Rewards to skill supply, skill demand and skill match-mismatch: Studies using the Adult Literacy and Lifeskills survey

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Richard Desjardins
Los Angeles, February 2014

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Chapter 1 Introduction

Background and rationale

Addressing a growing interest to understand the causes and consequences of skill mismatch

Policy interest in skill mismatch has surged in recent years with a number of national and international bodies giving it a high priority. In Europe for example, the identification and avoidance of mismatch including shortages and gaps, as well as the need to respond to future skill and competence requirements have been defined as a priority in the Bordeaux communiqué (European Commission, 2008). Accordingly, CEDEFOP has embarked on an ambitious programme of work to identify and monitor skill imbalances (CEDEFOP, 2010a; 2010b). Among various other countries recently producing skills strategies (e.g. Australia, the Czech Republic, Denmark, Estonia, Germany, Ireland, Japan, New Zealand, Norway, Poland), the UK Commission for Employment and Skills (2010) provides an exemplar of increased policy attention being focused on imbalances between skills demand and supply in the labour market.

Ongoing structural change and changing skill requirements makes it important to monitor the level and distribution of skills made available to labour markets. Not least, countries are increasingly interested to understand better the extent of key skills that are available to help sustain and increase the share of high-value added knowledge economy jobs in their economies. This is not just about the supply of available skills to the labour market, however. The efficiency of the allocation of workers to tasks and of the processes by which firms adapt to the supply of skills is also of increasing interest because this has a potentially significant impact on output. The misallocation of labour may result in lower output than is potentially possible as will a failure of firms to adjust tasks to the skills of workers. In a dynamic economy, efficient adjustment, both on the part of workers and firms is essential.

The analysis contained in this study is also motivated by an accompanying recent shift in academic and policy debates from a focus on overeducation or skill shortages to a more nuanced overview of imbalances that incorporates skill gaps and skill underutilization. In some cases, skill gaps are perceived as being more important than skill shortages. In fact, some projections tend to suggest that the supply of skills may outpace demand over the next decade leading to higher rates of overskilling (CEDEFOP, 2010b). Even so, policy concerns now include an emphasis on the need for tackling the negative consequences of skill underutilization rather than the need to scale back the supply of educated adults. Concerns about overeducation remain but are balanced by views that high levels of education are needed to meet the long run needs of the labour market and safeguard against rapid technical biased change and competition in the 21st century. A key concern is to ensure that work practices change in a way that makes effective use of higher educated workers' skills so as to limit skill atrophy and wasted opportunities to increase productivity. Increased numbers of highly educated workers may eventually *crowd out* lower educated workers and thereby exacerbate the problem of skill underutilization unless work practices change to foster a more effective utilisation of skills[1].

Current understandings of mismatch rest on a relatively weak knowledge base. Much of the analysis of mismatch issues has had a tendency to neglect the type of education undertaken, actual skills held, work experience and the fact that people engage in formal and non-formal learning both inside and outside of work over the lifespan, all of which contributes to a limited understanding of mismatch. This is partly a consequence of a reliance on what is easiest to measure and what we can measure, rather than what we should measure and would be feasible to do so. A key drawback to education

1 Crowding out refers to the process where individuals with higher levels of education secure employment in lower skill jobs at the expense of employment opportunities for those with lower levels of education (Hansson, 2007).
2 Please note that this thesis was completed in its entirety prior to the release of the PIAAC database on October 8th, 2013. Much of the analysis contained herein was designed to be replicated with PIAAC data once it was released. See Allen, Levels and van Der Velden (2013) and Levels, van Der Velden and Allen (2013) for

mismatch studies is the near exclusive reliance on quantity and qualification based measures of education such as years of schooling or educational attainment credentials.

As a consequence, some analysts have begun to revisit the conceptualisation and measurement of mismatch to refocus from education mismatch to skill mismatch. The UK Skills Survey is an exemplar of this shift in approach by researchers engaged in informing the mismatch debate. Having focused nearly exclusively on education mismatch issues, particularly the overeducation debate (e.g., Oosterbeek, 2000), academic research interest has over the last decade slowly moved toward the notion of skill mismatch (e.g. Mavromaras, McGuinness, O'Leary, Sloane & Wei, 2010) including the use of indirect and direct measures of skills rather than qualifications in analyzing mismatch. In doing so, the focus is increasingly on issues that arise as a consequence of approaching the issue from this perspective, namely skill gaps, skill underutilisation, skill growth and skill loss. These latter topics are not as readily seen as problematic or interesting when the focus is exclusively on qualification. The approach to conceptualising and measuring mismatch does seem to matter in terms of framing the policy relevant issues.

Skill mismatch is an important phenomenon that can be viewed from different perspectives. As an example, past policy concerns tended to focus on a perceived risk of increased *skill shortages* and *skill deficits* as a result of continued skill biased technical change in the economy. For example, much of the policy focus in the 1990s was on the need for skills upgrading and remedial training to respond to the twin challenges of deep structural change in the economy and an ageing workforce (OECD, 1996). While this continues to be a major concern, there is a realization that the issue is much broader than this.

Skill underutilization is now argued to be an equally important issue (CEDEFOP, 2010a). Recent evidence suggests it is a widespread phenomenon which has several implications including negative consequences for individual workers and the economy as a whole (see Krahn & Lowe, 1998; Boothby, 1999; OECD/Statistics Canada, 2005; OECD/Statistics Canada, 2011). Many highly qualified workers are found to underutilize their skills. Some view this as a problem of over-education (e.g., Oosterbeek, 2000), others view this as poor structural incentives for firms to invest in human capital and to efficiently make use of human capital by adjusting production in ways that are commensurate with the skills of the labour force (i.e., the *new political economy of skills* view put forth by, for example, Brown et al., 2001).

Using alternative and complementary measures of skill supply and skill demand to address mismatch

Despite some tendencies for analysts to do better justice to the problem of mismatch on the labour market, much of the growing literature on mismatch continues to be dominated by *education* or *qualification mismatch* rather than *skill mismatch*. This is because of a lack of data to address the latter. Although related, the two concepts should be clearly distinguished because they lead to different types of analyses and implications. In view of the forthcoming Programme for International Assessment of Adult Competencies (PIAAC) study which will contain direct measures of key information processing skills as well as indirect measures of the use of certain generic skills at work, this study aims to do a stock take of what is known about skill mismatch using prior surveys of adult skills as well as to investigate the consequences of skill mismatch on labour market outcomes (i.e., the 2003-2007 Adult Literacy and Lifeskills Survey – ALLS)[2]. Similar to ALLS, PIAAC contains direct measures of key information processing skills as well as measures of the use of certain generic skills at work, enabling a similar but more detailed and up to date analysis for a wide range of countries.

The focus in this study is on skill mismatch rather than education mismatch. The direct measures of skills together with information on the use of those skills made available by ALLS allow for a direct measure of skill mismatch. Advantages of this type of measure include a more enriched and nuanced analysis of mismatch issues. In particular, they compensate for the fact that qualifications are not necessarily good indicators of 'skills', which is certainly the case for workers who left the education system many years ago. While education mismatch has the advantage of being easier to measure and broader in its coverage of 'skills' – albeit indirectly – it has the disadvantage

2 Please note that this thesis was completed in its entirety prior to the release of the PIAAC database on October 8th, 2013. Much of the analysis contained herein was designed to be replicated with PIAAC data once it was released. See Allen, Levels and van Der Velden (2013) and Levels, van Der Velden and Allen (2013) for recently published analyses of skill mismatch issues using the PIAAC database.

of being much less precise because it does not factor in differences in the quality of similar qualifications and it does not take account of the possibility for skill gain or loss following the attainment of qualifications. For example, employees engage in adult education/training, and firms support adult education/training at various life cycle points of the worker which may or may not be related to qualifications. Skill mismatch is thus more amenable to analysis that considers important dynamic elements which surround the phenomena of mismatch, such as the possibility for skill gain or loss on the supply side, in addition to the changing content of jobs on the demand side.

An important disadvantage however, is that the skill mismatch measures used in this study are narrow in scope by focusing on select cognitive skills, and specifically literacy mismatch. Nevertheless, literacy skills are key information processing (or cognitive) skills that are important both in their own right and also because the development of other high level cognitive skills is dependent on their mastery. Literacy skills for example, are taking on a more significant role in today’s modern society and global knowledge economy as a consequence of disruptive technologies like Information and Communications Technologies.

Considering both the demand and supply sides of the labour market

A separate and perhaps more substantive reason for limited understandings of mismatch is a tendency for many mismatch related studies to emphasize the supply side of the labour market in generating mismatch. Arguably, this leads to and follows from the over- and under- education literature that focuses on education (or qualification mismatch) concepts and measures, However, theory from labour market economics and other fields suggest that there are a variety of pervasive and complex mechanisms that generate mismatch which require careful consideration. The demand side may be equally involved in generating mismatch, for example, in situations where employers under utilise the existing skills of workers.

Approaches that emphasise the supply side of the labour market in modelling labour market functioning as it pertains to skills, skill use and skill development, tend to portray skill mismatch as a phenomenon driven by supply side conditions. From this perspective, mismatch tends to be attributed to the inadequacies of the education and training system. In a situation of overeducation, for example, the response is that education and training systems should aim to reduce the number of qualifications they produce. Overall, education and training systems should ensure quality and be made to be more responsive to the needs of the labour market, and to offer more guidance at critical transition points to minimize mismatch.

Alternative literature grounded in the political economy of skills (e.g. Brown, Lauder and Green, 2001) instead emphasizes the demand side of the labour market in generating skill mismatch. From this perspective, mismatch tends to be attributed to the inadequacies of labour market practices and of employers to identify and correct for mismatch, either via the provision of additional education, or in terms of adjusting work and organisational practices in ways that optimize skill use and skill gain, and avoids skill loss over time.

These two approaches lead to very different views of skill mismatch, although they are not mutually exclusive. By extension the two approaches can lead to the formulation of very different types of policy responses to skill mismatch. Evidence suggests that there is a need for a more comprehensive and balanced view involving both the demand and supply sides when attempting to address mismatch issues for policy purposes.

In summary, doing justice to the complex ways in which mismatch is generated requires a more accurate and up to date measure of mismatch, one that reflects the possibilities for skill gain and skill loss over the lifespan, and reflects differences in the quality of qualifications. Addressing mismatch also requires a careful consideration of both the demand and supply sides of the labour market, so as to understand better the variety of factors which may have a negative impact on the effectiveness of skill formation, skill maintenance, and also skill use.

Overall purpose, specific objectives and relationship of the studies

The overall purpose of this study is to approach the analysis of skill match-mismatch from a balanced perspective, one that takes account of both supply-side and demand-side views of the labour market. This is done by considering skill supply characteristics associated with individual workers and skill demand characteristics associated with job and jobs tasks. The approach is informed by a perspective that builds on the human capital and returns to schooling literature that emphasizes supply side characteristics, a skill segmented view of the labour market arising from approaches to the sociology of work and skills which emphasizes the demand side, a political economy of skills perspective that considers firm behaviour and skill utilization, as well as labour market theories that consider both supply and demand sides of the labour market. In combining these approaches, the study seeks to reveal key aspects that are often overlooked, for example, when the issues under investigation are approached from a single perspective. Three distinct studies relating to this overall purpose along with supporting background material relevant to all three studies are presented as a collection and form this thesis.

The first study focuses on the earnings differentials' associated with the skill supply characteristics of individual workers, the skill demand characteristics of the job and job tasks that workers are employed in, and the interaction of specific skill supply and skill demand characteristics that materialize into either match or mismatch situations (Chapter 6). The specific objectives are to extend standard applications of returns to schooling as reflected by the Mincerian approach with three specific additional features: direct measures of key information processing skills; direct measures of the requirements of those key information processing skills; and, a measure of skill mismatch based on these two direct measures.

The second study builds on the first by replicating the analysis but by separate aggregated occupational groups (Chapter 7). The approach adapts a skill segmented view of the labour market by aggregating occupations into six types, enabling the estimation of the association between key information processing skills and earnings, both within and between different types of occupations. An important purpose is to acknowledge that there are different types of skills and that some may be more relevant to specific groups of jobs than others. The method used to construct the aggregated occupational classification is based on an analysis that considers the role of cognitive and other skills in relation to the nature of occupational tasks. Substantial premiums are found to be associated with specific types of occupations even after adjusting for within occupational differences in individual characteristics such as schooling, select cognitive skills, labour force experience and gender. The objective is to explore whether the association between skills and earnings is primarily driven by the relevance of those skills within specific types of occupations.

The third study is similar in its focus to the first two by including skill supply, skill demand and skill match-mismatch characteristics into the analysis, but the dependent variable is instead whether workers received any employer sponsored adult education/training in the 12 months preceding the survey (Chapter 8). The objective is to explore the relationship between participation in employer supported adult education/training and skill supply as well as skill demand characteristics.

An advantage of presenting these three studies together as part of a single monograph is that they share much of the same background, for example, relating to issues surrounding the conceptualization and measurement of mismatch. This shared background is gathered into separate chapters as follows:

- Chapter 2 attempts to disentangle some of the basic concepts and debates that are key to the issues addressed in the three studies. This brief discussion is helpful for the reader to distinguish between mismatch related concepts and to situate the related debates.
- Chapter 3 reviews the potential causes of skill mismatch.
- Chapter 4 reviews some of the key aspects to consider in conceptualizing and measuring mismatch. This brief discussion on the definition and measurement of mismatch is helpful for the reader to locate the concept and measure of mismatch that is operationalized for this study and presented in Chapter 5.
- Chapter 5 describes the dataset used throughout and presents data regarding the extent and socio-demographic make-up of skill mismatch. Notably, it also describes the definition and methodology for the skill mismatch measure operationalized in the thesis. Worth highlighting already at this stage, the skill mismatch measure used distinguishes between whether there is a match or mismatch between the everyday literacy related practices of workers and their actual literacy skills as measured in the 2003-2007 Adult Literacy and Lifeskills Survey (ALLS). The measure also distinguishes between low-skill match and high-skill match, an important but often overlooked distinction, which has important policy implications.

Limitations of the studies

Data used in the applied studies are based on a cross sectional study, namely the Adult Literacy and Lifeskills Survey (ALLS). Thus, the results represent a picture at one point in time only, and do not provide estimates of observed relationships over one's life cycle. A longitudinal study with all the variables of interest including direct measures of skills for representative populations is not yet available.

Also the data on adult education and training only refers to the twelve months preceding the survey. The analysis would be much more telling and complete with a record of adult education and training over the person's lifetime.

Another important limitation is the availability of measures of specific skills. The studies use the direct measure of literacy skills made available through the ALLS. While this measure is deemed to be good indicator of information processing skills or alternatively cognitive skills, it omits other important skills such as communication and interpersonal skills.

Many other missing variables limit the studies. For example, no empirical evidence on the hypothesized causal link between knowledge and skills and *productivity* is offered because only the *earnings* data is available. Ability is another variable that is not factored into the following research.

It should be emphasized, that the study does not identify or isolate causal effects with certainty, primarily because the data used does not provide suitable opportunity to do so. Although it is possible to use Instrumental Variable (IV) and other techniques (e.g. regression discontinuity) to attempt to isolate causality when working with cross-sectional data (see Nichols, 2007), no suitable instruments or other appropriate opportunity were identified for this study. Moreover, while useful in certain contexts, isolating causality was not deemed necessary for the essential points revealed in the empirical analysis.

In general, there are three necessary conditions for establishing causality (Johnson & Christensen, 2004). First, X must come before Y for X to cause Y. Most theories of causation invoke an explicit requirement that the cause precede the effect in time (Pearl, 2009). Second, there must be some degree of empirical association between X and Y. This is the relationship condition, namely that variables X and Y must be at least empirically related. It is the third condition that is arguably the most important, however, namely the need for a theoretical rationale to explain the causal relationship between X and Y. A full explanation for the causality to exist has to explain the mechanism through which it occurs and the conditions under which a relationship holds (Shadish, Cook & Campbell, 2001). Thus even when causality cannot be isolated using empirical methods, it can be argued, not without controversy, that causality may still be present on the basis of empirical association (i.e., correlations) and sensible theoretical discussion. This is assuming the temporal order condition is met, however. But in the complex human and social world, most variables of interest are related in dynamic and interactive ways over time, which makes it very difficult to isolate causality. For example, persistence or lag effects are very difficult to isolate even with the best of methods to establish causality (i.e., natural experiments or even controlled experiments with random assignment).

Causal directions among factors are thus hypothesized in this study. For example, this is done by the very use of regression analysis where variations in independent variables are modelled to explain variation in the dependent variable. However, these are merely hypotheses advanced on the basis of theory and other research as an attempt to model and make sense of observed variations in the data being analysed. The emphasis is on the use of statistical analysis to study covariation, not to verify causation implied by theory, but to reveal insights useful for theoretical reasoning, discussion and to understand better how the labour market may be operating. Assessing covariation in light of theoretical considerations, as well as the change in coefficients, and the change in explained variation provides important clues on the relative substantiveness of different factors, and can lead to important findings that stimulate interesting analysis and discussion vis-a-vis theoretical considerations and prior empirical research. Such an approach remains particularly practical and useful in the human and social sciences since most variables of interest are related in dynamic and interactive ways over time, making causality very difficult to model, isolate and verify empirically. This is not to say that attempting to identify causality empirically is not important, but simply that it is not the central focus or purpose of this study, and that this is left for further study.

Also worthwhile pointing out at this stage as this is related to the establishment of causality is the fact that it can be argued that there are endogeneity problems in the empirical models put forth in this study. For example, there are simultaneity effects between attaining higher levels of education and the direct key information processing skills measures made available by ALLS. It is not obvious how these simultaneity problems can be modelled in a static and linear empirical approach such as regression analysis. Endogeneity problems make it difficult to separate the relative contribution, for example, of education and information processing skills to earnings differentials, or of skill supply and skill demand characteristics. But this is only from an empirical perspective. For this reason, theory becomes all the more important. The plausibility of the relationships and of the relative contribution should be assessed and argued on the basis of theoretical reasoning. This is done not without controversy of course. Effort is made to discuss the significance and/or direction of bias when it arises but generally the endogeneity bias is not seen to be large or consequential enough to affect the main findings and inferences contained in this study. These types of biases, even if small, would certainly be more important if major policy programmes or large sums of money were at stake, for example, by suggesting that direct manipulation of independent variables would lead to potential impacts but this is not the case.

Overview of key findings from the studies

The link between mismatch and earnings

Evidence presented in this study suggests that skill demand characteristics appear to be as important as skill supply characteristics in explaining observed variation in earnings. Another important finding is the significance of the association between the requirement to read at work and earnings, which is independent of whether individuals have high or low levels of literacy proficiency. This is consistent with theories that place emphasis on the role of job characteristics in determining pay. In other words, skills matter for earnings but especially if they are required by the job. While this makes sense intuitively, a lot of the research on the returns to education and skills has nevertheless been dominated by a supply side view of the labour market, namely the human capital approach, which has tended to underplay the role of the demand side of the labour market (see discussion in Chapter 3).

Including supply and demand characteristics in an earnings function helps to reveal that both skill demand and skill supply characteristics are significant in explaining earnings differentials. In some cases, skill demand characteristics seem to matter as much as skill supply characteristics or even more in explaining earnings differentials. For example, workers who are in a situation of skill deficit are found to receive on average about 16% more in monthly earnings than those in a low skill match situation, even if they also have a low level of literacy proficiency. The difference is that these individuals are in jobs that involve more frequent reading. The finding confirms that some demand side characteristics display significant associations with earnings independent of the relevant skills held by individuals. At least this is the case for those determined to be in a skill deficit situation. Otherwise, the findings also confirm the idea that the type of job and job tasks are important for making skills of individuals relevant, and that there are substantive interactions between the worker and the job in determining marginal productivity and hence pay.

The link between earnings and the relevance of skill supply characteristics within occupational types

The premium that can be associated with key information processing skills such as literacy depends on the extent of the relevance of cognitive skills at the occupational level. However, within all types of occupations, employers do seem to allocate pay on the basis of the requirement to use those skills, regardless of whether individuals possess low or high levels of proficiency in those skills. Ironically, workers with the highest levels of information processing skills who may as a consequence be the most efficient in jobs requiring higher levels of literacy practice do not necessarily seem to be allocated to those jobs. This seems to point to difficulties that employers experience, especially within particular types of occupations, in observing and hence selecting on the basis of differences in key information processing skills, independent of other validated qualifications.

Unlike years of schooling, which act as validated qualifications, key information processing skills are not easily observed or validated. In fact, they are probably inferred from years of schooling, which is indeed a good predictor of information processing skills (Boudard, 2001), but this surely does not prevent mismatch and may even exacerbate it. A key point is that what happens outside and beyond schooling also affects skills. Without the proper validation of skills beyond reliance on formal qualifications, it is difficult for employers to infer actual skill profiles. Nevertheless, in many cases employers are forced to rely on validated qualifications. As a result of poor information, employers may have difficulties matching actual skills of employees with job tasks, particularly within certain types of occupations. In short, the nature of validation systems of knowledge and skills in different countries are likely to have a pervasive impact on the distribution of earnings and also skill mismatch.

The link between mismatch and further investment in human capital

Skill formation is not just a supply side issue; it is just as much a function of work tasks and work organisation on the demand side. Policies on skill formation thus need to take into account both the supply and the demand side. Particular attention should be paid to identifying the mechanisms that help to foster the optimal utilisation of the existing skill base. Otherwise, many workers even with high qualifications risk losing their information processing skills due to a lack of use, leading to an erosion of value of educational investments.

A key finding is that the skill content of jobs seems to have an even stronger association with participation in employer supported adult education/training than educational attainment or information processing skills. This is the case when comparing adjusted odds ratios which are on a comparable scale for each of the variables mentioned. Considerations of demand characteristics thus seem to be important in the decision to support further investment in human capital. This raises questions about the focus of recent thinking around skills for economic prosperity. Several policy documents have stressed that the answer to the present economic and social challenges is to improve the supply of skilled labour. This view tends to ignore the demand side and takes upskilling for granted or as inevitable. It also ignores the observation that the actual utilization of information processing skills is itself a major factor implicated in skill formation (i.e. leads to further training) as found in this study, and that large segments of the workforce are still not required to use their information processing skills at work. Evidence thus suggests that there is a need for a more comprehensive view involving both the demand and supply sides. Otherwise, a view based on the supply side only ignores the possibility that there may be structural conditions in the economy, as well as work and organisational practices that lower the demand for and utilization of skills, which in turn can affect not only investments in skill formation, but may lead to a lack of use of existing skills, and ultimately skill loss.

From the perspective of sustaining a good skill base for rapidly growing knowledge economies and addressing inefficiencies in the labour market that are due to skill deficits, it can be argued that public policy has an important role to play beyond relying almost exclusively on initial formal education to increase the supply of skills. For adults beyond initial education, governments have a role to play in fostering the adult education/training necessary to redress their low levels of proficiency in information processing skills.

Employers are found to direct support for adult education/training to many workers who could benefit from developing their information processing skills and hence could be more productive at work (i.e., workers in situations of skill deficit). Nevertheless, many workers in a skill deficit situation do not receive support. The role of public policy is thus particularly important because many other employers may lack the necessary incentives to invest in the information processing skills of their employees even if there may be a need as in situations of skill deficit. Unless employees' needs are clearly aligned with firms' needs and the risks to investment are minimal, employers' incentives are not necessarily aligned to support the development of 'general' or 'key information processing' skills.

Understanding better the investment behaviour of employers with respect to skill development is not only important within the context of skill mismatch, but also more generally. This is because employers are the single most important source of financing of adult education/training, and therefore, have a major impact in determining who receives further support to invest in the development of human capital and who does not. If as found in this study the tendency is for adult education/training opportunities to be allocated primarily to those who use the skills in question, the risk is that the skill base of the workforce will become increasingly bifurcated, with some workers attracting more investment for continued skill development and others left without any support. This is further exacerbated by the fact that high-skilled individuals already have the motivation to continue to learn, and that individual and job characteristics are found to be mutually reinforcing in promoting skill development (i.e., workers in high-skill match situations participate the most in further ongoing education and training and also receive the most employer support to do so).

Significance and main conclusions of the studies

The study is significant by offering a broad and interdisciplinary perspective of issues relating to the formation and use of human capital. This can be used as a basis for further studies to build on in their analysis of similar issues. Interdisciplinary approaches to analyzing human capital formation and human capital use avoid the risk of focusing on only one line of research. As an example, approaches that overlook peripheral and structural feedback effects will invariably lead to misguided policies. Of potential value are perspectives that delve into the role of different institutions or other structural relations in society which may either enhance or constrain the development and impact of human capital. In policy contexts, the human capital framework has thus far proven to be valuable because it offers a powerful means to inform and support education policy. But it is hoped that a use of the theory within a broader perspective will help to generate better policy relevant information. For example, taking account of different types of skills and also requirements to use different skills at work as is argued to be important in this study, is seen as highly relevant as economies become more skill intensive in the 21st century. These perspectives are essential for informing policy related debates and issues surrounding education and skill mismatch.

Economies and societies are increasingly dependent on knowledge and information, making a holistic approach to the analysis of human capital related issues all the more important. Individuals are facing ever-increasing demands that require them to devote time and other resources to learning, not just for work but also to balance other personal and social demands. Accordingly, this research attempts to contribute to a better understanding of the interaction between skill supply and skill demand in terms of their potential effects on skill development and on economic outcomes.

Three major points stand out from this study, which should be taken into account when considering skill supply and skill demand and not least the phenomena of skill mismatch:

- Firstly, it is important to equally consider how both the demand and supply side of the labour market are implicated in generating mismatch.
- Secondly, it is important to consider the dynamics of skill gain and skill loss over the lifespan of workers and how this interacts with changing job content.
- Thirdly, it is important to recognize the dynamics of the interaction between the supply of, and demand for, skills at the macro level.

The analysis also suggests that a certain degree of mismatch may be inevitable and normal. It may even be an important catalyst for stakeholders to respond to, setting off the adjustment processes necessary for long run productivity growth. What the natural or normal rate of mismatch is cannot be answered with certainty, but high rates are likely to suggest a need for active policies that foster adjustments.

Chapter 2 Distinguishing mismatch related concepts and debates

Introduction

This chapter attempts to disentangle some of the basic concepts and debates that are key to the issues addressed in this study. Mismatch is a phenomena that can be viewed from many different perspectives. The discussion can be helpful for readers to distinguish between mismatch related concepts and to situate the various related debates.

A brief overview of the over- and under- education debate (vertical mismatch)

Education mismatch (or *qualification mismatch*) has been the most studied concept of mismatch (e.g., Oosterbeek, 2000; Hartog, 2000; Dolton & Vignoles, 2000; Groot & Maasen van den Brink, 2000; Mendes de Oliveira, Santos & Kiker, 2000; Vahey, 2000; Daly, Buchel & Duncan, 2000; Sloane, 2007; Verhaest & Omey, 2006; Galasi, 2008; van der Meer, 2009; Korpi & Tåhlin, 2009). It refers to a situation in which the educational qualifications held by a worker differ from those perceived to be required either by the employer or the worker to carry out adequately the tasks associated with his/her job – either in terms of the requirement at the time the worker took up the job, or in terms of the current requirements of the job. Typically, measures of education mismatch are limited to three alternative categories, namely *overeducation* (or *over-qualification*), *undereducation* (or *under-*

qualification) and *required education* (or *required-qualification*). This approach pertains to the notion of *vertical mismatch*.

Overeducation has received more attention than undereducation and has been a major concern for several years. In particular, the vast expansion of tertiary systems over the past few decades in several OECD countries has led to growing fears of overeducation. As early as the 1970s, falling rates of return to college graduates in the United States were linked to the larger supply of graduates (Freeman, 1976). Freeman projected further declines but several studies eventually found the opposite (Bound & Johnson, 1992; Levy & Murnane, 1992; Katz & Murphy, 1992; Mincer, 1997; Goldin & Katz, 1999), namely a rising wage premium among US college graduates even as the number of graduates continued to increase. Several researchers have suggested that skill biased technical change helped sustain the demand for skilled labour even as supply kept increasing (Krueger, 1993; Acemoglu, 1999; Autor, Levy & Murnane, 2003).

Several studies have nevertheless found fairly large rates of overeducation over time. Duncan and Hoffman (1981) found an overeducation rate of 42% in the US in 1976, sparking an interest that would lead to numerous similar studies in several countries. There are several extensive reviews of these studies (see Hartog, 2000; Groot & Maasen van den Brink, 2000a; Sloane, 2003; McGuinness, 2006). A meta analysis of 25 studies done by Groot and Maassen van den Brink (2000) found overeducation rates ranging from 13 to 29% and undereducation rates ranging from 10 to 30 %, depending on the method of measurement (see section on measurement of mismatch). Although most studies generally find the incidence of undereducation to be 5 to 10 % lower than overeducation, undereducation appears to be a significant phenomena as well, suggesting that fears of overeducation do not do justice to a more complex set of issues surrounding education mismatch.

Groot and Maassen van den Brink (2000) also found that overeducation fell from an average of 29% in 1970s down to an average of 21% in 1990s which supports the notion that technical change helped sustain the demand for skilled labour in the face of the ever rising supply. Undereducation however also fell on average from 16% to 13% during the same period. Most recently, Galasi (2008) using the European Social Survey found an average rate of overeducation of about 33 % in Europe. An increase in overeducation rates in the last decade would indicate that the supply of highly educated workers is now outstripping the pace of skill-biased technical change. But trends are difficult to decipher from existing studies with McGuinness (2006) concluding that overeducation rates seem fairly stable over time, and Groot and Maasen van den Brink (2000) reporting that there is no indication that mismatches between education supplied and education required for the job have increased significantly in the 20 year period between the 1970s and 1990s. Mismatch rates are not only potentially linked to the economic cycle but also the context of both the educational system and the labour market. Galasi (2008) for example reported large differences by country in overeducation rates with estimates as low as 15% in the Netherlands to 79% in Estonia, suggesting that the problem is driven not only by the educational attainment profile of a country but also how the structure of demand for skills plays out in the context of the occupational and production profile of a particular country.

It is important to consider the over- and under- education debate within a framework which accounts for productivity growth and technical change over the long term and the impact of education, trade and industrial policy, and to acknowledge that there is presumably a natural rate of education mismatch. A key question is whether it is the demand for skills that is driving the supply or vice-versa? *Endogenous technical theory* suggests it is the latter, where increases in the supply of skilled workers induce skill-biased technical change, which in turn stimulates the labour demand for skills (see Acemoglu 1998 and 2002a). But while human capital theory, especially viewed within an endogenous growth framework provides a very powerful and appealing rationale for the economic value of education, as Alison Wolf (2003) has pointed out, unquestioned faith in education and human capital theory by policy makers should be avoided.

Partly as a consequence of ease of availability, a key drawback to education mismatch studies is the near exclusive reliance on quantity and qualification based measures of education such as years of schooling or educational attainment credentials. A tendency to neglect the type of education undertaken, actual skills held, work experience and the fact that people engage in formal and non-formal learning both at and outside of work over the lifespan often lead to a limited understanding of mismatch.

A brief overview of the 'right education' or 'right skills' debate (horizontal mismatch)

Rather than focus on the level of education and whether workers have 'too little' or 'too much' education, a more appropriate question might be to ask whether workers have the 'right' type of education to carry out their job successfully. Although this is arguably a more important issue, there are very few empirical mismatch studies focusing on the horizontal dimension (Robst, 2007), namely the mismatch between an individual's field of education and his/her occupation.

The *horizontal mismatch* approach moves away from an exclusive reliance on the level of education by taking into account the type of education. While touching on an important policy debate about whether different types of education are preparing individuals for jobs that are available, it is a difficult question to address empirically. Gauging mismatch based on the correspondence between field of study and occupation is possible. However few datasets contain both these variables, and when they do, sample sizes are typically too small. Moreover, operationalizing the concept is complicated. Firstly, many jobs cannot be matched with a specific field of education (e.g., manager, politician). Secondly, some types of education are designed to foster generic skills while others are much more specific in nature. For example, some fields of study focus on occupation-specific skills that may not easily transfer to other occupations, while others focus on more general skills (e.g. arts and humanities) that are applicable across a wide range of jobs. In countries where educational systems focus more on general skills and leave vocation specific skills to be learned on the job or through employer training, the issue of horizontal mismatch becomes rather ambiguous. This is further complicated by the fact that employers train and retrain their employees at different career points for various reasons (e.g., new job or work organization, new market or context, new knowledge or technology, new products or services etc...). Thus the relevance of the specific type of education is not always easy to establish even if it can be argued that qualifications are needed to obtain a job in the first place.

Taking into account the limitations, Robst (2007) used the 1993 US National Survey of College Graduates to find that about 55% of respondents are in a job that closely relates to their degree field, while 25% are in jobs that are somewhat related to their area of study and 20% are in jobs that are not related to their studies. Indeed, many individuals are found to obtain a qualification in a specific field only to work in a different field but the extent of mismatch varies sharply by field of study. A Swedish study by Nordin, Persson and Rooth (2010) using register data which helps to circumvent sample size problems found horizontal mismatch rates as high as 80% for biology graduates and rates as low as 4% for graduates who studied medicine. Their study focused on only Swedish born adults aged 28-39 who completed a college/university degree. Reflecting the difficulty of studying horizontal mismatch in practice, they also chose to exclude from the analysis less well defined occupations (e.g., managers, politicians, sportsmen and models) and fields of education (e.g., humanities, languages, general services and transports) that are either too vague and/or too difficult to match. Most of the fields of education left in their analysis were precise and matched one distinct occupation perfectly, but some fields of education were broader and matched two occupations (e.g. social sciences).

A brief overview on skill shortages

Skill shortages are distinct from the phenomenon of skill mismatch but the two concepts are closely related. Skill shortages refer to a situation where employers in specific sectors cannot find suitably qualified workers. This is in contrast to education or skill mismatch since the job is often left vacant and there is no match or mismatch between a worker and a job. However, it may nevertheless lead to a situation where vacant posts are eventually manned by workers who are under-qualified or under-skilled.

The main interest in skill shortages by policy makers are the potential negative consequences to economic growth, and particularly the negative effects of shortages on labour productivity. Substitutions to less productive unskilled workers are also suggested to negatively affect labour productivity (Haskel & Martin, 1993), and some have suggested that shortages slow the rate at which more efficient technologies and approaches to work organization are adopted (e.g., Foley & Watts, 1994; Forth & Mason, 2006).

Skill shortages can be cyclical, structural and/or geographical in nature. The latter is sometimes referred to as geographical mismatch where there are sufficiently skilled people in the labour market but they are not in locations easily accessible to those jobs. A link to business cycle is rather straightforward where cyclical periods of rapid economic growth can lead to increased skill shortages whereas economic slowdowns are likely to reduce shortages. Finally, shortage can be linked to structural changes for example brought on by the adoption of new technologies which require specific skills that are not readily available on the labour market (e.g. ICT skills).

Empirically, there are three widely used approaches to construct measures of skill shortage: employers ‘own assessments, indices based on job vacancies and wage growth models. These are discussed in more detail in Quintini (2010). On the basis of employers ‘own assessments, Quintini (2010) used the 2009 Talent Shortage Survey conducted by Manpower Inc. to reveal that the share of employers reporting recruitment difficulties in select OECD and non-OECD countries dropped in most countries between the 2007 and 2009 period. Given the onset of recession in most countries following the 2008 banking crisis, this data supports the strong cyclical nature of skill shortages. Nevertheless, many employers in several countries, about 30% on average, continue to report recruiting difficulties in the aftermath of the recent recession.

Distinguishing between education and skill mismatch

In contrast to education mismatch, *skill mismatch* is a more direct concept based on whether workers have the actual skills needed to carry out successfully required job tasks. Typically, measures of skill mismatch are limited to three alternative categories, namely *under-skilled (*or *skill deficit)*, *over-skilled* (or *skill surplus*) or *required skill*. In this study, the category ‘required skill*’* is split between those who are low-skilled and high-skilled. The conceptualisation and measurement of education and skill mismatch is elaborated in Chapter 4, but a few points are worth noting already at this stage.

First, the orientation, purpose and substance of education and skill mismatch concepts and their related debates which are discussed above are closely related and even intertwined, but the distinctions are important because how mismatch is conceptualized and measured can itself lead to major differences in exactly how the concerns are framed and investigated, including not least under which conditions and assumptions. For example, skill gain and skill loss are more relevant in the framing of skill mismatch compared to education mismatch.

Second, the two concepts may be perceived as complementary, one allowing for breadth and the other allowing for depth. Qualification mismatch has the advantage of being easier to measure and broader in its coverage of ‘skills’ – albeit indirectly – but has the disadvantage of being much less precise and it does not take account of the possibility for skill gain or loss beyond the attainment of qualifications. For example, employees engage in adult education/training, and firms support adult education/training at various life cycle points of the worker which may or may not be related to qualifications. Skill mismatch on the other hand, is much more precise and it takes account of skill gain or loss, but it is often very narrow in scope (e.g., literacy mismatch or numeracy mismatch). Still, it compensates for the fact that qualifications are not necessarily good indicators of ‘skills’. This is certainly the case for workers who left the education system many years ago.

Situating the over- and under- skilling debate

As mentioned earlier, skill mismatch is a phenomena that can be viewed from different perspectives. Past policy concerns tended to focus on a perceived risk of increased *skill shortages* and *skill deficits* as a result of continued skill biased technical change in the economy. *Skill underutilization* is now argued to be an equally important issue (CEDEFOP, 2010a). Many highly qualified workers are found to underutilize their skills. This can also be referred to as a *skill surplus*, or alternatively as *overskilling*. In addition, workers with low levels of skills are found to be employed in jobs which appear to have relatively high skills demands. This is referred to as a *skill deficit*, or alternatively as *underskilling*. Skill surpluses and deficits, or alternatively, overskilling and underskilling are also referred to as *skill gaps*.

This study investigates the extent of literacy mismatch and its distributon by socio-demographic characteristics in Chapter 5. Literacy skills are key information processing skills that are important both in their own right and because the development of other high level cognitive skills is dependent on their mastery. Literacy skills for example are taking on a more significant role in today’s modern society and global knowledge economy as a consequence of skill biased technical change. Disruptive technologies like

ICTs and the accompanying increasing mass of coded knowledge that appears in the form of written information are contributing to an ongoing change in the structure of demand for literacy skills both at work and in daily life. Their increasing relevance to productivity as economies shift to knowledge based production explains their relevance for policymakers.

Literacy *skill surpluses* are good for growing knowledge economies in the long run, but a lack of use of these skills or *skill underutilization* in the workplace may constitute a problem in the short run. This follows from the "use it or lose it" hypothesis (Krahn and Lowe, 1998; OECD/Statistics Canada, 1995) and practice engagement theory (Reder, 1994; 1998). Literacy skills are like muscles that develop if you use them, otherwise they can be lost. Literacy skills are not only a function of formal education but also a wide range of other practices that occur over the lifespan including social and cultural practices, and not least, work practices such as engagement in literacy related tasks at work (Desjardins, 2004). Practice engagement is thus important to nurture and develop skills (Reder, 2009a; 2009b). By extension workers who are deprived of the opportunity to perform complex literacy tasks may lose some of their skills proficiency.

The structural shift of OECD economies toward information and knowledge based economies in the early 1990s brought much attention to literacy and other key information processing skills. In the 1990s and early 2000s, the policy focus tended to be on the supply of basic skills needed in an information economy, and on the consequences of skill deficit for individual workers and the economy as a whole. Consequently the discussion was focused on individuals' literacy deficits and the need for training and upgrading. Much less thought was given to how a lack of use and low levels of demand for these skills is linked to skill loss (Krahn & Lowe, 1998) and by extension restricts large groups from receiving adult education and training. Evidence suggests that adults with higher levels of literacy skills are much more likely to take up training and receive employer sponsored training (OECD/Statistics Canada, 2005). Accordingly there has been a shift toward an increased concern about the demand for skills and employer practices which can either perpetuate or eliminate skill mismatch (e.g., Bevan & Cowling, 2007).

Chapter 3 The causes of mismatch: some alternative perspectives

Introduction

As pointed out by Quintini (2010), there has been no attempt so far to develop a unified theory of education or skill mismatch, but a number of alternative perspectives are useful for helping to understand a range of labour market imperfections which could be behind several of these types of skill imbalances. These include: human capital theory, technological change theory, career mobility theory, job search theory, signalling theory, job competition theory, labour market segmentation theory and assignment theory. Each alternative perspective is briefly discussed in turn below in the context of *how mismatch may arise or persist*. The discussion in this chapter focuses on implications of alternative perspectives for mismatch rather than earnings differentials but the two are intricately related making it difficult to neatly separate the two. Chapter 6 discusses some of the theories in relation to earnings more directly since that is the focus of that chapter. Also discussed are further reflections on potential reasons for observed skill imbalances which do not necessarily correspond neatly to a specific theory.

Labour market theories that are helpful for understanding the potential causes of mismatch

Human capital theory

Human capital theory (Schultz, 1961, 1975; Becker, 1962, 1964; Mincer, 1958, 1962, 1974) is an important starting point because it directly links education and skills to earnings. It is also the starting point used in Chapters 6, 7 and 8 to consider the empirical relationship between labour supply characteristics including education and skills and outcomes. Concepts such as education, skills and earnings form the cornerstone of the returns to schooling and skills literature. They are also key for studies that link education or skill mismatch to earnings differentials. While the theory can be viewed as a theory of individual and public investment behaviour regarding education, it can also be seen to form the bedrock of many other theories within the neoclassical framework which assume that wages are set competitively and reflect marginal productivity. This is the case whenever there is an implicit or explicit assumption that wages reflect the marginal contribution of a worker's skill, even if only as a starting point for discussing possible deviations from this assumption. For example, assignment theory, or assortative matching models are premised on these assumptions, at least as a starting point (see Becker, 1973; Eeckhout & Kircher, 2011). This is in contrast to other theories which de-emphasize the potential link between skills, productivity and earnings (i.e., labour market segmentation theories).

Human capital theory can thus be seen to focus on the *productivity-enhancing* effects of education as in the returns to schooling literature, or be seen more broadly in the context of its core assumptions among education, skills, productivity and earnings, often taken as a starting point in other theories. In the context of education or qualification mismatch, the former perspective is especially relevant since returns to schooling are interpreted vis-à-vis *over*- and *under*- educated categories. In the context of skills mismatch and allocative mismatch (as in assortative models literature), the latter core assumptions within the human capital framework remain especially relevant.

In its application in the returns to schooling literature, the theory emphasizes the supply side of the labour market, or the characteristics of individual workers including skills in determining earnings. This is in contrast to theories that emphasize the nature of the job in determining earnings (e.g. job competition or labour market segmentation theory) or the importance of both individual and job characteristics, and especially their interaction as in assignment theory (discussed below).

Mismatch is not accounted for, per se, within the human capital framework. Rather, there is an implicit assumption that mismatch will set off an adjustment process so as to equate wages to the marginal contribution of a worker's skill in the long run. Although mismatch may arise, it is a deviation from the core assumptions linking education, skills, productivity and earnings. Quintini (2010) astutely points out complementary theories to the human capital framework (alternatively, core assumptions that wages reflect the marginal contribution of a worker's skill) which help to explain why mismatch may be observed in the short run and may even remain in the long run. These include *Technological Change theory*, *Career Mobility theory*, and *Search theory* which are discussed in turn below before addressing theories that emphasize the importance of job characteristics and those that consider the interaction between individual and job characteristics including the match or mismatch between the two.

