citizens, are more competent and deserving facilitate a self-reinforcing process. High-status actors are perceived to be more skilled and this enhances their capacity to claim status and rewards, which in turn serves as evidence that they must be more skilled. Simultaneously, some jobs are more complex than others, some require specific task-related knowledge to accomplish, and these demand-side skill attributes of jobs become status signals in their own right for claims to resources in future negotiations.

The simplest status hierarchies are local and refer to status within groups, such as skilled hunter or brilliant software engineer. These local categories will often reflect actual complexity in production tasks (Le Grand and Tåhlin 2013). Our point about status expectations is that local hierarchies additionally incorporate categorical expectations imported from the culture or endowed by job titles creating opportunities for closure, exploitation, and successful claims. Opportunities that are potentially independent of any inherent positional task or individual competency. Skill is misperceived all the time, while simultaneously operating as a powerful basis for legitimate claims over organizational resources and interactional status.
Organizations use complex divisions of labor to create products and services. Actors within organizations are linked through relationships of production, coordination, and resource flows. Jobs that are nearly universally recognized as skilled, such as professions like engineer or medical doctor, function primarily in complex divisions of labor. Skill, defined in terms of task complexity, is interdependent, not merely embodied in people or positions. As such, individual productivity is difficult to observe (Attewell 1990), as is positional skill (Steinberg 1990), and is better thought of as an attribution that follows from the ability of actors to effectively claim that they make productivity contributions (Godechot 2016).

This fundamental observation that skill is relational and observed in the context of the claims-making power of individuals and groups leads to four useful propositions for thinking about skill as a power resource in organizational claims-making and its relationship to socio-economic outcomes. First, the link between inferred skill and claims-making power is socially mediated, such that how an individual’s task competence is perceived as influenced by status characteristics. Second, skill itself is a social construction, only becoming “skill” when powerful actors define it as such. Third, skill is crucially dependent on social closure processes, which both create skill monopolies and generate the power of incumbents to exclude status groups that may weaken the ability to claim skill-based rewards. Finally, skill is fundamentally implicated in the relational production of exploitation.

**Skill as socially mediated**

In the human capital model employers are treated as calculators of merit who are able to recognize individual productivity. If they fail to recognize value produced, they are disciplined by the market until they properly reward skill or go bankrupt. But this assumes a fairly tight coupling of markets and firm behaviors, a coupling that is generally much weaker in the real world. Such loose coupling allows imperfect information and biases to creep into evaluations of productivity and thus who is more or less skilled (both at the job and individual levels). This can then allow particular biases about who is skilled to get institutionalized in particular markets which will further weaken the role of market competition (since the majority of actors hold these views).

The loose coupling of market competition and outcomes means that particular actors and their actions have to be perceived as “skilled,” and these perceptions can be mediated by a range of social factors. Perhaps the most commonly
identified socially mediating factors are status characteristics. Women are more likely to be perceived as less competent in tasks, especially culturally male-typed tasks, even when their performance is equivalent (Ridgeway 2011). Even when men and women are viewed similarly by employers those employers do not necessarily reward them similarly. Castilla (2008) finds that for men and women who have equivalent ratings on performance evaluations, men get bigger pay raises.

Correll et al. (2020) demonstrate that biases in how managers view the skills of employees and how they value those skills are shaped by the ambiguity of the workplace context. When evaluative criteria and processes are unclear, managers tend to rely on status-laden stereotypes to make sense of their skill calculations. These contexts then lead managers to view lower-status employees as less competent and value their contributions (even when they are equivalent) less. An ambiguous rating system enhances the likelihood of socially mediated perceptions of skill.

Status expectations theory extends these findings broadly into any status characteristic (Lovaglia et al. 1998). Other social factors beyond status characteristics can also shape skill evaluations. Social networks may also lead to perceptual biases. Perceiving those in your network as more skilled, and their contributions as more competent and important, seems to be widespread. For example, DiTomaso’s (2013) analysis of working-class white men suggests individuals are likely to overestimate the skills of themselves and those in their social network to the detriment of dissimilar actors outside of their network.

These processes further help us make sense of a new body of research that documents discrepancies across firms in how they remunerate similar skill sets. In particular, similar individual education levels are valued differently across workplaces. This has been shown for France, Sweden, and Germany (Abowd, Kramarz, and Roux 2006; Tomaskovic-Devey and Avent-Holt 2019). Additionally, Tomaskovic-Devey and Avent-Holt (2019) show that in Sweden the impact of three common measures of individual and positional skill – educational achievement, occupational skill, and individual’s stable earnings fixed effect – all have stronger influence on individual earnings with rising workplace inequality (see Figure 13.1). Melzer et al. (2018) find similar results for organizational variation in German immigrant–citizen wage gaps. The economic returns to skill are far from stable, but rather rise predictably in high-inequality contexts.

Ultimately, real-world variations in power and status, especially in the context of ambiguous evaluative contexts, are what makes it possible to deviate from
a pure human capital model. Some actors are able to obtain more, as wages or other job rewards, for their skill set than are others. RIT argues that the reason for this is because rewards have to be claimed by actors, and other powerful actors must agree with the claim being made.

Thus the link between attributions and skill must be made and legitimated. This does not mean that there is no linkage between the quality of individual tasks contributions, but it does mean that whether or not it exists depends crucially on the local rules of the game. Piece rate systems where workers doing exactly the same task with exactly the same tools and training might approach some pure merit-based evaluation (e.g. Petersen, Snartland, and Meyersson Milgrom 2007), but even in these systems there can be complexities associated with bargaining power, organizational context, and outcomes (Petersen 1992).

More fundamentally even in systems where productivity can be observed directly, it allows for skill-based claims among workers doing the same jobs, but does not determine the relative power of other actors in the organization to make claims on organizational resources. Employers often have the upper hand in setting piece rates and commissions, and from an RIT perspective
compensation rates refer to the relative power of collective groups to define what is measured as effort and how it is valued. The classic time and motion studies associated with Frederick Winslow Taylor (1911) make clear that the close counting of productivity is something to be manipulated by managers to raise production and control costs. Godechot (2016) in a contemporary treatment of financial market makers shows that those high-paid professionals were able to use accounting systems that counted profits after a trade was made, to make claims on bonus pools. The accounting device made it easy to think about productivity as something produced by traders, obscuring the role of the salespeople who brought clients to the firm and the technical engineers that made complex trade systems possible at all. These other skilled workers as a result earned less.

**Skill as socially constructed**

A second proposition takes the social influence of skill in a different direction, arguing that skills are not in fact objective phenomena. Instead, what counts as skills must be socially constructed. Skill has to be defined into and out of existence in concrete situations.

This perspective was articulated by scholars studying gender discrimination and comparable worth in the 1980s (Steinberg 1990). Comparable worth advocates argued that jobs predominantly performed by women were systematically devalued as having less skill, and the appropriate remedy was to effectively degender the jobs within an explicit rating system for differential task complexity skill sets. Warhurst, Tilly, and Gatta (2017) extend this into the new economy by focusing on how soft skills have become a dominant explanation for what counts as valuable skills in the service-oriented sectors that dominate the wealthiest countries. These they note are inherently subjective traits whose value is constructed within a “discourse of merit.”

At this point, the case for the social construction of skills is strongest in the service economy, especially where aesthetic labor is employed (Mears 2011; Misra and Walters 2022). When your core skill set is embodied in how you look, social judgments trump all other plausibly objective criteria.

Otis and Wu (2018) provide a strong empirical and theoretical case for understanding skill as a social construction. They argue that defining some work as “unskilled” is an achievement. It requires workers, managers, and customers to converge on a definition of particular kinds of work as requiring less skill than
others. They demonstrate this with an analysis of two Chinese work settings that each require workers to complete similar tasks. In both workplaces some workers did what employers defined as manual labor and others did what were defined as interaction with customers. In one workplace the manual workers were valued more than the interactional workers, while in the other setting it was reversed. The key was that in the first setting the manual workers were male and this was used to demote predominantly female interactive workers as “deficient” in their skills. In the second workplace service workers were predominantly from urban areas, and this status distinction parlayed into defining them as more skilled than the largely rural origin manual workers.

Hanley (2014) provides an example of powerful workers redefining their own work as valuable. The context is the introduction of computers in the mid-20th-century global conglomerate General Electric (GE). While we often discuss computing technology as mediating or moderating particular skill sets, she shows that its power at GE was in allowing managers to redefine what productivity itself was. No longer was manufacturing labor defined as the source of value creation; instead managers valorized their own work of organizing and bringing together technology and labor as the key ingredient in organizational productivity. Thus, they were able to parlay a technological innovation into defining themselves as the most productive employees.

Skill and social closure

RIT describes social closure as one of the fundamental inequality installing mechanisms, through which actors access and monopolize organizational resources. When skills claims are institutionalized within particular jobs, they tend to generate linked social closure devices through which powerful actors close off access to skilled work to a circle of similar eligibles.

Occupational closure happens when occupational groups control access to education, skills, and employment. Access to socially constructed skill and the workplace power derived from particular occupations can be limited to particular people. Kim Weeden (2002) spelled out five mechanisms through which occupations become closed off to outsiders and thereby increase their workplace power: credentialing, licensing, certification, unionization, and professional association. These mechanisms often operate through state–occupation relationships. That is, representatives of an occupation petition the state to allow them to form a licensing or certification board or a union or
professional association and to pass laws to require that employers only hire individuals belonging to or meeting the standards of these occupations.

From the perspective of RIT, occupational closure via the state increases the power of particular actors to get access to jobs in the organizations associated with closure in markets (e.g. medical doctors in hospitals), but also make those actors more powerful within organizations in making claims on organizational resources. One of the most interesting results from our study of class inequality in Australian and U.S. workplaces, was that in some workplaces the average core production workers actually out-earned the average manager (Avent-Holt and Tomaskovic-Devey 2010). This was the result of exactly the type of occupational closure processes Weeden identified. Workers out-earn managers in firms dominated by core workers with professional certification – hospitals, engineering firms, accounting practices, law firms, and the like. In these cases the closure-based power of the occupation was stronger than the more typical authority-based advantages of managers.

The closure idea has been most closely associated with occupational and professional licensure, but education is probably the more widespread basis for closure. Professions typically have a closure-based educational requirement. Some professions like medicine or the law have also lobbied state governments to award those degree holders’ legally enforceable monopolies over tasks and use their professional power to control the organizations they work in (Abbott 1988). Many occupations, like engineers and computer scientists, have created expectations that jobs will be linked to specific degrees, but lack the backing of the state to enforce these closure rules. In these cases the closure rules must be installed in firm-level job descriptions. Even the simple job requirement of holding a high school degree excludes anyone who did not graduate from high school. It is a weak closure mechanism, but a closure mechanism nonetheless.

That educational degrees are closure mechanisms, making some people eligible for jobs and excluding others, does not imply that they are not often functional in terms of required skills for particular jobs. They may be or they may simply be imperfect signals that employers can use to eliminate candidates and simplify selection decisions. While closure rules strengthen the claims-making position of the preferred status groups, whether or not they are actually tied to production competencies is an empirical question. On the other hand, they always limit competition, exclude out-groups, and generate access to organizational resources.

When Max Weber originally put forward the notion of closure it was strongly tied to the process by which elite groups both produced and reproduced their
superior social status. Rivera (2012) studied the recruitment practices of elite firms – global consultancies, white shoe law firms, and investment banks. These firms were distinguished by their power to charge very high prices to clients. What she found was a two-stage process in which the firms first recruited from a narrow set of elite universities – Harvard, Princeton, Yale, Stanford, and the like – largely ignoring grades and coursework and other human capital signals, and then screened on cultural similarity to current employees. Depending on the firm, appropriate qualifiers might include playing a particular sport, being bookish, or liking math. Screening seemed much more like the process one would use to pick a spouse or a friend than the meritocratic stories favored by many social scientists.

Karen Ho’s (2009) ethnography of financial service firms identified recruitment from the same set of elite universities identified by Rivera. She additionally observed a consensus narrative on Wall Street during the period of financialization that because they went to elite universities their young employees were the smartest people of their generation. The firms actively promoted this narrative to legitimate their claims to steer the investment and organizational design decisions of other firms. To be globally influential the firms presented themselves as populated by the smartest people in the world. Prestigious university degrees became the status signifier of firm intelligence. This self-congratulatory cultural story when wed to skyrocketing incomes no doubt produced the status confirmations that justified both high salaries and the exploitation of low-status, less smart, less hardworking exchange partners by financial service firms.

Both occupational and educational closure have strong linkages to other status-based closure patterns. The expansion of equal opportunity in access to higher education in reaction to the social movements for equal rights reduced gender-, ethnic-, and race-based closure in access to educationally certified jobs. This is quite clear in the historical comparison of racial and gender integration after the equal opportunity laws were enacted in the 1960s (Stainback and Tomaskovic-Devey 2012). Racial minorities and women made strong gains in professional occupations, precisely because the educational system became more open and education-based closure is stronger than sex- and race-based closure for admittances into professional occupations. Progress was much slower in managerial jobs, where personal trust-based closure predominates and in the skilled trades where peer training and union-based closure are more powerful.

Gender- and racial-based closure remain particularly strong in fields where network-based access to high-skill/high-pay jobs predominates. The most
familiar examples are the very high-paid jobs in finance (Lin and Neely 2017) and engineering (Cech 2013) firms. Engineering, like finance, economics, and computer science, is interesting in that skill monopolies are not enforced by state-level professional certification, but rather are claims within workplaces that become recognized by employers and enforced by already powerful workers with an interest in socially constructing their power via occupational titles and linked educational degrees. All four of these “professions” have been particularly resistant to the incursions of women and minorities into their ranks. All continue to be characterized by particularly exclusionary workplace cultures (Alegria and Branch 2015; Lundberg and Stearns 2019; Roth 2011).

Skill and exploitation

While the RIT conceptualization of closure is quite conventional, and easily traced back to the classical Weberian version (Weber 1947), the same cannot be said of exploitation. In RIT exploitation is a relationship in which one party uses power to gain at the expense of another. In the traditional Marxian formulation exploitation is the extraction of value from workers (Wright 1997). In RIT any categorical distinction will suffice, as long as in the relationship some actor takes advantage of their relative power to take a resource from someone else. Thus exploitation can be based on gender or race and operate both within a labor process and between firms and their customers or suppliers. Categorical distinctions tend to both generate and morally legitimate power differentials and these power differentials enable exploitation.

We have already seen how skill can be the basis of categorical power through both claims-making and closure mechanisms. In a meritocratic story skill is simply rewarded, but it is our position that skill is primarily a claims-making device used to shift organizational resources from “less skilled” to “more skilled” actors. Because skill is so easily legitimated it is a particularly effective claims-making device. That more educated workers should be paid more than less educated workers is simply taken for granted.

Low-skilled workers are particularly easy to exploit, especially in the absence of organized protection via the state or labor unions. In the United States low-skilled workers lack institutional protections against exploitation. Studies of wage theft suggest that money is literally stolen from the least powerful workers. For example, Bernhardt et al. (2009) found that fully one-quarter of low-wage workers did not receive the legally prescribed minimum wage. Two-thirds of the low-wage workers surveyed experienced at least one
pay-related violation in the prior workweek, which Bernhardt and colleagues estimate to be about a 15 percent wage loss for the average low-wage worker. Among low-skill workers, wage theft is less common among whites, men, citizens, and workers with long tenure. Race differences were particular pronounced with foreign-born Latinos having the highest rate of wage theft, and African Americans’ wages were stolen at three times the rate of whites in low-wage jobs.

Workers who can successfully appeal to skill-based claims may be able to shift resources toward themselves. Earlier we learned that in the U.S. there was an institutional shift from thinking about workers as the source of value in production to conceiving of managers as the source of value (Hanley 2014). If this was the case, then managers’ claims-making power over value should have correspondingly shifted. Consistent with this, managers were among the biggest winners during the post-1980 rise in U.S. income inequality (Goldstein 2012). In this sense managers’ ability to extract organizational resources for themselves grew, exploiting both owners and lower-level employees.

When firms change their compensation practices to favor high performers, they may be creating skill-based exploitation. Since high performers’ skills are observed through a categorically constructed lens, typically reifying powerful claims and ignoring the essentially social nature of production, performance and bonus pay systems, while facially meritocratic, are exploitation devices. In the U.S. bonus and commission performance-based pay systems are associated with increased earnings inequality (Lemieux, MacLeod and Parent, 2009), and the benefits primarily accrue to highly qualified and white workers (Hanley 2011). In a study of New Zealand firms using linked employer–employee data, Fabling, Grimes, and Maré (2012) find that performance pay systems do not influence the average wage in firms, but are associated with increased wage inequality within firms, benefiting mostly male managers. Firm-level productivity does not change, but internal distributions of income do. In a study of rising earnings inequality between 1995 and 2010 in Germany, also using linked employer–employee data, Schweiker and Groß (2016) document a clear pattern of declining bonus payments for lower-level workers and rising bonuses for those in the top 1 percent. This shift in bonus payments, reflecting shifts in pay practices more generally, strongly favor the top 10 percent of employees in German firms, with the top 1 percent particularly benefiting. When performance-based systems are advertised to link pay more closely to productivity, they often operate as reward systems for already advantaged workers at the expense of lower-power employees in the firm.
The power to exploit can also be cultural in nature, such that exploiters are able to gain because an exploitable group is culturally devalued in routine interactions. This status valuation process helps explain why sociologists have repeatedly found that when women enter occupations previously held by men, the wages attached to those jobs are likely to decline (England, Allison and Wu, 2007; Levanon, England and Allison, 2009). We can see this devaluation process as exploitative in that it is a shift of organizational resources away from an occupational group because the incumbents of those jobs are less culturally valued. Where that money goes is an open question that few have attempted to answer, and will probably vary from organization to organization based upon its particular inequality regime. But in an analysis of North Carolina firms Tomaskovic-Devey and Skaggs (1999) found that such devaluations of female-dominated jobs had no impact on employers’ profits but led to higher wages for male workers. In a study of non-western immigrants in Sweden, Tomaskovic-Devey et al. (2015) found a pattern of income transfers from immigrants to native Swedes, but only among white-collar workers in high-inequality workplaces.

Finally, even the most skilled workers are typically just that: workers. The technology heroes, lauded in meritocratic accounts, are most often subordinate to bigger bosses – capitalists, state bureaucrats, executives of one sort or another. The most heroic displays of invention, deeply skilled transformation of production processes, products, and technologies, are in our contemporary age typically subordinated to greater powers. In Erik Olin Wright’s (1997) account skilled workers are in contradictory class positions. They have power relative to other workers, perhaps even professional autonomy relative to managerial authority, can make claims on status and organizational resources, but what tasks their skills are put to are determined by someone else. Sometimes this means their skills are used by employers to invent new ways to exploit others. This might be engineers figuring out how to make less powerful workers work harder as in Taylorism, marketing professionals encouraging households to buy goods that they do not need, accountants and lawyers inventing franchising relationships for big-brand hotels or restaurants, or computer scientists inventing algorithms to extract extra overdraft fees from bank customers. When firms are figuring out how to exploit workers, customers, or their dependent suppliers, it is skilled workers, the heroes of technological triumphalism, that they turn to.
Conclusion

RIT provides a model for thinking about inequality that highlights the relations of power that generate exploitation and social closure through actors’ claims on resources. We think sociologists should treat skill as embedded within those relations of power, and have offered some tools to help do this more effectively than the meritocratic ideal rooted in the human capital and status attainment models. Skills are social at their core, and have to be produced in those same power relations that generate exploitation, social closure, and claims-making. Relations of power should be the focus of any skill-based account of inequality within sociology.

References

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Schweiker, Michael, and Martin Groß. 2016. “Organizational environments and bonus payments: Rent destruction or rent sharing?” Research in Social Stratification and Mobility 47: 7–19.
The concept of job skill requirements plays a significant role in several research areas related to labor markets and education, as well as more general discussions of social trends and public policy. Perhaps the most prominent recent research in this area is the extensive literature on skill-biased technological change (SBTC), which attributes inequality growth since 1980 to rising job skill requirements resulting from the growth of computer use at work. In this extension of human capital theory, new technology increases job task complexity, which raises the demand for more educated workers, who are best suited to perform newly important tasks (Goldin and Katz 2008). Inequality grows when growth in educational attainment fails to keep pace with the growth in job complexity. Although the exact argument has evolved in response to both changes in inequality trends (Autor, Levy, and Murnane 2003) and new waves of computing technology (Frey and Osborne 2017), most in the SBTC tradition agree that jobs requiring university education are growing faster than middle- and low-skilled jobs.

However, SBTC theory initially inferred growing skill requirements indirectly based on increasing education wage premiums before shifting to rather abstract measures of job content found in sources such as the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET). Although both of these occupation-level data sets have measures of required education, SBTC studies avoided them and similar measures available in worker-level surveys, even as they made extensive use of task items that presumably represent facets of employers’ demand for varying levels of education. This bifurcation presumably reflected neoclassical assumptions that labor markets match workers to jobs efficiently and workers are paid their marginal product, implying the requirements of job always reflect the human capital of the workers holding them (McGuinness 2006, p. 389; Autor 2013, p. 189f.). The result is a somewhat contradictory situation. SBTC theory argues jobs increasingly require higher education and SBTC research grew willing to engage the issue of job complexity with direct measures, rather than relying
on proxies like workers' own educational attainment or wages. However, most SBTC research still uses only specific measures of job complexity and avoids relating them to measures of overall job educational requirements, which was, in some sense, the original object of research interest and policy advice.

Part of this reluctance may stem from the example of the job mismatch literature, which freely uses measures of job-required education to investigate the prevalence worker–job mismatch and the implications for workers of holding a job whose educational requirements are different from their own level of education. Studies typically show that education mismatch between jobs and workers is not uncommon even among university graduates. Workers whose own education exceeds their job’s required level are less satisfied with their jobs and paid less than workers with the same education whose jobs require that education level (McGuinness 2006). This suggests overeducation is a significant problem even for university graduates, though findings on trends over time are much less consistent. Nevertheless, given SBTC argues there is a shortage of university graduates it is not surprising proponents are unsympathetic to evidence of overeducation and avoid the demand-side measures of educational requirements that are central to this line of research, perhaps questioning the validity of such measures altogether. Interestingly, research on educational mismatch, for its part, has not used specific task measures greatly either. This points to a significant gap in understanding regarding the relationship between these two kinds of measures of job complexity.

However, the larger problem is that despite the use of task measures, SBTC claims regarding rising educational requirements still generally rely on indirect evidence. The task measures drawn from O*NET and many similar sources use highly abstract constructs and scales without a clear relationship to levels of education, and research makes little effort to relate the two in a detailed way. Direct measures of job education requirements are essential to address the questions raised by SBTC and related theories, as are measures of job tasks for which education is presumably useful preparation. This is not to say that job task measures should cover only skills learned in school, but they should be devoted significantly to understanding the use of school-related skills on the job given the interest in this specific question and the data gaps that remain even after much research.

This chapter seeks to demonstrate the validity of job-required education as a basic social indicator and to investigate its substantive meaning in terms of more specific task measures, which reveal the specific uses to which education is put in the workplace. In so doing this chapter addresses substantive questions regarding job complexity as well as more specific concerns regarding the
meaning of job-required education. Proponents of SBTC theory and others claim more jobs require tertiary-level skills—do they? And how would one know? The problem with inferring changing job content from indirect measures, such as increasing education wage differentials, is that there may be other explanations, such as institutional factors, that produce the same effect or otherwise explain a large part of inequality growth. And even if one is convinced educational requirements are increasing the indirect approach cannot shed light on which skills imparted by education are increasingly important. At some point one wants direct evidence regarding rising job educational requirements and some concrete sense of the specific skills involved.

Data and general approach

Data

The data for this chapter are from the survey of Skills, Technology, and Management Practices (STAMP), a two-wave, nationally representative refreshed panel survey of wage and salary workers in the United States age 18 and over. The first wave was conducted mostly in 2005 and respondents were reinterviewed for the second wave conducted mostly in 2008, along with a new and smaller representative sample. The Wave 1 survey (n=2,304) contained about 166 unique items related to job characteristics, as well as others related to personal characteristics. Survey questions covered cognitive, interpersonal, and physical job tasks, computing and non-computing technology used at work, closeness of supervision, degree of autonomy and authority, use of teams and other employee involvement practices, promotion opportunities, aspects of job insecurity (e.g., automation, outsourcing), workload, and job satisfaction. The average interview length was approximately 28 minutes. The Wave 2 survey (n=2,237) made slight changes but was otherwise comparable to Wave 1. Both waves were conducted in Spanish for respondents who preferred using that language; others unable to be surveyed due to limited English proficiency were excluded from the sample.

Measurement approach

A central goal of STAMP was to improve both the quality of individual measures and the coverage of key dimensions of job content. Wherever feasible, survey items were phrased in terms of concrete facts, events, and behaviors rather than abstract constructs and judgments. Wherever possible, response options were constructed to have absolute meanings, permitting more objec-
tive interpretations compared to data based on vague quantifiers, Likert response formats and other five-point rating scales, and factor-analytic scales. Not all items can achieve this level of concreteness while remaining generally valid for the diverse jobs found in a modern economy and sometimes rating scales are unavoidable, but items that are behaviorally explicit and response options with absolute meanings are the ideals that guided the survey construction. Given the recognized need for better data, STAMP assumed concrete items and response options were more likely to have common meanings across respondents and would reduce interpretive challenges for researchers.

