WHAT PREDICTS SKILLS MISMATCH IN CANADA?

by

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ABSTRACT

There is a vast body of literature relating to the causes and economic impacts of skills mismatch. Although skills mismatch has become an important area for research and policy development, the measures that have been used to define the phenomenon vary considerably, both in academic research and government analysis. Consequently, it is challenging to understand and make generalizations about the impact of skills mismatch on individual, firm, and economic productivity. Therefore, this paper develops a potentially informative measure of skills mismatch by utilizing the OECD's Canadian PIAAC data. Using this measure, the factors that predict under-skilling and over-skilling in employment are estimated using a multinomial logistic regression model. The most significant predictors of skills mismatch in terms of literacy, numeracy, and problem-solving skills are among Canadian immigrants, individuals with higher levels of educational attainment, and individuals with parents or guardians that have higher levels of educational attainment.

DEDICATION

For God, whose forgiveness and love gives me reason to live.

For Sara, whose continuous encouragement will always be cherished, and to whom I will love endlessly and sacrificially forever.

For my family, whose unfailing belief in me has inspired and enabled me in all facets of life.

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1.0 INTRODUCTION

A topic that is of growing importance for policy development is the causes, prevalence, and effects of skills mismatch (Cappelli, 2014). Workers are considered to be skill-matched when their skill level (supply of skills) is equivalent to the skill requirements of their jobs (demand for skills). Skills mismatch occurs when the skills possessed by workers are higher or lower than the skill requirements of their jobs. Workers that are over-skilled, because they have more skills than what their job requires, are considered under-utilized since some of their skills are not being applied at work. Conversely, workers that are under-skilled, because they have fewer skills than their job requires, are considered over-utilized since they are applying their maximum level of skill but are unable to fulfill the skill requirements of their job.

Skills mismatch has received significant attention in recent years in both academic and government organizations; arguably because of new developments in research that indicate that skill surpluses and deficits are widespread in the workplace (Quintini, 2011b). Allen, Levels, and van der Velden (2013) suggest that the recent surge in research is due to a common belief among researchers that skills mismatch has serious consequences on performance, productivity, and rewards for workers that experience the phenomenon. International organizations and governments prioritize investing in research on skills mismatch due to the concern that it will have a negative impact on social welfare and overall economic productivity (OECD, 2015a; OECD, & Statistics Canada, 2011). Although the topic has become important for policy development and research, the measures that have been developed to define what is meant by skill mismatch varies considerably, both in academic research and government analysis. Consequently, it is challenging to understand and make generalizations about the impact of skill mismatches on firm and economic productivity.

There is a vast body of literature relating to the causes and the economic impacts of skills mismatch, but how the term is defined and measured varies greatly. Even among recently published articles, there is no clear agreement on what method is best for defining skills mismatch (Allen et al., 2013; Pellizzari & Fichen, 2013; Perry et al., 2014). Moreover, many measures of skills mismatch rely on proxies for determining the supply of and demand for skills. This is problematic because understanding and measuring skills mismatch is important for economic performance. Therefore, developing a robust measure for skills mismatch is of prime importance because understanding its prevalence and effects will assist in the development of effective economic and social policy within Canada.

Skills are foundational to every country's economy in relation to both aggregate economic performance and individual success in the labour market (Quintini, 2014). The stock of human capital within an economy is largely impacted by the skills possessed by the overall population (Perry, Wiederhold, & Ackermann-Piek, 2014). As the stock of productivity-enhancing skills increases in an economy, labour market flexibility also increases. Therefore, a high-skilled workforce is able to adapt more quickly to labour market fluctuations and changes in economic conditions.

The skills that an individual acquires are categorized as either cognitive or non-cognitive. Cognitive skills encompass literacy, numeracy and problem-solving, and are seen as foundational for the success of developed economies in the 21st century (OECD, 2012, 2013a). Researchers have demonstrated that higher cognitive skills are systematically related to higher wages, suggesting that modern knowledge-based economies significantly value the cognitive skills that are often required to succeed in the labour market (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2014; OECD, 2013a). In contrast, non-cognitive skills are comprised of attributes such as leadership and communication, and have also been shown to lead to higher wage returns; however, data availability is limited in this area (Balcar, 2014). The development of both cognitive and non-cognitive skills can be beneficial for individual participation and performance in the labour market. As the stock of human capital increases in the economy, technological progression also increases, which leads to economic growth (Desjardins & Rubenson, 2011). However, skills should be used effectively in order to achieve levels of individual and firm productivity that result in growth. In an ideal situation, workers should deploy their skills in such a way that their job-relevant skills are not being under-utilized or over-utilized. This ideal is very unlikely to be achieved throughout an economy, but is still important if a society aims to pursue an efficient allocation of skills.

Changes in the structure of the Canadian economy through demographic and technological shifts are expected to bring about increasing discrepancies between the supply of, and demand for, skills in the labour market (Miner, 2014). These changes have the potential to generate a skills shortage in certain sectors of the economy, which will result in a widespread gap between the skills that people have and the skills that employers are looking for. These expected changes and associated consequences are examples of an expected disequilibrium in the supply of and demand for skills. Some disequilibrium in the supply and demand for skills is normal and is expected to be present in the labour market as the job search process takes time; however, extensive disequilibrium is problematic. Addressing this type of imbalance is important for assessing economic performance because prolonged skills mismatch can have consequences on economic efficiency. Furthermore, the effective use of skills at work is what leads to an efficient allocation of skills in the economy, because workers deploy their skills optimally on the job, which leads to greater productivity and higher quality output.

The first objective of this paper is to develop a robust measure of skills mismatch using data from the Organization for Economic Co-operation and Development's (OECD) Program for the International Assessment of Adult Competencies (PIAAC). I will assess some of the most prominent measures for skills mismatch that are being utilized by other researchers on the PIAAC database. Moreover, I will develop and test a new method for measuring skills mismatch that combines the logic and assumptions from other prominent researchers in the field. I will compare this new method to two other methods that are used by prominent researchers in the field of skills mismatch and determine which measure is potentially informative in order to understand the predictors and extent of skills mismatch in Canada. Using the Canadian data from the PIAAC survey, I will seek to answer the following question: what predicts skills mismatch in Canada?

In this report, I will demonstrate a potentially informative measure of skills mismatch that will draw attention to the impact of skills mismatch on individuals, firms, and the economy. Section 2.0 includes a literature review on the differences between educational mismatch and skills mismatch, the theoretical foundations of skills mismatch, the empirical methods used to measure skills mismatch and the associated impact on labour market outcomes, followed by a set of hypotheses and a conclusion. A detailed description of the data, methods, model, and variables that are used in this study is discussed in section 3.0. The results of the preliminary and main analysis are presented in section 4.0. Section 5.0 contains a discussion on the interpretation of the results, the associated implications, the potential for further research, and the limitations of this study. Section 6.0 contains a brief conclusion.

This study develops a potentially informative measure for skills mismatch in the Canadian context using PIAAC data. The strongest predictors of skills mismatch, in terms of statistical significance and magnitude, are consistently among Canadian immigrants, those with higher levels of educational attainment, and those with parents or guardians that have higher levels of educational attainment. Location, gender, age, and years since immigration are also predictors of skills mismatch.

2.0 LITERATURE REVIEW

2.1 Introduction

The accumulation of skills is fundamental for successful economies. Skills are related to both aggregate economic performance and individual success in the labour market. However, skills must be allocated and utilized effectively in the labour market in order to achieve efficiency that will result in better aggregate and individual performance. Skills mismatch arises when there is a discrepancy between the skills possessed by workers and the skills required by their jobs. Persistent skills mismatch implies inefficiency and is a sign of an unhealthy labour market, since individuals are being under-utilized or over-utilized in the workplace. Various labour market outcomes are affected by skills mismatch in the workplace, including wages and job satisfaction. Additionally, government officials and academics are concerned about skills mismatch having a negative impact on social welfare and overall economic productivity. International economic and social policy development hinges upon understanding this phenomenon in greater detail. Therefore, understanding the various measures and methods used to operationalize skills mismatch is of great importance. Theoretical frameworks for the causes and impact of skills mismatch are largely impacted by the definition of "skill".

It is important to distinguish between two concepts before establishing a theoretical framework for the causes of mismatch: skills mismatch and educational mismatch. Skills mismatch is the discrepancy between the skill level of a worker and the skill requirements for that worker's job. In contrast, educational mismatch[1] is the discrepancy between the educational attainment of a worker and the standard

[1] Educational mismatch is also referred to as credential mismatch or qualification mismatch.

educational requirements for that worker's job. As research has evolved, the two concepts have become distinct rather than interchangeable (Desjardins & Rubenson, 2011; Quintini, 2011b).

Educational attainment has commonly been used as a proxy for skill supply, which is problematic because it does not adequately take into account the heterogeneity of skills among differing levels of attainment. Educational attainment is likely to reflect skills to some extent, but looking exclusively at credentials to determine skills mismatch is insufficient for the following reasons: (1) student performance varies at each education level and field of study; (2) credentials reflect only the skills that are learned from formal training; (3) skills that are learned from labour market experience are not considered; and (4) some of the skills that are acquired from formal education are likely to deteriorate over time if they are not used (Krahn & Lowe, 1998; Quintini, 2011a). By definition, credentials are not skills; however, they do provide an indication of a potential set of skills. Understanding educational mismatch is valuable because the associated policy implications have relevance, given that persistent over-education is indicative of wasteful public and private investments in education, and under-education is indicative of under-investment in education and training. However, research indicates that educational mismatches do not necessarily denote skill mismatches (Allen & van der Velden, 2001; Allen & de Weert, 2007; Levels, Allen, & van der Velden, 2014). It is therefore important to measure actual skills mismatch rather than use proxies to measure its extent and effects.

Studies that examine educational mismatch focus predominantly on over-education because of the expanding supply and demand for tertiary education in developed economies over the last few decades (Chevalier, 2003; Duncan & Hoffman, 1981; Groot & Maassen van den Brink, 2000; Hartog, 2000; Leuven & Oosterbeek, 2011; Levels et al., 2014; McGuinness, 2006; Quintini, 2011a; Robst, 1995, 2007; Sloane, 2003). Researchers describe educational mismatch as being either vertical or horizontal. Vertical mismatch implies that there is a difference in the *level* of education, whereas horizontal mismatch implies that there is a difference in the *type* of education between workers and their job requirements. Several methods exist that measure the supply of and demand for education within jobs, including: analyzing mismatch via self-reporting, general educational requirements for occupations, or the estimated distribution of educational attainment within occupational groups (Chevalier, 2003; Duncan & Hoffman, 1998; Hartog, 2000; Levels et al. 2014). Similar methods are used for measuring skills mismatch. It is important to recognize that the studies on educational mismatch do not measure skills mismatch as defined in this paper: educational attainment is viewed as an indirect measure of skills. Therefore, skills mismatch is a more precise measure for what educational mismatch, in part, attempts but fails to explain. Henceforth, educational and skills mismatch must be seen in this light, related but distinct from one another.

2.2 Theoretical foundations of skills mismatch

Modern day labour markets are characterized by various imperfections, including but not limited to: wage rigidities, imperfect information about workers' skills, matching frictions, and limitations on workers' geographic mobility (Quintini, 2011b). Imperfections provide an explanation for why mismatch exists in the labour market, both among the unemployed and employed. This study will focus only on mismatch among the employed population, but the theoretical principles underlying the causes of skills imbalances are similar for both segments of the labour market.

There are various economic theories that attempt to provide an understanding of the labour market and what precipitates skill mismatch. The main theories that are relevant to the concept of mismatch are human capital theory, technological change theory, career mobility theory, search theory, signalling theory, and assignment theory. The main premise behind *human capital theory* (HCT) is that knowledge enhancement through education and training develops the skills that lead to higher productivity and wages, ultimately resulting in economic growth (Becker, 1962; Mincer, 1958, 1974; Schultz, 1961). Within the neoclassical framework of economics, HCT suggests that mismatches are a short-term phenomenon since firms adjust their production processes in order to maximize their stock of human capital, or workers find a new job that maximizes their production potential and earnings. Therefore, market forces will lead to equilibrium in the long-run. HCT provides a primitive notion of how the economy functions. The theory focuses entirely on the supply side of the labour market and assumes that the accumulation of human capital is the sole determinant for changes in earnings. Nevertheless, this theory is foundational to the evolution of labour market theories.

Romer (1990) posits that human capital accumulation accelerates growth in an economy, which is a fundamental assumption embedded within *technological change theory*. HCT does not explicitly account for technological change and the associated labour market effects. Technology development is continual in modern economies, but an adjustment process that takes place when employers and workers decide what technologies to invest in or learn. Technological change often adjusts the skill requirements that are needed for jobs, which can lead to mismatch. As new technologies are adopted, skills that were once productivity-enhancing may become obsolete.

Alternately, workers may seize the opportunity to develop skills that are related to new technologies because it will serve to enhance their skillset. Technological change has been viewed by some as cause for the hollowing out of medium-skilled occupations, thus leading to greater wage polarization and inequality (Acemoglu & Autor, 2010; Kolev & Saget, 2010). As new technologies are adopted, high-skilled workers are required and favoured in the labour market over workers that do not have the skills to deal with technological change. This is referred to as skill-biased technological change. Skill-biased technological change can induce demand for certain skills within some occupations and sectors of the economy, which can be advantageous for some while disadvantageous for others (Acemogly & Autor, 2012). Katz (1999) argues that technology enhancements will boost the stock of human capital if proper adjustments are made in a timely manner. The ongoing race between technology and human capital accumulation changes the marketplace for skills, which inevitably leads to some inequality and skills imbalances (Goldin & Katz, 2008). It is the speed at which adjustments are made in the labour market that will determine the extent of these imbalances.

Career mobility theory, pioneered by Sicherman and Galor (1990), suggests that as individuals progress in their career, the ongoing acquisition of human capital and job tenure in one occupation increases the likelihood of occupational mobility and higher returns. This theory contrasts the view that job tenure decreases the likelihood of occupational mobility (Jovanovic, 1979). The likelihood of career mobility decreases over time, which indicates that the incidence of occupational mobility is highest among young, educated individuals. Therefore, over-education and its associated effects are temporary as individuals find their way into jobs that match their skill level (Desjardins

& Rubenson, 2011; Robst, 1995). According to career mobility theory, mismatch is considered to be a temporary phenomenon until workers optimize their skills and become matched for their jobs.

In contrast to human capital theories and career mobility theory, *search theory* and *signalling theory* explain mismatch based on the premise that there is imperfect information between employers and workers during the job search process (Arrow, 1973; McCall, 1970; Spence, 1973; Stigler, 1962). Search theory focuses on the individual-level decisions that are involved in the transition from unemployment to the labour market. Imperfect information can lead to workers being placed in jobs that do not optimize their skillset, which can affect firm productivity. This lack of information between both parties leads to workers signalling their competence levels to potential employers in order to stand out. In comparison, signalling theory emphasizes that workers use their qualifications as a means for showcasing their abilities to employers, who then select workers on the basis of requiring less investment in training and a greater likelihood of enhancing firm productivity (Arrow, 1973; Spence, 1973; Weiss, 1995). Therefore, qualifications act as a sorting mechanism for employers. In reality, there are many other skills beyond qualifications that are valued by employers and are used by individuals as a display of their competence level.

Lastly, *assignment theory* builds upon previous theories, but stresses the importance of both individual and job characteristics such that additional investments in human capital depend on the job-worker match (Sattinger, 1993, 2012; Tinbergen, 1956). Within this framework, both the supply and demand for labour play an important role, as workers are assigned to jobs that match their skillset and the skill requirements of their jobs. Skill supply and demand are therefore viewed as two parallel continuums.

Assignment theory predicts that productivity is maximized when both continuums are aligned and joined together, like the rungs of a ladder. High-skilled individuals will be assigned to more complex jobs, and low-skilled individuals will be assigned to simpler jobs. This framework acknowledges heterogeneity in both the supply of and demand for skills, and allows for an adjustment process between the two. However, imperfect information can lead to workers being placed into jobs that do not optimize their skillset. For example, employers could misread the skillset of workers and place them into complex jobs that do not accurately reflect their competence level, or workers could take jobs that do not match their skillset for any number of reasons (e.g., financial or circumstantial reasons). Therefore, persistent skills mismatch is possible in assignment theory. Long-term skills mismatch is indicative of inefficiency in the labour market, which warrants detailed study of the phenomenon.