Technological change theory

A discussion on technological change is seen as important in the context of this thesis for promoting an understanding of possible mismatch situations within a dynamic framework of possible changes to the production process over the lifespan of workers. For example, some of the policy considerations discussed in relation to alternative mismatch situations in the concluding chapter arise due to the posibility of technological change generating mismatch. Examples include:

- Situations where workers had the required skills but requirements increased due to innovation (deficit situation)
- Situations where workers had the required skills but requirements decreased due to innovation (surplus situation)

Technological change is now widely recognized as a driving force behind productivity and economic growth, but as a phenomenon it has often been treated as external to the functioning of the economy. *Technological change* *theory* (Romer, 1990; Aghion & Howitt, 1997) attempts to integrate this phenomenon and draw out how technological change comes about and can be harnessed. The primary interest is to understand better the course and rate of the change so it can be influenced through policy. It is, therefore, important to enhance our understanding of the effect of skills including mismatch on technical change, and vice-versa.

It can be argued that the core assumptions in the human capital framework implicitly assume that employers will either adjust their technologies to optimize the use of skills, or alternatively, that workers will search for a better fit elsewhere. Acemoglu (1998, 2002a; 2002b) suggests that the skill level of the labour supply may affect the demand for skills by employers leading to skill-biased technical change and finds some evidence to support this claim. This is not to deny that there are a range of structural barriers to technological change and there may be a lack of incentives for firms to adopt new technologies. Skill shortages is one example but the simple fact that costs are involved may delay adjustments to production processes or lead to the avoidance of change altogether especially if the incentives for long run maximization of productivity are not properly aligned.

Mismatch can be affected in several ways by technological change. First, it may lead to skill underutilization because of the cost and other barriers associated with adopting new technologies or in changing the ways in which work is organized. This may lead to a loss of the skills that were gained as a result of increased educational investments and may result in lost opportunities to enhance productivity. To avoid wastage, policy must ensure that firms have appropriate incentives to make full use of available skills, including the incentives to invest in technical change and making the necessary adjustments to the production process to increase productivity.

Secondly, firms in sectors that are subject to change may have an incentive to hire workers with more qualifications than are actually needed in order to ease labour adaptations in the future. This may lead to a perceived observation of overeducation. It may also lead to overskilling but only to the extent that education adds to the supply of skills. Hiring more employees with more skills than necessary might serve as an insurance policy for firms that operate in rapidly changing and uncertain markets. The problem with this line of reasoning is that the prospect of skill loss associated with the lack of skill use is ignored. Still, the costs of compensating for skills loss may be less than the costs of hiring someone new.

Thirdly, as technical progress occurs and the qualification requirements for new entrants are upgraded, many individuals who already employed will appear to be ‘undereducated’. But this does not take account of the non-formal education and skill development activities undertook by the individuals after being hired. Thus while workers may be observed as undereducated they may not be underskilled. Hartog (2000) suggested that undereducated workers are usually expected to have above-average abilities but he does not distinguish whether the person may have been hired ‘undereducated’ or the person became ‘undereducated’ as a result of technical progress. Many workers may be truly underskilled due to the rapid change in technologies for which they have little prior exposure or competencies to deal with.

The following sub-section discusses technological change theory further by focusing on the implications of changes in the mix of jobs and job tasks. This is important for understanding skill mismatch because neither employees, nor employers have full information regarding how the nature of job tasks is likely to evolve over time.

The changing mix of jobs and job tasks

The *hollowing out hypothesis* claims that the demand for medium skilled workers is declining on the basis of a rise in high-wage and low-wage jobs, and a decline in medium-wage jobs, i.e., wage polarization (Kolev & Saget, 2010). In their analysis of labour market trends in the US and European Union economies, Acemoglu and Autor (2010) provided evidence of broad-based increases in employment in high-skill and low-skill occupations relative to medium skilled occupations (i.e., job or skill polarization). They also provide evidence of a broad diffusion of new technologies which they suggest may have served to directly substitute capital for labour in tasks that were previously performed by moderately skilled workers.

Computers tend to be singled out as the culprit for *hollowing out*. Computerization may reduce the demand for medium skilled workers, namely by serving as a substitute for medium level job tasks, for example, routine cognitive tasks (Autor, Levy & Murnane, 2003). Others have earlier maintained that the introduction of new technologies requires more skilled workers and that the two are complements (Katz, 2000; Bartel & Lichtenberg, 1987). Evidence on the net effect of the complementary and substitution effects of technological change appear to support the hollowing out hypothesis, but more research is necessary to understand the patterns and their implications.

Hollowing out is closely related to the *deskilling* of jobs but the two are not identical. The former refers more directly to the change in the mix of jobs, whereas *deskilling* as well as *upskilling* refer more directly to changes in the mix of tasks within jobs.

Braverman (1974) questioned the notion that *upskilling* goes hand in hand with technological progress. Instead, he suggested that it will lead to *deskilling*. He noted the division of work tasks, stronger control by the employers through scientific management resulting in de-qualification, and the use of computer technologies to routinize and mechanise non-manual work.

Despite intense debates among scholars, evidence regarding tendencies for deskilling or upskilling remains ambiguous (Spenner, 1983; Gallie, 1991; Valla, 1990; Åberg, 2002). This is partly due to varying understandings of skills and considerable variation in the way the demand for skill has been assessed (Moore, 1982; Valla, 1990). There is however, little evidence of widespread deskilling as postulated by Braverman (Gallie, 1991; Spenner, 1983, Åberg, 2002). Deskilling cannot be ruled out, however. It is likely that some deskilling is occurring as technological change affects production and work processes.

There is also some evidence suggesting that changes to the occupational structure over time are skill-biased, but this is primarily with regard to a change in the mix of jobs (Osterman, 1995; Åberg, 2002). For example, using the educational requirements of jobs as criteria, evidence supports the view that the labour market increasingly is requiring a better qualified labour force. But this ignores the possibility for qualification inflation and overeducation.

Providing a more nuanced analysis of how the structure of labour demand has been evolving, Autor et al. (2003) examined changes in the task composition of work. Using representative US data on job task requirements from 1960 to 1998, they found that routine cognitive (e.g., search, operators) and manual work (e.g., assembly line) have been steadily declining since 1980 which they attribute to the impact of computers. Non-manual work which is difficult to reduce to routines (e.g., nurses, truck drivers) is also observed to be in decline since 1970. In contrast, they find that cognitive tasks that are non-routine such as those that involve interaction or are analytic in nature have continued to increase sharply since 1970. Their findings confirm that jobs which are based on routine tasks are disappearing because computers are able to perform such tasks more cheaply. But their findings also confirm that changes to the structural composition of occupations is skill-biased since job growth is found to be concentrated in high-skill jobs which are based on complex and non routine tasks.

In summary, there is evidence that the skill content of jobs is changing over time. This is reflected in increases of requirements within some jobs as well as increases in the number of high-skill jobs. There is however, also evidence of a reduction in the number of medium-skill jobs.

To the extent that upskilling and deskilling processes are operating, either directly via changes in the mix of job tasks, or indirectly via changes in the mix of jobs, skill mismatch is likely to arise. To be sure, the dynamics around technical change may have important and unpredictable impacts on skill mismatch. The net effect of skill demand changes on mismatch is not clear. Some jobs may be subject to deskilling leading to overeducation and overskilling, whereas some jobs may be subject to upskilling leading to undereducation and underskilling.

Career mobility theory

Occupational mobility or the changing of job tasks performed over one’s career is now common place in most OECD countries. But the rate of career mobility tends to be highest among younger and more highly educated labour market participants. In other words, the upward trajectory is much higher for well educated youth. Sicherman and Galor (1990) who originate the theory suggest that wage penalties for overeducated workers are compensated by better promotion prospects. This theory is helpful for explaining the high incidence of youths in the overeducation and overskilled categories, but is less helpful in explaining the career mobility of undereducated workers as pointed out by Büchel and Mertens (2004). It is plausible to postulate that as youths gain more experience and more information, they are more likely to move into higher level occupations. To the extent that the theory operates, overeducation is a temporary phenomenon over the life cycle and should correct itself as youths find their way into jobs that match better their skills, and overeducation should decline with age.

Even so, there are various barriers to career mobility which must be understood, monitored and alleviated where possible so as to avoid skill loss among youths as well as the loss of opportunities to increase productivity. Barriers may include a lack of information, a lack of opportunities due to poor market conditions, or they may include structural deficiencies in certain occupational areas where mobility is restricted for a wide variety of reasons.

Search theory

Search theory can help to explain mismatch because of imperfect information available to employees about the nature of production processes, and to employers regarding employees' actual skills. Eekhout and Kircher (2011) emphasizes the role of such *frictions* and associated *search costs* as being the important source of mismatch. When workers are looking for a job, they do not necessarily have good or accurate information about jobs and may accept a job offer in which the job tasks are not commensurate with their qualifications or skills. Some workers may not obtain a job that suits their potential, especially youths whose levels of education are increasing. For example, younger workers may be in transition seeking to find good jobs but lack opportunity or networks to help them find the right jobs. The ongoing search for better jobs and better matches by these individuals drives mobility and wage growth (see Jovanovich, 1979). Others may lack competences to find a job; and/or may need reschooling or retraining to suit available opportunities. Still others may have given up and accepted limited or narrow career paths that are substandard to their potential because of a lack of alternative or forthcoming opportunities and too many education and training barriers or other labour market barriers.

Signalling theory

Signalling theory (see Arrow, 1973; Spence, 1973; Riley, 1976; Weiss, 1995) emphasizes the *productivity-identifying*, *allocative*, *sorting*, *screening*, *positional*, or matching effects of educational credentials. There are several variants to this type of theory (e.g., credentialism, sheepskin model). The theory brings into question the relationship between education and skills in the set of core assumptions emanating from human capital theory, which raises important distinctions between overeducation and overskilling, or alternatively between undereducation and underskilling. However, this theoretical perspective is not inconsistent with the asumption that wages reflect the marginal contribution of a worker's skill. The primary difference with human capital theory is to emphasize the role of education in the matching function, and to suggest that education may not necessarily add to skills and that it is not the only source of skills or skill development.

A common feature among signalling theories is that there is asymmetric information in the market place between individuals and employers; the latter do not have perfect information concerning the skills of potential employees (e.g. Stigler, 1961; Spence, 1973; Arrow, 1973). These theories also share the main premise that qualifications carry probabilistic information regarding difficult to observe characteristics which are relevant to job performance including cognitive and non-cognitive skills. Qualifications are thus viewed as merely signals which suggest that the holder is more likely to be: more productive, a more efficient trainee and thus less costly to train, and more likely to adjust efficiently to unforeseen change. Although some extreme versions of this theory rule out the productivity-enhancing effects of education such as the *sheepskin model*, most do not preclude the possibility that education also enhances skills.

While critics have pointed out that education may just be an expensive way of sorting or allocating workers to jobs and may add little to the skills supply, especially at the margin, a matching process is nevertheless necessary. Employers have imperfect information regarding the likely performance of potential employees. Thus they face a dilemma when they are hiring and have little choice but to infer applicants' abilities to perform by relying for example on their qualifications which are validated and widely recognised. Indeed, there are findings (e.g., Black & Lynch, 1996: 266) which suggest that educational credentials are important to employers when hiring, and thus play an important role in providing access to occupations.

Signalling theories are important when interpreting the findings of this study because literacy skills are difficult to observe in the day to day functioning of the labour market. Direct measures of skills are made available from large scale studies like IALS, ALLS and PIAAC but employers do not generally use the tools needed to directly assess the actual literacy proficiency of potential employees. Thus it is interesting to observe whether they are rewarded above and beyond officially recognized credentials. While difficult to observe initially, these skills may be more discernible to employers following a certain period of tenure, and may be rewarded above and beyond officially recognized credentials accordingly. This helps to answer the question of whether actual skills lead to higher pay beyond the signalling effects of education (see Chapter 6).

The allocative nature of qualifications via signalling effects may induce overeducation via the *inflation* and *crowding out* mechanisms. These have different implications for education and skill mismatch depending on a variety of alternative scenarios.

Before describing these scenarios, it is useful to highlight the incentives for individuals to obtain higher levels of education. It can be argued that individuals and many employers, perhaps a growing number, have incentives which are aligned to induce overeducation. Employers with attractive opportunities have the incentive to hire individuals with higher levels of education for a variety of reasons – the most obvious is to select the most able workers. In itself, this does not lead to overeducation, but it provides individuals with the incentive to secure attractive opportunities and higher paying jobs. Alternatively, some employers have the incentive to hire individuals with higher levels of education than may be required, for example, to maintain a more flexible and adaptable workforce as an insurance policy against unforeseen changes in the future. This adds further to the demand for qualifications and the incentives to obtain them.

Qualification inflation may arise for at least two reasons, both leading to actual or perceived overeducation. First, as more and more people obtain higher levels of education, the information or discriminatory content and hence signalling value of higher qualifications may be diminished. Second, there may be deterioration in the quality of qualifications as more and more people seek to obtain them. For example, standards may fall, effectively increasing the unobserved heterogeneity of individuals for a given level of education. Workers may thus have attained qualifications that are not commensurate with their actual level of skills. In either case, employers may as a response upgrade the educational requirements needed for certain jobs but not the actual job content. As inflation of this nature ensues, the productivity-identifying effects of education are distorted, feeding further inflation. This mechanism leads to a number of alternative implications that are worth noting in order to highlight the potentially pervasive and complex ways in which signalling may generate mismatch.

First, if qualifications attained and required have both increased, but there are no real changes to actual skills and required skills, then the additional education induced by inflation effects does not have any enhancing effects on productivity. Nevertheless, it helps to preserve its productivity-identifying effects. However, this is at an inflated cost to those who pay for education.

Second, workers who are already employed in jobs that are subject to qualification inflation may appear as undereducated, even if the job content of their job does not change.

Third, if qualifications overstate actual skills, for example, because of deterioration in the quality of education, then perceived overeducation may actually be accompanied by underskilling.

Fourth, if qualifications accurately reflect actual skills (i.e., educational investments are adding to the actual skill supply), then the overeducation will be accompanied by overskilling. In this scenario, higher educated and thus higher skilled individuals may have an advantage in securing employment in lower skill jobs, *crowding out* the employment opportunities for those with lower levels of education. Unless employers change work practices and adopt complementary technologies to make use of the accompanying skill surpluses, *skill underutilization* will arise, contributing to wasted opportunities to increase productivity, a loss of income, and the loss of the potential value that was created through educational investments because of the risk of skill loss associated with lack of use.

Job competition theory

Job competition theory (see Thurow, 1975) is very similar to signalling theories but with an important deviation from standard neoclassical assumptions, namely that individuals' earnings do not necessarily reflect their marginal productivity. That is, earnings and other rewards are no longer primarily a function of a worker's skills or productivity. Instead, the theory emphasizes the characteristics of the job in determining earnings (e.g., pay determined by wage setting institutions).

Signalling however, still operates at full strength in the matching of workers to jobs and individuals are seen to compete for top jobs on the basis of their level of education. The incentive for individuals is to invest in additional education to preserve their place in the hiring queue even if they do not need it to perform their eventual job tasks. People are competing for good jobs that pay well. Moreover, individuals may signal their capabilities other than by their credentials. For example, some workers may be able to signal that they have some of the important skills needed for the job simply by being better at communicating and demonstrating results or attitudes necessary for the job. Nevertheless, they may have low levels of other skills such as literacy or problem solving skills. Others may have access to networks which are an important source of labour market entry and reflect important sociological elements.

According to this theory, employers are interested in better educated workers because they are seen as being less costly in terms of training and adjusting to change. In terms of mismatch, the implications of this theory are very similar to signalling. One exception is that underskilled or undereducated workers may be successful in competing for higher skilled jobs and thus earn more than would otherwise be predicted by their level of qualifications or skills.

Labour market segmentation theory

Labour market segmentation theory (see Doeringer &Piore, 1971; Cain, 1976; Duncan & Hoffman, 1979) offers a useful framework for exploring mismatch. The main premise is similar to job competition theory in the sense that it is the job characteristics, not individual ones which are relevant in the earnings function. This theory emphasizes the characteristics of jobs and job markets, rather than the characteristics of individuals in explaining labour market outcomes (Duncan & Hoffman, 1979). Many proponents of the theory have suggested that worker productivity and pay are determined more by the job and its technology than by the human capital of the worker (see Velloso, 1995).

Segmentation theory views the labour market as being composed of two or more segments. The different labour markets operate under different circumstances such as regulations, technology, demand and supply conditions, which lead to varying salaries and other benefits as well as other outcomes (e.g., promotion, job security, access to training and human capital development, etc.). Originally, segmentation theory distinguished between two segments: a secondary and a primary sector, known as dual labour market theory or “dualism”. Typically, the primary sector is viewed as consisting of ‘good’ jobs with security and high pay and the secondary sector by low-wage jobs, poor returns to human capital, and a high degree of job insecurity. Alternatively, the theory could be used to argue that in certain segments, matching skilled workers to skilled jobs may be easier or more applicable. Similarly, matching unskilled workers to unskilled jobs may also be easier.

The theory implies that there are various barriers which constrain mobility between segments. Thus while there may be a surplus or deficit of skills in one sector of the economy, these skills are not easily deployed to other areas of the economy. Examples of barriers may include social and cultural norms, but also simply the level and type of qualifications and cumulative work experience. The theory helps to account for the possibility of horizontal mismatch.

Assignment theory

Assignment theory (see Sattinger, 1980; 1993; Hartog, 1981; 1985; 1986a; 1986b; Tinbergen, 1956) emphasizes both individual and job characteristics, making it an ideal candidate for exploring the match-mismatch between a worker’s skill profile and the skill content of their job. The model acknowledges the heterogeneity of both workers and jobs. Pay can thus be driven by both the characteristics of the individual and of the job. A high-skill match pays best, but depending on whether it is the job or individual characteristics that matter most, it is not clear whether overskilled workers earn more than underskilled workers. If rewards are more closely tied to productive jobs than productive workers, for example, then the underskilled could earn more than overskilled workers, and vice versa, if rewards are more closely tied to individual characteristics.

Applications of the theory are usually premised on assumptions that wages are set competitively and reflect the marginal contribution of a worker’s skills, but there is also an acknowledgement of the importance of the nature of the job and fit between worker and job in terms of the type and level of skills. While job characteristics become important, applications typically remain within the neoclassical assumptions of competitive wage setting and link between earnings, skills and marginal productivity (Becker, 1973). For example, Eekhout & Kircher (2011) argue that it is not possible to identify whether more productive workers are sorted in more productive jobs, because wages reflect a worker’s marginal product. In contrast, job competition or labour market segmentation theory emphasize the possbility for a disconnect between earnings and marginal productivity.

Assignment theory recognizes the possibility that employers do not necessarily adjust their technologies, for example, because workers have higher levels of skills. Thus it introduces the possibility for persistent skill mismatch. Eekhout & Kircher (2011) found that search costs may be consistent with this.

The operation of the matching function may depend on signalling but according to the theory, the most efficient solution, even if it is hardly feasible, is to assign workers in a top-down fashion according to their skill level. The highest skilled individuals are assigned to the highest skilled jobs applying the same assignment method down to the lowest skilled individual and lowest skilled job.

Not surprisingly, several studies have found *Assignment* theory to be the most consistent with findings on mismatch and its association with wages (Duncan & Hoffman, 1981; Hartog & Oosterbeek, 1988; Sloane, Battu & Seaman, 1999; McGuinness, 2006). Abowd, Kramarz and Margolis (1999) attempted to separate out the contribution of the person and the job in the determination of wages. However, this is very difficult in practice, especially under scenarios of completementarity or matches between workers and firms, because a firm (or job) wage premium may be due to selection of productive workers and not due to genuine firm side effects. Symetrically, what appears to be due to the worker, may be because of the firm. However, the definition of match-mismatch situations as used and applied in this study to estimate wage differentials associated with the different situations, suggests that mismatched workers with low literacy skills but in jobs requiring high levels of practice in literacy activities earn much more than mismatched workers with high literacy skills but in jobs requiring low levels of literacy practice. The former are potentially low productivity workers for the kind of job they are working in but otherwise are in productive jobs that pay well (see Chapter 6).

Discrimination theory

A final theory that deserves mention in relation to potential causes of mismatch is discrimination theory. It suggests that personal characteristics of workers which are unrelated to productivity are also valued on the labour market (Arrow, 1971). For example, women and immigrants may be subject to skill mismatch more than otherwise because discriminatory mechanisms may be operating on educational markets, on the one hand, to constrain skill development, and on the other hand, on labour markets to constrain them from making full use of their skills. Chapter 5 takes a closer look at the distribution of mismatch by age, gender and immigrant status.

Further reflections on potential reasons for observed skill imbalances

In addition to the above theories, there is other less formalized but related explanations for why skill mismatch may be observed. Other reasons that are taken up include political economic objectives such as pursuing, perhaps unwittingly, a low, high or mixed skills strategy; and the unobserved heterogeneity of workers.

Market vs coordinated strategies

It is possible that the skills of some workers are underutilised because employers pursue low-skills strategies and/or simply mismanage the potential of their employees. For example, the structure and distribution of work tasks may not be well suited to the actual skills base of the workforce. This might be due to lack of incentives to pursue high-skills strategies. Structural conditions which surround the labour market and depend on coordinated governance, for example, may play an important role in influencing the demand for, and use of, skills. These conditions may include institutional structures which underpin relations between employers, workers and the state; legal structures; and, incentive structures which are designed to encourage the adaptation of technical change and the training of the workforce, not just skilled workers but also low and medium skilled workers.

While policy makers have argued that mismatch problems can be solved by improving the supply of skills, some scholars point to structural conditions in the economy which lower the demand for and utilization of skills (see e.g. Brown, Green and Lauder, 2001). Some have pointed to evidence suggesting that: "…many employers are competing on the basis of relatively low-skill, standardized production strategies and price-based competition that require only a limited range of low-level skill from the bulk of the workforce" (Lloyd and Payne, 2006, p. 151).

Unobserved heterogeneity

Finally, mismatch may simply reflect unobserved heterogeneity among workers including their skills, attitudes and preferences. For example, some workers may just not care whether they use their skills or they may have other preferences. They have graduated and obtained credentials but do not have a preference to pursue opportunities that are commensurate with their skill set. Others may have good levels of specific skills such as literacy but otherwise have low capabilities. Chevalier (2003) for example, suggested that increased access to education in the UK has met more low ability students entering the tertiary sector. Interestingly, Lindqvist and Vestman (2010) find strong evidence that men who fare poorly in the labour market lack non-cognitive rather than cognitive ability, something which is more difficult to observe or measure comparatively.

Chapter 4 Review of the conceptualisation and measurement of mismatch

Introduction

This chapter considers some of the issues around the conceptualization and measurement of mismatch in order to help the reader situate the measure of skill match-mismatch used in this study.

The conceptualisation of mismatch

Recent years have witnessed a growing literature based on the concept of 'education mismatch', 'qualification mismatch' or otherwise referred to as 'undereducation' and 'overeducation' (see e.g., Oosterbeek, 2000; Miller, 2007; Sloane, 2007; Dolton & Silles, 2008; Korpi & Tåhlin, 2009; van der Meer, 2009; Chevalier & Lindley, 2009). A closely related and often overlapping strand of studies focuses on alternative measures that are more closely tied to the concept of 'skill mismatch', namely 'underskilling' and 'overskilling', or alternatively 'skill deficit' and 'skill surplus/skill underutilization'(see e.g., Krahn & Lowe, 1998; OECD/Statistics Canada, 2005; Mavromaras, McGuinness & Wooden, 2007; Mavromaras, McGuinness & Fok, 2009a; 2009b; Mavromaras, McGuinness, O'Leary, Sloane & Wei, 2010; Ryan & Sinning, 2009; OECD/Statistics Canada, 2011). There are fewer studies using the latter concepts partly due to the lack of data and the difficulty in measuring skill mismatch, but the advantages are apparent and interest appears to be on the rise (e.g., CEDEFOP, 2010a).

Given that *education mismatch* and *skill mismatch* are closely related, the discussion draws from both strands of literature. As mentioned the two concepts are not identical, but the orientation, purpose and substance of the underlying debates are closely related. Nevertheless, the distinctions are important because how mismatch is conceptualized and measured can itself lead to major differences in exactly how the concerns are framed and investigated, including not least under which conditions and assumptions.

As an example, findings on *education mismatch* have in many studies been interpreted as evidence that there is over-investment in formal education/qualifications, and/or that the educational system is ineffective in providing the skills needed for the labour market. Such interpretations are debatable for many reasons:

- Firstly, they ignore the fact that education serves a broader purpose than just providing the skills needed on the labour market.
- Secondly, they assume that qualifications truly reflect the supply of skills as well as the demand for skills, ignoring the heterogeneity inherent in standardized classifications.
- Thirdly, they assume that a person's skills are defined by his/her qualifications once and for all, ignoring the possibility for skill gain and skill loss over the lifespan, including the role of adult education/training and learning in the workplace.
- Fourthly, they presume that the structure of demand for skills is fixed or changes only very slowly.
- Lastly, they ignore the role of technological and organizational innovation, the structure of work settings, and workplace/organizational practices in helping to shape the skills needed and to make use of existing skills.

Recognizing these complexities requires a more accurate and up to date measure of mismatch, one that reflects the possibilities for skill gain and skill loss over the lifespan, and reflects differences in the quality of qualifications. Addressing mismatch also requires a careful consideration of the demand side, so as to understand better the variety of factors which may have a negative impact on the effectiveness of skill formation, and also skill use.

When examining mismatch the following considerations are important to note. The first is conceptual. Skills and qualifications are not the same thing, even if qualifications are supposed to signify skills. This is not only because of the variety and complexity of the processes involved in defining qualifications, but also because the process of skill formation and skill loss extend over the entire lifespan. Qualifications reflect only the situation at a given point in time, and other than for recent graduates, this is often in the very distant past. These distinctions are particularly important when considering appropriate strategies for dealing with skill shortages and/or skill mismatches.

The second regards measurement. How should actual and required qualifications or skills be measured when empirically assessing mismatch between workers and jobs? To what extent do typical indicators such as years of schooling, level of education, credentials or other measures actually reflect qualifications or skills, and what are appropriate measures of the use of those qualifications or skills? The extent to which the measures can be operationalized to do justice to the underlying concepts being measured is a major challenge and has been approached in a variety of ways.

The measurement of mismatch

Education mismatch

The definition and measurement of education and skill mismatch varies widely. As outlined by Verhaest and Omey (2006; see also Groot & Maasen van den Brink, 2000), there are at least four major ways to approach the measurement of 'over- and under- education' or 'educational mismatch'. Quintini (2010) has further specified these approaches as either self reported, normative, or statistical approaches:

Self-reported

- Direct Self-Assessment (DSA): Respondents are asked to subjectively assess whether they feel over- or under- educated for their position or if it just right (e.g., Groeneveld, 1997).
- Indirect Self-Assessment (ISA): Respondents are asked to subjectively assess what they feel is the required educational level to do their job (e.g., Hartog & Oosterbeek, 1988; Frei & Sousa-Poza, 2011) or alternatively what they feel is the required

educational level to obtain their job (e.g., Duncan & Hoffman, 1981; Sicherman, 1991; Sloane, Battu & Seaman, 1999), and then over- and under- education is assessed by the analyst by comparing this level with the actual educational level of the respondent.

Normative

- Job Analysis (JA): Analysts subjectively determine the required level of education on the basis of occupational descriptions such as those in the US Dictionary of Occupational Titles (DOT) (e.g., Rumberger, 1987; McGoldrick & Robst, 1996).

Statistical

- Realised Matches (RM): Analysts objectively determine the required level of education on the estimated distribution of educational attainment within each occupational group (e.g., Verdugo & Verdugo, 1989; Mendes de Oliveira, Santos & Kiker, 2000; Bauer, 2002).

Verhaest and Omey (2006) provided an extended discussion of the pros and cons of each method. In brief, subjective reports by respondents are always vulnerable to measurement error which can vary from respondent to respondent. While RM is based on a statistical approach and is the most objective method it is also the most problematic as the required level of education is determined solely by the characteristics of the employees in those jobs while the actual requirements of the job are ignored (i.e., there is an endogeneity problem).

Although Hartog (2000) concluded that JA is the preferred method, it is likely that a combination of the methods, depending on available data, is the best solution. While the JA method is normative and based on a qualitatively oriented subjective approach, it can be argued that the analyst has the advantage of devising a scheme based on all available information and thus to control for the subjectivity that is present in self reported measures. However, the ability of analysts to control subjectivity is arguable. Combining the JA approach with further information such as actual distributions of educational attainment (i.e., RM method) and subjective measures (i.e., DSA or ISA), if available should help to minimize measurement error. For example, Chevalier (2003) mixes the normative or

JA approach with the self reported approach to obtain a more refined measure of overeducation.

Whatever the method, education mismatch is based on the use of qualification or attainment based measures in order to decipher and summarize both the skills individuals actually have and the skills required in jobs. But to what extent do qualifications do justice to actual skills held and required? As mentioned above, qualifications are not the same thing as actual skills.

Skill mismatch

To avoid the shortcomings of translating job requirements into qualifications, some researchers have devised a more direct approach by asking respondents directly about the extent of the use of their skills in their job. For example, in the Household Income and Labour Dynamics in Australia (HILDA) survey, there are self reported responses on a seven point scale to the statement “I use many of my skills and abilities in my current job”. Those who disagree are treated as overskilled and vice versa those who agree are treated as underskilled (see e.g., Halaby, 1994; Mavromaras, McGuinness & Wooden, 2007).

Alternatively, respondents can be asked about the extent of use of a series of specific skills (e.g., literacy, numeracy, problem solving, teamwork, etc...) in their job (see e.g., UK Skills Survey). This has the advantage of helping to assess the required level of the specific skills needed to carry out job tasks and bypasses the shortcomings of translating job requirements into qualifications. However, it may be narrower in the sense that not all specific skills are feasible to assess via survey instruments.

The method used for deriving mismatch in this study relies on this latter approach, focusing on usage of specific skills at work. The measure of mismatch used in this study is defined in detail in the next chapter.

Chapter 5 The data: Adult Literacy and Lifeskills survey

Introduction

This chapter describes the dataset, sample and variables used for this study. The same dataset is used for analyses throughout the study. The definition and methodology used to define skill mismatch is also described. The extent of match- mismatch between workers' literacy skills and their literacy use in the workplace as well as the socio-demographic profile of skill match-mismatch is also presented in this chapter.

The Adult Literacy and Lifeskills survey

The analysis in this study makes use of the Adult Literacy and Lifeskills Survey (ALLS) data, which was collected between 2003 and 2007 in ten countries. Participating countries include Australia, Bermuda, Canada, Hungary, Italy, the Netherlands, Norway, New Zealand, Switzerland and the United States. Eight countries are included in the analysis contained throuhgout this study. Australia is excluded because access to the data was not possible, and Bermuda is excluded due to the the small size of the country and its specific labour market conditions, i.e., there is a strongly bifurcated labour market with the majority of high skills jobs being in the financial sector and occupied by immigrants.

The ALLS is a second generation study following the 1994-1998 International Adult Literacy Survey (IALS). The IALS and ALLS surveys were large-scale co-operative efforts undertaken by governments, national statistics agencies, research institutions and multi-lateral agencies. These are the world's first internationally comparative surveys of adult skills undertaken in several rounds of data collection between 1994 and 2007. Specifically, these studies are international comparative assessments of key information processing skills that also collected comparable background information. See Murray, Kirsch and Jenkins (1998) for a detailed description of the methodology used in the IALS and OECD and Statistics Canada (2005) for ALLS.

In brief, IALS and ALLS are based on a unique combination of household survey methodologies (as in the case of Labour Force Surveys) and direct skill assessment methods. For each country that participated, large scale representative samples of adults aged 16 to 65 were drawn and face to face interviews were conducted to collect information for the Background Questionnaire (BQ) (for approximately 40 minutes) and administer a test (approximately one hour in duration) to respondents. The most advanced and state of art statistical methods were used at all stages of the studies to minimize both sampling and non-sampling errors. The former was achieved by example through state of the art sampling procedures and verification procedures, as well as weighting methods. The latter was achieved by enforcing strict standards and guidelines including interviewer training, translation verification, and reliability scoring methods to name a few.

Each participating country in ALLS used a multi-stage probability sample design with stratification and unequal probabilities of respondent selection. Response rates vary by country and are reported in OECD and Statistics Canada (2011). They range from 40% in Switzerland to 82% in Bermuda. For the IALS study, a study very similar in nature to ALLS, non-response bias studies were conducted as a follow up in select countries (see Darcovich, Binkley, Cohen, Myrberg and Persson, 1998). The conclusion being by and large that with post-adjustments to population weights, the results for this kind of study indicate that the magnitudes of non-response bias were small in the case of the Canadian and Swedish IALS surveys. Selection problems seem to have been well dispersed with percentages of persons at both the highest and lowest ends of the literacy skills distribution being affected. Moreover, benchmarking adjustments related to major socio-demographic variables (e.g., region, age, sex and education) used in post-adjustment weighting methods mitigated selection problems. For the United States, survey non-response was deemed as being perhaps as large or larger than the combined sampling and measurement variance of the literacy tests in some cases, but that it was unlikely to be large enough to affect the survey's major findings and inferences. For both IALS and ALLS, non-response analysis was not as extensive or as definitive as desired. For the ALLS study, no specific non-response follow-up studies were carried out systematically but due to similar survey methods and procedures used in IALS, as well as patterns of responses and response rates, the impact of non-response could be deemed to have had similar impacts. Namely, for the countries that did do non-response follow-up studies in IALS, the magnitude of bias introduced into estimates appears to have been small, and hence of little consequence.

There is nevertheless a need to compensate for the non-response that occurred at varying levels. Therefore, the estimation of population parameters and the associated standard errors is dependent on the survey weights. All participating countries used the same general procedure for calculating the survey weights. However, each country developed the survey weights according to its particular probability sample design. In this study, a sampling weight is used to calculate all estimates in order to take into account complex survey designs and thus adjust for sampling error.

A note on access to the data

It is worthwhile to note that complete microdatasets for the ALLS study can be acquired from Statistics Canada, with the exception of the data for Australia. The public microdata files for select countries do not contain continuous data for age and wages. This is the case for Canada and the United States. However, agreement was reached with Statistics Canada and the US National Centre for Educational Statistics to access the continuous age and wage data remotely in order to run the analyses contained in this study.

Sample sizes and target population

Table 5.1 shows that the total sample size of the target population of all adults aged 16 to 65 in the eight countries included is 59,183 cases. In this study, adults aged 16 to 24 were excluded since many of these adults are in full-time or part-time studies, yet many are also participating in the labour market to varying degrees making it difficult to ascertain their degree of labour market attachment. This exclusion reduces the overall sample size to 49,803 cases. Also excluded from the analysis were adults who were not employed at the time of the survey or at any time during the preceding 12 months. This is because no data were collected from these adults regarding their earnings or occupation. After all exclusions, the sample size is reduced to 38,448 cases.

Table 5.1 Sample sizes by population

	All adults aged 16-65	All adults aged 25-65	Adults aged 25-65 employed at time of survey or in 12 months preceding survey
Canada	20059	16485	13102
Hungary	5575	4574	2996
Italy	6853	5706	3461
Netherlands	5617	5136	3930
New Zealand	7128	6046	5092
Norway	5411	4415	3843
Switzerland	5120	4662	3751
United States	3420	2779	2273
Total	59183	49803	38448

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Variables and descriptive statistics

The following provides an overview and basic descriptive statistics for all the variables used in this study. To begin, emphasis is placed on the key independent variables used, namely the direct measure of literacy skills, self-reported measures of skill use, and the interaction between the two that culinate into the skill match-mismatch variable devised for this study. This is followed by the two dependent variables of focus, namely participation in employer supported adult education and training and monthly earnings. Finally, basic descriptives are provided for all other independent variables used in the studies.

Direct measures of skill in ALLS

Foremost, this study makes use of the unique direct measures of skill made available by ALLS, including prose literacy and document literacy. Numeracy skills were also measured in the ALLS but are not included in this study in a systematic way. This is primarily because the main results presented in this study are very similar whether the focus is on literacy or numeracy skills, or literacy or numeracy mismatch. The author has performed extensive analysis using both types of measures and has determined that due to very high corelation between the two domains, the same kind of overall results emerge even if there are in some cases nuanced differences at the country level that may be of interest for further study. Due to space and time constraints, the analysis of numeracy skills and numeracy mismatch has been left for further study. Together, these direct measures of skills are referred to as key information processing skills.

These skills are believed to be vitally important skills, because they provide a fundamental means to acquire knowledge and skills in a variety of other contexts. They are needed to learn print-based material, to communicate and not least to inform decision-making at all levels. Thus they are likely to be relevant for productivity and hence earnings in all occupations. In this sense information processing skills involves general skills that are applicable to everyone. While they are not all inclusive indicators of human capital, they are thought to be key skills that facilitate the acquisition of other more specific types of human capital.

It is important to note that these direct skill measures include not only the possible impact of education in developing those skills, but also the possible impact of learning in multiple contexts over the lifespan. In this sense they are broader measures than schooling or educational attainment. At the same time, they are much narrower measures of skills since education reflects other skills such as non-cognitive skills. In this way, years of schooling, or educational attainment are complementary to the ALLS measures of key information processing skills.

Among the skills measured, two key information processing skills are used for this study, namely prose and document literacy (OECD/Statistics Canada, 2000; 2005). These are defined as follows:

- *Prose literacy* – the knowledge and skills needed to understand and use information from texts including editorials, news stories, brochures and instruction manuals.
- *Document literacy* – the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables and charts.

There is no arbitrary standard distinguishing adults who have or do not have these skills. For example, many previous studies have distinguished between adults who are either "literate" or "illiterate". Instead, these studies conceptualized and measured proficiency along a continuum (denoted on a scale ranging from 0 to 500 points) and this is used to identify how well adults use information to function in society and the economy. Each score denotes a point at which a person has an 80 per cent chance of successfully completing tasks that are associated with a similar level of difficulty. For the prose and document literacy domains as well as the numeracy domain, experts have defined five broad levels of difficulty, each corresponding to a range of scores.

As an example, the following describes the five broad levels for the prose scale:

- *Level 1* (0-225 points) – Most of the tasks in this level require the respondent to read relatively short text to locate a single piece of information which is identical to or synonymous with the information given in the question or directive. If plausible but incorrect information is present in the text, it tends not to be located near the correct information.
- *Level 2* (226-275 points) – Some tasks in this level require respondents to locate a single piece of information in the text; however, several distractors or plausible but incorrect pieces of information may be present, or low-level inferences may be required. Other tasks require the respondent to integrate two or more pieces of information or to compare and contrast easily identifiable information based on a criterion provided in the question or directive.
- *Level 3* (276-325 points) – Tasks in this level tend to require respondents to make literal or synonymous matches between the text and information given in the task, or to make matches

that require low-level inferences. Other tasks ask respondents to integrate information from dense or lengthy text that contains no organizational aids such as headings. Respondents may also be asked to generate a response based on information that can be easily identified in the text. Distracting information is present, but is not located near the correct information.

- *Level 4* (326-375 points) – These tasks require respondents to perform multiple-feature matches and to integrate or synthesize information from complex or lengthy passages. More complex inferences are needed to perform successfully. Conditional information is frequently present in tasks at this level and must be taken into consideration by the respondent.
- *Level 5* (376-500 points) – Some tasks in this level require the respondent to search for information in dense text which contains a number of plausible distractors. Others ask respondents to make high-level inferences or use specialized background knowledge. Some tasks ask respondents to contrast complex information.

On the basis of a straight average, the prose scale is combined with the document scale to denote literacy skills in this study. Table 5.2.A shows the mean and standard deviation by country for the prose and document scale, as well as the combined prose and document scale and numeracy scale. Table 5.2.B shows the proportion of adults aged 25-65 employed at time of survey or in 12 months preceding survey who score at each level for the prose, document and combined prose and document scales. Levels 4 and 5 are combined since so few adults score Level 5 on any of the scales.

Table 5.2.A Mean scores and standard deviation direct skill scores on a scale ranging from 0 to 500 points, by type of direct skills measure, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Prose literacy		Document literacy		Combined prose and document literacy		Numeracy	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Canada	285	52	285	53	285	52	278	54
Hungary	276	45	275	49	275	45	283	46
Italy	238	54	235	56	237	53	243	48
Norway	293	42	298	50	296	44	289	45
Netherlands	283	42	288	45	286	43	295	49
New Zealand	282	48	285	52	283	49	277	55
Switzerland	274	45	279	48	276	45	292	47
United States	274	51	275	53	275	51	268	56
Total	276	50	278	54	277	51	278	53

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.2.B Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level on the prose, document and combined prose and document scales

	Level 1			Level 2			Level 3			Level 4/5		
	P	D	L	P	D	L	P	D	L	P	D	L
							%					
Canada	13	13	12	27	27	27	40	38	39	21	22	22
Switzerland	15	13	12	37	35	36	35	36	38	13	17	14
Italy	41	44	40	35	32	35	20	20	20	5	5	5
Norway	6	7	6	25	23	23	47	40	45	22	30	26
United States	16	17	16	31	31	31	39	36	38	14	17	16
New Zealand	12	12	11	28	27	27	44	41	43	17	20	19
Netherlands	8	8	8	32	27	28	47	46	48	14	19	17
Hungary	13	15	13	37	35	37	37	36	38	13	14	13
Total	15	16	15	31	30	30	39	36	39	15	18	16

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Notes: P=prose literacy; D=document literacy; L=combined prose and document literacy

Derived measures of skill use used in this study

This study also makes use of the self reported measures of skills use made available by ALLS. A range of questions were posed to respondents regarding their literacy and numeracy related behaviours at work. These are self reported measures, on a likert scale, of the extent to which adults engage in various literacy and numeracy related activites at work.

Scale reliability was ascertained on the basis of Cronbachs alpha with reliability generally following within the range of .75 to .83 or higher (Nunnally, 1978). Three sum scales were created: reading at work, writing at work and numeracy at work.

Analysis revealed that the six items pertaining to reading at work formed a reliable scale (cronbachs alpha=.845). The six items are as follows: How often <do/did> you read or use information from each of the following as part of your main job? Would you say at least once a week, less than once a week, rarely or never (a) Letters, memos or e-mails; (b) Reports, articles, magazines, or journals; (c) Manuals or reference books including catalogues; (d) Diagrams or schematics; (e) Directions or instructions; and, (f) Bills, invoices, spreadsheets.

Similarly, analysis revealed that the five items pertaining to writing at work formed a reliable scale (cronbachs alpha=.775). The five items are as follows: How often <do/did> you write or fill out each of the following as part of your main job? Would you say at least once a week, less than once a week, rarely or never: (a) Letters, memos or e-mails; (b) Reports, articles, magazines, or journals; (c) Manuals or reference books including catalogues; (d) Directions or instructions; and, (e) Bills, invoices, spreadsheets or budget tables.

Finally, analysis revealed that the six items pertaining to numeracy at work formed a reliable scale (cronbachs alpha=.757). The six items are as follows: How often <do/did> you do each of the following as part of your main job? Would you say at least once a week, less than once a week, rarely or never: (a) Measure or estimate the size or weight of objects; (b) Calculate prices, costs, or budgets; (c) Count or read numbers to keep track of things; (d) Manage time or prepare timetables; (e) Give or follow directions or use maps or street directories; and, (f) Use statistical data to reach conclusions.

Results for each of the three sum scales were indexed on a scale ranging from 1 (never or rarely) to 3 (at least once a week) points. Table 5.3.A shows means and standard deviations for the three scales. Table 5.3.B shows more detailed results for the reading at work scale by describing the proportiions of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of intensity of the index (similar results for writing and numeracy can be found in Table A.5.1 and A.5.2 in the Data Appendix for Chapter 5). Levels of intensity were derived using a combination of quartile ranges and the approximate variety and frequency of engaging in additional activities.