Items were also designed specifically to represent a wide range of intensity or complexity to avoid floor and ceiling effects, often forming Guttman-style hierarchies in which people responding positively to higher-level items (e.g., use calculus at work) have a high probability of responding positively to all or most lower-level items (e.g., perform multiplication/division at work). Following item response theory, ideal measures of job demands would use the same scale to measure both person abilities and job characteristics, permitting direct comparisons of jobs and workers. Thus, asking someone if their job requires lifting 25 kilos permits direct comparison with personal strength ability in a way that asking if a job requires lifting “heavy” loads does not. In the present context, this means trying to measure job tasks involving school skills in such a way that the tasks can be described plausibly in terms of different levels of schooling, such that one could say a university-educated worker is or is not using university-level math on their job, for example. This is a difficult standard to achieve consistently, but it represents the ideal.

By contrast, the rating scales used by O*NET and many other data sources generally have no obvious substantive interpretation outside of the survey itself and do not correspond clearly to different objective levels of complexity or easily understood categories of educational achievement or other person characteristics. If job skill demands and educational requirements are to be tracked directly, the goal must be measures of job content that (1) have objective, easily interpreted meanings, (2) represent a hierarchy of complexity and, wherever possible, (3) correspond roughly to levels of education. Although the task approach to labor market outcomes has flourished since STAMP was conducted, the behavioral meanings of most measures used in that research are not obvious nor is their connection to levels of education, despite interest in precisely this aspect of jobs. If one argues that more complex skills imparted by education are increasingly used on the job the logical next step would be to collect direct evidence bearing on this question.
Task measures

While survey items on the level of education required for one’s job provide a general answer, STAMP items on math, reading, writing, and problem-solving tasks open up what is otherwise a black box and help explain the substantive meanings of those levels. The choice of math, reading, and writing (i.e., numeracy and literacy) was driven by their recognition as key functions of general education, and figure prominently in educational testing in the United States, including high-school performance exams and university entrance exams. If general education is more than simply a sorting device (Bills 2003), then one would expect math, reading, and writing to be used on the job and to influence judgements of jobs’ required education level. As noted, ideally, job-side measures of tasks should be clearly interpretable and have a complexity gradient that can be related at least roughly to levels of person-side education. Mathematics approximates this ideal most closely as it is a relatively well-structured domain whose varying levels of complexity can be represented by a series of behaviorally specific items, from simple counting to the use of calculus and other higher math that can be related easily to levels of education.

Reading and writing are not as easy to measure on a unidimensional complexity dimension or to characterize in terms of grade equivalents or levels of schooling. Although think tanks, journalists, and other commentators may claim average workplace reading requirements have risen from 10th-grade to 12th-grade levels or from 11 to 13 years of schooling, the empirical basis for these kinds of statements is elusive. Educational psychology often uses some combination of average word length and average sentence length to capture text complexity. A prominent evaluation of college performance in the U.S. uses the presence of 20-page writing assignments as indicative of college-level writing requirements (Arum and Roksa 2011, p. 37). STAMP incorporates this principle by measuring reading and writing demands using a combination of text length and kind of text, with the latter having a moderate complexity gradient.

Math, reading, and writing cover core areas of education that may be assumed to be relevant for the performance of a wide range of jobs. However, this does not exhaust the possible relevance of education to jobs. People face many cognitive demands at work that do not require doing much math, reading, or writing. Although it is not typically a distinct subject of instruction, the development of general reasoning and thinking skills is woven into nearly all academic courses. Likewise, varying levels of general reasoning and thinking skills are woven into the fabric of job tasks as opposed to tasks drawing more directly on specific school skills. However, despite the importance of general cognitive
skills, operationalizing this implicit activity in concrete terms is challenging. STAMP items on the frequency of simple and complex problem-solving performed on the job capture the use of general reasoning and thinking skills on the job with an effective difficulty gradient. However, level of problem-solving has no natural unit and the relationship between levels of this scale and levels of education must be established empirically rather than designated à priori.

Two significant areas of school-related cognitive skills remain. Field of study refers to extensive bodies of formal knowledge but is relevant only for persons with specialized vocational, post-secondary, and tertiary education, and tends to have occupation-specific rather than general applicability. Nevertheless, job-required education level may be driven significantly by use of this kind of knowledge even when a job scores relatively low on the measures of more general cognitive skills described above. For example, a hotel manager might report relatively simple math, reading, and writing tasks but extensive use of the domain knowledge acquired through a hospitality degree program, explaining the job’s designation as requiring tertiary education. Again, a survey would have to go beyond asking for field of study, a person-side measure, and would have to ask the extent to which workers use the knowledge from their program of study at work to produce a job-side measure. Unfortunately, this is one area that was not anticipated in the construction of STAMP, which lacks such items, though they would help fill important gaps in understanding how school matters for work.

There is also the question of how to measure the skill level of the myriad discrete, narrow tasks found across the occupational spectrum, which usually require rather brief training. This includes many computer-related tasks, but also other qualitatively diverse, freestanding skills often applicable to particular occupations (e.g., simple bookkeeping tasks, calculating net present values, administering intravenous drugs, long-haul truck driving, operating a pneumatic jackhammer). These skills can be acquired in various institutions (e.g., general or vocational secondary school, post-secondary/non-tertiary schools) or through some combination of experience, on- or off-job training, or apprenticeships. Insofar as they are highly job-specific and acquired in school outside a formal field of study, they will be difficult to capture and to use in models explaining levels of required education. However, narrow tasks found across a wide range of jobs, like computer tasks, can be measured and used as predictors of required education, as can tasks learned on the job, as described below.

For many years almost all these narrow skills were the “dark matter” of job complexity. They clearly exerted great influence on job skill requirements but
were largely unobserved in the data. This is no longer the case. O*NET collects information on approximately 19,500 highly granular, occupation-specific, “task statements” and the Burning Glass jobs database has more than 16,000 task statements scraped from internet job postings. However, these highly specific descriptors present a data reduction problem. The tasks often apply to small subgroups of jobs and appear incommensurate with one another, an example of what is called “the curse of dimensionality.” Unfortunately, there is no accepted framework or coding system for scoring or classifying these kinds of skills comparable to standard occupational classification systems, even in the case of transversal job tasks. Time required for learning the job or on-the-job training (OJT) is one of the few ways to capture the great diversity of narrow and specific job tasks on a common scale that has an absolute meaning.

However, time required for OJT presents a problem for understanding the meaning of required education level. While some of these skills may require a certain level of education as a foundation, other job-specific skills are non-academic in nature and learning the latter through experience substitutes for formal education. Thus, moderately high OJT times for administrative support workers may help explain why their jobs might require a bachelor’s degree, while the same level of OJT explains why skilled trades jobs do not need such a degree. Because OJT may either require a foundation of formal education to build upon or act as a substitute for formal education, its ability to explain levels of required education will be attenuated in analyses of the labor market overall. Differentiating occupations according to whether their OJT complements formal education or not is beyond the scope of the present chapter, so analyses of the relationship between OJT and required education below should be viewed as exploratory.

To summarize, the preceding argues that the level of education required by jobs is expected to be strongly related to the complexity of workplace numeracy and literacy tasks, general reasoning requirements, formal degree-related knowledge (omitted here), and, ambiguously, time required for learning one’s job. If education matters for work because of the cognitive skills it imparts, one expects that task variables involving the use of those skills will explain a significant percentage of the variance in job-required education. More strongly, SBTC claims regarding rising education requirements lead one to expect that beyond a simple association there is a more direct or absolute correspondence between required education and task complexity. The natural interpretation of the educational upgrading position is that jobs requiring a university-level education, for example, will require tasks plausibly considered university-level, not simply more complex tasks than those performed in jobs requiring less education.
In practice, this kind of direct correspondence may be difficult to establish both because of ambiguity regarding the scoring of task items in terms of education levels and because of the inevitable gaps in the items’ coverage of the possible ways in which education might be relevant for jobs. However, aside from the unintended omission of field of study from STAMP, the inclusion of time required to learn the job would cover many of the otherwise unobserved cognitive job requirements that might drive required education level. One exception is general knowledge, which is often acquired through formal education but whose use on the job is difficult to measure in surveys because its application in practice is so diffuse.

Nevertheless, it is also likely that required education is driven by noncognitive educational outcomes or correlates, such as organizational skills, good judgment, diligence, other regular work habits, and social skills, such as teamwork and agreeableness, some of which have received significant attention in recent years (e.g., Heckman and Kautz 2012). Other qualities often associated with education that affect hiring, such as etiquette, speech patterns, personal appearance and style, self-presentation and other status markers, and certain aspects of personality and values, move even more clearly into the realm of cultural capital (Bourdieu 1977) and other education-related personal qualities cited by theories of class reproduction focusing on education’s hidden curriculum or socialization function (Bowles and Gintis 1976). It is worth noting in this context that it is not always easy to disentangle utilitarian or technical task requirements from matters of style, as tasks like running effective meetings and making effective presentations require cultural capital or competence as well as more specifically cognitive skills, like verbal skills and reasoning.

These diverse noncognitive characteristics tend to be associated with educational attainment and may influence survey responses regarding the education required by jobs. However, these characteristics are often difficult to capture reliably in surveys because they are either implicit and outside respondents’ conscious awareness or are subject to yea-saying biases and artificially low variance across respondents because they evoke stereotypical social virtues (e.g., “how important to your job is working well with others?”). Therefore, while one would expect measures of “hard skills” to explain a meaningful proportion of the variation in educational requirements, it would not be surprising if some meaningful proportion remains unexplained due to the omission or poor measurement of these largely noncognitive variables, as well as due to more obvious reasons like measurement error and the omission of field of study.

The implications of noncognitive drivers of job education requirements for SBTC theory are somewhat ambiguous. Aspects of this domain, such as cul-
tural style, render education suspect as a bona fide job requirement. Even aside from issues surrounding the legitimacy of cultural capital as a job requirement, in SBTC theory it is increasing demand for cognitive skills acquired through schooling, particularly university education, that explains the rise in the college wage premium and increasing inequality more generally, though the theory does not preclude effects of computer use on nonroutine interpersonal tasks as well. STAMP contains measures of interpersonal tasks that were designed to avoid the kinds of social desirability biases noted above but had limited success. Given the nature of these data, interpersonal task measures warrant separate treatment and are excluded from this chapter. Because the influence of noncognitive job tasks will appear mostly in the residual in models below there will be no way to compare the relative effects of cognitive and noncognitive job tasks on required education level. However, if the large number of cognitive job task items in STAMP leave a great deal of variation in job-required education unexplained, it will beg the question as to the meaning of the unexplained portion and spur a search for additional predictors.

The analyses below investigate the meaning of job-required education in light of the issues raised above.

**Relationships between job-required education and job tasks**

Comparing job required education to educational attainment

At the most basic level, one expects job-required education to be correlated with individual scales measuring school skills like numeracy, literacy, and problem-solving tasks performed at work and that these relationships will be stronger than the associations between personal education and job tasks. The top panel of Table 14.1 shows the correlations between job task scales and both workers’ personal education and the education required by their job for Wave 1 (left) and Wave 2 (right) of the STAMP survey. In every case, the correlation between job tasks and job-required education exceeds the correlation between tasks and workers’ personal education, with the difference averaging 0.10 in Wave 1 and 0.08 in Wave 2. In both waves, required education is correlated most strongly with reading, writing, and level of computer use, followed by complex problem-solving, level of math use, and (ln) job learning times (Wave 1), with simple problem-solving, management position, and (ln) job learning times (Wave 2) trailing behind.
### Table 14.1
Correlations between education measures, job tasks, and personal characteristics

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**Note:** The Difference columns were calculated by subtracting the correlations between tasks and personal education from the correlations between tasks and job-required education.

The reasons for these differences remain to be explored more deeply, but one can note that the STAMP items on problem-solving were the first to measure this aspect of job complexity rigorously, but no doubt significant random measurement error remains. General reasoning requirements on the job are likely much more important than indicated but more items might be needed to improve its measurement. The lower correlation with math tasks relative to literacy tasks may reflect the fact that few people use more than simple arithmetic on the job (see below), though the correlation between required education and a complex math sub-scale is lower than the correlation with the full scale
shown in Table 14.1. The lower correlations with job learning times may reflect the extent to which skills needed for work differ from those learned at school.

The stronger relationships between tasks performed on the job and the level of education required by the job indicate that the latter provides a better measure of job complexity, the construct of interest in SBTC research, than the common supply-side proxy, personal educational attainment, which research in the human capital tradition tends to use. The middle row shows the correlation between personal education and job-required education in both waves is strong (0.72), but far from unity. This shows job-required education provides somewhat different information than personal education and that that information has a stronger relationship to the kinds of tasks people perform on their jobs.

By comparison, the bottom panel of Table 14.1 shows correlations between both measures of education and other key personal characteristics (gender, race/ethnicity, age) for Waves 1 and 2. The correlations are generally low and differ little across personal and job-required education in both waves.

Predictors of job required education

If all core education-related skills contribute to the level of required education one would find most partial relationships are significant in models predicting required education that include all task variables together. Likewise, insofar as the education required by jobs reflects skills rather than cultural capital and other noncognitive criteria, one would expect the variables included in the model would explain a substantial share of the variance. When math, reading, writing, problem-solving, and (ln) job learning times are entered together in a model, all dimensions predict years of required education in both Wave 1 (model 1, Table 14.2a) and Wave 2 (model 1, Table 14.2b). These five dimensions alone explain 50% (Wave 1) and 46% (Wave 2) of the variance in job-required education.

Although some cognitive dimensions are known to be absent from this model (general knowledge, field of study) or ambiguously related to required education (job learning time), the fact that the $R^2$ remains below unity raises the possibility that other tasks or unmeasured noncognitive characteristics associated with education might be affecting the result, in addition to the effects of unavoidable measurement error. Although a fuller treatment of this issue is beyond the scope of the present chapter, some leverage can be gained by adding indicators for managerial and supervisory roles, which are relatively well measured and can be interpreted as indicators of leadership tasks, as well
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**Note:** Standard errors in parentheses ***p<.01, **p<.05, *p<.10.

**Table 14.2b** Regression of required education on job tasks and personal characteristics (Wave 2)
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<tr>
<td>IT apps (#)</td>
<td>0.084***</td>
<td>0.028*</td>
<td>0.083***</td>
<td>0.027</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.017)</td>
<td>(0.021)</td>
<td>(0.017)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IT level (max=11)</td>
<td>0.054***</td>
<td>0.044***</td>
<td>0.048**</td>
<td>0.041***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.015)</td>
<td>(0.020)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supervisor (=1)</td>
<td>-0.266**</td>
<td>0.032</td>
<td>-0.236**</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.083)</td>
<td>(0.104)</td>
<td>(0.083)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manager (=1)</td>
<td>0.091</td>
<td>0.211***</td>
<td>0.122</td>
<td>0.234***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.075)</td>
<td>(0.095)</td>
<td>(0.076)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Personal education</td>
<td></td>
<td></td>
<td>0.549***</td>
<td>0.548***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(years)</td>
<td></td>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.007</td>
<td>0.152**</td>
<td>0.042</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.076)</td>
<td>(0.060)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-0.929***</td>
<td>-0.255*</td>
<td>-0.133</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.181)</td>
<td>(0.138)</td>
<td>(0.110)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>-0.755***</td>
<td>-0.154</td>
<td>0.025</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.204)</td>
<td>(0.154)</td>
<td>(0.123)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other race/ethnic</td>
<td>0.163</td>
<td>0.034</td>
<td>0.115</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.190)</td>
<td>(0.142)</td>
<td>(0.113)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>0.015***</td>
<td>0.008***</td>
<td>0.006**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.197)</td>
<td>(0.201)</td>
<td>(0.242)</td>
<td>(0.203)</td>
<td>(0.263)</td>
<td>(0.274)</td>
</tr>
<tr>
<td>Adj R²</td>
<td>0.455</td>
<td>0.477</td>
<td>0.669</td>
<td>0.024</td>
<td>0.478</td>
<td>0.671</td>
</tr>
<tr>
<td>N</td>
<td>2,195</td>
<td>2,124</td>
<td>2,120</td>
<td>2,198</td>
<td>2,105</td>
<td>2,103</td>
</tr>
</tbody>
</table>

**Note:** Standard errors in parentheses ***p<.01, **p<.05, *p<.10.
as class position. Cognitive task measures are also extended with scales relating to computer-related or information technology (IT) tasks. Both sets of variables are associated with required education in Model 2 for both waves, but the effects are not large or always positive and significant and the increment to $R^2$ is small.

While the inclusion of well-measured interpersonal task variables might improve predictive power, Model 3 adds personal educational attainment to capture all of the possible pathways through which personal education predicts job-required education beyond those already in the model. In both waves, each year of personal education is associated with a job that requires somewhat more than an additional half-year of education after controlling for job tasks and organizational position. When personal education is the only predictor, the coefficient is 0.75 (Wave 1) or 0.76 (Wave 2) (not shown), so the task variables in Model 3 explain about one-third of education’s total effect on a job’s required education. The bivariate model explains 56% of the variance in both years, but this is only about 5–8 percentage points greater than the share explained by the task items in both waves (Model 2). In other words, a small set of facet-specific scales performs almost as well as the overall measure of everything schooling contributes to job requirements. However, the combined model (Model 3) represents a substantial increment to both the tasks-only and the education-only models, explaining about 67% of the variance in job-required education in both waves. This is an 18 or 21 percentage-point increment compared to the tasks model, depending on the survey wave. Both the size of the partial coefficient for educational attainment and its contribution $R^2$ mean that much of its influence on job required education remains unexplained after controlling for facet-specific task variables. This may reflect the power of cultural capital and other non-cognitive consequences of educational attainment. Clearly, there is more to be learned regarding the particular aspects of education that are important for work and the substantive meaning of job required education. Some portion of the remaining one-third of the variance undoubtedly reflects random measurement error, but there is also the possibility of systematic, construct-irrelevant variance, such as possible effects of social status on self-reported job educational requirements.

The bottom rows of Tables 14.2a and 14.2b show the effects of gender, race/ethnicity, and age on self-reports of job-required education. When these personal characteristics are entered as a group by themselves in Model 4, gender has no effect in either wave and while there is a small positive effect (~0.155 years) when all other predictors except personal education are included (Model 5), the effect becomes very small and insignificant once education is added in models for both waves (Model 6). In the full model for Wave 1, blacks report
their jobs require 0.18 fewer years of education than whites controlling for all covariates. The effect of age is more robust but also small in substantive terms, as 30 years is associated with less than 0.25 additional years of job-required education (Model 6). The inclusion of gender, race/ethnicity, and age in model 6 adds 0.4% (Wave 1) and 0.2% (Wave 2) to the variance explained in Model 3. Therefore, differential item functioning does not seem to be a serious problem, nor does it account for the unexplained variance remaining in Model 3. Aspects of social status captured by gender, race/ethnicity, and age do not seem to affect self-reported job-required education appreciably.

Absolute correspondence between job tasks and levels of required education

Finally, while the preceding investigated whether reports of job required education are associated with more skilled tasks, there is the question as to whether the skill level of tasks corresponds in an absolute sense to the levels of education with which they are associated. For example, do university-level jobs involve tasks that can be considered university-level and, if so, what are they? Tables 14.3a and 14.3b show the percentage of jobs performing different numeracy, literacy, and problem-solving tasks by level of job-required education. The top two lines show sample sizes and (weighted) percentage of jobs by required education. The items under each heading comprise the additive scales or variables used in Tables 14.1 and 14.2. Because they are intended to have a complexity gradient, prevalence rates generally decrease as one reads down columns within constructs as item difficulty increases. Reading across rows, task prevalence is expected to increase as job-required education rises.

The mathematics domain follows the expected pattern quite consistently with the one exception that workers reporting their jobs requiring high-school plus vocational education also report performing more geometry and/or trigonometry on their jobs than most jobs requiring higher levels of education. However, this is sensible given the nature of jobs in the skilled trades, so violations of strict ordinality are not unexpected in this case. The more striking aspect of this panel is that while almost everyone uses some basic math skills on their job, the proportions drop once one moves beyond simple tasks like counting, addition/subtraction, multiplication/division, and doing math with fractions, decimals, and percentages. Aside from jobs requiring vocational training, few jobs requiring less than a bachelor’s degree require high-school-level math. Among jobs requiring some college, somewhat more (Wave 2) or less (Wave 1) than 20% of jobs use simple algebra to solve for a single unknown. Among jobs requiring a BA, about 10% involve calculus or some higher-level math, though about 25% use inferential statistics, which could be considered college-level.
Table 14.3a  Complexity of job tasks by required education (Wave 1)

<table>
<thead>
<tr>
<th></th>
<th>&lt; HS</th>
<th>HS</th>
<th>HS+voc</th>
<th>&lt; BA</th>
<th>BA</th>
<th>postgrad</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent (weighted)</td>
<td>7.6</td>
<td>42.6</td>
<td>6.3</td>
<td>16.5</td>
<td>20.8</td>
<td>6.3</td>
</tr>
<tr>
<td>N</td>
<td>117</td>
<td>822</td>
<td>125</td>
<td>403</td>
<td>574</td>
<td>241</td>
</tr>
</tbody>
</table>

**Math**
1. Any math | 89.8 | 93.5 | 93.7 | 95.4 | 96.3 | 94.8 |
2. Add/subtract | 60.1 | 84.8 | 87.4 | 91.4 | 95.0 | 94.3 |
3. Multiply/divide | 42.6 | 73.7 | 80.2 | 84.2 | 92.9 | 93.1 |
4. Fractions, decimals | 22.1 | 58.2 | 81.0 | 76.3 | 87.3 | 89.9 |
5. Algebra (basic) | 1.8 | 9.7 | 29.8 | 17.3 | 36.8 | 41.8 |
6. Algebra (complex) | 1.5 | 3.6 | 13.5 | 6.3 | 18.0 | 22.7 |
7. Geometry/trig | 1.5 | 7.3 | 27.4 | 12.5 | 23.7 | 24.8 |
8. Statistics | 1.1 | 2.3 | 9.3 | 10.4 | 26.4 | 40.9 |
9. Calculus | 0.3 | 2.0 | 1.0 | 3.2 | 9.4 | 15.7 |

**Reading**
1. Any reading | 79.6 | 96.1 | 96.6 | 99.2 | 100.0 | 99.7 |
2. One page | 34.7 | 74.6 | 84.6 | 94.7 | 98.6 | 99.4 |
3. Five pages | 12.5 | 35.0 | 54.9 | 66.5 | 86.4 | 97.3 |
4. News articles, et al. | 8.0 | 25.0 | 37.3 | 49.3 | 71.7 | 86.8 |
5. Professional articles | 6.9 | 17.7 | 33.0 | 48.6 | 69.8 | 91.1 |
6. Books | 11.3 | 38.4 | 55.2 | 64.3 | 81.9 | 84.6 |

**Writing**
1. Any writing | 62.3 | 88.3 | 92.3 | 98.0 | 99.8 | 99.7 |
2. One page | 14.9 | 44.2 | 53.7 | 76.0 | 92.2 | 96.8 |
3. Five pages | 2.6 | 8.7 | 13.0 | 22.3 | 53.9 | 72.0 |
4. News articles, et al. | 2.7 | 2.6 | 1.8 | 6.3 | 21.6 | 40.1 |
5. Books/prof’l arts | 2.6 | 0.2 | 0.5 | 0.5 | 5.4 | 24.3 |
<table>
<thead>
<tr>
<th></th>
<th>&lt; HS</th>
<th>HS</th>
<th>HS+voc</th>
<th>&lt;BA</th>
<th>BA</th>
<th>postgrad</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Problem-solving, easy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>13.7</td>
<td>3.6</td>
<td>4.2</td>
<td>0.7</td>
<td>0.0</td>
<td>0.3</td>
</tr>
<tr>
<td>Rarely</td>
<td>17.0</td>
<td>13.2</td>
<td>5.4</td>
<td>4.2</td>
<td>2.6</td>
<td>1.9</td>
</tr>
<tr>
<td>Sometimes</td>
<td>35.5</td>
<td>30.6</td>
<td>21.7</td>
<td>24.1</td>
<td>15.9</td>
<td>18.8</td>
</tr>
<tr>
<td>Often</td>
<td>33.9</td>
<td>52.6</td>
<td>68.7</td>
<td>71.0</td>
<td>81.5</td>
<td>79.0</td>
</tr>
<tr>
<td><strong>Problem-solving, hard</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Never</td>
<td>31.6</td>
<td>15.0</td>
<td>9.4</td>
<td>2.6</td>
<td>2.3</td>
<td>0.8</td>
</tr>
<tr>
<td>Rarely</td>
<td>37.0</td>
<td>31.1</td>
<td>18.1</td>
<td>14.7</td>
<td>8.6</td>
<td>6.2</td>
</tr>
<tr>
<td>Sometimes</td>
<td>29.1</td>
<td>40.1</td>
<td>59.0</td>
<td>57.2</td>
<td>50.1</td>
<td>41.9</td>
</tr>
<tr>
<td>Often</td>
<td>2.3</td>
<td>13.8</td>
<td>13.5</td>
<td>25.5</td>
<td>39.0</td>
<td>51.1</td>
</tr>
<tr>
<td><strong>Job learning times</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean weeks</td>
<td>16.6</td>
<td>27.6</td>
<td>50.1</td>
<td>35.1</td>
<td>49.7</td>
<td>61.7</td>
</tr>
<tr>
<td>Median weeks</td>
<td>2.5</td>
<td>14</td>
<td>38</td>
<td>14</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td><strong>Computer use</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>IT apps (mean)</td>
<td>0.8</td>
<td>2.6</td>
<td>3.1</td>
<td>5.1</td>
<td>6.7</td>
<td>6.9</td>
</tr>
<tr>
<td>IT level (max=11)</td>
<td>1.0</td>
<td>2.9</td>
<td>3.9</td>
<td>5.5</td>
<td>6.5</td>
<td>6.6</td>
</tr>
</tbody>
</table>

The figures for jobs requiring a postgraduate education are 5 to 15 percentage points higher.