There are other theories that attempt to cite the sources of imperfection pertaining to skills, including unobserved differences among worker and employer preferences, attitudes, and expectations (Desjardins & Rubenson, 2011). For example, some people may voluntarily choose not to deploy their skills on the job, or employers may mismanage the potential of their workers. It is also possible that employers could hire workers that are initially under-skilled for their jobs with the intention of training them to become adequately skilled. Additionally, workers may face barriers that cause them to remain employed in jobs that do not match their skillset. Some of these potential barriers include: a lack of awareness about alternate opportunities in the labour market, a genuine lack of opportunities in the labour market, financial or circumstantial constraints that prevent geographic mobility or investment in formal training, and employers that are unwilling to support training their employees.

Researchers have attempted to explain which theoretical perspectives best reflect the concept of mismatch (Duncan & Hoffman, 1981; Hartog & Oosterbeek, 1988; Sloane, Battu, & Seaman, 1999; McGuinness, 2006). Assignment theory is generally accepted as the most consistent with findings on mismatch and its effects on wages (Desjardins & Rubenson, 2011; Quintini, 2011b). Most researchers have attempted to develop a framework for educational mismatch utilizing the theories identified above. I will apply the same principles to advance and contribute to the current research that is being conducted on skills mismatch.

2.3 Skills mismatch and its impact on labour markets

Current research has highlighted that there is a wage premium associated with under-education, and a wage penalty associated with over-education, relative to individuals that have the same level of education and that are educationally matched for their jobs (Hartog, 2000; Mavromaras, McGuinness, O'Leary, Sloane, & Wei, 2013; Quintini, 2011b). However, there is evidence that suggests skill heterogeneity partially explains the wage effects associated with educational mismatch (Allen & van der Velden, 2001; Chevalier, 2003; Levels et al., 2014; Mavromaras et al., 2013; McGuinness, 2006). These findings have prompted research that is focused on the incidence of skills mismatch and its effects on labour market outcomes. Interestingly, researchers have struggled to accomplish this task for many years due to data limitations.

Directly comparing the skills that workers have and the skill requirements of their jobs would be an ideal measure of skills mismatch. Unfortunately, no direct measures of skill supply and demand are currently available on a large-scale. Therefore, alternative measures are used in order to study skills mismatch. Regardless of which measure is used, as individuals acquire skills they become less likely to be under-skilled and more likely to be over-skilled. Direct measures using cognitive skills such as literacy and numeracy and indirect measures such as self-reported measures, are two approaches that are used to measure skills mismatch. Direct measures are advantageous because they measure specific skills that are lacking or in excess, but they only provide partial information on the overall incidence of skills mismatch. Self-reported measures are advantageous because they provide information on the overall incidence of skills mismatch, but they do not take into account the specific skills that are lacking or in excess (Quintini, 2011b). The incidence of over-skilling is consistently higher among self-reported measures, which is probably due to biases associated with the type of information that is collected and utilized. Depending on the method and country being studied, the incidence of skills mismatch can be nearly 50% of the working population (Quintini, 2011b).

Research shows that over-skilling in literacy is more likely to be among young workers, workers in non-supervisory jobs, the self-employed, and part-time workers (Krahn & Lowe, 1998). Recent research also indicates that men are more likely than women to be over-skilled, individuals with high educational attainment are more likely to be over-skilled and less likely to be under-skilled, and immigrants are less likely than non-immigrants to be over-skilled and more likely to be under-skilled (Pellizzari & Fichen, 2013). However, the types of skills assessments within the studies of skills mismatch may significantly impact the findings related to immigrants. Overall, women experience more difficulty finding employment than men, which could lead to them taking jobs that do not match their skillset. It is also possible that women use their skills less frequently in their jobs because of the types of jobs they typically have. Moreover,

over-skilling is likely to be present among individuals with higher credentials, given that there are some similarities between educational mismatch and skills mismatch. Over-education is prominent in developed countries, including Canada, due to an emphasis on higher education. Immigrants are more likely to be over-educated for their jobs because their foreign credentials are often not recognized in Canada, they tend to be unfamiliar with the official languages, and are likely to experience racial discrimination (Quintini, 2011b). These factors can also affect the extent to which immigrant status predicts skill mismatches, which has been shown to be true within the domain of literacy, but not numeracy (Pellizzari & Fichen, 2013). This is not surprising, given that the assessments of literacy skills are likely to be disadvantageous for immigrants. Therefore, although immigrants are often over-educated for their jobs, it is not necessarily true that they will also be over-skilled in terms of the cognitive skills that are often measured in skills assessments. Furthermore, the longer that immigrants remain in Canada, the more they integrate into society. As they become integrated, their labour market outcomes improve and job mobility increases (Godin, 2008). This could be indicative of immigrants finding jobs that require higher skills, which is likely to increase the propensity to be skill-matched for their jobs. Therefore, as immigrant duration increases, skill mismatches could become less likely.

Research on educational mismatch indicates that the core working-age population is less likely to be mismatched (Hanushek et al., 2014). This is expected to be the case with skills mismatch as well, given that there are some similarities between educational and skills mismatch. Career mobility theory and assignment theory assume that over time workers will generally become appropriately skilled for their jobs. Therefore, as age and work experience increase it is expected that skill mismatch will be less prominent. However, some research has shown that literacy skills will become more specialized over time and may lead to an overall decline for workers that become appropriately skilled for their jobs, since their job tasks become focused and routine (Desjardins & Rubenson, 2011). Accordingly, as age increases so does the incidence of being under-skilled (Desjardins & Rubenson, 2011).

Most studies that measure skills mismatch involve international comparisons. The results from these studies indicate that the incidence and effects of skills mismatch varies significantly from one country to another. Allen et al. (2013) identify differences within countries in addition to between countries. The authors recognize that labour market characteristics and the economic structure within countries are likely to exhibit variation in terms of skills mismatch and its effects. It is important to recognize that provincial economies and population characteristics vary significantly within Canada, which is likely to affect the distribution of skills to some extent. Several tests are conducted on the PIAAC data to verify the extent of skills mismatch across provinces and territories. Results indicate that there is not a tremendous amount of variation, with the exception of the Territories and some of the Atlantic Provinces. It is likely that structural economic differences in the Atlantic Provinces and Territories give rise to skills mismatch. Perhaps fewer opportunities are available in these regions relative to other parts of the country, which may lead to an increased likelihood of over-skilling, since individuals may be willing to accept jobs that do not match their skillset. However, it is also possible that individuals in these regions are more likely to be under-skilled because high-skilled workers tend to seek out opportunities in other areas of the country. Moreover, if this type of migratory behaviour persists over time, it could increase the ratio of under-skilling relative to over-skilling in these areas.

Another way to test for geographic variation in the incidence of skills mismatch is to use population density, although no current studies have used such variables to observe differences in skills mismatch. Urban areas in Canada are typically hubs for culture and innovation, and usually have more diverse labour markets than lesser-populated areas (Trovato, 2009). By having more opportunities in urban areas, it draws people to these areas, and could increase the likelihood of workers being appropriately skilled for their jobs. However, individuals that work in non-urban areas where there are less diverse labour markets may tend to be skill-mismatched for their jobs. These individuals are likely to be attached to their non-urban locales, because of strong ties to their communities. Individuals that have a large network of friends and family in a given region are less likely to migrate to seek better employment opportunities. Therefore, skills mismatch could be more likely to occur in non-urban areas of the country.

Aboriginal Canadians and French Canadians are two important minority groups in Canada. Many social policies are aimed at protecting the rights of both of these people groups in order to preserve their socio-cultural identities. Currently no study has embarked on observing skills mismatch differences between the general population and both of these groups, largely because of data limitations. PIAAC data provides a unique opportunity to observe the extent to which Aboriginal status and having a French mother tongue predicts skill mismatches. Aboriginal Canadians face many barriers to education and employment that may increase the likelihood of being skill mismatched relative to non-Aboriginals (Merrill, Bruce, & Marlin, 2010). Overall, Aboriginal peoples in Canada have lower levels of educational attainment, income, and poorer labour market outcomes compared to their non-Aboriginal counterparts (Cooke & O'Sullivan, 2014).

Therefore, it is likely that under-skilling will be present in the Aboriginal population due to the barriers and challenges faced within Aboriginal communities. Additionally, it is possible that there are socio-cultural differences between French Canadians and non-French Canadians that could play a role in determining the extent of skill mismatches; however, no such evidence exists in current literature. In most parts of Canada except for Quebec, French Canadians are a minority language group. Therefore, it is possible that discrimination or language barriers could affect the incidence of skill mismatch among French Canadians.

A common proxy for socio-economic background that is common in sociological research is the education level of an individual's parent or guardian. Traditionally, attaining higher levels of education opens up more opportunities with higher rewards in the labour market. Therefore, individuals that have parents with higher levels of education are more likely to grow up in an environment that encourages and emphasizes the pursuit of higher education and skills (Finnie, 2012). In contrast, individuals that grow up in households with parents without higher education do not tend to have the same opportunities (Finnie, 2012). Therefore, it is likely that under-skilling will occur among individuals whose parents have lower levels of educational attainment, and that over-skilling will occur among individuals whose parents have higher levels of educational attainment.

Certain occupational levels are expected to predict skills mismatch (Allen et al., 2013).[2] Workers in higher-level occupations are more likely to be under-skilled and less likely to be over-skilled (Allen et al., 2013). Higher-level occupations contain more

[2] Occupational levels are measured by aggregating occupational categories into groups that approximate job complexity.

demanding job duties and generally require a diverse skillset. Therefore, workers in these occupations are more likely to be over-utilized, which is equivalent to under-skilled. The authors point out that occupational variation is one important factor in determining the incidence of skills mismatch.

Studies on both educational and skills mismatch show that workers that are over-educated, or over-skilled for their jobs, tend to be paid less than their matched counterparts, and tend to be less satisfied with their jobs. These individuals are considered to be under-utilized for their job, which decreases their satisfaction and wages relative to matched individuals. Under-educated and under-skilled workers tend to be paid more than their matched counterparts. These individuals are considered to be over-utilized for their jobs, which increases their wages relative to matched individuals. The effects of mismatch on labour market outcomes are less severe for skills mismatch than educational mismatch (Allen et al., 2013; Perry et al., 2014). Additionally, the effects of educational mismatch on wages and job satisfaction are lessened when skill differences are accounted for among different education levels (Allen & van der Velden, 2001; Levels et al., 2014; Quintini, 2011a, b). Overall, the impact of skills mismatch on labour market outcomes is less severe than educational mismatch, but still existent. This could be due to mismatch being more related to occupation-specific or generic skills than to the literacy and numeracy skills, or that employers successfully adapt job content according to the skills of their employees (Quintini, 2014).

The effects of over-skilling on workers are more severe than under-skilling, which has been shown using Australian panel data (Mavromaras et al., 2013). This study finds that women experience wage penalties and job dissatisfaction more severely than men do. The authors also argue that mismatch is more damaging for women than men. Other researchers have argued that over-education and over-skilling may lead to greater job mobility because of the associated wage penalties and lack of job satisfaction (Allen & van der Velden, 2001; Quintini, 2011b). Job mobility is likely to affect firm productivity in the short-run, but the extent of this effect has not been studied in detail (Quintini, 2011b). If skills mismatch is pervasive in an economy it may lead to structural issues and persistent unemployment (Quintini, 2011b).

2.4 Conclusion

Skills must be allocated and utilized effectively in the labour market in order to achieve efficiency that will result in better aggregate and individual performance. Various labour market imperfections lay the groundwork for the reasons why some workers are employed in jobs that they are under-skilled or over-skilled for. Variations of human capital theory provide the theoretical foundations for what precipitates skills mismatch in an economy. At the aggregate level, government officials and academics are concerned about the negative impact skills mismatch could have on social welfare and overall economic productivity. At the individual level, various labour market outcomes are affected by skills mismatch in the workplace, including wages and job satisfaction. Over-skilled workers tend to earn less, and under-skilled workers tend to earn more, than their skill-matched counterparts do. Additionally, job satisfaction is lessened for these individuals. Women are less likely to be over-skilled for their jobs than men are. Younger workers and immigrants are more likely to be under-skilled for their jobs. Individuals with higher educational attainment are more likely to be over-skilled for their jobs.

2.5 Hypotheses

Based on the literature review the following hypotheses are examined:

1. Workers that reside in the Atlantic Provinces and Territories are more likely to be under-skilled than the rest of Canada.
2. Workers that reside in urban areas are less likely to be under-skilled than non-urban areas.
3. Female workers are more likely to be under-skilled and less likely to be over-skilled than male workers.
4. There is an aging effect associated with skills mismatch, such that older workers are more likely to be under-skilled than younger workers, and younger workers are more likely to be over-skilled than older workers.
5. Immigrant workers are more likely to be under-skilled and less likely to be over-skilled than Canadian-born workers.
6. As immigrant duration increases, immigrant workers are less likely to be under-skilled and more likely to be over-skilled.
7. Aboriginal Canadian workers are more likely to be under-skilled and less likely to be over-skilled than non-Aboriginal Canadian workers.
8. French Canadian workers are more likely to be under-skilled and less likely to be over-skilled than non-French Canadian workers.
9. Workers with higher levels of education are less likely to be under-skilled and more likely to be over-skilled.
10. Workers that have parents or guardians with higher levels of education are less likely to be under-skilled and more likely to be over-skilled.
11. Workers in higher-level occupations are more likely to be under-skilled and less likely to be over-skilled.

3.0 DATA, METHODS, MODEL & VARIABLES

3.1 Data

The Program for International Assessment of Adult Competencies is an initiative of the OECD. The purpose of the PIAAC is to collect, distribute, and analyze data that will assist government organizations in understanding the distribution of skills in a population in order to improve policy development. PIAAC is an international survey that attempts to capture the level, distribution, and utilization of both hard and soft skills among the adult population (PIAAC, 2015). The Survey of Adult Skills is the main output of the PIAAC and will henceforth be referred to as ‘PIAAC’, or ‘the Survey’, for simplicity.

PIAAC is made up of two main components: a direct skills assessment and a background questionnaire that includes a module on the use of skills. The Survey was administered to people in 24 countries, including the United States, Australia, Japan, the United Kingdom, and Canada. It was designed with complex sampling methods so that comparisons could be made between and within countries. The direct assessment focused on proficiencies in three domains of foundational skills: literacy, numeracy, and problem-solving in technology-rich environments. The literacy, numeracy, and problem-solving measures within PIAAC are considered to be essential information-processing skills for three reasons:

1. They are necessary for integrating and participating in the labour market, education and training, and social and civic life;
2. They are highly transferable in various social and professional contexts; and
3. They are “learnable”, which can help guide policy development (OECD, 2013d).

Respondents were given a prescribed amount of time to complete various tasks pertaining to each domain that they participated in. The problem-solving domain is the only domain that was administered solely through a computer-based assessment. In the literacy and numeracy domains, respondents had the option to do a paper-based assessment. The sample size is lower for the problem-solving domain, because some individuals refused or they were not able to complete the assessment via computer. Respondents were assigned scores for each domain that range between zero and 500. These scores were then collapsed into proficiency levels to help facilitate meaningful comparisons between groups (OECD, 2015b).[3]

The second component of PIAAC is comprised of the background questionnaire, which identifies important socio-demographic and socio-economic information, including but not limited to: income, labour force activity, current occupation, educational attainment, immigrant status, gender and age. The background questionnaire also measured skill usage in everyday life and in the workplace. Cognitive and interpersonal abilities were taken into account, such as the degree to which individuals utilize literacy, numeracy, communication, and computer skills at home and at work. This section of the background questionnaire asked respondents to rank their cognitive and interpersonal abilities using a Likert scale.

The Canadian portion of PIAAC was administered by Statistics Canada on behalf of several partners. In-home interviews took place between November 2011 and June 2012; most of which involved a computer-based survey, but some people opted for a paper-based version (PIAAC, 2015). Respondents were able to select French or English as their language for the interview and assessment. Rigorous sampling methods were

[3] See Appendix A for a detailed description of each proficiency level.

applied before data collection, which enabled generalizable results for each Province and Territory. Stratified random sampling and clustering were used. One advantage of PIAAC data is that minorities, which are often under-represented in other surveys, were oversampled in most provinces and territories in order to provide adequate information about Aboriginals, immigrants, and official-language minorities (PIAAC, 2015). All PIAAC databases that are distributed to users internationally eliminate any confidential information that could violate the privacy of respondents who participated in the Survey.

The Province of New Brunswick purchased the PIAAC Restricted-Use File (RUF) through Statistics Canada for Canadian data. A senior economist of the Province is the data custodian for the PIAAC database. That individual ensures that users of PIAAC in New Brunswick understand and follow all of the guidelines outlined in the contract between the Province and Statistics Canada. I gained access to the PIAAC RUF through my employment with the Province. All of the results that are presented in this document abide by the requirements that are expected for all users of PIAAC in Canada and internationally. Only aggregate data is released in order to ensure confidentiality of the participants. STATA version 13 and SPSS version 22 are the statistical software programs that were used to generate the results in this paper.