Table 5.3.A Mean scores and standard deviation of reading, writing and numeracy practice at work on a scale ranging from 1 (never or rarely) to 3 (at least once a week) points, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Reading at work index		Writing at work index		Numeracy at work index	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Canada	2.25	0.62	2.07	0.71	1.91	0.71
Hungary	1.67	0.65	1.60	0.66	1.68	0.71
Italy	1.78	0.67	1.57	0.65	1.72	0.73
Netherlands	2.23	0.62	2.05	0.67	1.74	0.71
New Zealand	2.33	0.60	2.14	0.70	1.96	0.73
Norway	2.24	0.54	1.94	0.62	1.90	0.70
Switzerland	2.27	0.56	2.19	0.63	1.80	0.72
United States	2.25	0.61	2.09	0.70	1.94	0.72
Total	2.13	0.65	1.96	0.70	1.83	0.72

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.3.B Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of intensity of a reading at work index

	Frequency and variety of reading at work (6 types of activities)				
	Low intensity (never up to 1-2 activities sometimes)	Medium-low intensity (up to 4 activities sometimes)	Medium-high intensity (at least 4-5 activities sometimes or fewer weekly)	High intensity (at least 6 activities sometimes or many weekly)	Missing
			%		
Canada	24	17	19	40	0
Hungary	59	16	9	14	3
Italy	52	16	10	17	6
Netherlands	25	18	21	36	0
New Zealand	20	17	18	46	0
Norway	20	25	22	32	1
Switzerland	18	21	22	34	5
United States	24	17	21	38	0
Total	30	18	18	32	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: See Data Appendix for Chapter 5 for Tables A.5.1 and A.5.2 covering writing and numeracy at work.

Derived measures of skill match-mismatch used in this study

The method used for deriving mismatch in this study follows from the skill mismatch approach described in Chapter 4. The focus is on the usage of specific skills at work as described in the preceding section, but there is also a comparison of usage vis-à-vis direct measures of the skills needed to engage in tasks related to those skills. A unique advantage of the ALLS data is that they allow for detailed information on skill use in jobs to be combined with directly observed measures of skills. Direct measures of skills also help to avoid the drawbacks of translating actual skills into qualifications. The disadvantage is that only few direct measures of skills are available from ALLS, namely literacy and numeracy. As argued earlier, however, literacy and numeracy skills, as they are defined and measured in ALLS (see OECD/Statistics Canada, 2005), make up an important part of information processing skills, which are becoming increasingly important in today's knowledge based economy. As mentioned, only literacy match-mismatch is elaborated in this study since an analysis of numeracy mismatch leads to very similar results in terms of the main conclusions.

Literacy match and mismatch is determined on the basis of reported engagement in literacy related tasks at work and direct measures of the literacy skills of workers. The approach is adapted from a methodology devised by Krahn and Lowe (1998). Persons with reading engagement scores below the median were assigned to the "low to medium-low engagement" category (low-skill job), and those scoring above were assigned to the "medium-high to high-engagement" category (high-skill job). The median corresponds to engagement in at least one literacy related activity at least once a week. Similarly, persons scoring at skills Levels 1 and 2 on the combined prose and document literacy scale were assigned to the "low-skills" category, and those scoring at Levels 3 and 4/5 were assigned to the "high-skills" category. The approach combines the observed skills and skill use variables to arrive at four match and mismatch categories as follows (the derivation of numeracy mismatch is analogous):

- Low-skill, low- to medium-low engagement→ LOW-SKILL MATCH
- Medium to high-skill, medium-high to high- engagement→ HIGH-SKILL MATCH
- Low-skill, medium-high to high- engagement→ DEFICIT MISMATCH
- Medium to high-skill, low- to medium-low engagement→ SURPLUS MISMATCH

Despite the strength of these data there are at least two caveats that are important to keep in mind which may contribute to an under or over estimate of the level of skill match-mismatch:

- First, it is not clear to what extent the literacy and numeracy behaviours that respondents were asked about in the Adult Literacy and Lifeskills Survey (ALLS) reflect the range of text-based tasks that are important for labour market success. However, evidence from the Essential Skills Research Project run by Human Resource Development Canada, which examined the reading requirements in a sample of entry-level jobs, suggests that the ALLS questions do capture some of the major dimensions of on-the-job reading.

- Second, the ALLS measures cover only the incidence and frequency of literacy and numeracy behaviours, and ignore the dimensions of criticality and complexity. The Human Resource Development Canada's Essential Skills Research Project as well as some other research literature, suggests that frequent behaviours, such as reading reports, may have relatively little impact on job performance. Thus incidence and frequency alone may misrepresent the true importance of these behaviours.

It should be noted however, that analysis of these measures show systematic variation across industry, occupation, and education categories as one would expect from reasonably valid measures of literacy and numeracy behaviours.

The extent of literacy match-mismatch

The extent of literacy match-mismatch which is based on the described methodology in the preceding section is displayed in Tables 5.4 for the eight countries included in this study. A number of important results are worth noting.

First, the proportion of literacy matches is about 57-67% depending on the country. This is not surprising, since one would expect that over time workers with higher skills would find their way into jobs requiring more skills, whereas those with few skills would not move up the career ladder.

Second, literacy mismatch is a widespread phenomenon with 29-41% of workers having skills that do not match the requirements of their job, depending on the country. A certain level of mismatch is to be expected. However, what this level is (10%, for example) cannot be answered with certainty. High rates are likely to suggest a need for active policies that foster adjustments.

Third, literacy skill deficits are apparent in every country, but the magnitude varies. Approximately 7-23% of the workforce can fall into this category, depending on the country. High rates of skill deficits signal a need for an increased effort to train persons in those jobs.

Fourth, the reserve of skills, skill surplus or alternatively skill underutilization pertaining to literacy also varies substantially by country, ranging from 13-34%. While a skill surplus is good for growing knowledge economies in the long run, a lack of skill use in the workplace may be problematic in the short run because it exposes workers to the risk of skill loss. High rates of skill surplus signal a need to encourage employers to adapt organizational and work practices which ensure that existing skills are used and not lost over time as a consequence of a lack of use.

It should be noted that the rate of low- and high- skill matches in different countries is likely to be a function of the education and skill profiles, and hence level of economic and social development, of those countries. It is not surprising to see large differences between countries at different levels of economic and social development, but large differences among high-income countries are surprising. Notably, the high rate of low-skill matches and low rate of high-skill matches in Italy stands out. Of the countries participating in ALLS, Italy displays very low rates of literacy skill among its population as is measured in the study. Evidence from IALS and ALLS has confirmed that qualifications do not accurately reflect key information processing skills like literacy. In particular, these studies have shown revealing differences in countries' educational outcomes (see OECD and Statistics Canada, 2005; 2011). For example many high-school graduates in a given country can be found to be as highly skilled as university graduates in another country. Direct measures of literacy skills help to reflect what happens after qualifications are gained but also very much quality differences in qualifications. This illustrates the value of having direct measures of key information processing skills in addition to information regarding qualifications when evaluating the human capital stock of nations. Furthermore, there is a low average level of reading engagement at work in Italy as well as Hungary when compared to other countries, explaining in part the comparatively high rates of low-skill match in those countries (see Table 5.3.A and B). Low levels of reading practice at work in these countries might be related to work and organisational differences as well as cultural differences in coping with or approaching work tasks.

Table 5.4 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each derived category of literacy match-mismatch

	High-skill match	Surplus mismatch (overskilling)	Deficit mismatch (underskilling)	Low-skill match	Missing
			%		
Canada	42	19	17	22	0
Hungary	16	34	7	41	3
Italy	11	13	17	55	6
Netherlands	42	19	16	24	0
New Zealand	43	18	20	19	0
Norway	42	27	13	18	1
Switzerland	33	15	23	24	5
United States	36	17	23	24	0
Total	33	20	17	28	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.

The following three sub-sections looks at the socio-demographic make-up of literacy mismatch by considering the distributions by age, gender and immigration status.

Literacy mismatch by age

Figure 5.1 presents average results across countries showing the incidence of literacy match-mismatch for three age cohorts ranging from 25-35, 36-50 and 51-65. More detailed country by country results can be found in Table A.5.3 in the Data Appendix for Chapter 5. In all countries, literacy surpluses are highest among younger adults aged 25-35. In Hungary and Norway, the incidence of literacy surpluses is high with around 32-38% of younger adults with this profile (see Table A.5.3 in appendix to Chapter 5).

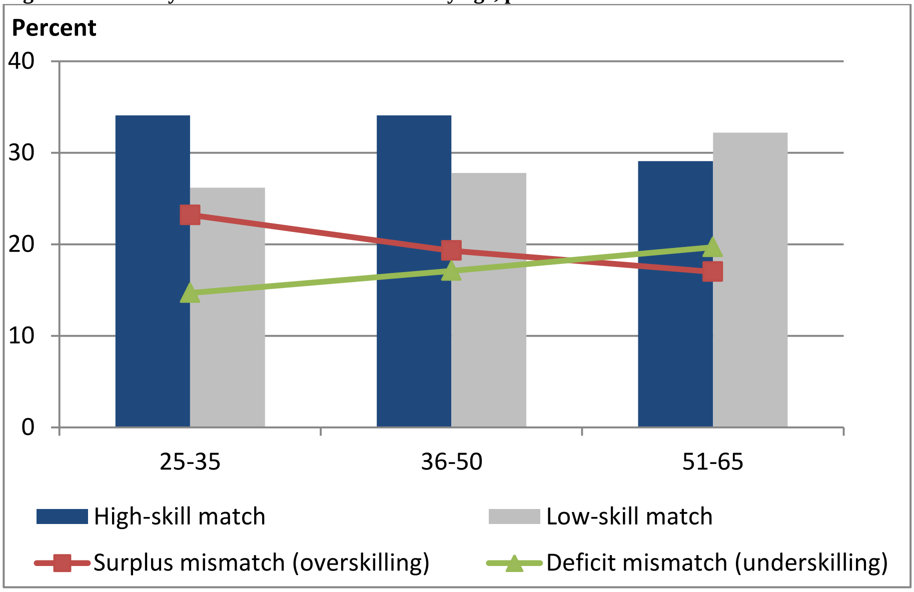
Conversely, literacy skill deficits are found to be more common among older workers and less prevalent among younger adults. In Italy, the incidence of literacy deficits does not vary markedly by age. Switzerland features a relatively high incidence of literacy skill deficit among older age cohorts (31%).

The relatively higher overall incidence of literacy skill surplus among younger adults is perhaps not surprising since they are more likely to be employed in temporary or entry level jobs, in which skill demands are not necessarily commensurate with their area of study or level of literacy skills.

This is consistent with career mobility and search theory (see Chapter 3). As younger adults gain experience, many are likely to move into jobs requiring higher levels of literacy skills. In other words, the degree of match should naturally increase with age as workers find their way into jobs that have a better fit with their level of skills.

It is not possible to discern whether mismatch persists as people gain labour market experience from the ALLS data. Still, notable levels of literacy skill surpluses are found among older age cohorts. This suggests there may be some persistence of mismatch over time. Only in Italy and Switzerland is the incidence of literacy surplus among older cohorts less than 15%, but nevertheless it remains at least 10% in all countries.

Figure 5.1 Literacy match-mismatch situations by age, pooled data



Source: Adult Literacy and Lifeskills survey, 2003-2007.
Notes: Results are averaged over countries who participated in ALLS. See Data Appendix for Chapter 5 for the corresponding data table (Table A.5.3) and more detailed country by country results.

Literacy mismatch by gender

Gender differences in skill mismatch as revealed in Figure 5.2 are noteworthy. The proportion of women who experience literacy skill surplus is more than men, in some cases by a wide margin, while proportion of men who experience literacy skill deficits is more than women. This means that there are generally more women than men in jobs that do not make full use of their literacy skills. Conversely, there are more men than women in jobs that require a high level of engagement in literacy related practices, even if they have low levels of literacy skills.

Women are traditionally disadvantaged, not least on labour markets, which may point to more systematic underutilization of their skills based on discrimination and other allocation mechanisms that are operating on the labour market.

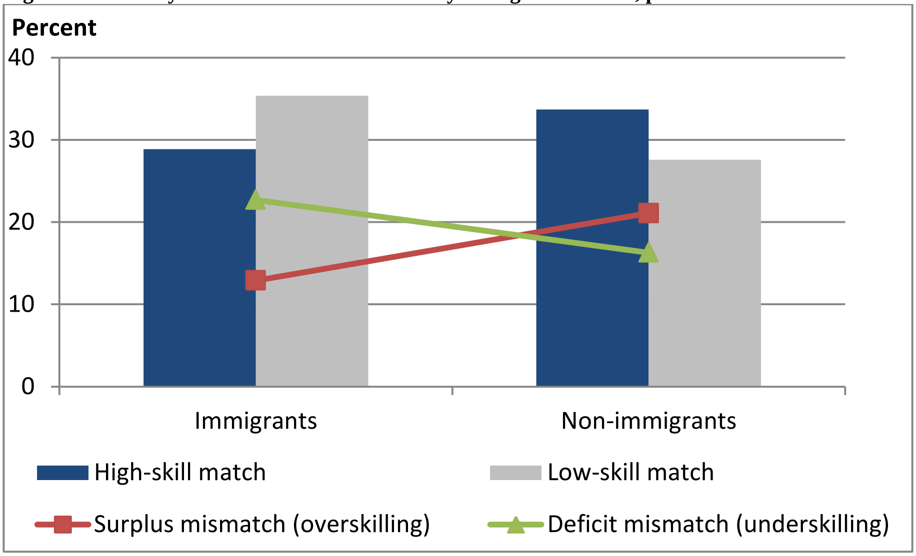
Figure 5.2 Literacy match- mismatch situations by gender, pooled data

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Notes: Results are averaged over countries who participated in ALLS. See Data Appendix for Chapter 5 for the corresponding data table (Table A.5.4) and more detailed country by country results.

Literacy mismatch by immigration status

The difference between the proportion of immigrants and non-immigrants who are found to be in a literacy surplus situation on the labour market can be substantial. Figure 5.3 depicts the average pattern across coutnries. In Table A.5.5 in the Data Appendix for Chapter 5 shows that this is especially the case in Canada, the Netherlands, and the United States where there are about 9%, 9% and 13%, respectively, more non-immigrants than immigrants in a literacy surplus situation. Other countries with less pronounced differences include Norway, the Netherlands, New Zealand and Switzerland. This is not surprising since many immigrants must adapt to and develop the local language which can be crucial for demonstrating literacy skills in the host country's language. Indeed, in countries with high immigration rates, like Canada, New Zealand, Switzerland and the United States, immigrants are found to be more likely to be in a literacy deficit situation than in a literacy surplus situation.

Figure 5.3 Literacy match-mismatch situations by immigration status, pooled data



Source: Adult Literacy and Lifeskills survey, 2003-2007.
Notes: Results are averaged over countries who participated in ALLS. See Data Appendix for Chapter 5 for the corresponding data table (Table A.5.5) and more detailed country by country results.

Employer sponsored adult education and training

The analysis in Chapter 8 focuses on employer sponsored adult education and training as the dependent variable. It examines skill supply and skill demand characterisitics in relation to the odds of receiving employer support for training. Table 5.5 provides the participation rate in adult education and training by type of support. On average across countries, about 23% of adults aged 25-65 employed at time of survey or in 12 months preceding survey received adult education/training during the 12 months preceding the interview which was employer supported.

Table 5.5 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey participating in adult education/training during the 12 months preceding the interview, by type of support

	Employer financed programme or course	Other financed programme or course	Other participation - financing unknown	Did not participate	Missing
			%		
Canada	25	17	14	44	0
Hungary	11	7	4	78	1
Italy	7	11	5	72	6
Netherlands	33	10	6	52	0
New Zealand	--	--	--	--	--
Norway	35	14	8	44	0
Switzerland	28	18	8	37	9
United States	25	19	19	38	0
Total	23	14	9	52	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Notes: New Zealand did not collect data on sources of support.

Recent work suggests that literacy mismatch is an important correlate of participation in adult education/training and that this varies by source of financing (Rubenson, Desjardins & Yoon, 2008). It is thus interesting to contrast the relationship between mismatch and participation to other sources of financing, even if the focus of Chapter 8 is on employer supported adult education/training. This is because employees who do not receive employer support may nevertheless choose to participate and this is related to whether they are in a match or mismatch situation at work.

Figure 5.4 shows how participation with different sources of support vary with whether workers are in a literacy match or mismatch situation (see Table A.5.6 in the Data Appendix for Chapter 5 for results by countries). The patterns are more or less consistent across countries. Four findings stand out as follows.

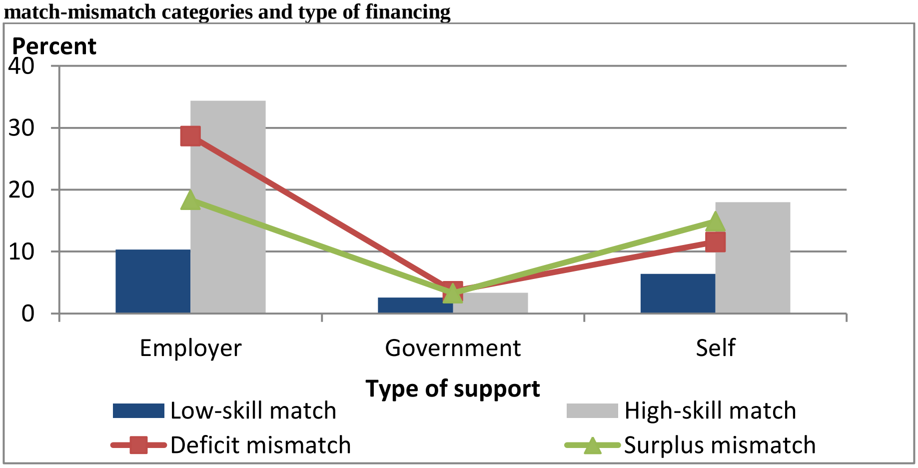
First, workers in high-skill matches tend to participate more in adult education/training than any other workers (52%). Workers in a deficit mismatch situation feature the second highest rate of participation (43%) followed by those in a surplus situation (35%). The lowest participation rates are among workers in a low-skill match situation (19%).

Second, employers display the highest propensity to invest in workers which are in high-skill matches, supporting around 31% of adults aged 25-65 employed at time of survey or in 12 months preceding survey. This is followed by those in deficit situations (24%), surplus situations (19%) and low-skill match situations (10%).

Third, workers in high-skill matches display the highest propensity to self finance their investment in adult education/training (18%) followed by those in surplus situations (15%), deficit situations (12%) and low-skill match situations (6%).

Fourth, government financing appears to equally reach those in high-skill matched (3%) and surplus situations (3%) (i.e., those who are already have high levels of proficiency in key information processing skills) compared to those who are in deficit mismatch (4%) or low-skill match situations (3%) (i.e., those who have low levels of proficiency in key information processing skills). The findings here point to inadequate strategies for targeting the low-skilled with public funds. Furthermore, this is consistent with findings that reliance on market based approaches and performance criteria used to allocate funding for targeted strategies end up benefiting those who already have the most skills because they are most likely to succeed.

Figure 5.4 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey participating in adult education/training during the 12 months preceding the interview, by match-mismatch categories and type of financing



Source: Adult Literacy and Lifeskills Survey, 2003-2007.
Notes: Results are averaged over countries who participated in ALLS (excluding New Zealand who did not collect data on sources of financing). See Data Appendix for Chapter 5 for the corresponding data table (Table A.5.6) and more detailed country by country results.

Earnings

The analysis in Chapters 6 and 7 focus on earnings as the dependent variable. They examine skill supply and skill demand characterisitics in relation to the log of monthly earnings.

As in all surveys, the quality of the earnings data is an important issue. Table 5.6.A summarizes the percentage of cases with missing earnings data. Missing data were imputed using the multiple imputation functing in STATA and based on linear regression of earnings on key socio-demographic indepedents (country, age, gender, immigration status and education). The data were also inspected for outliers and the decision was made to trim the bottom and top end of the earnings distribution to avoid extreme outliers. This involved the calculation of the 1st and 99th percentiles and trimming the distribution down to these values. Table 5.6.B compares the means and standard deviations before and after trimming, and also after imputation. For most countries, the difference in mean before and after trimming is marginal while the standard deviation narrows somewhat. However, imputation increases the standard deviation in most countries, particularly those with the higest proportion of missing earnings data (i.e., Hungary and Italy).

Table 5.6.A. Missing data on monthly earnings, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Sample size	Number of cases with non-missing earnings data	Number of cases with missing earnings	Per cent of cases with missing earnings
Canada	13102	10562	2540	19
Hungary	2996	1788	1208	40
Italy	3461	1937	1524	44
Netherlands	3930	2964	966	25
New Zealand	5092	4540	552	11
Norway	3843	3534	309	8
Switzerland	3751	2813	938	25
United States	2273	1959	314	14
Total	38448	30097	8351	22

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.6.B. Descriptive statistics for monthly earnings data, comparison of imputed and non-imputed values, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Log earnings		Log earnings with trimming of outliers at 1st and 99th percentiles		Log earnings trimmed and with imputed data for missing values	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Canada	7.74	0.77	7.74	0.70	7.75	0.71
Hungary	6.83	0.62	6.82	0.60	6.84	0.65
Italy	7.36	0.56	7.35	0.53	7.36	0.61
Netherlands	7.68	0.79	7.67	0.74	7.63	0.74
New Zealand	7.56	0.86	7.56	0.82	7.55	0.82
Norway	7.60	0.88	7.62	0.80	7.62	0.79
Switzerland	7.83	0.80	7.83	0.79	7.78	0.79
United States	7.83	1.00	7.82	0.84	7.83	0.83
Total	7.59	0.86	7.58	0.80	7.55	0.81

Source: Adult Literacy and Lifeskills survey, 2003-2007.

All other variables used

The remainder of this chapter provides basic descriptive statistics for all the other independent variables used in the studies.

Age and experience

Table 5.7.A shows the mean and standard deviation for age and experience. Experience is derived following the standard linear transformation of age minus years of schooling minus six. Table 5.7.B shows the proportion of adults aged 25-65 employed at time of survey or in 12 months preceding survey in each of three age categories used for the logistic regression analysis.

Table 5.7.A. Descriptive statistics for age (continuous) and experience, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Age		Experience	
	Mean	Std. dev.	Mean	Std. dev.
Canada	42	10.1	23	11.3
Hungary	41	9.9	22	10.5
Italy	41	9.7	24	11.3
Netherlands	43	10.2	23	11.6
New Zealand	43	10.7	23	11.5
Norway	43	10.6	24	11.8
Switzerland	43	10.3	24	11.3
United States	42	10.5	23	10.9
Total	42	10.3	23	11.3

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.7.B. Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey in each age category (3-categories)

	Age groups		
	25-35	36-50	51-65
		%	
Canada	29	47	24
Hungary	36	43	21
Italy	33	46	21
Netherlands	27	47	25
New Zealand	28	44	28
Norway	30	43	27
Switzerland	28	44	27
United States	30	46	25
Total	30	45	25

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Gender

Table 5.8 shows the proportion of men and women in the sample.

Table 5.8 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey who are men

	Women	Men
	%	
Canada	47	53
Hungary	48	52
Italy	37	63
Netherlands	47	54
New Zealand	49	51
Norway	47	53
Switzerland	45	55
United States	49	52
Total	46	54

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Education

Table 5.9.A summarizes the percentage of cases with missing education data, which is marginal ranging from 0-2% depending on the country. Nevertheless, to avoid deletion of cases, missing data were imputed using the multiple imputation function in STATA and based on linear regression of years of schooling on key socio-demographic independents (country, age, gender and immigration status). The data were also inspected for outliers and the decision was made to trim the top end of the distribution to a maximum value of 27 since the few cases with numbers coded above this were interpreted as potential errors. As expected, means and standard deviations change very little before and after trimming and imputation. Table 5.9.B shows the proportion of adults aged 25-65 employed at time of survey or in 12 months preceding survey in each of three education categories used for the logistic regression analysis.

Table 5.9.A Missing data and descriptive statistics for years of schooling, adults aged 25-65 employed at time of survey or in 12 months preceding survey

	Number of cases with missing years of schooling	Per cent of cases with missing years of schooling	Years of schooling		Years of schooling trimmed for outliers		Years of schooling trimmed for outliers and missing data	
	n	%	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Canada	0	0	13.87	3.50	13.87	3.49	13.87	3.49
Hungary	71	2	12.89	3.38	12.88	3.34	12.87	3.34
Italy	13	0	11.52	3.89	11.52	3.89	11.51	3.90
Netherlands	0	0	14.22	3.81	14.22	3.78	14.22	3.79
New Zealand	0	0	13.92	3.15	13.92	3.15	13.92	3.15
Norway	6	0	13.06	3.17	13.06	3.17	13.06	3.17
Switzerland	39	1	13.57	3.56	13.57	3.56	13.57	3.55
United States	1	0	13.78	3.31	13.78	3.31	13.79	3.32
Total	130	0	13.36	3.57	13.35	3.57	13.35	3.57

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.9.B Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of educational attainment

	Less than upper secondary	Upper secondary	Higher than upper secondary	Missing
		%		
Canada	15	31	55	0
Hungary	16	53	31	0
Italy	43	44	14	0
Netherlands	24	39	37	0
New Zealand	8	40	52	0
Norway	12	42	44	2
Switzerland	11	59	30	0
United States	10	47	44	0
Total	17	44	38	0

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Parent's education

Table 5.10 shows the proportion of adults in the included sample by level of parents' education. Parents' education is taken as the higher of mother or father's education. Missing values are not imputed but controlled for in the analysis so that cases with missing data are not excluded from the analysis. Parameter estimates for missing categories are not reported in the data table.

Table 5.10 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of parents' educational attainment

	Less than upper secondary	Upper secondary	Higher than upper secondary	Missing
		%		
Canada	37	33	27	3
Hungary	29	56	14	2
Italy	80	15	4	1
Netherlands	54	22	22	2
New Zealand	22	44	28	6
Norway	39	39	22	1
Switzerland	23	48	23	5
United States	22	46	30	2
Total	38	38	21	3

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Immigrant status

Table 5.11 shows the proportion of adults in the included sample who are immigrants and non-immigrants. The definition of immigrant is based entirely on whether adults were born in the country or not. Missing values are not imputed but controlled for in the analysis so that cases with missing data are not excluded from the analysis. Parameter estimates for missing categories are not reported in the data table.

Table 5.11 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey who are foreign-born

	Immigrant	Non-immigrant	Missing
		%	
Canada	22	78	0
Hungary	2	98	0
Italy	2	98	0
Netherlands	6	94	0
New Zealand	26	74	0
Norway	6	94	0
Switzerland	21	75	5
United States	15	85	0
Total	12	87	1

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Occupation

Table 5.12.A shows the proportion of adults in the included sample in each of three occupation categories used for the analysis in Chapter 6 and 8. Missing values are not imputed but controlled for in the analysis so that cases with

missing data are not excluded from the analysis. Parameter estimates for missing categories are not reported in the data table.

Table 5.12.B shows the proportion of adults in the included sample in each of six occupation categories used for the analysis in Chapter 7. A major aspect to the analysis contained in Chapter 7 is to examine results by type of occupation. The derivation of the six category version of occupational type is discussed in detail in Chapter 7 since this is part of the focus of that chapter.

Table 5.12.A Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each category of occupation (3-categories)

	Skilled	Semi-skilled	Unskilled	Missing
			%	
Canada	48	46	6	0
Hungary	28	55	12	5
Italy	34	44	8	13
Netherlands	56	38	5	1
New Zealand	45	50	5	0
Norway	37	51	5	8
Switzerland	55	33	6	6
United States	48	44	8	0
Total	44	45	7	4

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 5.12.B Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each category of occupation (6-categories)

	1	2	3	4	5	6	Missing
				%			
Canada	11	15	15	21	13	24	2
Hungary	5	11	10	20	17	31	5
Italy	5	10	11	21	13	25	15
Netherlands	12	15	20	21	12	17	4
New Zealand	12	15	17	19	12	25	0
Norway	5	7	14	13	19	17	26
Switzerland	10	18	19	17	12	14	9
United States	11	13	14	22	16	24	0
Total	9	13	15	19	14	22	8

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Notes: 1= Knowledge (expert); 2= Management; 3= Information (high-skill); 4= Information (low-skill); 5= Services (low-skill); 6= Goods (manufacturing).

Industry

Table 5.13 shows the proportion of adults in the included sample in each of nine industry categories. Missing values are not imputed but controlled for in the analysis so that cases with missing data are not excluded from the analysis. Parameter estimates for missing categories are not reported in the data table. The derivation of this variable is based on a reclassification of the 2-digit ISIC (international standardized industry classification) according to OECD (2003).

Table 5.13 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each category of industry

	Industry type									
	1	2	3	4	5	6	7	8	9	Missing
	%									
Canada	5	11	17	26	5	7	20	5	5	0
Hungary	7	13	11	19	8	7	14	5	4	11
Italy	5	12	11	24	4	8	22	4	5	5
Netherlands	5	7	20	36	5	6	13	4	3	1
New Zealand	3	10	17	28	5	8	18	4	8	0
Norway	4	7	14	34	4	8	16	6	2	5
Switzerland	7	8	23	26	5	5	13	4	3	6
United States	6	8	18	29	6	10	18	4	2	0
Total	5	10	16	28	5	7	17	4	4	4

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Notes:
1= High-technology manufacturing; 2= Low-technology manufacturing; 3= Knowledge-intensive market services; 4= Public administration, defence, education & health; 5= other community, social & personal services; 6= Utilities & Construction; 7= Wholesale, retail, hotels & restaurants;
8= Transport and storage; 9= Primary industries.

Firm size

Table 5.14 shows the proportion of adults in the included sample in each of five firm size categories. Missing values are not imputed but controlled for in the analysis so that cases with missing data are not excluded from the analysis. Parameter estimates for missing categories are not reported in the data table.

Table 5.14 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each category of firm size

	Number of employees					
	<20	20-99	100-499	500-999	>=1000	Missing
	%					
Canada	29	14	12	7	36	4
Hungary	33	22	12	4	11	18
Italy	45	12	7	3	21	12
Netherlands	25	16	16	7	30	6
New Zealand	40	16	13	6	24	2
Norway	18	13	19	10	22	19
Switzerland	33	16	15	5	20	11
United States	27	16	13	5	36	3
Total	31	16	13	6	25	9

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Data Appendix for Chapter 5

Table A.5.1 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of intensity of a writing at work index

	Frequency and variety of writing at work (3 types of activities)				
	Low intensity (never or rarely)	Medium-low intensity (about 1 activity sometimes)	Medium-high intensity (up to 1-2 activities weekly)	High intensity (at least 2 activities weekly)	Missing
	%				
Canada	20	28	22	30	0
Hungary	43	30	13	11	3
Italy	42	30	13	9	6
Netherlands	18	31	26	25	0
New Zealand	17	27	22	35	0
Norway	18	39	24	18	1
Switzerland	11	27	26	31	5
United States	19	27	23	31	0
Total	24	30	21	24	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table A.5.2 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey at each level of intensity of a numeracy at work index

	Frequency and variety of numeracy at work (2 types of activities)			
	Low intensity (never or rarely)	Medium intensity (up to 1-2 activity sometimes)	High intensity (more than one activity weekly)	Missing
	%			
Canada	27	47	26	0
Hungary	42	37	18	3
Italy	39	35	20	6
Netherlands	39	41	20	0
New Zealand	26	43	31	0
Norway	27	45	27	1
Switzerland	33	40	23	5
United States	27	45	28	0
Total	33	42	24	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table A.5.3 Literacy match-mismatch situations, by country, by age

		High-skill match	Surplus mismatch (overskilling)	Deficit mismatch (underskilling)	Low-skill match	Missing
				%		
Canada	25-35	45	23	15	17	0
	36-50	43	17	18	22	0
	51-65	36	17	18	29	0
Hungary	25-35	17	38	7	36	3
	36-50	15	32	7	44	3
	51-65	16	29	8	44	3
Italy	25-35	13	15	17	48	7
	36-50	11	12	16	58	4
	51-65	7	10	18	58	8
Netherlands	25-35	48	22	12	19	0
	36-50	43	19	16	22	0
	51-65	32	15	19	33	0
New Zealand	25-35	40	19	20	21	0
	36-50	45	17	20	17	0
	51-65	42	16	21	21	0
Norway	25-35	47	32	8	12	1
	36-50	43	27	13	16	1
	51-65	33	21	17	27	2
Switzerland	25-35	36	15	21	25	3
	36-50	36	16	21	21	6
	51-65	23	13	31	30	4
United States	25-35	36	18	20	27	0
	36-50	36	16	25	23	0
	51-65	37	16	24	23	0
Total	25-35	34	23	15	26	2
	36-50	34	19	17	28	2
	51-65	29	17	20	32	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Source data for Figure 5.1.

Table A.5.4 Literacy match-mismatch situations, by country, by gender

		High-skill match	Surplus mismatch (overskilling)	Deficit mismatch (underskilling)	Low-skill match	Missing
				%		
Canada	Men	42	15	20	23	0
	Women	41	23	14	22	0
Hungary	Men	15	30	8	46	2
	Women	17	38	6	36	3
Italy	Men	11	11	18	55	6
	Women	10	16	15	54	5
Netherlands	Men	46	12	19	23	0
	Women	37	26	12	26	0
New Zealand	Men	45	13	23	19	0
	Women	41	22	18	19	0
Norway	Men	44	23	14	19	1
	Women	39	32	11	16	1
Switzerland	Men	39	9	26	20	5
	Women	25	22	20	30	4
United States	Men	38	14	25	24	0
	Women	35	20	21	25	0
Total	Men	34	16	19	29	2
	Women	31	25	15	28	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Source data for Figure 5.2.

Table A.5.5 Literacy match-mismatch situations, by country, by immigrant status

		High-skill match	Surplus mismatch (overskilling)	Deficit mismatch (underskilling)	Low-skill match	Missing
				%		
Canada	Immigrants	32	12	20	37	0
	Non-immigrants	45	21	16	18	0
Hungary	Immigrants	23	45	3	28	2
	Non-immigrants	16	33	7	41	3
Italy	Immigrants	16	16	23	39	5
	Non-immigrants	11	13	17	55	5
Netherlands	Immigrants	17	10	14	59	0
	Non-immigrants	43	19	16	22	0
New Zealand	Immigrants	39	15	24	22	0
	Non-immigrants	44	19	19	18	0
Norway	Immigrants	31	23	10	36	0
	Non-immigrants	42	27	13	17	1
Switzerland	Immigrants	23	12	29	36	0
	Non-immigrants	37	17	23	23	0
United States	Immigrants	21	6	27	47	0
	Non-immigrants	39	19	23	20	0
Total	Immigrants	29	13	23	35	0
	Non-immigrants	34	21	16	28	1

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Source data for Figure 5.3.

Table A.5.6 Per cent of adults aged 25-65 employed at time of survey or in 12 months preceding survey participating in adult education/training programmes/courses during preceding 12 months to survey, by source of support, skill match-mismatch situation and country

		Low-skill match	Deficit mismatch	Surplus mismatch	High-skill match	Over all
	Source of support[1]			Participation rate		
Canada	Any source	20	39	38	56	42
	Employer	9	25	19	36	25
	Government	4	3	3	3	3
	Self	8	11	17	20	15
Hungary	Any source	11	30	15	37	18
	Employer	6	21	8	23	11
	Government	1	1	1	1	1
	Self	3	10	7	14	7
Italy	Any source	9	36	20	35	18
	Employer	3	16	6	14	7
	Government	2	8	4	5	4
	Self	3	10	8	16	7
Netherlands	Any source	20	47	38	56	43
	Employer	14	36	26	45	33
	Government	1	3	2	2	2
	Self	5	9	11	11	10
New Zealand[2]	Any source	28	51	48	62	51
Norway	Any source	25	55	45	59	49
	Employer	16	44	27	45	35
	Government	4	3	8	5	5
	Self	6	9	13	13	11
Switzerland	Any source	30	48	48	61	48
	Employer	16	32	23	40	29
	Government	3	2	2	3	3
	Self	13	20	28	28	22
United	Any source	19	43	41	61	43
	Employer	8	26	19	38	25
	Government	4	6	3	6	5
	Self	6	13	19	24	16
Total[3]	Any source	19	43	35	52	37
	Employer	10	29	18	34	23
	Government	3	4	3	3	3
	Self	6	12	15	18	13

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Source data for Figure 5.4.
1. Sources of support are not mutually exhaustive since respondents could report more than one source of support. Therefore, the sum of the participation rates for each source add up to more than the total participation rate “by any source”. Participation rates by other sources of support (e.g., union, free…) are very small ranging from 1-3% and are thus not reported here. 2. New Zealand did not collect data on sources of support. 3. New Zealand is excluded from the total and also from the analysis in Chapter 8 because there is no data on whether adults received employer support.

Chapter 6 Earnings differentials associated with skill supply and demand characteristics

Introduction

This chapter aims to estimate alternative earnings functions in order to compare the relationship between labour supply characteristics and earnings on the one hand, and between labour demand characteristics and earnings on the other. The focus is on labour supply and labour demand characteristics that relate to skills, in particular, direct measures of skills and skill use, as well as situations of skill match or mismatch between the observed skills of workers and the extent to which they report using those skills at work. In addressing these aims, data from the 2003 Adult Literacy and Life Skills Survey (ALLS) as described in Chapter 5 is used. The purpose is to understand better the earnings differentials of workers vis-a-vis their skill profiles, the extent to which they use their skills in their jobs, as well as in situations of skill match or mismatch.

The analysis seeks to extend standard applications of returns to schooling as reflected by the Mincerian approach with three specific additional features:

- Direct measures of key information processing skills
- Self-reported measures of the requirements to use those key information skills at work
- A measure of skill mismatch based on these two measures.

The chapter is organized as follows. First, various theoretical perspectives on the earnings function are discussed. Second, a brief review of previous research on earnings differentials that make use of direct measures of skills is provided. Third, a set of empirical models based on alternate specifications of the earning function are presented. Fourth, empirical estimates are provided.

Finally, there is a concluding discussion of the results, including in situations of deficit or surplus mismatch.

Discussion of theoretical perspectives on the earnings function

There are a range of theoretical approaches which provide an explanation of observed earnings differentials. Some of these closely relate to each other and can be used in combination to add explanatory value. The discussion in this section centres on three distinct approaches. The starting point is grounded in standard applications of returns to schooling analysis which emphasizes the supply side of the labour market in determining earnings. This is well grounded in the human capital approach. The second emphasizes the demand side of the labour market in determining earnings, which is grounded in a collection of theories pertaining to some form of labour market segmentation. These two distinct approaches are not necessarily mutually exclusive. Both mechanisms are likely to coexist and jointly operate to determine earnings. Further, one mechanism may dominate over the other in certain contexts, and vice-versa in other contexts. The third approach to earnings differentials emphasizes the interaction between the supply and demand side of the labour market, which is grounded in assignment theory and relates to skill mismatch.

The role of the supply side in determining earnings

Returns to schooling and skills research has been dominated by a supply side view of the labour market, and particularly by the human capital approach. While this has been a very productive area of research, there are a number of limitations that are worth pointing out.

The neoclassical approach and human capital theory

Within the neoclassical economic framework, individuals who contribute more to the final value of production are assumed to earn more. Complementing this is the theory of human capital – also discussed more directly in relation mismatch in Chapter 3 – whose core premise suggests that the relative contribution of individuals depends on the knowledge, skills and other attributes embodied within them (Blaug, 1976). On this basis, those with more human capital, holding all other variables constant, should be more productive, and hence earn more.

This approach however, makes a number of assumptions. Chief among them, it tends to assume that rates of return to human capital hold whatever an individual's job. The type of job is seen to have little relevance and is more or less ignored.

Empirical applications in line with this approach have flourished since the early 1960s, despite evidence that contradicts such assumptions. We know for example, that jobs and pay are not distributed strictly on the basis of worker qualifications and that there are numerous other factors at play. Rewards to individual characteristics, for example, are not observed to be equivalent in all jobs. Nevertheless, there is much evidence to suggest that the more skilled an individual, the more likely he/she is to be rewarded.

Key questions remain however, such as which skills and for what jobs do the returns accrue to. Skills are not homogeneous, nor are jobs. For example, some jobs require manual skills while others require cognitive skills. Most applications of human capital to the study of returns to schooling tend to ignore that there are different types of qualifications and skills that are needed to complete different tasks in different occupations. Skills tend to be conceptualized as a one big bundle that is linear in growth, and assumed to be a function of schooling. Most importantly, empirical applications tend to rely almost exclusively on years of schooling as an indicator of human capital because this is the data that is most widely available and cheapest to collect.

Without direct and more complex measures of human capital, empirical studies are constrained by the assumption that those with a specified level of schooling have similar knowledge, skills and other attributes. Evidence suggests otherwise. Qualifications for do not accurately reflect key information processing skills such literacy and numeracy skills (OECD/Statistics Canada, 2005). People receive education of varying quality and they gain or even lose skills as they move beyond the age of having completed their schooling or qualifications.

In recent years, intense efforts have been made to provide direct measures of skills for both research and policy, precisely to address the shortcomings of qualification based proxies of skills. One such example includes the direct measures of key information processing skills made available through the International Adult Literacy Survey (IALS) and its successor, the Adult Literacy and Lifeskills Survey (ALLS), which is used in this study. Accounting for key information processing skills offers a unique opportunity to enrich analyses and explore hypotheses concerning the relationship between skills and earnings in greater detail. Information processing skills are merely one aspect of human capital, but the manner in which they are defined makes them a good proxy of cognitive skills.

The analysis in this study thus seeks to extend standard applications of returns to schooling as reflected by the Mincerian approach with direct measures of key information processings skills. Using direct measures allows for specific skills to be separately valued from the many characteristics that education is supposed to indirectly measure. It also allows for an improved understanding of the correspondence between the inputs and outputs of the human capital formation process. If a particular skill is valued independently from schooling, then schooling may continue to proxy for other characteristics. Singling out specific skills and valuing them is a potentially useful exercise since it can help identify policies, which target certain skills for development and maintenance throughout working life.

The role of the demand side in determining earnings

Variables that account for the demand side of the labour market such as job, occupational or work characteristics tend to be overlooked in the returns to schooling literature. An alternative approach to specifying the earnings function is to place more emphasis on the demand side of the labour market. The main premise of this approach is that earnings are primarily driven by the type of job that individuals manage to obtain, and that individual characteristics play a lesser role than purported by human capital theory (alternatively, that wages reflect the marginal contribution of a worker's skill). At the extreme, this specification contends that earnings and marginal productivity reside in the job, not the individual (see Jaoul-Grammare, 2007; Sattinger, 1993; Cain, 1976; Thurow, 1975).

Labour market segmentation theories

The theory of labour market segmentation has traditionally differed from human capital theory in terms of its focus. As discussed in Chapter 3, but more directly as a potential cause of mismatch, this theory emphasizes the characteristics of jobs and job markets, rather than the characteristics of individuals. Conceived broadly, there is a collection of labour market segmentation theories (Cain, 1976). For example, job competition theory can be considered within this family as it also emphasises job characteristics. The latter suggests that marginal productivity and pay is attached to the job, and individuals compete to obtain the best jobs (Thurow, 1975). In this theory, individual characteristics are relevant to the extent that they help individuals compete for good jobs, but they do not necessarily affect productivity and hence pay, at least directly. Individual characteristics might affect productivity indirectly however, by helping individuals to learn how to do the job tasks more efficiently.

A common feature of all labour market segmentation theories is that rewards to individual characteristics are not equalized throughout the labour market. Namely, rewards depend on the segment of the labour market where one manages to obtain a job. Job, occupational or work characteristics thus become potentially important determinants of earnings.

The role of both the supply and demand sides in determining earnings

The third approach considered in this study considers the role of both the supply and demand sides of the labour market. Essentially, the intention is to maintain a human capital approach while seeking to account for the nature of the job and possbility for mismatch between workers and jobs. A useful starting point and framework for considering this further is assignment theory. Considering both supply and demand side characteristics is essential for examining the relationship match and mismatch situations and earnings.

Assignment theory

Assignment theory suggests that both individual and job characteristics are relevant for predicting earnings. As discussed in Chapter 3, but more directly as a potential cause of mismatch, this theory emphasizes that neither the individual's education or skill profile nor the requirements of the job alone are sufficient to determine earnings. Both should be considered jointly. The model acknowledges the difference between individual levels of characteristics and the levels of such characteristics required in the job.