Almost all jobs require some reading on the job, but the numbers begin to drop noticeably for jobs requiring less than some college even when the question refers to reading continuous text that is as short as one page long. Only about one-third of high-school-level jobs and two-thirds of some-college jobs require reading text that is five pages long. Even among jobs requiring a BA, only 56% of jobs require reading texts that are at least 25 pages long (Wave 2 only). About 70–85% of jobs requiring a BA or above involve reading articles in newspapers and trade magazines, articles in professional journals, and books, while the figures for both high-school groups and some-college jobs are mostly in the range of 25–50%. The original hope was that these items on kinds of reading would form a clear hierarchy of complexity, potentially equitable plausibly to levels of education, but their performance fell short of this goal.

Writing on the job shows a much sharper gradient than reading. While large majorities in most job categories do some limited form of writing at work,
### Table 14.3b Complexity of job tasks by required education (Wave 2)

<table>
<thead>
<tr>
<th></th>
<th>&lt; HS</th>
<th>HS</th>
<th>HS+voc</th>
<th>&lt; BA</th>
<th>BA</th>
<th>postgrad</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Percent (weighted)</strong></td>
<td>8.3</td>
<td>40.4</td>
<td>5.6</td>
<td>19.0</td>
<td>20.6</td>
<td>6.1</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>80</td>
<td>698</td>
<td>112</td>
<td>442</td>
<td>599</td>
<td>289</td>
</tr>
<tr>
<td><strong>Math</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Any math</td>
<td>83.4</td>
<td>90.6</td>
<td>97.6</td>
<td>96.8</td>
<td>97.3</td>
<td>95.5</td>
</tr>
<tr>
<td>2. Add/subtract</td>
<td>73.1</td>
<td>83.5</td>
<td>90.9</td>
<td>93.1</td>
<td>94.9</td>
<td>95.2</td>
</tr>
<tr>
<td>3. Multiply/divide</td>
<td>59.0</td>
<td>68.1</td>
<td>84.5</td>
<td>83.7</td>
<td>91.5</td>
<td>94.2</td>
</tr>
<tr>
<td>4. Fractions, decimals</td>
<td>40.5</td>
<td>54.9</td>
<td>73.7</td>
<td>77.7</td>
<td>87.2</td>
<td>88.6</td>
</tr>
<tr>
<td>5. Algebra (basic)</td>
<td>5.0</td>
<td>8.6</td>
<td>24.0</td>
<td>23.1</td>
<td>33.0</td>
<td>38.0</td>
</tr>
<tr>
<td>6. Algebra (complex)</td>
<td>3.2</td>
<td>4.2</td>
<td>11.4</td>
<td>9.2</td>
<td>17.6</td>
<td>21.5</td>
</tr>
<tr>
<td>7. Geometry/trig</td>
<td>5.6</td>
<td>8.6</td>
<td>22.3</td>
<td>13.2</td>
<td>20.5</td>
<td>25.1</td>
</tr>
<tr>
<td>8. Statistics</td>
<td>1.8</td>
<td>3.6</td>
<td>8.8</td>
<td>8.2</td>
<td>23.4</td>
<td>37.5</td>
</tr>
<tr>
<td>9. Calculus</td>
<td>1.1</td>
<td>1.1</td>
<td>2.8</td>
<td>5.5</td>
<td>10.1</td>
<td>17.0</td>
</tr>
<tr>
<td><strong>Reading</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Any reading</td>
<td>84.5</td>
<td>92.8</td>
<td>99.4</td>
<td>98.0</td>
<td>99.9</td>
<td>97.8</td>
</tr>
<tr>
<td>2. One page</td>
<td>48.2</td>
<td>70.9</td>
<td>87.7</td>
<td>91.1</td>
<td>96.4</td>
<td>97.2</td>
</tr>
<tr>
<td>3. Five pages</td>
<td>10.6</td>
<td>36.7</td>
<td>53.5</td>
<td>63.6</td>
<td>84.4</td>
<td>93.5</td>
</tr>
<tr>
<td>4. Twenty-five pages</td>
<td>6.0</td>
<td>14.2</td>
<td>27.5</td>
<td>32.2</td>
<td>56.4</td>
<td>70.9</td>
</tr>
<tr>
<td>5. News articles, et al.</td>
<td>5.8</td>
<td>22.5</td>
<td>35.0</td>
<td>47.1</td>
<td>62.4</td>
<td>79.9</td>
</tr>
<tr>
<td>6. Professional articles</td>
<td>2.2</td>
<td>17.2</td>
<td>36.2</td>
<td>44.3</td>
<td>66.8</td>
<td>83.9</td>
</tr>
<tr>
<td>7. Books</td>
<td>15.5</td>
<td>36.6</td>
<td>44.8</td>
<td>58.3</td>
<td>72.9</td>
<td>83.2</td>
</tr>
<tr>
<td><strong>Writing</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Any writing</td>
<td>77.5</td>
<td>86.0</td>
<td>95.5</td>
<td>96.4</td>
<td>99.7</td>
<td>98.2</td>
</tr>
<tr>
<td>2. One page</td>
<td>13.1</td>
<td>48.1</td>
<td>55.6</td>
<td>75.0</td>
<td>90.7</td>
<td>95.2</td>
</tr>
<tr>
<td>3. Five pages</td>
<td>0.6</td>
<td>7.1</td>
<td>11.7</td>
<td>24.5</td>
<td>55.5</td>
<td>70.0</td>
</tr>
<tr>
<td>4. Twenty-five pages</td>
<td>0.0</td>
<td>1.0</td>
<td>3.2</td>
<td>4.9</td>
<td>20.4</td>
<td>31.3</td>
</tr>
</tbody>
</table>
the percentages drop dramatically when it comes to writing text that is even a single page long. Less than half of high-school-level jobs involve writing text that is at least one page long as a regular part of their job, though over 90% of jobs requiring a BA or above do so. However, only about 55% of BA-level jobs require writing documents that are at least five pages long and only about 20% require writing documents that are at least 25 pages long (Wave 2 only). If writing 20- or 25-page documents is considered a college-level task, then 80% of college-level jobs do not require writing at this level of difficulty. Even among jobs requiring more than a BA, the proportion writing 25-page documents is below one-third.

Problem-solving is divided into two categories: those involving problems that can be solved easily by oneself or after some help from others and problems that are difficult and require a long time to think of a solution. For both items and in both waves the mass shifts with remarkable consistency from

<table>
<thead>
<tr>
<th></th>
<th>&lt; HS</th>
<th>HS</th>
<th>HS+voc</th>
<th>&lt; BA</th>
<th>BA</th>
<th>postgrad</th>
</tr>
</thead>
<tbody>
<tr>
<td>5. News articles, et al.</td>
<td>0.4</td>
<td>1.6</td>
<td>3.0</td>
<td>5.2</td>
<td>18.4</td>
<td>30.4</td>
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<td>6. Books/prof’l arts</td>
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<td>0.0</td>
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**Problem-solving, easy**

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<td>Never</td>
<td>10.9</td>
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<td>2.8</td>
<td>1.6</td>
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<tr>
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<td>10.7</td>
<td>24.4</td>
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<tr>
<td>Often</td>
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<td>53.5</td>
<td>81.8</td>
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**Problem-solving, hard**

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<td>Never</td>
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<td>Rarely</td>
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<td>Sometimes</td>
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**Job learning times**

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<td>Mean weeks</td>
<td>17.3</td>
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<td>33.8</td>
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<tr>
<td>Median weeks</td>
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<td>14</td>
<td>38</td>
<td>14</td>
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**Computer use**

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<th>&lt; BA</th>
<th>BA</th>
<th>postgrad</th>
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<tbody>
<tr>
<td>IT apps (mean)</td>
<td>0.8</td>
<td>2.5</td>
<td>3.9</td>
<td>5.5</td>
<td>7.2</td>
<td>6.8</td>
</tr>
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<td>IT level (max=11)</td>
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<td>3.9</td>
<td>5.7</td>
<td>6.8</td>
<td>6.4</td>
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lower to higher frequencies as job-required education increases. Although it is difficult to assign levels of problem-solving to levels of education on an á priori basis, as an empirical matter the share of jobs that often involve complex problem-solving increases from 12% to 14% for high-school jobs to between one-third and one-half for jobs requiring at least a BA.

Job learning times are not easy to characterize in terms of levels of education, so it is not easy to evaluate how the two measures align in an absolute sense. However, the mean and, less strongly, the median show the expected progression with level of required education, except for jobs requiring vocational education, which break the pattern, as one might expect. These are the jobs for which on-the-job learning is most likely to substitute for academic education as a source of job-related skill acquisition. Nevertheless, for other education categories the complexity of occupation-specific tasks learned on the job may be an important reason the jobs have a certain level of required education even though they do not include level-appropriate math, reading, and writing tasks. In these cases, the length and content of OJT may require a certain level of foundation skills provided by formal education even though the numeracy and literacy tasks do not seem commensurate with this level of education.

STAMP contains several measures of the complexity of computer tasks performed on the job. This is a key set of tasks that emerged after 1980, has relevance across a wide range of occupations, and arises naturally in discussions regarding the effects of technology on inequality. However, little attention has been devoted to measuring IT competency requirements of jobs. The measures presented in Table 14.3 are the total number of software applications used on the job, based on an extensive inventory, and self-rated complexity of computer skills required on the job. Respondents who used computers at work answered this question on a scale ranging from 0 to 10 and their scores were incremented by 1 to permit non-users to be assigned a zero score, so the recoded variable used here ranges somewhat awkwardly from 0 to 11. Both scales show a monotonic relationship with required education in both waves, except for a small drop among postgraduates in Wave 2. Other measures in STAMP, such as whether respondents performed programming and the time required to learn the most complex job-specific program, are not included in the software inventory and would require more space to discuss, though they may be easier to relate to education levels in an absolute sense.

It should be noted that the items on specific job tasks and the question regarding the overall level of education required by the job were asked in widely separated sections of the STAMP survey, so that it is unlikely that the relationships between them were due to a response set, that is an artificial consistency due
to respondents’ desires to avoid appearing inconsistent. Likewise, the items in the computer software battery were asked individually as yes/no questions so it would be challenging for respondents to ensure that the overall count variable was consistent with self-reported job-required education. In general, it seems unlikely that the observed associations between job tasks and job-required education is artifactual.

Finally, it should be noted that jobs do not need to have tasks appropriate to its required education level across all domains. If task complexity varies within jobs across domains, the education required will likely reflect the level of the most complex tasks rather than the average or each domain considered singly. Investigating this possibility would require constructing a task score representing the maximum across all domains and examining its relationship to required education to determine if jobs require level-appropriate tasks in at least one domain. Examining all tasks together is left for future extension of this work and even in this case the unavoidable omission of field of study would make the results provisional.

Conclusion

Education is central to human capital theories of wage determination. However, despite nearly 60 years of human capital research large gaps in knowledge remain regarding the exact use of school skills at work. Claims regarding trends in job skill requirements that build on human capital theory also underpin SBTC theories of inequality growth. Following human capital theory SBTC research initially used only indirect measures of job skill trends, like college wage premiums. However, even after shifting to direct measures of job requirements SBTC research relied on overly abstract facet-specific measures while avoiding more precise measures of required education because of their awkward implications for the underlying theory. Everyone agrees that workers are matched to jobs on the basis of education to a significant degree, but because the mismatch literature showed overeducation was common among university graduates the notion that worker education as a supply-side measure implies a complementary demand-side concept of job-required education was avoided or rejected.

Nevertheless, the implication that measures of required education lack validity is contradicted by measures of job tasks that are framed in terms of objective facts and behaviors and have a clear difficulty gradient. Job-required education correlates more strongly with these job task measures than does workers’
personal education, partial effects of tasks on required education are robust, and a small set of such measures explain 45–50% of the variance in required education. Showing an absolute correspondence between scale items and levels of required education is feasible for certain domains and more challenging for others but there is a remarkably consistent pattern using the disaggregated measures. Jobs with higher reported education requirements usually involve higher levels of math, reading, writing, problem-solving, and computer use and longer job learning times. More work is needed to understand the kinds of tasks performed in jobs requiring different levels of education, including measures of the relative use of detailed field of study for those with university and specialized vocational education. Nevertheless, from the rich array of specific task indicators that are available in STAMP it is clear that measures of required education have clear and sensible meanings in terms of the numeracy, literacy, general reasoning, and other tasks performed on the job.

Notes

1. This work was supported by the National Science Foundation (grant number IIS-0326343), the Russell Sage Foundation, and the Wisconsin Alumni Research Fund. I would like to thank Maury Gittleman and Michael Wolf for helpful comments.
2. For further details on the STAMP survey, see Handel (2016b).
3. The rest of this section draws heavily on Handel (2015), which should be consulted for further details.
4. For further discussion of this and other issues with O*NET, see Handel (2016a).
5. An important exception is the case of narrow skills that are certified through formal coursework, programs, or other “microcredentials.”
6. In the case of certificates, one could have objective indicators of their presence or counts of their numbers, but the problem of developing a correspondence between them and level of education would remain for many, though not necessarily all, certificates.
7. Quadratic specifications for age do not improve the fit of the model (not shown).

References


Introduction

How well individuals are prepared for their labor market entry and later occupational careers is highly dependent on both individuals’ skill acquisition and the skill requirements of their jobs. Both skill supply and demand are shaped by national education systems: the former because education systems structure learning opportunities, and the latter because such systems structure the pool of the available labor force (e.g., Rauscher 2015). Conversely, economic factors and associated occupational structures influence national educational systems, as partly argued by the political economy literature (e.g., Busemeyer 2015). In this chapter, we focus on how education systems shape individuals’ skills acquisition; however, such education-system “effects” are of course embedded in national variations in occupational structures, which impact the configuration of educational systems.

Our understanding of the acquisition of general skills (or competences) in primary and secondary education (until the end of compulsory education) and the inequalities therein have greatly been enhanced with the expansion of international large-scale student assessments since the mid-1990s and early 2000s, such as the Progress in International Reading Literacy Study (PIRLS), the Programme for International Student Assessment (PISA) and the Trends in International Mathematics and Science Study (TIMSS). Trends vary significantly between countries and over time; for example, we observe declining means of literacy proficiency in a number of European countries and a rising performance in Asian countries.

Research on skill formation and inequality in tertiary education is much less common and lacks good macrolevel indicators for institutional differences in higher education systems, which are comparable to the well-established indicators of education-system differences in (upper) secondary education (e.g., tracking/external differentiation, vocational orientation in upper-secondary
education, or standardization) developed by Bol and van de Werfhorst (2013). Moreover, tertiary education research focuses more on participation in (or access to) education and its returns and less on the skills acquired in these educational programs (e.g., Reimer and Jacob 2011). One important exception is the U.S. longitudinal study by Arum and Roksa (2011, 2014), which assessed gains in students’ general skills (such as critical thinking, analytical reasoning, problem solving and writing skills) during college and found only meager gains.

Examining the overall importance of education systems for skill acquisition and skill inequalities requires going beyond participation in education before labor market entry and addressing cross-national differences in worker training and lifelong learning, on the one hand, and how educational certificates and related individuals’ competences affect individuals’ job placement, on the other. The latter influences not only returns to education (e.g., in terms of earnings or occupational status) but also the interplay of skill acquisition, maintenance, and loss over individuals’ life courses (e.g., Zull 2006). Both lifelong and workplace learning have received less attention in education research. First, this is because, conceptually, adult learning occurs not only as a highly institutionalized process in educational institutions but also at the workplace; second, this is because, empirically, few existing (especially longitudinal) data sources include skill measures for adults. The International Adult Literacy Survey (IALS, administered between 1994 and 1998), the Adult Literacy and Life Skills Survey (ALL, 2003–2007) and especially the Survey of Adult Skills (PIAAC, Programme for the International Assessment of Adult Competencies, which started in 2012) have increased the available research on adults’ competences and lifelong learning; however, they are only cross-sectional studies and only include measures for general competences (e.g., numeracy or literacy).

A still unresolved issue in education research is how to measure occupational skills that are learnt in educational institutions/programs (such as in vocational upper-secondary education and training or tertiary education). Some progress in assessing employees’ skills has been achieved in labor market research by measuring skills used in the workplace. Examples are the so-called task-based approach (based on population surveys that examine which skills workers use in the workplace), comprehensive databases of worker attributes and job characteristics (such as the U.S.-based Occupational Information Network O*NET), or expert judgments of required skills of standardized job titles at the occupation level (such as the Dictionary of Occupational Titles (DOT)) (Handel 2017). The underlying assumption of these approaches is that only in-demand skills and properly exercised skills will be rewarded (Liu and Grusky 2013). Arguably, there might be discrepancies between the
skills required by the job and the set of skills that employees actually possess. Thus, although we know something about the distribution of (required and exercised) occupational skills, we still lack knowledge about the levels of occupational skills possessed (not only exercised) by adults and how much of these skills are learned in educational programs versus in the workplace.

Against this background, we start with a short discussion on schooling and skill acquisition, followed by some considerations of skill acquisition in postsecondary education and adult life. We then briefly review institutional approaches to the role of education in the economy and finally discuss the relationship between skills and educational degrees and how this relationship is influenced by educational systems. We conclude the chapter with some remarks on how the interplay between skills and education systems improves our understanding of labor market inequalities and provide some suggestions for future research.

Schooling as productive skill enhancement?

Throughout the education system, a major task of schooling is to foster various sorts of skills among students. In primary education, much attention is devoted to general skills such as reading and writing skills and mathematics, which are meant to build a foundation for further learning. In secondary education, the attention shifts to differentiation toward different “futures”, with students entering different tracks, streams or levels of schooling to prepare for either the labor market or further education. Upper-secondary vocational and postsecondary education, then, aims to develop more specific skills toward a work field.

Despite strong consensus about this core task of schooling, there is much debate about the extent to which educational institutions indeed generate skills. Obviously, there would be fewer reading, writing, mathematics, and other domain-specific skills in the absence of schooling. By comparing learning trajectories during school months and summer holiday months, research shows that more learning occurs in the school months than in the summer months, especially among less advantaged socioeconomic groups (Downey 2020). This line of research concludes that schools reduce inequality in skill acquisition caused by children’s social environment, relative to a counterfactual situation in which no schooling exists. A more critical literature comparing the skill distributions before schooling starts with the distributions throughout primary education in the U.S. shows that the relative position of students in these
distributions is very stable, and thus, the extent of the socioeconomic gaps in children’s competences hardly changes during primary school (Bradbury et al. 2015). Similar results have been found for Germany (Passaretta and Skopek 2021; Skopek and Passaretta 2021). In contrast, socio-economic achievement gaps are smaller in Australia, Canada and the UK for different reasons (e.g., universal health insurance, universal preschool and additional school resources for students from disadvantaged families) (Bradbury et al. 2015). These country differences highlight that individuals’ skill acquisition is influenced not only by the characteristics of education systems and families but also by societal conditions in which schooling and learning are embedded (Borgna et al. 2019).

Looking at how important skills are for economic growth (and are thus “productivity-enhancing”), some scholars have highlighted a stronger predictive power of (measured) general cognitive skills on economic growth and income distributions than of educational degrees or years of schooling (e.g., Checchi and van de Werfhorst 2018; Hanushek and Woessmann 2008). Hence, one may conclude that the improvement of students’ skills is more important than educational expansion in terms of diplomas per se. Such an optimistic perspective on skill acquisition relates to classical structural-functionalist sociological theory, which argues that the production and reward of skills—rather than the premodern allocation on the basis of social origin—create an “efficient” sorting of individuals into the stratification order (Barone and van de Werfhorst 2011).

However, the idea that education produces productivity-enhancing cognitive skills is only one perspective on how education is related to labor market success and inequalities. Cognitive skills explain less than 20 percent of educational differentials in earnings and occupational status (Bowles and Gintis 2002; see also Barone and van de Werfhorst 2011; Heisig et al. 2019). So-called noncognitive skills, including traits that optimize employers’ authority over workers and personality traits, have been shown to be influential as well (e.g., Borghans et al. 2008; Jackson 2006). Additionally, the task-based approach illustrates the relevance of cognitive and noncognitive skills, as (cognitive) analytical and (non/cognitive) managerial skills are increasingly rewarded in the U.S. labor market (Liu and Grusky 2013). However, research on whether and how schools foster children’s acquisition of noncognitive skills is still very rare. For a long time, personality traits were assumed to be stable and socially inherited (Goldthorpe 1996). Recent research demonstrates, however, that noncognitive skills are changeable and trainable (e.g., Bleidorn et al. 2019). This unsettled debate renders the role of various sorts of skills in the intergenerational mobility process as an urgent area of research.
Skill formation in (young) adult life

A substantial proportion of young adults continue their schooling with vocational education and training (VET) or higher education (HE) programs; later in life, they can engage in learning via adult training measures. Approximately half of the under-25-year-old individuals in advanced economies enter tertiary education and more than a third of them graduate before the age of 30 (OECD 2021: 190, 200). Moreover, approximately half of the 25- to 64-year-old individuals surveyed in the Adult Education Survey (AES) participated in formal and/or nonformal adult education and training in 2016 (OECD 2021: 134). These participation rates in tertiary education and adult training vary significantly across countries.

The questions of how postcompulsory education systems and the wider political economy structure young people's skill acquisition and labor market integration have received considerable attention in research. Societies differ in their relative balance toward generating occupation-specific or general skills (Bills and van de Werfhorst 2017; Hall and Soskice 2001; Maurice et al. 1986; Shavit and Müller 1998). This literature argues that the higher occupation specificity of postcompulsory education (i.e., educational programs with strong orientations of curricula toward the acquisition of specific vocational skills) immediately fosters productivity-enhancing and valuable skills for employers. This consideration applies not only to VET systems but also to HE systems (e.g., Leuze 2007; van de Werfhorst 2004).

This research consistently demonstrates that graduates in countries with more occupation-specific postcompulsory education systems transition not only faster into the labor market but also more often into jobs that match their formal qualifications. More recent research also highlights within-country differences in the matching of fields of VET or HE programs and jobs for a strong occupation-specific education system. The so-called linkage strength approach, which was developed by DiPrete et al. (2017), conceptualizes degrees (strength) of occupational specificity of educational programs by the linkage between educational programs and job placements; the degree is high when a large number of graduates from one VET or HE program (defined by level and field) cluster in a narrow set of occupations, and vice versa, it is weak when graduates are found to work in a large number of different occupations. For example, in all countries studied, health programs are highly occupation specific, while the linkage strength of business and administration programs is rather low (DiPrete et al. 2017).
Based on this linkage strength approach, research shows that the between-country differences in occupational specificity of educational systems reported in typology-based research are due to compositional differences in terms of fields of VET and HE programs rather than to differences in the strength of the association between program fields and job placement. Elbers et al. (2021) found that job placements of graduates from occupation-specific programs are similar in Germany and France, which are two countries known to have quite distinct skill equilibria. However, Germany has a much higher share of occupation-specific programs (in both the VET and HE systems) than France, which results in the aggregate-level, between-country differences observed in typology-based studies.

In recent years, there has been an ongoing debate about the advantages and disadvantages of acquiring occupation specific skills in young adulthood. The so-called vocational decline thesis by Hanushek et al. (2017) states that the advantages of vocational programs in smoothing school-to-work transitions reverse into a disadvantage across the working life because of a faster depreciation of vocational skills over the life course. This research relies again mainly on the simple differentiation between vocational and general types of education. This dichotomy has been criticized for not properly operationalizing the assumed underlying mechanism, namely, that “occupational specificity is indeed the main mechanism through which vocationally schooled graduates gain a benefit when entering the labor market and suffer a penalty in later life” (Forster and Bol 2018: 177).

Using the aforementioned linkage strength approach, Forster and Bol (2018) found for the Netherlands—a country with a rather high enrollment in VET programs—that the employment probabilities of graduates from highly specific programs are higher than those for graduates from less specific programs and that these differences only vanish after the age of 60. Moreover, Forster et al. (2016) demonstrated that the assumed vocational decline is not typically associated with systems with a strong vocational orientation. In contrast, the vocational decline in the later life course is particularly strong in more general-skills-oriented educational systems. Therefore, while Hanushek et al. (2017) interpreted the pattern of vocational decline as a risk of VET systems per se, the pattern is more likely to reflect individual differences in careers between educational groups.

Turning to adult education and training, research (across countries) consistently shows that participation in adult training exacerbates rather than mitigates educational disparities (see literature review in Bills and van de Werfhorst 2017). One reason for this finding is that job characteristics (e.g., job
tasks, type of work contract, firm size) are strong predictors of adult training participation (e.g., Ehlert 2020; Görlitz and Tamm 2016; Hornberg et al. 2021; Korpi and Tåhlin 2021; Schindler et al. 2011). Thus, the positive relationship between educational attainment and adult training participation is mediated by workers’ job placements. It should be noted, however, that only the study by Hornberg et al. (2021) accounts for workers’ skills, which is important as skills and job placements are strongly related (Heisig et al. 2019). Finally, very little is known about skills growth by means of adult training programs.

Institutional characteristics of education systems and skill formation

Societies differ significantly in how education is organized, and such differences are reflected in the types and distribution of skills found in societies. Initially, more from a social mobility than skills perspective, Turner (1960) differentiated between sponsored (i.e., socially reproductive) and contest (i.e., meritocratic) mobility regimes. Later contributions more evidently addressed skills, in particular those that consider the uniformity versus the differentiation of the skills obtained in the education system (e.g., Allmendinger 1989; Shavit and Müller 1998). Various dimensions of educational systems relate to uniformity versus differentiation of skills.

First, educational systems have been classified according to the extent and timing to which students are sorted into different skill trajectories (school tracks). Late-selecting educational systems (most of which start around the age of 16 and are thus present in upper-secondary education) have all reformed their selection rules over the course of the past 60 years (van de Werfhorst 2019). After compulsory education, and mostly starting with upper-secondary education, tracking then sorts students into academic and vocational tracks related to different sorts of skills (general versus occupational skills).