PIAAC is a cross-sectional dataset that contains information on individuals between ages 16 and 65 in each Province and Territory. The Canadian portion of the survey contains information about 27,285 Canadians. Each observation is given a weighted value that enables the sample to be representative of the Canadian population between ages 16 and 65, totalling 23,381,067 individuals. The three domains of literacy, numeracy, and problem-solving were calibrated, analyzed, and scaled, resulting in ten sets of plausible values for each respondent according to each domain. Skills are latent variables in PIAAC that are estimated using item-response-theory models (IRT). IRT allows for some imputation of proficiency scores for each individual, since not everyone in the survey completed the exact same assessment. The ten plausible values are used to reduce bias and deal with the complicated sample design of PIAAC. The Canadian PIAAC data applies the delete-one jackknife (JK1) replication method and multiple imputation approach for plausible values to derive appropriate weights and variance estimates (PIAAC, 2013c). Eighty replicate weights were derived per individual for the Canadian sample. Similar approaches have been used in other international surveys involving direct assessments of competencies, such as the International Adult Literacy Survey (IALS) and the Program for International Student Assessment (PISA).[4]

3.2 Methods

3.2.1 Methods from previous research

There have been various studies done in order to determine what is the most appropriate method for understanding skills mismatch; however, researchers are unable to come to a consensus. The division is largely attributable to data issues. Currently there are no large-scale databases that adequately measure the supply of and demand for skills in an objective manner. Data pertaining to the supply of skills is abundant; however, the demand side of the equation is lacking, particularly within the same databases. Consequently, researchers must resort to the best available information from data sources that contain some combination of objective and subjective criteria in order to determine the incidence and effects of skill discrepancies in the labour market. To

[4] See the OECD's Technical Report on PIAAC for more detailed information on the sample and methods used to construct variables (OECD, 2013c).

this end, researchers have turned to PIAAC data because of its recency and overall strength.

Currently there are two basic approaches to measure skills mismatch: self-reported or direct approaches (Perry et al., 2014). The self-reported approach is based on asking workers how well their skills match to the skill requirements of their jobs. In contrast, the direct approach involves directly comparing the skills workers have to the skill requirements of their jobs. Skill requirements can be measured through self-reporting, or by obtaining occupation-specific skill levels (Pellizzari & Fichen, 2013). Any information involving self-reporting is subject to a number of limitations, including but not limited to, the social desirability bias, overconfidence, and an implicit assumption that workers have the ability to accurately assess the skill requirements of their jobs. PIAAC data provides information on all of these approaches. However, researchers use a number of different methods within each approach.[5]

The first method involves the self-reported approach by using a combination of two variables to identify skills mismatch. The two questions are:

1. Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job? (Over-skilled)
2. Do you feel that you need further training in order to cope well with your present duties? (Under-skilled) (OECD, 2013b)

Respondents are required to answer either yes or no to both questions. The first question is intended to identify individuals that are over-skilled. The second question is intended to identify individuals that are under-skilled. In theory, combining the responses together should uniquely identify both aspects of skills mismatch, and for respondents

[5] See Perry et al. (2014) evaluation of the pros and the cons of each method.

that answered no to both questions it should identify individuals that are adequately skilled for their jobs. However, this is not the case.

Table 3.1

Self-reported skills mismatch

	Under-skilled	
Over-skilled	Yes	No
Yes	23%	66%
No	3%	8%

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data.

Table 3.1 shows that there approximately 23% of the sample answered yes to both questions, which implies that some respondents are simultaneously over-skilled and under-skilled. Only 8% of respondents are considered skill matched for their jobs. This finding is counter-intuitive, as it is expected that most individuals should be skill-matched for their jobs. These results call into question the validity of using these questions to identify skills mismatch. Ultimately, the questions can be interpreted in many different ways; for instance, respondents could have been thinking about different skills when answering each question. Therefore, using this method to identify skills mismatch is inadequate, or at best very weak. Perry et al. (2014) acknowledge these limitations, and explicitly state "[t]he self-reported measure in PIAAC should … not be used for measuring skill mismatch" (p. 148).

Direct approach for measuring skills mismatch

Another method for measuring skills mismatch involves using the direct approach, which involves comparing the literacy and numeracy proficiency levels in PIAAC, to skill use at work. In theory, this approach captures the skill supply in an objective manner through the cognitive assessments, but relies on self-reported information to measure the demand for skills in the workplace. Respondents are asked a series of questions that indicate the frequency with which they use specific skills pertaining to their jobs. They are asked to rank the frequency on a scale of one to five: (1) never; (2) less than once a month; (3) less than once a week but at least once a month; (4) at least once a month but not every day; and (5) every day.

By combining the reading and writing skills used at work and averaging the results, it generates a scale that represents a respondents overall literacy use at work. The same process is applied to numeracy skill use at work. Both of these scales are tested for internal consistency by obtaining a value for Cronbach's alpha. Cronbach's alpha provides a reliability coefficient that uses the mean of inter-item correlations to measure the stability of a scale (Warner, 2008). In applying this logic to PIAAC data, I obtained alpha values greater than 0.8 for the literacy and numeracy scales, which is well above the generally accepted threshold for reliability (>0.7) (Warner, 2008).[6,7]

Literacy and numeracy proficiency levels range from zero to five, but can be recoded such that levels zero and one are collapsed together. This facilitates an easy comparison between individual skill levels and skill use at work. In theory, any difference between a worker's skill level and skill use can be used to define skills mismatch. However, this method is limited because it relies on self-reported skill use at work, which is prone to bias (Hartog, 2000; Perry et al., 2014). Furthermore, skill level is based on information-processing tasks, whereas skill use is based on frequency of use. These limitations challenge the validity of this construct for skills mismatch (Pellizzari & Fichen, 2013; Allen et al., 2013).

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[6] See Appendix B for the specific questions that are included in the scales for literacy and numeracy skill use at work.
[7] SPSS version 22 was used to compute Cronbach's alpha.

Allen et al. (2013) aim to improve the validity of the previous method by standardizing literacy and numeracy skill levels and skill use at work. Each respondent's standardized skill use at work is subtracted from his or her standardized skill level. Given that these variables are mean-centred, any deviation from zero represents a respective negative or positive change in standard deviation away from the mean. A value of zero indicates that an individual's skill level is matched for the skill requirements of his or her job. As values depart from zero in a positive direction, it represents being over-skilled. In contrast, as values depart from zero in a negative direction, it represents being under-skilled. Allen et al. (2013) use 1.5 standard deviations above or below the mean as the cut-off for determining skill mismatch.[8] Therefore, individuals that are beyond the positive cut-off point are over-skilled and individuals that are beyond the negative cut-off point are under-skilled. Likewise, individuals that fall within the boundary of each cut-off point are considered skill-matched for their jobs. The authors note that this measure of skills mismatch is "the extent of skill use relative to one's own skill level" (Allen et al., 2013, p. 4).

This new and improved method is intended to make skill level and skill use comparable to one another by standardizing both variables. However, this method is not exempt from limitations. It still uses self-reported information, and the authors only use one of the plausible values, suggesting that most of the results do not change significantly (Allen et al., 2013). Using only one plausible value in PIAAC can result in biased standard errors and inaccurate parameter estimates (Rutkowski, Gonzalez,

[8] The authors do not provide justification for using 1.5 standard deviations as a cut-off; neither do other researchers in the literature relating to skills mismatch. They discuss this as a limitation of their research, and argue that 1.5 is a more realistic characterization of the incidence of skills mismatch, rather than 1.0 or 2.0 standard deviations, which are considered to be too lenient and too strict.

Joncas, & von Davier, 2010). All plausible values should be used in order to accurately reflect individual proficiency scores. Perry et al. (2013) explicitly show how using different plausible values can result in biased results by replicating the Allen et al. method (Allen method) and generating and comparing the results for each plausible value. Another possible limitation with this method is the arbitrary cut-off point of plus or minus 1.5 standard deviations (Allen et al., 2013; Perry et al., 2014).

Pellizzari and Fichen (2013) also criticize the Allen method. These authors suggest that the construct for mismatch provided by Allen et al. is insufficient because skill level and skill use are constructed differently, and therefore, should not be directly compared. As a result, Pellizzari and Fichen (2013) derived what is considered to be the official skills mismatch measure for the OECD. The OECD method uses a different direct approach by obtaining general occupation-specific skill levels. As a first step, respondents within each country that are skill matched, according to the self-reported method, are grouped together by one-digit occupational codes. The authors use the first digit of the 2008 International Standard Classification of Occupations (ISCO) codes to define ten broad occupational groups. The ISCO codes are based upon occupational classifications that are defined by the International Labour Organization. The occupational classifications are organized and grouped into four-digit codes, of which there are 436. The four-digit codes are aggregated into three-digit (130), two-digit (43), and one-digit groups (10).[9] The 5th and 95th percentile of proficiency scores within each occupational group is defined for self-reported skill-matched individuals. Respondents

[9] Example of ISCO occupational classifications:
9321: Hand packers;
932: Manufacturing labourers;
93: Labourers in mining, construction, manufacturing and transport;
9: Elementary occupations

that fall within this range compose the final skill match category for each occupational group. Individuals with proficiency scores that are above or below this prescribed range are considered over- or under-skilled, respectively, relative to others in the same occupational group. This method assumes that workers within the same occupational groups have similar job requirements.

Perry et al. (2014) and Allen et al. (2013) both point out fundamental issues with the OECD method and critique its usefulness. First, this method builds upon the self-reported method of defining skills mismatch, which has severe limitations that have already been explained in detail. Furthermore, by using broad occupational groups to define skill mismatch, this method fails to account for skill heterogeneity within each occupational group. There are dozens of occupations within most broad groups that may contain vastly different skill requirements. Moreover, some occupational groups contain a very small number of self-reported skill matches, which makes the 5th and 95th percentiles questionable as the basis for distinguishing between skill matches and mismatches. An additional problem with this method is the treatment of plausible values (Perry et al., 2014). The plausible values are averaged to generate the range of skill-matched respondents. These averaged ranges are applied back to the full sample to derive skill mismatches. This method may lead to biased results (Rutkowski et al., 2010).[10] The OECD method for defining skills mismatch is questionable primarily because of using the self-reported method as a means for defining its skill-matched base.

The last method used in recent research to define skills mismatch by utilizing a direct approach is introduced by Perry et al. (2014), and combines some of the strengths

[10] The alternative is to use all plausible values independently and then average the results to derive one estimate at a time.

from previous methods while also accounting for some of their limitations. This method avoids using any self-reported information, which increases the sample size enough to use two-digit ISCO codes instead of one-digit ISCO codes. This accounts for some of the skill heterogeneity problem with the OECD method. Proficiency scores are standardized for each country and occupational group, and cut-off points of plus or minus 1.5 standard deviations is used to define the boundaries for skill-matched and skill-mismatched individuals. Therefore, individuals are over-skilled or under-skilled when their skills are at least 1.5 standard deviations above or below the mean, relative to others in the same occupational group. In an effort to increase the robustness of this method, only occupational groups with at least 30 observations are used. One strength of this method is that it avoids using any self-reported information when determining skills mismatch, which has been shown to increase biases. Another strength is that instead of using only one plausible value or averaged plausible values, this method generates ten sets of skill mismatch variables per individual. Ten sets of results are generated for any estimate and the results are averaged to produce one final estimate. However, a limitation of this model is that it depends on occupational groups having at least 30 observations. This is good for reliability but problematic if there are several occupational groups that have to be excluded, which may be the case depending on the country being studied.

The self-reported method and the OECD method both produce weak measures of skill mismatch. The main weakness of the Allen method is that it uses self-reported skill use at work to compare with assessed skill level. However, the extent to which this is a weakness is not known. In theory, it is weak because of the potential biases associated with self-reported information and only using one plausible value. Perry et al. (2014)

redefine this method by accounting for all plausible values. This improves the validity of the measure, but the other potential limitations remain. The main weakness of the Perry et al. method (Perry method) is that it uses occupational groups to define individual skill requirements. Some, but not all, skill heterogeneity within occupations is accounted for by using two-digit occupational groups. Additionally, this method is limited insofar as it uses the average skill levels within occupational groups to benchmark individual performance.

3.2.2 Methods used in this study

Direct approaches are useful when measuring skills mismatch because they do not rely on self-reported information. The Allen and Perry methods both use the cognitive skills assessments to determine skill levels, but they differ in terms of how they define the skill requirements of a worker's job. The Allen method uses self-reported information, whereas the Perry method uses occupation-specific skill levels. Given that both of these methods differ significantly in terms of the way they define the skill requirements of a worker's job, I have decided to combine both concepts to construct a new method for measuring skills mismatch. This method will be referred to as the Hybrid method.

The Hybrid method combines the concepts from both the Allen and the Perry methods. The Hybrid method uses a standardized comparison of each respondent's assessed skill level and skill use at work, relative to others in the same two-digit occupational group. The boundary for skill-matched and skill-mismatched individuals is plus or minus 1.5 standard deviations away from the mean in each occupational group. Although researchers have acknowledged the potential limitations of using 1.5 as a cut-off measure, I decided to use it because it is used by researchers in the area of skill mismatch. All ten plausible values are used in the analysis, which follows the Perry method and the redefined Allen method. The occupational groups are based on the 2011 National Occupation Classification (NOC) instead of the 2008 ISCO. The NOC is an occupational classification that is unique to Canada. The NOC codes are based upon occupational classifications that are defined by Statistics Canada. The occupational classifications are organized and grouped into four-digit codes, of which there are 500. The four-digit codes are aggregated into three-digit (140), two-digit (40), and one-digit (10) groups.[11] The first digit of the NOC codes represents broad occupational groups, and the first two digits represent major occupational groups. Small sample sizes in each occupational group are not an issue in the Canadian data.[12]

Recent studies on skills mismatch focus on its effects on labour market outcomes in order to determine the validity of the construct of mismatch that is used. For example, Perry et al. (2014) show that the R-squared estimates of the refined Allen method and their own method are essentially the same insofar as they measure the effects of skills mismatch on earnings. In order to decide which method will be used in my research, each method must first be adjusted for the Canadian context. Therefore, I have decided to replicate the refined Allen method and the Perry method in order to compare the distribution of skills mismatch within Canada for the literacy and numeracy proficiency domains. I will use the 2011 NOC in order to define the two-digit major

[11] Example of NOC occupational classifications:
3222: Dental hygienists and dental therapists;
322: Technical occupations in dental health care;
32: Technical occupations in health;
3: Health occupations
[12] See Appendix C for a description of the codes and labels for each group.

occupational groups for the Perry and Hybrid methods. All ten plausible values will be used for each method.

Some restrictions are applied to the final sample of Canadian data for each method. The final sample is restricted to employees who work at least 30 hours per week, which is the minimum for full-time work in Canada (Statistics Canada, 2012a). Students and apprentices are excluded from the sample. These restrictions are in line with what other researchers have done when measuring skills mismatch, although their studies relate to labour market outcomes (Allen et al, 2013; Perry et al., 2014). Even still, the exclusion of students, apprentices and part-time workers is justified because the extent to which these workers deploy their skills in the workplace is likely to be affected by their limited attachment to the labour market. Excluding self-employed workers is not easily justifiable. It is possible that self-employed individuals may exhibit different characteristics in terms of their skills relative to employees, and therefore, could be valuable to include as a control variable. Nevertheless, they remain excluded from the sample in order to make the results in this study comparable to previous research. The final restricted sample contains 13,587 observations, which is representative of 11,719,125 individuals throughout Canada.

3.3 Model

I will use a multinomial logistic regression model in order to determine the predictors of skills mismatch in Canada. Multinomial logistic regression is used to estimate the extent to which changes in a set of independent variables predicts changes in a categorical dependent variable (Warner, 2008). Multinomial logistic regression is conceptually similar to running multiple logistic regressions at once. However, multinomial logistic regression reduces errors relative to running multiple logistic regressions, particularly Type 1 error.[13] Logistic regression involves a dependent variable that is dichotomous (i.e., has values zero and one). In these models, the probability of an outcome is measured given a set of independent variables while holding all else constant. Multinomial logistic regression involves a categorical dependent variable with at least three values, where one of those values becomes a reference category, or base outcome. All other values in the dependent variable are measured one at a time relative to the base outcome; hence being similar to running multiple logistic regressions at once. The parameter estimates within a multinomial logistic regression are based on maximum likelihood estimation.[14] I will apply this model to the three different methods of measuring skills mismatch across each applicable domain of PIAAC data.