This approach is advantageous for at least two reasons. First, it allows for the possibility to recognize that human capital is multi-faceted and that certain types of skills may be more relevant in some occupations than others. Many studies ignore this and by extension the different types of qualifications and skills that are needed to complete the tasks of those occupations. For example, years of schooling regardless of whether there are vocationally oriented or comprehensive, are often treated as equivalent in studies estimating the relationship between schooling and/or skills and earnings. Second, it allows for the possibility to recognize that individual characteristics are rewarded differently in different jobs. Whether an individual is employed on a factory-line or in a position with a lot of decision making responsibility makes a difference on how their skills are valued.

In practice, separating rewards to individual characteristics (worker effects) from from rewards to job characteristics (firm effects) is difficult. A firm (or job) premium may be due to selection of productive workers and not due to genuine firm side effects. Symetrically, what appears to be due to the worker, may be because of the firm (see Abowd, Kramarz & Margolis, 1999; Eeckhout & Kircher, 2011). This is especially the case in situations of complementarity between workers and jobs, or alternatively in match situations. However, in mismatch situations, it is possible to see whether it is the relevant individual or job characteristics that relate more or less to earnings differentials, as is attempted in this study.

Skill match-mismatch

Considering both the supply and demand sides of the labour market allows for the possibility to acknowledge that not everyone are in jobs that suit their skills profile, and that this may have an impact on their earnings. Taking into account whether individuals are matched or mismatched with the requirements of their job allows for the possibility to test whether it is the supply side or the demand side of the labour market that matters most in predicting earnings, at least in situations of mismatch.

Previous research on earnings differentials that make use of direct measures of skills

Previous research suggests that key information processing skills, as measured by the IALS and ALLS, are significantly related to labour market outcomes, including less unemployment, higher earnings and a greater probability of being in a high-skilled occupation, independent of educational attainment.

At least four major findings stand out from these and other empirical studies that have made use of direct measures of skill.

First, the importance of key information processing skills such as literacy proficiency is substantive and may have increased over time. For example, Green and Riddell (2001), adjust for literacy proficiency and educational attainment simultaneously using a Mincerian type approach. They use the Canadian IALS data and find significant returns to literacy proficiency on the order of 3.0 to 3.5% for every 10-point increase in literacy on a scale of 0 to 500. In Murnane, Willet, Braatz and Duhaldeborde (2001), three types of skills were examined, namely academic skills, skills at completing elementary tasks quickly, and self-esteem, confirming the importance of basic skills in the US labour market. Rivera-Batiz (1992), using the Young Adult Literacy Survey (YALS) data, showed that quantitative literacy has an independent association with earnings over and above the association with initial education. Murnane, Willet and Levy (1995) found that the importance of basic skills increased between the 1970s and mid 1980s.

Second, controlling for literacy proficiency reduces the return to education (OECD and HRDC, 1997). Osberg (2000: 8) for example, reported results which indicated that 40-45% of the economic return to education is attributable to literacy proficiency. The measures of key information processing skills in IALS and ALLS has been closely linked to cognitive skills, which implies that the residual return attributed to education is predominantly due to the non-cognitive skills which education can be thought to be implicated in helping to form.

Third, returns to direct measures of skills can vary significantly between countries. For example, Devroye and Freeman (2001) concluded that in the United States people are sorted on the labour market by literacy proficiency more than any other country. Blau and Kahn (2001) confirmed this by suggesting that knowledge and skills play a significant role in explaining relatively high US wage inequalities. Leuven (2001) also found that the relation between schooling and cognitive scores is steeper in the United States than in other countries. In contrast, Tuijnman (2000) found that the Polish labour market pays for educational qualifications and for work experience but does not independently reward key information processing skills like literacy proficiency.

Fourth, the returns to cognitive and non-cognitive skills differ between the high- and low- skilled segments of the labour market. Using Swedish military enlistment data, Lindqvist and Westman (2009) found that cognitive skills are a stonger predictor of wages for skilled workers and of earnings above the median.

Models to estimate differences in earnings associated with skill supply and skill demand characteristics

A series of models are estimated in order to observe changes in the parameters of the characteristics associated with skill supply and skill demand characteristics.

Labour supply characteristics

The first two models to be estimated are limited to individual characteristics, or alternatively supply characteristics. In particular, the emphasis is on skill supply characteristics. The point of departure for these two models is grounded in an adaptation of a widely used specification of an earnings function, namely, the Mincer equation:

$$\ln[Y_i] = \beta_0 + \beta_S S_i + \beta_X X_i + \varepsilon_i \qquad (1)$$

Where,

- Y_i are the earnings of individual *i*
- S_i is the vector of skills of individual *i*

- X_i is the vector of other individual characteristics of individual i
- β_S is the vector of average growth rate of earnings for each skill in vector S
- β_X is the vector of coefficients for each individual characteristic in vector X
- ε_i is the residual, assumed distribution $\varepsilon_i \sim N(0, \sigma^2)$

Earnings, denoted by Y, are a function of skills, S, and other observable characteristics of the individual, X (e.g., gender, immigration status). The error term, ε, is assumed to be normally distributed with a mean of zero as follows: $E(\varepsilon|S,E,X)=0$.

A major implication of this model is that people with higher levels of skills earn more, independent of other individual characteristics which are observable. The vector of coefficients, β_s, consists of the ex post average growth rates of earnings associated with each additional skill. In this particular formulation, the growth rates are assumed to be constant for all levels of skills. A non-linear relationship between skills and earnings however, can easily be substituted into this formulation to allow for rates of growth to differ by level of skills.

Although equation (1) is more general in its specification of the human capital that may affect earnings, it is based on two different frameworks developed by Mincer (1958, 1974). See Heckman, Lochner and Todd (2005) for an extended discussion of the underlying assumptions of these two approaches.

Labour supply characteristics: Base Mincerian model

Most research based on the Mincer equation, including Mincer's own work, however, has focused on the average rate of return to additional schooling, rather than skills, and has incorporated another proxy for skills into the model, namely work experience. Schooling and work experience are meant to reflect the skills that individuals have accumulated over their lifespan, and in turn capture the extent to which accumulated skills may affect their earnings. While there are other factors implicated in the formation of skills, such as training, and there are different types of skills, such as cognitive and non-cognitive skills, using years of schooling and work experience as proxies for human capital is practical since these measures are readily available.

Psacharopoulos (1981) and Psacharopoulos and Patrinos (2004) provided extensive surveys of research based on this original formulation.

Equation (2) helps to bridge the general formulation in (1) with widely available measures that proxy human capital. It models skills, S, using a measure of schooling (ED) and a proxy for work experience (EXP – typically modelled in quadratic form). Both of these are used to proxy unobservable skills.

$$S_i = \gamma_{ED} ED_i + \gamma_{AGE} EXP_i + v_i \qquad (2)$$

The error term, v_i, represents the measurement error associated with unobserved skills, which may be correlated with earnings in (1), and may lead to bias in the parameters associated with schooling and experience. This represents a limitation. See Card (1999) for a discussion of the potential effect of unobserved variables, self-selection, misspecification and the measurement error of observed variables on bias. Several studies have attempted to used techniques to correct for endogeneity problems caused for example by omitted variables or measurement error when investigating the returns associated with additional years of schooling. Angrist and Krueger (1991) use a quarter of birth strategy. Card (1995) uses proximity to a college as an Instrumental Variable (IV). Harmon and Walker (1995) exploit changes in minimum school leaving age as possible IVs, and del Bono and Galindo-Rueda (2007) use month of birth. Typically, higher estimates for the parameter associated with years of schooling are found when compared to the OLS estimates. Angrist and Imbens (1994) suggest that this is because the IV controls tend to pick up on the average returns to education for those whose behaviour is altered by the instrument. They call this *Local Average Treatment Effects* (LATE). If returns to schooling were homogeneous then IV estimates would be more stable, but if returns are heterogeneous the estimates are likely to vary with the instrument used. Card (1999) concluded on his review of research on the returns to schooling that the average rate of return is probably only slightly below the OLS estimate (due to potential ability bias – an omitted variable bias), but that there is some variation in return to education with observable factors (i.e., returns to education are heterogeneous). Specifically, IV estimates tend to be bigger than OLS estimates probably because the interventions exploited pick up the returns for a group for whom it is large. In brief, the magnitude of bias associated with schooling parameters is unlikely to be large enough to impede the purpose of the analysis or to affect the main results of the model. It is worthwhile to highlight that the purpose of the analysis here is not so suggest that a policy manipulation of the extent of schooling experienced by individuals could lead to worthwhile returns. This is a topic that has been explored at length in the economics of education over the last four decades and is not the purpose of this study.

Limiting other individual characteristics to gender (MEN) and immigration status (NIMM) yields the base Mincerian model that is initially estimated.

$$\begin{aligned}&\ln[Y_i] = \beta_0 + \beta'_{S1} ED_i + \beta'_{S2} EXP_i + \\ &\beta_{MEN} MEN_i + \beta_{NIMM} NIMM_i + \varepsilon'_i\end{aligned} \tag{3}$$

Labour supply characteristics: Augmented Mincerian model with direct measure of literacy skills

If all the skills in vector S were observable and measurable, the corresponding regression coefficients could be interpreted as a vector of implicit prices, which estimates the approximate economic value associated with each skill. Not all skills are observed, however. To deal with this, Green and Riddell (2001) introduced two separate vectors, one for observed skills (S^o), and one for unobserved skills (S^u), as shown in equation (4).

$$S_i = (S_i^o S_i^u) = S_i^o + S_i^u \tag{4}$$

Further, Green and Riddell (2001) suggested that unobservable skills, S^u, can be proxied by a set of inputs, namely education attainment or years of schooling, experience and possibly others, as these are assumed to produce unobservable skills. Substituting (4) into (1) introduces equation (5), where $\varepsilon_i' = \beta_s \nu_i + \varepsilon_i$. The error term, v_i, is the measurement error associated with unobservable skills.

$$\ln[Y_i] = \beta_0 + \beta_s^o S_i^o + \beta_s^u S_i^u + \beta_X X_i + \varepsilon'_i \tag{5}$$

As described in Chapter 5, the Adult Literacy and Lifeskills Survey (ALLS) data used for this study contain a direct measure of literacy skills (SKILL), which is taken as a measure of observable skills (S^o). Separately, years of schooling (ED) and a proxy for work experience (EXP) are taken as a set of

inputs that are assumed to produce other unobservable skills, S^u. Finally, gender (MEN), and immigration status (NIMM), which are known to be significant predictors of individual earnings, are adjusted for in all models. This yields the augmented Mincerian model with direct measure of literacy skills as follows
in equation (6).

$$\ln[Y_i] = \beta_0 + \beta_1 SKILL_i + \beta_2 ED_i + \beta_3 EXP_i + \beta_4 MEN_i + \beta_5 NIMM_i + \varepsilon_i' \quad (6)$$

Labour demand characteristics

The next model to be estimated focuses on the demand side of the labour market. In particular, the emphasis is on skill demand characteristics. Whereas returns to schooling specifications often predict earnings only as a function of worker quality, the emphasis in this model is on skill requirements, R, and other job characteristics, J.

$$\ln[Y_i] = \beta_0 + \beta_R R_i + \beta_J J_i + \varepsilon_i \quad (7)$$

Where,

- R_i is a vector of skills requirements at work for individual i
- J_i is a vector of other job characteristics for individual i
- β_R is a vector of average growth rate of earnings for each skill in vector R
- B_J is a vector of coefficients for each individual characteristic in vector J

An implication of this model is that people who are in jobs that require higher levels of skills use earn more, independent of other job characteristics which are observable. The vector of coefficients, β_R, consists of the ex post average growth rates of earnings associated with higher levels of skills requirements.

Reading (READ), writing (WRITE) and numeracy (NUM) are taken as skill requirements at work. Occupation (OCC), industry (IND) and firm size (FIRM) are taken as other job characteristics. This yields the labour demand characteristics model as follows in equation (8).

$$\begin{aligned} \ln(Y_i) = \beta_0 + [\beta_1 OCC_i + \beta_2 IND_i + \beta_3 FIRM_i\ ] + \\ [\beta_4 READ_i + \beta_5 WRITE_i + \beta_6 NUM_i\ ] + \varepsilon_i \end{aligned} \tag{8}$$

Labour supply and demand characteristics

The final two models incorporate aspects of both the supply and demand side of the labour the market.

All labour supply and demand characteristics

All supply and demand side characteristics are included in one model, formally stated in Equation (9),

$$\ln[Y_i] = \beta_0 + \beta_s^o S_i^o + \beta_s^u S_i^u + \beta_X X_i + \beta_R R_i + \beta_J J_i + \varepsilon_i^{'} \tag{9}$$

and yielding the estimation model stated in Equation (10).

$$\begin{aligned} \ln(Y_i) = \beta_0 + [\beta_1 SKILL_i] + [\beta_2 ED_i + \beta_3 EXP_i] + \\ [\beta_4 MEN_i + \beta_5 NIMM_i] + [\beta_6 OCC_i + \beta_7 IND_i + \beta_8 FIRM_i\ ] + \\ [\beta_9 READ_i + \beta_{10} WRITE_i + \beta_{11} NUM_i] + \varepsilon_i^{'} \end{aligned} \tag{10}$$

Labour supply and demand characteristics augmented with a skill match/mismatch variable

The final model interacts the observed measure of literacy skill (S^0) with requirement to read at work (R) which culminates in skill match-mismatch variable (M), as shown in Equation (11).

$$\ln[Y_i] = \beta_0 + \beta_s^u S_i^u + \beta_X X_i + \beta_J J_i + \beta_M M_i + \varepsilon_i^{'} \tag{11}$$

Where,

- M_i is a variable reflecting situation of skill match-mismatch for individual *i* (4 categories: high-skill match, low-skill match, surplus mismatch, deficit mismatch)
- β_M is a vector of average growth rate of earnings for each match-mismatch situation

This corresponds to the estimation model stated in Equation (12)

$$\begin{aligned} \ln(Y_i) &= \beta_0 + [\beta_1 ED_i + \beta_2 EXP_i] + [\beta_3 MEN_i + \beta_4 NIMM_i] \\ &+ [\beta_5 OCC_i + \beta_6 IND_i + \beta_7 FIRM_i] + [\beta_8 MATCH_i] + \varepsilon_i' \end{aligned} \tag{12}$$

Estimation results

It can be argued that there are endogeneity problems in the proposed models. For example, endogeneity exists in the skill augmented Mincerian model because education affects the development of literacy skills and literacy skills affect the take up and attainment of education. Similary, skill supply characteristics affects the type of job obtained and hence the skill demand characteristics of one's job. It's not obvious how this can be modelled in a static and linear empirical approach such as regression analysis.

As a consequence, the estimation results should be interpreted as correlations, not causal effects, which is an important limitation to this study. Endogeneity problems also make it difficult to separate the relative contribution, for example, of education and information processing skills, or of skill supply and skill demand characteristics.

Nonetheless, a look at the correlations in light of the theoretical discussion, as well as the change in coefficients, and the change in explained variation provides important clues on the relative substantiveness of each variable, and still leads to important findings that stimulate interesting analysis and discussion vis-a-vis theoretical considerations and prior empirical research.

Each empirical specification is driven by the theoretical considerations and specifications highlighted in this chapter and in Chapter 3. However, several standard considerations were taken into account and several specification tests were conducted to refine the measures used and how. In general, the residuals are near homoscedastic, independently distributed and near normal in all cases, although they do exhibit slight negative skewness and a peaked distribution. But the very large sample size means that the t-tests are fairly robust under these distributional conditions. A careful analysis of adjusted R-squared for each step of each model was performed (summarized in Table A.6.1 in the Data Appendix for Chapter 6) to examine the specifications and particularly whether variables were relevant or not to add. In all cases, each variable or set of variables included in sequential fashion adds to adjusted R-squared. Only whether the respondent was an immigrant seems to become nearly redundant and also writing and numeracy practices at work appear to be quite redundant to the reading at work variable.

It is important to note that all results are based on a pooled analysis including all countries but adjusted with dummy controls for each country since there are important level effects in the distribution of earnings across countries.

Detailed results for each model are discussed below and can be found in Table 6.1 to Table 6.6.

Results for labour supply characteristics models: base and skill augmented Mincerian models

Consistent with previous research based on the Mincerian approach, the average growth in monthly earnings associated with an additional year of schooling is approximately 6.3%, as shown in Table 6.1.

Augmenting the model with a direct measure of literacy skills, reduces the strength of years of schooling as a predictor of earnings. The average growth in earnings per additional year of schooling is about 19% less when literacy proficiency is accounted for in the model.

Independent of their level of schooling, workers who rank one percentile higher in the distribution of literacy proficiency, receive on average about .3% more in monthly earnings. Thus, workers who are 10 percentiles higher on the literacy skill distribution earn 3% more.

Table 6.1 Model with labour supply characteristics, base and augmented models (equations 3 and 6)

	Base Mincerian model (equation 3)			Augmented Mincerian model with direct measure of literacy skills		
	β	p	s.e.	β	p	s.e.
Constant	6.309	.00	.03	6.304	.00	.03
Experience						
Experience	0.025	.00	.00	0.026	.00	.00
Experience-squared	-0.0004	.00	.00	-0.0004	.00	.00
Men (reference=women)	0.495	.00	.01	0.498	.00	.01
Non-immigrants (reference=immigrants)	0.061	.00	.01	0.025	.04	.01
Years of schooling	0.063	.00	.00	0.051	.00	.00
Information processing skills						
Literacy (percentiles)				0.0030	.00	.00
Adjusted R-squared	0.296			0.305		

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Country is adjusted for in each model but coefficients are not reported in the table.

Results for labour demand characteristics model

As can be seen from Table A.6.1 (found in the Data Appendix for Chapter 6), job characteristics alone are found to relate to earnings significantly, explaining about 29% of the total variance in earnings. This is in contrast to about 30% of the variance that is explained when only labour supply characteristics are accounted for in the model.

Table 6.2 shows that working in a skilled occupation is associated with a substantive earnings premium of about 40%. Similarly, working in a very large firm, one with over 1000 employees is associated with a substantial earnings premium of about 20%, independent of whether the job is skilled work or not. Interestingly, job requirements that are linked to the processing of texts are highly rewarded, with premiums ranging from 10% for medium low engagement to 29% for high engagement. This is the case even after controlling for the type of occupation and industry.

Table 6.2 Model with labour demand characteristics (equation 8)

	β	p	s.e.
Constant	7.293	.00	.03
Reading at work (reference=low)			
Medium low engagement	0.100	.00	.01
Medium high engagement	0.180	.00	.01
High engagement	0.288	.00	.01
Writing at work (reference=low)			
Medium low engagement	0.094	.00	.01
Medium high engagement	0.145	.00	.01
High engagement	0.200	.00	.01
Numeracy at work (reference=low)			
Medium engagement	0.096	.00	.01
High engagement	0.056	.00	.01
Occupation (reference=unskilled)			
Skilled	0.405	.00	.02
Semi-skilled	0.121	.00	.02
Industry (reference = primary industries)			
High-technology manufacturing	-0.035	.14	.02
Low-technology manufacturing	-0.103	.00	.02
Knowledge-intensive market services	-0.159	.00	.02
Public administration, defence, education & health	-0.300	.00	.02
Other community, social & personal services	-0.309	.00	.02
Utilities & Construction	0.066	.00	.02
Wholesale, retail, hotels & restaurants	-0.362	.00	.02
Transport and storage	-0.053	.03	.02
Firm size (reference= < 20 employees)			
20-99 employees	0.104	.00	.01
100-499 employees	0.157	.00	.01
500-999 employees	0.165	.00	.02
>=1000 employees	0.201	.00	.01
Adjusted R-squared	0.267		

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Country is adjusted for in each model but coefficients are not reported in the table.

Results for labour supply and demand characteristics model

Adjusting for both individual and job characteristics accounts for over 37% of the total variance in earnings (see Table A.6.1 in the Data Appendix for Chapter 6). This is a substantial gain in explained earnings compared to when labour supply or demand characteristics are considered in isolation.

Accounting for labour demand characteristics substantially reduces (on the order of about 47%) the increase in average monthly earnings which were associated with additional schooling in the preceding models, even if schooling premiums remain significant at about 2.7%.

Likewise, the earnings increase associated with a one percentile increase in the ranking of the literacy skill distribution drops to 0.1% (a near 67% drop). This suggests that premiums associated with literacy skills depend on the nature of the job, i.e., they are present only if those skills are required by the job. There are many workers who have a high level of literacy skills but do not necessarily work in jobs that require those skills to a great extent. Thus, after adjusting for the requirement to read at work, the premium associated with literacy skills is nearly eliminated.

In fact, reading at work stands out as one of the largest predictors of earnings. Table 6.4 presents results from a model run that includes continuous versions of the variables reading, writing and numeracy at work, and presents standardized coefficients to enable a better comparison of effect sizes. Table 6.4.A adjusts for occupation while 6.4.B does not adjust for occupation. It is important to compare results with and without adjustment for occupation since skill intensity of occupation is implied in the 3-categories (skilled, semi-skilled and unskilled) and this relates to the degree of cognitive requirements associated with work tasks such as reading at work.

It can be seen in Table 6.4.A that when reading, writing and numeracy at work are all accounted for, the coefficient for reading at work (10.1%) is nearly the same as the coefficient associated with years of schooling (11.5%). That is, a one standard deviation increase in years of schooling is associated with a premium of 11.5% relative to average years of schooling, while a one standard deviation increase in the index of reading at work is associated with an additional premium of 10.1% relative to average reading at work. When writing and numeracy at work are excluded and only reading at work is included, the premium associated with reading (14.5%) exceeds the years of schooling premium (11.8%). While reading, writing and numeracy at work are highly correlated, it can be seen that reading at work has the strongest relationship to earnings out of the three.

Table 6.3 Model with labour supply and demand characteristics – all variables (equation 10)

	β	p	s.e.
Constant	6.395	.00	.04
Experience			
Experience	0.023	.00	.00
Experience-squared	-0.0004	.00	.00
Men (reference=women)	0.436	.00	.01
Non-immigrants (reference=immigrants)	0.005	.69	.01
Years of schooling	0.027	.00	.00
Information processing skills			
Literacy (percentiles)	0.001	.00	.00
Reading at work (reference=low)			
Medium low engagement	0.041	.00	.01
Medium high engagement	0.109	.00	.01
High engagement	0.164	.00	.01
Writing at work (reference=low)			
Medium low engagement	0.085	.00	.01
Medium high engagement	0.135	.00	.01
High engagement	0.187	.00	.02
Numeracy at work (reference=low)			
Medium engagement	0.051	.00	.01
High engagement	-0.009	.41	.01
Occupational type (reference=unskilled)			
Skilled	0.343	.00	.02
Semi-skilled	0.123	.00	.02
Industry type (reference = primary)			
High-technology manufacturing	-0.015	.54	.03
Low-technology manufacturing	-0.079	.00	.02
Knowledge-intensive market services	-0.049	.02	.02
Public administration, defence, education & health	-0.173	.00	.02
Other community, social & personal services	-0.209	.00	.02
Utilities & Construction	0.008	.74	.02
Wholesale, retail, hotels & restaurants	-0.187	.00	.02
Transport and storage	-0.039	.13	.03
Firm size (reference= < 20 employees)			
20-99 employees	0.103	.00	.01
100-499 employees	0.140	.00	.01
500-999 employees	0.173	.00	.02
>=1000 employees	0.171	.00	.01
Adjusted R-squared	0.371		

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Country is adjusted for in each model but coefficients are not reported in the table.

Table 6.4 Model with labour supply and demand characteristics – all variables: comparison of standardized betas for skill and skill use related variables

A. Adjusted for occupation

	Reading, writing and numeracy practices at work included		Only reading practice at work included		Only writing practice at work included		Only numeracy practice at work included	
	Standard-ized β	p	Standard -ized β	p	Standard-ized β	p	Standard-ized β	p
Years of schooling	0.115	.00	0.118	.00	0.124	.00	0.143	.00
Information processing skills								
Literacy (0-500	0.056	.00	0.056	.00	0.065	.00	0.076	.00
Reading at work								
Index scale 1-3	0.101	.00	0.145	.00				
Writing at work								
Index scale 1-3	0.07	.00			0.128	.00		
Numeracy at work								
Index scale 1-3	-0.009	.11					0.041	.00
Adjusted R-squared	0.370		0.368		0.366		0.356	

B. Unadjusted for occupation

	Reading, writing and numeracy practices at work included		Only reading practice at work included		Only writing practice at work included		Only numeracy practice at work included	
	Standard-ized β	p	Standard-ized β	p	Standard-ized β	p	Standard-ized β	p
Years of schooling	0.154	.00	0.16	.00	0.169	.00	0.208	.00
Information processing skills								
Literacy (0-500 scale)	0.073	.00	0.074	.00	0.086	.00	0.108	.00
Reading at work								
Index scale 1-3	0.127	.00	0.186	.00				
Writing at work								
Index scale 1-3	0.09	.00			0.166	.00		
Numeracy at work								
Index scale 1-3	-0.01	.06					0.057	.00
Adjusted R-squared	0.355		0.352		0.350		0.331	

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Country, experience, gender, immigration status, industry and firm size adjusted for in the model but not shown.

Results for skill match-mismatch models

Table 6.5 presents results for the final model which includes an interaction between the literacy skills of individuals and the extent of reading at work, namely different literacy match-mismath situations (low-skill match; high-skill match; deficit mismatch; and surplus mismatch). Results are presented with and without adjustment for occupation. Only the latter are discussed here, but it can be seen that the pattern is very similar, and that only the level of the premium increases when occupation is not adjusted for in the model.

Workers with high levels of literacy skills who are employed in jobs that require high levels of engagement in reading at work are found to earn a 26.8% premium over workers with low levels of literacy skills who are employed in jobs that only require low levels of engagement in reading at work. Interestingly, workers who are in a deficit situation – that is, they have low levels of literacy skills but are employed in jobs that require high levels of engagement in reading at work – are also found to earn a substantial premium (15.9%). Workers in surplus situation also earn a premium, albeit much smaller (5.9%), for their literacy skills even if they self-report that they do not engage much or at all in reading at work.

Table 6.5 Model with labour supply and demand characteristics featuring skill match and mismatch situations between literacy skills and literacy skill use, adjusted and unadjusted for occupation

	Unadjusted for occupation			Adjusted for occupation (equation 12)		
	β	p	s.e.	β	p	s.e.
Constant	6.403	.00	.03	6.420	.00	.04
Experience						
Experience	0.023	.00	.00	0.023	.00	.00
Experience-squared	-0.0004	.00	.00	-0.0004	.00	.00
Men (reference=women)	0.446	.00	.01	0.440	.00	.01
Non-immigrants (reference=immigrants)	0.023	.05	.01	0.016	.17	.01
Years of schooling	0.044	.00	.00	0.031	.00	.00
Literacy match-mismatch (reference=low skill match)						
Deficit mismatch	0.217	.00	.01	0.159	.00	.01
Surplus mismatch	0.092	.00	.01	0.059	.00	.01
High skill match	0.353	.00	.01	0.268	.00	.01
Occupational type (reference=unskilled)						
Skilled				0.401	.00	.02
Semi-skilled				0.156	.00	.02
Adjusted R-squared	0.344			0.364		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Note: Country is adjusted for in each model. Industry and firm size are also included in both these models but not included here since the parameters do not change and are not the focus of the remainder of the analysis.

Table 6.6 presents results for a variation of the model depicted in Equation 12. Namely, literacy skills and and the extent of skills requirements as denoted by writing and numeracy at work are added back into the model along with the interaction between the literacy skills of individuals and the extent of reading at work. This allows for a read of the premium strictly associated with the type of match or mismatch. A deficit mimatch pays off (7.6%) in relation to a low skill job while a surplus mismatch does not, even if workers have high levels of literacy skills.

Table 6.6 Model with labour supply and demand characteristics featuring skill match and mismatch situations between literacy skills and literacy skill use, adjusting for literacy skill and other skill use

	Unadjusted for occupation			Adjusted for occupation		
	β	p	s.e.	β	p	s.e.
Constant	6.360	.00	.04	6.395	.00	.04
Experience						
Experience	0.023	.00	.00	0.023	.00	.00
Experience-squared	-0.0004	.00	.00	-0.0004	.00	.00
Men (reference=women)	0.443	.00	.01	0.438	.00	.01
Non-immigrants (reference=immigrants)	0.007	.56	.01	0.006	.62	.01
Years of schooling	0.037	.00	.00	0.028	.00	.00
Literacy match-mismatch (reference=low skill match)						
Deficit mismatch	0.099	.00	.01	0.076	.00	.01
Surplus mismatch	0.005	.72	.02	0.002	.90	.02
High skill match	0.168	.00	.02	0.139	.00	.02
Information processing skills						
Literacy (percentiles)	0.001	.00	.00	0.001	.00	.00
Writing at work (reference=low)						
Medium low engagement	0.138	.00	.01	0.099	.00	.01
Medium high engagement	0.207	.00	.01	0.157	.00	.01
High engagement	0.280	.00	.01	0.215	.00	.01
Numeracy at work (reference=low)						
Medium engagement	0.058	.00	.01	0.055	.00	.01
High engagement	0.005	.66	.01	0.000	.97	.01
Occupational type (reference=unskilled)						
Skilled				0.350	.00	.02
Semi-skilled				0.127	.00	.02
Adjusted R-squared	0.355			0.371		

Source: Adult Literacy and Lifeskills survey, 2003-2007.
Note: Country is adjusted for in each model. Industry and firm size are also included in both these models but not included here since the parameters do not change and are not the focus of the remainder of the analysis.

Discussion and implications

Overall the results confirm that job characteristics including skill requirements are at least as important as individual characteristics in their relationship to earnings. Earnings are found to be significantly related to labour supply characteristics (gender, experience, schooling, information processing skills) as well as labour demand characteristics (level of engagement in reading, writing and numeracy practices at work, type of occupation, type of industry, and firm size).

Findings related to the relationship between earnings and various labour supply and demand characteristics are grouped and discussed in turn with a focus on: skill supply characteristics; skill demand characteristics; and skill match-mismatch.

The earnings increase associated with skill supply characteristics

The results provide support for the human capital specification. Namely, individuals with more schooling are found to receive more in monthly earnings on average whatever the specification estimated in this study. Separating the skill supply into an observable and unobservable component however, reveals at least two findings about the relationship between skill supply characteristics and earnings that are worth pointing out.

First, the results reveal the importance that the labour market places on key information processing skills like literacy by valuing them independently from years of schooling. While schooling is an important factor contributing to the development of literacy proficiency, the two are not perfectly correlated – something that labour markets seem to recognize. This is perhaps not surprising since educational attainment measures do not reflect quality differences in the schooling received by labour market participants, nor do they reflect skill gain or skill loss that may occur after the point at which qualifications were gained. For example, some adults who have low levels of schooling but have high proficiency in literacy are rewarded accordingly. Conversely, many adults who have higher levels of schooling but have low proficiency may be penalized on the labour market.

Second, accounting for proficiency in literacy skills, which are closely related to cognitive skills, reduces the growth rate in earnings associated with additional education by nearly 19%. This is less than that found in previous research. The Canadian and American labour markets have been found in previous research to reward literacy proficiency more highly. For example, Osberg (2001) found that in Canada, literacy proficiency reduced the earnings associated with additional education, by nearly 40-45%. The results in this study however, are based on a pooled dataset including eight countries.

Singling out specific skills and valuing them is a potentially useful exercise. Firstly, it recognizes that there are a variety of skills, some of which may be more relevant in certain types of jobs. Secondly, it can help to identify skills that are highly valued, and help to identify policies, which can target certain skills for development and maintenance throughout working life.

The earnings increase associated with skill demand and skill supply characteristics

Including all the supply and demand characteristics considered in this study in an earnings function reveals a number of important findings.

First, labour demand characteristics are as important as labour supply characteristics in explaining variation in earnings differentials (see Table A.6.1 in the Data Appendix for Chapter 6). Labour demand characteristics considered in this study explain about the same total variance in earnings than the labour supply characteristics considered (29% vs 30%). Together, accounting for both labour demand and labour supply characteristics explains about 37% of the total variance in earnings.

Second, the results provide support for the superiority of earnings specifications which emphasize both the supply and demand sides of the market, or alternatively assignment theory, as has been found in previous research (e.g., see Hartog, 1985; 1986a; 1986b; Sattinger, 1993).

Third, when measures of skill supply (i.e., years of schooling and literacy skill measures) are accounted for in combination with measures of skill demand (i.e., reading, writing and numeracy engagement), the extent of reading engagement at work displays among the highest degree of association with earnings. This is case when schooling, literacy skills and reading at work are all put on a standardized scale (see Standardized coefficients in Table 6.4).

Fourth, the *broad* measure of skill supply, namely years of schooling, remains significant in the fully adjusted model, but its magnitude is reduced by over 47% compared to the base Mincerian model. This implies that for a given level of education, earnings are significantly related to the type of tasks individuals are required to perform in their job – in particular the extent of engagement in text-based tasks (such as those involving reading, writing and numeracy) that the job entails. Conversely, for a given level of engagement in text-based tasks, those with more education continue to earn more on average. This makes sense since education provides other skills which may be required at work but are not accounted for in the model.

Fifth, the *specific* measure of skill supply, namely literacy skills, has a substantially reduced relationship to earnings in the fully adjusted model including all labour supply and demand characteristics considered. This suggests that the requirement to read or write at work is more important in its relationship to earnings than actually having the skills to carry out these tasks. It suggests that while some workers have high levels of literacy skills, they do not necessarily get rewarded for this, precisely because they do not engage in tasks that require those skills. Conversely, it suggests that some workers receive a higher pay, even if they do not have a level of literacy skills that is commensurate with the literacy skill requirements of their job.

Together, the findings suggest that on average, the characteristics of the job are equally as important as the characteristics of the individual in explaining earnings differentials – a finding often overlooked when modelling only skill supply characteristics. The main implication of this is the need to consider more carefully the joint contribution of individual and job characteristics to marginal productivity (see Eekhout & Kircher, 2011). This finding also points to the relevance of considering whether low- and high-skill workers are either matched or mismatched in either low- or high- skill jobs when attempting to explain earnings differentials.

The earnings increase associated with skill match-mismatch situations

The results suggest that skill supply characteristics are significant factors associated with earnings, but not entirely independent of skill demand characteristics. In other words, skills matter for earnings but mostly if they are required by the job.

These findings are important because many workers are not in jobs that best suit their skills profile. The incidence of skill mismatch is not trivial. A number of findings are worth pointing out from the final earnings specifications which considered whether workers are in situations of skill match or mismatch.

First, having a *high* level of literacy skills and working in a job that *requires* a high level of engagement in reading emerges as one of the strongest characteristics relating to earnings differentials. Workers who are in this high-skill match situation receive on average about 27% more in monthly earnings than workers who are in a low-skill match situation. Results for the high- and low- skill match situations fit with the intuitive scenario skills matter for earnings but mostly if they are required by the job.

Second, having a *high* level of literacy skills and working in a job that *does not require* a high level of engagement in reading is associated with a small wage premium. This is in comparison to those working in a job with similar low-skill requirements but only have a low level of literacy skills. This small premium falls to zero when literacy skills are adjusted for suggesting that even within the surplus mismatch category, there is enough heterogeneity in skill requirements for a small reward for those who have higher literacy skills. Still, the results suggest that skills alone are not enough – people need to be in jobs that require their skills in order to be rewarded for their skills. This is somewhat analagous to the wage penalty associated with overeducation that is discussed in the qualification mismatch literature. While this result is not confirmed here, it has been found that some workers earn less than the less skilled for the same job, i.e., they experience a wage penalty. Such a penalty might reflect a number of unobserved reasons. For example, these workers may have high levels of certain skills but otherwise have lower capabilities. Alternatively, they may have less tenure and be prone to changing jobs more often.

Lastly, having a *low* level of literacy skills and working in a job that *does require* a high level of engagement in reading is associated with a substantial pay premium. Workers who are in this skill deficit mismatch situation receive on average about 16% more in monthly earnings than those who also have a low level of literacy skills but who engage very little in literacy related activities at work. The finding confirms that demand side characteristics display significant associations with earnings independent of one's human capital.

The finding lends support to the idea that for some workers in certain jobs, their pay is attached more to the marginal productivity of their job, not necessarily the marginal productivity that the individual brings to that job. In some cases, this may happen at the extreme such as that predicted by job competition or labour segmentation theory where only the marginal productivity of the job is said to matter.

Otherwise, the findings also confirm the idea that the type of job and job tasks are important for making skills of individuals relevant (an important demand side consideration), and that there are substantive interactions between the worker and the job in determining marginal productivity and hence pay. That is, interactions between the worker and the job they are performing, as in assignment theory, matters. A particular job may indeed be linked to a range of marginal productivity and hence pay, but individuals can still make a difference – namely the more highly skilled operate in the upper range of marginal productivity as reflected in the higher average pay found for those in high-skill match situations.

Data Appendix for Chapter 6

Table A.6.1 Adjusted R-squared showing variation in monthly earnings explained by each factor as stand-alone and as increments within each model estimated

	R-square for each factor	Labour supply character-istics		Labour demand charact-eristics	Labour supply and demand character-istics		Labour supply and demand character-istics - accounting	
		A	B		A	B	A	B
		Incremental adjusted R-squared						
Labour supply characteristics								
Experience	0.14	0.14	0.14		0.14	0.14	0.14	0.14
Men	0.24	0.24	0.24		0.24	0.24	0.24	0.24
Non-immigrants	0.14	0.24	0.24		0.24	0.24	0.24	0.24
Years of schooling	0.19	0.30			0.30		0.30	0.30
Literacy skills	0.17	0.31	0.27		0.31			0.31
Skill match-mismatch	0.21						0.33	0.33
Labour demand characteristics								
Read at work	0.22			0.22	0.33	0.30		
Write at work	0.20			0.23	0.34			0.34
Numeracy at work	0.16			0.23	0.34			0.34
Occupation	0.21			0.25	0.35			0.35
Industry	0.17			0.28	0.36			0.36
Firm size	0.17			0.29	0.37			0.37
Total		0.30	0.27	0.29	0.37	0.30	0.33	0.37
Incremental R-square for each following factor relative to model with only basic labour supply factors								
Years of schooling		0.06						
Literacy skills			0.03					
Schooling and literacy skills		0.07						
Reading at work						0.06		
Schooling, literacy and reading at work					0.09			

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Table A.6.2 Model with labour supply characteristics, base models with and without imputed wages

	Base model – missing data for wages			Base model – missing data for wages imputed		
	β	p	s.e.	β	p	s.e.
Constant	6.221	.00	.03	6.309	.00	.03
Country (reference=United States)						
Switzerland	-0.016	.33	.02	-0.032	.04	.02
Italy	-0.382	.00	.02	-0.374	.00	.02
Norway	-0.173	.00	.02	-0.190	.00	.02
Canada	-0.074	.00	.02	-0.082	.00	.02
New Zealand	-0.266	.00	.02	-0.277	.00	.02
Netherlands	-0.202	.00	.02	-0.227	.00	.02
Hungary	-0.936	.00	.02	-0.960	.00	.02
Experience						
Experience	0.031	.00	.00	0.025	.00	.00
Experience-squared	-0.0005	.00	.00	-0.0004	.00	.00
Men (reference=women)	0.493	.00	.01	0.495	.00	.01
Non-immigrants (reference=immigrants)	0.062	.00	.01	0.061	.00	.01
Years of schooling	0.065	.00	.00	0.063	.00	.00
Adjusted R-squared	0.289			0.296		
Sample size	30097			38448		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models with United States as a reference category and shown here, but not shown in the remainder of the tables in this chapter.

Table A.6.3 Model with labour supply characteristics, augmented model with literacy

	Augmented model - literacy (score scale)			Augmented model - literacy (percentile scale)		
	β	p	s.e.	β	p	s.e.
Constant	5.944	.00	.03	6.304	.00	.03
Experience						
Experience	0.026	.00	.00	0.026	.00	.00
Experience-squared	-0.0003	.00	.00	-0.0004	.00	.00
Men	0.499	.00	.01	0.498	.00	.01
Non-immigrants	0.013	.28	.01	0.025	.04	.01
Years of schooling	0.051	.00	.00	0.051	.00	.00
Information processing skills						
Literacy (0-500 scale)	0.0020	.00	.00			
Literacy (percentiles)				0.0030	.00	.00
Adjusted R-squared	0.306			0.305		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Table A.6.4 Model with labour supply characteristics, augmented model with numeracy

	Augmented model - numeracy (score scale)			Augmented model - numeracy (percentile scale)		
	β	p	s.e.	β	p	s.e.
Constant	5.945	.00	.03	6.318	.00	.03
Experience						
Experience	0.026	.00	.00	0.026	.00	.00
Experience-squared	-0.0004	.00	.00	-0.0004	.00	.00
Men	0.473	.00	.01	0.474	.00	.01
Non-immigrants	0.015	.21	.01	0.026	.03	.01
Years of schooling	0.049	.00	.00	0.050	.00	.00
Information processing skills						
Numeracy (0-500 scale)	0.002	.00	.00			
Numeracy (percentiles)				0.004	.00	.00
Adjusted R-squared	0.309			0.308		

Source: Adult Literacy and Lifeskills survey, 2003-007. Notes: Country is adjusted for in all models but not shown here.

Table A.6.5 Model with labour supply characteristics, augmented model with literacy and numeracy

	Augmented model - literacy and numeracy (percentile scale)		
	β	p	s.e.
Constant	6.314	.00	.03
Experience			
Experience	0.027	.00	.00
Experience-squared	-0.0004	.00	.00
Men	0.481	.00	.01
Non-immigrants	0.021	.08	.01
Years of schooling	0.049	.00	.00
Information processing skills			
Literacy (percentiles)	0.001	.00	.00
Numeracy (percentiles)	0.003	.00	.00
Adjusted R-squared	0.308		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Chapter 7 Earnings differentials associated with skill supply and demand characteristics from a skill-segmented perspective

Introduction

This chapter adapts a skill-segmented view of the labour market to examine earnings differentials' associated with skill supply and demand characteristics. The skill-segmented view is operationalized by defining six occupational types in terms of their typical job tasks and in turn the broad skill types required for performing successfully these tasks. The approach effectively disaggregates the between and within occupation earnings differentials associated with select skill supply and demand characteristics. Within and between estimates are calculated by specifying interaction effects between occupational types and select skill supply and demand characteristics. Findings are then interpreted in terms of existing theories of wages. The chapter also considers the extent of skill match-mismatch within each of the occupational groups defined from a skill-segmented perspective. As in Chapter 6, interactions between a specific skill supply characteristic, namely a direct measure of an information processing skill, and a specific skill demand characteristic, namely the requirement to use that skill, define the different skill match-mismatch situations considered.

The analysis extends the standard Mincerian approach with two specific features. First, as in Chapter 6, the analysis makes use of a direct measure of human capital when estimating the relationship between skills and earnings. The information processing skills measure from ALLS is used in order to supplement other less precise indicators such as years of schooling. Second, the association between earnings differentials and skill supply and demand characteristics is partitioned into between and within associations following a skill-segmented view of the labour market.

The chapter is significant notably for adapting a labour-segmented view of labour markets. The adaptation is done from a human capital perspective, hence the notion of a "skill-segmented" view of the labour market. That is labour markets are segmented according to the skills set required to work in those broad types of jobs. It is assumed that the relevance of broad skill types differs according to the typical job tasks that characterize different occupational types. This view acknowledges heterogeneity in labour markets and allows the association between earnings differentials and skill supply and demand characteristics to vary according to their relevance in different occupational types.

The chapter is organized as follows. First, some background is covered to provide context to the chapter. Second, theoretical perspectives on human capital and labour-market segmentation are reviewed and adapted into a skill-segmented perspective of the labour market. Third, previous research related to this approach is summarized briefly. Fourth, the data is described and a set of models are specified to operationalize the Minceraian approach with extensions adapting the skill-segmented view. Fifth, results are provided. Finally, there is a summary of key findings and a concluding discussion of the results.

