Empirical Research in Vocational Education and Training, Vol. 3(1), 2011, 55–70

Vertical differentiation of work tasks: conceptual and measurement issues

Michael Tåhlin*

Swedish Institute for Social Research (SOFI),
Stockholm University

Abstract

This paper contains an overview of conceptual and measurement issues related to the vertical differentiation of work tasks. The main conclusions – based on a synthetic literature review and measurement examples from the Swedish Level of Living Survey (LNU) and the European Social Survey (ESS) – 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, horizontal – as opposed to vertical – variation in work content is well captured by the distinction between working with people, data and things (PDT). Broad task indicators of PDT are now included in the LNU and ESS surveys. 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.

Keywords: job complexity, skill requirements, cognitive skills, education, learning, training, work tasks, job rewards, wages, skill matching, ORU model, job performance, productivity, job evaluation, survey indicators, European Social Survey (ESS), Swedish Level of Living Survey (LNU)

1. Introduction

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

* Address for correspondence: Michael Tåhlin, Swedish Institute for Social Research (SOFI), Stockholm University, SE-106 91 Stockholm, e-mail: michael.tahlin@sofi.su.se
Acknowledgements: An early version of this paper was presented at the T.A.S.K.S workshop, Institute for Employment Research (IAB), Nuremberg, 17–18 May 2010. Thanks to the workshop participants, in particular Francis Green, Michael Handel and Daniela Rohrbach-Schmidt, as well as to Carl le Grand, Martin Hällsten, Tomas Korpi, Ryszard Szulkin, Donald Tomaskovic-Devey and two anonymous reviewers for helpful comments.

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' perspective alike. This paper gives an overview of what job complexity is, why it is the central vertical dimension of working life, and how it can be validly and reliably measured.

The following main points will be made: First, job complexity is the level of cognitive capacity needed in order to carry out the daily work tasks of a job in a satisfactory manner. Second, job complexity is a strong predictor of individual productivity (job performance) and therefore of wages. It is also the major determinant of learning at work, and therefore of work-life careers as well as living conditions outside work that depend on cognitive capacity. Third, 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 recently been extended into a standardized multi-country framework.

There are several important reasons 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 (performance, wages, 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, helps develop such abilities further, and helps create new abilities; a negative learning environment has the opposite effects, potentially to the point of causing skill decline.

The paper is organized as follows. I begin by reviewing research from several disciplines that converges on the conclusion that job complexity is the central dimension of work content, including a discussion of the causal mechanisms involved. I then turn to measurement issues and describe the content and properties of job complexity indicators. A concluding section sums up the discussion and offers suggestions for future research.

2. Job complexity – the primary dimension of work: an interdisciplinary overview of research

Three disciplines have given important contributions to understanding how work content is structured vertically and how it affects work-related outcomes such as wages, careers and well-being. These disciplines are economics, psychology and sociology. 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 of 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. I give a brief overview of contributions from these three directions 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 educational 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 & Woessman, 2008).

Human capital models typically ignore the job side of skills and cognition, however. Sociological research on stratification, by contrast, has jobs – usually in the form of occupations – in focus. In essence, sociological status models (Duncan, 1961; Stevens & Featherman, 1981; Hauser & 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 which act as transmitters of educational input to monetary output. This comes very close to being a latent indicator of educational requirements of the job. Indeed, the correlation between status (or prestige) and manifest measures of educational requirements tends to be very high.

In the industrial and organizational (I-O) psychology (and human resource management) tradition of job analysis and evaluation (see, e.g. McCormick, 1979; Fine & Cronshaw, 1999; Brannick & Levine, 2002; Landy & Conte, 2010: ch. 4; for recent developments, see Morgeson & 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 structure of inequality is ultimately based on universally held social norms rather than being an outcome of power struggles between actors with conflicting interests (cf. England & 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. Successful performance of difficult tasks appears to command respect, probably more than any other factor does.