3.4 Variables

The dependent variable for each model is a categorical variable with three values: under-skilled, appropriately skilled, and over-skilled.[15] The reference category represents individuals that are appropriately skilled, or skill-matched. Individuals that are under-skilled and over-skilled compose both of the dimensions of skills mismatch, and are coded as one and three in the model. The reference category is coded as two, which is the base outcome for each model. Table 3.2 shows the descriptive statistics for the dependent variables used in the final models. The same thing is shown for the independent variables in Table 3.3.

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[13] Type 1 error occurs when a true null hypothesis is rejected (false positive).
[14] See the STATA reference manual for a description of the functional form of a multinomial logistic regression (StataCorp, 2013).
[15] Although the dependent variable appears to be ordered, by taking the difference between the standardized values of skill levels and requirements, it leads to one of three levels in which the order does not matter. An ordered logistic regression was also tested. The results between the two models were almost identical.

Table 3.2

Descriptive statistics for the dependent variables used in the final model

Variable	Frequency	Percentage
Literacy		
Under-skilled	797,546	6.8%
Skill-matched	10,203,462	87.3%
Over-skilled	690,568	5.9%
Numeracy		
Under-skilled	755,076	6.5%
Skill-matched	10,174,281	87.0%
Over-skilled	762,218	6.5%
Problem-solving		
Under-skilled	640,192	6.4%
Skill-matched	8,668,141	86.6%
Over-skilled	698,081	7.0%

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. Skill-matched represents individuals that fall within +/- 1.5 standard deviations from the mean proficiency score within each occupational group. Under-skilled represents individuals that are less than -1.5 standard deviations from the mean proficiency score within each occupational group. Over-skilled represents individuals that are greater than 1.5 standard deviations from the mean proficiency score within each occupational group.

Table 3.3

Descriptive statistics for the independent variables used in the final model

Variable	Frequency	Percentage
Regions		
Atlantic Provinces: 0=No, 1=Yes	801,837	6.8%
Territories: 0=No, 1=Yes	41,612	0.4%
Other Canada: Reference category	10,875,676	92.8%
Population density		
Non-urban (<100,000): Reference category	4,466,238	38.1%
Urban (>=100,000): 0=No, 1=Yes	7,252,886	61.9%
Gender		
Male: Reference category	6,487,832	55.4%
Female: 0=No, 1=Yes	5,231,293	44.6%
Age groups		
Age 16 to 24: 0=No, 1=Yes	940,918	8.0%
Age 25 to 34: 0=No, 1=Yes	2,835,886	24.2%

Age 35 to 44: Reference category	2,904,834	24.8%
Age 45 to 54: 0=No, 1=Yes	3,218,726	27.5%
Age 55 to 65: 0=No, 1=Yes	1,818,761	15.5%
Immigrant status		
Canadian-born: Reference category	8,764,891	74.8%
Immigrants: 0=No, 1=Yes	2,954,234	25.2%
Immigrant duration		
Canadian-born: Reference category	8,764,891	74.9%
Years since immigration: Values range from 1 to 60	2,954,234	25.1%
Aboriginal status		
Non-Aboriginal: Reference category	11,394,615	97.2%
Aboriginal: 0=No, 1=Yes	324,510	2.8%
Mother tongue		
Non-French: Reference category	9,077,812	77.5%
French: 0=No, 1=Yes	2,641,312	22.5%
Education levels		
High school or less: Reference category	3,480,580	29.7%
Post-secondary, less that bachelor’s: 0=No, 1=Yes	4,573,736	39.1%
Post-secondary, bachelor’s or above: 0=No, 1=Yes	3,656,988	31.2%
Parental education levels		
Less than high school: Reference category	2,706,997	24.4%
Post-secondary, less than bachelor’s: 0=No, 1=Yes	4,225,421	38.1%
Post-secondary, bachelor’s or above: 0=No, 1=Yes	4,145,044	37.4%
Occupational groups		
Mgmt.: 0=No, 1=Yes	1,453,158	12.4%
Business, Fin., Adm.: 0=No, 1=Yes	1,976,811	16.9%
Sciences: 0=No, 1=Yes	1,175,075	10.1%
Health: 0=No, 1=Yes	716,799	6.1%
Ed., Law, Gov. Serv.: 0=No, 1=Yes	1,449,295	12.4%
Art, Culture, Rec.: 0=No, 1=Yes	206,252	1.8%
Sales and serv.: Reference category	2,063,184	17.6%
Trades, Trans., Equip.: 0=No, 1=Yes	1,719,954	14.7%
Nat. Res., Agric.: 0=No, 1=Yes	198,783	1.7%
Mfg., Utilities: 0=No, 1=Yes	734,308	6.3%

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data.

The Canadian PIAAC data contains a derived variable that indicates the province or territory of residence for each respondent. A dichotomous variable was generated for the Atlantic Provinces (New Brunswick, Nova Scotia, Prince Edward Island, and

Newfoundland and Labrador), and another for the Territories (Yukon, Northwest Territories, and Nunavut). All of the other provinces compose the reference group in each model (British Columbia, Alberta, Saskatchewan, Manitoba, Ontario, and Quebec).[16]

The Canadian PIAAC data contains a derived variable that indicates if a respondent resides in an urban or rural area. This variable has four categories that are based on population centres as defined by Statistics Canada. The four categories are: rural areas with a population of less than 1,000; small population centres with a population ranging from 1,000 to 29,999; medium population centres with a population ranging from 30,000 to 99,999; and, large population centres with a population of at least 100,000. In order to distinguish non-urban from urban, I generated a dichotomous variable that represents urban areas with a population of at least 100,000. The reference group consists of all other areas that fall outside of these boundaries.

PIAAC data contains a variable on the gender of each respondent. This variable is recoded in order to identify if respondents are females; the reference category is males. Gender differences have been accounted for in other studies that examine skills mismatch and its effects on labour market outcomes.

PIAAC data contains a categorical variable that provides the age of each respondent. This variable is recoded into groups that are similar to the typical ten-year age groups that are used in the Canadian Census of Population, the Labour Force Survey, and in many research publications. The groups are: ages 16 to 24, ages 25 to 34, ages 35 to 44, ages 45 to 54, and ages 55 to 65. These groups are used to facilitate an

[16] Several tests were conducted on measuring skills mismatch in each province. The only large variations that were present were among the regions that appear in the model.

easy comparison between the usual core working-age population, youth, and older workers. Dichotomous variables are generated for each age group. Ages 35 to 44 is used as the reference category.

PIAAC data contains a dichotomous variable for immigrant status. Immigrant status indicates that the respondent was not born in Canada. The reference category is non-immigrants, or the Canadian-born. Years since immigration is an additional variable pertaining to immigrants. It is a continuous variable ranging from zero to 60. I recoded the variable such that value zero is collapsed into value one. The Canadian-born population represents value zero, which is the reference category.

PIAAC data contains a dichotomous variable for Aboriginal status. Aboriginal status indicates that the respondent is First Nations, Métis, or Inuit. The reference category is non-Aboriginals.

PIAAC contains a derived variable that indicates the mother tongue of each respondent. Mother tongue refers to the language that the respondent first learned as a child and still understands at the time of the Survey. The mother tongue variable contains four values: English, French, bilingual, and other. The bilingual respondents are recoded based on variables contained in the background questionnaire by assuming that the first mother tongue reported for each respondent is their primary mother tongue. A dichotomous variable is generated for French, with non-French as the reference group.

PIAAC data contains a derived categorical variable for the highest educational attainment of each respondent. This variable collapses educational attainment into four groups that are based on the International Standard Classification of Education (ISCED): less than a high school diploma; a high school diploma; a post-secondary certificate or diploma below a bachelor's degree; and a post-secondary diploma for a bachelor's degree or above. Four dichotomous variables are generated based on these categories. The reference group is composed of the two lowest attainments.

PIAAC data contains a derived categorical variable for the highest educational attainment for the parents or guardians of each respondent.[17] Dichotomous variables are derived that represent three categories of the initial variable: neither parent has attained a high school diploma; at least one parent has attained a post-secondary certificate or diploma below a bachelor's degree; and, at least one parent has attained a bachelor's degree or higher. Three dichotomous variables are generated based on these categories. The reference category is the lowest attainment.

The Canadian PIAAC data contains a derived categorical variable for the current occupation of each respondent according to the 2011 NOC. NOC codes are provided at the four-digit level. The first digit of the NOC codes represents broad occupational groups, and the first two digits represent major occupational groups. The one-digit and two-digit codes are derived for each respondent.[18] Ten dichotomous variables are generated for each of the broad occupations. The sales and service major occupational group is the reference category. The construct of skills mismatch for the Perry and Hybrid methods both involve occupational groupings at the two-digit level according to the NOC codes. The independent variables used in the models involve one-digit NOC codes. It is possible that, when aggregated, certain occupational groups are more likely to predict skills mismatch.[19]

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[17] Any reference to parents from this point forward represents parents or guardians.
[18] See Appendix B for a description of the codes and labels for each group.
[19] The occupational groups used as independent variables within the model are at the one-digit level. The construct for skills mismatch involves two-digit occupational groups. Tests were implemented in order to ensure that including the aggregated occupational variables did not compromise the results from the model.

Work experience, broad industry classifications, participation in formal and non-formal job-related training, wages, educational mismatch, and alternate measures for many of the independent variables were considered as part of the final models. However, after a series of tests, I determined that each of these factors should be excluded or exchanged. Work experience and age are substitutes in the model, as they each measure approximately the same thing. The main disadvantage of using age instead of work experience is that age does not account for individuals that entered the labour market later in life and consequently have less experience. However, using age facilitates a clear interpretation in terms of predicting skills mismatch. For the purposes of this research, age can be thought of as a proxy for work experience.

Broad industry classifications based on the 2012 National American Industry Classification System (NAICS) were considered for the models but I excluded them because of a high degree occupational heterogeneity within each group, which limits the value of uncovering differences by industry. In addition, the sample size was too low in some of the industries. Participation in formal and non-formal job-related training was also considered for the models but I excluded them on the basis that the underlying variable definitions are too broad and only measured participation in the last 12 months. Wage and educational mismatches were both considered for the models but I omitted them because of potential multicollinearity with the other independent variables (e.g., educational attainment).

4.0 RESULTS

4.1 Preliminary results

The first step towards answering the research question in this study is to compare some of the commonly used methods for measuring skills mismatch. Only then can it be determined which model is a potentially informative method for measuring the factors that predict skills mismatch in Canada.

Table 4.1

Proportion of skills mismatch for each method by proficiency domain in Canada

Method	Under-Skilled	Skill-Matched	Over-Skilled
		Literacy	
Allen	8.7%	81.4%	9.9%
Perry	6.8%	87.3%	5.9%
Hybrid	11.9%	74.7%	13.3%
		Numeracy	
Allen	9.7%	80.5%	9.8%
Perry	6.5%	87.0%	6.5%
Hybrid	11.4%	77.1%	11.6%
		Problem-Solving	
Perry	6.4%	86.6%	7.0%

Note. The sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data.

Table 4.1 shows that there are large differences when the methods are compared within each domain. Perry et al. (2014) echo this finding within the numeracy domain. The Perry method contains the lowest proportions of skill-mismatched individuals, and the Hybrid method contains the largest proportions. Table 4.1 amplifies the need to understand what each measure conveys, given that each method is highly sensitive to its construct of mismatch.

Table 4.2

Pearson-r correlation between each proficiency domain

Measure	Literacy & Numeracy	Literacy & Problem-solving	Numeracy & Problem-solving
Pearson r	0.843	0.821	0.749

Note. The sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data.

Table 4.2 presents the Pearson-r coefficients that indicate the extent to which proficiency scores in each domain are correlated. The scores in each domain exhibit strong positive correlations with one another. That implies that they each increase linearly with some variation. Literacy and numeracy scores have the strongest positive correlation, followed by literacy and problem-solving, and then by numeracy and problem-solving. Additionally, the Pearson-r value for literacy and numeracy skill use at work is 0.532. In Table 4.1, the distribution of skills mismatch is similar for each method when results are compared between domains. This is not surprising given that the scores in each domain are positively correlated, and so are the literacy and numeracy use at work variables. That should result in relatively similar distributions along each measure of skills mismatch.

The multinomial regression results from the Allen, Perry, and Hybrid methods are shown in Table 4.3 and 4.4 for literacy skills.[20] The results from tables 4.3 and 4.4 show the parameter estimates, the robust standard errors of each estimate, and the corresponding level of statistical significance based on the output generated from the multinomial logistic regression model. The levels of significance, or alpha levels, are 0.05, 0.01, and 0.001. Some other researchers that measure skills mismatch use the same alpha levels. The sample size and pseudo-R^2 estimates for each method are at the

[20] See Appendix D for the same results for numeracy skills.

bottom of the tables. The parameter estimates, or coefficients, represent log-odds. These values are not easily interpretable on their own, but they are useful insofar as they compare to other estimates in the model.

Table 4.3

Comparison of under-skilled relative to skill-matched in literacy

	Allen method		Perry method		Hybrid method	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regions						
Other Canada (ref.)						
Atlantic	0.155	(0.152)	0.122	(0.201)	0.124	(0.140)
Territories	0.593**	(0.212)	0.853*	(0.349)	0.599**	(0.227)
Population density						
Non-urban (ref.)						
Urban	-0.115	(0.156)	0.090	(0.192)	-0.100	(0.147)
Gender						
Male (ref.)						
Female	-0.021	(0.155)	0.143	(0.187)	0.004	(0.113)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	-0.259	(0.359)	0.040	(0.375)	-0.104	(0.317)
Age 25 to 34	-0.076	(0.227)	-0.341	(0.294)	-0.161	(0.205)
Age 45 to 54	0.470*	(0.187)	0.495*	(0.229)	0.341*	(0.163)
Age 55 to 65	0.432*	(0.214)	0.721**	(0.258)	0.307	(0.195)
Immigrant status						
Non-immigrant (ref.)						
Immigrant	1.248***	(0.255)	2.232***	(0.291)	1.082***	(0.176)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	-0.014	(0.009)	-0.029**	(0.010)	-0.011	(0.008)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	0.199	(0.192)	0.384	(0.251)	0.189	(0.147)
Mother tongue						
Non-French (ref.)						
French	-0.166	(0.141)	0.240	(0.182)	-0.119	(0.118)
Education levels						
< PSE (ref.)						
PSE < bach.	-0.097	(0.170)	-0.747***	(0.168)	-0.104	(0.145)
PSE >= bach.	-0.786***	(0.223)	-1.341***	(0.267)	-0.501**	(0.166)

Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	-0.123	(0.173)	-0.595***	(0.185)	-0.152	(0.137)
Parent PSE >= bach.	-0.250	(0.208)	-0.727***	(0.217)	-0.241	(0.144)
Occupational groups						
Sales and serv. (ref.)						
Mgmt.	0.432	(0.253)	0.342	(0.315)	0.364	(0.205)
Business, Fin., Adm.	-0.121	(0.225)	0.156	(0.251)	0.106	(0.179)
Sciences	-0.053	(0.305)	0.628*	(0.308)	0.310	(0.219)
Health	0.385	(0.312)	0.575	(0.404)	0.480*	(0.244)
Ed., Law, Gov. Serv.	0.497*	(0.230)	0.570	(0.324)	0.453*	(0.186)
Art, Culture, Rec.	-0.432	(0.641)	-0.570	(0.761)	-0.288	(0.697)
Trades, Trans., Equip.	0.405	(0.231)	-0.120	(0.277)	0.156	(0.201)
Nat. Res., Agric.	0.236	(0.677)	-0.211	(0.419)	0.481	(0.494)
Mfg., Utilities	-0.511	(0.326)	-0.176	(0.339)	-0.198	(0.260)
Constant	-2.464***	(0.291)	-2.853***	(0.348)	-2.069***	(0.226)
N	12,575		12,589		12,575	
Pseudo-R^2	0.055		0.108		0.044	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

Table 4.4

Comparison of over-skilled relative to skill-matched in literacy

	Allen method		Perry method		Hybrid method	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regions						
Other Canada (ref.)						
Atlantic	-0.003	(0.137)	-0.045	(0.159)	-0.016	(0.129)
Territories	-0.351	(0.440)	0.110	(0.499)	-0.303	(0.504)
Population density						
Non-urban (ref.)						
Urban	0.224	(0.145)	0.055	(0.218)	0.215	(0.126)
Gender						
Male (ref.)						
Female	0.065	(0.139)	-0.533**	(0.191)	0.132	(0.121)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	0.713***	(0.199)	-0.039	(0.343)	0.536**	(0.186)
Age 25 to 34	0.503**	(0.166)	0.274	(0.222)	0.41**	(0.157)
Age 45 to 54	-0.287	(0.204)	-0.204	(0.226)	-0.239	(0.149)
Age 55 to 65	-0.351	(0.230)	-0.439	(0.294)	-0.421*	(0.183)