Seen from a skill perspective, early selection mostly relates to the speed and ultimate level of attainment of skills for different groups of students (Strello et al. 2021), while the existence of a strong VET sector more clearly indicates separate sorts of skills. Research suggests that early tracking is more clearly associated with larger inequalities in skills and educational degrees.

Although empirically associated with (early) tracking, strong firm-based VET systems are more inclusive, as they help foster the occupation-specific skills of school leavers with lower schooling attainment and thereby improve their
chances of being employed in skilled jobs (Brunello and Checchi 2007; Heisig and Solga 2015; Shavit and Müller 1998). Strong VET systems “are relatively effective in mitigating skill inequality” (Green and Pensiero 2016: 761). For a large group of young people, such programs provide relatively standardized curricula (often also mandating mathematics or national language on all upper-secondary programs) and durations of training in both general competences and vocational skills, accompanied by relative parity of esteem between the different tracks. Moreover, a pioneering causal study using longitudinal survey data from Denmark suggested a positive impact on conscientiousness of vocational training participation but not of general upper-secondary education (Birkelund 2022).

Another uniformity-differentiation aspect of skill formation concerns the standardization of educational systems. Standardization can come in different forms; a common distinction is the standardization of input and of output. Input standardization concerns the standardization of schools’ resources to harmonize the educational process (e.g., school budgets, teacher education or curriculum standardization). It relates to the extent to which national or regional governments standardize the organization of learning processes or the idea that schools can make their own decisions in this regard (i.e., the extent of school autonomy). Research shows that input standardization negatively affects student learning, while school autonomy affects it positively (e.g., Checchi et al. 2014). Output standardization involves standardized means by which to assess student outcomes, such as standardized tests and examinations. Standardized examinations are associated with higher levels of performance and lower socioeconomic inequalities (Bishop 1999; Bol et al. 2014; Woessmann 2005). From a skills perspective, the standardization of input and output is likely to homogenize the skill level within categories of education. In the stratification literature, such homogenization is expected to strengthen the link between qualifications and labor market attainment, although support for this hypothesis is mixed at best (Levels et al. 2014; Shavit and Müller 1998).

Despite these clear differences between educational systems, it is also important to draw attention to the Stanford School of Institutionalism. Its basic idea is that there exists a tendency toward the uniformization of educational systems across modern societies (e.g., Schofer and Meyer 2005). Seen from a skills perspective, Meyer’s (1977) cultural “World Society” model emphasizes the rise of the focus on general skills serving the modernization of the state (e.g., in the fields of literacy, mathematics and history) and of national policies promoting educational expansion. Expansion and uniformization can be explained by a cultural theory of institutional change that posits that
educational institutions are adopted beyond what is necessary or functional for a particular society.

**Institutional differences in the relationship between skills and educational certificates**

Finally, we discuss how skills are related to educational degrees, how differences between education systems influence this relationship and the labor market values attached to skills and degrees as two dimensions of education. For a long time, only levels of formal qualification (educational certificates/degrees) were used in social mobility and labor market research. The various large-scale assessments of competences show that educational certificates or often-used years of education are not ideal proxies for skills because of the large skill heterogeneity present within educational groups (see, e.g., Heisig 2018; Heisig and Solga 2015). Because of this within-group heterogeneity and because skill formation processes (including losses) do not end with initial education, some scholars argue to use direct measures of skills instead of relying on educational credentials. For example, Vera-Toscano et al. (2017: 217) stated that “Whilst the formal education received is constant after exiting the educational system, skills reflect competences more accurately”. This corresponds to the discussion about the importance of skills versus educational degrees for economic growth (see Section 2). However, although an individual’s skills vary over the life course, only focusing on skills in later life and ignoring educational degrees would be throwing the baby out with the bathwater for several reasons.

First, research on lifelong learning has consistently demonstrated a strong positive association between educational degrees and training participation (see Section 3). In other words, later skill formation processes do not substitute but rather complement and increase inequality in early educational attainment.

Second, skills are not easily observable by employers, especially before hiring. Thus, educational certificates are not only proxies of skills in research but also serve as a “signal” of workers’ prospective productivity and training costs in real life (see Bills 2003). Correspondingly, research shows that job placement is highly dependent on educational certificates, even after accounting for workers’ actual skills (e.g., Araki 2020; Heisig et al. 2019). This research has also revealed that the signaling value or the “skill transparency” of educational certificates—that is, how informative formal qualifications are about individuals’ skills—varies by the characteristics of education systems (Andersen and van de Werfhorst 2010). For example, based on PIAAC data, research shows
that the skill transparency of educational degrees (operationalized as skill gaps between educational groups and skill homogeneity within educational groups) is higher in countries with stronger (ability-related) tracking systems (Heisig 2018; Heisig and Solga 2015).

Third, educational certificates constitute an “institutionalized bottleneck of skill supply”, especially in countries with high “reliance on credential-based recruitment” for jobs (Liu and Grusky 2013: 1335, 1339). Hence, above and beyond skills, educational certificates structure individuals’ job placement by defining who is “entitled” to what kind of job—also known as mechanisms of occupational closure (or opportunity hoarding; Tilly 1998; Tomaskovic-Devey and Avent-Holt 2019). The basic idea of opportunity hoarding is that organizations match organizationally external categories to internal categories to lower transaction costs for organizational tasks (such as hiring) and to increase organizational stability (Tilly 1998: 80f.). Educational certificates, which are provided by education systems and recognized as legitimate allocation criteria (Meyer 1977), are such external categories, as they are mirrored by educational requirements and job levels within firms. VET systems, such as the German firm-based VET system, are such an institutional bottleneck of skill supply, even though they are beneficial for individuals’ occupation-specific skill formation and smooth transitions into skilled jobs at labor market entry (e.g., Brzinsky-Fay and Solga 2016: Shavit and Müller 1998).

In sum, educational systems with strong tracking, strong vocational orientation in upper-secondary education, and more limited tertiary enrollment generate a higher skill transparency of educational degrees; because of this higher skill transparency, the countries who utilize such systems are also characterized by a stronger relationship between educational attainment and occupational status (Andersen and van de Werfhorst 2010; Heisig et al. 2019).

These different aspects indicate, in contrast to the abovementioned claim by Vera-Toscano et al. (2017), that the “allocative effect of educational attainment” (Liu and Grusky 2013: 1353) cannot be underestimated for both skill formation processes and labor market success over the life course. Educational qualifications are important for allocating individuals into jobs and occupations and thereby into different learning environments. We should rather continue to look at skills and educational qualifications as two well-established and equally important socially constructed dimensions of education that both impact individuals’ labor market opportunities, from both an empirical and a theoretical perspective. Even if skills are empirically more important than qualifications for economic growth and income distributions (Section 2), it is also true that qualifications maintain their legitimated signaling function,
thereby leading to formal and informal processes of inclusion and exclusion into further skill development and associated rewards.

Concluding remarks and outlook for future research

Our review of research on skills and education systems demonstrates that a better understanding of how educational systems influence skill acquisition contributes to our understanding of why skills—but also educational certificates above and beyond skills—are rewarded in labor markets.

While research on general (domain-specific) skills such as numeracy, literacy or science competences has grown in recent years, research on the skill formation of vocational skills and noncognitive skills is still rare. For the former, we mentioned the difficulty of measuring which occupation-specific skills have been learned in education and across the life course. Thus far, research is able to study occupation-specific skills that are used in and required by the workplace (however, they probably do not display all actual occupation-specific skills possessed by individuals).

Moreover, most of the skill literature focuses on skills that are directly productive for the economy. Other skills receive less attention, although they may be equally important for sustaining a society (and thus also labor markets), for the democratic involvement of citizens, or for the personal development necessary to simply flourish as human beings (Allen 2016; van de Werfhorst 2017). Furthermore, the skills needed to develop and work with information and communication technology (ICT) are understudied, especially in light of the ongoing technological changes; i.e., with artificial intelligence progressing with a rapidity unseen before.

The most urgent task to improve our knowledge of individuals’ skill acquisition and maintenance is to develop longitudinal skills assessments over the entire educational and work career. First, with cross-sectional data and approaches, it is difficult to assess causal relationships between learning, skills, and outcomes. Second, the extent to which earlier skill formations impact later-life skill formations is not well understood. One possibility is that individuals with higher levels of skills obtained in initial education also generate more skill development in later life, thereby producing Matthew effects. However, another possibility is that educational systems (such as strong VET systems) support substituting a lack of skills produced in initial education with having firms invest more in their workers’ skill development (Bills and van...
de Werfhorst 2017; see also Section 3). For individual countries, longitudinal data have become more widely available; for example, through register data on examinations at various stages in the school career, such as in the Netherlands Cohort Study on Education (Haelermans et al. 2020), or through large-scale data projects, such as the German National Education Panel Study (NEPS; Blossfeld and Roßbach 2019), comparative longitudinal skill assessments are yet unseen but crucial to understanding how educational systems (and their connection to labor markets) foster skill formation over the life course.

Finally, existing research on returns to skills strongly relates to a meritocratic “human capital” explanation for inequalities. Alternative theories have been proposed that criticize a taken-for-granted optimal matching between skills and returns. As discussed above, the theoretical account of educational certificates as an institutional bottleneck or the relational perspective of inequality open the view on who is able to define the value of certain contributions (such as “skills”) to the organization (Tomaskovic-Devey and Avent-Holt 2019). The cultural sociological perspective on valuation also suggests paying more attention to the endogenous process of how the value of different skills is determined (Lamont 2012). As alternatives to the human capital perspective, these perspectives deserve further attention to develop a better understanding of the relevance of skills to labor markets.

Notes

1. Noncognitive skills refer to “patterns of thought, feelings, and behavior” (Borghans et al. 2008: 974). Despite ongoing discussions, we will use the term noncognitive skills in the interest of readability.

2. The country-level correlation between tracking and strength of the VET system is 0.48 (van de Werfhorst 2011).

References


Introduction

A well-functioning labor market with a high employment rate requires an efficient supply of skills, where it is important to find the right employees, develop them and keep them in the company. The provision of skills depends on the functioning of the labor market and wage formation. Moreover, what is sufficient competence for a given job is not static. The demands of working life change over time and look different in different sectors. It is therefore important that there are opportunities to complement knowledge and skills throughout working life.

Issues relating to the supply of skills are thus an important issue for both the state and for the social partners, as well as for individual employers and employees. In some respects, the social partners have common interests, while in other respects they differ. Trade unions and individuals may have an interest in a shortage of employees with an education that the employer wants or is obliged to employ for certain tasks. However, the shortfall should not be so great that the employer is unable to provide for its skills. Extensive skill supply problems run the risk of hampering economic growth and increasing unemployment in the long run.

Employers and their organizations, in turn, are interested in the fact that there is a surplus of people with the right skills for the tasks to be performed and that the employees’ skills are sufficient throughout the employment period.

Finally, the public sector, for its part, wants public investment in education to enable people to quickly establish themselves in the labor market, earn income and pay taxes, making public investment profitable and welfare-enhancing. They also want to ensure that people with a certain education match the demand as well as possible. Both surpluses and deficits of skilled labor have negative effects on the economy. This is perhaps especially true for the more...
expensive educations. When it comes to low-cost education, where the individual bears the greatest cost in terms of lost earnings, the public sector can be more generous.

All in all, there are thus strong driving forces for the education and training systems to be reasonably compliant with the needs of the labor market. However, the fact that different parties have different interests and that education takes time and cannot adapt quickly to new needs in the labor market makes the area full of challenges.

The common interest of the social partners in the development of professions and industries, in issues of skill supply, skill requirements and the possibility of controlling the supply of required labor, is consequently of great importance. This has an impact on the negotiations of the social partners – negotiations that, of course, are closely linked to wage formation and thus cannot be treated in isolation from negotiations on wages, general terms and conditions and other matters. The collective agreements are namely a package of agreements in several different areas that must be accommodated within the employers’ cost limits.

Wage formation takes place in a market between employers and employees. This market is affected by a number of different external factors, where market forces are limited to a certain extent. The state and the social partners often set rules to limit the full effect of market forces. This is done, for example, through the introduction of statutory or collectively agreed minimum wages or through the general declaration of collective agreements, where the latter occurs in many Western countries. This type of intervention in wage formation sets up a floor for how low wages can be; generally throughout the labor market or in a particular sector or occupational group and more. In the Nordic countries, this market impact does not take place through legislation, but mainly through collective agreements and a high level of collective agreement coverage.

Such wage floors established either by law or in Sweden by collective agreements create thresholds into the labor market that increase the risk of unemployment for people with low education and an education that is not relevant or viable in the labor market in which they find themselves. In this context, agreements on forms of employment with a given educational content, that the social partners’ parties have reached, should be mentioned. These agreements, sometimes referred to as vocational introduction agreements or establishment jobs, allow wages below the minimum wage in the collective agreements for a shorter period of time. The purpose is to make it easier for groups with a weak establishment in the labor market to obtain jobs that include training
initiatives. The traditional apprenticeship systems, with low starting salaries for those without work experience, are another way of dealing with this situation.

Another form of market influence is various types of restrictions on individual wage setting, where collective agreements may, for example, contain individual guarantees or tariffs that affect employers’ ability to fully use wages as a means of control. Wage formation is also affected by how well the supply of skills works and by the rules that exist about what knowledge or formal qualifications are required in different jobs. The latter rules can be both statutory and/or contractual. All in all, this can create a shortage or abundance of different categories of workers in the labor market, which in turn can affect both the wage situation and the actions of the social partners.

This chapter discusses several different aspects of the supply of skills with a special focus on the social partners. Initially, the commonly cited human capital theory is described, which emphasizes the importance of human capital as a wage-influencing factor. This is followed by an overview of the structure of wage agreements and an analysis of the more direct role of the social partners in relation to the supply of skills, for example through requirements for being allowed to work in a given profession. After this, the training that takes place in the workplace by already employed people is discussed and the obstacles and driving forces for this type of further training. Finally, the possibilities for retraining between occupations and work throughout working life are discussed. This type of agreement is common in Sweden, but unusual outside the Nordic region.

Salary and skills

The human capital theory

There are a number of economic theories that attempt to explain wage differences in the labor market. The commonly cited human capital theory highlights the knowledge and skills that workers have acquired through formal schooling and on-the-job-training. According to the theory, differences in wages reflect the fact that different occupations differ with regard to requirements for the size and direction of human capital.

With regard to on-the-job training, human capital theory distinguishes between company-specific and general on-the-job training, where the willingness to pay for the education differs. When it comes to firm-specific on-the-job
training, neither the company nor the individual wants to bear the entire cost – it is often shared between them. Regarding general on-the-job training, it is paid for by the individual. The employer doesn’t want to pay a cost that benefits all possible employers.

Therefore, according to the theory, it is probable that most of the staff training offered by the companies is of a firm-specific nature. The fact that this training is often fully paid for by the employer and not shared between the parties doesn’t violate the theory; here the training cost can be seen in a broader perspective and also include the employee’s willingness and commitment to training as a cost that the individual is willing to carry.

Structural transformation of the qualification requirements

There is a continuous structural transformation of the qualification requirements in the labor market – both in terms of formal school education and the on-the-job-training that takes place in companies. The markedly increased demands on the workforce that have taken place in recent decades can be seen in a sharp expansion of the number of educational places at universities and colleges, but also in the fact that certain educations have been extended, such as the educations for preschool teachers, biomedical analysts and nurses. The structural transformation of the competence requirements is also reflected in changed professional structures where nannies and care assistants are replaced by preschool teachers and assistant nurses in Sweden, but also by the introduction of teachers’ ID. The background to the development is complex and is not only based on changes in the content of the work. Different groups in working life have had different strategies for increasing their group’s status and thereby improving wages and other conditions.

In Sweden in the private business sector, the educational requirements are to a much lesser extent formally regulated. The mix of the number of salaried employees and workers in many private enterprises has, however, changed over a long period of time. The proportion of salaried employees has gradually increased and the proportion of workers has gradually decreased. Within the group with working occupations, there has also been a shift toward increasingly qualified occupations. In an increasingly knowledge-oriented economy, the demands on employee training throughout working life have also increased, where staff competence has become an increasingly important competitive factor for countries that cannot and do not want to compete with low wages. The importance of staff training also becomes even more important when the labor market is relatively tightly regulated through labor market legislation, and where the supply of skills can not only be solved with new recruitments.
The important role of the social partners

In Sweden, it is the social partners who, in negotiations, supported by legislation and state insurance systems, determine the basic conditions in the labor market. The legislation constitutes a framework within which the social partners have great freedom to regulate and improve the more detailed conditions for the employees. Large parts of the legislation in the field of labor law are semi-dispositive. This means that trade unions and employers can agree on deviations from the legislation in agreements. In most situations, they are given the freedom to deviate both upwards and downwards.

The areas that are subject to negotiation for the social partners are extensive. The most notable concerns wages and other terms of employment as well as collective agreements on pensions. However, the agreements also concern transition and insurance in the event of, for example, illness, work injury and parental leave. Unlike in other countries, the right to regulate employment conditions through collective agreements is in principle the same for the public sector as for the private sector.

The previously strong position of the payroll plan systems in the public sector, where differences in length of education and work experience greatly affected wages, has been replaced by increasingly individual wage setting. This means that traditional wage equations with education and work experience as explanatory factors explain an increasingly smaller part of the wage differences in Sweden, even though knowledge is often an important wage criterion in wage setting. In addition, education and skills development are still important areas for the social partners to ensure both companies’ skills supply and competitiveness. The return on education affects both the willingness to study and those who want to study for these professions.

The role of human capital in wage formation is also evident in the social partners’ commitment to issues that deal with the supply of skills. This can be anything from influencing education dimensioning to established competence requirements for these educations. There are also ongoing institutional changes that affect the conditions for wage formation. This may involve a change in power relations between the state and the social partners, as well as a change in the focus on labor market policy and more. The state’s influence on wage formation has diminished and changed direction over time. Today, it is the social partners who have full responsibility for wage formation.
Collective agreements on wages

Since the end of the 1990s, a central part of wage formation has been that industry agreements constitute a norm for the rate of increase in labor costs, and thus also for the wage increase space specified in subsequent central collective agreements signed in the labor market. Now, however, the central wage agreements do not always contain numerical conditions for the size of the wage increases, but this is sometimes handed over by central parties to the local parties.

It is thus the level of bargaining that distinguishes central wage formation from local wage formation, but also the right to take industrial action. In almost all cases, this is not an opportunity at the local level. In a system with central wage formation, the size of wage increases is negotiated by trade unions and employers’ organizations at national level, while in a system with local wage formation, it takes place at firm level and under a peace obligation. A common agreement structure is a structure where central parties affirm the local influence, but where a wage increase space is specified in the central agreement in case the local parties fail to.

Although many central collective agreements contain numerical conditions for the size of wage increases, these are usually expressed as minimum levels. This means that local wage formation is more widespread in the labor market than at first glance, but also that local wage formation is strongly influenced by the central level due to the strong normative role that industry agreements have had on wage formation. Statistics on wage outcomes nevertheless show that there is also room for maneuver within the framework of the pattern-setting role of the competitive sector in the wage formation that can be used to change wage relations. Relationship changes that are sometimes driven by changing skills needs and requirements.

Few central collective agreements in Sweden contain specified wage levels for different occupational groups with different educational backgrounds. It is really only in the agreements that contain tariff-wage systems where this is available. However, education occurs as a wage factor in many of the central agreements that contain minimum wages. Of the approximately 650 collective agreements on wages that exist in Sweden, approximately 250 agreements contain specified levels for the lowest wages. Minimum wages are found above all in agreements signed by trade unions for workers and by the trade union Unionen (the largest civil servants’ union in the private sector). There is no uniformity in how the social partners choose to design the minimum wage system in the various collective agreements. In the LO’s unions’ agreements,
there is a great deal of variation in how the minimum wages are designed. Here, positions/occupational groups are often used as a basis for dividing the minimum wage in addition to age and length of employment. Minimum wages for employees with or without vocational training are also common. In salaried employees’ agreements, the minimum wage is usually determined by age and sometimes by length of employment.

On some occasions, special wage initiatives have been made in the collective agreements with a focus on vocationally trained people in the central agreements. It has been a matter of increasing the total wage space that is to be distributed to, above all, professionally trained healthcare staff. This is to secure the supply of skills. But most often this market adjustment takes place in the form of relative wage movements entirely at the local level and not in the central collective agreements. Furthermore, job evaluation and wage mapping are not areas in the collective agreement negotiations for central union parties. This work leaves the social partners entirely to the local parties.

**Skill supply**

A company’s supply of skills is ensured by the employees possessing both basic skills and more specific professional skills, but also that the employees undergo continued training throughout working life. The historically first method of regulating the supply of skills is the traditional apprenticeship system. It is a model that still characterizes the education system in many European countries. The model involves a form of educational employment from relatively young years. The idea is that the education takes place by working in a profession under the supervision of a fully educated and gradually learning more and more qualified elements in the profession. The wage level increases as the knowledge in the profession deepens. Graduates received a journeyman’s certificate and later a master’s certificate as a diploma and this made it possible to practice the profession freely.

In the Nordic countries, with Denmark as something of an exception, the rapid transition from an agricultural to an industrial society meant that the guild system for regulating vocational education remained a relatively marginal phenomenon. The Saltsjöbaden Agreement from 1938 meant that the apprenticeship system in industry disappeared and that the model only survived in the construction sector and in certain smaller trades. Instead, it was the public sector, primarily the state and the municipalities, that was responsible for the development of the Swedish school system. This has meant an increasingly
uniform compulsory basic school education which, among other things, has reduced the skewed recruitment to higher education, but also contributed to a general increase in the average length of education of the population.\textsuperscript{7}

With regard to the position and design of vocational education, this has been the subject of review for a long time, where not least the organizational structure has been subject to significant changes. The connection between the social partners and the education system has remained weaker in Sweden than in the countries that retained their apprenticeship system. In these countries, the supply of skills is often designed in institutional tripartite bodies. The Swedish skills supply is instead more fragmented and the differences between different industries and businesses are large.

Training requirements in working life

In comparison with many European countries, Sweden has had a comparatively low degree of regulation regarding the educational requirements required in different professions. The regulation of professions otherwise has a long history in Europe and builds on the guild system. An important step away from this regulation in Sweden was when the freedom of trade was implemented in 1864. This decision meant that the guild system ceased in Sweden. Another important step in this direction was the December compromise between unions and employers in 1906. It was agreed that employers would be free to employ and dismiss. What the union won in the negotiations was freedom of association and a far-reaching right to take trade union action. Through these decisions, Sweden chose a different path than many countries in the rest of Europe, were they maintained a higher degree of regulation in many professions.\textsuperscript{8}

But of course there are elements of regulations in Sweden as well. A review from 2014 of regulations in Sweden shows that just over a third of these occupations are in healthcare.\textsuperscript{9} Another large category of occupations are those that handle hazardous substances and devices that pose risks to both third parties and the worker. Occupations that are linked to traffic are also highly regulated. In addition to this, there are also licenses, certifications and authorizations in the private sector for various professional categories that are not based on any government regulation. They may have grown up on a voluntary basis or by, for example, insurance companies setting requirements to be willing to provide insurances.

In recent decades, the certificate of professional competence and the like have spread to more and more professions. Teachers and curators are professions
that require a license. Assistant nurses have been promised a protected professional title by the government. Requests for the introduction of license requirements have primarily been driven by trade unions. In addition to quality assurance of the profession, the certificate of professional competence has been judged to increase the status of the profession, and in turn also judged to have a positive effect on salaries. The fact that only people with a license are allowed to perform certain tasks means that there is a restriction on the supply of people with adequate education.

The previously more principled opposition to regulations on educational requirements in working life has eased. In more and more areas, it has become more common to require some form of professional competence certificate. There may be several reasons for this. One is that more and more unions see this as a fruitful strategy to improve the status and conditions. But even from an employer’s perspective, there may be advantages to some form of professional competence certificate among employees. It can be about ensuring the requirements and goals of the business, but also that requirements for Swedish certification in order to perform certain tasks reduce, for example, competition from companies in other EU countries – in an increasingly integrated European labor market. In this respect, both the employee and the employer side can agree that some form of state regulation of the profession is desirable.

Also from a government perspective, there is an increased interest in ascertaining the need for professional qualifications in order to promote and secure development in various activities. This has meant that the state has accepted that more and more, relatively large, occupational groups have become identification professions or equivalent.

Skill supply is a common interest for the social partners and the state, which is expressed in different ways. In some areas, for example in healthcare, collaboration between the social partners and education providers is relatively well developed, while in other industries there are often shortcomings in terms of collaboration with the public education system. Instead, there are often established joint bodies and various types of agreements to ensure the supply of skills and facilitate establishment in the labor market. In several collective agreements, there are regulations concerning employment with educational content. Within the LO unions’ agreement areas, these can be vocational training agreements – often in industries with a tradition of apprenticeships. In other areas, this is regulated by minimum wages that are adapted to age or to age and level of education.
In summary, the ever-increasing demands for specialist competence mean that the need for collaboration around the supply of skills is growing. Neither internal staff training nor apprenticeship systems are sufficient to manage the supply of skills. Even in industries that in principle have completely unregulated occupations, such as the area of trade, initiatives have recently been taken to strengthen collaboration around the supply of skills.

**Upskilling – the right to education in employment**

Staff training is an important complement to the formal training system for companies to cope with international competition. The ability of companies to adapt in a regulated labor market is determined in part by the ability to further train their staff. Staff training also plays an important role in new hires. It is also common for companies to provide some form of staff training in Sweden, but both the nature of the training and the length of the training may differ. There are mainly two statistical sources that examine the prevalence of staff training, one is aimed at companies and the other at employees.\(^{10}\)

According to the survey of staff training in companies in 2015,\(^ {11}\) it appears that nine out of ten companies offer their employees staff training. Small companies with 10–50 employees arranged staff training to a lesser degree than the larger ones. The study also shows that the companies’ provision of staff training is relatively evenly distributed between companies in different industries. However, when it comes to staff participation in training, there are significantly greater differences. The highest participation was found in the mineral extraction industry, where almost nine out of ten employees participated in courses, which can be compared with less than four out of ten employees in the industry where participation was lowest – namely the hotel and restaurant industry. In total, just over half (52 percent) of the employees participated in some form of staff training according to the Continuing Vocational Training Survey.