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 & Hunter, 1984; Schmidt & 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 is, 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 .4, indicating substantial common variance but clearly imperfect substitutability. However, when limiting the estimation to a small sub-set of studies covering the same narrow dimension of performance as both objectively and subjectively assessed, the correlation is much higher, around .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, and are often not meaningful or even possible.

Furthermore, deciding what to count and how is rarely free from 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 reliability estimation in Visweswaran et al., 1996).

Some research indicates that there exists a general factor in performance ratings. In a meta-analysis, Visweswaran et al. (2005) find that such a factor accounts for around 60 percent of the variance in rated performance, net of measurement error. A state-of-the-art assessment concludes that systematic performance ratings are often of high quality: «There is increased recognition that subjectivity does not automatically translate into rater error or bias and that ratings are most likely valid reflections of true performance and represent a low-cost mechanism for evaluating employees» (Arvey & Murphy, 1998: 163). Recently, the concept of employee performance has tended to expand from the well-established domain of job-specific task requirements into additional factors, such as organizational citizenship (prosocial) performance, counterproductive work behavior (norm violation) and adaptive performance (adjusting to new demands); see Van Iddekinge and Ployhart (2008: 898ff.) for an overview. This expansion, however, still seems empirically immature: «(T)heory appears to have outpaced practice with respect to the use of some of these newer types of criteria» (Van Iddekinge & Ployhart, 2008: 904).

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. The causal interpretation of this finding in psychology is that high-ability individuals are selected into complex jobs. In the sociological literature on work and personality (Kohn & 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 (of the ORU type as spelled out below; see Handel, 2003, for an overview of the skill matching literature) would appear to support the reciprocal interpretation.

The main conclusion from the review above of findings from three disciplines is that job complexity is the central job characteristic to consider in accounting for vertical differentiation the world of work. But why are employers prepared to pay more for high-skill work than for low-skill work? Presumably, because high-skill work is more productive than is low-skill work. Suppose that a given task is carried out by two different persons, one more skilled in task-relevant ways than the other. In any given amount of time, the more skilled person will produce more value, quantitatively and/or qualitatively, than the less skilled person will. Assume further that this difference across individuals is reproduced across tasks, such that some tasks or task sets are designed to optimally fit the capacities of workers with different amounts of skill. If two tasks with different amounts of required skill are carried out by the same individual, performance of the more skilled task will produce more value than performance of the less skilled task will. With skill-based sorting of workers across tasks, these differences in output value are reinforced. A challenging work content develops the worker's skills further, while a routine work content may actually depress a worker's skills by letting them atrophy.

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 & Hunter, 2004); (2) occupations are strongly graded by ability (Cain & Treiman, 1981; Gottfredson, 1986); (3) occupations are strongly graded by complexity (ability requirements) (Cain & Treiman, 1981; Gottfredson, 1986; Tåhlin, 2007a, le Grand & Tåhlin, 2010); (4) occupations are strongly graded by prestige (Treiman, 1977); (5) occupations are strongly graded by wages (Ganzeboom et al., 1992; le Grand & Tåhlin, 2010); (6) the occupational gradients by ability, complexity, prestige and wages are strongly correlated (Ganzeboom et al., 1992; le Grand & Tåhlin, 2010); (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 & Dunn, 1988; Brannick & Levine, 2002; Landy & Conte, 2010); (8) there is a strongly positive interaction effect between ability and complexity on performance (Hunter & 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 & Hoffman, 1981; Rubb, 2003; see further below); (10) complexity has a strong effect on ability (Kohn & Schooler, 1983; Schooler et al., 2004), i.e. the ability-complexity link is not only, or even mainly, due to occupational selection by ability. In sum, the combined evidence expressed by the stylized facts above would seem to clearly indicate that complexity has a causal, positive and strong impact on productivity.

Table 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, close to non-existent. An important purpose of the foregoing review has been to indicate the usefulness of cross-fertilization in this regard.