Immigrant status						
Non-immigrant (ref.)						
Immigrant	-0.843**	(0.302)	-1.627***	(0.362)	-0.826***	(0.248)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	0.020	(0.012)	0.033	(0.018)	0.017	(0.010)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	-0.084	(0.262)	-0.106	(0.312)	-0.071	(0.213)
Mother tongue						
Non-French (ref.)						
French	0.266	(0.142)	-0.232	(0.160)	0.274**	(0.105)
Education levels						
< PSE (ref.)						
PSE < bach.	0.116	(0.153)	0.495	(0.285)	0.192	(0.175)
PSE >= bach.	0.444*	(0.174)	1.292***	(0.281)	0.569***	(0.171)
Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	0.040	(0.188)	0.610*	(0.243)	0.118	(0.157)
Parent PSE >= bach.	0.144	(0.175)	0.889***	(0.233)	0.158	(0.156)
Occupational groups						
Sales and serv. (ref.)						
Mgmt.	-0.904***	(0.236)	-0.489	(0.304)	0.317	(0.178)
Business, Fin., Adm.	-0.525**	(0.200)	-0.003	(0.266)	0.199	(0.183)
Sciences	-0.310	(0.259)	-0.658	(0.340)	0.295	(0.201)
Health	-0.293	(0.290)	0.057	(0.372)	0.403	(0.227)
Ed., Law, Gov. Serv.	-0.578*	(0.260)	-0.515	(0.293)	0.292	(0.178)
Art, Culture, Rec.	-0.239	(0.447)	-0.679	(0.873)	-0.065	(0.429)
Trades, Trans., Equip.	0.234	(0.198)	-0.246	(0.297)	0.207	(0.215)
Nat. Res., Agric.	0.452	(0.422)	0.307	(0.715)	-0.095	(0.595)
Mfg., Utilities	0.341	(0.238)	0.480	(0.427)	0.116	(0.273)
Constant	-2.433***	(0.263)	-3.405***	(0.393)	-2.545***	(0.244)
N	12,575		12,589		12,575	
Pseudo-R^2	0.055		0.108		0.044	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

Table 4.3 and 4.4 indicate that each method produces similar results for the predictors of skills mismatch, but with some notable differences. The Allen and Hybrid methods have similar results, both in terms of the magnitude and direction of each estimate and its variance, with the exception of occupational groups. Both methods exhibit similar statistically significant results, except for occupational groups. This is not surprising given that the only difference between the two methods is the population base that the skill mismatch boundaries are drawn from. The Allen method is based on the total population, whereas the Hybrid method is based on two-digit occupational groups. It is likely that most of the skill-mismatched individuals are the same between the two methods. The Perry method produces some similar results, but many of the parameter estimates are greater in magnitude or are in different directions. Although some of the statistically significant parameter estimates match the other two methods, many are different. This, combined with the fact that this method contains the lowest proportion of skill-mismatched individuals, indicates that this method probably captures a much different group than the Allen and Hybrid methods. This provides further evidence that each measure of mismatch is highly sensitive to its construct, which again points to the need to identify what each method conveys.

When regression analysis is completed using PIAAC data, version 13 of STATA does not allow estimates to be stored in its memory, at least not when using the “repest” command.[21] This is because STATA has to compute ten separate analyses for each plausible value and the 80 replicate weights. However, the STATA output is able to produce pseudo-R^2, or McFadden’s R^2. Although it is not preferred, pseudo-R^2 can be used as a diagnostic test to compare models (Hosmer, Lemeshow, & Studivant, 2013; Menard, 2000). Therefore, comparing pseudo-R^2 between models will be used to judge which method will be used for the final estimations in this study.

[21] “Repest” is a command written by Francesco Avvisati and François Keslair of the OECD. The command is designed specifically for estimation with weighted replicate samples and plausible values. The command does not store estimates. It is available via the OECD website.

When comparing the three methods across the literacy domain, the Perry method contains the highest pseudo-R^2 estimates (0.108 and 0.107). This is also exhibited within the numeracy and problem-solving domains. The Perry method was chosen for the final model on this basis. The Perry method avoids using any self-reported information and it compares individual skills relative to others in the same occupational group. I performed a series of tests on the model by adding or substituting different independent variables and using Bayesian Information Criterion (BIC) by generating regression results based on only one plausible value.[22]

4.2 Main results

Previous research that measures skills mismatch within PIAAC does not consider the problem-solving domain. The following analysis examines skills mismatch according to all three domains; literacy, numeracy, and problem-solving. This is a major advantage of using the Perry method. The problem-solving domain may contain biases because it only includes individuals that were willing and able to complete a computer-based assessment. However, this potential bias does not invalidate the results as long as we remember the type of individuals this domain represents and interpret the results carefully. The following tables and associated results include coefficients for under-skilled and over-skilled mismatches relative to skill-matched individuals, while holding all other variables constant. All of the results were tested with different skill mismatch boundaries.[23] Instead of using plus or minus 1.5 standard deviations (SD) as the boundary, boundaries of 2.0 SDs and 1.0 SD were applied to each model. Boundaries of

[22] The BIC results are generated using an alternate command in STATA that is provided by the OECD, called “piaacreg”, followed by “estat ic”. The “piaacreg” command allows for estimates from the final plausible value to be stored and analyzed.
[23] See Appendix E for the results in the literacy domain.

2.0 SDs and 1.0 SD are stricter and more lenient categories for determining what individuals are categorized as skill-mismatched. The results indicate that each boundary contains similar results in terms of the significance of each estimate. In addition, almost all of the parameter estimates increase or decrease somewhat linearly. This helps to verify the boundaries used in the results, as we know that the results are not anomalies.

Table 4.5

Skill mismatches relative to skill matches in literacy

	Under-skilled		Over-skilled	
Variable	Coef.	S.E.	Coef.	S.E.
Regions				
Other Canada (ref.)				
Atlantic	0.122	(0.201)	-0.045	(0.159)
Territories	0.853*	(0.349)	0.110	(0.499)
Population density				
Non-urban (ref.)				
Urban	0.090	(0.192)	0.055	(0.218)
Gender				
Male (ref.)				
Female	0.143	(0.187)	-0.533**	(0.191)
Age groups				
Age 35 to 44 (ref.)				
Age 16 to 24	0.040	(0.375)	-0.039	(0.343)
Age 25 to 34	-0.341	(0.294)	0.274	(0.222)
Age 45 to 54	0.495*	(0.229)	-0.204	(0.226)
Age 55 to 65	0.721**	(0.258)	-0.439	(0.294)
Immigrant status				
Non-immigrant (ref.)				
Immigrant	2.232***	(0.291)	-1.627***	(0.362)
Immigrant duration				
Non-immigrant (ref.)				
Years since immigration	-0.029**	(0.010)	0.033	(0.018)
Aboriginal status				
Non-Aboriginal (ref.)				
Aboriginal	0.384	(0.251)	-0.106	(0.312)
Mother tongue				
Non-French (ref.)				
French	0.240	(0.182)	-0.232	(0.160)

Education levels				
< PSE (ref.)				
PSE < bach.	-0.747***	(0.168)	0.495	(0.285)
PSE >= bach.	-1.341***	(0.267)	1.292***	(0.281)
Parental education levels				
Parent < PSE (ref.)				
Parent PSE < bach.	-0.595***	(0.185)	0.610*	(0.243)
Parent PSE >= bach.	-0.727***	(0.217)	0.889***	(0.233)
Occupational groups				
Sales and serv. (ref.)				
Mgmt.	0.342	(0.315)	-0.489	(0.304)
Business, Fin., Adm.	0.156	(0.251)	-0.003	(0.266)
Sciences	0.628*	(0.308)	-0.658	(0.340)
Health	0.575	(0.404)	0.057	(0.372)
Ed., Law, Gov. Serv.	0.570	(0.324)	-0.515	(0.293)
Art, Culture, Rec.	-0.570	(0.761)	-0.679	(0.873)
Trades, Trans., Equip.	-0.120	(0.277)	-0.246	(0.297)
Nat. Res., Agric.	-0.211	(0.419)	0.307	(0.715)
Mfg., Utilities	-0.176	(0.339)	0.480	(0.427)
Constant	-2.853***	(0.348)	-3.405***	(0.393)
N	12,589		12,589	
Pseudo-R^2	0.108		0.108	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

The results from Table 4.5 show that immigrant status, education levels, and the education levels of parents are the most statistically significant estimates for both aspects of skill mismatch. Individuals residing in the Territories are more likely to be under-skilled in literacy relative to any other place in the country with a coefficient of 0.853 (p<0.05). The Atlantic Provinces and urban areas do not exhibit any significant difference between the under-skilled and over-skilled population. Women are less likely to be over-skilled in literacy compared to men (-0.533; p<0.01). The results indicate that, with the exception of the lowest age category, as age increases so does the likelihood of being under-skilled in literacy, although only age 45 to 54 (0.495; p<0.05) and age 55 to 65 (0.721; p<0.01) are significant. The reverse is also true, where the likelihood of being over-skilled decreases with age, however none of the results are significant. Immigrants are more likely to be under-skilled (2.232; p<001) and less likely to be over-skilled (-1.627; p<0.001) relative to the Canadian-born population. For each additional year since immigration, immigrants are less likely to be under-skilled (-0.029; p<0.01). The results for Aboriginals and French-speaking Canadians are not statistically significant. As individual levels of education increase, the likelihood of being under-skilled decreases, and the likelihood of being over-skilled increases. The coefficients for being under-skilled increase in magnitude from -0.747 (p<0.001) for individuals with a post-secondary credential below a bachelor's degree, to -1.341 (p<0.001) for individuals with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.478 (not significant) for individuals with a post-secondary credential below a bachelor's degree, to 1.292 (p<0.001) for individuals with at least a bachelor's degree. The same pattern occurs for individuals that have parents or guardians with higher levels of education. The coefficients for being under-skilled increase in magnitude from -0.595 (p<0.01) for parents with a post-secondary credential below a bachelor's degree, to -0.727 (p<0.01) for parents with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.610 (p<0.05) for parents with a post-secondary credential below a bachelor's degree, to 0.889 (p<0.001) for parents with at least a bachelor's degree. Individuals in occupations relating to natural and applied sciences are more likely to be under-skilled (0.628; p<0.05) relative to sales and service occupations. None of the other major occupational groups exhibit significant differences.

Table 4.6

Skill mismatches relative to skill matches in numeracy

	Under-skilled		Over-skilled	
Variable	Coef.	S.E.	Coef.	S.E.
Regions				
Other Canada (ref.)				
Atlantic	0.283	(0.210)	-0.149	(0.187)
Territories	0.788**	(0.283)	-0.203	(0.303)
Population density				
Non-urban (ref.)				
Urban	0.047	(0.202)	-0.039	(0.186)
Gender				
Male (ref.)				
Female	0.482**	(0.176)	-0.979***	(0.197)
Age groups				
Age 35 to 44 (ref.)				
Age 16 to 24	-0.117	(0.435)	0.284	(0.308)
Age 25 to 34	-0.047	(0.272)	0.230	(0.247)
Age 45 to 54	0.498*	(0.215)	-0.029	(0.214)
Age 55 to 65	0.759**	(0.255)	-0.167	(0.283)
Immigrant status				
Non-immigrant (ref.)				
Immigrant	1.877***	(0.303)	-1.190***	(0.351)
Immigrant duration				
Non-immigrant (ref.)				
Years since immigration	-0.022*	(0.010)	0.028	(0.016)
Aboriginal status				
Non-Aboriginal (ref.)				
Aboriginal	0.498*	(0.242)	-0.080	(0.351)
Mother tongue				
Non-French (ref.)				
French	-0.216	(0.171)	-0.245	(0.166)
Education levels				
< PSE (ref.)				
PSE < bach.	-0.820***	(0.171)	0.839**	(0.304)
PSE >= bach.	-1.428***	(0.245)	1.654***	(0.307)
Parental education levels				
Parent < PSE (ref.)				
Parent PSE < bach.	-0.446*	(0.186)	0.410	(0.258)
Parent PSE >= bach.	-0.668**	(0.245)	0.774***	(0.238)
Occupational groups				

Sales and serv. (ref.)				
Mgmt.	0.528	(0.303)	-0.579*	(0.259)
Business, Fin., Adm.	0.178	(0.273)	-0.019	(0.250)
Sciences	0.611	(0.316)	-0.993***	(0.307)
Health	0.406	(0.410)	0.176	(0.337)
Ed., Law, Gov. Serv.	0.525	(0.319)	-0.556*	(0.253)
Art, Culture, Rec.	0.215	(1.023)	-1.041	(0.937)
Trades, Trans., Equip.	0.034	(0.307)	-0.483	(0.280)
Nat. Res., Agric.	0.020	(0.507)	0.141	(0.628)
Mfg., Utilities	-0.165	(0.373)	0.087	(0.376)
Constant	-2.983***	(0.384)	-3.283***	(0.423)
N	12,589		12,589	
Pseudo-R^2	0.107		0.107	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

The predictors of skills mismatch in numeracy from Table 4.6 are similar to the results for literacy, but more of the results are significant. According to the model, individuals residing in the Territories are more likely to be under-skilled in numeracy relative to anywhere else in Canada with a coefficient of 0.788 (p<0.01). Women are more likely to be under-skilled (0.482; p<0.01) and less likely to be over-skilled (-0.979; p<0.001) in numeracy compared to men. As age increases so does the likelihood of being under-skilled in numeracy, although only the older age groups have significant results. The coefficient for age 45 to 54 is 0.498 (p<0.05), and for age 55 to 65 is 0.759 (p<0.01). Immigrants are more likely to be under-skilled (1.877; p<0.001) and less likely to be over-skilled (-1.190; p<0.001) relative to the Canadian-born. For each additional year since immigration, immigrants are less likely to be under-skilled (-0.022; p<0.05). Aboriginals are more likely to be under-skilled in numeracy relative to non-Aboriginals (0.498; p<0.05). As individual levels of education increase, the likelihood of being under-skilled decreases, and the likelihood of being over-skilled increases. The coefficients for being under-skilled increase in magnitude from -0.820 (p<0.001) for individuals with a post-secondary credential below a bachelor's degree, to -1.428 ($p<0.001$) for individuals with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.839 ($p<0.01$) for individuals with a post-secondary credential below a bachelor's degree, to 1.654 ($p<0.001$) for individuals with at least a bachelor's degree. The same pattern occurs for individuals that have parents or guardians with higher levels of education. The coefficients for being under-skilled increase in magnitude from -0.446 ($p<0.05$) for parents with a post-secondary credential below a bachelor's degree, to -0.668 ($p<0.01$) for parents with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.410 (not significant) for parents with a post-secondary credential below a bachelor's degree, to 0.774 ($p<0.001$) for parents with at least a bachelor's degree. Individuals in management occupations are less likely to be over-skilled (-0.579; $p<0.05$) relative to sales and service occupations. Additionally, individuals in occupations relating to natural and applied sciences (-0.993; $p<0.001$) and education, law and social, community and government service (-0.556; $p<0.05$) are less likely to be over-skilled.