This is a slightly lower proportion than that reported in the Adult Education Survey (AES).\(^ {12}\) According to AES 2016, 59 percent of those employed aged 25–64 participated in staff training over a 12-month period. This study also showed that permanent employees participated in staff training to a greater extent than fixed-term employees (65 percent and 41 percent, respectively). Staff training was also most common among occupational groups that require university qualifications and in managerial occupations. This could explain
some of the industry-specific differences in participation in the Continuing Vocational Training Survey above.

As mentioned earlier, the human capital theory differs between firm-specific and general on-the-job training, where the company’s willingness to pay for training differs. In Sweden, employers account for the majority of staff training and according to Statistics Sweden’s staff training statistics for 2010, the majority is general (60 percent). The study also showed that 94 percent of the training was completed during working hours.

The fact that employers generally bear the costs and that staff training is seldom company-specific probably means that there is an underinvestment in staff training at present, as companies bear the bulk of the financial risk for the investments. This risks being inhibiting for both companies and society at large, but the staff training is also difficult for the social partners to deal with. The fact that much of the training is general may also be due to the fact that it is simply such training that the company needs. The training in different variants of digital tools, which should be a source of many staff trainings, can rarely be company-specific as these tools are rarely developed by the individual company. These digital tools are probably used by several different companies in a given industry.

The social partners have in several cases reached agreements on guidelines for skills development at work. It can be about emphasizing the importance of mapping the individual employee’s development needs, but also about that competence development must be noticed, stimulated and rewarded. But most often the agreements are about guidelines and not direct commitments concerning competence development.

Reskilling – the right to education after leaving employment

The purpose of the collective agreement is to determine what applies in an employment, regardless of who the employer chooses to employ. Skills supply issues have always been an important part of these agreements. The social partners wanted to create driving forces for education, which made it possible to employ enough people with the right qualifications.

During the late 1950s the first steps were taken to also regulate the conditions for those who left a job and enable retraining for another job in adulthood.
During this time, unemployment was very low and the shortage of labor was great. The most acute economic problem was high and volatile inflation. As the functioning of wage formation is an important part of this problem, talks were held between the government and the social partners about the need to push inflation down to reasonable levels without increasing unemployment and reducing workers' real wages.

Two possible solutions were highlighted. One was that wage negotiations should be coordinated; this was a proposal from the employers. This means that LO and The Swedish Employers’ Confederation (SAF) negotiated wages for all workers. This means that all social partners knew approximately which wage increases other groups would receive and it had a dampening effect on inflation. This in turn led to the centralization of power among the social partners.

The second solution, developed by the trade unions, was a model for economic growth and low inflation. According to the model, the union would pursue a solidarity wage policy. It meant that the profit situation in a given company would not affect the wages. Efficient companies could make increased profits, reinvest it and grow further. Those less efficient, who did not generate profit, would in the long run be eliminated. The people that lost their jobs should instead be helped to others, where there was a shortage of labor. Good financial support in the event of unemployment, help with retraining or relocation were necessary components in this model. It was considered at this time that the state would bear these costs.

The benefit for society as a whole was great – the policies kept inflation down and increased the structural transformation in the business sector. It was, and still is, unique that unions affirm that some of their members become unemployed. This position would probably not have taken place if the central level in the union had not been strengthened by the coordinated wage negotiations.

The civil servants did not consider that active labor market policies were catered sufficiently enough to their needs. The result of this criticism was a new agreement between salaried employees (PTK) and employers (SAF) to improve both the financial compensation and the support given to salaried employees in the event of redundancies. Later, when the state also considered that they would need to restructure their operations, a similar agreement was written in the state sector.

LO, which organized the workers, considered that labor market policy should be a state matter. It was not until 2004 that an organization was created with
the aim of getting people back to work. The last to introduce a similar agree-
ment was the municipal sector. Redundancies had been unusual in this sector,
but in 2012 the parties in municipal activities also created a transition agency.17

The experience of these agreements on transition has been good. Follow-ups
of those who undergo the interventions indicate that most people quickly
get a job again. Scientific evaluations show that these types of facilities have
positive results in the longer term, while the short-term effects shine with
their absence. Many other labor market initiatives have on the contrary led to
negative results.

Conclusions

In European countries with relatively strongly organized workers, different
models for organizing the labor market were chosen at an early stage. These
early choices have affected the issues of skill supply. In Sweden, but also in the
other Nordic countries, with Finland as something of an exception, a line was
drawn between what was the responsibility for the social partners and what
was the commitment of the state. In countries such as Germany, Switzerland
and Austria, but also to some extent the Netherlands, Belgium and France,
tripartite solutions were increasingly relied on between the public sector and
organizations of the employers and the workers.

The Nordic labor market model has given the social partners a larger inde-
pendence. However, issues on the border between the social partners and the
public sector have had difficulties to find a satisfactory organization. One of
these areas is vocational training. General education has to a lesser extent been
negatively affected. It does not require a close collaboration with the social
partners.

In Sweden, the organization of vocational training has been fragmented and
the social partners’ influence has been weak. This has meant that the scope
and focus of this education corresponds to a lesser extent to the needs of the
social partners. The choice made in the Saltsjöbaden Agreement in 1938 to
end apprenticeships in industry reinforced this development. However, the
Swedish Labor Market Board (now the Swedish Public Employment Service)
became an important player in this area. The social partners had a great deal
of influence over the activity of this authority. Labor market training became
an important part of the supply of skills, especially in industry. With the deep
economic and political crisis of the nineties and their lack of legitimacy, due
to the increasing discontent from the employer’s organization, this system stopped working.

The change of the upper-secondary school at the same point, which meant that the dimensioning of different educations was primarily governed by the student’s choice and the freedom of establishment for independent schools, entailed further problems for the supply of skills in working life. The problems have increased gradually despite the efforts made by the social partners in various industries. The new transition package for flexibility, adaptability and security concluded between the main organizations in the private sector and the state in 2022 can be the beginning of a new era.

The opportunity for further and recurrent education and transition facilities has been significantly expanded. The social partners again take greater responsibility at the central level. The missing link in the Swedish labor market model is possibly able to reconnect. This agreement provides a new opportunity to create institutions that counteract the fragmentation of the supply of skills in Sweden.

Notes

1. Depending on how high the minimum levels are, they might affect thresholds for labor market entry.


3. The signaling theory may well be regarded as a partially competing theory to the human capital theory. It is emphasized here that education acts as a signal about the individual’s underlying productivity. The theory of compensatory wage differences instead emphasizes that the wage differences reflect that employment also differs with regard to work environment and job security and more. Furthermore, there are different discrimination theories where different forms of discrimination are highlighted to explain unjustified wage differences.

4. The payroll plan system meant that each position was placed in a grade, where each grade was in turn divided into salary classes according to length of employment.


6. The Swedish Trade Union Confederation (LO) is the central organization for 14 affiliates that organize workers within both the private and the public sectors.


10. The Continuing Vocational Training Survey (CVTS) is a survey aimed at companies and the Adult Education Survey (AES) is aimed at individuals.


14. Now a part of the Confederation of Swedish Enterprise.
16. The council for negotiation and cooperation (PTK) is a joint organization of 25 member unions for salaried employees in the private sector.

References

Skills and macro-level economic inequality

Tomas Korpi, Michael Tåhlin and Johan Westerman

Wage determination at the micro and macro levels

Economic inequality, including wage dispersion, is typically examined within individual countries. Countless studies of inequality in material living conditions exist, and continue to be carried out, providing estimates of economic differences within countries as well as of changes in these differences. Cross-country comparisons of inequality also abound, yet comparisons of wage inequality rates – i.e., labor income – are rare. While research on the welfare state and social policy formation tends to assess inequality in household disposable income as part of its regular cross-nationally comparative agenda, comparisons of national labor markets with regard to wage dispersion are relatively few and far between. The present chapter contributes to filling this gap.

The variation in labor income (per time unit) at the micro level (between individuals) and at the macro level (between countries) is mainly (but not exclusively) caused by variations in productivity. The variation in productivity, in turn, is caused by the variation in (a) individual abilities and skills and (b) opportunities to use these skills; i.e., in access to positions with productivity-related characteristics. But skill is not the main explanation of the macro variation in economic inequality; i.e., of international (and temporal) differences in inequality rates: Skill is important – but why does the pay-off to skill vary? Institutional factors are essential to consider as fundamental (or distal) explanatory factors.

In accounting for international variation in wage inequality rates, it is clear that (a) both skills and institutions are important determinants of inequality, and (b) the impact of institutions is much larger than the impact of skills. For example, using data from the International Adult Literacy Survey (IALS), a forerunner of the more recent Programme for International Assessment of Adult Competencies (PIAAC) that we use in our empirical analyses below,
Devroye and Freeman (2001) show that differences across countries in the wage pay-off to skills account for around five times as much of the international variation in within-country wage inequality as cross-national differences in within-country skill dispersion.

Why does the pay-off to skills differ so much across countries? This is the main question we attempt to answer in the present chapter. The differential pay-off to skills is not the only determinant of the international variation in wage inequality, but it is the most important systematic source. Uncovering the mechanisms involved in its influence is hence vital in order to understand how economic inequality comes about. Institutions in a wide sense are likely to play a leading role in this process.

Growth and distribution

Economic life in general and the labor market in particular has two fundamental properties: growth and distribution. These two stand in a complex relationship to each other (see, e.g., Aghion et al. 1999, Ostry et al. 2014 for reviews). The impact of growth on distribution was long viewed from the perspective of the Kuznets curve according to which economic development initially leads to a rise in (earnings) inequality, an increase that later is reversed. Growth would thus first increase inequality during the transition from agriculture to manufacturing and then decrease inequality as manufacturing matured. However, the rise in inequality before the end of the millennium put this into question, and interest turned to factors that could generate growth and inequality simultaneously. Central among these were globalization, organizational change and skilled-biased technical change, all transformative processes believed to further economic growth and increasing wage and earnings differentials. The changes to production occurring in developed economies in the wake of these transformations would thus increase demand for certain types of skills at the expense of others, a process leading to rising wage inequality. The impact of growth on inequality is in other words uncertain, or variable.

As for the impact of inequality on growth, interest traditionally focused on the functional distribution of income, the distribution of income across the factors of production land, labor and capital. Specific interest was here attached to the wage share, the share of GDP going to workers’ wages, as workers are likely to consume most of their earnings and saving little. A growing wage share would consequently generate less savings, leaving little to be reinvested and therefore leading to lower growth. The links between the earnings distribution and
growth also have attracted some attention in that real or perceived inequality might lead to reforms to the tax and transfer systems, reforms that in turn may increase as well as decrease growth.

Less attention has in contrast been paid to the direct effects of wage inequality on production and growth, aside from the standard economic expectation of sizeable wage differentials providing productivity-enhancing incentives. Nonetheless, efficiency wage theory outlines arguments for why greater inequality might stimulate work effort and thereby productivity and growth, something that also holds for some tournament models. But a counteracting mechanism is that productivity can be improved by wage compression: high wage floors might stimulate skill growth to meet requirements set by high minimum wages (see, e.g., Acemoglu and Pischke 1999; Tåhlin 2004). Wage equality may also generate growth via other routes, for instance through increased cooperation among workers as well as labor-saving investments by employers. A compressed wage structure may furthermore lead to growth at the industry level through the elimination of unproductive and unprofitable firms as well as generating additional profits among productive and profitable firms, profits that may subsequently be reinvested (for an overview, see Erixon 2015). In sum, the relationship between inequality (here wage inequality) and growth is complex and theoretically indeterminate. Empirical analyses are therefore required. The scarcity of such analyses is one important reason to carry out the present exploratory study.

In thinking about this issue it is useful to consider the concept of institutions, defined as rules of the game, both formal and informal (cf. North 1991). Institutions are formed, reformed, and molded on the basis of purposeful action (including the unintended consequences of such action). Growth and distribution therefore relate differently to institutions: while growth is essentially uncontested (with few exceptions, high growth is always preferred over low growth, ceteris paribus), the wideness of distribution is highly contested, with large differences in preferences across population groups and between organized interests (partly on the basis of beliefs about how distribution affects growth). Labor market institutions are here a prime example as their main purpose is to affect distribution, not growth. To achieve or maintain a high growth rate (a general desire) is a restriction on the design and redesign of labor market institutions, but the main purpose of labor market institutions is to modify distribution (a contested desire). Other institutions such as banks may in contrast be said to aim at generating growth, and although these too may be contested it is seldom with the same fervor. Finally, some institutions can be said to target both distribution and growth. Here the main example
would be educational institutions, which in comparison with the other two types could be said to be largely uncontested.

Still, some aspects of growth are socially contested. First, some argue that growth – at least in most of its current forms – is detrimental for the natural environment, and should therefore be kept low (for recent estimations of the trade-offs involved, see, e.g., Hickel 2019). Second, some argue that while high growth is desirable, it is less important to achieve than is a more equal distribution, so even if equality reduces growth, it is a price worth paying (see, e.g., Layard 2005). This view is based on the belief that individual well-being is more affected by relative than absolute rewards. Third, growth rate volatility – the frequency and width of cyclical swings – is typically less tolerated by those who prefer relatively equal distributions, because worker categories with low labor market rewards to begin with tend to be more affected than others by economic downturns.

However, institutions designed to affect distribution may also impact growth, and vice versa. Some institutional regulations intended to promote equality might hurt efficiency by reducing social mobility and weakening work and employment incentives. These include generous unemployment insurance, reducing incentives to re-enter the labor market, high labor taxation, reducing employer incentives to hire new employees, and strict employment protection legislation, reducing social mobility.

Conversely, efficiency promotion might hurt equality by contributing to uneven economic growth across market sectors and/or worker categories. Investments may thus take the form of either financial or productive investments, with potentially very different implications for equality. Likewise, investments in certain types of production processes may further the demand for some workers at the expense of others, e.g., by raising returns to ICT complementary skills.

Such trade-off patterns between equality and efficiency need not dominate their overall associations. With regard to equality institutions, regulation designed to enhance individual security can also improve efficiency by maintaining high levels of resources and aspirations among individuals, thus sustaining productive labor market activities. Concerning efficiency institutions, similar double-edged arguments apply. For example, spending on research and development has been found to have a mixed impact on inequality, innovative companies sometimes pay higher wages also to low-skilled workers and innovation generates social mobility that might displace incumbent firms and
employees and lift newcomers. In short, the net relation between the institutional promotion of efficiency and equality is not clear.

Further, the two kinds of institutions are sometimes intertwined. Innovation might require regulation and protection to overcome inertia and resistance. Incumbent companies with their employees and their public patrons might form powerful alliances against innovation and change. Hence, state regulation of markets can be instrumental in promoting innovation. Such regulation is useful to ensure fair competition and pluralistic markets, to protect displaced workers with welfare state support, to sustain (limited) rents as incentives by protecting intellectual property, and to hold public patrons in check in order to avoid corruption.

In formulating a general framework to guide our empirical analyses, we begin by noting the interdependence between inequality and growth that we briefly considered above: Inequality at any given time-point is essentially a cross-sectional slice of a set of continuous growth processes. Accordingly, the rate of wage inequality at any given time-point is an aggregation of individual wage growth curves with different starting points.

The growth curves in turn are determined by four main factors:

- micro-level skills (individual and job productivity)
- macro-level economic growth (aggregate productivity change)
- institutions affecting and interacting with these two, and
- time elapsed since the start of each growth process.

When accounting for the cross-national variation in wage inequality rates, it is hence essential to take growth-determining factors into account. Previous research on causes of wage inequality has in contrast used a partial framework, neglecting the tight links between inequality and growth.

**Data and estimation**

To measure wage inequality, we use micro data from the Programme for International Assessment of Adult Competences (PIAAC) carried out by the OECD in 2012. Five rates of inequality are estimated as wage returns to skill in various forms: returns to education (in standard Mincer models), to matched education (in ORU models), to class (ISCO 2, professional occupations, relative to ISCO 9, elementary occupations), to numeric skills (PIAAC test
performance), and to on-the-job skill use (a composite of self-reported cognitive and data tasks). These five rates, estimated separately by gender, are combined into one wage inequality measure using principal components factor analysis (single factor). To measure employment rates, institutional traits and economic output, we use macro data from public sources; see further below. The micro- and macro-level data are combined in correlation and regression analyses, including factor analyses.

Altogether, 22 OECD countries are included in the empirical analysis below. Grouping the countries geographically the set includes two nations in Asia (Japan, South Korea), five in central Europe (Austria, Belgium, France, Germany, the Netherlands), three in Eastern Europe (Czech Republic, Poland, Slovakia), five English-speaking countries (Canada, Ireland, New Zealand, UK, USA), four Nordic countries (Denmark, Finland, Norway, Sweden) and three countries in Southern Europe (Greece, Italy, Spain).

While distribution (or inequality) is a cross-sectional slice of a set of growth rates, economic output is the accumulated aggregate result of these growth rates. We measure this output here by combining the level of GDP per capita, indicating the aggregate economic development level of a country, and the average wage level, indicating the economic development level of a country transmitted, via institutional factors, to the labor market.

With regard to institutions, a number were mentioned in the discussion above of the links between inequality and growth. We distinguish between two basic kinds of institutions: those promoting economic growth and those promoting economic equality. In our empirical analyses we will attempt to determine (a) how these two kinds of institutions are associated with each other, and (b) how they affect economic wealth and distribution.

Institutions can in other words be designed to promote efficiency by enabling the transformation of human capital into economic output through several channels. In addition to public spending on (high-quality) education, these channels include protection of property, guaranteeing of contracts, separation of judiciary and political power, assuring competitive markets, and protecting intellectual property (through, e.g., patents).

In general terms, equality-promoting institutions compress distributions of economic rewards in the labor market by “curtailing the discretion of employers in setting wages” (Carbonaro 2006, p. 1820). More specifically, such regulation includes increasing the power of individual workers through collective organization, via both union density and collective bargaining coverage,
ensuring human capital resilience by active labor market policies, and minimizing individuals’ market vulnerability by developing and maintaining social safety nets.

A common point of departure in examining the role of institutional factors in cross-nationally comparative research is regime models of various kinds (see Gallie 2011 for a comprehensive overview). The regimes typically resemble institutionally based clusters of nations that also tend to be geographically proximate. Despite their merits, such models suffer from well-known weaknesses of which one is regime internal heterogeneity.

Here, we use a different approach. The idea is to build, via factor analysis, continuous scales of institutional traits on which each country has a value rather than produce a set of country groups. There are several advantages of the scale approach (see, e.g., Tåhlin 2013, including a previous application). First, regime internal heterogeneity is not a problem, since each country has its own value. Second, a continuous scale is easier and more efficient to use statistically than is a set of categories, especially when estimating associations with other variables. Third, a scale based on a number of items is more reliable than single items, since it is based on the common variance of the items and thus excludes item-specific error variance. Fourth, by using only common variance across indicators, measurement validity is enhanced because theoretical interest in a set of related items is typically tied to an underlying concept which cannot be measured perfectly but is reflected approximately by each item; the partial validities of individual indicators are thus combined into a theoretically superior common factor. Fifth, related to validity, extracting a common factor from a set of individual items accords well with the notion of institutional structure, i.e., with interrelated parts forming a larger entity rather than an aggregate of independent pieces.

We measure equality-promoting institutions by four indicators: (a) Union density; (b) Collective bargaining coverage; (c) Active labor market programs (ALMP) spending, estimated as the program participant share of the unemployed; and (d) General social spending, as a share of GDP. Efficiency-promoting institutions are in turn measured by three indicators: (a) Ease of doing business, which is an index of business climate produced by the World Bank; (b) Innovation friendliness, an index produced by the World Intellectual Property Organization (WIPO, a United Nations agency); and (c) Social mobility, a measure of job shift rates supplied by the OECD.

The underlying causal process we attempt to indicate empirically can be seen as a macro-level version of a standard micro-level model where Skills >>
Jobs >> Income. Using this causal chain at the macro level translates to Skills input >> Employment quantity and quality >> Economic output. This macro process is augmented by institutions that (a) determine skills input, (b) interact with how skills affect employment and (c) interact with how employment affects economic output.

We will here seek to explore these relationships using scatter plots to illustrate how the different variables relate to each other as well as simple linear regression analyses to examine the joint relationships while controlling for some basic background factors. The Online Appendix contains the data used for all analyses below as well as detailed information on data sources.

Table 17.1  Factor analyses (principal components) of seven institutional traits related to promotion of efficiency and equality

<table>
<thead>
<tr>
<th></th>
<th>Efficiency</th>
<th>Equality</th>
<th>Efficiency</th>
<th>Equality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation</td>
<td>0.86</td>
<td>0.30</td>
<td>0.89</td>
<td></td>
</tr>
<tr>
<td>Business</td>
<td>0.94</td>
<td>0.02</td>
<td>0.95</td>
<td></td>
</tr>
<tr>
<td>Mobility</td>
<td>0.79</td>
<td>-0.28</td>
<td>0.78</td>
<td></td>
</tr>
<tr>
<td>ALMP</td>
<td>0.35</td>
<td>0.70</td>
<td></td>
<td>0.72</td>
</tr>
<tr>
<td>Collective bargaining</td>
<td>-0.39</td>
<td>0.78</td>
<td></td>
<td>0.78</td>
</tr>
<tr>
<td>Social spending</td>
<td>-0.23</td>
<td>0.83</td>
<td></td>
<td>0.83</td>
</tr>
<tr>
<td>Union density</td>
<td>0.32</td>
<td>0.82</td>
<td></td>
<td>0.82</td>
</tr>
<tr>
<td>Factor’s Eigenvalue</td>
<td>2.72</td>
<td>2.59</td>
<td>2.32</td>
<td>2.49</td>
</tr>
<tr>
<td>Factor’s share of total variance</td>
<td>0.39</td>
<td>0.37</td>
<td>0.77</td>
<td>0.62</td>
</tr>
</tbody>
</table>

Note: 22 OECD countries, data from OECD, UN, World Bank, 2010–2012 (for details, see Online Appendix). Factor loadings; varimax rotated solution (columns 1 and 2) and single factors (columns 3 and 4).

Promoting efficiency and equality

The initial factor analysis (principal components) of the seven institutional indicators listed above, assumed to be tied to efficiency and equality promotion, indicates as expected the existence of two dimensions; see Table 17.1. What is arguably an efficiency-promoting factor is positively tied to innovation rates, business climate and labor market dynamism indicated by job mobility. The second factor can be interpreted as an equality-promoting cluster, positively linked to union density, collective bargaining coverage, active labor market policies and general social spending.
Figure 17.1 cross-classifies these two factors with each other, locating the 22 OECD countries in the two-dimensional institutional space of efficiency (vertical axis) and equality (horizontal axis) promotion. Is there a trade-off between the two, as sometimes suggested?

Essentially, the answer to this question is no: according to the overall pattern of countries, the regression line is almost flat. The correlation between the two institutional dimensions is close to zero (Pearson’s $r = 0.03$). However, examining the figure more closely reveals some interesting geographical patterns. Excluding the Nordic countries, located in the upper-right quadrant, would thus generate a negative correlation suggesting some trade-off. Nevertheless, within Europe as a whole there is a positive association (opposite to a trade-off), regardless of whether or not the Nordic countries are included.
Furthermore, country size seems to matter. Among countries with relatively large populations there is thus a trade-off; among smaller countries the opposite association holds. Arguments suggesting a general correlation between institutional traits tied to equality and efficiency, in either direction, are thus weak. Instead, correlations differ markedly by country groups, according to geography (likely reflecting institutional configurations) and population size.

Figure 17.2a reveals, as expected, that there is a clear positive association between (supposedly) efficiency-promoting institutions and the level of economic wealth (average wages and GDP per capita); the correlation is strong: .57. Likewise, as shown by Figure 17.2b, there, again as expected, is a clear negative association between (supposedly) equality-promoting institutions and wage inequality (wage returns to skills); the correlation is as high as -.74.

Source: Data from OECD, UN, World Bank, 2010–2012 (for details, see Online Appendix).

Figure 17.2a  Efficiency-promoting institutions (horizontal axis) and economic wealth (composite of average wage level and GDP/capita, vertical axis), cross-classified. Standardized scales (mean 0, s.d. 1) based on factor analysis (principal components), 22 OECD countries.
Besides wage dispersion, two other kinds of labor market inequality are also of interest to examine: employment gaps (by sex, age, education and ethnicity) and skill distributions (dispersions in skill supply and demand). Concerning both employment gaps and skills dispersion, the associations with equality promoting institutions are close to zero (r = 0.05 and -0.03, respectively). These associations are not shown in figure form (but are included in the regression analyses in Table 17.2 below).

So far, the standard expectations are mostly supported:

- Efficiency-promoting institutions are positively linked to economic wealth.
- Equality-promoting institutions are positively tied to economic equality.

Source: Data from OECD, UN, World Bank, 2010-2012 (for details, see Online Appendix).