Table 1: Summary of conceptual and measurement components in five research fields

	Individual capacity	Capacity requirements of jobs	Productivity	Wages	Market or firm focus
Human capital models	manifest	absent	latent	manifest	market
Occupational status models	manifest	latent	latent	manifest	market
Work and personality models	manifest	manifest	latent	absent	market
Job analysis and evaluation	manifest	manifest	latent	manifest	firm
Job performance	manifest	manifest	manifest	latent	firm

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

3. Measurement: the Swedish Level of Living Survey (LNU) and the European Social Survey (ESS)

Having thus established the central importance of job complexity in understanding vertical differentiation at work, we now turn to how complexity can be measured. Job complexity is defined as the level of cognitive capacity that the job's tasks require in order for satisfactory performance of the tasks to be achieved. This cognitive capacity may consist of both innate abilities and 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 signalling 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 & 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 time line, with different arenas in the forefront during different phases of the process. The time line 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. 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 time 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 below, with examples from two surveys, one national Swedish survey and one multi-country European survey.

3.1 Job complexity indicators in the LNU survey

The first Swedish Level of Living Survey (LNU) was conducted in 1968, and has since been replicated five times, in 1974, 1981, 1991, 2000, and 2010 (data collection for the most recent wave began in April 2010 and will be completed by early 2011). The LNU surveys are based on personal interviews with a random sample of the adult (age 19–75) population. The number of respondents is between 5,000 and 6,000, of whom around 3,000 are employed. The non-response rate in 2000, when the last survey was completed, was 24%. The survey questionnaire contains large batteries of descriptive indicators on working conditions and several other life domains. (For detailed information, see SOFI, 2010.)

Job complexity is measured by three indicators in the LNU surveys. The first concerns the educational requirements of the job, measured by the following survey questions: «Is any schooling or vocational training above elementary schooling needed in your job?» (YES, NO.); IF YES: «About how many years of education above elementary school are needed?» (NUMBER OF YEARS). The second complexity indicator measures the time of training after job entry that is required before the job tasks can be carried out reasonably well: «Apart from the competence required to get a job such as yours, how long does it take to learn to do the job reasonably well?» (RESPONSE SCALE): «1 day or less», «2–5 days», «1–4 weeks», «1–3 months», «3 months to 1 year», «1–2 years», «more than 2 years»).

Both the educational requirements indicator and the training time indicator use time scales. Time measures have several attractive features. First, they are interval-level scales, which are desirable but rare in survey research. Second, they permit meaningful quantitative cross-category comparisons, between persons, between jobs, and between persons and jobs. The person-job comparability allows straightforward analyses of mismatch, for example (see further below). Third, time measures are concrete enough for survey respondents to provide reliable answers, because time is a unit that is relatively easy to think about, yet abstract enough to allow comparisons across qualitatively distinct categories (such as jobs and persons). Fourth, an important advantage of time measures of complexity is that informal skill formation, such as learning by doing, can be quantified in a manner which avoids heavily skewed response distributions (a major problem with most alternative indicators of informal learning and training).

The third indicator of job complexity concerns continuing learning: skills learned on the job after the initial phase of job training and learning. In this case, it is difficult to design a measure directly based on amounts of time, since the meaning of the concept «continuing» implies that there is no end of the process. Therefore, a survey question of a less precise type is used: «To what extent does your work involve learning new things?» (RESPONSE SCALE: «to a very large extent», «to a large extent», «to some extent», «to a small extent», «not at all»).

In the 1991 wave of the LNU survey, re-interviews with a random sub-sample of respondents were made around two weeks after the original interview. These data were used to estimate reliabilities. Test-retest correlations for the three job complexity indicators were generally high, with some variation between them: 0.88 for educational requirements, 0.76 for initial job learning requirements, and 0.71 for continuing learning. These high reliabilities together with the strong validity indicated above (the tight conceptual link between job complexity and learning) thus provide evidence of very good measurement properties of the complexity indicators.

Descriptive statistics for the job complexity indicators and correlations between complexity, education and wages are shown in table 2. The data are from the most recently completed wave of the LNU survey (2000).