Table 4.7

Skill mismatches relative to skill matches in problem-solving

	Under-skilled		Over-skilled	
Variable	Coef.	S.E.	Coef.	S.E.
Regions				
Other Canada (ref.)				
Atlantic	0.270	(0.237)	-0.042	(0.183)
Territories	0.677*	(0.302)	-0.076	(0.583)
Population density				
Non-urban (ref.)				
Urban	0.080	(0.177)	0.127	(0.188)
Gender				
Male (ref.)				
Female	0.154	(0.164)	-0.402*	(0.205)

Age groups				
Age 35 to 44 (ref.)				
Age 16 to 24	-0.554	(0.490)	0.333	(0.309)
Age 25 to 34	-0.255	(0.313)	0.145	(0.274)
Age 45 to 54	0.705**	(0.253)	-0.529	(0.272)
Age 55 to 65	1.023***	(0.271)	-1.265**	(0.446)
Immigrant status				
Non-immigrant (ref.)				
Immigrant	1.870***	(0.371)	-1.413**	(0.451)
Immigrant duration				
Non-immigrant (ref.)				
Years since immigration	-0.025*	(0.011)	0.032*	(0.016)
Aboriginal status				
Non-Aboriginal (ref.)				
Aboriginal	0.203	(0.277)	-0.049	(0.339)
Mother tongue				
Non-French (ref.)				
French	0.439*	(0.186)	-0.345	(0.207)
Education levels				
< PSE (ref.)				
PSE < bach.	-0.586**	(0.207)	0.499*	(0.243)
PSE >= bach.	-0.757**	(0.274)	0.924**	(0.293)
Parental education levels				
Parent < PSE (ref.)				
Parent PSE < bach.	-0.551**	(0.196)	0.732*	(0.295)
Parent PSE >= bach.	-0.831***	(0.244)	0.940**	(0.316)
Occupational groups				
Sales and serv. (ref.)				
Mgmt.	-0.102	(0.295)	-0.158	(0.316)
Business, Fin., Adm.	-0.238	(0.274)	0.264	(0.275)
Sciences	0.303	(0.282)	-0.606	(0.379)
Health	0.304	(0.335)	0.057	(0.393)
Ed., Law, Gov. Serv.	-0.078	(0.318)	-0.231	(0.309)
Art, Culture, Rec.	-0.235	(0.627)	-0.315	(0.703)
Trades, Trans., Equip.	-0.192	(0.297)	-0.340	(0.367)
Nat. Res., Agric.	-0.027	(1.562)	0.372	(0.796)
Mfg., Utilities	-0.175	(0.383)	0.269	(0.470)
Constant	-2.731***	(0.391)	-3.323***	(0.462)
N	10,644		10,644	
Pseudo-R^2	0.093		0.093	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

The predictors of skills mismatch in problem-solving from Table 4.7 are similar to the results for literacy and numeracy, but there are some differences in terms of which estimates are significant. According to the model, individuals residing in the Territories are more likely to be under-skilled in problem-solving relative to anywhere else in Canada (0.677; $p<0.05$). Women are less likely to be over-skilled in problem-solving compared to men (-0.402; $p<0.05$). As age increases, so does the likelihood of being under-skilled in problem-solving. The coefficient for age 45 to 54 is 0.705 ($p<0.01$), and for age 55 to 65 is 1.023 ($p<0.001$) for under-skilled. Conversely, the likelihood of being over-skilled decreases as age increases. The coefficient for age 45 to 54 is -0.529 (not significant), and for age 55 to 65 is -1.265 ($p<0.01$) for over-skilled. Immigrants are more likely to be under-skilled (1.870; $p<0.001$) and less likely to be over-skilled (-1.413; $p<0.01$) relative to the Canadian-born. For each additional year since immigration, immigrants are less likely to be under-skilled (-0.025; $p<0.05$) and more likely to be over-skilled (0.032; $p<0.05$). Individuals whose mother tongue is French are less likely to be over-skilled in problem-solving relative to non-French (-0.439; $p<0.05$). As individual levels of education increase, the likelihood of being under-skilled decreases, and the likelihood of being over-skilled increases. The coefficients for being under-skilled increase in magnitude from -0.586 ($p<0.01$) for individuals with a post-secondary credential below a bachelor's degree, to -0.757 ($p<0.01$) for individuals with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.499 ($p<0.05$) for individuals with a post-secondary credential below a bachelor's degree, to 0.924 ($p<0.01$) for individuals with at least a bachelor's degree. The same pattern occurs for individuals that have parents or guardians with higher levels of education. The coefficients for being under-skilled increase in magnitude from -

0.551 (p<0.01) for parents with a post-secondary credential below a bachelor's degree, to -0.831 (p<0.001) for parents with at least a bachelor's degree. The coefficients for being over-skilled increase in magnitude from 0.732 (p<0.05) for parents with a post-secondary credential below a bachelor's degree, to 0.940 (p<0.01) for parents with at least a bachelor's degree. None of the occupational groups exhibit significant results in problem-solving skills mismatch.

There are some commonalities between the three domains of skills mismatch. The strongest predictors of skills mismatch, in terms of statistical significant and magnitude, are consistently among Canadian immigrants, those with higher levels of educational attainment, and those with parents or guardians that have higher levels of educational attainment. Each model demonstrates that women are less likely to be over-skilled, that immigrants that stay longer in Canada are less likely to be under-skilled, and that residents of the Territories are more likely to be under-skilled.

Another way to present the results from the model involves using relative risk ratios.[24] The relative risk ratio for each estimate transforms the estimated coefficients into a measure of relative risk by taking the exponent. For a unit change in a predictor variable, the relative risk of under-skilling or over-skilling relative to being skill-matched is expected to change by a factor of the respective parameter estimate, provided that other variables are held constant. Values between zero and one indicate that the relative risk for a predictor will decrease by a factor of that amount, whereas values greater than one indicate that the relative risk for a predictor will increase by a factor of that amount. Estimated coefficients with negative values will correspond to relative risk ratios that are between zero and one. Conversely, estimated coefficients with positive

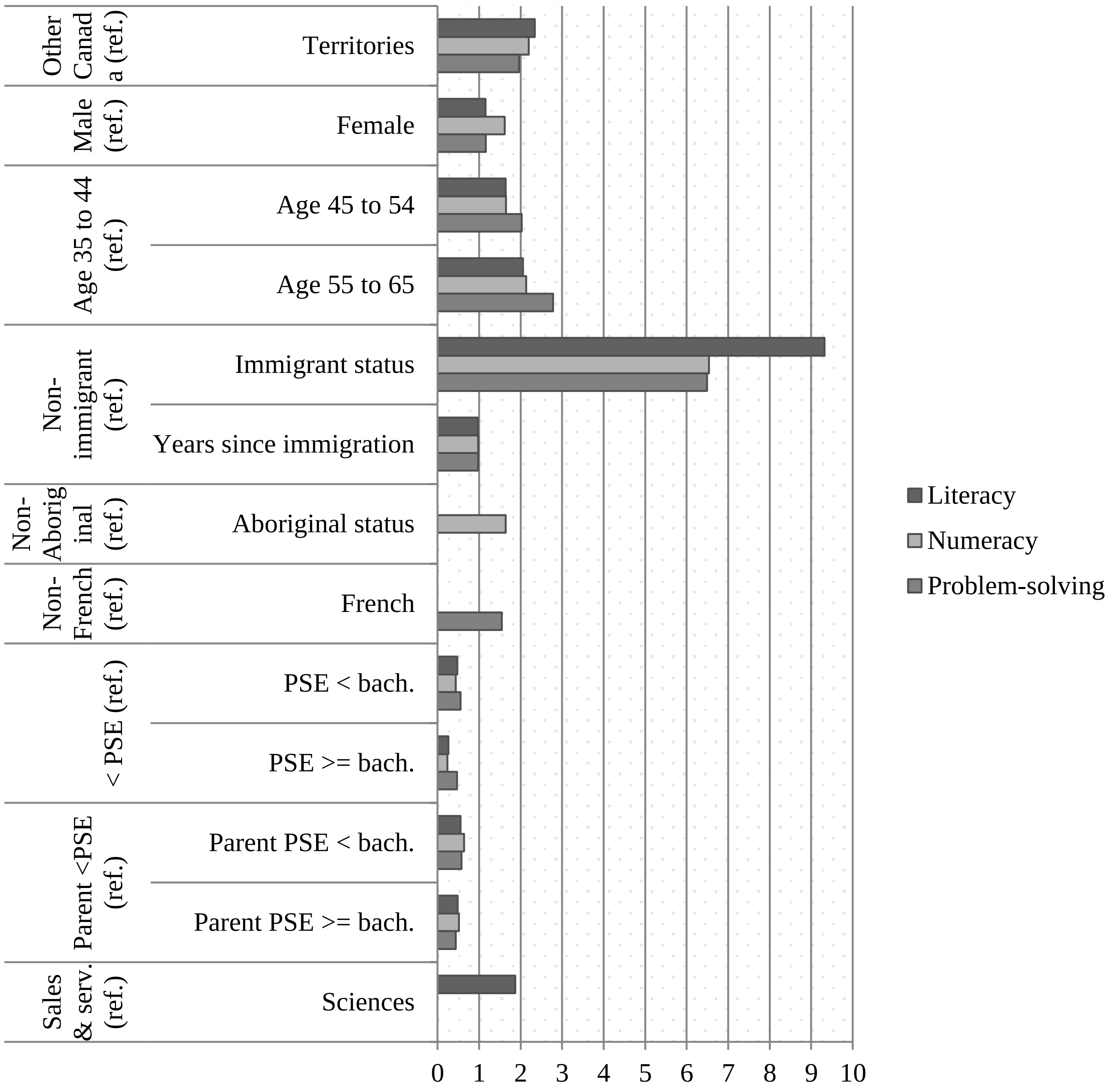
[24] See the STATA reference manual for a description of relative risk ratios (StataCorp, 2013).

values will correspond to relative risk ratios that are greater than one. Below, Figures 4.1 and 4.2 plot the relative risk ratios for statistically significant parameter estimates according to the three skill domains for under-skilling and over-skilling relative to being skill-matched. Both figures demonstrates that the results are similar between each domain, and clearly shows which factors are less and more likely to predict skills mismatch in Canada.[25]

[25] Full results for the relative risk ratios are available upon request.

Figure 4.1

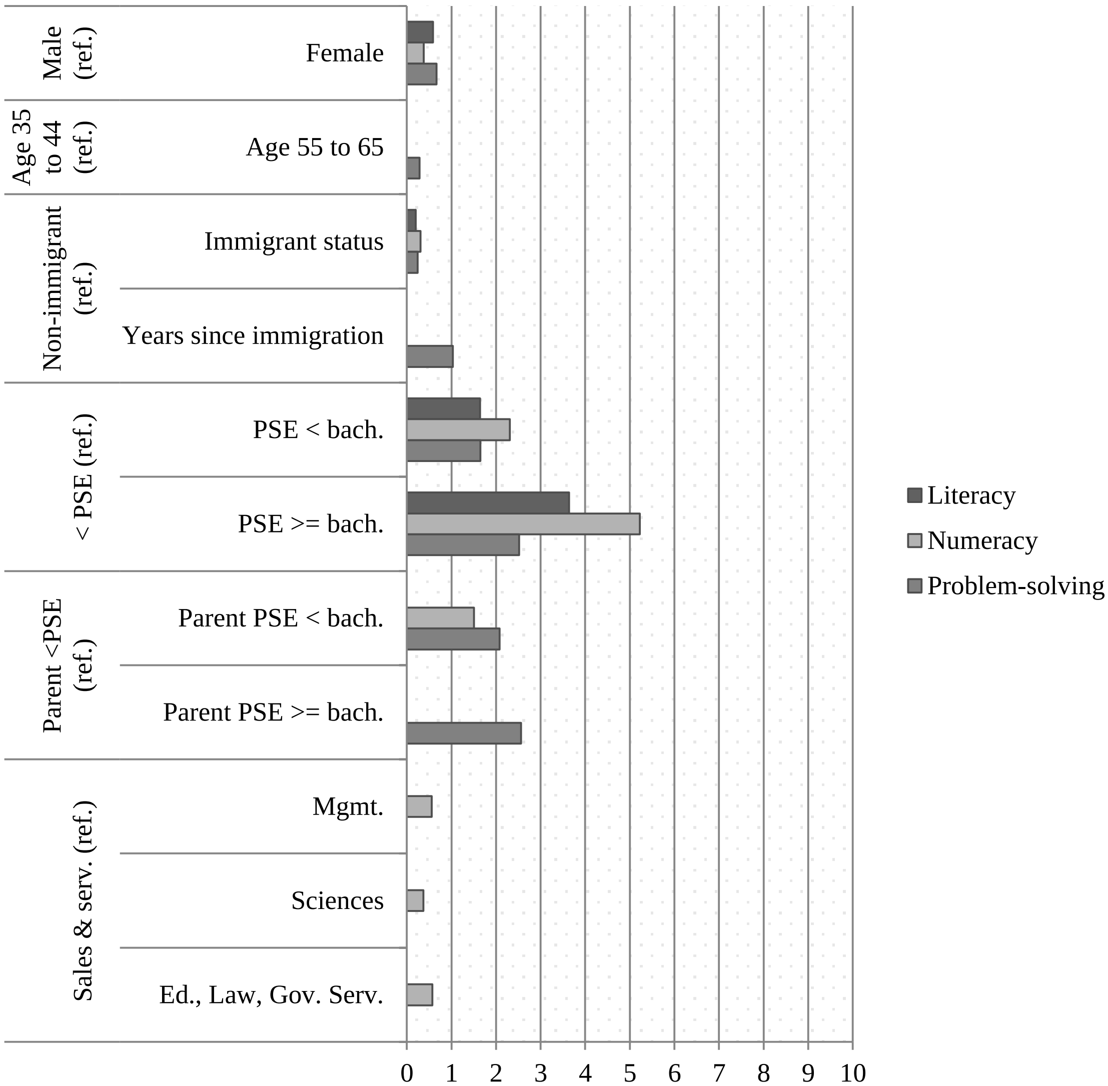
Under-skilling relative to skill-matched in literacy, numeracy and problem-solving



Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. Relative risk ratios are used as values for this figure. Only statistically significant results are presented.

Figure 4.2

Over-skilling relative to skill-matched in literacy, numeracy and problem-solving



Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. Relative risk ratios are used as values for this figure. Only statistically significant results are presented.

5.0 DISCUSSION

5.1 Discussion

Having a skilled population and workforce in Canada is a priority for both federal and provincial governments alike. Greater skill development helps lead to a prosperous economy because individuals obtain more diversity in their skillsets, which enables broader employment prospects. However, skill development only has a positive impact on the economy when individuals are able to utilize their skills that are relevant in the workplace, in addition to other skills that are not necessarily job-relevant. An efficient allocation of skills can only be achieved when the skill levels of workers are matched to their jobs. Otherwise, workers are skill-mismatched for their jobs, which can have negative consequences on individuals, firms, and the economy. The central purpose of my research was to understand the predictors of skills mismatch in Canada. The first step in this process was to develop a potentially informative measure of skills mismatch. The method I used involves comparing proficiency scores within occupational groups for each domain of literacy, numeracy and problem-solving skills. Other researchers that have used PIAAC to study skills mismatch have opted to utilize alternative methods, many of which are shown to be weak for various reasons.

After a detailed analysis on what predicts skills mismatch in Canada, I utilized the Perry method in order to test my hypotheses concerning which factors predict skills mismatch in the workplace. To begin, I predicted that workers that reside in the Territories and Atlantic Provinces are more likely to be under-skilled for their jobs than other Canadians. Previous research indicates that economic differences within countries are likely to affect the incidence and effects of skills mismatch. Moreover, there are structural differences in the economies in these regions compared to the rest of Canada, which influences the geographical distribution of skills. My research findings indicate that this is true for the Territories in all three domains of literacy, numeracy, and problem-solving skills, with literacy producing the strongest effect. Although the provincial economies in Atlantic Canada are structurally different from most other provinces, these differences do not significantly affect the incidence of skills mismatch in any of the three domains. There are many Aboriginal communities in the Territories that are more likely to face barriers to education and skills development, which could explain why workers from the Territories are more likely to be under-skilled for their jobs.

For my second hypothesis, I predicted that workers in densely populated areas of at least 100,000 are less likely to be under-skilled. Urban areas typically have more diversity and labour market opportunities, and therefore, tend to attract workers from lesser-populated areas. However, my research findings indicate that workers in urban areas are neither more nor less likely to be skill-mismatched than workers in non-urban areas in any of the three domains. Although unemployment rates are usually higher in non-urban areas, many workers in these areas are employed in the same job for many years that they are adequately skilled for. Perhaps this is the cause for no effect in the urban variable.

My third hypothesis predicted that female workers are more likely to be under-skilled and less likely to be over-skilled than male workers. Research indicates that women tend to work in jobs that do not match their skillset as well as men, and that women use their skills less frequently due to the type of jobs they typically have. The findings from my research confirm that women are more likely to be under-skilled, but only in terms of numeracy skills. The findings also confirm that women are less likely to be over-skilled, which is true in all three domains, most notably among numeracy skills. This finding could be explained by job functions being different between men and women, even within the same occupational group. If men are expected to work more with numbers, this could lead to deteriorating numeracy skills over time for women since they are not actively applying numeracy skills to their jobs relative to men. However, women are less likely to be over-skilled in all three domains, not just numeracy. Perhaps gender discrimination plays a role in the incidence of skills mismatch. If women are discriminated against in the workplace, they may become less likely to make occupational changes, which may lead to skill deterioration over time. Furthermore, women may be less likely to make occupational adjustments because of family obligations (e.g., pregnancy, looking after children). Women that take time off due to childbearing could face a considerable disadvantage compared to men, because men could accumulate additional skill usage and advancement during the time that women have off from work. This factor could contribute to women working in jobs that provide them with security, whereas men could be more likely to pursue career advancement since they have fewer family obligations. If this were true, then men could tend to have more opportunities and ambition to expand their cognitive abilities than women, and could therefore be more likely to be over-skilled in their current occupation.