**Figure 17.2b** Equality-promoting institutions (horizontal axis) and wage inequality (wage returns to skills, vertical axis), cross-classified. Standardized scales (mean 0, s.d. 1) based on factor analysis (principal components), 22 OECD countries
Table 17.2  Regression of inequality (wages, employment, skills) and wealth (composite of average wage level and GDP/capita) on equality-promoting institutions, efficiency-promoting institutions and population size

<table>
<thead>
<tr>
<th></th>
<th>Wage inequality</th>
<th>Employment gaps</th>
<th>Skills dispersion</th>
<th>Economic wealth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equality inst.</td>
<td>-0.60***</td>
<td>0.04</td>
<td>0.06</td>
<td>0.58**</td>
</tr>
<tr>
<td></td>
<td>(4.0)</td>
<td>(0.3)</td>
<td>(0.3)</td>
<td>(3.6)</td>
</tr>
<tr>
<td>Efficiency inst.</td>
<td>0.05</td>
<td>-0.83***</td>
<td>-0.55*</td>
<td>0.51**</td>
</tr>
<tr>
<td></td>
<td>(0.4)</td>
<td>(-6.4)</td>
<td>(-2.8)</td>
<td>(3.5)</td>
</tr>
<tr>
<td>Population size</td>
<td>0.35*</td>
<td>-0.08</td>
<td>0.17</td>
<td>0.37*</td>
</tr>
<tr>
<td></td>
<td>(2.3)</td>
<td>(-0.5)</td>
<td>(0.8)</td>
<td>(2.3)</td>
</tr>
<tr>
<td>R²(adj.)</td>
<td>0.61</td>
<td>0.65</td>
<td>0.19</td>
<td>0.56</td>
</tr>
</tbody>
</table>

**Note:** Significance levels: *** <= 0.001; ** <= 0.01; * <= 0.05; 22 OECD countries, data from OECD, UN, World Bank, 2010–2012 (for details, see Online Appendix); standardized regression coefficients (t-values in parentheses).

But what about unintended (or commonly unanticipated) consequences of efficiency-promoting institutions for equality – and of equality-promoting institutions for efficiency? The empirical patterns (not shown in figure form) indicate that efficiency-promoting institutions are positively (but very weakly) associated only with wage inequality (wage returns to skills, r = 0.08) and actually seems to promote equality in important respects, by strongly reducing employment gaps (r = -0.83) and compressing skill distributions (r = -0.53). Further, equality-promoting institutions have a quite strong positive correlation with economic wealth (average wages and GDP per capita; r = 0.44).

Table 17.2 shows results from a set of regression analyses where equality and efficiency-promoting institutions are considered jointly, together with country (population) size, in accounting for inequality and wealth. The results indicate, first, that equality institutions promote wage equality (Column 1) and economic wealth (Column 4) but do not reduce employment gaps (Column 2) or skill dispersion (Column 3). Second, efficiency institutions promote economic wealth (Column 4) and reduce employment gaps (Column 2) as well as skill dispersion (Column 3) but do not affect wage inequality (Column 1).

The patterns displayed in the table in other words corroborate the findings discussed above, but also provide some evidence that the unintended consequences of efficiency- and equality-promoting institutions may be mostly
beneficial. This is further underscored by Figure 17.3 showing the association between economic wealth and wage inequality. The correlation is close to zero, clearly implying that efficiency and equality typically do not trade off; rather, they appear to be quite possible to achieve in combination.

Concluding summary

This chapter has examined distribution and growth, or equality and efficiency, in a joint framework exploring cross-national differences in wage inequality rates on the basis of cross-sectional micro-level and macro-level data from 22 OECD countries around 2012. Differences between countries in their rates of wage inequality are strongly linked to cross-national variation in the strength of equality-promoting institutions: union density, collective bargaining cov-
verage, active labor market policies and general social spending. Furthermore, international variation in levels of economic wealth (GDP per capita and average wages) is associated with efficiency-promoting institutions: business climate, innovation friendliness and work–life mobility.

In general, there appear to be few trade-offs between equality and efficiency:

- Overall correlations between the two kinds of institutions, as well as between the two kinds of outcomes, are close to zero
- Efficiency-promoting institutions reduce employment and skill dispersion (but not wage inequality) more strongly than equality institutions do
- Equality-promoting institutions raise economic output at least as much as efficiency institutions do.

The pattern of cross-national variation in equality and efficiency conforms to commonly distinguished geographical clusters (Anglo, Nordic, Central, Eastern and Southern Europe), reflecting different institutional configurations.

Country (population) size and location appear to be important contextual factors for how equality and efficiency are determined and associated with each other. The close-to-zero overall correlation between equality and efficiency is the aggregate outcome of (a) a positive (reinforcing) association among smaller countries and among European countries, and (b) a negative (trade-off) association among larger countries and non-European countries.

We conclude that cross-national differences in the rate of wage inequality to a large extent can be accounted for by the international variation in equality-promoting institutions. Importantly, such institutions appear to be quite compatible with the presence of other institutions that tend to promote economic efficiency. Of course, our empirical study of these relationships has been exploratory and quite limited in scope; hence, while suggestive, our findings are highly preliminary. It is an important task for future research to more firmly establish both empirical patterns and the mechanisms involved in producing them. Distribution and growth are determined together, and equality and efficiency can apparently be jointly pursued. Analytical work ahead should use this fundamental dependence as a point of departure.
Notes

1. Aside from the references below, examples include Pontusson et al. (2002), Hanushek et al. (2015) and Hope and Martelli (2019).
2. For a relatively rare example of previous work along these lines, see Kenworthy (2010).

References

In this chapter, I would like to address questions of ethical and social philosophy that arise once we see that meaningful work is central in human flourishing: in a just society, is meaningful work available for all people? Who should do the necessary work that undermines the well-being of the workers performing it? And how can we expand opportunities for meaningful work for more people? In some respects, these are old questions, as utopian social theorists have for centuries envisioned ways in which communities can provide good work and minimize bad work for citizens. In the contemporary philosophical literature, Paul Gomberg (2007) proposes that egalitarian communities share forms of routine unskilled work that harm workers when undertaken as full-time occupations. This chapter is partly a meditation on the merits and limits of Gomberg’s proposal, which on my view can provide a partial solution to problems that arise in conjunction with work and well-being. We have no complete solution to unhappy moral problems created by occupations of routine labor, and I believe we should acknowledge that work that allows us to thrive is a limited social good. The limitedness of meaningful work is not a reason to reject the normative claim that meaningful work is central in human well-being, nor is it a reason against working to transform social organizations so as to increase opportunities for meaningful work. If we have reason to avoid dreaming of a world in which all people are self-actualized, we also have reason for measured optimism, when we look at the transformation of working institutions over the long term.

The question of whether meaningful work is available to everyone, when asked in the context of philosophical literatures that examine the impact of the quality of work upon the worker, appeals implicitly to what I call eudemonistically meaningful work, or work that contributes to human flourishing by developing or exercising agency, skills or capabilities of workers. As I was at pains to demonstrate in *Meaningful Work* (2016), work that is not eudemonis-
tically meaningful is not necessarily meaningless altogether; meaningful work is a multifaceted concept, and unskilled routine work can bear meaning not only in serving purposes but also in providing a source of honor or pride and in contributing to a community. In this way, elements of meaningful work are available to many people. But even if nearly all work has elements of meaning, work still may harm the worker. Working extensively at eudemonistically meaningless work stifles the flourishing of a worker and, in particular, can diminish her cognitive capabilities, her drive toward self-determination and her sense of self-worth. Thus, an intractable problem for social theorists concerns who will perform eudemonistically meaningless work in a community of moral equals in which, from an objective point of view, the flourishing of any one person has the same importance as that of any other person.

In what follows, I look first in sections 1 and 2 at the limited availability of eudemonistically meaningful work and at proposals to share forms of work that are not eudemonistically meaningful. In section 3, I explore the implications of the fact that sharing work represents only a partial solution to problems of work and well-being. Most important among these implications is that even in a well-ordered community, not all people will flourish. This is a hard truth that we should accept, at the same time that we work for structural transformations that bring opportunities for meaningful work into reach for more people. The chapter closes in section 4 with a discussion of ethics as a more adequate arena than politics for expanding opportunities for human flourishing through meaningful work.

On the limited availability of eudemonistically meaningful work

Eudemonistically meaningful work appears to be a limited good, and its limited availability arises ultimately, even if not exclusively, from a need of human communities to have some people perform work that bears extrinsic value and social purpose but that is, in itself, routine, wearisome, stultifying, disgusting, dangerous or otherwise unpleasant. If one is inclined to hope that an ideal well-ordered society will transform or eliminate undesirable forms of work, Russell Muirhead reminds us in Just Work that “in some cases, no amount of fiddling with the conditions of work makes the work more interesting, elevating, challenging or varied. The wars that sometimes need to be fought, the messes cleaned, the fuel mined, the food picked – all point to the likelihood that some work will be endemically dangerous, dirty, physically demanding and intellectually deadening” (2004, 32).
Granting that some social divisions of labor are a part of human life, there is nevertheless a range of ways that communities and businesses can potentially organize labor, and a range of ways to assign, acknowledge and remunerate less meaningful work. One of the guiding arguments of James Bernard Murphy’s *Moral Economy of Labor* is that social divisions of labor result from a constellation of moral and political choices, as communities have considerable flexibility in assigning tasks to persons, such that the assignment of persons to tasks “is always fraught with meaning” (1993, 45). Describing the division of labor in a pin factory, Adam Smith assumes that a division of tasks naturally results in a corresponding division of workers: one man to draw a wire, another to straighten it, another to cut it, and so forth. Murphy, however, emphasizes a distinction originally made by Marx between a technical division of labor – in which processes of working are divided into steps – and a social division of labor that assigns discrete tasks to different workers. He argues that not all technical divisions of labor necessarily entail social divisions of labor; it is possible that one worker can efficiently tackle a number of discrete tasks, albeit there are limits to what one person can do (Murphy 1993, chapter 2 and especially p. 20).

Moreover, empirical studies of experiments in job design show a variety of social divisions of labor are equally commensurate with efficiency and productivity, and increasingly detailed divisions of labor tend to give diminishing returns in efficiency (Murphy 1993, 29–30, 45). Degrading the character of labor undermines worker morale, which undermines productivity. To increase productivity, some firms have experimented with job enlargement, in which workers rotate from task to task, as well as job enrichment, in which workers take responsibility for projects from conception to execution (Murphy 1993, 29–30 and 45). These experiments in job design highlight possibilities for organizing work in ways that reduce monotony for workers, teaching us to set aside assumptions that efficiency and productivity require social divisions of labor in which each task demands its own worker. Let us turn then to examine some of the morally imaginative proposals concerning social divisions of labor.

First, as a response to problems of unfulfilling work, a few social philosophers suggest that human communities can someday cease assigning people to perform such work. The old dream that advancements in technology will someday allow machines and robots to perform the worst occupations is a dream now revitalized by twenty-first-century developments in robotics. These developments promise that in a new industrial revolution, robots will toil in factories, laboratories, food industries and other service sectors, freeing people for more meaningful work or for the pursuit of other ambitions and creative activities. Replacing workers with machines would produce unpar-
alleled cost-savings for companies, but profit-maximizing capitalists are not alone in welcoming a revolution in robot-workers: the hope that dispiriting and dreary work will be done by machines is also an element of some classic conceptions of socialism. Oscar Wilde, for instance, writes in *The Soul of Man under Socialism*:

> All unintellectual labor, all monotonous, dull labor, all labor that deals with dreadful things, and involves unpleasant conditions, must be done by machinery. Machinery must work for us in coal mines and do all sanitary services, and be the stoker of steamers, and clean the streets, and run messages on wet days and do anything that is tedious or distressing. (1993, 298)

But such a proposal is not a complete solution to the problem of unfulfilling work: as Arendt notes in *The Human Condition* in discussing the fundamental limitations of technology in easing the burdens of maintaining life, hundreds of gadgets in the kitchen and a half dozen robots in the cellar cannot fully replace the labor of human beings: someone must operate these technologies, which are not always time-saving and which cannot perform all drudgeries (1958, 122). Moreover, robots and machines cannot do all the work of caring for others who cannot care for themselves, which can be joyous and pleasant but also draining and burdensome. Caring is a human activity involving communication, human touching and empathetic interaction; a society that would outsource childrearing and caring of sick, aged or disabled persons to fully automated institutions would be a dystopia and, as one author writes, “an abandonment of people to machines” (Bubeck 2002, 162).

### On sharing work

As an alternative to the old dream in which no person need perform undesirable work, some egalitarian social philosophers entertain suggestions to share unwelcome work, in order that no one need perform such work as an occupation and, instead, all confront an opportunity to pursue fulfilling work. In contemplating this idea, the philosophical mind often turns immediately to Karl Marx, who suggests in *The German Ideology* that a communist society will regulate production so that no citizen labors exclusively at a single sphere of activity, in order that self-realization will be possible for all (Marx and Engels 1976, 47). Marx’s vision of a society without confining occupational divisions of labor is commonly dismissed as utopian fancy, but in revised form part of his core idea and his critique of oppressive divisions of labor live on in the writings of contemporary egalitarian philosophers of work. At the end of
Justice and the Politics of Difference, Iris Marion Young critiques hierarchical divisions of labor – in which some people acquire authority to conceive, plan and exercise skills in work while others primarily follow orders and perform routine or automated tasks – as unjust and illegitimate in the context of a community of morally equal persons (1990, 214–225). Like other political theorists who follow her, Young clarifies that a critique of hierarchical divisions of labor is not a critique of occupational specialization: specialization resulting in individual mastery of special knowledge, skill or techniques is not only socially advantageous but also, as Murphy adds, the very foundation for dignity and pride among craftsmen (1993, 9).

More recently, in How to Make Opportunity Equal, Paul Gomberg argues that achieving genuine equality requires abolishing social divisions of labor. In contrast to routine work, complex skilled work forms part of what makes a good human life, for contributing to a community through work that demonstrates mastered complex abilities elicits prestige and esteem, whereas life occupations of routine work tend to damage self-development and self-esteem (Gomberg 2007, 73 and 66–74). Insofar as a community remains founded on divisions of routine and complex labor, some members have “lives of disadvantage, lives of mind-numbing labor, social inferiority, and diminished social esteem” (Gomberg 2007, 166). Sharing routine labor would allow all people (particularly those who otherwise labor exclusively at routine work) an opportunity to pursue self-development and contribute complex work to communities. Sharing routine work and allowing all an opportunity for complex work is thus a matter of what Gomberg calls contributive justice. Whereas matters of distributive justice concern what individuals receive from communities, contributive justice concerns what individuals can offer to communities.

It is important to appreciate that the purpose of Gomberg’s proposal is not to abolish all divisions of labor, nor is it a suggestion that people perform work that they lack competency to perform. The philosopher takes issue only with divisions of labor in which some enrich themselves through the development and exercise of complex skills while others perform only routine operations; he has no objection with job specializations, which are necessary for complex societies, in which workers master a subset of a broad body of human social knowledge. In highlighting connections between exercising complex skills and achieving dignity, social esteem and self-esteem, Gomberg writes that a community of equals must be one in which no one’s life need be consumed by routine work, so that everyone can train for mastery of some complex skill; opportunity to do so can be unlimited. But a community of equals is not one in which everyone performs every task to which they are inclined: “People should not do things for which they are untrained or unqualified,” he clarifies.
“If we share routine labor, those now confined to routine tasks will have the opportunity to acquire qualifications and master new knowledge according to their interests … In order to contribute an ability, one must show that one has mastered it” (2007, 76–77).

Some may attempt to counter a proposal that we share routine labor by arguing that, in a just society, advantages of complex work, such as stimulation, satisfaction, or social and self-esteem, could accrue to all kinds of work, if only routine work carried a higher social value. But such an objection runs up against a considerable body of empirical literatures, such as that of Arthur Kornhauser (1965) or Melvin Kohn and Carmi Schooler (1983), which demonstrate that complex, challenging work enhances cognitive capacities and self-esteem, and that non-use of cognitive abilities in one’s life work lowers self-esteem and intellectual development while increasing personal “discouragement, futility and feelings of failure” (Kornhauser 1965, 29). Gomberg adds that the lack of esteem attached to occupations of routine work “is not an artifact of arbitrary evaluations”; routine workers do not receive the social and self-esteem that human beings naturally receive upon mastery of complexity, which elicits admiration on account of the level of difficulty, intelligence, beauty or skill exercised in the activity (2007, 70, 73).

Gomberg’s proposal to share routine work rests on norms of justice, but in fact both moral and prudential reasons can motivate practices of sharing labor. Rotating job assignments in an organization represents one way of communally sharing work, and it contributes to the flourishing of an organization in multiple ways. For example, many Japanese firms practice job rotation, among other methods of work organization that draw on the knowledge and skill of all employees, with results of innovative success as well as efficiency (Koike 1996). The practice of job rotation is also accepted as a training method in some businesses and non-profit organizations in the United States, as moving employees through different jobs within a department, or across departments in an organization, develops a range of skills, knowledge and personal contacts that prepare promising employees for management positions. Job rotation can alleviate worker burnout or fatigue and help prevent repetitive stress injuries in mechanical work. It has been shown to improve worker satisfaction, increase outputs and reduce absenteeism and employee turnover in occupations that would otherwise be excessively monotonous (Friedmann 1961, 21–28).

At the level of large-scale societies, however, proposals to share routine work run up against a litany of objections and obstacles, as critics appeal to values of efficiency and productivity, as well as to a need to respect individual occupational choices and diversities of interests and talents. Sharing routine labor is
morally meritorious but runs up against fundamental limitations as a solution to social problems of work and flourishing. The practice appears feasible in contexts of households and smaller communities or organizations – particularly those united around shared goals, egalitarian values, and a spirit of caring for well-being of one another – but it is doubtful that larger societies could fully implement practices of sharing routine labor. Larger societies would face problems of implementation and accountability, and unless societies resort to dystopian bureaucratic intrusion into the lives of individuals, they realize ideals of contributive justice only imperfectly, in varying ways and measures. One fundamental issue is that larger societies are not entirely like egalitarian households in which a manageable number of people regularly interact, communicate face to face, hold one another accountable for shared duties, offer skills to one another freely, and care for the well-being of one another.

In any case, sharing routine work would not alone solve problems of work and flourishing, for not all oppressive work is simple and routine, readily mastered and thus sharable. Routine work like basic cleaning represents only a subset of a broader class of work that undermines or threatens the flourishing of a worker. There are many examples of skilled jobs that are integral to maintaining social functioning but that are not safe or pleasant for workers themselves: consider, for instance, septic tank technicians, sewer inspectors, glass makers, high-rise window washers, rodent control specialists, medical waste processors, and decomposition analysts at crime scenes. Given the skill level required, these jobs are not sharable. They do offer the satisfaction of serving the needs of communities through the use of developed skills, but aspects of these jobs, such as unpleasant smells, confrontations with disgusting substances, risks of serious injury and accidental dousings with waste, can impinge worker well-being and make them difficult to endure. The ongoing management of sizeable quantities of dirt, muck, and animal or human waste or remains, especially when combined with physical strain and stifling environmental conditions, makes some of these jobs endemically grueling. But due recognition, remuneration, and shortened working days that enable workers to enjoy life outside of work would to some extent alleviate the oppressive qualities of these and other occupations.

When feasible, sharing bad work can be commendable in bringing a community closer to ideals of human flourishing and equality, for unpleasant work is less oppressive for those who merely take a turn at it, and sharing bad work prevents some from flourishing at the expense of others. But sharing is not a comprehensive solution, even when paired with other measures, including reducing the amounts of stultifying work that people must perform, such as by outsourcing such work to machines, cleaning up after oneself rather than
leaving one’s dirt for others to pick up, amply remunerating less meaningful work, acknowledging the value of work that is important but that does not support flourishing, increasing opportunities for occupational mobility and skill training, or reducing the hours of the working day.

That not all people flourish

Although, collectively, the solutions mentioned above could take a community remarkably far in pursuing social justice, it appears unlikely that a community can ensure that everyone will flourish: structural transformations and fundamental shifts in dominant social values could make meaningful work available to many people, but meaningful work cannot be guaranteed to everyone, and it is almost certainly not available to everyone outside of utopias. On the one hand, there is, in essence, a dark side in discussions of human flourishing, in which not everyone flourishes, and sometimes some flourish at the expense of others. It is perhaps natural to turn away from this dark side and, in a sense, both flights into utopian working arrangements and arguments to the effect that all work has dignity are attempts to turn away from the ugliness wherein some lack good work and suffer for the comfort or flourishing of others. But I believe this dark side must be acknowledged and, further, the fact that not every person has or can have meaningful work does not undermine an argument that meaningful work is integral to human flourishing, as I argue in what follows. Yet it is also important to see that the fact that not all people will flourish, because not all can have eudemonistically meaningful work, is not a reason to avoid social and economic transformations that will bring flourishing and meaningful work into reach for more people.

Whereas a number of writers on work and the good life begin from the premise that justice demands that we share the good life – a premise that leads some to propose that we share the worst forms of work – I would emphasize that justice can demand only that we try to bring opportunities for the good life within the reach of more people, or that we strive to create optimal social conditions for universal flourishing. The human condition never contained a promise that everyone will flourish, and it is not a deficiency of a normative theory of the good that not everyone flourishes. The purpose of a theory of human flourishing is to illuminate what it means to live a good human life, and such a theory can serve as a foundation for individual choice-making and social change; such a theory is inherently prescriptive and should be unbounded by present (and by presently foreseeable) social distributions of goods.
In response to those who find it unsettling or unacceptable to believe that not everyone flourishes because not everyone has meaningful work, for example because the centrality thesis may thereby appear elitist or undemocratic, I would first note that the flourishing or good life is not available to all people, regardless of the particular components that one includes as part of flourishing. A common conception of the good life might include wealth, power, luxuries or fame, but these goods are not available to all people, as some people’s lives are poor, powerless, lacking in amenities and relatively unrecognized. If one favors a more modest conception of the good life, in which living well requires, minimally, enough money to live comfortably and enough joy to make life worthwhile, again the good life is not within reach for all people, as, sadly, many people live in wretched poverty or suffer through joyless depressed lives.

To regard a theory of human flourishing as undemocratic because not all people flourish appears to rest on a misunderstanding of the purpose of philosophical accounts of human flourishing, which are inherently normative enterprises. A normative analysis may serve on some occasions to justify existing social arrangements and individual life choices, but ethics is concerned foremost with how we ought to live, and only tangentially with social or psychological rationales for existing arrangements and life choices. As elements of ethics, accounts of flourishing serve first to illuminate human ideals; secondarily, they can also serve as foundations for advocating social change.

In brief, part of the purpose of a theory of human flourishing is to illuminate a need for change in individual lives and social organizations, and to this end it is fruitful to explore solutions to social problems that undermine human flourishing. The solutions to problems of undesirable work reviewed here – including sharing routine work, outsourcing unfulfilling work to machines, reducing the working day and fairly enumerating and recognizing the value of many forms of work – cannot guarantee that opportunities for meaningful work will be available to all people, but this lack of a guarantee is not a reason to avoid transforming working institutions so that work promoting psychological health and self-development becomes possible for more people.

There may be no ultimate remedy to the lingering dark side of work and flourishing, wherein some people do not have richly meaningful work and hence do not fully flourish. At this juncture, some may turn to value pluralism, which I briefly consider below (for a more elaborate discussion, see Veltman 2016, chapter 6). But I should like to underscore first that asserting that a person does not flourish is not tantamount to asserting her life lacks value: there is no inconsistency in claiming, on the one hand, that not every person leads an excellent human life, for some lack meaningful or fulfilling work or other
basic goods, and on the other hand that every person’s life has intrinsic worth. Indeed, it is precisely an equality of worth and potential in all human life that provides a foundation for discouraging forms of work that undermine human agency, dignity and capabilities, even if not all such work can be eliminated entirely.

At the root of value pluralism are the important questions, “Is it not possible that people can achieve happiness without meaningful or fulfilling work?” and “Why can work that lacks meaning – or a life that lacks work altogether – not be chosen autonomously and reasonably by a person who has other life priorities?” In responding, I would begin by referring the value pluralist to the empirically well-documented impact of work on cognitive capabilities, autonomous agency and self-respect (see the review in Veltman 2016; esp. chapter 2). Given this profound impact, a desire for meaningful work is clearly more than a mere individual preference or a subjective taste.

A person is unlikely to fare well in life if he is out of work or if he lacks good work, for even if he can secure some of the goods enumerated above from sources such as family or leisure activities, he can be expected to lack a fuller array of the psychological, social, moral and economic goods that flow primarily from good work and, accordingly, he will not thrive. Accordingly, well-ordered societies provide opportunities for meaningful work, individuals would be well advised to pursue these opportunities, and the philosophical view of value pluralism, which casts work as having no special significance in an individual’s life (see, e.g., Arneson 1987), is false.

Value pluralists appear to imagine individuals as reasonably choosing meaningless work in exchange for meaningful leisure or greater freedom, which can facilitate all kinds of worthy private pursuits. In responding to the view that people can lead satisfying, excellent or virtuous lives while working unchallenging jobs, Gomberg (2007) notes that the relevant question for social justice should not be whether it is possible for a person to lead a good life without challenging, complex work but whether social organization makes it more or less likely that a person will do so. In essence, in thinking about how social institutions can improve working life, we must consider what social structures are likely to produce or encourage in human communities, rather than what is merely possible for persons to achieve in a given context.

Without meaningful work even the rich lack important human goods and virtues, such as a sense of purposiveness, pride and accomplishment that flow from work in which one utilizes oneself in contributing to the world. Indeed, it may be for the reason that work brings several benefits that most of the
abundantly rich work (see, e.g., Muirhead 2004) and that a majority of people incorporate work when asked to envisage a fantasy life of economic freedom. In a classic study that has since been replicated and expanded with similar results, Morse and Weiss (1955) asked men and women in both blue collar and professional occupations whether they would continue to work if they won the lottery and faced no economic need for work. A vast majority (80%) answered that they would continue to work even without an economic need to do so (Gini and Sullivan 1987 review a number of similar studies).

In light of the impact work has upon workers, I would like to turn next to address questions concerning how communities can support the provision of meaningful work.