Background

Data available from ALLS offers a direct measure of information processing skills that is used in this study, namely literacy skills. These are believed to be vitally important skills, because they provide a fundamental means to acquire knowledge and skills in a variety of other contexts. They are needed to learn print-based material, to communicate and not least to inform decision-making at all levels. Thus they are likely to be relevant for productivity and hence earnings in all occupations. In this sense literacy involves general skills that are applicable to everyone. They are not all inclusive indicators of human capital, however, they are believed to be key information processing skills that facilitate the acquisition of other more specific types of human capital.

Even though they are likely to be important and relevant for all, the ALLS data shows that there are observed differences in levels of information processing skills among individuals (OECD & Statistics Canada, 2005). Furthermore, the relevance of information processing skills and its impact on productivity and hence earnings is likely to vary according to different types of occupations. For example, occupations in which tasks are dominated by the involvement of print-based material or other information processing tasks are more likely to demand and hence reward information processing skills than other occupations that are dominated by manual tasks.

While information processing may be more relevant in some occupations, recent trends including technically-biased change and the increasing use of Information Communication Technologies (ICTs) have perhaps increased the relevance of information processing skills in all occupations and will continue to do so. For this reason, it is useful to consider the relationship between information processing skills and earnings, while at the same time acknowledging that its relevance for productivity is likely to depend on the type of occupation.

Previous research suggests that information processing skills, as measured by the ALLS, have a significant relationship to labour market outcomes, including less unemployment, higher earnings and a greater probability of being in a high-skilled occupation, independent of educational attainment. In particular, Green and Riddell (2001) find that in Canada information processing skills as measured by the International Adult Literacy Survey (IALS) (a study similar to ALLS) have a significant association with earnings, which is above and beyond the association with education. Using a Mincerian type approach, they attribute the earnings premium associated with information processing skills to cognitive skills, and the premium associated with education to non-cognitive skills, such as teamwork and interpersonal skills. They find that there are significant returns to information processing skills on the order of 3.0 to 3.5 per cent for every10-point increase (on a scale from 0 to 500) in information processing skills[3].

Green and Riddell (2001) and other analyses, which have produced similar findings, did not consider the potential heterogeneity of labour markets, in

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3 These returns are for weekly log earnings. In this chapter, monthly log-earning are used.

terms of the relevance of information processing skills to productivity and hence earnings. Thus findings tend to be highly aggregate and may conceal important differences in terms of the relationship between information processing skills and earnings in different occupations. The analysis presented in this chapter builds on Raudenbush and Kasim (2002), which uses the National Adult Literacy Survey (NALS) data and thus only considered the American labour market.

Theoretical perspective

There is an extensive body of research literature devoted to the study of factors that can explain observed earnings differentials. Some of the major theories commonly put forth have already been outlined in Chapter 3. The following reiterates some of the key points already made and adapts them for the purposes of this chapter.

A core premise of the neoclassical economic framework is that individuals who contribute more to the final value of production should also earn more. On the heels of this, a core premise of human capital theory is that the relative contribution of individuals depends on the knowledge, skills and other attributes embodied within them. On this basis, those with more human capital, holding all other variables constant, should be more productive (see Chapter 3).

The following elaborates on an important assumption associated with this proposition, namely the existence of a single labour market, one that distributes jobs and pay strictly on the basis of worker qualifications, and that knowledge and skills are of pre-eminent importance in the labour market. In reality, human capital is multi-faceted and certain types of skills may be more relevant in some occupations than others, giving rise to a skill-segmented view of the labour market. Introducing a skill-segmented view relaxes the assumption of a single labour market, or alternatively, that skills carry the same value in different jobs. Moreover, depending on how it is operationalized, it can also acknowledge the complexity and diversity of human capital, where some skills are more important in some occupations than others. As an example, Lindqvist and Westman (2009), although not referring or making direct links to labour-market segmentation theory, found that the returns to cognitive skills differ in low vs high skill segments of the labour market.

The theory of labour-segmented markets, which was popularised by Doeringer and Piore (1971), has traditionally differed from human capital theory in terms of its focus. It has tended to emphasize the characteristics of jobs and job markets, rather than the characteristics of individuals (Duncan & Hoffman, 1979). The theory suggests that different labour markets operate under different circumstances such as regulations, technology, demand and supply, which leads to varying pays and benefits. Many proponents of the theory have suggested that worker productivity and pay are determined more by the job and its technology than by the human capital of the worker (see Velloso, 1995). These conclusions are mostly based on studies that view labour-segmentation as a function of industry. In many such studies, job characteristics are not viewed from the point of view of the individual characteristics (i.e., human capital) needed to carry out occupational tasks.

In contrast, there are other studies (e.g., Osberg, Wolff & Baumol, 1989; Raudenbush & Kasim, 2002) that have considered labour-segmentation as a function of occupation. This approach explicitly makes individual characteristics such as human capital relevant, since they are needed to carry out the tasks of different occupations. Osberg *et al.* (1989) state that because of subcontracting and other developments, industry-based classifications of economic activity are becoming increasingly unreliable, and thus there is a need to emphasize the occupational composition of the labour force.

The latter approach to viewing labour-segmentation allows for the possibility to consider whether the returns to qualifications and skills vary by different types of occupations. Many studies ignore this and by extension the different types of qualifications and skills that are needed to complete the tasks of those occupations. For example, years of schooling regardless of whether they are vocationally oriented or comprehensive, are often treated as equivalent in studies estimating the relationship between schooling and/or skills and earnings. Similarly whether an individual is employed on a factory-line or in a position with a lot of decision making responsibility is often ignored. This is no doubt in part due to data limitations. But the differentiation of these factors is likely to be important when estimating the relationship between human capital and earnings.

Another important theory that relates to the analysis undertaken in this study is signalling theory (Arrow, 1973; Spence, 1973; Stiglitz, 1975; Riley, 1976;

Weiss, 1995). Because employers have imperfect information concerning potential employees, such as their ability and future productivity, they face a dilemma when they are hiring. So they have little choice but to infer applicants' abilities to produce by relying on their qualifications that are validated and recognised, such as educational attainment. In short, the theory suggests that education acts as a signalling, or screening device for unobserved characteristics. Even though education is only a proxy for human capital, it is suggested that it is vitally important by serving as screening or filtering function. Indeed, there are findings (e.g., Black & Lynch, 1996: 266), which suggests that educational credentials are important to employers when hiring, and thus play an important role in providing access to occupations.

Signalling theory is important when interpreting the findings of this study because information processing skills are difficult to observe. The ALLS offers a direct measure that is used in this study but employers do not generally have the tools to directly measure information processing skills. Therefore, because information processing skills may not be precisely observed in the day to day functioning of the labour market, it is interesting to observe whether they are rewarded above and beyond officially recognized credentials[4], which usually act as proxies for skills.

Previous research

Previous findings suggest that returns to skills vary by occupation. Using the National Adult Literacy Survey (NALS) data, Raudenbush and Kasim (2002) borrow Osberg et al.'s (1989) labour-segmented view of an information economy to explore the relationships among social inequalities, inequality in information processing skills and inequality in employment and earnings, both within and between occupational types. They associate "good" occupations with relatively well paying information occupations. In their analysis, the average estimate for information processing skills was

4 This chapter only considers years of schooling as credentials, and not educational attainment. The continuous measure of schooling enables the modelling of interaction effects.

approximately 25 per cent of the contribution of education to earnings. A one standard deviation increase in information processing skills was associated with an approximate 18 per cent increase in hourly earnings, but this varied by occupational type. For example, they find that in the American labour market the relationship between information processing skills and earnings is steeper in information occupations than non-information occupations.

Shifts in occupational structures in favour of high-skilled occupations and evidence of a general "upskilling" within most occupations (OECD, 2001) suggests it is important to consider how the relationship between the distribution of skills and earnings can vary between different occupational types. For example, it is expected that information processing skills are more relevant to occupations within the information economy. In order to consider this proposition in a tractable way, it is useful to group occupations in relatively few categories, which are distinguished by common expectations and broad skill types. This section discusses select attempts to reclassify occupations for specific analyses set within an information economy context, including the one used for further analyses. For more detailed profiles of skills in relation to occupations, see the Essential Skills Project outlined in HRDC (2001).

The aggregated occupational approach originates from a study by Wolff and Baumol (1989), who classify occupations as either belonging to the information or non-information sectors of the economy, in order to decompose shifts in the occupational structure of the U.S. economy over the period 1960 to 1980. Within the information-producing sector, they distinguish between occupations that produce 'knowledge' and those that produce 'data'. The occupations that produce knowledge are described as being involved in the generation and dissemination of new conceptual categories, relationships, and hypotheses; and those that produce data are described to be involved in the manipulation, transmission, and storage of symbolic information within previously defined categories (Osberg et al., 1989: 2). 'Goods' and 'service' occupations are considered non-information occupations.

Using a similar approach, Lavoie and Roy (1998) reclassify Canadian occupational data to consider the relative growth of knowledge workers as a potential factor affecting the composition of final output, productivity shifts and intra-industry substitution between different types of workers. They modify Wolff and Baumol's classification by adding a 'management' category, and take the latter's combined 'data/services' category into account. Added emphasis is placed on the role of 'knowledge' occupations in the economy and this category is further sub-divided into 5 categories: pure science, applied science, computer science, engineering and social sciences and humanities. The rationale used to classify occupations into the six main categories involves a subjective analysis of the typical tasks performed by workers in different occupations as well as their typical knowledge base.

Raudenbush and Kasim (1998, 2002) also use Wolff and Baumol's classification scheme. Using the U.S. National Adult Literacy Survey (NALS) data, they apply a Hierarchical Linear Modelling (HLM) approach to investigate gender and ethnic discrimination between and within aggregated occupations in terms of economic inequalities, holding social inequalities in schooling and information processing skills constant.

Boothby (1999) and Béjaoui (2000) extend the research of Lavoie and Roy (1998), which leads to an advanced reclassification of occupational data in terms of required skill types. Using Principal Components Analysis among 43 indices, Béjaoui (2000) finds clusters representing five broad skill types: authority-management skills; cognitive skills; communication skills; gross motor skills; and fine motor skills. Béjaoui constructs the indices by giving scores to each occupation based on the requirements described in the 1971 Canadian Classification and Dictionary of Occupations (CCDO), which represent general education, physical abilities and other different aptitudes. Boothby (1999) builds on the work of Béjaoui and reclassifies occupations into seven categories: 'knowledge', 'management', 'data', 'data manipulation', 'services', 'skilled goods', and 'other goods'. To do this, Boothby performs a Discriminant Analysis, which treats the occupational category as the classification variable and Béjaoui's five skill type scores as the basis for classification.

The reclassification scheme outlined in Boothby (1999) is adapted for the analysis presented in this chapter. A major difference is its application to the 1988 International Standardized Classification of Occupations (ISCO-88) which was made available in ALLS for all countries who participated in the study. Boothby's approach used a rigorous and consistent criterion to reclassify occupations on the basis of required skills, namely Béjaoui's (2000) broad skill type scores. Note that the category labels derived by Boothby (1999) are different than in the other studies mentioned (e.g., Osberg et al.'s, 1989; Raudenbush & Kasim, 1998, 2002; Lavoie & Roy, 1998). By using a more rigorous approach, Boothby (1999) found considerable variation in the nature of the occupational tasks within the categories defined in previous studies. This led to a modified aggregated occupational classification with additional occupational types. The occupation types used in this analysis are very similar to Boothby's except that "knowledge" is referred to as "knowledge (expert)", "data" is referred to as "information (high-skill)", "data manipulation" is referred to as "information (low-skill)", "services" is referred to as "services (low-skill)", and "skilled goods" and "other goods" categories are grouped together as "goods (manufacturing)" because this distinction proved to be too difficult to apply to ISCO-88.

Data

The Adult Literacy and Lifeskills Survey (ALLS) as described in Chapter 5 is used for this study. Table 7.1 provides additional descriptive statistics by the aggregate occupational groups derived for the analysis in this chapter. Appendix A outlines the assignment of 4-digit 1988 International Standardized Classification of Occupation (ISCO-88) codes into the six aggregated occupational types: "knowledge (expert)", "management", "information (high-skill)", "information (low-skill)", "services (low-skill)", and "goods (manufacturing)". Several cases did not contain 4-digit ISCO codes, but only 1 or 2- digit versions which I was not able to classify – these cases are in the missing category. The missing data are adjusted for in the analysis so that the cases are not excluded but their results are not reported in the tables.

Table 7.1 Descriptive statistics by type of occupation (6-categories)

	Sample	Log earnings (trimmed and imputed)		Years of schooling (trimmed and imputed)		Literacy scores (0 to 500 scale)	
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Knowledge (experts)	3763	8.03	0.74	16.7	3.3	305	41
Management	5094	7.85	0.79	14.1	3.3	288	45
Information (high-skills)	6355	7.68	0.72	15.3	3.2	295	43
Information (low-skill)	7507	7.40	0.74	13.3	2.8	281	45
Services (low-skill)	5317	7.14	0.82	11.9	3.0	257	51
Goods (manufacturing)	8051	7.48	0.76	11.4	3.0	255	52
Missing	2361	7.52	0.80	12.9	3.9	275	51
Total	38448	7.55	0.81	13.4	3.6	277	51

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 7.1 (cont'd) Descriptive statistics by type of occupation (6-categories)

	Sample	Read at work index (1 to 4)		Experience		Men	
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Knowledge (experts)	3763	8.03	0.74	16.7	3.3	305	41
Management	5094	7.85	0.79	14.1	3.3	288	45
Information (high-skills)	6355	7.68	0.72	15.3	3.2	295	43
Information (low-skill)	7507	7.40	0.74	13.3	2.8	281	45
Services (low-skill)	5317	7.14	0.82	11.9	3.0	257	51
Goods (manufacturing)	8051	7.48	0.76	11.4	3.0	255	52
Missing	2361	7.52	0.80	12.9	3.9	275	51
Total	38448	7.55	0.81	13.4	3.6	277	51

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Models

The model adopted to estimate the association between information processing skills and earnings closely follows the general Mincerian (1974) model, where the logarithm of individual earnings are expressed as a linear function of years of schooling, log-labour force experience, and other influences such as gender. But since the Mincerian approach is limited by the assumption of a single homogenous labour market, in which all human capital is assumed to be equivalently relevant, the current approach is extended, by incorporating a skill-segmented interpretation of the modern labour market as per the theoretical perspective discussed above. Raudenbush and Kasim (1998, 2002) pioneered and applied this extended perspective by analysing the NALS data available for the United States. While they used a hierarchical linear model, this study uses interaction effects models to approach very similar specifications.

The point of departure is to estimate occupational premiums as follows:

$$\begin{aligned}&\log Y = \beta_0 + \beta_1 occ1 + \beta_2 occ1 + \beta_3 occ2 + \\ &\beta_4 occ3 + \beta_5 occ4 + \beta_6 occ5 + r\end{aligned} \tag{1}$$

This is then extended by building on the same specification as in Chapter 6, namely equation 2 as follows:

$$\log Y = \beta_0 + \beta^S S + \beta^Z Z + r \tag{2}$$

Where,

- Y is the earnings of individual i
- S is the vector of skill supply characteristics for individual i
- β^S are the coefficients associated with the vector of skill supply characteristics
- Z_i is the vector of other predictors for individual i
- β^Z are the coefficients associated with the vector of other predictors
- r is the residual, with assumed distribution $r \sim N(0, \sigma^2)$

The intent is to estimate occupational premiums after adjusting for the effects of labour supply characteristics, which are averaged across the occupational types, as in equation (3).

$$\begin{aligned}&\log Y = \beta_0 + \beta_1 occ1 + \beta_2 occ1 + \beta_3 occ2 + \\ &\beta_4 occ3 + \beta_5 occ4 + \beta_6 occ5 + \beta^S S + \beta^Z Z + r\end{aligned} \tag{3}$$

Where,

- *occ1* is the category "knowledge (expert)" jobs
- *occ2* is the category "management" jobs
- *occ3* is the category "information (high-skill)" jobs
- *occ4* is the category "information (low-skill)" jobs
- *occ5* is the category "service (low-skill)" jobs
- β_0 is the intercept for "occ6" which is the category "goods (manufacturing)" jobs

Much of the ocupational premiums are presumably associated with the average level of schooling or skill needed to access different occupational types. However, within occupational types, the variation in years of schooling and/or skills is likely to continue being associated with earnings. In other words, once a worker accesses expert type occupations due to the acquisition of at least some higher education, there are expert workers with more or less education and/or skill. To address this empirically, Equation (4) specifies a model to differentiate the between occupational effects of schooling and within occupational effects of schooling as follows:

$$\begin{aligned} \log Y = \beta_0 + \beta_1 \overline{ED}_j + \beta^{ED} ED + \beta^{ED1} ED * occ1 + \\ \beta^{ED2} ED * occ2 + \beta^{ED3} ED * occ3 + \beta^{ED4} ED * occ4 + \\ \beta^{ED5} ED * occ5 + \beta^{Z} Z + r \end{aligned} \tag{4}$$

Where,

- $\overline{ED}_j$ is the average level of schooling associated with occupation j=1,....6
- β_1 is an estimate of the between occupation association between years of schooling and earnings differentials
- B^{ED} is an estimate of the within occupation association between years of schooling and earnings for occupation type 6 (the reference group)
- B^{ED1} is an estimate of the within occupation association between years of schooling and earnings for occupation type 1

- B^{ED2} is an estimate of the within occupation association between years of schooling and earnings for occupation type 2
- B^{ED3} is an estimate of the within occupation association between years of schooling and earnings for occupation type 3
- B^{ED4} is an estimate of the within occupation association between years of schooling and earnings for occupation type 4
- B^{ED5} is an estimate of the within occupation association between years of schooling and earnings for occupation type 5

The same is done to examine the between and within occupational premium associated with literacy skills (SKILL) (Equation 5), and with reading at work (READ) (Equation 6) as follows.

$$\log Y = \beta_0 + \beta_1 \overline{SKILL}_j + \beta^{ED} SKILL + \beta^{ED1} SKILL * occ1 + \beta^{ED2} SKILL * occ2 + \beta^{ED3} SKILL * occ3 + \beta^{ED4} SKILL * occ4 + \beta^{ED5} SKILL * occ5 + \beta^{Z} Z + r \quad (5)$$

$$\log Y = \beta_0 + \beta_1 \overline{READ}_j + \beta^{ED} READ + \beta^{ED1} READ * occ1 + \beta^{ED2} READ * occ2 + \beta^{ED3} READ * occ3 + \beta^{ED4} READ * occ4 + \beta^{ED5} READ * occ5 + \beta^{Z} Z + r \quad (6)$$

Results

All within occupation estimates are to be interpreted as differences to the occupational group which was used as a reference group – in this case the "goods (manufacturing)" type occupations. For this reason significance estimates reported by occupational types are based on a t-test of the statistical difference to the parameter from the reference group, namely 'goods (manufacturing)' occupations. Tables A.7.1, A.7.2 and A.7.3 restate all estimates but differences to the reference group are calculated and significance estimates reported are based on a t-test of the statistical difference of the parameter to zero (instead of the difference to the reference group).

Table 7.2 highlights that all results are adjusted for by country. Note that the constant corresponds to the average monhtly log earnings in the United States.

Table 7.2 The null model with the United States as the reference for the constant

	β	p	s.e.
Constant	7.83	.00	.01
Country (reference=United States)			
Canada	-0.08	.00	.02
Hungary	-0.99	.00	.02
Italy	-0.47	.00	.02
Netherlands	-0.20	.00	.02
New Zealand	-0.28	.00	.02
Norway	-0.21	.00	.02
Switzerland	-0.05	.01	.02
Adjusted R-squared	0.14		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Occupational premium

Table 7.3 shows the unadjusted occupational premiums associated with each occupational type. Effectively, these are derived by taking the ratio of each occupational type's expected earnings to the expected earnings of 'goods (manufacturing)' type occupations. For example, workers in knowledge type occupations earn on average about 43% more than workers in goods manufacturing types occupations.

Table 7.3 Unadjusted occupational premiums: OLS regression of log monthly earnings on type of occupation and country (equation 1)

	β	p	s.e.
Constant	7.81	.00	.01
Country (reference=United States)			
Canada	-0.09	.00	.02
Hungary	-0.95	.00	.02
Italy	-0.44	.00	.02
Netherlands	-0.22	.00	.02
New Zealand	-0.31	.00	.02
Norway	-0.16	.00	.02
Switzerland	-0.08	.00	.02
Occupation type (reference=goods manufacturing)			
Knowledge (experts)	0.43	.00	.02
Management	0.30	.00	.01
Information (high-skill)	0.11	.00	.01
Information (low-skill)	-0.12	.00	.01
Services (low-skill)	-0.37	.00	.01
Adjusted R-squared	0.22		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 7.4 adjusts the occupational premiums using the skill augmented Mincerian model discussed in Chapter 6. Results show that even after controlling for skill supply characteristics at the individual level, including years of schooling, literacy skills and labour force experience, as well as gender, significant inter-occupational effects remain[5].

The unadjusted and adjusted occupational premiums follow the same pattern. Namely, "Knowledge (expert)", "management", and "information (high-skill)" type occupations are on average profiled with the highest premiums. "Service (low-skill)" type occupations are profiled with the lowest average level of earnings, significantly below "goods (manufacturing)" type occupations. "Information (low-skill)" type occupations are profiled with the

5 Other variables indicating social origin such as parents' years of schooling were not found to have statistically significant effects and thus were removed from the analysis. See Green and Riddell (2001) for an analysis of the effect of literacy and education on earnings while controlling for immigrant status and parent's education. See also Raudenbush and Kasim (2002) for an extensive analysis of the effect of social origins on earnings inequalities in the American labour market using hierarchical linear modelling.

second lowest average level of earnings, also significantly below "goods (manufacturing)" type occupations.

Table 7.4 Adjusted occupational premiums: OLS regression of log monthly earnings on type of occupation, years of schooling, literacy skills and other factors (equation 3)

	β	p	s.e.
Constant	6.56	.00	.03
Occupation type (reference=goods manufacturing)			
Knowledge (experts)	0.29	.00	.02
Management	0.26	.00	.01
Information (high-skill)	0.14	.00	.01
Information (low-skill)	0.00	.82	.01
Services (low-skill)	-0.18	.00	.01
Adjustment for years of schooling and literacy skills (average over occupation types)			
Years of schooling	0.04	.00	.00
Literacy (percentiles)	0.002	.00	.00
Other standard factors adjusted for in models			
Country (reference=United States)			
Canada	-0.09	.00	.02
Hungary	-0.92	.00	.02
Italy	-0.17	.00	.02
Netherlands	-0.24	.00	.02
New Zealand	-0.30	.00	.02
Norway	-0.09	.00	.02
Switzerland	-0.42	.00	.02
Experience	0.02	.00	.00
Experience-squared	-0.0003	.00	.00
Men (reference=women)	0.46	.00	.01
Non-immigrants (reference=immigrants)	0.06	.00	.01
Adjusted R-squared	0.33		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Schooling premium

Instead of fully saturating occupational premiums in a way that accounts for all possible observed and unobserved differences at the occupational level, as was done in Table 7.4, Table 7.5 shows results for when only *average years of schooling at the occupational level* are adjusted for. This is interpreted as the between occupational effect of schooling on earnings.

Interestingly, the explained variance is very similar for the models estimated and presented in Tables 7.4 and 7.5 (R-squared equal to about .33 vs .326) suggesting that average years of schooling at the occupation level accounts for a very large part of observed occupational premiums.

Table 7.5 Schooling premiums between and within occupations: OLS regression of log monthly earnings on average level of schooling by occupation and years of schooling within occupation, and other factors (equation 4)

	β	p	s.e.
Constant	6.155	.00	.135
Premium associated with additional average years of schooling at occupational level (between occupation effect)			
Average years of schooling at occupation level	0.035	.00	.010
Premium associated with additional years of schooling within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.038	.00	.002
Difference to coefficient intercept			
Knowledge (experts)	0.006	.08	.004
Management	0.012	.00	.002
Information (high-skill)	0.001	.85	.003
Information (low-skill)	-0.004	.04	.002
Services (low-skill)	-0.015	.00	.001
Adjustment for literacy skills (average over occupation types)			
Percentile ranking on the literacy scale	0.0024	.00	.000
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.092	.00	.015
Italy	-0.423	.00	.015
Norway	-0.167	.00	.015
Canada	-0.092	.00	.015
New Zealand	-0.301	.00	.015
Netherlands	-0.240	.00	.015
Hungary	-0.925	.00	.015
Experience	0.024	.00	.001
Experience-squared	-0.0003	.00	.000
Men (reference=women)	0.469	.00	.008
Adjusted R-squared	0.326		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

The coefficient for average years of schooling at the occupation level suggests that a one-year difference in the average years of schooling between occupational types represents an approximate 3.5% difference in earnings (see Table 7.5). For example, Table 7.6 shows that a difference of 5.4 years in average schooling between those in "knowledge (expert)" (16.71 average years of schooling) and "goods (manufacturing)" (11.36 average years of schooling) occupations is associated with an average premium in earnings of 18.83% for workers in "knowledge (expert)" occupations compared to workers in "goods (manufacturing)" occupations. Meanwhile, it can be seen from Table 7.4 that the comparable occupational premium was 29%. This means that average years of schooling at the occupational level explain about 65% of the total variance in earnings observed between occupations. An important point that follows however, is that workers who access "knowledge (expert)" occupations are likely to obtain some occupational premium associated with "knowledge (expert)" occupations regardless of their own level of schooling.

Looking at the schooling premium within occupations, we can see from Table 7.4, that the average within occupation premium associated with schooling is 4 %. This suggests that regardless of occupational type, workers earn on average about 4% more for each additional year of schooling. This is however, net of selection effects into certain types of occupations since the occupational premium is accounted for in the model. But the actual within occupation premium associated with schooling does vary considerably from the average within occupations. Table 7.6 summarizes the between and within occupation premiums associated with years of schooling. For example, for workers within "goods (manufacturing)" occupations, the premium associated with schooling is on average approximately 3.8 % for each additional year of schooling, but for workers in "management" occupations it is on average about 5%. Also see Obserg (1989) for findings about the economic return to educational attainment by aggregated occupational types.

Table 7.6 Summary and calculation of between occupation and within occupation premium associated with years of schooling

	Calculation of between occupation premium associated with average levels of schooling				Calculation of within occupation premium associated with average levels of schooling
	(1)	(2)	(3)	(2)x(3)x100	Difference to coefficient intercept x 100
	Average years of schooling	Additional average years of schooling associated with each occupation	Premium associated with additional average years of schooling at occupational level	Between occupation premium associated with average level schooling (%)	Within occupation premium per year of schooling (%)
Knowledge (experts)	16.71	5.4	0.035	18.83	4.424
Management	14.14	2.8	0.035	9.79	5.008
Information (high-skill)	15.32	4.0	0.035	13.94	3.843
Information (low-skill)	13.33	2.0	0.035	6.93	3.405
Services (low-skill)	11.86	0.5	0.035	1.76	2.275
Goods (manufacturing)	11.36	--	--	--	3.786

Note: calculations are made on the basis of the estimated coefficients reported in Table 7.5.

Information processing skill premium

Similarly, instead of fully saturating occupational premiums in a way that accounts for all possible observed and unobserved differences at the occupational level, as was done in Table 7.4, Table 7.7 shows results for when only the *average level of literacy skills at the occupational level* is adjusted for.

Note that because years of schooling and literacy skills are highly correlated, especially at an aggregated level of analysis (i.e., when considering averages at the occupational level), both factors are not simultaneously significant at the between level of analysis. Thus one can only adjust for average levels of schooling or literacy skills at the between level in separate analyses.

The coefficient for average percentile rankings on the literacy scale distribution at the occupation level suggest that a one-percentile difference in the average percentile ranking between occupational types represents an approximate 1% difference in earnings (see Table 7.7).

Table 7.7 Information processing skill premium between and within occupations: OLS regression of log monthly earnings on average percentile ranking of literacy skills by occupation and literacy skills within occupation, and other factors (equation 5)

	β	p	s.e.
Constant	6.099	.00	.045
Premium associated with additional average percentile ranking on literacy skill scale at occupational level (between occupation effect)			
Average percentile ranking at occupation level	0.010	.00	.001
Premium associated with percentile ranking within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.0030	.00	.000
Difference to coefficient intercept			
Knowledge (experts)	0.0002	.60	.000
Management	0.0016	.00	.000
Information (high-skill)	-0.0009	.01	.000
Information (low-skill)	-0.0019	.00	.000
Services (low-skill)	-0.0024	.00	.000
Adjustment for years of schooling (average over occupation types)			
Years of schooling	0.037	.00	.001
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.093	.00	.015
Italy	-0.419	.00	.015
Norway	-0.171	.00	.015
Canada	-0.091	.00	.015
New Zealand	-0.301	.00	.015
Netherlands	-0.239	.00	.015
Hungary	-0.920	.00	.015
Experience	0.023	.00	.001
Experience-squared	-0.0003	.00	.000
Men (reference=women)	0.483	.00	.008
Adjusted R-squared	0.324		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

The average within occupation premium associated with literacy skills is 0.2% for every increase in percentile ranking on the literacy scale (see Table 7.4). That is, regardless of occupational type, workers earn on average about 2% for every 10 percentile increase in ranking on the literacy scale. This is net of selection effects into certain types of occupations. However, this is only an average across occupations and Table 7.7 reveals that this within occupation premium varies considerably from the average.

Table 7.8 summarizes the between and within occupation premiums associated with literacy skills. For workers within "service (low-skill)" occupations, the premium associated with literacy skills is on average approximately 0.7 % for every 10 percentile increase in ranking on the literacy scale, but for workers in "management" occupations it is on average about 4.6%. In general, the premium associated with literacy skills is higher in occupational types in which literacy would be expected to be more important for the types of tasks associated with those occupations.

An important observation is that while workers in "information (low-skill)" occupations possess relatively high average levels of literacy skills, they get a low return for literacy skills since these skills are not necessarily relevant for their jobs. This means that any analysis of the returns to literacy skills that do not take into account heterogeneity of different types of occupation and particularly the relevance of these skills to particular jobs can produce misleading overall average estimates.

Table 7.8 Summary and calculation of between occupation and within occupation premium associated with additional percentile rankings on the literacy scale

	Calculation of between occupation premium associated with average level of percentile ranking on literacy scale				Calculation of within occupation premium associated with percentile ranking on literacy scale
	(1)	(2)	(3)	(2)x(3)x100	Difference to coefficient intercept x 100
	Average percentile ranking on literacy scale	Additional average percentile ranking associated with each occupation	Premium associated with additional average percentile ranking at occupation level	Between occupation premium associated with percentile ranking on literacy scale (%)	Within occupation premium per additional percentile ranking on the literacy scale (%)
Knowledge (experts)	67.1	28.3	0.010	29.09	0.32
Management	56.9	18.1	0.010	18.65	0.46
Information (high-skill)	60.3	21.5	0.010	22.08	0.22
Information (low-skill)	53.6	14.8	0.010	15.18	0.11
Services (low-skill)	38.6	-0.2	0.010	-0.18	0.07
Goods (manufacturing)	38.8	--	--	--	0.30

Note: calculations are made on the basis of the estimated coefficients reported in Table 7.7.

Reading at work premium

A similar analysis is done but focusing on reading at work premiums. Consistent with the findings reported in Chapter 6, the premiums associated with reading at work are significant and appear to be very large even after controlling for skill supply characteristics like years of schooling and a direct measure of key information processing skills (i.e., literacy skills). While the between occupation effect is not significant (see Table 7.9), the within occupation premium is relatively high within all types of occupations (see Table 7.10). Even for workers in "goods (manufacturing)" type occupations, an additional point on the index of reading at work ranging from 1 to 4, is associated with about 16.2% additional pay.

Table 7.9 Reading at work premium between and within occupations: OLS regression of log monthly earnings on average reading at work by occupation and reading within occupation, and other factors (equation 6)

	β	p	s.e.
Constant	6.351	.00	.104
Premium associated with additional average level of reading at occupational level (between occupation effect)			
Average reading at work at occupation level	-0.011	.76	.038
Premium associated with unit index of reading at work within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.162	.00	.007
Difference to coefficient intercept			
Knowledge (experts)	0.073	.00	.012
Management	0.058	.00	.011
Information (high-skill)	0.031	.00	.010
Information (low-skill)	-0.011	.16	.008
Services (low-skill)	-0.057	.00	.005
Adjustment for years of schooling and literacy skills (average over occupation types)			
Years of schooling	0.028	.00	.001
Percentile ranking on the literacy scale	0.002	.00	.000
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.065	.00	.015
Italy	-0.342	.00	.015
Norway	-0.185	.00	.015
Canada	-0.093	.00	.015
New Zealand	-0.318	.00	.015
Netherlands	-0.225	.00	.015
Hungary	-0.815	.00	.015
Experience	0.021	.00	.001
Experience-squared	0.000	.00	.000
Men (reference=women)	0.434	.00	.008
Adjusted R-squared	0.346		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table 7.10 Summary and calculation of between occupation and within occupation premium associated with reading at work

	Calculation of between occupation premium associated with average level of reading at work				Calculation of within occupation premium associated with reading at work
	(1)	(2)	(3)	(2)x(3)x100	Difference to coefficient intercept x 100
	Average level of reading at work (index ranging 1 to 4)	Additional average index unit of reading by each occupation	Premium associated with additional reading at work at occupation level	Between occupation premium associated with level of reading at work (%)	Within occupation premium per index unit of additional reading at work (%)
Knowledge (experts)	3.3863	1.0	0.000	0.00	23.48
Management	3.2534	0.8	0.000	0.00	22.02
Information (high-skill)	3.1472	0.7	0.000	0.00	19.33
Information (low-skill)	2.9553	0.5	0.000	0.00	15.05
Services (low-skill)	2.3306	-0.1	0.000	0.00	10.51
Goods (manufacturing)	2.4091	--	--	--	16.19

Note: calculations are made on the basis of the estimated coefficients reported in Table 7.9.

Key findings and discussion

Summary of key findings

There are observed occupational premiums even after adjusting for within occupational differences in individual characteristics such as schooling, information processing skills, labour force experience and gender. This suggests that there are systematic differences in characteristics at the occupational level that can explain observed differences in individual earnings. Moreover, it suggests that there are well paying occupations.

The occupation level association between earnings and average levels of schooling associated with different types of occupations explains about 65% of the variation in occupational premiums. In other words, those with more years of schooling tend to benefit from the occupational premiums that are associated with well paying occupations simply because more schooling may give them access to those occupations.

The within occupation premium associated with schooling is significant, but it varies among occupational types. Consequently, in some occupational types years of schooling is a more relevant factor in terms of explaining differences in earnings than in other types of occupations.

Similarly, the within occupation premium associated with literacy skills is significant, but it varies among occupational types. Consequently, in some occupational types information processing skills are more relevant factor in terms of explaining differences in earnings than in other types of occupations. Notably, workers in knowledge economy type jobs (i.e., "knowledge (expert)", "management", and "information (high-skill)") seem to secure the highest rewards for their literacy skills.

The premiums associated with reading at work are significant and appear to be substantial within all occupations even after controlling for skill supply characteristics like years of schooling and a direct measure of literacy skills.

Discussion

This study cannot determine with any certainty whether the occupational premiums that are observed arise because individuals in those occupational types are more productive and hence contribute more to the final value of production. There are many other factors or characteristics at the occupational level, which are not considered here and may explain the observed premiums. Keeping with the theoretical perspective discussed above, however, two separate measures of human capital are considered as potential factors that can account for these occupational premiums.

Indeed, an indirect measure of human capital, namely years of schooling, is found to account for nearly two-thirds of the occupational premiums. This makes sense since years of schooling is something easily observable and can be used as tool for sorting people into different types of occupations. In fact, qualification systems are closely entwined with occupational structures, in some cases much more evidently than others, and in some countries much more so than in others.

When allocating jobs and pay, employers rely on prior experience and other factors beyond schooling to successfully infer the skill profiles of individuals. The extent to which employers are successful at doing this within occupational types, however, is a different matter since individual characteristics tend to cluster in different types of occupations. It can thus be more difficult for employers to precisely differentiate skill profiles within occupational types. While information processing skills such as literacy skills are more difficult for employers to observe than years of schooling, it appears that in some occupational types, pay is partly allocated on the basis of these skills being observed. This is not surprising since the ALLS direct measures of skill capture some of the depreciation or appreciation of skills that can occur after schooling. For example, as workers build a track record within occupational types, their information processing skills may be more easily discernable over time and hence may come to be rewarded.

Human capital is multi-faceted. So which human capital are these measures indicating: cognitive skills, leadership skills, communication skills, fine or gross motor skills, etc…? Among the skills listed, the ALLS information processing skills measure relates closely to cognitive skills, whereas years of schooling may indicate a broader range of skill types. Even further, cognitive skills are also multi-faceted where literacy proficiency, for example, is only one element, albeit a very important one (i.e., key information processing skills), among others such as problem solving, planning, understanding of abstract concepts, etc…

The method used in this study to derive the six aggregated occupational types is based on five indices representing broad skill types that are deemed required to carry out the occupational tasks of different occupations. These are cognitive skills, authority-management skills, communication skills, fine motor and gross motor skills. Table 7.10 indicates that substantial premiums are observed for occupations that require cognitive, authority-management, and communication skills the most. For example, management occupations tend to require all three of these skills comparatively more than other occupations and also tend to pay the highest premiums. Moreover, the three occupational types requiring cognitive skills the most, namely "knowledge (expert)", "information (high-skill)" and "management" occupations display the highest premiums. This suggests that cognitive skills are significantly rewarded on the labour market.

Individuals with higher levels of information processing skills as well as more years of schooling, on average tend to cluster in these latter occupations. Since information processing skills are a good indicator of cognitive skills, this result suggests that on average there is a good match between the observed skills of individuals and the skill requirements of the occupations they work in. But this does not necessarily follow a neat pattern. In particular, many workers in "information (low-skill)" and "service (low-skill)" occupations possess relatively high levels of schooling and/or relatively high levels of cognitive skills, but they generally have fewer possibilities to make use of these skills and hence are rewarded much less for them. This relates to the problem of skill mismatch elaborated in earlier chapters and returned to in the next chapter.

To be sure, the findings in this chapter suggest that the reward to information processing skills depends on the extent of the relevance of cognitive skills at the occupational level. The same can be said for the return to years of schooling. But the latter is problematic since it does not inform on the type of human capital, and hence the differential relevance of skills in explaining earnings differentials in different occupations. For example, vocational schooling may emphasize the formation of fine and gross motor skills, whereas academic style schooling may emphasize the formation of cognitive skills. The relevance of either will depend on the type of occupation one is employed in. In this analysis the type of schooling is not controlled for but a type of cognitive skills, namely literacy skills, is controlled for which helps to reveal some of these nuances empirically .

Table 7.11 Standardized scores of required broad skill types by occupational types

Occupational Types	Occupational premium[1] (%)	Standardized scores of required broad skill types[2]				
		Cognitive skills	Authority - management skills	Communication skills	Fine motor skills	Gross motor skills
Management	36	1.75	1.66	1.35	-0.34	-0.11
Data	29	1.23	0.81	0.70	0.32	0.02
Knowledge	21	2.12	1.03	0.78	0.85	0.08
Skilled goods	16	0.44	0.57	0.12	0.10	0.25
Data manipulation	3	0.11	0.08	0.30	-0.46	-0.44
Service	-34	-0.60	-0.32	0.05	-0.37	-0.07
Other goods	--	-1.06	-0.86	-0.73	-0.04	0.00

Occupational types are ranked in descending order according to the occupational premiums.
Sources:
1. Canadian Adult Literacy Survey (1994).
2. Béjaoui (2000).
Notes: Occupational premiums calculated as a percentage relative to the expected weekly log-earnings of 'other goods' occupations.

While employers may have difficulties in observing and hence selecting on the basis of differences in information processing skills independent of other validated qualifications, they do seem to allocate pay on the basis of the requirement to read in specific jobs. This seems to be the case within all types of occupations. Ironically, workers with the highest levels of information processing skills who may as consequence be most efficient in jobs requiring higher levels of literacy practice, do not necessarily seem to be allocated to those jobs. In particular, the incidence of surplus and deficit mismatch seems to be among the highest for "information (low-skill)" types of occupations (see Table 7.12).

Table 7.12 Literacy mismatch by occupational type

	Low-skill match	Deficit mismatch	Surplus mismatch	High-skill match	Missing
			%		
Knowledge (expert)	7	15	15	62	1
Management	15	23	14	47	1
Information (high-skill)	13	17	21	48	1
Information (low-skill)	22	20	23	34	1
Service (low-skill)	49	13	24	14	1
Goods (manufacturing)	49	16	20	15	1
All occupations	28	17	20	33	2

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Concluding remark

In occupations where the within occupation premium associated with information processing skills is weak, one of two things or a combination thereof may be implied: (a) information processing skills are weakly related to productivity and hence earnings, or (b) employers have difficulty observing and hence selecting on the basis of differences in information processing skills independent of other validated qualifications.

Unlike years of schooling, which act as validated qualifications, information processing skills are not easily observed and hence validated. In fact, they are probably inferred from years of schooling, which is indeed a good predictor of information processing skills (Boudard, 2001). What happens outside and beyond schooling also affects skills, however. Without the proper validation of skills it is difficult for employers to infer actual skill profiles. As a result of poor information, employers may have difficulties matching actual skills of employees with job tasks. Instead they are forced to rely on validated qualifications. In short, validation systems of knowledge and skills are likely to have a pervasive impact on the distribution of earnings and also skill mismatch.

Data Appendix for Chapter 7

Table A.7.1 Schooling premium between and within occupations: OLS regression of log monthly earnings on average level of schooling by occupation and years of schooling within occupation, and other factors (Table 7.5 restated with differences to coefficient intercept calculated)

	β	p	s.e.
Constant	6.155	.00	.135
Premium associated with additional average years of schooling at occupational level (between occupation effect)			
Average years of schooling at occupation level	0.035	.00	.010
Premium associated with additional years of schooling within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.038	.00	.002
Difference to coefficient intercept (CALCULATED)			
Knowledge (experts)	0.044	.00	.002
Management	0.050	.00	.002
Information (high-skill)	0.038	.00	.002
Information (low-skill)	0.034	.00	.002
Services (low-skill)	0.023	.00	.002
Adjustment for literacy skills (average over occupation types)			
Percentile ranking on the literacy scale	0.0024	.00	.000
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.092	.00	.015
Italy	-0.423	.00	.015
Norway	-0.167	.00	.015
Canada	-0.092	.00	.015
New Zealand	-0.301	.00	.015
Netherlands	-0.240	.00	.015
Hungary	-0.925	.00	.015
Experience	0.024	.00	.001
Experience-squared	-0.0003	.00	.000
Men (reference=women)	0.469	.00	.008
Adjusted R-squared	0.326		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table A.7.2 Information processing skill premium between and within occupations: OLS regression of log monthly earnings on average percentile ranking of literacy skills by occupation and literacy skills within occupation, and other factors (Table 7.7 restated with differences to coefficient intercept calculated)

	β	p	s.e.
Constant	6.099	.00	.045
Premium associated with additional average percentile ranking on literacy skill scale at occupational level (between occupation effect)			
Average percentile ranking at occupation level	0.010	.00	.001
Premium associated with percentile ranking within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.0030	.00	.0003
Difference to coefficient intercept (CALCULATED)			
Knowledge (experts)	0.0032	.00	.0003
Management	0.0046	.00	.0002
Information (high-skill)	0.0022	.00	.0002
Information (low-skill)	0.0011	.00	.0002
Services (low-skill)	0.0007	.02	.0003
Adjustment for years of schooling (average over occupation types)			
Years of schooling	0.037	.00	.001
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.093	.00	.015
Italy	-0.419	.00	.015
Norway	-0.171	.00	.015
Canada	-0.091	.00	.015
New Zealand	-0.301	.00	.015
Netherlands	-0.239	.00	.015
Hungary	-0.920	.00	.015
Experience	0.023	.00	.001
Experience-squared	-0.0003	.00	.000
Men (reference=women)	0.483	.00	.008
Adjusted R-squared	0.324		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Table A.7.3 Reading at work premium between and within occupations: OLS regression of log monthly earnings on average reading at work by occupation and reading within occupation, and other factors (Table 7.9 restated with differences to coefficient intercept calculated)

	β	p	s.e.
Constant	6.351	.00	.104
Premium associated with additional average level of reading at occupational level (between occupation effect)			
Average reading at work at occupation level	-0.011	.76	.038
Premium associated with unit index of reading at work within types of occupations (within occupation effect)			
Coefficient intercept (goods)	0.162	.00	.007
Difference to coefficient intercept (CALCULATED)			
Knowledge (experts)	0.235	.00	.010
Management	0.220	.00	.008
Information (high-skill)	0.193	.00	.008
Information (low-skill)	0.151	.00	.006
Services (low-skill)	0.105	.00	.008
Adjustment for years of schooling and literacy skills (average over occupation types)			
Years of schooling	0.028	.00	.001
Percentile ranking on the literacy scale	0.0016	.00	.000
Other standard factors adjusted for in model			
Country (reference=United States)			
Switzerland	-0.065	.00	.015
Italy	-0.342	.00	.015
Norway	-0.185	.00	.015
Canada	-0.093	.00	.015
New Zealand	-0.318	.00	.015
Netherlands	-0.225	.00	.015
Hungary	-0.815	.00	.015
Experience	0.021	.00	.001
Experience-squared	-0.0003	.00	.000
Men (reference=women)	0.434	.00	.008
Adjusted R-squared	0.346		

Source: Adult Literacy and Lifeskills survey, 2003-2007.