For my fourth hypothesis, I predicted that there is an aging effect associated with skills mismatch: older workers are more likely to be under-skilled than younger workers, and that younger workers are more likely to be over-skilled than older workers. Previous research and theories indicate that individuals will become appropriately skilled for their jobs over time. Younger workers tend to be over-skilled for their jobs as they start their careers, whereas older workers tend to be under-skilled for their jobs, as cognitive skills tend to decline over time as job tasks become routine. The findings from my research confirm that older workers are more likely to be under-skilled than younger workers in all three domains, most notably among problem-solving skills. The findings do not exhibit any significant differences in terms of younger workers and their tendency to be over-skilled in any of the three domains. However, older workers are much less likely to be over-skilled in terms of problem-solving skills. In educational mismatch literature, younger workers are much more likely than older workers to be over-educated. The same cannot be said for skills mismatch, at least not to the same extent as educational mismatch.

My fifth hypothesis predicted that immigrant workers are more likely to be under-skilled and less likely to be over-skilled than Canadian-born workers. Current research that indicates that immigrants are more likely to struggle in the labour market due to a lack of proficiency in the official languages, a lack of foreign credential recognition, and discrimination. These factors can lead to immigrants being underemployed and over-utilized in the workplace. Accordingly, the findings from my research confirm the hypothesis in all three of the skill domains, particularly among literacy. Immigrants are statistically more likely to be under-skilled in numeracy and problem-solving; however, the greatest disparity is in literacy, where immigrants face an even greater disadvantage. Immigrants are also significantly less likely to be over-skilled compared to their Canadian-born counterparts; however, the disparity is not as immense between skill domains. Therefore, although immigrants face barriers concerning skills mismatch in Canada, the greatest disadvantage is for individuals that are under-skilled in literacy. These findings are not surprising in terms of literacy skills, however it is important to recognize that immigrants are one of the strongest predictors of skills mismatch in all of the skill domains. Research on educational mismatch indicates that foreign credentials are often not recognized, which is suspected to be the main cause of over-education among immigrants. The findings from my research indicate that although immigrants are more likely to be over-educated, they are not more likely to be over-skilled according to literacy, numeracy, or problem-solving skills.

For my sixth hypothesis, I predicted that as immigrant duration increases, immigrant workers are less likely to be under-skilled and more likely to be over-skilled. Research on immigrant outcomes in Canada indicates that, as immigrants integrate into society, their labour market outcomes improve and job mobility increases. This leads to immigrants becoming employed in jobs that require higher skills, which reduces the likelihood of being under-skilled and may also increase the likelihood of being over-skilled. The findings from my research confirm that for each additional year since immigration, immigrants are less likely to be under-skilled in all three of the skill domains, particularly among literacy. Additionally, for each additional year since immigration, immigrants are more likely to be over-skilled in the problem-solving domain. These findings provide evidence that immigrants successfully integrate into the Canadian labour market over time, ascertaining key cognitive skills along the way that assist in bringing them out of disadvantaged positions.

My seventh hypothesis predicted that Aboriginal Canadian workers are more likely to be under-skilled and less likely to be over-skilled than non-Aboriginal Canadian workers. Research indicates that Aboriginals are more likely to face various barriers to skills development and educational attainment. The findings from my research confirm that Aboriginal Canadian workers are more likely to be under-skilled, but only among numeracy skills. Perhaps the barriers faced in Aboriginal communities relate more to numeracy skill development rather than literacy or problem-solving skills. The results do not indicate that Aboriginal workers are less likely to be over-skilled, suggesting that the skills of Aboriginal workers are not much different from non-Aboriginals.

For my eighth hypothesis, I predicted that French Canadian workers are more likely to be under-skilled and less likely to be over-skilled than non-French Canadian workers. This hypothesis is based on an assumption that socio-cultural differences, discrimination and language barriers could play a role in determining the incidence of skills mismatch among French Canadians. The findings from my research confirm that French Canadians are more likely to be under-skilled, but only among problem-solving skills. The results do not indicate that French Canadians are less likely to be over-skilled. These findings indicate that overall French Canadians possess similar skillsets compared to their non-French counterparts.

My ninth hypothesis predicted that workers with higher levels of education are less likely to be under-skilled and more likely to be over-skilled. Research indicates that over-education is commonplace in the Canadian labour market: as individual educational attainments increase, skill development occurs, which corresponds with a greater likelihood of being over-skilled. The findings from my research confirm this hypothesis, particularly within the numeracy skill domain. These findings are not surprising, however it is important to recognize that educational attainment is one of the strongest predictors for skills mismatch in all of the skill domains.

For my tenth hypothesis, I predicted that workers that have parents or guardians with higher levels of education are less likely to be under-skilled and more likely to be over-skilled. Previous research indicates that individuals that have parents with higher educational credentials are more likely to grow up in an environment where the pursuit of skills and higher education is valued. Individuals with parents that have lower educational credentials tend to have fewer opportunities for skills development. The findings from my research confirm this hypothesis, particularly among literacy and problem-solving skills. These findings are not surprising, however it is important to recognize that the educational attainment of parents, a proxy for socio-economic status, is one of the strongest predictors of skills mismatch in all of the skill domains.

For my final hypothesis, I suggested that workers in higher-level occupations are more likely to be under-skilled and less likely to be over-skilled. Workers in higher-level occupations contain more demanding job duties and generally require a diverse skillset, which therefore, impacts how they are matched for their occupation. The results from my research do not clearly support this hypothesis in the literacy or problem-solving skill domains. However, the numeracy skill domain indicates that workers in management occupations, natural and applied science occupations, and education, law, community and government service occupations are less likely to be over-skilled.

Overall, the findings from each skill domain are very similar. Workers with low levels of educational attainment, whose parents have low levels of educational attainment, that reside in the Territories, immigrants, and older workers are the most likely to be under-skilled. These individuals are vulnerable to long-term under-skilling in the labour market. However, immigrants that remain in Canada become more likely to lift themselves out of being under-skilled for their jobs. Men, non-immigrants, those with high levels of educational attainment, and those with parents that have high levels of educational attainment are the most likely to be over-skilled. Although these individuals are not subject to the same vulnerabilities as the under-skilled, they are employed in jobs that under-utilize their skillsets, which is also problematic. Some findings that are unique to this study include: (1) workers in the Territories are much more likely to be under-skilled than other locations in Canada; (2) male workers are more likely to be over-skilled in all skill domains, and female workers are more likely to be under-skilled in numeracy; (3) younger workers are not more likely to be over-skilled in any skill domain; (4) immigrant workers that are new to Canada have a significant skills disadvantage in the labour market, but this disadvantage vanishes after integrating into Canadian society; (5) Aboriginal workers are more likely to be under-skilled in numeracy; (6) French Canadian workers are more likely to be under-skilled in problem-solving; and (7) a higher education levels of parents or guardians is one of the strongest predictors of skills mismatch.

5.2 Implications

The findings from my research indicate that skills mismatch is predicted by various factors in Canada: location, gender, age, immigrant status, immigrant duration, Aboriginal status, mother tongue, level of education, level of education of parents, and occupation. The most prominent factors, in terms of statistical significance and magnitude, across the three skill domains of literacy, numeracy, and problem-solving include all of the above except for Aboriginal status, mother tongue, and occupation.

Most workers probably experience a period of being skill-mismatched for their jobs, but what threshold is acceptable for this phenomenon in the Canadian economy? Moreover, how many skill-mismatched individuals experience long-term skills mismatch? Given that we know persistence on both ends of the spectrum is inefficient, and generally has negative consequences on these individuals, their employers, and the economy, should action be taken to combat this issue? If skills mismatch is becoming more common among Canadians, how can we expect to have a productive workforce? Furthermore, how can we expect unemployment rates to decrease and participation rates to increase when a significant portion of workers are more likely to be dissatisfied in their jobs because they are over- or under-utilized?

Federal and provincial government officials, researchers, and employers should consider this topic and the questions I have raised. Perhaps efforts should be put towards improving the skills of the vulnerable populations I have identified. If we fail to allocate skills efficiently in the economy, the negative effects could be long-term and detrimental. It is important for governments and academic researchers to work together to develop strategic initiatives that will prevent issues such as skills mismatch from becoming a greater phenomenon in Canada. Employers should also aim to increase the skills of their workforce. Placing individuals into jobs that their skillset is not matched for may be anti-productive. Although training costs are viewed as a drawback, there should still be incentive for employers to invest in training, since it is likely to improve employee productivity, satisfaction and loyalty, particularly if it increases profit or is of some other value to society.

The findings from my research yield similar results from previous studies; however, no studies have embarked on the level of detail I provided with respect to the predictors of skills mismatch. Furthermore, I have uncovered some unique aspects to skills mismatch in the Canadian labour market. My research has set out to lay the groundwork for skills mismatch research in the Canadian context. Several other researchers have measured skills mismatch, but most focus on international comparisons, the impact of skills mismatch on labour market outcomes, and use only one skill domain. My research has focused on Canada specifically, has focused on the predictors of skills mismatch, and has used all three of the skill domains within PIAAC. Hopefully researchers that utilize the Canadian PIAAC data to study skills mismatch will find my research valuable.

5.3 Recommendations for further research

There are a number of opportunities for further research relating to skills mismatch. A key area involves developing a superior method for measuring the phenomenon. The direct approach that is used in my research is still not ideal, even though it is a potentially informative method when using PIAAC data. Future research could involve a direct approach to measuring both the supply of and demand for skills. Understanding what employers actually demand for skill requirements is an essential part of understanding the true extent of skills mismatch. Expanding the skills that are used to define skills mismatch would also be valuable (e.g., non-cognitive skills, occupation-specific skills). Currently no such data exists on an international scale, but perhaps these elements should be considered for the next round of PIAAC data collection.

In the future it may be valuable to use Canadian PIAAC data to look at the effects of skills mismatch on labour market outcomes in Canada. Specifically, future research could consider understanding skills mismatch disparities between immigrant cohorts and the Canadian-born, and how this will impact the labour market in Canada. Immigration is a key method that is used to achieve population growth in Canada. Therefore, it would be valuable to research the differences between immigrants and the Canadian-born. Other research could look at how occupational changes affect the incidence and effects of skills mismatch over time. However, this would require panel data similar to what researchers in Australia have done.[26] This type of research in the Canadian context could uncover what factors tend to cause skills mismatch and to what extent the phenomenon persists. Therefore, longitudinal research could be a priority in the future. Understanding these topics would be invaluable for policy development.

Lastly, future research could consider the impact of skills mismatch on the Canadian economy from a macroeconomic perspective. Understanding the effects that skills mismatch has on worker and firm productivity and GDP would quantify how much of an issue skills mismatch truly is on the Canadian economy. This research would be valuable for policy decision-making, because monetary savings targets could be set and measured for reducing the extent of skills mismatch in the labour market.

5.4 Limitations

PIAAC is a survey of individuals, and is therefore prone to limitations, errors and biases that are common to most surveys, including human error, false reporting, failure to understand survey questions, non-response bias, and the social desirability bias. All information within PIAAC is self-reported, except for the skills assessment components. Additionally, the cross-sectional nature of PIAAC presents more limitations. Cross-sectional data is a snapshot in time, which prevents the possibility of accounting for unobserved individual differences across time, and limits the ability to infer causation.

The complexity of PIAAC data is both advantageous and disadvantageous. Although statistically robust estimates are produced in the output from PIAAC, the three skill domains of literacy, numeracy, and problem-solving contain partially imputed values. Therefore, the central variables within PIAAC that are used to define skills mismatch are subject to possible imputation errors. There could also be errors in the

[26] See Mavromaras et al. (2013)

sampling methodology, or the design of the questionnaire. However, these types of errors are less likely given the extensive effort that was put towards ensuring the reliability and validity of PIAAC data on an international scale.

The construct for skills mismatch used in the final model of this paper focuses only on cognitive skills, which is a limitation. A truly accurate and reliable measure of skills mismatch would broaden its scope to include non-cognitive skills and occupation-specific skills, both of which are relevant in the labour market, but neither is available in PIAAC. Another limitation with the final model is that it only partially accounts for skill heterogeneity within occupations by using two-digit occupational groups instead of groups that are more specific. Ideally, the full four-digit occupational codes would be used in order to account for skill differences between occupations, but the sample size is insufficient for the bulk of occupations. Each occupational group also relies on the same boundary of plus or minus 1.5 standard deviations from the mean to define skills mismatch, which is another limiting assumption. This assumption implies that approximately 87% of workers are skill-matched and 13% are skill-mismatched within each occupational group. It is possible, if not likely, that the boundary within each occupational group is not homogeneous. Furthermore, the boundary I chose is based on being consistent with other studies on skills mismatch rather than for theoretical reasons.

Due to the complexity of PIAAC data, I was unable to perform certain tests that could have lead to a better understanding of the validity of each method that was used to measure skills mismatch. Additionally, perhaps there are variables that I omitted from the final model that should have been included, which could result in biased results. By excluding the self-employed, apprentices, students, and part-time workers, I might have omitted important factors that predict skills mismatch in Canada. Lastly, by including only the employed population, it is possible that a selection bias is present within my analysis.

6.0 CONCLUSION

Having a skilled workforce is a priority for all levels of government in Canada. As individuals develop their skillsets, it leads to a prosperous economy, since they are able to broaden their employment prospects. However, skill development only has a positive economic impact if the skills that individuals acquire are operationalized in the labour market. Ideally, the skills that individuals have will be matched to the skill requirements of their jobs. Otherwise, skills mismatch occurs, which implies that skills are not allocated efficiently in the economy. Academic researchers and government officials both recognize the importance of skills mismatch in the international marketplace for skills. Several studies have aimed to understand how skills mismatch affects overall economic performance, firm productivity, and individuals labour market outcomes. The findings from these studies indicate that skills mismatch produces negative economic, firm and individual outcomes. Therefore, studying skills mismatch in Canada is a valuable endeavour.

My research set out to lay the groundwork for skills mismatch research in the Canadian context. The primary purpose of this study was to understand the predictors of skills mismatch in Canada by using the OECD's Survey of Adult Skills (PIAAC). I determined a potentially informative method for measuring skills mismatch and applied this method to address my research question. I predicted that various demographic and socio-economic factors would increase or decrease the likelihood of workers being skill-mismatched. A multinomial logistic regression model was developed to reflect my hypotheses.

A major advantage of my research is that it measures skills mismatch according to the three cognitive skill domains of literacy, numeracy, and problem-solving, which no other academic study has done thus far. Overall, the findings from each skill domain are very similar. The strongest predictors of skills mismatch, in terms of statistical significance and magnitude, are consistently among Canadian immigrants, those with higher levels of educational attainment, and those with parents or guardians that have higher levels of educational attainment. Location, gender, age, and years since immigration are also strong predictors of skills mismatch. Some findings that are unique to this study include:

- Workers in the Territories are much more likely to be under-skilled than other locations in Canada;
- Males workers are more likely to be over-skilled in all skill domains, and female workers are more likely to be under-skilled in numeracy;
- Younger workers are not more likely to be over-skilled in any skill domain;
- Immigrant workers that are new to Canada have a significant skills disadvantage in the labour market, but this disadvantage vanishes after integrating into Canadian society;
- Aboriginal workers are more likely to be under-skilled in numeracy;
- French Canadian workers are more likely to be under-skilled in problem-solving; and,
- A higher education level of parents or guardians is one of the strongest predictors of skills mismatch.

The findings from my research yield results that are similar to previous studies in terms of the factors that predict skills mismatch; however, my research has uncovered some additional factors that were not shown in previous research. Furthermore, no other researchers embarked on the level of detail I provided by including all three of the skill domains. Moreover, most other researchers focus on the effects of skills mismatch without carefully considering the method they use for measuring the incidence of skills mismatch.

Workers that are skill-mismatched are likely to experience various negative consequences that affect the performance of their employers and the economy overall. Therefore, in order to take action to prevent these negative consequences, policy-makers should consider the findings from my research in order to identify what groups of people are likely to be skill-mismatched. Efforts could then be aimed at improving the skills of the vulnerable populations I have identified and at tempering the extent of over-skilling. As a society, if we fail to allocate skills efficiently in the economy, the negative effects could be long-term and detrimental. It is important for governments and academic researchers to work together to develop strategic initiatives that will prevent issues such as skills mismatch from becoming a greater phenomenon in Canada.