**Ethical and political implications of the centrality of meaningful work in human flourishing**

The centrality of meaningful work in human life does not itself entail a mandate on the part of governments, businesses or other employing organizations to provide meaningful work to people as a matter of right. The centrality thesis is a normative claim with open social and political implications, and specific arguments must be given to justify any particular program of social and political reform in light of the importance of meaningful work in living well. Still, I would join others in asserting that a decent social and political order does not undermine human flourishing but, on the contrary, promotes opportunities for acquiring basic human goods, including meaningful work. Among other philosophers, John Rawls argues that a well-ordered society provides opportunities for meaningful work, as the lack of meaningful work undermines a person’s sense of security, self-respect and social membership (Rawls 1996, lix). Although Rawls does not treat the topic of work in any detail, his claim that a well-ordered society provides meaningful work captures what is perhaps the right picture of a network of social institutions – including but not limited to businesses, non-profit organizations, hospitals, schools, universities, families and government agencies – together providing opportunities for meaningful work. This picture is not one in which the state takes responsibility for distributing meaningful work or for determining what makes work meaningful. If indeed a well-ordered society provides opportunities for meaningful work, a key question in this context concerns how social organizations can support this provision. Let us turn now to examine this question.
Foremost, businesses and other employing organizations support the provision of meaningful work by creating and sustaining jobs that pay a living wage and that allow people to contribute knowledge and skills to communities. Not all jobs fit this bill, and as I discussed above, sharing routine labor and utilizing machines for eudemonistically meaningless work promise some success in ameliorating oppression in working life and in making meaningful work possible for more people. Additional possibilities and methods for social change include community and consumer activism rooted in ethical judgments of businesses whose activities are short of what is right, even if in the confines of what is legal. The starting point for such change is greater public awareness of the realities of working life: affluent persons in particular should come to see that our comfortable and pleasant lives depend on the toil of workers whose suffering is ordinarily shielded from our view in, for instance, the misery of the maquiladoras or in sweatshops around the globe. These forms of work undermine the health of workers, imposing mind-numbing repetition and physical strain upon people who toil for extremely low pay amid noxious chemicals while stuck at workstations, sometimes unable to get up and move about freely. Consumers have a tendency to ignore this dark underbelly of their purchases and, as Russell Muirhead writes in *Just Work*, “to wish away the bad work we make necessary, and to turn away from those who do such jobs” (2004, 173). Overcoming this ignorance and confronting the suffering of those whose work is bad is an important first step in envisioning and implementing a diverse handful of solutions to problems of bad work.

In addition to public awareness of realities of oppressive work, both labor laws and ethical judgments merit a place in regulating working life in a liberal democracy, as ethics transcends the law, and there are limits to what the law can achieve in promoting employee well-being. The force of law appears more suitable than the influence of ethical judgments in responding to problems of damaging work, whereas providing opportunities for meaningful work—which is a matter of promoting what is good rather than merely preventing or penalizing what is bad—lies in the sphere of ethics rather than politics.

Political coercion cannot ensure all moral action. In the context of work, it is hardly advisable to promote an economic system in which businesspeople believe their only obligation is to obey the law. A strong business and professional ethics provides insurance against moral failures, and in terms of providing employment, integrity in business requires an understanding of social roles and responsibilities of businesses and a consideration of the well-being of employees. As businesses impact human well-being not only in *what* they produce or provide but also in *how* they do so, it is fair to say that a business or other employing organization can merit moral esteem insofar as it has
a manner of production that enhances the flourishing of its employees; such an organization merits moral disesteem insofar as its manner of production imposes largely meaningless, stultifying or damaging work upon people.

If it appears wildly impractical to imagine substantial ethical transformations in the internal operations of profit-minded businesses and other employing organizations, I ask the reader to consider for a moment the considerable measures of moral progress that workplaces have achieved in some quarters of the world in the twenty-first century. In many countries, it is now commonplace to maintain as ideals – and to instantiate in practice in varying degrees – rational and fair hiring processes, non-discriminatory and harassment-free workplaces, equitable wages and freedom from threats, abuse and profanity while on the job. None of these ideals was in place a century ago, when the dominant mode of the production of commodities in the U.S. was the factory system, in which factory foremen used close supervision, abuse, profanity and threats to motivate faster and harder work, and in which work was highly insecure, poorly paid, fraught with pay inequities and ethnic discrimination, and not uncommonly secured through nepotism, favoritism and bribery (Jacoby 2004). Those of us lucky enough to reside in the rich countries of today already live in workplace utopias in comparison with the factories of the late 1800s, when it would have been difficult to see possibilities for the sort of change now becoming reality. Appreciating the moral progress achieved in past centuries highlights the abilities of human communities to transcend and reinvent given workplace structures and should lead us toward a position of open-mindedness in entertaining possibilities for transforming elements of working life that stifle human development or undermine human dignity.

Fundamentally, promoting healthy and meaningful work is a matter of ethics. Prioritizing people over profit, treating workers with respect, respecting the intelligence of working people and creating opportunities for people to contribute developed skills are basic ethical principles not only for employing organizations but also for communities at large. Such principles can work in tandem with more radical social and political initiatives, such as eliminating or reducing occupations of routine labor, instituting a universal basic income that would improve the bargaining position of workers or overthrowing capitalism. It is worth entertaining the more radical solutions, for social and political organizations are not unchanging elements of a natural order but variable human constructions. Without a firmly and widely implanted sense of ethics concerning workers, however, social and political transformation means little and may indeed never take root.
Note

1. This chapter is adapted with permission from Andrea Veltman, *Meaningful Work* (Oxford University Press, 2016).

References


ability-complexity link 7
academic achievement 42
academic community 2
academic education 253
academic upper-secondary degree 95
Acemoglu, D. 46–7
active labor market programs (ALMP) 295
Adult Education Survey (AES) 261, 282
AES. See Adult Education Survey (AES)
African American’s wages 228
agency 2, 9, 26–8, 33–4, 36, 304–5
agency-communion duality 33
aging 162–4
ALMP. See active labor market programs (ALMP)
Almstedt Valldor, A. 65–81
altruism 183–6, 191–4
analytical skills 155
Andersson, A. B. 103–18
antidiscrimination laws 65
apprenticeship system 279–80
Arendt, H. 308
Aristotle’s theory of human flourishing 130
Arneson, R. 314
artificial intelligence 267
assimilation 148, 150–51, 153
attachment disorder 184
attainment 198, 202, 206, 212
educational 2, 65, 105, 156, 180, 184, 198, 202, 204, 206, 212, 232–3, 241–3, 265–6
labor markets 156, 264
occupational 37–8, 42, 148, 212
ORU models of wage 12
automation 38, 235
automatization 44
autonomy 140, 183, 229, 233, 264
Autor, D. H. 8, 43–4
Avent-Holt, D. 217–30
bargaining
collective 294–6
level of 278
model 23
position 22
power 22, 45–6, 48, 122, 222
traditions 5
wage. See wage bargaining
Baumol, W. 56
beauty 218, 310
Becker, G. S. 37, 177, 181, 186–7
Benedict, R. 42
Bernhardt, A. 227–8
Big Five 40
biological sex
definition of 26
gender and 25
Blau, P. 37
Bol, T. 258, 262
Bourdieu, P. 39–40
Bowles, S. 37–8
brain, executive functioning power of 163
British Skills and Employment Surveys (SES) 122, 125
Browning, H. 52
business climate 295–6
business sector 276, 284
capitalism 45, 47, 121, 139, 317
capitalist diversity 137
care services 182–3
caring capabilities 182
categories of 178, 184
care for children 185, 189
definition of 178
development of 188
for physical functioning 179
and self-regulation 180, 190
types of 178
caring labor 183, 185, 192–4
Carneiro, P. M. 162
categorical distinctions 218, 227
Cattell, R. B. 163
Cedefop (European Centre for the Development of Vocational Training) 2
chain-reactive process 32
channeling mechanisms 146–7
Charles, M. 70
childbearing 26–7, 29, 34
children 26, 40–1, 151, 184–5, 187, 190, 193
academic success of 39
capabilities of 188–9
cognitive capabilities 188
competences 260
of immigrants 150
problem-solving skills 180
social environment 259
socioeconomic gaps in 260
socioeconomic progress among 145
Chinese work settings 224
Chiswick, B. R. 148
Chudnovskaya, M. 85–99
civil servants 278, 284
claims making 218, 220, 228, 230
device 227
position 225
Clark, C. 54
class 33
differences 24
formation 103
and gender, measurement of 19
hierarchy 150
identity 105
inequality 23
models 23
non-tautological measures of 34
relevance 25
reproduction, theories of 240
rewards 24
schemas 29
standard measures of 28, 31
structure 150
theories 22
work content measures of 30
closure 106, 219, 224–7, 230, 266
cognitive abilities 4–6, 10, 162–3, 310
cognitive capacity 3, 10, 55, 310
cognitive decline 161–4, 167, 173
cognitive functioning 162–3, 177, 179–80
cognitive map of occupations 26
cognitive skills 2, 37–9, 43, 46–8, 161–2, 191, 193, 238–40, 260, 260. 267
of adults 161
change with age 163
data 164
depreciation of 161
descriptive analyses 167
higher-order 162
measurements 165
propensity score matching 167
school-related 238
cognitive tasks 188, 247
Coleman, J. 47
collective agreements 274–5, 277, 281, 283
purpose of 283
in Sweden 278
on wages 278–9
collective wage bargaining 294–6, 301–2
college-level jobs 252
college wage premium 241, 254
common support 171
communicative skills 146, 148, 153, 155
communion 26–8, 33–4
community 2, 88, 188, 306, 309, 311–12, 316
compensating differentials 192, 195
compensation practices 228
competitive markets 10, 294
complementary occupation-based indicators 55
computer skills, self-rated complexity of 253
contemporary labor markets 53, 145
Continuing Vocational Training Survey 282–3
continuous learning 11
contributive justice 309, 311
control group 168, 170–2
convergence 122, 131, 135, 138
coordinated wage negotiations 284
Correll, S. J. 221
country-specific institutional traits 32
covariation 29, 70, 109
credentialing 224
credentials 10, 38, 67, 180, 198–200, 215, 219, 265
cross-national comparisons 2, 289–90, 295, 301–2
common variance 295
continuous scale 295
growth curves, wage inequality 293
institutional factors 295
internal heterogeneity 295
regime models 295
scale based 295
wage determination, micro and macro level 289–90
wage pay-off, skills 290
crystallized intelligence 163
cultural capital 37, 39–40, 240–1, 243, 247
cultural/culture 48, 66, 127, 139, 163, 219, 227
influence 26
of national groups 41–2
social explanations 87
tradition 25
decision-making 42, 45, 86–7, 89, 121, 126, 128–31
decomposition 69–79, 311
deferred gratification 41–3
demand explanations 55–6
demand side 9–10, 38, 43, 146, 149–50, 219, 234, 254
descriptive statistics 73, 76, 93, 108, 165–6
devaluation process 229
devmental psychology 184
Dictionary of Occupational Titles (DOT) 20–1, 233, 258
Dierdorff, E. C. 9
digital tools 283
dignity 309, 312, 314
DiPrete, T. A. 261
discrimination 39, 65, 68, 80, 146, 150, 155, 232, 317
distributive justice 309
DiTomaso, N. 221
division of labor 8, 22, 25–6, 28–9, 105
divorces 185
Doeke, M. 47
Dorn, D. 44
DOT. See Dictionary of Occupational Titles (DOT)
dual frame of reference 149
Duncan Dissimilarity Index (DI) 70, 91–2
Duncan, G. J. 11, 197, 199, 202, 204–5, 207
Duncan, O. D. 37
Eagly, A. 26, 28–9
earnings 37, 42–6, 156, 177, 180, 185, 191, 197–9, 197–9, 201–3, 201–4, 207–9, 211–13, 221, 228, 258, 260, 274, 290
education and 5
structure of 2
Ebner, C. 9
economic development 1–2, 55–6, 290, 294
economic growth 5, 39, 47, 65, 260, 265–6, 273, 284, 290, 292–4
economic hardship 150
economics 2, 4, 8, 185, 187, 189–91, 197, 211, 227
economic wealth 300–2
efficiency promoting institutions 295, 298–9
equality promoting institutions 294–5, 299
and wage inequality 301
educational attainment 2, 65, 105, 145, 156, 180, 184, 202, 206, 212, 233–4, 241, 247, 263, 265–6
educational certificates 258, 265–8
educational choices 88, 90
educational closure 226
educational/education. See also education systems
categories of 264
Combination of level of 91
content 274, 281
credentials 203, 205
degrees 106, 149, 225, 257, 259–60, 263, 265
differences in 149
disparities 262
employment 279
gendered choices in 87
groups 262, 265–6
institutions 258–9, 265
to jobs 237
levels of 234, 239, 248
linked inequalities 217
literature, sociology of 87
offspring and required years of 206
of parental job and respondent job 205
programs 258–9, 261
providers 90, 281
psychology 237
public investment in 273
research, unresolved issue in 258
scale and levels of 238
and training systems 274
wage association 5
wage premiums 233
demand-side measures of 234
formal 106–9, 146, 151–2
gaps 153
indicators of 14
initial decline of 59
variation in 240
education systems 266
characteristics of 265
description of 257
differences between 264
importance of 258
institutional characteristics of 263
late-selecting 263
schooling as productive skill
enhancement 259
skill formation in (young) adult life 261
efficiency, function of 148
egalitarian views 65
Elbers, B. 262
elementary occupations 79–80, 132
emerging service occupations 80
emotional intelligence 180
emotional qualities 184
employees 13, 58, 67, 69, 71, 73, 75, 78, 221, 226, 228, 273–4, 276, 279, 281–4, 310, 316–17
categories of 139
commitment and performance of 139
expectations of 140
in high-strain jobs 133–4
influence of organisational decisions 129–30
intermediate and lower-skilled 138
involvement practices 235
market power 121
with medium skills 75
psychological stress among 132
in skill groups 125
social class among 22
employment 44, 47, 54–6, 58–9, 68–9, 71, 75, 80, 121–2, 125, 134, 137–8, 156, 201, 204, 224, 262, 273–4, 276–7, 279, 283–5
composition of 59
education after leaving 283
gaps 299
in gender-balanced/atypical fields 89–90
protection 292
relations 22, 137–9
right to education in 282
trends 51, 55–6
England, P. 177–94
equality-efficiency association 292, 298–9
eternal (constant) duality 33
ethics 47, 180, 305–7, 309
ethnicity 38, 40, 243, 247–8, 299
ethnicization 146, 156
ethnic stratification 145–6, 150, 155
eudemonistically meaningful work 305–6, 312
EU Labour Force Surveys (EU-LFS) 69
European occupational sex segregation 69
European Social Survey (ESS) 11, 104, 107–8, 117
experience 33, 38, 70–1, 80, 82, 89–90, 94, 98–9, 122, 132, 134, 137, 157, 164, 168, 170, 183, 185, 199, 201, 212, 217, 238, 275, 277, 285
exploitation 219–20, 226–30
institutional protections against 227
skill and 227
extensive skill supply problems 273
externalities 188–91, 193
Fabling, R. 228
face discrimination 150
factor analysis 28–30, 294–9, 301
Falk, A. 47
family life 33, 201
family responsibilities 67–8
Farkas, G. 37–48
female
employees 76, 129
friendly jobs 68
homemaker role 66
labour force participation 69–70, 73, 80
occupations 29, 31, 78
service sector 65
femininity 25–7
Figlio, D. 41–2, 46
financial compensation 284
financialization 226
financial services 56, 226
Fine, S. 20–1
Finnish Quality of Work Life Survey for the period 1977–2013 122
firm-based skill formation 13
firm-level job descriptions 225
firm-level productivity 228
firm-specific nature 276
Fisher, A. G. B. 54
fluid intelligence 163–4
Folbre, N. 177–94
formal education 145, 238, 240, 265
Forster, A. G. 262
Freeman, R. B. 290
Friberg, J. H. 145–57
full-time education 109, 113
functional distribution of income 290
functionalism 1, 23
functional job analysis 20–1
future skill investments 148
Gallie, D. 121–41
Ganzeboom, H. B. G. 5
Gatta, M. 223
gender
balanced/atypical fields, previous education and employment in 88–9
bias 27
class and 34
closure 226
composition 78
differences 26, 85
discrimination 223
environment 89
equality in labor market 85
field 89
industry 86
non-tautological measures of 34
program 94
and sex 26
standard measures of 28, 31
typical program choice 87
wage gap 27, 35
work content measures of 30
gender inequality 27, 67
in field of study 86
study of 86
in vocational education and training (VET) 86
gender segregation 75, 78, 85–8, 91–2, 98
in educational system 85–6
in labor market 86
in Sweden 85
gender-typed (female or male) work 19
general education, functions of 122, 237, 285
General Electric 224
general skills 257–9, 261–2, 264
acquisition of 257
German Ideology, The (Marx) 308
Germany 45, 51–2, 71, 107, 221, 228, 262, 285, 294
A RESEARCH AGENDA FOR SKILLS AND INEQUALITY

Gintis, H. 37–8
globalization 44, 68, 290
Global Preference Survey (GPS) 41
Godechot, O. 223
Goldin, C. 10, 43, 51, 55, 67–8, 80, 233
Goldthorpe, J. 107
Goleman, D. 180
Gomberg, P. 305, 309–10, 309–10, 314
Gottfredson, M. R. 180
Grimes, A. 228
grouping occupations 19
group-specific intercepts 111
Grusky, D. B. 10, 70
Guttman-style hierarchies 236