Table 2: Descriptive statistics and correlations; job complexity indicators, LNU 2000

			Correlations			
	Mean	Standard deviation	Wage	Education	Educational requirements	Initial job learning
Education	3.78	2.86	.34			
Educational requirements	3.05	2.63	.48	.58		
Initial job learning	1.12	1.10	.42	.20	.40	
Continuing job learning	2.42	1.08	.22	.22	.32	.33

The descriptive statistics show that the mean educational requirements among employees are just over three years beyond compulsory school, which is about three quarters of a year shorter than the average amount of post-compulsory schooling completed. This aggregate difference indicates that a substantial fraction of all employees are over-educated, in the sense that their education is longer than what is required in their jobs. At the individual level, around one third of all employees in Sweden had an amount of schooling at least two years in excess of their job requirements at the time of the survey (2000). I return briefly below to the mismatch issue (see Korpi & Tåhlin (2009a) for a detailed analysis of educational mismatch, based on the LNU surveys). The average learning time required after job entry until the job tasks can be carried out reasonably well is slightly above one year. Finally, the continuing learning scale has an average of 2.4 on the 0–4 scale, indicating that most jobs contain substantial amounts of learning. Of the three measures of job complexity, the dispersion is clearly smallest in continuing learning, probably in part due to less precise measurement, although the reliabilities of the indicators are generally high as shown above.

The correlations in table 2 clearly show the importance of job requirements relative to individual education for labor market rewards. First, the correlation between education and educational requirements is substantially below unity (.58), indicating far from perfect matching. Thus, job requirements are not simply a reflection of individual human capital. Rather, the two are distinct although related factors. Second, job complexity seems to be more important than individual education for wages. Both educational requirements and initial job learning requirements are more strongly correlated with wages than individual education is. The difference is fairly large, especially between education and educational requirements. Third, learning on the job, both initial and continuing learning, is more strongly linked to educational requirements than to individual education. This is not surprising: the need for job-related skill development can be expected to be more dependent on the character of the job than on the character of the individual. More complex jobs naturally involve more skill development than less complex jobs do. Still, the correlations in table 2 contradict the widespread notion that the advantage in training opportunities on the job enjoyed by the initially more highly educated, a recurrent pattern shown in many countries and perceived as a major inequality problem in the context of life-long learning, is primarily tied to individual education rather than to skill requirements of jobs (for a detailed analysis of this issue, «the training gap», see Korpi & Tåhlin, 2009b).

The consequences of skill mismatch for labor market rewards are commonly analyzed in the framework of ORU models (ORU = Over, Required, Under), originally designed by Duncan and Hoffman (1981). These models use the same basic form as Mincer (1974), but decompose attained education (in years) into three parts defined in relation to the educational requirements of the job held as expressed by the equation

$$AE = RE + OE - UE,$$

where AE denotes attained education, RE is the required amount of education in the job that the worker holds, OE is the amount of education attained by the worker that is in excess of what the current job requires, and UE is the amount of education required by the job that is in excess of what the worker has attained. Hence, OE is zero for correctly matched and undereducated workers, while UE is zero for correctly matched and overeducated workers. The equation thus reduces to AE = RE for the correctly matched, to AE = RE + OE for the overeducated, and to AE = RE – UE for the undereducated.

There are two attractive traits of this decomposition. First, conceptually, it combines the information on attained and required education while fully retaining the continuous character of both dimensions. This allows an assessment of separate payoffs to years of attained education dependent on the nature of the job match as revealed by earnings (or other rewards) regressions. Second, empirically, the main pattern of results from this model has turned out to be remarkably robust across both time and countries. The following results from cross-sectional wage regressions have been found in virtually all published studies, regardless of time and place (see Rubb (2003) for an overview): (a) the wage effects of both RE and OE are positive while the wage effect of UE is negative, and (b) the impact of RE exceeds the impact of OE and UE. Put differently, overeducated workers earn more than correctly matched workers in the same kind of jobs, but less than correctly matched workers with a similar amount of education. The converse pattern holds for undereducated workers: they earn less than correctly matched workers in the same kind of jobs, but more than correctly matched workers with a similar amount of education. Table 3 shows the corresponding estimates based on LNU survey data from the four waves from 1974 to 2000.