Chapter 8 Skill supply and demand characteristics and further investment in human capital

Introduction

This chapter aims to examine how both labour supply and demand characteristics may influence participation in adult education/training. Particular emphasis is placed on skill use at work as well as situations of skill match or mismatch between the observed skills of workers and the extent to which they report using those skills at work. As in previous chapters, the analysis is based on the data from ALLS which is described in Chapter 5. The purpose is to understand better the relationship between participation in adult education/training and workers' skills profiles, the extent to which those skills are used in their jobs, as well as in different situations of skill match or mismatch.

The theoretical discussion is generalized to apply to all types of adult education/training, but the empirical analysis and discussion focuses primarily on employer supported adult education/training. This is partly for the sake of parsimony but also because employers are the single most important source of financing of adult education/training (see for e.g., OECD/Statistics Canada, 2005), and therefore, have a major impact in determining who receives adult education/training and who does not. Participation in adult education/training however, is not solely dependent on employer support, nor is it solely the decision of employers, making it difficult to maintain a neat distinction between the multiple and often overlapping factors that affect participation. In the case of employer supported adult education/training, it is a joint decision, and it is argued in this chapter that this decision depends on both labour supply and demand characteristics. The analysis however, can easily be extended to understand better how both labour supply and demand characteristics may be related to adult education/training which is instead supported by governments or solely by the individual. Thus some empirical results are presented by source of financing to allow for an overview but the focus remains primarily on employer supported adult education/training.

The chapter is organized as follows. First, a variety of theoretical perspectives are brought together to consider how both individual and structural characteristics come together to influence participation in adult education/training. An emphasis is placed on the skill dimensions of both labour supply and demand. Second, a set of empirical models are introduced to explore the correlates of employer supported adult education/training. Third, empirical estimates are presented. Finally, there is a concluding discussion of results and the stage is set for the overall concluding discussion of this study. In the next and final chapter, the results of this chapter are linked to potential strategies for addressing skill mismatch, including in situations of deficit or surplus mismatch.

Theoretical perspectives: the role of observed skills, skill use and skill mismatch in participation

Interpreting patterns of participation in the context of skills, skill use at work and skill mismatch requires careful consideration of the potential role of diverse factors including both individual and structural characteristics. The discussion in this section draws on elements from three bodies of literature, namely from economics of education, sociology of education, and adult education, which provide insights into how labour supply and demand characteristics may come together to influence participation in adult education/training.

Economics of education perspective: participation depends on cost/benefit ratios for participant and sponsors

From an economics perspective, human capital theory is the dominant framework for studying behavioural aspects of investing in education and training (Becker, 1964; Woodhall, 2001; Riddell, 2004; also see discussion of this theory in relation to mismatch in Chapter 3). The starting point is that individuals make a decision to invest based on an evaluation of the costs and benefits (Becker, 1964). The prediction of this theory is that the likelihood of participating increases as a function of the cost/benefit ratio (US Department of Education, 1998, p. 13).

Employers' incentives to invest in the adult education/training of their employees depend on expected benefits such as increased productivity, quality, and competitiveness of the firm, and not least as in the case of individuals, the cost/benefit ratio (Becker, 1964; Hum & Simpson, 2004; Vignoles, Galindo-Rueda & Feinstein, 2004). Following Becker's distinction between "general" and "specific" skills (Becker, 1964), it is expected that employers are only willing to support training that develops specific skills. This is because employers face too high risks of not being able to recuperate costs associated with investing in general skills, since employees may be able to use their general skills in other jobs.

Contrary to Becker's theory however, there is much evidence to suggest that firms invest in the development of general skills (see review by Eide & Showalter, 2010). However, this seems to apply under certain circumstances that vary depending on individual and/or structural characteristics. Evidence suggests, for example, that employers channel support to workers who are most likely to gain from adult education/training (Vignoles et al., 2004), which helps to optimize the cost/benefit ratio, shorten the payback period and thus minimize the risk of losing their investment to other employers. Multi-stakeholder models that help to pool risks and funds, such as tripartite arrangements between employers, the state, and unions in the Nordic countries, also seem to encourage adult education/training that fosters the formation of both general as well as specific skills (Eide & Showalter, 2010).

Sociology of education perspective: participation depends on structural factors at macro and micro levels

Despite Becker's work and that of others in the economics of training on integrating the employer perspective, applications of human capital theory have in general been criticized for not going far enough in terms of acknowledging the role of social structures and thus for being too individualistic in their approach. Blaug (1976) discussed the amenability of human capital theory to “methodological individualism” and the underlying role of personal agency in decision making.

Sociologists in particular have pointed out that structural elements associated with inequalities of income and education have tended to be reduced to individual psychological deficits in applications of human capital theory, rather than treated as outcomes of inequalities in power, wealth, and influence (Torres, 1996). Accordingly, sociologists have tended to emphasize that the decision to invest in human capital is also shaped by the role of social and economic institutions (government policy, organizations, industries, markets, and social classes) at the macro level, and the structure of work settings at the micro level (Brown, Green & Lauder, 2001).

Adult education perspective: participation depends on individual and structural factors

Building on sociological understandings, recent adult education research has attempted to integrate and elaborate the role of structural dimensions in shaping participation patterns (Rubenson & Desjardins, 2009; Ure & Saar, 2008). This should be seen as a response to the shortcoming of much adult education research on participation that otherwise has had a tendency to focus almost exclusively on the individual decision to participate, while ignoring the potential role of employers, and wider structures at both the micro and macro levels.

The dominance of a psychological orientation is evident in Cross’s (1981) *chain of response-model* that has come to dominate much adult education research on participation. This model takes the individual as the starting point and employs psychological concepts to explain why some adults participate while others do not. Cross (1981) argues that this does not mean that societal aspects are ignored. At the same time, her approach does not elaborate on the relationship between participation and broader structural characteristics embedded in economic, social, cultural and not least public policy contexts. The importance of addressing these latter aspects is supported by findings on cross national patterns of participation (see Desjardins, Rubenson & Milana, 2006; Illeris, 2004a; Statistics Finland, 2000). Evidence suggests that participation is best understood in terms of societal processes and structures as well as their interaction with individual consciousness and activity (Rubenson & Xu, 1997; Rubenson & Desjardins, 2009).

Synthesizing the perspectives: a model for understanding the role of skills, skill use and skill mismatch in participation

In summary, existing theoretical and applied work by economists, sociologists and recent research in adult education suggest that both individual and structural characteristics of work, the economy and society come together to influence participation in adult education/training. The following elaborates on an analytical model that draws in both individual and structural aspects which are explicitly linked to skills and skill use, and may affect participation. The purpose is to form a heuristic device that makes explicit the theoretical foundations underlying the empirical models of the correlates of participation which are estimated in this study.

The interplay between individual and structural characteristics in influencing participation

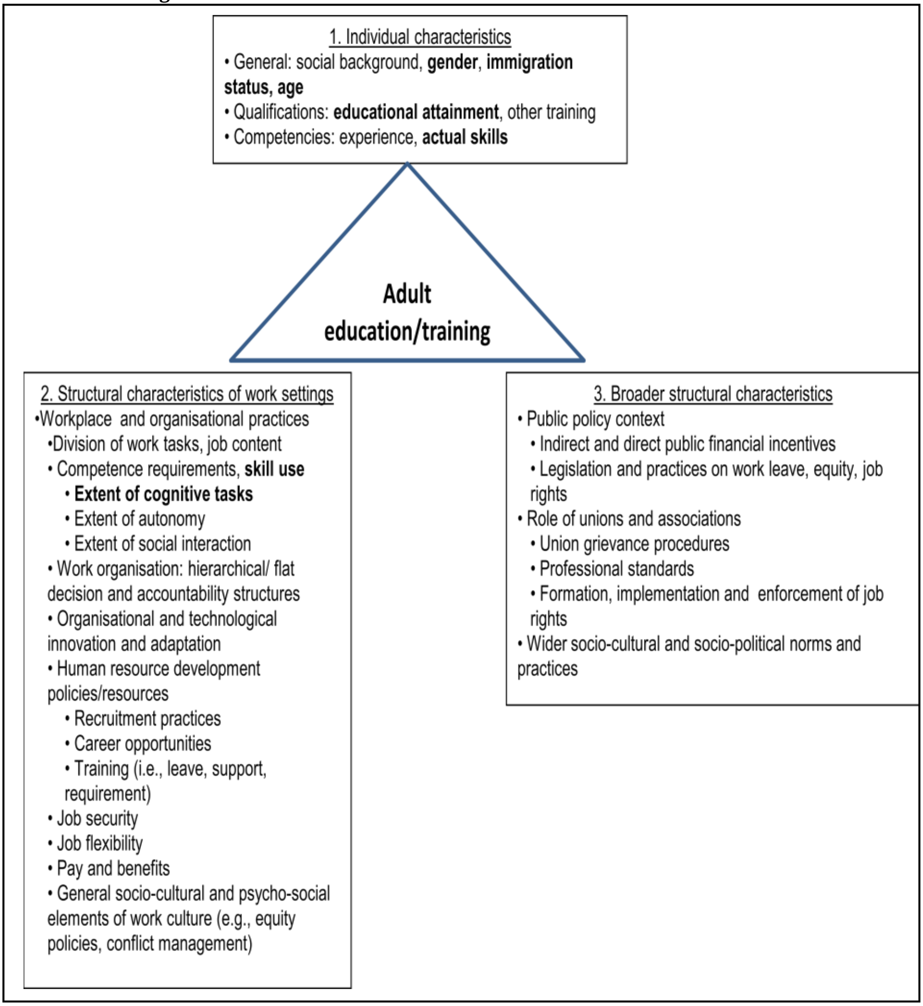
The structure of work settings as well as broader structural characteristics of the economy and society may facilitate or constrain opportunities to participate in adult education/training (Brown, Green & Lauder, 2001; Illeris, 2004b; Sawchuk, 2006). Thus the decision to participate lies not only in personal resources but also in workers' access to, and their positions in, those structures. Further, the two are inherently linked because individuals' access to, and position in, those structures is a function of their personal profile.

Helms-Jørgensen and Warring (2003) provided a fruitful analytical framework for considering how structural characteristics such as societal and institutional structures come together with individual consciousness and activity to shape learning in the workplace. In their model, learning in the workplace is conditioned by three elements: characteristics of employees (experience, education, training, and social background), characteristics of the technical-organizational learning environment (division of work and work content, autonomy and application of qualifications, possibilities of social interaction, strain and stress), and the social-cultural learning environment (communities or work, cultural communities, political communities). Based on an adaptation of their work, Figure 8.1 highlights the interplay between individual characteristics and different levels of structural characteristics, namely those of work settings and the broader social, political and cultural environment, which can all influence the distribution of participation in adult education/training.

The structural characteristics of work settings which influence participation are a function of a variety of organizational and workplace practices as listed in box 2 in Figure 8.1. The organizational forms and their actions which are embedded in work settings emerge and persist through conscious rational-choice designs. Among others, these choices are driven by the pursuit of objectives, negotiated stakeholder models, compliance with legislation, and responses to structural incentives. But these are also conditioned by broader structural characteristics such as cognitive, cultural and political conventions which are inherent to prevailing social thoughts and actions. In summary, a variety of forces – including technological demands, professional association standards, union grievance procedures, legislation and judicial mandates for equal employment opportunities – converge to form, transform or reform work settings, and in turn, influence participation.

Another relevant strand of research is that of the so called "Institutionalists". These scholars argue that a number of the above mentioned forces are converging to transform the workplace into a legalized institution in which employees increasingly expect a sense of participatory citizenship in their work roles (Kalleberg, Knoke, Marsden & Spaeth, 1996). "Organizational citizenship" is a concept coined to understand better the emergence of norms and expectations about employee job rights and benefits, including access to, and support for, participation in adult education/training (Kalleberg *et al.*, 1996).

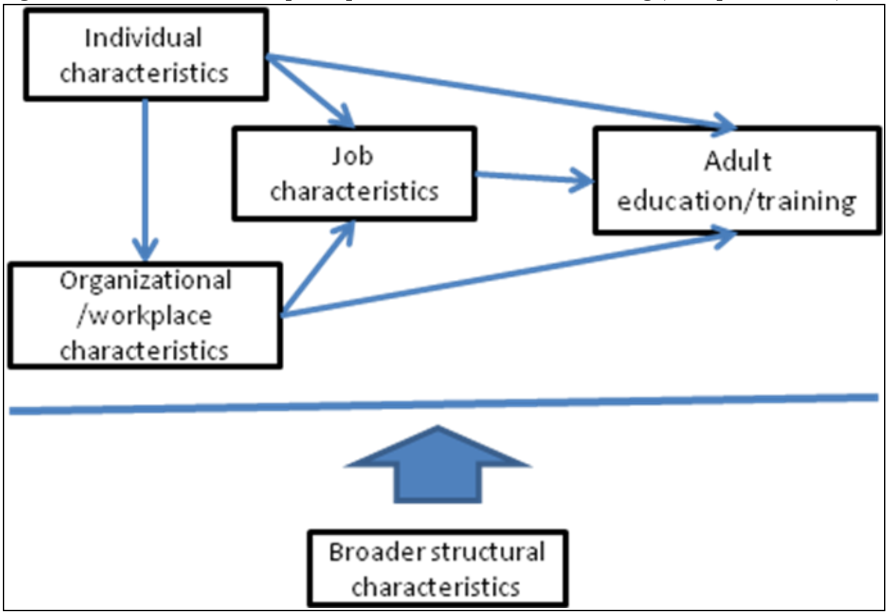
Figure 8.1 Individual and structural characteristics which are relevant for participation in adult education/training



A conceptual model of the factors related to participation: emphasis placed on the role of workers' skills and the use of those skills at work

This section draws emphasis to the role of skills and skill use in accounting for who participates in employer supported adult education/training and under which circumstances. The model depicted in Figure 8.2A illustrates the interplay between individual characteristics, job characteristics, organizational characteristics, and broader structural characteristics at the macro level, such as the socio-political situation, and how these jointly influence the chances of participating in adult education/training. The conceptual model is used as a guide to e*mpirical*ly explore the relationship of individual characteristics and participation on the one hand, and job characteristics and participation on the other (see Figure 8.2.B). Also considered is the extent to which being in a skill match or mismatch situation may play a role.

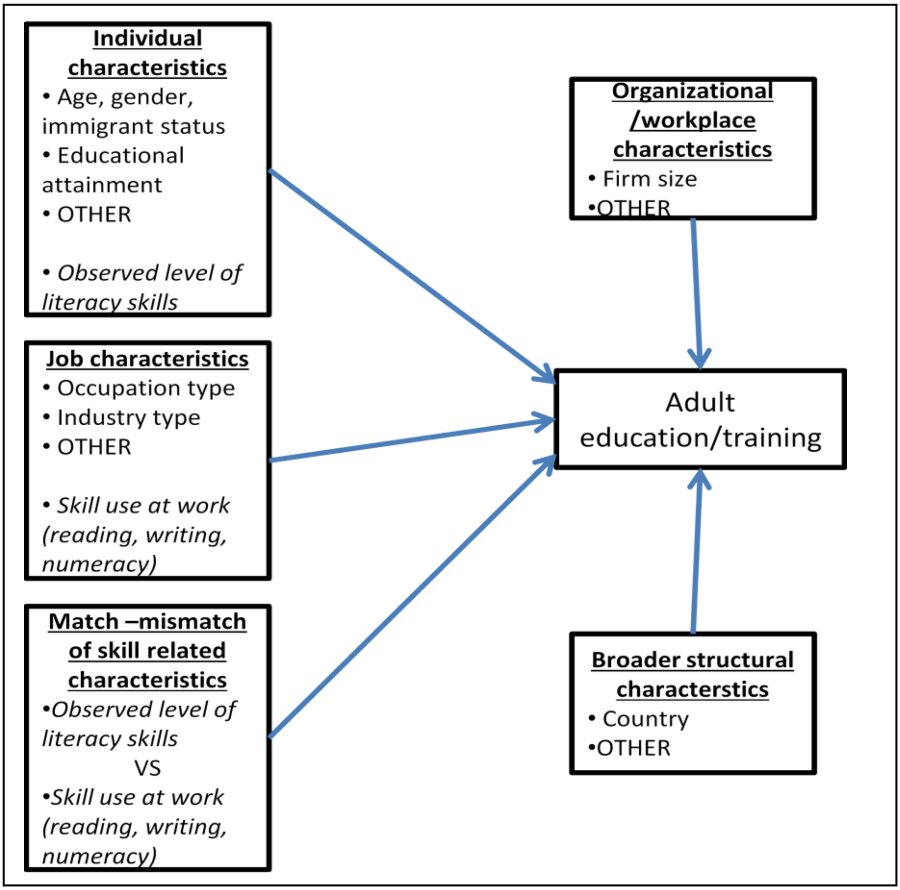
Figure 8.2.A Factors related to participation in adult education/training (conceptual version)



The logic of the model presented in Figure 8.2.A is as follows: individuals entering a workplace have certain personal characteristics– such as personality traits, family background, acquired educational qualifications – which not only influence the kind of organisations that hire them, but also determine the types of job they are qualified for. The characteristics of the employing organisation such as firm size, the degree of technology application, labour relations, the composition of workforce, and internal labour market, influence the types of jobs available at the workplace and interact with individual characteristics to influence each worker's job characteristics, such as literacy and cognitive related demands at work, the degree of autonomy and teamwork, and level of responsibility.

In turn, these factors influence the likelihood of accessing further learning opportunities. Individual characteristics, particularly educational attainment, directly and indirectly influence a person's readiness to invest in adult education/training as well as his/her chances of receiving support from his/her employer. Organizational and workplace characteristics, directly and indirectly, as well as through an interaction with job characteristics, influence the chances of receiving adult education/training. Job characteristics also have a direct influence on the likelihood of receiving employer-supported adult education/training. These factors are all subject to influences from broader structural characteristics such as: prevailing ideologies; political, social and economic objectives of a nation; social structures; government interventions and contemporary political and economic situations.

Figure 8.2.B Factors related to participation in adult education/training (operational version)



The operational version of the model in Figure 8.2.B is simplified into a single equation. This enables a simple and focused comparison of the relative influence of each of the various individual (age, gender, immigration status, educational attainment, information processing skills) and job characteristics (occupation and industry type, skill use at work) as well as organizational/work-place (firm size) and broad structural characteristics (country).

Empirical model of the correlates of participating in employer supported adult education/training

In addition to examining the links between the supply of information processing skills and participation on the one hand, and between the demand for information processing skills and participation on the other, the empirical analysis also considers the potential role of the interaction between the supply of, and demand for, information processing skills as reflected in the literacy match-mismatch variable.

In previous research, the supply of skills has been typically characterized by an individual's level of education. The ALLS dataset contains a direct measure of information processing skills, thus allowing for the indirect but broader measure of educational attainment to be complemented. This allows for a more comprehensive set of measures that help to account for skill supply. The ALLS dataset also contains measures of reading engagement at work which allow for the demand for information processing skills to be factored into an analysis of the correlates of participation. Together, the measure of information processing skills combined with indirect measure of reading engagement at work allow for a direct measure of skill match-mismatch as described in Chapter 5.

As has been shown in previous analyses (e.g., Boudard & Rubenson, 2003), job characteristics such as firm size are important correlates of participation in employer supported adult education/training. It is therefore, of interest to explore further the issue of whether it is job or individual characteristics that matter most in accounting for who participates and receives employer financing to do so. Key correlates of participation are included in the model as per Boudard and Rubenson (2003). These include age, education and information processing skill level, all of which reflect individual characteristics and more specifically human capital. Other socio-demographic variables of interest include gender and immigration status, which are known to interact with human capital and be related to labour market outcomes. These are also viewed as characteristics of labour supply. In contrast, firm size and skill use at work such as reading, writing and numeracy engagement are viewed as job characteristics, or alternatively labour demand characteristics.

Figure 8.2B summarizes the models graphically while equations 1 to 3 summarize the model formally.

$$Participation_i = \beta_0 + \mathrm{B}^{Demand} S_i + \mathrm{B}^{Supply} Z_i \quad (1)$$

$$B^{Demand} = B_{HC}^{Demand} + B_{Other}^{Demand} \quad (2)$$

$$B^{Supply} = B_{HC}^{Supply} + B_{Other}^{Supply} \quad (3)$$

Where,

- Participation is the probability of participation in employer supported training in last 12 months
- B_0 is a constant
- S_i is the vector of labour demand characteristics
- B^{Demand} are the coefficients associated with the vector of labour demand characteristics
- Z_i is the vector of labour supply characteristics
- B^{Supply} are the coefficients associated with the vector of labour supply characteristics

As in Chapter 6, a number of models are empirically estimated in order to observe changes in the parameters of the characteristics associated with skill supply and demand. Equations 4 to 8 specify these empirical models. All residuals are assumed to be independently and identically normally distributed. Error terms are therefore omitted for simplicity.

The starting point is the base model estimating the coefficients associated with labour supply characteristics. This is stated as follows in Equation (4):

$$\log it(p) = b_0 + [b_1 AGEGRP + b_2 MEN + b_3 NIMM + b_4 EDLEV] \quad (4)$$

Similar to Chapter 6, the base model is augmented with a direct measure of literacy skills made available in ALLS (Equation 5). This is done to estimate separately the potential role of a broader indicator of human capital, namely educational attainment, and a more specific indicator of human capital, namely literacy skills.

$$\log it(p) = b_0 + [b_1 AGEGRP + b_2 MEN + b_3 NIMM + b_4 EDLEV + b_5 SKILL] \quad (5)$$

Next, a model including only the factors associated with labour demand characteristics is estimated (Equation 6).

$$\log it(p) = b_0 + [b_1 OCC + b_2 IND + b_3 FIRM + b_4 READ + b_5 WRITE + b_5 NUM] \quad (6)$$

The full model including all the labour supply and demand characteristics is specified in Equation (7).

$$\log it(p) = b_0 + [b_1 AGEGRP + b_2 MEN + b_3 NIMM + b_4 EDLEV + b_5 SKILL] + [b_6 OCC + b_7 IND + b_8 FIRM + b_9 READ + b_{10} WRITE + b_{11} NUM] \quad (7)$$

The final model includes both labour supply and demand characteristics but augments the model with a skill match-mismatch variable, which picks up on the interaction between certain skill supply and demand characteristics (Equation 8).

$$\log it(p) = b_0 + [b_1 AGEGRP + b_2 MEN + b_3 NIMM + b_4 EDLEV] + [b_5 OCC + b_6 IND + b_7 FIRM] + [b_8 MATCH] \quad (8)$$

Where,

- p is the probability of participation in employer supported training in last 12 months
- AGEGRP is age: 16-35, 36-50 and 51-65 (reference)
- MEN is a dummy variable for gender (men is reference)
- NIMM is a dummy variable for immigration status (non-immigrant is reference)
- EDLEV is education level: More than upper secondary, upper secondary and less than upper secondary (reference)
- SKILL is information processing skills level: Level 4/5, Level 3, Level 2 and Level 1 (reference)
- OCC is occupation type: skilled, semi-skilled, unskilled (reference)
- IND is industry type: high-technology manufacturing; low-technology manufacturing; knowledge-intensive market services; public administration, defence, education & health; other community, social & personal services; utilities & construction; wholesale, retail, hotels & restaurants; transport and storage; primary industries (reference)
- FIRM is firm size: 500 or more employees, 200-499, 20-199, less than 20 (reference)
- READ is reading engagement at work: High intensity, medium high intensity, medium low intensity and low intensity (reference)
- WRITE is writing engagement at work: High intensity, medium intensity, low intensity (reference)
- NUM is numeracy engagement at work: High intensity, low intensity (reference)
- MATCH is skill mismatch: high-skill match, surplus mismatch, deficit mismatch and low-skill match (reference)

and,

$$\log it(p) = \ln\left[\frac{p}{1-p}\right]$$

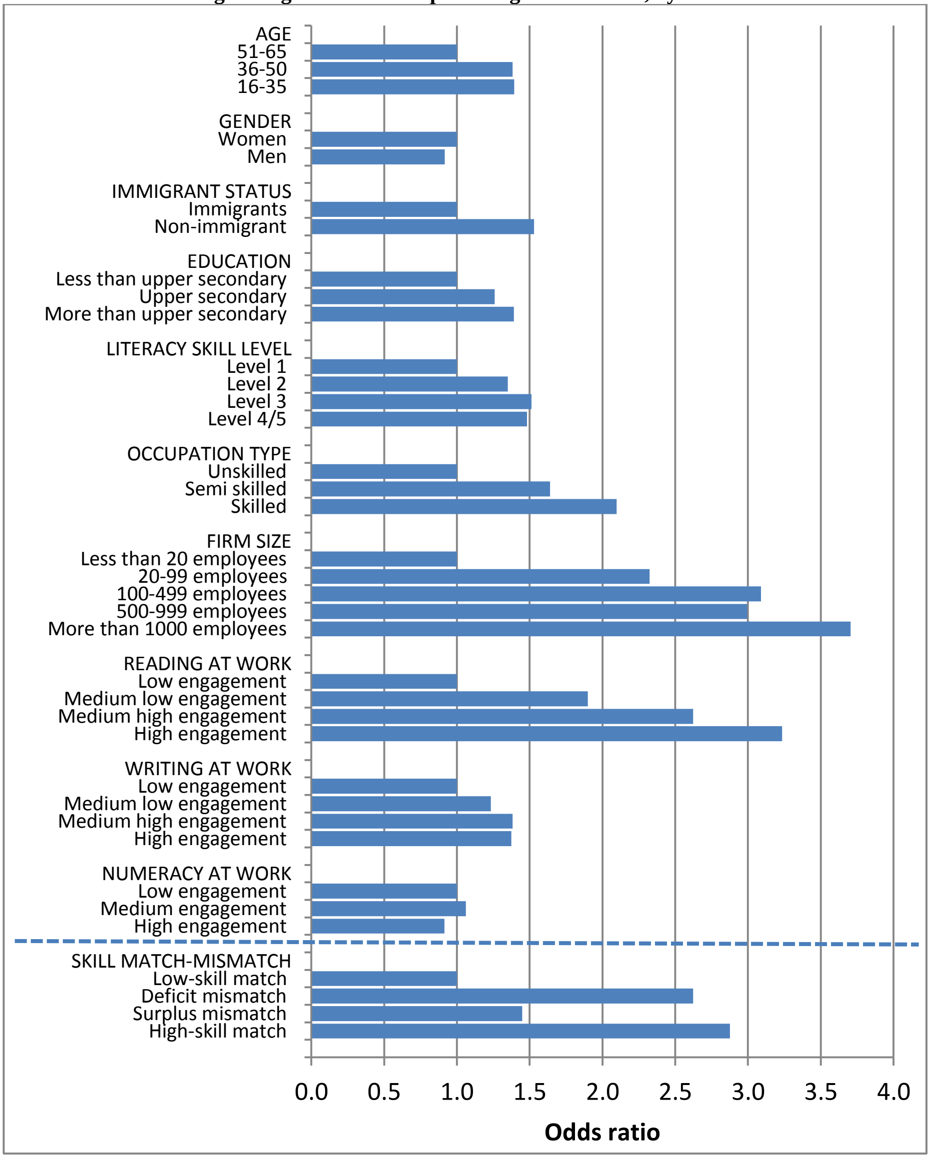
Logistic regression is used to estimate the odds of participating in employer supported adult education/training (see Hosmer & Lemeshow, 1989). The dependent variable is a dichotomous variable indicating whether an individual has participated or not. The goal is to find a reasonable model to describe the relationship between participation in employer supported adult education/training and a set of individual as well as job characteristics. The parameters that are generated are a logit transformation of the probability of presence of participation, which maximize the likelihood of observing participation in employer supported adult education/training. The data tables however, present the odds ratios as per example presented in Equation 9. Therefore, it is important to note that the standard errors are linked to the logit transformation of the odds.

$$odds = \frac{p}{1-p} = e^{b_0 + b_1 AGEGRP + b_2 MEN + b_3 NIMM + b_4 FIRM + b_5 EDLEV + b_6 SKILL} \quad (9)$$

Estimation results

It is important to note that all results are based on a pooled analysis including all countries but adjusted with dummy controls for each country since there are important level effects in the participation rate in adult education and training across countries.

Figure 8.3 Odds ratios showing the likelihood of adults aged 25 to 65 receiving employer supported adult education/training during the 12 months preceding the interview, by various correlates



Source: Adult Literacy and Lifeskills survey, 2003-2007.

Notes: 1. Estimates for age, gender, immigrant status, education, occupation type, firm size and skill mismatch can be found in Table 8.3

2. Estimates for skill match-mismatch can be found in Table 8.4 (column with results adjusted for occupation).

The most important results are summarized in Figure 8.3. The results confirm that chances of participating in employer supported adult education/training are unequally distributed. The likelihood of participation with employer support is found to be significantly related to labour supply characteristics (gender, immigration status, age, level of education, information processing skill level) as well as labour demand characteristics (firm size and level of engagement in reading, writing and numeracy practices at work).

More detailed results for each model are discussed below and can be found in Table 8.1 to Table 8.5.

Results for labour supply characteristics models and discussion

Table 8.1 presents results for the first models which focus on only individual, or alternatively, labour supply characteristics, namely educational attainment, immigration status, gender and age. In the base model, educational attainment is found to be the strongest correlate of participation in employer supported adult education/training. Adults who have completed upper secondary are about 2 times more likely to have participated in employer supported adult education/training compared to those who did not complete upper secondary. The odds ratio climbs to 3.5 times for adults who attained a level of education higher than upper secondary.

From the employer's point of view, higher educated adults may be perceived as more trainable or more efficient trainees. On this basis, employers may be inclined to channel their support to adults who have more education. This is significant because employer-supported adult education/training is a substantial component of total adult education/training (OECD/HRDC, 1997; OECD/Statistics Canada, 2005). To the extent this is the case, it would also reflect a tendency to exacerbate inequalities associated with access to education/training and the concomitant economic and social outcomes.

Immigration status, gender, and age are also important correlates. Immigrants, women, and older adults aged over 50 are found to be the least likely to have participated in employer supported adult education/training. Non-immigrants are about 1.8 times more likely to have participated in employer supported adult education/training than immigrants. Men are about 1.1 times more likely to have participated in employer supported adult education/training than women. Likewise, younger cohorts ranging from ages 25 up to 50 are about 1.4 times more likely to have participated in employer supported adult education/training when compared to adults aged 51 to 65. Employers thus seem to be more likely to invest in early and mid career aged workers than older workers.

Augmented model with direct measure of literacy skills

Enhancing the model with an additional indicator of human capital, observed literacy skills, reduces the strength of education as a predictor. Similar to the pattern observed in respect to educational attainment, people with higher levels of literacy skills are more likely to have participated in employer supported adult education/training. Adults with at least Level 3 literacy proficiency were over two times more likely to have participated in employer supported adult education/training than adults with the lowest level of literacy skills. Overall, education and literacy skills were both found to have a strong relationship with the likelihood of having participated in employer supported adult education/training.

In the same way as those with higher levels of education, workers with higher levels of literacy skills may be perceived by employers as more trainable. Educational credentials and the measure of literacy skills in ALLS both share the feature of reflecting readiness to learn and trainability. One's actual level of literacy skills however, is more difficult to observe than educational credentials. Information processing skills such as literacy have to be inferred through a more direct or detailed evaluation of individual task performance such as on-the-job experience or track record. This is information typically sought by employers when hiring, and by extension can affect decisions to support adult education/training – above and beyond the information that is revealed by educational credentials.

Indeed, employer support appears to be directed to those with higher litercy skills above and beyond what would be expected from someone with a given level of education. Thus, the literacy skills measure in ALLS may reflect individual capabilities more precisely than credentials. To the extent that these skills are observed by employers, it may in part explain the higher rates of access of more proficient adults to employer-supported adult education/training.

Perhaps this is to be expected since literacy skills are seen as a necessary for engaging not only in adult education/training but also in many job tasks, especially those that are text-based (e.g., ICT-based tasks). Furthermore, analysis from the ALLS data has confirmed that not all adults with the same level of education display the same level of information processing skills including literacy (OECD/Statistics Canada, 2000; 2005). The quality of education received varies substantially within countries, and also because adults can maintain, enhance or lose their information processing skills such as literacy depending on the extent to which they use them at work and in daily life, as well as the extent of adult education/training they continue to receive as they age (OECD/Statistics Canada, 2005).

Table 8.1 Model with labour supply characteristics, base and augmented models (equations 4 and 5)

	Base model (equation 4)			Augmented model (equation 5)		
	Odds ratio	p	s.e.	Odds ratio	p	s.e.
Age (reference=51 to 65)						
25-35	1.4	.00	.04	1.3	.00	.04
36-50	1.4	.00	.04	1.4	.00	.04
Gender (reference=women)						
Men	1.1	.00	.03	0.9	.00	.03
Immigrant status (reference=immigrants)						
Non-immigrants	1.8	.00	.05	1.6	.00	.05
Education (reference=less than upper secondary)						
Upper secondary	2.0	.00	.06	1.7	.00	.06
Higher than upper secondary	3.5	.00	.05	2.7	.00	.06
Information processing skills (reference=literacy level 1)						
Literacy Level 2				1.7	.00	.07
Literacy Level 3				2.2	.00	.07
Literacy Level 4/5				2.4	.00	.07
Cox and Snell R-squared	0.121			0.127		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Results for labour demand characteristics model and discussion

Table 8.2 presents results for the model focusing on only job, or alternatively, labour demand characteristics such as type of occupation and industry, firm size and the extent of engagement in reading, writing and numeracy at work.

Occupation and industry are broad indicators of job type. Workers in ‘low technology manufacturing’, ‘wholesale, retail, hotels and restaurants’, and ‘knowledge-intensive market services’ are less likely to have participated in employer supported adult education/training than employees in primary industries. Not surprisingly, workers in skilled or semi-skilled positions are more likely to have participated in employer supported adult education/training than unskilled labourers.

As found in previous research, firm size is a strong correlate of participation. This is a broad indicator which may incorporate the effects of many structural aspects of work settings which are correlated with firm size. For example, larger firms are more likely to have explicit human resource policies/resources, internal career opportunities and may be linked to increased job security. Workers in firms with at least 500 employees were found to be over three times more likely to have participated in employer supported adult education/training than those in firms with less than 20 employees.

The nature of work tasks as reflected by the extent of engagement in reading practices is found to have a strong relationship with the likelihood of employers extending support to their employees for the purposes of investing further in the development of their human capital. The premium associated with reading engagement at work is in the same order of magnitude as firm size. Workers who reported high engagement in reading at work are about 3.6 times more likely to have participated in employer supported adult education/training than workers who reported low engagement. Even those who reported medium-low or medium-high engagement in reading at work are at least two times more likely to have participated. High engagement in writing and numeracy practices is also linked to a higher likelihood of participating.

It can thus be inferred from the findings that jobs which require higher levels of literacy practice are associated with greater access to adult education/training. Further, other cognitive skills such as problem solving, planning, and organizational skills are likely to be associated with jobs that require comparatively high levels of reading practice. This may in part explain why the literacy practice at work measure is a better predictor of participation in adult education/training than the direct, but narrower measure, of information processing skills such as literacy in ALLS. In summary, jobs that require comparatively higher levels of literacy skills seem to be associated with more learning, especially of the type that is organized.

Table 8.2 Model with labour demand characteristics (equation 6)

	Odds ratio	p	s.e.
Reading at work (reference=low)			
Medium low engagement	2.0	.00	.06
Medium high engagement	2.9	.00	.06
High engagement	3.6	.00	.06
Writing at work (reference=low)			
Medium low engagement	1.3	.00	.06
Medium high engagement	1.5	.00	.07
High engagement	1.5	.00	.07
Numeracy at work (reference=low)			
Medium engagement	1.1	.01	.04
High engagement	1.0	.35	.05
Occupational type (reference=unskilled)			
Skilled	1.7	.00	.09
Semi-skilled	1.3	.00	.09
Industry type (reference = primary)			
High-technology manufacturing	1.0	.69	.12
Low-technology manufacturing	0.7	.00	.12
Knowledge-intensive market services	0.9	.55	.11
Public administration, defence, education & health	1.1	.48	.10
Other community, social & personal services	1.0	.68	.12
Utilities & Construction	1.0	.88	.12
Wholesale, retail, hotels & restaurants	0.8	.01	.11
Transport and storage	1.0	.80	.12
Firm size (reference= < 20 employees)			
20-99 employees	2.4	.00	.05
100-499 employees	3.1	.00	.05
500-999 employees	3.0	.00	.07
>=1000 employees	3.8	.00	.05
Cox and Snell R-squared	0.183		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Results for labour supply and demand characteristics model

Table 8.3 presents results for the model adjusting for all labour supply and demand characteristics considered. The values of most parameters are similar in size to those of the preceding models other than those variables that reflect the skills of the labour supply and the skill content of jobs. On the labour supply side, educational attainment and observed literacy skills remain significant but their strength as predictors is reduced. Likewise, on the labour demand side, occupational type and reading engagement remain significant correlates but their strength as predictors is diminished. In relative terms, the labour supply characteristics lose much more of their strength than the labour demand characteristics. This suggests that the skill content of jobs is significantly associated with participation in employer supported adult education/training, independent of the skills' profile of workers.

Firm size continues to be a strong correlate of participation in employer supported adult education/training. Even after adjusting for a range of labour supply characteristics, the odds ratios associated with working in a firm of at least 100 employees remain at three or higher.

Interestingly, the extent of literacy practices at work remains a particularly strong predictor of participation in employer supported adult education/training, even after taking into account individual characteristics which proxy the level of human capital, namely educational attainment and level of literacy skills. Even workers who reported medium-low engagement in reading at work are nearly two times more likely to have participated in employer supported adult education/training than workers who reported low engagement. This represents a higher chance of participating than for those who have attained higher than upper secondary or who have attained the highest level of information processing skills.

Table 8.3 Model with labour supply and demand characteristics – all variables (equation 7)

	Odds ratio	p	s.e.
Age (reference=51 to 65)			
25-35	1.4	.00	.04
36-50	1.4	.00	.04
Men (reference=women)			
Men	0.9	.01	.03
Immigrant status (reference=immigrants)			
Non-immigrants	1.5	.00	.06
Education (reference=less than upper secondary)			
Upper secondary	1.3	.00	.06
Higher than upper secondary	1.4	.00	.06
Information processing skills (reference=literacy Level 1)			
Literacy Level 2	1.3	.00	.07
Literacy Level 3	1.5	.00	.07
Literacy Level 4/5	1.5	.00	.08
Reading at work (reference=low)			
Medium low engagement	1.9	.00	.06
Medium high engagement	2.6	.00	.06
High engagement	3.2	.00	.06
Writing at work (reference=low)			
Medium low engagement	1.2	.00	.06
Medium high engagement	1.4	.00	.07
High engagement	1.4	.00	.07
Numeracy at work (reference=low)			
Medium engagement	1.1	.12	.04
High engagement	0.9	.06	.05
Occupational type (reference=unskilled)			
Skilled	1.5	.00	.09
Semi-skilled	1.2	.02	.09
Industry type (reference = primary)			
High-technology manufacturing	1.0	.69	.12
Low-technology manufacturing	0.7	.01	.12
Knowledge-intensive market services	0.9	.45	.11
Public administration, defence, education & health	1.1	.51	.11
Other community, social & personal services	1.0	.71	.12
Utilities & Construction	1.0	.93	.12
Wholesale, retail, hotels & restaurants	0.8	.02	.11
Transport and storage	1.0	.83	.12
Firm size (reference= < 20 employees)			
20-99 employees	2.3	.00	.05
100-499 employees	3.1	.00	.05
500-999 employees	3.0	.00	.07
>=1000 employees	3.7	.00	.05
Cox and Snell R-squared	0.190		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Results for skill match-mismatch models and discussion

Table 8.4 presents results for the model that adjusts for both labour supply and demand characteristics, but substitutes skill supply as denoted by literacy skills and skill demand as denoted by reading at work with a varaible interacting the two characterstics and depicting different literacy match-mismatch situatios: low-skill match, deficit mismatch, surplus mismatch and high-skill match (as described in Chapter 5). Results are shown with and without adjustment for occupation since occupation is itself denoting an implied level of skill (i.e., skilled, semi-skilled and unskilled).

Firm size continues to dominate as a predictor. However, being in a high-skill match or deficit situation ranks among the strongest predictors of participating in employer supported adult education/training. It is important to note that both these categories (high-skill match and deficit mismatch) reflect medium- to high-engagement in reading practices at work, which are characteristics attached to the job.

These results provide a much more nuanced picture of the correlates of participation in employer supported adult education/training. For example, while having a high level of literacy skills is found to be associated with an increased likelihood of receiving employer support for participating in adult education/training, there is a sharp difference between those who need to use those skills at work and those who do not.

Adults in high-skill match situations – that is, those who do have the skills and report using them at work – attract the most employer support because they are likely to be in high performance jobs that require continuous learning and development. They also have a good foundation for further learning.

Adults in deficit mismatch situations – that is, those who do not have the required skills but report frequent engagement in activities at work which could make use of those skills – are also attracting employer support but probably for different reasons. One possible reason is the need to upgrade their skills in response to skill biased technological change. While a need for investment in adult education/training might be present however, the key information processing skills such as literacy skills necessary for efficient learning are at low levels. Low levels of proficiency in literacy skills act as a barrier to investment in skill development, for both employees and employers. The findings show that many employers circumvent this barrier and nevertheless direct support for adult education/training to those who need it most. The conditions under which employers opt to do so or not, need to be better understood for policy purposes.