habit 40
Bourdieu’s concept of 40
Haldén, K. 65–81
Handel, M. 233–55
Hanley, C. 224
Hanushek, E. A. 37, 41–2, 46–7, 262
happiness 181, 314
hard skills 240
Haupt, A. 9
health 56, 58, 66, 106, 109, 126, 133, 136, 165, 168, 177, 179–81, 183, 260–1, 313, 316–17
Heckman, J. J. 38, 40, 42, 162
height 218
Hermansen, A. S. 145–57
higher education (HE) programs 261–2
higher education systems, institutional differences in 257
higher-skilled workers 45, 138
higher vocational education (HVE) 85, 87
choice 94
dominant program in 96
enrollment in 90
field of study 91
fields of training 89
goal of reducing gender segregation 88
participation 89
person’s enrollment in 91
program choice 89
system 87
high-skilled occupations 28, 67–8, 75, 80
high-skilled workers 45
hippocampal atrophy 163
Hirschi, T. 180
Hoffman, S. D. 11, 197, 199, 204–5, 207
Hofstede, G. H. 41
Hofstede, G. J. 41
Ho, K. 226
household
income 109–14
production 177
How to Make Opportunity Equal
(Gomberg) 309
human capabilities
adequate theory of 187
theory of 177
capabilities
for caring 182
cognitive functioning 179
human needs 178
for physical functioning 179
for self-regulation 180
conceptualization of 177
costs of obtaining 186
description of 177
developing capabilities 186
form of 148, 181, 184
importance of 275
inadequacies of the neoclassical view 190
investment 179
models 2, 5, 220
resources 65
size and direction of 275
theory 1, 145–6, 148–9, 186–7, 189, 191, 199, 217–18, 222, 233, 254, 275, 283–4
wage equations 10
wage formation 277
Human Condition, The (Arendt) 308
human flourishing 130, 305–6, 311–13, 315–17
dark side 312
good life 313
meaningful work 305–6, 312, 315–17
theory 312
as undemocratic 313
human life
material structure of 33
universal traits of 34
human needs 177–8, 183
human resource management 1, 4, 9
human services 60
expansion of 56
growth in 57
jobs within 58
upgrading from 59
HVE. See higher vocational education (HVE)
IALS. See International Adult Literacy Survey (IALS)
identical skills 162
immigrants
descendants of 155
groups of 156
labor market 150
native-born descendants of 156
and native skill gaps 155
occupational sorting of 145
immigration 109, 145–6, 156, 165
long-term consequences of 146
status 165
incentives 148
inclusive institutions 46
income distribution 111, 260, 266
income transfers from immigrants 229
incorporate educational requirements 117
individuals
abilities 4
beliefs 90
characteristics 4
cognitive and noncognitive skills of 39
decision-making 86
educational choice 90
education levels 221
labor market 266
productivity 3, 220
rational choice 88
resources 4
skill acquisition 260
wage setting, restrictions on 275
industrial and organizational (I-O)
psychology 6
classifications 54
structure 126
comprehensive perspective on 3 and differentiation 19
in human capital 37
study of 37
inflation 284
influenced beliefs 28
information technology (IT) tasks 247
innovation 217, 224, 292–3, 295–6, 302
inputs 187
institutional/institutions 5, 46–8, 67, 238, 258–9, 289–302, 305, 308, 313–15
contexts 56, 86
variation 24
intelligence 163–4, 180, 226, 267, 317
types of 163
intergenerational assimilation 151
intergenerational inequality research 206
intergenerational linkages 203
intergenerational mobility 201–2, 211–12, 212, 301
intergenerational ORU 207
intermediate skills 131, 135
International Adult Literacy Survey (IALS) 258, 289
International Standard Classification of Occupations (ISCO) 69, 76
intractable poverty 46
investment 40, 42, 47, 148, 161–2, 177, 185–91, 193, 201, 226, 273, 283, 291–2
JA. See job analysis (JA)
Jagelka, T. 38, 40, 42
Jencks, C. 37–9
job analysis (JA) 4–5, 7, 20–2, 205
approach 205
used systems of 7
job complexity 3, 5, 8, 22, 233
aspect of 242
dark matter of 238
definition of 10
importance of 9, 12
measurement 9
and productivity 7
specific measures of 234
terms of 5
valid indicator of 11
wage regressions by 13
job content
dimensions of 235
measures of 236
job learning 253
times 241, 243, 250, 252–3, 255
job performance 3–4, 6–7, 10, 12, 40
psychological literature on 6
job quality 121–4, 126, 132, 136–40
dimensions of 132
index 137
indicators 127
level of 136
polarisation 122
skill differentials in 137
job required education 243
and job task content 241
substantive meaning of 247
jobs
basic task structure of 21
characteristics of 34, 185, 235, 258,
262
complexity of 55
educational requirements of 5, 12,
235
evaluation 279
human workers in 44
insecurity 121, 126–7, 134–6, 235
mismatch 234
mobility 9, 296
performance 7
placement 262, 265
requirements 34, 198, 200, 225,
240–1, 247, 254
retention 201
rewards 222
rotation 310
skill distribution of 44
task complexity of 218
job security 135
of women 135
job skill requirements
concepts of 233
data and general approach 235
job skills 153, 239
estimated gaps in 151
job strain 132, 139
job structure 31, 121–2, 139
job tasks 11, 20, 37, 43, 48, 67, 128, 148,
233–6, 234–7, 239, 241–2, 241–54
Justice and the Politics of Difference
(Young) 309
Just Work (Muirhead) 306, 316
Karlin, A. 47
Kautz, T. D. 38, 40, 42
Kirkegaard, E. O. W. 47
Kjellström, C. 273–87
knowledge 10, 39, 106–7, 117, 127, 139,
149, 162–3, 183–4, 238–40, 243,
254, 259, 273, 275–7, 279, 307,
309–10, 312
society 68, 124
Kohn, M. 310
Kornhauser, A. 310
Korpi, T. 204, 289–303
Kristal, T. 45–6
Kuznets, S. 290
labor
complex divisions of 220
divisions 33
by class 22
by gender 25–6
historical 28
organizational 218
force, gender composition of 70–1
qualities 23
shortage 284
supply 66
labor markets 2, 9, 25, 27, 32, 34, 38, 161
attainments 156
basic conditions in 277
collective agreements signed in 278
contemporary 53
demand side of 10
in destination country 149
disadvantages 146, 149
for earnings 185
and education 233
entry 257
functioning of 273
inequalities 259
institutions 5, 291
distribution 291
economic rewards 294
growth and distribution 290–92
high growth rate 291–2
integration 261
legislation 276
occupations in 51
over time 59
policy 277, 284
position 199
research by measuring skills 258
rewards 22, 29
sectors 54
security 121
(dis)similarities in 90
skills 51
composition of work in 60
mismatch for 11
requirements in 59
upgrading in 65, 68
Spanish 13
stratification in 19, 197
structural locations in 104
structure of 19
success 38
values 265
women in 71
work 68
workers in 275
labor sharing
complex work 309
job rotation 310
large-scale societies 310
specialization 309
unpleasant work 311
unwelcome work 308
language 9, 43, 155, 179, 184
learning among immigrants 148
skills 148
leadership tasks, indicators of 243
learning
new things 131
phase of 11
time 123, 126
least skilled workers 200
Leibenstein, H. 56
level of education 165
Levels, M. 161–73
liberal market economy 45, 121
licensing 224–5
lifelong learning 258, 265
Likert response formats 236
Lindh, A. 103–18
linguistic skills 148
literacy 162, 164–7, 170, 237, 239, 242,
248, 255, 257–8, 264, 267, 289
tasks 242
Liu, Y. 10
LNU (Swedish Level of Living Survey) 11–14, 21, 34, 57–8
lodging, provision of 54
Long-Term Orientation (LTO) 41
low-skill occupations 146–7
macro-economy 134
macrosocial variables 47
Magnusson, C. 19–35
major occupational groups 66, 70, 73,
75–80
male-dominated fields 88
male dominated occupations 29, 65
managerial skills 260
managerial work 23
manual jobs 24, 32, 153
manual labor 55, 224
manual occupations 107, 116, 150
manual tasks 24–5, 29, 43
manual work 24–5, 52, 104, 106–7, 109,
113, 132, 145, 224
Maré, D. C. 228
marked skill gradient 131
market adjustment 279
market competition, loose coupling of
220
market globalisation 121, 138
market mechanisms 32
market production 187
market services 54, 56, 58–61
Marxian formulation exploitation 227
Marx, K. 103, 130, 227, 307–8, 308
mathematics 237, 248, 259, 264
math skills 192, 248
Mead, M. 42
meaningful work 305–7, 312–17
centrality, ethical and political
implications 315–17
eudemonistically 305–8
human flourishing 312–15
<table>
<thead>
<tr>
<th>Term</th>
<th>Page Numbers</th>
<th>Source/Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>sharing</td>
<td>308–11</td>
<td></td>
</tr>
<tr>
<td>well-ordered societies</td>
<td>314</td>
<td></td>
</tr>
<tr>
<td>medium-skilled group</td>
<td>78</td>
<td>Melzer, S. M. 221</td>
</tr>
<tr>
<td>medium-skilled occupational category</td>
<td>78</td>
<td>Mendez, I. 42</td>
</tr>
<tr>
<td>mental health</td>
<td>180</td>
<td></td>
</tr>
<tr>
<td>meritocracy</td>
<td>217, 217</td>
<td></td>
</tr>
<tr>
<td>metaphysical dualism</td>
<td>179</td>
<td></td>
</tr>
<tr>
<td>Meyer, J. W.</td>
<td>264</td>
<td></td>
</tr>
<tr>
<td>micro-macro links</td>
<td>47</td>
<td></td>
</tr>
<tr>
<td>mid-level gender</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td>Midtbøen, A.</td>
<td>145–57</td>
<td></td>
</tr>
<tr>
<td>migration background</td>
<td>86, 89</td>
<td></td>
</tr>
<tr>
<td>Miller, P. W.</td>
<td>148</td>
<td></td>
</tr>
<tr>
<td>Mincer, J.</td>
<td>11, 197, 199</td>
<td></td>
</tr>
<tr>
<td>Mincer model</td>
<td>293</td>
<td></td>
</tr>
<tr>
<td>mind-body duality</td>
<td>38, 179</td>
<td></td>
</tr>
<tr>
<td>M-index value</td>
<td>79</td>
<td></td>
</tr>
<tr>
<td>minimum wages</td>
<td>32, 44, 227, 274, 278–9, 281, 291</td>
<td></td>
</tr>
<tr>
<td>Minkov, M.</td>
<td>41</td>
<td></td>
</tr>
<tr>
<td>monetary wealth</td>
<td>54</td>
<td></td>
</tr>
<tr>
<td>Moral Economy of Labor (Murphy)</td>
<td>307</td>
<td></td>
</tr>
<tr>
<td>moral progress</td>
<td>317</td>
<td></td>
</tr>
<tr>
<td>Morse, N.</td>
<td>315</td>
<td></td>
</tr>
<tr>
<td>most skilled workers</td>
<td>200</td>
<td></td>
</tr>
<tr>
<td>motivation</td>
<td>130, 148, 167, 177–9</td>
<td></td>
</tr>
<tr>
<td>Muirhead, R.</td>
<td>306, 316</td>
<td></td>
</tr>
<tr>
<td>multinomial logistic regression</td>
<td>86, 91–2, 96–8</td>
<td></td>
</tr>
<tr>
<td>multinomial regression models</td>
<td>94–5</td>
<td></td>
</tr>
<tr>
<td>Murphy, J. B.</td>
<td>307, 309</td>
<td></td>
</tr>
<tr>
<td>Mutual Information (MI) index</td>
<td>66, 69</td>
<td></td>
</tr>
<tr>
<td>myriad discrete</td>
<td>238</td>
<td></td>
</tr>
<tr>
<td>national character studies</td>
<td>42</td>
<td></td>
</tr>
<tr>
<td>national context</td>
<td>86</td>
<td></td>
</tr>
<tr>
<td>national groups</td>
<td>41, 48</td>
<td></td>
</tr>
<tr>
<td>national institutions</td>
<td>46, 121</td>
<td></td>
</tr>
<tr>
<td>National Longitudinal Survey of Youth</td>
<td>203, 205, 211</td>
<td></td>
</tr>
<tr>
<td>1979 (NLSY79)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>neoclassical theory</td>
<td>177, 187, 190–1</td>
<td></td>
</tr>
<tr>
<td>NEPS (German National Education Panel Study)</td>
<td>268</td>
<td></td>
</tr>
<tr>
<td>Netherlands</td>
<td>86, 107, 148, 262, 268, 285</td>
<td></td>
</tr>
<tr>
<td>networks</td>
<td>150, 188, 203, 218, 221, 233, 258, 266, 315</td>
<td></td>
</tr>
<tr>
<td>new home economics</td>
<td>177, 185, 189</td>
<td></td>
</tr>
<tr>
<td>noncognitive educational outcomes</td>
<td>240</td>
<td></td>
</tr>
<tr>
<td>noncognitive job tasks</td>
<td>241</td>
<td></td>
</tr>
<tr>
<td>noncognitive skills</td>
<td>37–9, 41–3, 46, 48, 161, 164, 260</td>
<td></td>
</tr>
<tr>
<td>children’s acquisition of disadvantaged individuals</td>
<td>260</td>
<td></td>
</tr>
<tr>
<td>measures of research</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td>research on</td>
<td>42</td>
<td></td>
</tr>
<tr>
<td>non-manual occupations</td>
<td>67, 107, 113</td>
<td></td>
</tr>
<tr>
<td>non-manual work</td>
<td>24–5, 108–9, 113, 117</td>
<td></td>
</tr>
<tr>
<td>nonmarital births</td>
<td>185</td>
<td></td>
</tr>
<tr>
<td>nonroutine jobs</td>
<td>43–4</td>
<td></td>
</tr>
<tr>
<td>normal ageing</td>
<td>163</td>
<td></td>
</tr>
<tr>
<td>Norway</td>
<td>107, 145, 151, 153, 156</td>
<td></td>
</tr>
<tr>
<td>labor market</td>
<td>146, 153, 156</td>
<td></td>
</tr>
<tr>
<td>numeracy</td>
<td>162, 164–5, 167–8, 171–3, 237, 239, 248, 253, 258, 267, 269</td>
<td></td>
</tr>
<tr>
<td>skills</td>
<td>164–7, 168, 171</td>
<td></td>
</tr>
<tr>
<td>Nylander, E.</td>
<td>85–99</td>
<td></td>
</tr>
<tr>
<td>objective measures</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>occupational attainment</td>
<td>37–8, 148, 212–13</td>
<td></td>
</tr>
<tr>
<td>occupational careers</td>
<td>257</td>
<td></td>
</tr>
<tr>
<td>occupational incumbents</td>
<td>19, 28</td>
<td></td>
</tr>
<tr>
<td>Occupational Information Network (O*NET)</td>
<td>2, 14, 16, 21, 203, 205, 233–4, 234, 236, 239, 258</td>
<td></td>
</tr>
<tr>
<td>occupational mobility</td>
<td>312</td>
<td></td>
</tr>
<tr>
<td>occupational/occupation</td>
<td>69</td>
<td></td>
</tr>
<tr>
<td>categories</td>
<td>79, 109, 111, 124</td>
<td></td>
</tr>
<tr>
<td>by educational requirements</td>
<td>110</td>
<td></td>
</tr>
<tr>
<td>gender segregation in</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>closure</td>
<td>226</td>
<td></td>
</tr>
<tr>
<td>coding</td>
<td>58</td>
<td></td>
</tr>
<tr>
<td>composition</td>
<td>66, 68, 78</td>
<td></td>
</tr>
<tr>
<td>concept</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>by employers</td>
<td>65</td>
<td></td>
</tr>
<tr>
<td>groups of 70, 73, 80, 104, 123, 229</td>
<td></td>
<td></td>
</tr>
<tr>
<td>change in segregation within</td>
<td>77</td>
<td></td>
</tr>
<tr>
<td>rankings of 122</td>
<td></td>
<td></td>
</tr>
<tr>
<td>incumbents of 20</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>licensure</td>
<td>225</td>
<td></td>
</tr>
<tr>
<td>maturity</td>
<td>198</td>
<td></td>
</tr>
<tr>
<td>prestige</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>ratings of</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>scale</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>ranking</td>
<td>109</td>
<td></td>
</tr>
<tr>
<td>self-direction</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>sex distributions</td>
<td>30</td>
<td></td>
</tr>
</tbody>
</table>
skill requirements in 151
specificity 262
specific programs 262
specific skills 262
stratification 4
titles 203
upskilling 75, 80
occupational sex segregation 65–6, 68
across time and countries 67
on average 66, 73–4
change in 73
data and sample 69
empirical strategy 69
within Europe 71, 79
persistent 66
skills and 67, 80
variables 69
occupational skills 107–8, 112, 145, 258
analytical strategy and modelling
111
data 107
intergenerational assimilation in 151
levels of 259
main results 112
profiles 148, 151, 153
requirements 145
subjective social status 104–5,
112–13, 116
theoretical background 104
theoretical perspectives on
immigrants 148
occupational specialization 309
occupational structure 2, 37, 43, 69, 73,
103, 106, 111, 113, 117, 257
occupation-education-destination (OED)
framework 202
occupation matching 198–203, 211–12
consequences of 200
forms of 200
for individuals and households 201
Oesch, D. 51, 107
offspring education 206
attainment and earnings of 198
and labor market outcomes 203
ORU estimates of 206
on-the-job learning 12–14, 253
on-the-job-training (OJT) 67, 239, 275
opposite-gender dominated program
94–5
oppressive work 311, 316
organizational context 222
organizational inequality regimes 218
organizational performance 9
organizational psychology 9
origin-education-destination (OED)
framework 198
ORU model 197–8
combined generations 209
evidence from 199
intergenerational 198, 202, 204, 207
parental components 202
standard 199
Otis, E. 223
overeducation 197–201, 204, 212, 234.
See also ORU model
across careers 200
analyses of 197
evidence points to 201
overqualification, definition of 200
Ozak, O. 47
Panel Study of Income Dynamics (PSID)
11, 199
parental education 87, 165, 203, 205–8,
211–12
analytical approach and research
design 203
parental generation, gender differences
in 198
parental overeducation 204, 206
components of 205
effects of 206
parental surplus education 202, 206–10
parental surplus occupation 198, 202,
206–12
parents 87–8, 146, 148, 150, 165, 168–9,
172, 180, 184, 187–90, 194, 202,
206–7, 211–13
parent-to-child social mobility 37
Parsons, T. 27
participants/participation 28, 65, 68–70,
73, 79–80, 85, 89–90, 126–7, 127,
129, 139, 258, 262–5, 282–3
gender-composition of 90
indicators of 126
pay-off to skills 289–90
payroll plan systems 277, 286
pecuniary rewards 185
peer training 226
Penn World Tables 111
people oriented tasks 29–31
people-oriented work 21, 32–3
performance
ability and complexity on 7
dimension of 6
individual-level determinant of 6
measures 6
useful predictors of 6
personal education 241–7, 255
personality 9, 149
personal services 54–6, 58–60, 129, 132, 191
category 59
workers 123
personal traits 9, 149
person-side education 237
physical capabilities 179, 181
physical disamenities 185
physical functioning 177, 179
physical health 126, 133, 179
physical skill 148, 179, 183–5
physical tasks 188
PIAAC. See Programme for
International Assessment of Adult Competencies (PIAAC)
piece rate systems 222
pluralism 313–14
polarization 8, 121–2, 124–39
evidence of 124, 129, 135
literature on 124
policy development, process of 2
political economy 44, 190, 257, 261
poor nations 46, 179
population aging 162
population size 298, 300, 302
positional status inequality 105
postcompulsory education systems 261
post-industrial economy 68
post industrialism 68
power 1, 5, 22–7, 42–6, 48, 75, 106, 139, 163, 180, 188, 191, 217–30, 247, 256, 284, 293
models 22–4
preferences 41, 55, 117, 181–2, 186, 188, 191, 193, 291, 314
prestige, ratings of 19
Price, B. 43
primary school 260
private hybrid 87
production
globalization of 44
structural locations in 104
technical demands of 44
productive value 23, 139
productivity 1, 3, 5–7, 12, 14, 23–5, 32, 55–6, 60, 148, 200, 220, 222–4, 228, 260–1, 265, 289, 291, 307
and bargaining power 48
close counting of 223
evaluations of 220
growth in 32
impact on 7
mechanism 23
work rewards via 8
product-oriented work 85
professionals 23
competence 280–1
licensure 225
occupations 75, 80, 226, 293, 315
skills 22
structures 276
professions, regulation of 280
Programme for International Assessment of Adult Competencies (PIAAC)
2, 162, 164, 168, 173, 265, 289, 293
Programme for International Student Assessment (PISA) 2, 41, 257
Progress in International Reading Literacy Study (PIRLS) 257
propensity 90, 99, 162, 170–2, 182
score matching 162, 167–8, 168, 171–2
PSID. See Panel Study of Income Dynamics (PSID)
psmatch2 procedure 170
psychological health 126–7, 131
psychological well-being 126–7, 133, 136
psychology 4, 8
contribution of 6
psychotherapy 181
public goods 193
public hybrid 87
qualification requirements, structural transformation of 276
qualified occupations 276
race 38, 40, 130, 189, 218–19, 226–8, 243, 248
racial based closure 226
racial hierarchy 150
rational choice
  economic perspective 66
  economic theories 66
  explanations 87–8
Rawls, J. 315
reading 183, 237–8, 241, 243–4, 248, 251, 253, 255, 257, 279
realized matches (RA) 205
reasoning 1, 7, 29, 151, 163, 179, 187–8, 237–40, 242, 255, 258
recurrent education 286
regime models 295
regulations 121–2, 179–80, 182, 280–1, 291, 293–4
Relational Inequality Theory (RIT) 217–18
  central premise of 218
  conceptualization of closure 227
  perspective 219
  perspective compensation rates 223
  social science approaches 218
  starting premise of 218
relational work 26–7
relationship changes 278
relative skill levels 124–6, 139
relative social standing, temporal shifts in 117
religious tradition 25
reskilling 283
reward systems 228
rich nations 45–6, 48
risk aversion 41–2, 181
risk-taking 41–2
RIT. See Relational Inequality Theory (RIT)
Rivera, L. A. 226
Robinson, J. A. 46–7
robots 33, 308
role clarity 9
routine labor 305, 309–11, 316–17
  and job rotation 310
  and justice 310
  larger societies 311
  sharing 309–11, 316
  social and self-esteem 310
  unhappy moral problems 305
salary 185, 235, 275
sales/service occupations 109
same-gender dominated program 88, 94
satisfaction 103, 185, 201, 235, 310–11
SBTC (Skill-biased technological change) 233–5, 239–41, 243, 254
SBTC theory. See skill-biased technological change (SBTC) theory
scale occupations 105
Schooler, C. 310
school skills 234, 236–7, 241, 254
scientific evaluations 285
secondary education 86, 92, 98, 257–9, 263–4, 266
segregation
  decomposition of change in 77
  indexes 72
  level of 75
self-concepts 26
self-determination 127, 130, 306
  psychological needs for 127
self-esteem 38, 106, 309–10
self-investment 186–7, 189, 193
self-rated health question 165
self-regulation 180–1, 186, 189–91, 193
  aspect of 186
  capabilities for 180
self-reported job required education 254
self-worth 306
Sen, A. 177
seniority 187
service definitions 52–5
service expansion 31–3, 51–60, 80
  accounts of 55
  common indicator of 54
  definition of 54
  demand explanations of 56
  documenting trends in 53
  industry-based estimates of 55
  and skill 55
  skill-change in 58
  traditional supply- and demand accounts of 59
  and care 29
  categories 53–4
  employment, composition of 56
expansion 31–3, 51–9
product 54
worker category, heterogeneity of 107
service sector 55, 60
definition of 53
expansion 51
SES. See British Skills and Employment Surveys (SES)
sex
bias in skill evaluation 29
and gender 25
segregation 71, 79–80
stereotypical traits 66
sex composition 71
of labour force 68
signaling 10, 265–6
Singelmann, J. 52
Skaggs, S. 229
skill acquisition 192, 253, 257–61, 267
skill and job quality
development 130
job insecurity 134
levels and occupational groups 122
overall job quality 136
polarisation 126
in size of skill groups 124
task discretion and influence over organisational decisions 127
work intensity and job strain 132
skill and power
and exploitation 227
and social closure 224
as socially constructed 223
socially-mediated 220
skill-based claims 222, 228
skill-biased technological change (SBTC)
theory 233
claims regarding educational requirements 234
job education requirements for 240
proponents of 235
skilled groups 135
skilled labor, surpluses and deficits of 273
skilled occupations 80
skilled work 44–5, 67, 79, 121, 138, 200, 223, 227, 229, 244, 305, 309
eudemonistically meaningful work 306–8
flourishing people 312–15
meaningful work 315–17
sharing work 308–12
skilled workers 223, 227, 229
skill equilibria 262
skill formation 1–2, 11, 13, 257–8, 261–8, 270
skill groups 121, 124, 128–9, 135
definition of 122
differences in 121
employees in 132
sharp polarization between 122
skill mismatch 11, 198, 200
and authority 24
of job’s work tasks 3
and upgrading 60
skills 51
acquisition 164
analyses 2, 4
attributes of jobs 219
attributions and 222
and authority 24
definition of 223
demand 10, 38, 185, 236
development 12, 126–7, 130, 132, 138–9, 192, 267
differentials 150, 155
dispersion 290, 300, 302
distribution of 37, 263
economic conception of 2
and educational certificates 265
formation 2, 11, 264
during life cycle 161
processes 265–6
fundamental observation 220
at home or at work 165
importance of 145
knowledge and 273
measurement 10, 242
mismatches 200
notion of 217
and occupational sex segregation 80
parallel development of 52
polarization 121
provision of 273
salary and 275
secular changes in 59
service expansion and 55
social construction of 223
supply 2, 10, 57, 266, 273–4, 279–81, 285, 299
supply of 273, 275, 279, 281
trajectories 263
types of 146, 163, 263
unequal distribution of 146
upgrading 31–3, 51–3, 55–6, 58, 60, 65, 124
view of 1
skills and inequality 1
research literature on 10
research on 1
Skills, Technology, and Management Practices (STAMP) survey 235, 237, 241
complexity of computer tasks 253
construction of 238
field of study from 240
measures in 253
Smith, A. 307
social capital 155, 188
social class 39
among employees 22
social closure devices 224
social construction of skill 233
'social-democratic' regimes 121
'social democratic' welfare state 145
social networks 188, 221
social norms 90
experiences of 88
social partners 273–5, 277–8, 280–1, 283–6
direct role of 275
negotiation for 274, 277
parties 274
power among 284
role of 277
social recognition and esteem 103
social spending 295–6, 302
social status focus, theory and empirical research on 112
social stratification
researchers 202
study of 37
social structure 4, 38, 190
analyses 1
aspects of 3
social systems 27, 47
socio-cultural theories 66
sociodemographic controls 109, 112, 116
sociodemographic groups 37
socio-demographic variables 86, 88–90, 184
socio-economic outcomes 198, 217, 220
socio-economic standing 198, 202
socioeconomic status 104–5
socio-emotional skills 38, 148, 153, 155
sociological status models 5
sociological stratification research 109
soft skills 149, 223
Solga, H. 257–68
Soul of Man under Socialism, The (Wilde) 308
special wage initiatives 279
specific skills 139–40, 173, 239, 259, 262–3, 266–7
staff training 282–3
importance of 276
survey of 282
STAMP survey. See Skills, Technology, and Management Practices (STAMP) survey
standard occupational classification systems 239
standard sociodemographic controls 109
status expectations 219, 219, 221, 221
status hierarchies 107, 149, 219
stop working 164, 172
stratification, sociological research on 5
structural change 31, 78, 80
structural-functionalist sociological theory 260
structural movements 33
structural shifts 31
subjective social status 103, 105, 107–8, 111, 115
analitical feature of 116
country differences in 111
occupational skills and 112, 116
predicted divide in 116
predicted values of 116
relevance for 115
substantial bearing on 116
variation in 115
substantial common variance 6
sufficient reliability, skill measures of 108
supervision 7, 235, 279, 317
supply explanations 55–6
surplus education 197–8, 207
consequences of 200
position 201
surplus occupation 197–8, 201–2, 204, 206–12
surplus rewards 23
Sweden 51–2, 57, 60, 85–6, 90, 98, 107, 221, 229, 276–8, 280, 282–3, 285–6
administrative register data from 90
collective agreements in 278
educational system 85
elements of regulations in 280
forms of education in 86, 91
labor force participation of men and
women 85
private business sector 276
school system 279
SNI categorization 91
social partners 277
staff training in 282
Swedish Employers’ Confederation (SAF) 284
Swedish Level of Living Survey (LNU).
See LNU
Swedish Occupational Classification (SSYK) format 91
Syk, E. 51–61

Tåhlin, M. 1–15, 19–35, 123, 204, 289–303
tasks
competence 219–20
complexity 218, 220, 223, 233, 239, 254
discretion 127–30, 133, 140
divisions 150
statements 239
substantive complexity of 55
Taylor, F. W. 223
Taylorism 229
technical professionals 51
technical skills 218
technological change 9, 31, 43, 121, 134, 138–9, 205, 233, 267
technology
communication and internet 56
impact of 56
temporary disequilibrium 199
tertiary education 51, 53, 60, 66–7, 98, 238, 257–8, 261
things-data-people (TDP) 14, 20–2
thinking skills 237–8
Tilly, C. 223
time trends Europe 65–6, 69, 71, 73, 75, 78–9
Tomaskovic-Devey, D. 217–30
tracking 257, 263, 266, 268
trade
freedom of 280
unions 281
traditional apprenticeship systems 275, 279
traditional wage equations 277
treatment group 168, 170, 173
Treiman, D. 5–6, 14, 23, 103, 105–6, 217
Trends in International Mathematics and
Science Study (TIMSS) 257
triumphalism 229
Turner, R. H. 263
UK’s Standard Occupational
Classification 122
undereducation 197, 204–6, 211–12
for job allocation 198
parameters 204
unemployment 107, 134, 140, 273–4, 284, 292
issues of 87
risk of 274
unintellectual labor 308
union density 294–6, 301–2
unionization 44, 224
United Kingdom 45, 107, 213
United States 43, 45, 48, 51–2, 140, 148, 185, 199, 227, 235, 237, 310
universal basic income 317
unjust meritocracy 217
upskilled occupational structure 115
upskilling 282
urbanicity 204
use-it-or-lose-it hypothesis 162–3, 171
US General Social Survey (GSS) 105
vague quantifiers 236
value creation, source of 224
value pluralism 313–14
van der Velden, R. 161–73
van de Werfhorst, H. G. 148, 257–68
Van Tubergen, F. 148
Veltman, A. 305–18
Vera-Toscano, E. 265–6
verbal skills 240
Verdugo, N. T. 205
Verdugo, R. R. 205
Vigna, N. 107
vocational decline thesis 262
vocational education 2, 9, 85–7, 98–9, 248, 253, 255, 261, 279–80
position and design of 280
youths in 87
vocational education and training (VET) systems 2, 9, 86, 261–3, 266
vocational schooling 108
vocational secondary school 238
vocational skills 261–2, 264, 267
vocational training 45, 86–7, 248, 264, 279, 281–2, 285
agreements 281
participation 264

Wacquant, L. 39
wage bargaining 273–5
collective agreements 278–9
human capital theory 275–6
social partners 277
structural transformation of qualification requirements 276
wage formation 273–5, 278
functioning of 284
human capital in 277
state’s influence on 277
wage inequality 45
compressed wage structure 291
data and estimation 294–6
determination, micro and macro level 289–90
differential pay-off to skills 290
efficiency 291, 296, 301
equality 296
and efficiency associations 292
promoting institutions 295, 298–9
factor analysis 296
growth
curves 293
and distribution 290–93
promotion of 296
regression of 300
and wage share 290
wages 4, 32
collective agreements on 278
compression 291
determination 11, 254, 289–90
dispersion 289–90
gains 222
gap 221
growth 32, 44, 293
job complexity and 12
mapping 279
outcomes 278
regression by job complexity 13
setting 277
Warhurst, C. 223
Weberian sense 105
Weberian version 227
Weber, M. 104, 225
Weeden, K. A. 224–5
Weisskopf, T. 182–3
Weiss, R. 315
well-being 4, 126–7, 130, 133, 136, 177–8, 180, 183–4, 292, 305–6, 311, 316
well-functioning labour market 273
Wennemo, I. 273–87
Westerman, J. 51–61, 289–303
white-collar professionals 51
Wilde, O. 308
within-group heterogeneity 265
Witteveen, D. 197–213
Woessmann, L. 37, 47
behavioral differences 26
biological and hormonal differences 25
decision-making processes 87
labor force participation of 85
labor market 27, 59
work
based training 122
complexity, indicator of 21
experience 165
fundamental unit of 20
intrinsic quality of 121
manual and non-manual 108
organization, employee influence over decisions about 130
performance, uncertainty of 22
work content 3, 30
  indicators of 22
  with standard measures 30
  structure of 20, 28
workers
  attributes 258
  bargaining power of 45
  job mismatch 234
  level of education 197
  skills 38
  well-being 127
worker self-assessment (WA) 205
workforce 70, 73, 75, 78, 84, 124, 138, 145–6, 211, 276
working life, training requirements in 280
work intensity 126, 132–3
  highest levels of 134
  and job insecurity 136
  measure of 132
  median level of 133
work-life
  differentiation, horizontal dimension of 28
  hierarchies 3
  inequality 12, 19
research on 20
  structure of 21
issues, psychological research on 9
workplace 224
  context, ambiguity of 221
  cultures 227
  learning 258
work tasks 3–4, 14, 20, 32–4, 66, 68, 106–9, 113, 115, 127, 156
economic research on 8
  and requirements 20
World Intellectual Property Organization (WIPO) 295
Wren, A. 59
Wright, E. O. 229
writing 237–8, 249–53, 255, 258–9, 309
Wu, T. 223
Ye, R. 85–99
young adults 261–2
Young, I. M. 309
Zamarro, G. 42
Zilibotti, F. 47