Table 3: ORU models, LNU 1974–2000. Economic returns (ln wage) to three educational match components (measured in years; experience parameters and a gender dummy are included in the equations, but estimates are not shown in the table)

	1974	1981	1991	2000
Excess educational requirements	3.9	4.2	4.1	3.1
Matched education	7.4	5.8	5.7	6.1
Excess education	2.1	1.8	1.8	1.8

As can be seen, the typical ORU model results described above are replicated here. Matched education (middle line), i.e. years of individual education corresponding to educational requirements of the job, give 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 which 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 & Tåhlin, 2009b). 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 paper, 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.

3.2 Job complexity indicators in the European Social Survey (ESS)

The European Social Survey (ESS) was first carried out in 2002, and has since been replicated four times: in 2004, 2006, 2008, and 2010 (data collection for the most recent wave began in September 2010 with estimated completion by early 2011). ESS is an academically-driven social survey covering around 30 European nations, within and beyond the EU, on the basis of rigorous comparative methodology. It is funded through the European Commission's Framework Programs, the European Science Foundation and national funding bodies in each country. The ESS is based on personal interviews with random samples of the adult (age 16+) population in each nation. The number of respondents per country is around 2,000, of whom around 1,000 are employed. Non-response rates are between 30 and 50%. The questionnaire contains both permanent and rotating modules, with the latter being focused on a specific theme or topic selected on the basis of competition between extensive proposals from international research teams. In 2004, one rotating module was «Work, family and well-being», and inter alia contained a questionnaire section on job characteristics, with the job complexity indicators modelled on the Swedish LNU survey described above. This module has subsequently been selected to appear a second time, in the 2010 wave of ESS (for detailed information on ESS, see www.europeansocialsurvey.org).

The formulations of the three job complexity indicators in ESS 2004 and 2010 are as follows. Educational requirements: «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?» (NUMBER OF YEARS). Initial on-the-job learning: «If somebody with the right education and qualifications replaced you in your job, how long would it take for them to learn to do the job reasonably well?» (RESPONSE SCALE: «1 day or less», «2–5 days», «1–4 weeks», «1–3 months», «more than 3 months, up to 1 year», «more than 1 year, up to 2 years», «more than 2 years, up to 5 years», «more than 5 years»). Continuing on-the-job learning: «My job requires that I keep learning new things» (RESPONSE SCALE: «not at all true», «a little true», «quite true», «very true»).

Table 4 shows results for five countries from regression analyses of log wages (per hour) on the three components of skill requirements. 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.

Table 4: Wage regressions by job complexity in five countries, ESS 2004. B coefficients (upper row) and t-values (lower row)

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

Notes: Wages are logged, educational requirements and intitial job learning are measured in years, continuing learning is measured by a scale 0–3. Pooled regression (column 1) includes country dummies.

As can be seen, job complexity and wages are strongly related in all countries in the table. (For an extended discussion of these and related results, see Tåhlin, 2007b. Similar results for a larger set of countries, eleven including the five in table 4, are reported in le Grand and Tåhlin, 2010.) 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 lies between 0.4 and 0.6 in all countries, which must be considered very high. Correlations of that magnitude are rare in social science; given the fairly limited number of respondents in the present case they are quite remarkable.

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 relatively 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 conception 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.

4. 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 people, data and things (PDT), as shown by research based on the US job classification systems DOT (Cain & Treiman, 1981; Fine & Cronshaw, 1999) and its successor O∗NET (Jeanneret et al., 1999). Broad task indicators of PDT are now included in the LNU and ESS surveys, with data collection currently (2010–11) underway. 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.

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