Table 8.4 Model with labour supply and demand characteristics featuring skill match and mismatch situations between literacy skills and literacy skill use, adjusted and unadjusted for occupation

	Unadjusted for occupation			Adjusted for occupation (equation		
	Odds ratio	p	s.e.	Odds ratio	p	s.e.
Age (reference=51 to 65)						
25-35	1.4	.00	.04	1.4	.00	.04
36-50	1.4	.00	.04	1.4	.00	.04
Men (reference=women)						
Men	0.9	.00	.03	0.9	.00	.03
Immigrant status (reference=immigrants)						
Non-immigrants	1.6	.00	.06	1.6	.00	.06
Education (reference=less than upper secondary)						
Upper secondary	1.5	.00	.06	1.4	.00	.06
Higher than upper secondary	1.8	.00	.06	1.6	.00	.06
Skill match-mismatch (reference=low skill match)						
Deficit mismatch	2.8	.00	.05	2.6	.00	.06
Surplus mismatch	1.5	.00	.06	1.4	.00	.06
High skill match	3.2	.00	.05	2.9	.00	.05
Firm size (reference= < 20 employees)						
20-99 employees	2.4	.00	.05	2.4	.00	.05
100-499 employees	3.1	.00	.05	3.2	.00	.05
500-999 employees	3.0	.00	.07	3.1	.00	.07
>=1000 employees	3.7	.00	.05	3.8	.00	.05
Occupational type (reference=unskilled)						
Skilled				1.8	.00	.09
Semi-skilled				1.4	.00	.09
Cox and Snell R-squared	0.181			0.184		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Adults in surplus mismatch situations – or those who are found to underutilize their literacy skills in the workplace – still attract some employer support but less than those in high-skill match and deficit mismatch situations. These adults have good levels of proficiency in literacy skills but they are likely facing difficulties in making the transition to a career path that makes full use of their literacy skills. Their current employers are also not taking advantage of the fact that they have key information processing skills for efficient learning, and the fact that they offer opportunities to adopt technologies and workplace practices that could help to increase productivity.

Separately, it is worth noting that workers in surplus mismatch situations tend to have the second highest overall participation rate when other sources of support are also considered (i.e., employer as well as government and self supported participation), primarily because they have a high tendency to self finance their participation (see Table A.5.6 in Data Appendix for Chapter 5).

Together these findings support the notion that employer support for adult education/training is influenced by favourable demand side characteristics (i.e., high-skill job tasks, large firm) principally, but that individuals with favourable supply side characteristics (i.e., highly skilled, high education, young) combined with favourable demand side characteristics (i.e., high-skill match) benefit the most from employer support.

Table 8.5 presents results for a variation of the model depicted in Equation 8. Namely, literacy skills and and the extent of skills requirements as denoted by writing and numeracy at work are added back into the model along with the interaction between the literacy skills of individuals and the extent of reading at work. This allows for a read of the likelihood to receive employer support strictly associated with the type of match or mismatch. The odds ratio for workers in a deficit mismatch situation and high-skill match situation remain elevated at around 2.2.

Table 8.5 Model with labour supply and demand characteristics featuring skill match and mismatch situations between literacy skills and literacy skill use, adjusting for literacy skill and other skill use

	Unadjusted for occupation			Adjusted for occupation		
	Odds ratio	p	s.e.	Odds ratio	p	s.e.
Age (reference=51 to 65)						
25-35	1.4	.00	.04	1.4	.00	.04
36-50	1.4	.00	.04	1.4	.00	.04
Men (reference=women)						
Men	0.9	.00	.03	0.9	.00	.03
Immigrant status (reference=immigrants)						
Non-immigrants	1.5	.00	.06	1.5	.00	.06
Education (reference=less than upper secondary)						
Upper secondary	1.3	.00	.06	1.3	.00	.06
Higher than upper secondary	1.6	.00	.06	1.5	.00	.06
Skill match-mismatch (reference=low skill match)						
Deficit mismatch	2.2	.00	.06	2.1	.00	.06
Surplus mismatch	1.2	.01	.08	1.2	.01	.08
High skill match	2.2	.00	.07	2.1	.00	.08
Information processing skills (reference=literacy Level 1)						
Literacy Level 2	1.4	.00	.07	1.4	.00	.07
Literacy Level 3	1.5	.00	.09	1.5	.00	.09
Literacy Level 4/5	1.5	.00	.10	1.4	.00	.10
Writing at work (reference=low)						
Medium low engagement	1.6	.00	.06	1.5	.00	.06
Medium high engagement	1.9	.00	.06	1.7	.00	.06
High engagement	1.9	.00	.06	1.8	.00	.07
Numeracy at work (reference=low)						
Medium engagement	1.1	.02	.04	1.1	.02	.04
High engagement	1.0	.38	.05	1.0	.37	.05
Firm size (reference= < 20 employees)						
20-99 employees	2.4	.00	.05	2.4	.00	.05
100-499 employees	3.1	.00	.05	3.2	.00	.05
500-999 employees	3.0	.00	.07	3.1	.00	.07
>=1000 employees	3.8	.00	.05	3.8	.00	.05
Occupational type (reference=unskilled)						
Skilled				1.6	.00	.09
Semi-skilled				1.3	.00	.09
Cox and Snell R-squared	0.186			0.187		

Source: Adult Literacy and Lifeskills survey, 2003-2007. Notes: Country is adjusted for in all models but not shown here.

Discussion and implications

Findings related to the relationship between adult education/training and various labour supply and demand characteristics are grouped and discussed with emphasis on two themes: skill supply characteristics and skill demand characteristics. The discussion on skill match-mismatch is taken up in Chapter 9 as part of the synthesis and concluding remarks.

The role of skill supply characteristics in employer supported adult education/training

Consistent with prior research (e.g., Boudard and Rubenson, 2003), supply side characteristics which approximate the skills of individuals are found to play an important role in determining who receives employer adult education/training. In terms of the employee's decision to participate these characteristics may reflect the individual's capacity and motivation to take up adult education/training. In terms of the employer's decision to provide support for participation, the individual's characteristics may act as signals that are used to ascertain trainability. A distinction however, is worth making between two types of signals, each of which may be emitted at different stages because they are either more easy or difficult to accurately discern.

The role of credentials

First, there are characteristics that may operate as 'signals' of potential trainability which are more easily observed such as educational credentials, gender, age and ethnic background. Credentials for example, are visible when the hiring decision is made. Indeed, the findings in this study confirm the conclusion that employers use education credentials as signals for not so easy to observe skills not only when hiring, but also in their decision to support adult education/training. It has long been contended that education credentials may act as a 'signalling' device (Blaug, 1976; Thurow, 1975; Woodhall, 2001; also see discussion on signalling theory in relation to mismatch in Chapter 3). In line with discrimination theory, other supply side characteristics which are easily observed such as gender, age and ethnic background are also perhaps used as 'signals' of potential trainability. Training decisions based on these types of signals are presumably perceived by the employer as reducing the risks of investing in unstable or un-trainable employees (Holtzer, 1996).

The role of key information processing skills

Second, there are characteristics which are not as easily observed and may change over time such as actual skills. Credentials are inadequate signals of skills since large proportions of the workforce are found to have low levels of proficiency in key information processing skills even for those with higher levels of qualifications. There are several reasons for this, including heterogeneity in quality of schooling as well as possibilities for skill gain and skill loss over the life span. The findings in this study suggest that even if these are more difficult to observe, employers do seem to recognize key information processing skills above and beyond what would be signalled from credentials or qualifications. Accordingly, they appear to channel support to those who have the highest proficiency in key information processing skills, which is not necessarily those who have the highest credentials.

Ultimately, employers are likely to be most interested in those who already have a good level of proficiency in key information processing skills, so as to focus on the complementary aspects of training and thus the building up of specific skills.

Implications

The tendency for employers to support those who already have a good level of proficiency in key information processing skills and neglect those that do not has important implications for the development of the skill base of a nation and especially for inequality. This is exacerbated by the fact that employers are the most important investor in skill formation beyond schooling.

The risk is that the skill base will become increasingly bifurcated, with skilled workers attracting more investment for continued skill development and less skilled workers will be left without any support. This is further exacerbated by the fact that high-skilled individuals already have the motivation to continue to learn, as indicated by their willingness to self-finance, while low-skilled workers are much less inclined to invest in themselves (see Table A.5.6 in the Data Appendix for Chapter 5). Such tendencies on the market may do little to address potential skill shortages and/or the inefficiencies associated with skill deficits.

The role of skill demand characteristics in employer supported adult education/training

The second key finding is that the skill content of jobs seems to have an even stronger association with participation in employer supported adult education/training than educational attainment or key information processing skills. This is the case when comparing odds ratios which are on a comparable scale for each of the variables mentioned. The influence of demand characteristics tends to outweigh the influence of supply characteristics. This raises a number of issues.

Skill utilization drives investment in skill formation but upskilling may not be inevitable

First, it raises questions about the focus of recent thinking around skills for economic prosperity. Several policy documents have stressed that the answer to the present economic and social challenges is to improve the supply of skilled labour. This view tends to ignore the demand side and takes upskilling for granted or as inevitable. It also ignores the observation that the actual utilization of key information processing skills is itself a major factor implicated in skill formation as implied by the findings in this chapter, and that large segments of the workforce are still not required to use their information processing skills at work. Evidence thus suggests that there is a need for a more comprehensive view involving both the demand and supply sides.

Otherwise, a view based on the supply side only ignores the possibility that there are structural conditions in the economy that lower the demand for and utilization of skills, which in turn can affect not only investments in skill formation, but may lead to a lack of use of existing skills, and ultimately skill loss. For example, Brown, Green and Lauder (2001) pointed to structural conditions in the British economy that lower the demand for and utilization of skills. This is an issue that merits further investigation.

The link between adult education/training, skill use, innovation and industrial relations

Second, the findings draw attention to the link between employers' decisions to invest in the skill development of their employees on the one hand, and industrial relations, organizational and workplace practices, technological and organizational innovation, skills utilization and skill mismatch on the other.

Recent research on these links point to the institutional emergence of norms about employee job rights and benefits (e.g., Vignoles et al., 2004; Meredith, 2008). Some employers have been found to actively promote human resource development practices which encourage strong ties between the organization and its employees (Kalleberg *et al.*, 1996). The aim of these practices is to induce the commitment of employees to the organization via job security, comprehensive benefits and career opportunities (*ibid*). Adult education/training which helps them enhance those roles is increasingly becoming an issue of employee-job rights or part of the benefit package.

Implications

Skill formation is not just a supply side issue; it is just as much a function of work tasks and work organisation on the demand side. Policies thus need to take into account both the supply and the demand side. Particular attention should be paid to identifying the mechanisms that help to foster the optimal utilisation of the existing skill base. Otherwise, many workers even with high qualifications risk losing their information processing skills due to a lack of use, leading to an erosion of value of educational investments.

Chapter 9 Conclusions

Policy implications of different skill match-mismatch situations

A substantial proportion of the workforce is found to have levels of proficiency in information processing skills that do not match the level of requirement to use those skills in their jobs. Results based on the measure used in this study are similar in magnitude to those reported in studies making use of education mismatch measures. Skill surpluses and deficits are estimated to vary between 10 and 30%, depending on the country. But these do not correlate perfectly with education mismatch measures because as mentioned earlier, skills are not the same thing as qualifications.

It is important to consider education or skill mismatch in a dynamic framework that acknowledges the possibility for skill gain or loss on the supply side, and changing job content on the demand side. It is also important to acknowledge that a certain degree of mismatch may be inevitable and that there is probably a natural or normal rate of mismatch. What this rate is, cannot be answered with certainty, but high rates are likely to suggest a need for active policies that foster adjustments.

A number of policy implications follow from the findings on mismatch but these vary according to the different match-mismatch situations. Each is considered in turn below.

Match situations: distinguishing between low-skill and high-skill matches

The following focuses on workers who are in matched situations but a distinction is made between workers who are in low-skill vs high-skill match situations.

Situations where workers have low levels of information processing skills and these are not required for their job (low-skill match)

Even in the most advanced industrialised nations, large segments of the adult population have been found to have low levels of information processing skills (i.e., literacy and numeracy). According to ALLS and its predecessor (the International Adult Literacy Survey), the proportion of adults who score at Levels 1 or 2 on these skills ranges from 30-80% depending on the country. Levels 1 and 2 are thought to be too low for adults to cope with text-based tasks which are becoming increasingly common both at work and in daily life. For example, as a consequence of the ICT revolution. Low levels of information processing skills spread so widely poses a risk to the capacity of private and public organisations to innovate and increase productivity.

While many workers are found to have low levels of information processing skills, however, many appear to not necessarily require high levels of these skills to carry out their jobs tasks. The group of people in low-skill match situations ranges from 18-55% of the workforce depending on the country (see Table 5.4). Adults in this situation may be well-matched to the requirements of their job but nevertheless have low levels of information processing skills, which may have negative consequences for economic and social progress.

At the individual level, low levels of information processing skills may be associated with a heightened risk of experiencing economic and social disadvantage, typified by casual unfulfilling work and unemployment and often accompanied by psychological and health problems. At the societal level, high rates of low levels of information processing skills may not only constrain productivity growth, but may also reduce the capacity of nations to enable their citizens to:

- Cope with uncertainty and change;
- Maintain global competitiveness;
- Increase flexibility, responsiveness and preparedness of labour markets;
- Deal with issues of population ageing;
- Participate fully as citizens in democracy and civic society; and,
- Find complex solutions to emerging challenges.

Fostering participation in adult education/training thus equally applies to low-skilled adults even if they do not report requiring those skills at their current jobs. This is the case because it helps to maintain a flexible workforce, allows for the potential to expand high value added production, avoids de-moralizing routine work, may lead to improved quality of goods and services, and in general enables all citizens to participate fully in economic, civic and social life.

This is not without challenge, however. Workers in low-skill match situations are the least likely to invest in themselves (see Table A.5.6 in Data Appendix for Chapter 5). They are also found to receive the least employer support for developing or sustaining their skills. Employers are more likely to be interested in supporting the skill formation of workers who already have a good level of information processing skills. Accordingly, employers who offer low-skill jobs and employ low-skill workers may thus be locked in a low-skill equilibrium with little incentives to upgrade production processes or workers' skills (see Finegold and Soskice, 1988).

Situations where workers have the required information processing skills (high-skill match)

Workers in high-skill match situations are found to receive the most employer support for participating in adult education/training. This reinforces the notion that employers are keen to support those who already have a good level of proficiency in information processing skills. In this situation, incentives seem to be naturally aligned toward a high-skill equilibrium. The evidence confirms the intuitive idea that high skills and high-skill requirements are mutually reinforcing in promoting skill development.

Mismatch situations: distinguishing among the underlying reasons for observed skill deficits and skill surpluses

There are several reasons why mismatch may arise, and the relationship to adult education/training varies accordingly, as do the implications for policy (Messinis & Olekalns, 2007). The following considers the origin of different match-mismatch situations and how adult education/training and/or other policies may serve to ameliorate conditions under each set of circumstances. The skill mismatch measure used in this study does not distinguish among the different reasons that may underlie skill deficit and skill surplus situations. But these possible alternatives must nevertheless be carefully considered in light of the results.

Situations where workers never had the required information processing skills (deficit)

Among adults with low levels of proficiency in information processing skills, many are nevertheless found to require those skills to carry out their jobs tasks. This is the group of people in deficit mismatch situations, which ranges from 7-23% depending on the country (see Table 5.4). This group is much more likely to participate in employer supported adult education/training when compared to those who are in low-skill match situations. In fact, the group is nearly as likely to receive employer supported adult education/training as those in high-skill match situations. Although there is evidence to argue that adult education/training opportunities are fundamentally related to the needs of the job, high skills and high-skill requirements as mentioned above seem to be mutually reinforcing in promoting skill development.

The results found in this study are similar to those found in research based on education mismatch measures. Undereducated workers have been found to be more likely to participate in adult education/training when compared to matched workers who have the same qualifications (Büchel & Mertens, 2004; Verhaest & Omey, 2006). This is like comparing workers who are in deficit mismatch situations with those who are in low-skill match situations.

Unfortunately, the measures of mismatch used in this study do not allow to distinguish between workers who:

- Never had the required information processing skills;
- Had the required information processing skills, but those skills depreciated; and,
- Had the required information processing skills, but requirements increased due to innovation.

Each situation has different implications for policy and the role of adult education/training.

In the first situation, adults may never have had those skills, perhaps as a consequence of having had poor access to quality education. Policy must therefore ensure first and foremost quality education which delivers the information processing skills needed by all.

From the perspective of sustaining a good skill base for rapidly growing knowledge economies and addressing inefficiencies in the labour market that are due to low levels of proficiency in key information processing skills, it can be argued that public policy has an important role to play beyond relying almost exclusively on initial formal education to increase the supply of skills. For adults beyond initial education, governments have an important role to play in fostering the adult education/training necessary to redress low levels of information processing skills that are found among adult populations.

In particular, public policy has a role to play in helping to identify existing workers with low levels of information processing skills, devising schemes to incentivise (e.g., tax deductions) both employees and employers to invest in skill development, and in helping to coordinate with employers and other stakeholders efforts which aim to develop and implement basic skills programmes. Even more strongly, it has a role to play in mandating the conditions necessary for fostering investment (e.g., training rights, job-leave). Otherwise, many workers risk not obtaining adequate support to develop or sustain their information processing skills at levels deemed to be a minimum for coping with everyday skill demands in modern societies, not only at work but also in home, civic and social life.

The role of public policy is particularly important because employers may lack the necessary incentives to invest in the information processing skills of their employees even if they may otherwise eventually benefit from it, albeit in indirect and unforeseen ways (e.g., positive feedback effects from more highly skilled consumers). Unless employees' needs are clearly aligned with firms' needs and the risks to investment are minimal, employers' incentives are not necessarily aligned to support the development of 'general' or 'key information processing' skills. This is primarily an issue of costs and who should pay for the development of information processing skills needed not only for production, but also for consumption as well as for personal, civic and social life.

Situations where workers had the required information processing skills, but skills depreciated due to skill loss (deficit)

Other workers may find themselves in a skill deficit situation because their skills have depreciated over time. Allen and van der Velden (2002) highlighted different sources of skill depreciation ranging from ageing, career interruptions, lack of use of skills and technological/organizational change. The latter is discussed separately in the following section since it has a different set of implications.

The idea that certain skills depreciate with age is widely held in the cognitive sciences, but exactly at which point decline sets in and why is not entirely clear due in part to poor data (e.g., see Salthouse, 2009). In the economics literature, the idea already had some currency as early as the 1970s, with Rosen (1975) addressing this issue in the context of attempts to understand patterns of wage returns by age. Mincer and Ofek (1982) emphasized the 'use it or lose it' hypothesis, where skills are at risk of being lost if they are not used. For example, as a consequence of remaining outside the labour market for long periods or due to a lack of skill use. In the same line of reasoning, de Grip and van Loo (2002) suggest that skills deteriorate due to a lack of use, although they focus on obsolescence.

A related proposition is based on the "intellectual challenge" hypothesis (Staff, Murray, Deary & Whalley, 2004; Pazy, 2004; de Grip, Bosma, Willems & van Boxtel, 2007). Both the 'use it or lose it' and 'intellectual challenge' propositions suggest that skills are like muscles that develop if you use them, otherwise they can be lost. By extension, this may imply that workers who engage in simple and less challenging tasks than they are capable may thus lose some of their skills especially as they age.

The potential for skill loss poses a real risk to the value of educational investments which have increased markedly in most OECD countries over the last 40 years. In this scenario, the primary response is not necessarily only to foster adult education/training but may also include a wider consideration of work. Workplace and organizational practices, and the adoption of new technologies, particularly as they pertain to skill use, become directly implicated in any efforts to mitigate skill loss. What people do at work can even be designed to promote skill gain through practice effects. In contrast, routine labour practices may have a particularly negative long run consequence for skill loss and hamper opportunities that may otherwise exist for innovation.

With recent estimates that increasing proportions of the workforce will be over the age of 50 by 2050, concern for skill loss due to a lack of use takes on added significance. For example, Toossi (2002) estimated that about 20% of the US workforce will be over the age of 55 by 2050.

Situations where workers had the required information processing skills, but requirements increased due to innovation (deficit)

Workers may have had the skills required in their job in the past, but due to technological or organisational change, they now find themselves in situations in which they no longer have the required skills to perform successfully in their jobs. In this situation, skill deficits arise due to changes in job content or work environment not because of skill loss. For example, the introduction of ICTs can lead to an increased demand for skills (MacDonald & Weisbach, 2004; de Grip, 2006).

The primary response is to complement the introduction of changes with adult education/training. Many studies have shown that adult education/training can be complementary to technological change (e.g., Baldwin & Johnson, 1995). Indeed, this is a major reason why firms provide adult education/training (e.g., in Australia about 54% of training in firms is provide on this basis, ABS Survey of Education, Training and Information Technology, 2001).

Situations where workers have the required information processing skills, but requirements decreased due to innovation (surplus)

Among adults with medium to high levels of proficiency in information processing skills, many are nevertheless found to not require those skills to carry out their jobs tasks. This is the group of people in surplus mismatch situations, which ranges from 13-35% depending on the country (see Table 5.1A). This group are less likely to participate in employer supported adult education/training when compared to those who are in high-skill match situations, but they are much more likely than those who are in low-skill match situations.

The results found in this study are similar to those found in in research based on education mismatch measures. Overeducated workers have been found to be less likely to participate in adult education/training when compared to matched workers who have the same qualifications (Hersch, 1991; van Smoorenburg & van der Velden, 2000; Büchel & Mertens, 2004; Verhaest & Omey, 2006). This is like comparing workers who are in surplus situations with those who are in high-skill match situations. But overeducated workers have been found to be more likely to participate in adult education/training when compared to matched workers who are in similar jobs (Büchel, 2002; Verhaest & Omey, 2006). This is like comparing workers who are in surplus situations with those who are in low-skill match situations.

As in the case of deficit mismatch, the ALLS data do not allow to distinguish between workers who:

- Were matched with the required information processing skills, but due to innovation they are now overskilled (i.e., deskilling);
- Were never in a well-matched job, and may not have the specific skills to obtain a job that would make use of their information processing skills (i.e., horizontal mismatch, a lack of opportunity)

Although there is no evidence of widespread deskilling as discussed in Chapter 3, deskilling processes are a real possibility and cannot be ruled out. Braverman's deskilling thesis carries little currency today, but his understanding of skill polarization is very much alive (Tinker, 2002) and research as cited in Chapter 3, has found evidence of tendencies toward both skill and wage polarization (Kolev & Saget, 2010; Acemoglu & Autor (2010). This has been linked to the structure of work settings and other labour market practices. For example, Kalleberg (2003) argued that US employers in their search for greater flexibility in their employment systems have relied on numerical and functional flexibility which has fed polarization.

Numerical flexibility is achieved through the use of non-regular workers to handle fluctuation in production. In some workplaces, Kalleberg (2003) found that 'flexible' workers are treated as disposable with little control over their work and with few benefits and little access to further adult education/training.

Functional flexibility involves the use of "high performance work organizations" that tend to encourage workers participation in decision-making and teamwork and links employee performance with organizational performance. This form of flexibility is otherwise associated with good access to adult education/training, but Kalleberg (2003) warned that while some see the use of high performance work organizations as having spread widely (Linbeck & Snower, 2000; Osterman, 2000) there is convincing evidence to suggest that they are still not that prevalent in the service sector, which plays a dominant role in advanced countries. Further, longitudinal research does not find strong evidence to support the claims of major changes in work organization (le Grand, Szulkin & Thålin, 2004; Lloyd & Payne, 2006).

The implications here are similar to those already stated, namely that skill formation policies need to pay attention to the demand side too. In particular, it is worthwhile to consider more carefully how the structure of work settings, including work and organisational practices, as well as other labour market practices may impact skill development and the value of such investments over time.

Situations where workers have the required information processing skills but not other more specific skills (surplus)

As mentioned in Chapter 3, there is unobserved heterogeneity among workers. Specifically, some workers may have high levels of some skills such as literacy and numeracy but may otherwise have low capabilities. Being literate is not enough – some skills signal potential to be highly functional in modern workplaces but some workers may have difficulty translating those skills into action and results. Put another way, information processing skills may be necessary but not sufficient for the broader capabilities needed in the workplace.

In other cases, some workers may be in transition (mostly younger) seeking to find good jobs but lack opportunities, access to networks, and/or competences to find the right jobs. Adult education/training can be helpful to make the transition or retrain skills in a way that suits available opportunities.

Not least, an appropriate response to skill surpluses might involve active efforts to support the creation of more opportunities for high-skill and high-value added jobs.

Synthesis and concluding remarks

In summary, three major points can be elucidated from the analysis in this study, which should be taken into account when considering the phenomena of skill mismatch. Each is taken up in turn:

- Firstly, it is important to equally consider how both the demand and supply side of the labour market are implicated in generating mismatch.

- Secondly, it is important to consider the dynamics of skill gain and skill loss over the lifespan of workers and how this interacts with changing job content.
- Thirdly, it is important to recognize the dynamics of the interaction between the supply of, and demand for, skills at the macro level

Taking into account both the supply and demand sides of the labour market

The analysis contained in this study emphasised the importance of the demand side of the labour market in determining earnings, training and skill mismatch. Most importantly, it was emphasized that skill formation is not just a supply side issue; it is just as much a function of work tasks and work organisation on the demand side. Policies on skills thus need to take into account both the supply and the demand side. Particular attention should be paid to identifying the potential mechanisms that help to foster the optimal utilisation of the existing skills base. Otherwise, many workers even with high qualifications risk losing their skills due to a lack of use, leading to an erosion of value of educational investments.

It is perhaps useful at this stage to highlight two major competing approaches to viewing and modelling labour market functioning as it pertains to skills, skill use and skill development. These can lead to very different lenses with which to view skill mismatch. By extension it can lead to the formulation of very different types of policy responses to skill mismatch.

The first approach is well grounded in the neoclassical school of thinking, particularly the supply side view of the human capital model. From this perspective there is a tendency to emphasise the supply of skills in labour market functioning. On the one hand, concerns for skill deficits should be addressed by a supply response. In some cases, if the deficits are in specific skills rather than general skills, then the demand side should respond by taking on a supply side role, thus providing training to meet the required skills. On the other hand, if there is excess human capital on the labour market, then the models implicated in this approach imply that the market will adjust accordingly, for example by adopting technologies or work practices, in a way that makes use of existing skills. Alternatively, workers (or the supply of skills) will find more suitable matches, preferably with better guidance from the suppliers of skills. The demand side behaviours are not modelled or accounted for explicitly but rather implicitly assumed to function according to standard neoclassical assumptions, such as profit maximizing behaviour and perfect competition. Under these market conditions, interventions to the demand side such as industrial or other structural policies should be kept to a minimum. Such interventions are seen as sub-optimal because they introduce distortions to proper market functioning and governments do not have the necessary information to pick winners – markets are better positioned to do so.

From this perspective, skill mismatch tends to be seen as a phenomenon driven by supply side conditions. Mismatches are attributed to the inadequacies of the education and training system, since it is directly implicated in the formation of the skills supply. In a situation of overeducation, for example, the response is that education and training systems should aim to reduce the number of qualifications they produce. Overall, education and training systems should be made to be more responsive to the needs of the labour market, and to offer more guidance to minimize mismatch.

An alternative approach is well grounded in the new political economy of skills (Brown, Green & Lauder, 2001), which tends to focus on the demand side of the labour market. This approach draws on economic sociology and new institutionalism (Swedberg, 1996; Crouch & Streeck, 1997), which offers a pertinent critique of the supply side view of the human capital model. The approach emphasizes that economies can remain competitive without upgrading skills, and that the market does not necessarily provide the incentives consistent with a high-skills strategy or high-skills equilibrium. Routes to high-skill formation and the accompanying policies required vary a lot between countries, depending on their local conditions. As examples, the social partnership model of Northern Europe as well as the developmental model of Asian economies, are pointed to as economies that emphasize both supply and demand side policies in their approach to skills.

Skill mismatch as a phenomenon and thus the mix of policy implications, are seen quite differently when conditions and behaviours of the demand side of the labour market are taken into consideration.

The following lists several policy interventions that focus on the supply of, and demand for, skills, as well as coordination between the two:

- Policies that target the labour supply
- Make education more responsive to labour market demand
- Develop adult education and training systems and work based training
- Policies that target the labour demand
- Promote the adoption of technologies and practices that maximize complementarities to available skills
- Policies that coordinate the labour supply and demand
- Provide information and guidance
- Facilitate steering and promote coordinated stakeholder approaches
- The role of the state and policy
- The role of workers and organized labour
- The role of employers

Taking into account skill gain and skill loss over the lifespan vis-a-vis changing job content

Not only is there a need for a more comprehensive and balanced view involving both the supply and demand sides of the labour market to understand better skill formation, skill use, and not least skill mismatch, but also their dynamic interactions over the lifespan of workers.

Mismatch has often been treated uniformly even if it occurs at different career points. Whether mismatch is present for recent labour market entrants, early, middle or late career aged adults, can be for very different reasons, which have different policy implications.

Situating mismatch in a dynamic framework is thus important. Mismatch may arise because of skill gain or skill loss on the supply side. Alternatively, it may arise because of upskilling or deskilling on the demand side. If this is the case, then a more responsive education system, or better matching at the source, for example, as a consequence of good guidance, may do little to avert mismatch.

Taking into account the dynamic interactions between skill supply and skill demand at the macro level

It is fair to say that interactions between dynamic changes in skill supply and skill demand are poorly understood for policy purposes, sometimes leading to shortsighted arguments that the supply of educated adults should be scaled back or that it would be desirable to eliminate mismatch and have everyone efficiently pigeon holed in jobs that are commensurate with their skill set. Such efficiencies may sound good in principle but the problem is that these are conceived from a perspective that is firmly grounded in a partial equilibrium and static framework. For example, a certain degree of skill mismatch is perhaps not only inevitable due to the dynamic nature of supply and demand but may also be desirable because it might act as an important catalyst for productivity growth in the medium to long run.

Dynamics and interactions are a reality but very difficult to deal with analytically, both empirically and theoretically. Yet we know that skill supply is not fixed at the qualification point. Individuals experience skill gain and skill loss over the lifespan for a variety of reasons. We also know that skill demand is not fixed at job entry. Employers adopt technologies and practices in ways that can deskill or upskill certain jobs.

An important question is whether mismatch is necessarily a bad thing? A certain degree of mismatch may be inevitable and normal. As mentioned, it may even be an important catalyst for stakeholders to respond to, setting off the adjustment processes necessary for long run productivity growth. This reverts back to a key question: is it the demand for skills that is driving the supply or vice-versa? Endogenous technical theory suggests it is the latter. If this is the case, then overeducation may actually be a good thing.

References

Åberg, R. (2002). Överutbildning- ett arbetsmarknadspolitiskt problem?. In K. Abrahamson et. al. (eds), *Utbildning Kompetens och Arbete* (pp. 41-62). Lund: Studentlitteratur.

Abowd, J.M., Kramarz, F., & Margolis, D.N. (1999). High wage workers and high wage firms, *Econometrica*, vol. 67, no. 2, pp. 251-333.

Acemoglu, D. (1998). Why do technologies complement skills? Directed technical change and inequality, *Quarterly Journal of Economics*, vol. 113, pp. 1055-1090.

Acemoglu, D. (1999). Changes in unemployment and wage inequality and the labor market: An alternative theory and some evidence, *American Economic Review*, vol. 89, pp. 1259-1278.

Acemoglu, D. (2002a). Technology and the labor market, *Journal of Economic Literature*,vol. 40, pp. 7-72.

Acemoglu, D. (2002b). Directed technical change, *Review of Economic Studies*, vol. 69, pp. 781-810.

Acemoglu, D., & Autor, D. (2010). Skills, tasks, and technologies: Implications for employment and earnings, National Bureau of Economic Research, Cambridge, MA, Working Paper 16082.

Aghion, P., & Howitt, P. (1997). *Endogenous Growth Theory*. Cambridge: MIT Press.

Allen, J., Levels, M., & van der Velden, R. (2013). Skill mismatch and skill use in developed countries: Evidence from the PIAAC study, ROA Research Memorandum (RAO-RM-2013/17), Research Centre for Education and the Labour Market (ROA), Maastricht University.

Allen, J., & van der Velden, R. (2002). When do skills become obsolete, and when does it matter?. In A. de Grip, J. van Loo & K. Mayhew (eds), *The Economics of Skills Obsolescence: Theoretical Innovations and Empirical Applications* (pp. 27-50), Research in Labor Economics, vol. 21. Amsterdam: Elsevier Science.

Angrist, J.D., & Imbens, G.W. (1994). Identification and Estimation of Local Average Treatment Effects, *Econometrica*, vol. 62, no. 2, pp. 467-475.

Angrist, J.D., & Krueger, A.B. (1991). Does compulsotry schooling attendance afeect schooling and earnings?, *Quarterly Journal of Economics*, vol. 106, pp. 976-1014.

Arrow, K. (1971). The theory of discrimination, Department of Economics, Princeton University, Industrial Relations Section Working Papers.

Arrow, K.J. (1973). Higher education as a filter, *Journal of Public Economics*, vol. 2, pp. 193-216.

Autor, D., Levy, F., & Murnane, R. (2003). The skill content of recent technological change: An empirical exploration, *Quarterly Journal of Economics*, vol. 118, no. 4, pp. 1279-1333.

Baldwin, J.R., & Johnson, J. (1995). *Human Capital Development and Innovation: The Case of Training in Small and Medium Sized-Firms*. Ottawa: Statistics Canada.

Bartel, A.P., & Lichtenberg, F.R. (1987). The comparative advantage of educated workers in implementing new technology, *Review of Economics and Statistics*, vol. 69, no. 1, pp. 1-11.

Battu, H., Belfield, C., & Sloane, P. (2000). How well can we measure graduate over-education and its effects?, *National Institute Economic Review*, vol. 171, pp. 82-93.

Bauer, T. (2002). Educational mismatch and wages: A panel analysis, *Economics of Education Review*, vol. 21, pp. 221-229.

Becker, G.S. (1962). Investment in human capital: A theoretical analysis. *Journal of Political Economy*, vol. 70, no. 5-2, S9-S49.

Becker, G.S. (1964). *Human Capital: A Theoretical and Empirical Analysis with Special References to Education* (Editions revised in 1975 and 1993). Chicago: University of Chicago Press.

Becker, G.S. (1973).A theory of Marriage: Part I, *Journal of Political Economy*, vol. 81, pp. 813-846.

Béjaoui, A. (2000). L'évolution de la prime associée aux qualifications et son implication quant aux changements de la structures des salaries (dissertation). Montréal: Université de Montréal.

Bevan, S., & Cowling, M. (2007). Job matching in the UK and Europe, Sector Skills Development Agency, Research report RR25.

Black, S.E., & Lynch, L.M. (1996). Human capital investments and productivity, *American Economic Review*, vol. 86, no. 2, pp. 263-267.

Blau, F.D., & Kahn, L.M. (2001). Do cognitive test scores explain higher US wage inequality?, National Bureau of Economic Research, Cambridge, MA, Working Paper 8210.

Blaug, M. (1976). The empirical status of human capital theory: A slightly jaundiced survey, *Journal of Economic Literature*, vol. 14, no. 3, pp. 827-855.

Boothby, D. (1999). Literacy skills, the knowledge content of occupations and occupational mismatch, Applied Research Branch, Human Resource Development Canada, Hull, Quebec, Working Paper 99-3E.

Boudard, E. (2001). Literacy Proficiency, Earnings and Recurrent Training: A Ten Country Comparative Study. Stockholm: Institute of International Education.

Boudard, E., & Rubenson, K. (2003). Revisiting major determinants of participation in adult education with a direct measure of literacy skills, *International Journal of Educational Research*, vol. 39, pp. 265-281.

Bound, J., & Johnson, G. (1992). Changes in earnings differentials in the 1980s: Concordance, convergence, causes and consequences, National Bureau of Economic Research, Cambridge, MA, Working Paper 3901.

Braverman, H. (1974). *Labor and Monopoly Capital*. New York: Monthly Review Press.

Brown, P., Green, A., & Lauder, H. (2001). *High Skills: Globalization, Competitiveness, and Skill Formation.* Oxford: Oxford University Press.

Bryk, A.S., & Raudenbush, S.W. (1992). Hierarchical Linear Models: Applications and Data Analysis Methods. London: Sage Publications.

Büchel. F. (2002). The effects of overeducation on productivity in Germany: The firms' viewpoint, *Economics of Education Review*, vol. 21, pp. 263-275.

Büchel, F., & Mertens, A. (2004). Overeducation, undereducation and the theory of career mobility, *Applied Economics*, vol. 36, pp. 803–816

Cain, G.G. (1976). The challenge of segmented labor market theories to orthodox theory: A survey, *Journal of Economic Literature*, vol. 14, no. 4, pp. 1215-1257.

Card, D. (1999). The causal effect of education on earnings. In O. Ashenfelter and D. Card (eds), *Handbook of Labour Economics* (pp. 1801-1863). Oxford: Elsevier Science.

Card, D. (1995). Using Geographic Variation in College Proximity to Estimate the Return to Schooling. In L.N. Christofides, E.K. Grant, and R. Swidinsky (eds), *Aspects of Labour Market Behaviour: Essays in Honour of John Vanderkamp* (pp. 201-222). Toronto: University of Toronto Press.

CEDEFOP (2010a). *The Skill Matching Challenge: Analysing Skill mismatch and Policy Implications*. Luxembourg: Publications Office of the European Union.

CEDEFOP (2010b). *Skills Supply and Demand in Europe: Medium-term Forecast up to 2020*. Luxembourg: Publications Office of the European Union.

Chevalier, A. (2003). Measuring over-education, *Economica*, vol. 70, pp. 509-531.

Chevalier, A., & Lindley, J. (2009). Overeducation and the skills of UK graduates, *Journal of the Royal Statistical Society Series A*, vol. 172, no. 2, pp. 307-337.

Coulombe, S., Tremblay, J.F., & Marchand, S. (2004). *Literacy Scores, Human Capital, and Growth Across Fourteen OECD Countries*. Statistics Canada: Ottawa.

Cross, K.P. (1981). *Adults as Learners: Increasing Participation and Facilitating Learning*. San Francisco: Jossey-Bass.

Crouch, C., & Streeck, W. (1997). *Political Economy of Modern Capitalism*. London: Sage.

Daly, M.C., Buchel, G., & Duncan, G.J. (2000). Premiums and penalties for surplus and deficit education evidence from the United States and Germany, *Economics of Education Review*, vol. 19, pp. 169–178.

Darcovich, N., Binkley, M., Cohen, J., Myrberg, M., & Persson, S. (1998). Non-response bias. In Murray, T.S., Kirsch, I., & Jenkins, L. (eds), Adult Literacy in OECD Countries: Technical Report on the First International Adult Literacy Survey. Washington, D.C.: US Department of Education.

de Grip, A. (2006). Evaluating human capital obsolescence, Research Centre for Education and the Labour Market (ROA), Maastricht, Working Paper ROA-RM-2006/2E.

de Grip, A., & van Loo, J. (2002). The economics of skills obsolescence: A review. In A. de Grip, J. van Loo and K. Mayhew (eds), *The Economics of Skills Obsolescence:Theoretical Innovations and Empirical Applications* (pp. 1-26), Research in Labor Economics, vol. 21, Amsterdam: Elsevier Science.

de Grip, A., Bosma, H., Willems, D., & van Boxtel, M. (2007). Job-worker mismatch and cognitive decline, Institute for the Study of Labor (IZA), Discussion Paper 2956.

Dennison, E. (1962). The sources of economic growth in the United States and the alternatives before us, Committee for Economic Development, New York

Desjardins, R. (2004). Determinants of literacy proficiency: A lifelong-lifewide learning perspective, *International Journal of Educational Research*, vol. 39, no. 3, pp. 205-245.

Desjardins, R. (2005). Skills and nature of the workplace. In OECD/Statistics Canada (eds), *Learning a Living: First Results of the Adult Literacy and Lifeskills Survey*, (pp. 105-128). Paris and Ottawa: Authors.

Desjardins, R., Rubenson, K., & Milana, M. (2006). *Unequal Chances to Participate in Adult Learning: International Perspectives*. Paris: UNESCO.

Devroye, D., & Freeman, R. (2001). Does inequality in skill explain inequality of earnings across advanced countries, National Bureau of Economic Research, Cambridge, MA, Working Paper 8140.

Doeringer, P., & Piore, M. (1971). *Internal Labour Markets and Manpower Analysis*. Lexington, MA: Lexington Books.

Dolton, P.J. & Silles, M.A. (2008). The effects of over-education on earnings in the graduate labour market, *Economics of Education Review*, vol. 27, no. 3, pp. 125–139.

Dolton, P.J., & Vignoles, A. (2000). The incidence and effects of overeducation in the U.K. graduate labour market, *Economics of Education Review*, vol. 19, pp. 179–198.

Duncan, G.J., & Hoffman, S. (1979). On-the-job training and earnings differences by race and sex, *Review of Economics and Statistics*, vol. 61, no. 4, pp. 594-603.

Duncan, G.J., & Hoffman, S. (1981). The incidence and wage effects of overeducation, *Economics of Education Review*, vol. 1, no. 1, pp. 75–86.

Eeckhout, J., & Kircher, P. (2011). Identifying sorting – In theory, *Review of Economic Studies*, vol. 78, pp. 872-906.

Emilia Del Bono & Fernando Galindo-Rueda (2007). The Long Term Impacts of Compulsory Schooling: Evidence from a Natural Experiment in School Leaving Dates, CEE Discussion Papers 0074, Centre for the Economics of Education, LSE.

Finegold, D., & Soskice, D. (1988). The failure of training in Britain: Analysis and prescription, *Oxford Review of Economic Policy*, vol. 4, pp. 21-53.

Foley, P., & Watts, D. (1994). Skill shortages and training: A forgotten dimension in new technology, *R&D Management*, vol. 24, no. 3, pp. 279-289.

Forth, J., & Mason, G. (2006). Do ICT skill shortages hamper firms' performance? Evidence from UK benchmarking surveys, National Institute of Economic and Social Research, Discussion Paper 281.

Freeman, R. (1976). *The Overeducated American*. New York: Academic Press.

Frei, C., & Sousa-Poza, A. (2011). Overqualification: Permanent or transitory, *Applied Economics*, First published on: 01 April 2011 (iFirst), DOI: 10.1080/00036846.2011.554380

Eide, E.R., & Showalter, M.H. (2010). Human Capital. In D.J. Brewer and P. McEwan (section eds), *International Encyclopedia of Education*, *Economics of Education Section* (electronic version). Oxford: Elsevier.

European Commission (2008). The Bordeaux communiqué on enhanced European cooperation in vocational education and training. Communiqué of the European Ministers for vocational education and training, the European social partners and the European Commission, meeting in Bordeaux on 26 November 2008 to review the priorities and strategies of the Copenhagen process. Brussels: European Commission. Available from Internet: *http://ec.europa.eu/education/lifelong-learning-policy/doc/bordeaux_en.pdf* [cited 14.2.2011].

European Communities (2004). Facing the challenge: The Lisbon strategy for growth and employment, Report from the High Level Group chaired by Kim Kok, November.

Galasi, P. (2008). The effect of educational mismatch on wages for 25 countries, Institute of Economics, Hungarian Academy of Sciences, Budapest, Working Papers on the Labour Market 8-2008.

Gallie, D. (1991). Patterns of skill change: Upskilling, deskilling or the polarization of skills, *Work, Employment and Society*, vol. 5, no. 3, pp. 319–351.

Goldin, C., & Katz, L.F. (1999). The returns to skill in the United States across the twentieth century, National Bureau of Economic Research, Cambridge, MA, Working Paper 7126.

Green, D.A., & Riddell, W.C. (2001). *Literacy, Numeracy and Labour Market Outcomes in Canada*. Ottawa and Hull: Statistics Canada and Human Resource Development Canada.

Groeneveld, S. (1997). Passend meten, over definities en metingen van overscholing, *Tijdschrift voor Arbeidsvraagstukken*, vol. 13, no. 3, pp. 273–282.

Groot, W., & Maassen van den Brink, H. (2000). Overeducation in the labor market: A meta-analysis, *Economics of Education Review*, vol. 19, no. 2, pp. 149–158.

Halaby, C. (1994). Overeducation and skill mismatch, *Sociology of Education*, vol. 67, no. 1, pp. 47–59.

Hansson, B. (2007). “Effects of tertiary expansion: Crowding-out effects and labour market matches for the higher educated”, *OECD Education Working Papers* n°10. doi: 10.1787/085513474523

Harmon, C., & Walker, I. (1995). Estimates of the Economic Return to Schooling for the United Kingdom, *American Economic Review*, vol. 85, pp. 1278-1286.

Hartog, J. (1980). Earnings and capability requirements, *Review of Economics and Statistics*¸ vol. 62, no. 2, pp. 230-240.

Hartog, J. (1981). Wages and allocation under imperfect information, *De Economist*, vol. 129, no. 3, pp. 311-323.

Hartog, J. (1983). To graduate or not: Does it matter? *Economics Letters*, vol. 12, pp. 193-199.

Hartog, J. (1985). Earnings functions: Testing for the demand side, *Economics Letters*, vol. 19, pp. 281-285.

Hartog, J. (1986a). Allocation and the earnings function, *Empirical Economics*, vol. 11, no. 2, pp. 97-110.

Hartog, J. (1986b). Earnings functions: Beyond human capital, *Applied Economics*, vol. 18, no. 12, pp. 1291-1309.

Hartog, J., (2000). Over-education and earnings: Where are we and where should we go? *Economics of Education Review*, vol. 19, pp. 131–147.

Hartog, J., & Oosterbeek, H. (1988). Education, allocation and earnings in the Netherlands: Overschooling?, *Economics of Education Review*, vol. 7, no. 2, pp. 185–194.

Haskel, J., & Martin, C. (1993). Do skill shortages reduce productivity? Theory and evidence from the United Kingdom, *The Economic Journal*, vol. 103, pp. 386-394.

Heckman, J.J., Lochner, L.J., & Todd, P.E. (2005). Earnings functions, rates of return and treatment effects: The Mincer equation and beyond, Institute for the Study of Labor (IZA), Discussion Paper 1700.

Helms-Jørgensen, C., & Warring, N. (2003). Learning in the workplace: The interplay between learning environments and biographical learning trajectories. In H. Salling-Olsen, (ed.), *Adult Education and the Labour Market VII*, Volume B. Roskilde: Roskilde University Press.

Hersch, J. (1991). Education match and job match, *Review of Economics and Statistics*, vol. 73, pp. 140-144.

Holzer, H. (1996). *What Employers Want: Job Prospects for Less-educated Workers*. New York: Russell Sage Foundation.

Hosmer, D.W., & Lemeshow, S. (1989). *Applied Logistic Regression*. New York: John Wiley and Sons.

HRDC (2001, October 12). Readers' guide to essential skills profiles, Skills Information Division, Human Resource Development Canada, Hull, Quebec. Retrieved from http://www15.hrdc-drhc.gc.ca/english/readers_guide_whole.asp.

Hum, D., & Simpson, W. (2004). What are Canadians doing after school: An analysis of post-school training activity. In J. Gaskell and K. Rubenson (eds), *Educational Outcomes for the Canadian Workplace. New Frameworks for Policy and Research* (pp. 89-117). Toronto: University of Toronto Press.

Illeris, K. (2004a). A model for learning in working life, *Journal of Workplace Learning*, vol. 16, no. 8, pp. 431-441.

Illeris, K. (2004b). Lifelong learning and the low skilled, *International Journal of Lifelong Learning*, vol. 25, no. 1, pp. 15-28.

Jaoul-Grammare, M. (2007). The labour market segmentation: Empirical analysis of Cain's theory (1976), *Applied Economics Letters*, vol. 14, no. 5, pp. 337-341.

Johnson, B., & Christensen, L. (2004). *Educational Research: Quantitative, Qualitative and Mized Approached, Second Edition* New York: Pearson.

Jovanovic, B. (1979). Firm-specific capital and turnover, *Journal of Political Economy*, vol. 87, no. 6, pp. 1246-1260.

Judy, R., & D'Amico, C. (1997). *Workforce 2020: Work and Workers in the 21st Century*. Indianapolis, IN: Hudson Institute.

Katz, L.F. (2000). Technological change, computerization, and the wage structure. In E. Brynjolfsson and B. Kahin (eds), *Understanding The Digital Economy: Data, Tools, and Research* (pp. 217-244). Cambridge: MIT Press.

Katz, L., & Murphy, K. (1992). Changes in relative wages, 1963-1987: Supply and demand factors, *Quarterly Journal of Economics*, vol. 107, no. 1, pp. 35-78.

Kalleberg, A.L. (2003). Flexible firms and labor market segmentation: Effects of workplace restructuring on jobs and workers, *Work and Occupations*, vol. 30, pp. 154-175.

Kalleberg, A.L. (2006). *The Mismatched Worker*. New York: W.W. Norton & Company.

Kalleberg, A.L., Knoke, D., Marsden, P.V., & Spaeth, J.L. (1996). *Organizations in America: Analyzing their Structures and Human Resource Practices*. Thousand Oaks: Sage Publications.

Kiker, B., Santos, M., & Mendes de Oliveira, M. (1997). Overeducation and undereducation: Evidence for Portugal, *Economics of Education Review*, vol. 16, no. 2, pp. 111–125.

Kolev, A., & Saget, C. (2010). Are middle-paid jobs in OECD countries disappearing? An overview, International Labour Organization, Working Paper 96.

Korpi, T., & Tåhlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000, *Labour Economics*, vol. 16, pp. 183–193.

Krahn, H., & Lowe, G.S. (1998). *Literacy Utilization in Canadian Workplaces*. Ottawa and Hull: Statistics Canada and Human Resource Development Canada.

Krueger, A. (1993). How computers have changed the wage structure: Evidence from microdata, *Quarterly Journal of Economics*, vol. 110, pp. 33-60.

Lavoie, M., & Roy, R. (1998). Employment in the knowledge-based economy: A growth accounting exercise for Canada, Research Paper, Hull, Quebec, Applied Research Branch, Human Resources Development Canada.

le Grand, C., Szulkin, R., & Tåhlin, M. (2004). Överutbildning eller kompetensbrist? Matchning på den svenska arbetsmarknaden 1974–2000”. (“Overeducation or skill shortage? Matching in the Swedish labor market 1974–2000”). In M. Bygren, M. Gähler, and M. Nermo (eds), *Familj och arbete. Vardagsliv i förändring* (Family and Work. Everyday Life in Transition) (pp. 283–321). Stockholm: SNS Förlag.

Leuven, E. (2001). *Studies in the Economics of Training*. Amsterdam: Universiteit van Amsterdam.

Levels, M., van der Velden, R., & Allen, J. (2013). Educational mismatches and skills: New empirical tests of old hypotheses, ROA Research Memorandum

(RAO-RM-2013/18), Research Centre for Education and the Labour Market (ROA), Maastricht University.

Levy, F., & Murnane, R. (1992). U.S. earnings levels and earnings inequality; a review of recent trends and proposed explanations, *Journal of Economic Literature*, vol. 30, pp. 1333-1381.

Lewis (2007). Braverman, Foucault and the labor process: Framing the current high-skills debate, *Journal of Education and Work*, vol. 20, no. 5, pp. 397–415

Linbeck, A., & Snower, D.J. (2000a). Multitask learning and the recognition of work: From tayloristic to holistic organization, *Journal of Labor Economics*, vol. 18, no. 3, pp. 353-376.

Linbeck, A., & Snower, D.J. (2000b). The division of labor and the market for organizations, Institute for the Study of Labor (IZA), Discussion Paper 119.

Lindqvist, E., & Vestman, R. (2009). The labor market returns to cognitive and noncogntive ability: Evidence from the Swedish Enlistement, IFN Working Paper No 794, 2009, Research Institute of Industrial Economics, Stockholm.

Livingstone, D.W. (2005). Expanding conception of work and learning: Recent research and policy implications. In A. Cummings, N. Basica, A. Datnow, A.K. Leithwood, & D.W. Livingstone (eds), *International Handbook of Educational Policy Series*: Springer International Handbooks of Education, vol. 13. Retrieved February 3, 2006, from: *http://wall.oise.utoronto.ca/resources/Livingstone_Springerbook_ch52.pdf*

Lloyd, C., & Payne, J. (2006). Goodbye to all that? A critical re-evaluation of the role of the high-performance work organization within the UK skills debate, *Work, Employment and Society*, vol. 20, no. 1, pp. 151-165.

MacDonald, G., & Weisbach, M.S. (2004). The economics of has-beens, *Journal of Political Economy*, vol. 112, no. 1, pp. S289-S310.

Martin, I. (2003). Adult education, lifelong learning and citizenship: Some ifs and buts, *International Journal of Lifelong Learning*, vol. 22, no. 6, pp. 566-579.

Massé, P., Roy, R., & Gingras, Y. (2000). The changing skill structure of employment in Canada. In: K. Rubenson & H.G. Schuetze (eds), Transition to the Knowledge Society: Policies and Strategies for Individual Participation and Learning. Vancouver, BC: British Columbia Press.

Mavromaras, K., & McGuinness, S. (2007). Education and skill mismatches in the labour market: Editors' introduction, *Australian Economic Review*, vol. 40, no. 3, pp. 279–285.

Mavromaras K., McGuinness, S., & Fok, Y. (2009a). Assessing the incidence and wage effects of over-skilling in the Australian labour market, *Economic Record*, vol. 85, pp. 60-72.

Mavromaras K., McGuinness, S., & Fok, Y. (2009b). Overskilling dynamics and education pathways, Institute for the Study of Labor (IZA), Discussion Paper 4321.

Mavromaras K., McGuinness, S., O'Leary, N., Sloane, P., & Fok, Y. (2010). The problem of overskilling in Australia and Britain, *Manchester School*, vol. 78, no. 3, pp. 219–241.

Mavromaras, K., McGuinness, S., O'Leary, N., Sloane, P., & Wei, Z. (2010). Job mismatches and labour market outcomes: Panel evidence on Australian university graduates, Institute for the Study of Labor (IZA), Discussion Paper 5083.

Mavromaras, K., McGuinness, S., & Wooden, M. (2007). Overskilling in the Australian Labour Market, *Australian Economic Review*, vol. 40, no. 3, pp. 307–312.

McGoldrick, K., & Robst, J. (1996). Gender differences in overeducation: A test of the theory of differential overqualification, *American Economic Review*, vol. 86, pp. 280-284.

McGuinness, S. (2006). Overeducation in the labour market, *Journal of Economic Surveys*, vol. 20, pp. 387-418.

Mendes de Oliveira, M., Santos, M.C., & Kiker, B.F. (2000). The role of human capital and technological change in overeducation, *Economics of Education Review*, vol. 19, pp. 199–206.

Meredith. J. (2008). *Mechanics of Class: Social Structure and Action in the Apprenticeable Skilled Trades at a Canadian Dockyard* (dissertation), University of British Columbia.

Messinis, G., & Olekalns, N. (2007). Skill mismatch and training in Australia: Some implications for policy, *Australian Economic Review*, vol. 40, no. 3, pp. 300–306.

Miller, P.W. (2007). Overeducation and undereducation in Australia: Policy forum: Education and skill mismatches in the labour market, *Australian Economic Review*, vol. 40, no. 3, pp. 292–9.

Mincer, J. (1958). Investment in human capital and personal income distribution. *Journal of Political Economy*, vol. 66, no. 4, pp. 281-302.

Mincer, J. (1962). On-the-job training: Costs, returns, and some implications. *Journal of Political Economy*, vol. 70, no. 5-2, pp. 50-79.

Mincer, J. (1974). *Schooling, Experience, and Earnings*. New York: Columbia University Press.

Mincer, J. (1997). Changes in wage inequality, 1970-1990. In S.W. Polachek and J. Robst (eds), *Research in Labor Economics*, vol. 16, pp. 1-18.

Mincer, J. & Ofek, H. (1982). Interrupted work careers: Depreciation and restoration of human capital, *Journal of Human Resources*, vol. 17, no. 1, pp. 3-24.

Murnane, R.J., Willet, J.B., Braatz, M.J., & Duhaldeborde, Y. (2001). Do different dimensions of male high school students' skills predict labour market success a decade later? Evidence from the NLSY, *Economics of Education Review*, vol. 20, pp. 311-320.

Murnane, R.J., Willet, J.B., & Levy, F. (1995). The growing importance of cognitive skills in wage determination, *Review of Economics and Statistics*, vol. 77, no. 2, pp. 251-266.

Murray, T.S., Kirsch, I.S., & Jenkins, L.B. (1998). Adult Literacy in OECD Countries: Technical Report on the First International Adult Literacy Survey. Washington, DC: National Centre for Education Statistics.

Nichols, A. (2007). Causal inference with observational data, *The Stata Journal*, vol. 7, no. 4, pp. 507-541.

Nordin, M., Persson, I., & Rooth, D-O. (2010). Education–occupation mismatch: Is there an income penalty?, *Economics of Education Review*, vol. 29, pp. 1047–1059.

Nunnally, J.C. (1978). *Psychometric Theory*, 2nd ed. New York: McGraw-Hill.

OECD. (1989). *Education and the Economy in a Changing Society*. Paris: Author.

OECD (1996). *Lifelong Learning for All*. Paris: Author.

OECD (2001). *Education Policy Analysis*. Paris: Author.

OECD. (2003). *Science and Technology Scoreboard*. Paris: Author.

OECD/HRDC (1997). *Literacy Skills for the Knowledge Society: Further Results from the International Adult Literacy Survey*. Paris and Ottawa: Authors.

OECD/Statistics Canada (1995). *Literacy, Economy and Society: Results from the First International Adult Literacy Survey.* Paris and Ottawa: Authors.

OECD/Statistics Canada (2000). *Literacy in the Information Age: Final Report of the International Adult Literacy Survey*. Paris and Ottawa: Authors.

OECD/Statistics Canada (2005). *Learning a Living: First Report of the Adult Literacy and Lifeskills Survey*. Paris and Ottawa: Authors.

OECD/Statistics Canada (2011). *Learning for Life: Final Report of the Adult Literacy and Lifeskills Survey*. Paris and Ottawa: Authors.

Oosterbeek (2000). Editorial: Introduction to special issue on overschooling, *Economics of Education Review*, vol. 19, pp. 129–130.

Osberg, L. (1989). Paying information workers. In L. Osberg, E.N. Wolff, & W.J. Baumol, The Information Economy: The Implications of Unbalanced Growth (pp. 47-86). Halifax: Institute for Research on Public Policy.

Osberg, L. (2000). *Schooling, Literacy and Individual Earnings*. Ottawa and Hull: Statistics Canada and Human Resource Development Canada.

Osberg, L., Wolff, E.N., & Baumol, W.J. (1989). *The Information Economy: The Implications of Unbalanced Growth*. Halifax: Institute for Research on Public Policy.

Osterman, P. (1995). Skill, training, and work organization in American establishments, *Industrial Relations*, vol. 34, no. 2, pp. 125-146.

Osterman, P. (2000). Work reorganization in an era of restructuring: Trends in diffusion and effects on employee welfare, *Industrial and Labor Relations Review*, vol. 53, no. 2, pp. 179–196.

Pazy, A. (2004). Updating in response to the experience of lacking knowledge, *Journal of Applied Psychology*, vol. 53, pp. 436-452.

Pearl, J. (2009). *Causality: Models, Reasoning and Inference, Second Edition*. Cambridge: Cambridge University Press.

Psacharopoulos, G. (1981). Returns to education: An updated international comparison, *Comparative Education*, vol. 17, no. 3, pp. 321-341.

Psacharopoulos, G., & Patrinos, H.A. (2004). Returns to investment in education: A further update, *Education Economics*, vol. 12, no. 2, pp. 111-134.

Quintini, G. (2010). Over-qualified or under-skilled: A review of existing literature. OECD document for official use [DELSA/ELSA/RD(2010)2].

Raudenbush, S.W., & Kasim, R.M. (1998). Cognitive skill and economic inequality: Findings from the national adult literacy survey. Harvard Educational Review, 68(1), 33-79.

Raudenbush, S.W., & Kasim, R.M. (2002). *Adult Literacy, Social Inequality, and the Information Economy: Findings from the National Adult Literacy Survey*. Ottawa and Hull: Statistics Canada and Human Resource Development Canada.

Reder, S. (1994). Practice-engagement theory: A sociocultural approach to literacy across languages and cultures. In B.M. Ferdman, R.M. Weber and A.G. Ramirez (eds), *Literacy Across Languages and Cultures* (pp. 33-74). Albany: State University of New York Press.

Reder, S. (1998). Literacy selection and literacy development: Structural equation models of the reciprocal effects of education and literacy. In M.C. Smith (ed.), *Literacy for the Twenty-first Century: Research policy, practices and the National Adult Literacy Survey* (pp. 139-157). Westport, CT: Praeger.

Reder, S. (2009a). The development of adult literacy and numeracy in adult life. In S. Reder and J. Bynner, J. (eds), *Tracking Adult Literacy and Numeracy Skills: Findings from Longitudinal Research* (pp. 59-84). Routledge: New York.

Reder, S. (2009b). Scaling up and moving in: Connecting social practices views to policies and programs in adult education, *Literacy and Numeracy Studies*, vol. 16, no. 2, pp. 35-50.

Riddell, C. (2004). Education, skills and labour market outcomes: Exploring the linkages in Canada. In J. Gaskell and K. Rubenson (eds), *Educational outcomes* *for the Canadian workplace. New frameworks for policy and research* (pp. 21-55). Toronto: University of Toronto Press.

Riley, J.G. (1976). Information, screening and human capital. *American Economic Review*, vol. 66, no. 2, pp. 254-260.

Rivera-Batiz, F.L. (1992). Quantitative literacy and the likelihood of employment among young adults in the United States, *Journal of Human Resources*, vol. 27, pp. 313-328.

Robst, J. (2007). Education and job match: The relatedness of college major and work, *Economics of Education Review*, vol. 26, no. 4, pp. 397-407.

Romer, P (1990). Endogenous technological change, *Journal of Political Economy*, vol. 98, S71-S102.

Rosen, S. (1975). Measuring the obsolescence of knowledge. In F.T. Juster (ed.) *Education, Income and Human Behavior* (pp. 199-232). New York: McGraw-Hill.

Rubenson, K., & Desjardins, R. (2009). The impact of welfare state regimes on barriers to participation in adult education: A bounded agency model, *Adult Education Quarterly*, vol. 59, no. 3, pp. 187-207.

Rubenson, K., Desjardins, R., & Yoon E-S. (2007). *Adult Learning in Canada: A Comparative Perspective*. Statistics Canada: Ottawa.

Rubenson, K., & Xu, G. (1997). Barriers to participation in adult education and training: Towards a new understanding, In P. Bélanger and A. Tuijnman (eds), *New Patterns of Adult Learning: A Six-country Comparative Study*. Oxford: Pergamon Press.

Rumberger, R. (1987). The impact of surplus schooling on productivity and earnings, *Journal of Human Resources*, vol. 22, no. 1, pp. 24–50.

Ryan, C., & Sinning, M. (2009). Skill matches to job requirements, National Centre for Vocational Education Research, Australia, Research Report.

Salthouse, T. (2009). When does age-related cognitive decline begin? *Neurobiology of Aging*, vol. 30, no. 4, pp. 507-514.

Sattinger, M. (1980). *Capital and the Distribution of Labor Earnings*. Amsterdam: North Holland Publishing.

Sattinger, M. (1993). Assignment models of the distribution of earnings, *Journal of Economic Literature*, vol. 31, no. 2, pp. 831-880.

Sawchuk, P.H. (2006). Use-value and the re-thinking of skills, learning and the labour process, *Journal of Industrial Relations*, vol. 48, no. 5, pp. 593-617.

Schultz, T.W. (1961). Investment in human capital, *American Economic Review*, vol. 51, no. 1, pp. 1-17.

Schultz, T.W. (1975). The value of the ability to deal with disequilibria, *Journal of Economic Literature*, vol. 13, no. 3, pp. 827-846.

Shadish, W.R., Cook, T.D., & Campbell, D.T. (2001). *Experimental and Quasi-Experimental Designs for Generalized Causal Inference*. Boston: Houghton Mifflin.

Sicherman, N. (1991). Overeducation in the labour market, *Journal of Labour Economics*, vol. 9, no. 2, pp. 101–122.

Sicherman, N., & Galor, O. (1990). A theory of career mobility, *Journal of Political Economy*, vol. 98, no. 1, pp. 169-192.

Sloane, P.J. (2003). Much ado about nothing? What does the overeducation literature really tell us?. In F. Büchel, A. de Grip and A. Mertens (eds), *Over-education in Europe: Current Issues in Theory and Policy* (pp. 11-48). Massachusetts: Edward Elgar Publishing.

Sloane, P.J. (2007). Overeducation in the United Kingdom, *Australian Economic Review*, vol. 40, no. 3, pp. 286–291.

Sloane, P.J., Battu, H., & Seaman, P. (1999). Overeducation, Undereducation and the British Labour Market, *Applied Economics*, vol. 31, pp. 1437-1453.

Spence, A.M. (1973). Job market signalling, *Quarterly Journal of Economics*, vol. 87, no. 3, pp. 355-374.

Spenner, K.I. (1983) Deciphering prometheus: Temporal change in the skill level of work, *American Sociological Review*, vol. 48, no. 6, pp. 824–837.

Staff, R.T., Murray, A.D., Deary, I.J., & Whalley, L.J. (2004). What provides cerebral reserve?, *Brain*, vol. 127, pp. 1191-1199.

Statistics Finland (2000). *Adult Education Survey 2000*. Helsingfors: Statistics Finland.

Stern, D., & Tuijnman, A.C. (1997). Adult basic skills: Policy issues and a research agenda. In A.C. Tuijnman, I.S. Kirsch & D.A. Wagner (eds), Adult Basic Skills: Innovations in Measurement and PolicyAnalysis (pp. 1-16). New Jersey: Hampton Press.

Stigler, G. (1961). The economics of information, *Journal of Political Economy*, vol. 69, pp. 213-225.

Swedberg, R. (1996) (ed.). *Economic Sociology*. Cheltenham: Edward Elgar.

Thurow, L.C. (1975). *Generating Inequality: Mechanisms of Distribution in the U.S. Economy*. New York: Basic books.

Tinbergen, I. (1956). On the Theory on Income Distribution. *Weltwirtschaftliches Archive 77*, pp. 156-175

Tinker, T. (2002). Spectres of Marx and Braverman in the twilight of postmodernistic labour process research, *Work, Employment and Society*, vol. 16, no. 2, pp. 251–281.

Toossi, M. (2002). A century of change: The U.S. labor force, 1950-2050, *Monthly Labor Review*, vol. 125, no. 5, pp. 15-28.

Torres, C.A. (1996). Adult education for development. In A. Tuijnman. (ed.), *International Encyclopaedia of Adult Education and Training*, 2nd edition (pp. 213-221). Oxford: Pergamon Press.

Tuijnman, A.C. (2000). Education, literacy and wages in Poland in comparative perspective, Yellow Paper Series, Stockholm, Institute of International Education.

UK Commission for Employment and Skills (2010). Skills for jobs: Today and tomorrow: The national strategic skills audit for England 2010, volume one: Key findings, UK Commission for Employment and Skills.

US Department of Education (1998). Adult education participation decisions and barriers: Review of conceptual frameworks and empirical studies. National Center for Education Statistics, Washington D.C. Office of Educational Research and Improvement, Working Paper 98-10.

Ure, O.B, & Saar, E. (2008). Some Micro - Meso - Macro Relations In Lifelong Learning, LLL2010 Working Paper No 17. (accessed May 27, 2011) *http://lll2010.tlu.ee/publications/working-papers/lll2010-working-papers-on-overall-theoretical-framework/d13-2-lll2010-working-paper-17_ad-hoc.pdf/view*

Vahey (2000). The great Canadian training robbery: Evidence on the returns to educational mismatch, *Economics of Education Review*, vol. 19, pp. 219–227.

Valla, S.P. (1990). The concept of skill: A critical review, *Work and Occupations*, vol. 17, no. 4, pp. 379-398.

van der Meer, P.H. (2009). Investments in education: Too much or not enough?, *Economics Letters*, vol. 102, pp. 195–197.

van Smoorenburg, M., & van der Velden, R. (2000). The training of school leavers, complementarity or substitution?, *Economics of Education Review*, vol. 19, pp. 207-217.

Velloso, J. (1995). Income distribution and education. In M. Carnoy (ed.), *International Encyclopedia of Economics of Education, Second Edition* (pp. 230-234). Oxford: Pergamon Press.

Verdugo, R., & Verdugo, N. (1989). The impact of surplus schooling on earnings, *Journal of Human Resources*, vol. 22, no. 4, pp. 690–695.

Verhaest, D., & Omey, E. (2006). The impact of overeducation and its measurement, *Social Indicators Research*, vol. 77, pp. 419-448.

Vignoles, A., Galindo-Rueda, F., & Feinstein, L. (2004). The labour market impact of adult education and training: A cohort analysis, *Scottish Journal of Political Economy*, vol. 51, no. 2, pp. 266-280.

Weiss, A. (1995). Human capital vs. signalling explanations of wages, *Journal of Economic Perspectives*, vol. 9, no. 4, pp. 133-154.

Welch, F. (1970). Education in production, *Journal of Political Economy*, vol. 78, no. 1, pp. 35–59.

Wolf, A. (2003). *Does Education Matter?: Myths About Education and Economic Growth*. London: Penguin Books.

Wolff, E.N., & Baumol, W.J. (1989). Sources of postwar growth of information activity in the United States. In L. Osberg, E.N. Wolff and W.J. Baumol (eds), *The Information Economy: The Implications of Unbalanced Growth* (pp. 17-46). Halifax: Institute for Research on Public Policy.

Woodhall, M. (2001). Human capital: Educational aspects. In N.J. Smelser and P. Baltes (eds), *International Encyclopaedia of the Social and Behavioural Sciences* (pp. 6951-6955). Oxford: Elsevier.

Zuboff, S. (1988). *In the Age of the Smart Machine: The Future of Work and Power*. New York: Basic Books.

Appendix A. Classification of occupational types

A. Knowledge		B. Management	
1171	Accountants, auditors & other financial officers	1111	Members of Legislative Bodies
1173	Organization and methods analysts	1113	Government administrators
2111	Chemists	1115	Post office management occupations
2112	Geologists	1119	Officials and administrators unique to government
2113	Physicists	1130	General managers and other senior officials
2114	Meteorologists	1131	Management occupations, natural sciences and eng.
2131	Agriculturalists & related scientists	1132	Management occupations, social sciences and related
2133	Biologists and related scientists	1133	Administrators in teaching and related fields
2141	Architects	1134	Administrators in health and medicine
2142	Chemical Engineers	1135	Financial management occupations
2143	Civil engineers	1136	Personnel and industrial relations management
2144	Electrical engineers	1137	Sales and advertising management
2145	Industrial engineers	1141	Purchasing management
2146	Agricultural Engineers	1142	Services management
2147	Mechanical engineers	1143	Production management
2151	Metallurgical Engineers	1145	Management, constructing operations
2153	Mining Engineers	1146	Farm management
2154	Petroleum Engineers	1147	Management, transport and communications operations
2155	Aerospace engineers	1149	Other managers and administrators
2156	Nuclear Engineers	2350	Supervisors: Occupations In Library,
2157	Community planners	3330	Producers & directors, performing & audio-visual arts
2159	Professional engineers, nec	5130	Supervisors: Sales, commodities
2181	Mathmaticians, statisticians & actuaries	5170	Supervisor: Sales, services
2311	Economists		
2313	Sociologists, Anthropologists and Related		
2315	Psychologists		
2319	Others in social sciences, nec		
2341	Judges and Magistrates		
2343	Lawyers & notaries		
2351	Librarians, Archivists and Conservators		
2711	University teachers		
3111	Physicians & surgeons		
3113	Dentists		
3311	Painters, sculptors & related artists		
3331	Conductors, Composers and Arrangers		
3332	Musicians and Singers		
3351	Writers & editors		

C. Information (high-skill)	
1116	Inspectors & regulatory officers, government
1174	Personnel and related officers
1175	Purchasing officers & buyers
1176	Inspectors and regulatory officers, nec
1179	Other related to managment and administration
2117	Physical sciences techologists & technicians
2119	Occupations In Physical Sciences, n.e.c.
2135	Life sciences technologists & technicians
2139	Other occupations in life sciences, nec
2160	Supervisors: Other Occupations In archit. And engineering
2161	Surveyors
2163	Draughting
2164	Architectural Technologists and Technicians
2165	Engineering technologists & technicians
2169	Others in engineering or architecture, nec
2183	Systems analysts, computer programmers & other related
2189	Occupations In Mathematics, Statistics,
2331	Social workers
2333	Welfare & community services
2339	Social work & related fields, nec
2359	Occupations In Library, Museum and Archival
2719	University teaching & related, nec
2731	Elementary & kindergarten teachers
2733	Secondary school teachers
2739	Elementary & secondary school teaching & related, nec
2791	Community college & vocational school teachers
2792	Fine Arts Teachers, n.e.c.
2793	Post-secondary school teachers, nec
2795	Teachers of exceptional students, nec
2797	Instructors & training officers, nec
2799	Other teaching & related, nec
3115	Veterinarians
3117	Osteopaths and Chiropractors
3119	Health Diagnosing and Treating Occupations,
3130	Supervisors: Nursing, therapy and related assisting
3131	Nurses, registered
3136	Audio and Speech Therapists
3137	Physiotherapist

C. Information (high-skill) (cont'd)	
3138	Occupational therapist
3151	Pharmacists
3152	Dieticians & nutritionists
3153	Optometrists
3155	Radiological technologists & technicians
3156	Medical laboratory technologists & technicians
3169	Others in medicine & health, nec
3313	Product & interior designers
3314	Advertising & illustrating artists
3333	Occupations Related To Music and Musical
3334	Dancers and Choreographers
3335	Actors
3337	Radio & television annoucers
3355	Translators & interpreters
3359	Occupations In Writing, n.e.c.
3360	Supervisors: Sports & recreation
3370	Coaches, Trainers and Instructors, Sports
3371	Referees and Related Officials
3373	Athletes
3375	Coaches, trainers & instructors, sports & recreation
5131	Technical sales and related advisors
5191	Buyers, wholesale & retail trade
6116	Commissioned Officers, Armed Forces
6141	Funeral directors, embalmers and related
6141	Funeral Directors, Embalmers and Related
9110	Foremen/women: Air Transport Operating
9111	Air pilots, navigators & flight engineers
9113	Air transport operating support
9151	Deck officers

D. Information (low-skill)	
2349	Law & jurispudence, nec
2391	Educational & vocational counsellors
2399	Social sciences & related fields, nec
2511	Ministers of religion
4110	Supervisors: Stenographic and Typing
4111	Secretaries & stenographers
4113	Typists & clerk-typists
4130	Supervisors: Bookeeping, account-recording &
4131	Bookeepers & accounting clerks
4133	Cashiers & tellers
4135	Insurance, bank & other finance clerks
4137	Statistical Clerks
4139	Bookkeeping, Account-recording and Related
4140	Supervisors: Office Machine and Electronic
4141	Office machine operators
4150	Supervisors: Material recording, scheduling & dist.
4151	Production clerks
4153	Shipping & receiving clerks
4155	Stock clerks & related
4157	Weighers
4159	Material Recording, Scheduling and
4160	Supervisors: Library, File and
4161	Library & file clerks
4169	Library, file & correspondence clerks & related, nec
4170	Supervisors: Reception, information, mail & message dist.
4171	Receptionists & information clerks
4173	Mail & postal clerks
4179	Supervisors: Reception, information, mail & message dist.
4190	Supervisors: Other clerical and related, nec
4191	Collectors
4192	Claim adjusters
4193	Travel clerks, ticket, station and freight agents
4195	Personnel Clerks
4197	General office clerks
4199	Other clerical and related, nec
5133	Commercial travellers
5135	Sales clerks & persons, commoditities, nec

D. Information (low-skill) (cont'd)	
5171	Insurance sales
5172	Real estate sales
5173	Sales Agents and Traders, Securities
5174	Advertising sales
5177	Business services sales
5179	Sales, services, nec
5190	Supervisors: other sales
5199	Other sales, nec
9135	Railway transport operating support
9553	Telegraph operators

E. Services (low-skill)	
2513	Nuns and Brothers
2519	Religion, nec
3132	Orderlies
3134	Nurses, registered assistants
3135	Nursing attendants
3139	Nursing, therapy & related assisting
3158	Dental hygienists & assistants
3162	Respiratory technicians
3339	Others in performning & visual arts, nec
3379	Occupations In Sports and Recreation, n.e.c.
4172	Mail carriers
4175	Telephone operators
4177	Messengers
4194	Hotel clerks
5141	Street vendors & door-to-door sales
5143	Newspaper Carriers and Vendors
5145	Service station attendants
5149	Sales, commodoties, nec
5193	Route drivers
6111	Fire-fighter
6112	Police officer & detective
6113	Police Agents and Investigators, Private
6115	Guards & related security
6117	Other ranks, armed forces
6119	Protective services, nec
6120	Supervisors: Food & beverage prepartion & related
6123	Bartenders
6125	Food & beverage serving
6129	Food & beverage preparation & related, nec
6130	Supervisors: Lodging & other accomodation
6133	Lodging cleaners
6135	Sleeping-car and Baggage Porters
6139	Occupations In Lodging and Other
6142	Housekeepers, servants & related
6143	Barbers, hairdressers and related
6144	Guides
6145	Travel and Related Attendants, Except
6147	Guides

E. Services (low-skill) (cont'd)	
6149	Personal service, nec
6190	Supervisors: other service
6191	Janitors & cleaners
6193	Elevator operators
6198	Labour & other elementary, services
6199	Other services, nec
9119	Air Transport Operating Occupations, n.e.c.
9133	Conductors & brake operators, railway
9171	Bus drivers
9173	Taxi drivers & chauffers
9191	Subway and Street Railway Operating
9919	Other Occupations, n.e.c.

F. Goods		F. Goods (cont'd)	
2353	Technicians in library, museum and achival	8141	Metal Extruding and Drawing Occupations
3154	Dispensing Opticians	8143	Plating, Metal Spraying and Related
3157	Denturists	8146	Inspecting, Testing, Grading and Sampling
3161	Dental Laboratory Technicians	8148	Processing
3315	Photographers and Camera Operators	8149	Processing
3319	Occupations In Fine and Commericial Art,	8150	Foremen/women: Clay, Glass and Stone
4143	Electronic data-processing equipment	8151	Furnace and Kiln Workers: Clay, Glass and
6121	Chefs & cooks	8153	Processing
6160	Supervisors: Apparel and Furnishings	8155	Processing
6162	Laudering & dry cleaning	8156	Inspecting, Testing, Grading and Sampling
6165	Pressing Occupations	8158	Occupations In Labouring and Other
6169	Apparel and Furnishings Service	8159	Clay, Glass and Stone Processing, Forming
7113	Livestock farmer	8160	Processing
7115	Crop farmer	8161	Mixing and Blending Occupations,
7119	Farmer, nec	8163	Filtering, Straining and Separating
7180	Foremen: Other farming, horticultural &	8165	Processing
7183	Livestock farm workers	8167	Roasting, Cooking and Drying Occupations,
7185	Crop farm workers	8171	Crushing and Grinding Occupations,
7195	Nursery & related workers	8173	Coating and Calendering Occupations,
7196	Inspecting, Testing, Grading and Sampling	8176	Inspecting, Testing, Grading and Sampling
7197	Farm machinery operators	8178	Occupations In Labouring and Other
7199	Other farming, nec	8179	Processing
7311	Captains & other officers, fishing	8210	Foremen/women: Food, Beverage and
7313	Net, trap & line fishing	8211	Flour and Grain Milling Occupations
7315	Trapping and Related Occupations	8298	Occupations In Labouring and Other
7319	Fishing, Trapping and Related Occupations,	8299	Other Processing Occupations, n.e.c.
7510	Foremen: forestry & logging	8310	Machining
7511	Forestry cinservation	8311	Machining
7513	Timber cutting & related	8313	Machining
7516	Log inspecting, grading, sclaing & related	8315	Machining
7517	Log hoisting, sorting, moving & related	8316	Inspecting, Testing, Grading and Sampling
7518	Occupations In Labouring and Other	8319	Metal Machining Occupations, n.e.c.
7519	Forestry & logging	8330	Machining
7710	Formen: Mining & quarrying	8331	Machining
7711	Well drilling & related	8333	Machining
7713	Rock & soil drilling	8334	Machining
7715	Blasting	8335	Machining
7717	Mining & quarrying: cutting, handling &	8336	Inspecting, Testing, Grading and Sampling
7718	Labouring & other elementary, mining &	8213	Processing
7719	Mining & quarrying & related, nec	8215	Processing
8110	Foremen/women: Mineral Ore Treating	8217	Processing
8111	Crushing and Grinding Occupations, Mineral	8221	Fruit and Vegetable Canning, Preserving
8113	Mixing, Separating, Filtering and Related	8223	Processing
8115	Melting and Roasting Occupations, Mineral	8225	Sugar Processing and Related Occupations
8116	Processing	8226	Processing
8118	Processing	8227	Beverage Processing and Related
8119	Processing	8228	Processing
8130	Processing	8229	Processing
8131	Processing	8230	Processing
8133	Metal Heat-treating Occupations	8231	Processing
8135	Metal Rolling Occupations	8233	Processing
8137	Moulding, Coremaking and Metal Casting	8235	Wood Treating Occupations

F. Goods (cont'd)		F. Goods (cont'd)	
8236	Processing	8528	Fabricating & assembling
8238	Processing	8529	Fabricating & assembling
8239	Processing	8530	Foremen/women: Fabricating, Assembling,
8250	Processing	8531	Fabricating & assembling
8251	Processing	8533	Fabricating & assembling
8253	Processing	8534	Fabricating & assembling
8256	Inspecting, Testing, Grading and Sampling	8535	Fabricating & assembling
8258	Processing	8536	Inspecting, Testing, Grading and Sampling
8259	Processing	8537	Fabricating & assembling
8260	Foremen/women: Textile Processing	8538	Occupations In Labouring and Other
8261	Processing	8539	Fabricating & assembling
8263	Textile Spinning and Twisting Occupations	8540	Foremen/women: Fabricating, Assembling and
8265	Textile Winding and Reeling Occupations	8541	Fabricating & assembling
8267	Processing	8546	Inspecting, Testing, Grading and Sampling
8271	Knitting Occupations	8548	Occupations In Labouring and Other
8273	Textile Bleaching and Dyeing Occupations	8549	Fabricating & assembling
8275	Textile Finishing and Calendering	8550	Foremen/women: Fabricating, Assembling
8276	Inspecting, Testing, Grading and Sampling	8551	Patternmaking, Marking and Cutting
8278	Occupations In Labouring and Other	8553	Fabricating & assembling
8279	Processing	8555	Furriers
8290	Foremen/women: Other Processing	8557	Milliners, Hat and Cap Makers
8293	Processing	8561	Fabricating & assembling
8295	Hide and Pelt Processing Occupations	8562	Fabricating & assembling
8296	Inspecting, Testing, Grading and Sampling	8563	Fabricating & assembling
8337	Machining	8566	Inspecting, Testing, Grading and Sampling
8339	Machining	8568	Occupations In Labouring and Other
8350	Foremen/women: Wood Machining Occupations	8569	Fabricating & assembling
8351	Wood Patternmaking Occupations	8570	Foremen/women: Fabricating, Assembling and
8353	Wood Sawing and Related Occupations, n.e.c.	8571	Fabricating & assembling
8355	Planing, Turning, Shaping and Related Wood	8573	Moulding Occupations: Rubber, Plastic and
8356	Inspecting, Testing, Grading and Sampling	8575	Cutting and Finishing Occupations: Rubber,
8357	Wood Sanding Occupations	8576	Inspecting, Testing, Grading and Sampling
8359	Wood Machining Occupations, n.e.c.	8578	Occupations In Labouring and Other
8370	Foremen/women: Clay, Glass, Stone and	8579	Fabricating & assembling
8371	Cutting and Shaping Occupations: Clay,	8580	Fabricating & assembling
8373	Machining	8581	Fabricating & assembling
8376	Inspecting, Testing, Grading and Sampling	8582	Aircraft Mechanics and Repairers
8379	Machining	8583	Rail Transport Equipment Mechanics and
8390	Foremen/women: Other Machining and Related	8584	Fabricating & assembling
8391	Engravers, Etchers and Related Occupations,	8585	Fabricating & assembling
8393	Machining	8586	Inspecting, Testing, Grading and Sampling
8395	Patternmakers and Mouldmakers, n.e.c.	8587	Watch and Clock Repairers
8396	Inspecting, Testing, Grading and Sampling	8588	Fabricating & assembling
8399	Other Machining and Related Occupations,	8589	Fabricating & assembling
8510	Fabricating & assembling	8590	Fabricating & assembling
8511	Engine and Related Equipment Fabricating	8591	Jewellery and Silverware Fabricating,
8513	Fabricating & assembling	8592	Fabricating & assembling
8515	Aircraft Fabricating and Assembling	8593	Fabricating & assembling
8523	Fabricating & assembling	8595	Fabricating & assembling
8525	Business and Commercial Machines	8596	Inspecting, Testing, Grading and Sampling
8526	Fabricating & assembling	8598	Fabricating & assembling
8527	Precision Instruments and Related	8599	Fabricating & assembling

F. Goods (cont'd)		F. Goods (cont'd)	
8710	Construction	9518	Occupations In Labouring and Other Elemental
8711	Construction	9519	Printing & related, nec
8713	Construction	9530	Foremen/women: Stationary Engine and
8715	Construction	9531	Power Station Operators
8718	Construction	9539	Stationary engine & utilities equip operating & related
8719	Excavating, grading, paving	9550	Foremen/women: Electonic and Related
8730	Construction	9551	Radio and Television Broadcasting Equipment
8731	Construction	9555	Sound and Video Recording and Reproduction
8733	Construction	9557	Motion Picture Projectionists
8735	Construction	9559	Other electronic & related communications
8736	Inspecting, Testing, Grading and Sampling	9590	Foremen/women: Other Crafts and Equipment
8738	Occupations In Labouring and Other	9591	Photographic processing
8739	Construction	9599	Other Crafts and Equipment Operating
8780	Construction	9910	Supervisors and Foremen/women, n.e.c.
8781	Construction	9916	Inspecting, Testing, Grading and Sampling
8782	Construction	9918	Occupations In Labouring and Other
8783	Concrete Finishing and Related Occupations		
8784	Construction		
8785	Construction		
8786	Construction		
8787	Construction		
8791	Construction		
8795	Construction		
8796	Inspecting, Testing, Grading and Sampling		
9130	Foremen/women: Railway Transport		
9131	Locomotive Operating Occupations		
9139	Railway Transport Operating Occupations,		
9153	Engineering Officers, Ship		
9155	Deck Crew, Ship		
9157	Engine and Boiler-room Crew, Ship		
9159	Engineering officers, ship		
9170	Foremen: Motor transport operating		
9175	Truck drivers		
9179	Motor transport operating, nec		
9190	Foremen: Other transport equip. Operating		
9193	Rail Vehicle Operators, Except Rail		
9199	Other transport equip. Operating, nec		
9310	Foremen: Material handling & related, nec		
9311	Hoisting, nec		
9313	Longshore workers & freight handlers		
9314	Parcel Carriers, n.e.c.		
9315	Material handling equipment operators, nec		
9317	Packaging occupations		
9318	Labouring, other elementary, material handling		
9319	Other Material Handling and Related		
9510	Formen: Printing & related		
9511	Typesetting & composing		
9512	Printing press		
9513	Stereotyping and Electrotyping Occupations		
9514	Printing Engraving, Except Photoengraving,		
9515	Photoengraving		
9517	Bookbinding & related		

Source: Reclassification adapted from Boothby (1999) and Béjaoui (2000), and applied to the 1988 International Standardized Classification of Occupations (ISCO-88).
Notes: not elsewhere classified (nec).

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