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APPENDIX A

LITERACY: PROFICIENCY LEVELS AND DESCRIPTIONS

Level 5: 376-500. Contains about 1% of the Canadian population.
At this level, tasks may require the respondent to search for and integrate information across multiple, dense texts; construct syntheses of similar and contrasting ideas or points of view; or evaluate evidenced based arguments. Application and evaluation of logical and conceptual models of ideas may be required to accomplish tasks. Evaluating reliability of evidentiary sources and selecting key information is frequently a key requirement. Tasks often require respondents to be aware of subtle, rhetorical cues and to make high-level inferences or use specialized background knowledge.

Level 4: 326-375. Contains about 13% of the Canadian population.
Tasks at this level often require respondents to perform multiple-step operations to integrate, interpret, or synthesize information from complex or lengthy continuous, non-continuous, mixed, or multiple type texts. Complex inferences and application of background knowledge may be needed to perform successfully. Many tasks require identifying and understanding one or more specific, non-central ideas in the text in order to interpret or evaluate subtle evidence-claim or persuasive discourse relationships. Conditional information is frequently present in tasks at this level and must be taken into consideration by the respondent. Competing information is present and sometimes seemingly as prominent as correct information.

Level 3: 276-325. Contains about 38% of the Canadian population.
Texts at this level are often dense or lengthy, and include continuous, non-continuous, mixed, or multiple pages of text. Understanding text and rhetorical structures become more central to successfully completing tasks, especially navigating of complex digital texts. Tasks require the respondent to identify, interpret, or evaluate one or more pieces of information, and often require varying levels of inference. Many tasks require the respondent to construct meaning across larger chunks of text or perform multi-step operations in order to identify and formulate responses. Often tasks also demand that the respondent disregard irrelevant or inappropriate content to answer accurately. Competing information is often present, but it is not more prominent than the correct information.

Level 2: 226-275. Contains about 32% of the Canadian population.
At this level the medium of texts may be digital or printed, and texts may comprise continuous, non-continuous, or mixed types. Tasks in this level require respondents to make matches between the text and information, and may require paraphrasing or low-level inferences. Some competing pieces of information may be present. Some tasks require the respondent to:
• cycle through or integrate two or more pieces of information based on criteria
• compare and contrast or reason about information requested in the question
• navigate within digital texts to access and identify information from various parts of a document.

Level 1: 176-225. Contains about 13% of the Canadian population.
Most of the tasks at this level require the respondent to read relatively short digital or print continuous, non-continuous, or mixed texts to locate a single piece of information that is identical to or synonymous with the information given in the question or directive. Some tasks, such as those involving non-continuous texts, may require the respondent to enter personal information onto a document. Little, if any, competing information is present. Some tasks may require simple cycling through more than one piece of information. Knowledge and skill in recognizing basic vocabulary, determining the meaning of sentences, and reading paragraphs of text is expected.

Below Level 1: 0-175. Contains about 4% of the Canadian population.
The tasks at this level require the respondent to read brief texts on familiar topics to locate a single piece of specific information. There is seldom any competing information in the text and the requested information is identical in form to information in the question or directive. The respondent may be required to locate information in short continuous texts. However, in this case, the information can be located as if the text were non-continuous in format. Only basic vocabulary knowledge is required, and the reader is not required to understand the structure of sentences or paragraphs or make use of other text features. Tasks below Level 1 do not make use of any features specific to digital texts.

NUMERACY: PROFICIENCY LEVELS AND DESCRIPTIONS

Level 5: score between 376-500. Contains about 1% of the Canadian population.
Tasks at this level require the respondent to understand complex representations and abstract and formal mathematical and statistical ideas, possibly embedded in complex texts. Respondents may have to integrate multiple types of mathematical information where considerable translation or interpretation is required; draw inferences; develop or work with mathematical arguments or models; and justify, evaluate and critically reflect upon solutions or choices.

Level 4: score between 326-375. Contains about 11% of the Canadian population.
Tasks at this level require the respondent to understand a broad range of mathematical information that may be complex, abstract or embedded in unfamiliar contexts. These tasks involve undertaking multiple steps and choosing relevant problem-solving strategies and processes. Tasks tend to require analysis and more complex reasoning about quantities and data; statistics and chance; spatial relationships; and change, proportions and formulas. Tasks in this level may also require understanding arguments or communicating well-reasoned explanations for answers or choices.

Level 3: score between 276-325. Contains about 33% of the Canadian population.
Tasks at this level require the respondent to understand mathematical information that may be less explicit, embedded in contexts that are not always familiar and represented in more complex ways. Tasks require several steps and may involve the choice of problem-solving strategies and relevant processes. Tasks tend to require the application of number sense and spatial sense; recognizing and working with mathematical relationships, patterns, and proportions expressed in verbal or numerical form; and interpretation and basic analysis of data and statistics in texts, tables and graphs.

Level 2: score between 226-275. Contains about 32% of the Canadian population.
Tasks in this level require the respondent to identify and act on mathematical information and ideas embedded in a range of common contexts where the mathematical content is fairly explicit or visual with relatively few distractors. Tasks tend to require the application of two or more steps or processes involving calculation with whole numbers and common decimals, percents and fractions; simple measurement and spatial representation; estimation; and interpretation of relatively simple data and statistics in texts, tables and graphs.

Level 1: score between 176-225. Contains about 17% of the Canadian population.
Tasks at this level require the respondent to carry out basic mathematical processes in common, concrete contexts where the mathematical content is explicit with little text and minimal distractors. Tasks usually require simple one-step or simple processes involving counting; sorting; performing basic arithmetic operations; understanding simple percents such as 50%; or locating, identifying and using elements of simple or common graphical or spatial representations.

Below Level 1: score between 0-175. Contains about 6% of the Canadian population.
Tasks at this level require the respondents to carry out simple processes such as counting, sorting, performing basic arithmetic operations with whole numbers or money, or recognizing common spatial representations in concrete, familiar contexts where the mathematical content is explicit with little or no text or distractors.

PROBLEM-SOLVING IN A TECHNOLOGY-RICH ENVIRONMENT:

PROFICIENCY LEVELS AND DESCRIPTIONS

Level 3: score between 341-500. Contains about 7% of the Canadian population. At this level, tasks typically require the use of both generic and more specific technology applications. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g., a sort function) is needed to make progress towards the solution. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, and the criteria to be met may or may not be explicit. There are typically high monitoring demands. Unexpected outcomes and impasses are likely to occur. The task may require evaluating the relevance and reliability of information in order to discard distractors. Integration and inferential reasoning may be needed to a large extent.
Level 2: score between 291-340. Contains about 29% of the Canadian population. At this level, tasks typically require the use of both generic and specific technology applications. For instance, respondents may have to make use of a novel online form. Some navigation across pages and applications is required to solve the problem. The use of tools (e.g., a sort function) can facilitate resolution of the problem. The task may involve multiple steps and operators. The goal of the problem may have to be defined by the respondent, though the criteria to be met are explicit. There are higher monitoring demands. Some unexpected outcomes or impasses may appear. The task may require evaluating the relevance of a set of items to discard distractors. Some integration and inferential reasoning may be needed.
Level 1: score between 241-290. Contains about 30% of the Canadian population. At this level, tasks typically require the use of widely available and familiar technology applications, such as e-mail software or a web browser. There is little or no navigation required to access to the information or commands required to solve the problem. The problem may be solved regardless of respondents' awareness and use of specific tools and functions (e.g., a sort function). The tasks involve few steps and a minimal number of operators. At the cognitive level, the respondent can readily infer the goal from the task statement; problem resolution requires the respondent to apply explicit criteria; and there are few monitoring demands (e.g. the respondent do not have to check whether he or she has used the appropriate procedure or made progress towards the solution). Identifying contents and operators can be done through simple match. Only simple forms of reasoning, such as assigning items to categories, are required; there is no need to contrast or integrate information.
Below Level 1: score between 0-240. Contains about 15% of the Canadian population. Tasks are based on well-defined problems involving the use of only one function within a generic interface to meet one explicit criterion without any categorical, inferential reasoning or transforming of information. Few steps are required and no sub goal has to be generated.
Non-respondents: Contains about 19% of the Canadian population. This category includes those individuals who did not report previous computer experience, did not pass the ICT core test, or opted not to be assessed by a computer-based test.

(OECD, 2013d)

APPENDIX B

SCALES FOR LITERACY AND NUMERACY USE AT WORK

Questions pertaining to literacy use at work: How often do you usually…

1. Read directions or instructions?
2. Read letters, memos or e-mails?
3. Read articles in newspapers, magazines or newsletters?
4. Read articles in professional journals or scholarly publications?
5. Read books?
6. Read manuals or reference materials?
7. Read bills, invoices, bank statements or other financial statements?
8. Read diagrams, maps or schematics?
9. Write letters, memos or e-mails?
10. Write articles for newspapers, magazines or newsletters?
11. Write reports?
12. Fill in forms?

Questions pertaining to numeracy use at work: How often do you usually…

1. Calculate prices, costs or budgets?
2. Calculate fractions, decimals or percentages?
3. Use a hand-based or computer-based calculator?
4. Prepare charts, graphs or tables?
5. Use simply algebra or formulas?
6. Use advanced math or statistics such as calculus, complex algebra, trigonometry or regression techniques?

(OECD, 2013b)

APPENDIX C

NOC CODES AND LABELS FOR BROAD (1-DIGIT) AND MAJOR (2-DIGIT) OCCUPATIONAL GROUPS

0 Management occupations
- 00 Senior management occupations
- 01-05 Specialized middle management occupations
- 06 Middle management occupations in retail and wholesale trade and customer services
- 07-09 Middle management occupations in trades, transportation, production and utilities

1 Business, finance and administration occupations
- 11 Professional occupations in business and finance
- 12 Administrative and financial supervisors and administrative occupations
- 13 Finance, insurance and related business administrative occupations
- 14 Office support occupations
- 15 Distribution, tracking and scheduling co-ordination occupations

2 Natural and applied sciences and related occupations
- 21 Professional occupations in natural and applied sciences
- 22 Technical occupations related to natural and applied sciences

3 Health occupations
- 30 Professional occupations in nursing
- 31 Professional occupations in health (except nursing)
- 32 Technical occupations in health
- 34 Assisting occupations in support of health services

4 Occupations in education, law and social, community and government services
- 40 Professional occupations in education services
- 41 Professional occupations in law and social, community and government services
- 42 Paraprofessional occupations in legal, social, community and education services
- 43 Occupations in front-line public protection services
- 44 Care providers and educational, legal and public protection support occupations

5 Occupations in art, culture, recreation and sport
- 51 Professional occupations in art and culture
- 52 Technical occupations in art, culture, recreation and sport

6 Sales and service occupations
- 62 Retail sales supervisors and specialized sales occupations
- 63 Service supervisors and specialized service occupations
- 64 Sales representatives and salespersons - wholesale and retail trade
- 65 Service representatives and other customer and personal services occupations
- 66 Sales support occupations
- 67 Service support and other service occupations, n.e.c.

7 Trades, transport and equipment operators and related occupations
- 72 Industrial, electrical and construction trades

73 Maintenance and equipment operation trades
74 Other installers, repairers and servicers and material handlers
75 Transport and heavy equipment operation and related maintenance occupations
76 Trades helpers, construction labourers and related occupations
8 Natural resources, agriculture and related production occupations
82 Supervisors and technical occupations in natural resources, agr. and related production
84 Workers in natural resources, agriculture and related production
86 Harvesting, landscaping and natural resources labourers
9 Occupations in manufacturing and utilities
92 Processing, manufacturing and utilities supervisors and central control operators
94 Processing and manufacturing machine operators and related production workers
95 Assemblers in manufacturing
96 Labourers in processing, manufacturing and utilities

(Statistics Canada, 2015)

APPENDIX D

COMPARISON OF MODELS IN NUMERACY: UNDER-SKILLED RELATIVE TO SKILL-MATCHED

	Allen method		Perry method		Hybrid method	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regions						
Other Canada (ref.)						
Atlantic	0.113	(0.159)	0.283	(0.210)	0.103	(0.117)
Territories	0.55	(0.283)	0.788**	(0.283)	0.617*	(0.259)
Population density						
Non-urban (ref.)						
Urban	0.108	(0.156)	0.047	(0.202)	0.092	(0.149)
Gender						
Male (ref.)						
Female	0.319*	(0.148)	0.482**	(0.176)	0.293*	(0.133)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	-0.147	(0.285)	-0.117	(0.435)	-0.027	(0.278)
Age 25 to 34	0.032	(0.203)	-0.047	(0.272)	0.02	(0.184)
Age 45 to 54	0.098	(0.164)	0.498*	(0.215)	0.179	(0.174)
Age 55 to 65	0.248	(0.182)	0.759**	(0.255)	0.351*	(0.174)
Immigrant status						
Non-immigrant						
Immigrant	1.006***	(0.208)	1.877***	(0.303)	0.881***	(0.229)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	-0.008	(0.008)	-0.022*	(0.010)	-0.007	(0.008)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	0.028	(0.226)	0.498*	(0.242)	0.15	(0.171)
Mother tongue						
Non-French (ref.)						
French	-0.578***	(0.175)	-0.216	(0.171)	-0.482***	(0.142)
Education levels						
< PSE (ref.)						
PSE < bach.	-0.233	(0.137)	-0.82***	(0.171)	-0.147	(0.144)
PSE >= bach.	-0.887***	(0.183)	-1.428***	(0.245)	-0.558***	(0.168)
Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	-0.236	(0.177)	-0.446*	(0.186)	-0.202	(0.149)

Parent PSE >= bach.	-0.195	(0.203)	-0.668**	(0.245)	-0.179	(0.158)
Occupational groups						
Sales and serv. (ref.)						
Mgmt.	0.407	(0.262)	0.528	(0.303)	0.359	(0.261)
Business, Fin., Adm.	0.225	(0.204)	0.178	(0.273)	0.242	(0.190)
Sciences	-0.358	(0.267)	0.611	(0.316)	0.245	(0.229)
Health	-0.739	(0.434)	0.406	(0.410)	0.226	(0.341)
Ed., Law, Gov. Serv.	-0.572	(0.293)	0.525	(0.319)	0.256	(0.261)
Art, Culture, Rec.	-1.106	(0.849)	0.215	(1.023)	-0.173	(0.575)
Trades, Trans., Equip.	-0.23	(0.262)	0.034	(0.307)	0.338	(0.243)
Nat. Res., Agric.	0.216	(0.623)	0.02	(0.507)	0.709	(0.547)
Mfg., Utilities	-0.495	(0.347)	-0.165	(0.373)	0.064	(0.275)
Constant	-2.05***	(0.277)	-2.983***	(0.384)	-2.272***	(0.232)
N	12,580		12,589		12,580	
Pseudo-R^2	0.071		0.107		0.037	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

COMPARISON OF MODELS IN NUMERACY: OVER-SKILLED RELATIVE TO SKILL-MATCHED

Variable	Allen method		Perry method		Hybrid method	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regions						
Other Canada (ref.)						
Atlantic	-0.156	(0.118)	-0.149	(0.187)	-0.126	(0.123)
Territories	-0.078	(0.361)	-0.203	(0.303)	0.299	(0.362)
Population density						
Non-urban (ref.)						
Urban	0.257	(0.137)	-0.039	(0.186)	0.308**	(0.120)
Gender						
Male (ref.)						
Female	-0.218	(0.140)	-0.979***	(0.197)	-0.123	(0.113)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	0.384	(0.231)	0.284	(0.308)	0.232	(0.203)
Age 25 to 34	0.389*	(0.182)	0.23	(0.247)	0.294	(0.164)
Age 45 to 54	0.144	(0.188)	-0.029	(0.214)	0.041	(0.151)
Age 55 to 65	0.237	(0.221)	-0.167	(0.283)	0.203	(0.188)
Immigrant status						
Non-immigrant						
Immigrant	-0.832**	(0.274)	-1.19***	(0.351)	-0.785***	(0.233)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	0.016	(0.012)	0.028	(0.016)	0.015	(0.010)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	-0.379	(0.222)	-0.08	(0.351)	-0.172	(0.198)
Mother tongue						
Non-French (ref.)						
French	0.251*	(0.126)	-0.245	(0.166)	0.219	(0.114)
Education levels						
< PSE (ref.)						
PSE < bach.	0.552**	(0.190)	0.839**	(0.304)	0.435**	(0.154)
PSE >= bach.	0.734***	(0.229)	1.654***	(0.307)	0.742***	(0.180)
Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	0.088	(0.200)	0.41	(0.258)	0.106	(0.166)
Parent PSE >= bach.	0.337	(0.184)	0.774***	(0.238)	0.269	(0.166)
Occupational groups						

Sales and serv. (ref.)						
Mgmt.	-0.444	(0.306)	-0.579*	(0.259)	-0.342	(0.204)
Business, Fin., Adm.	-0.043	(0.286)	-0.019	(0.250)	-0.136	(0.195)
Sciences	0.562*	(0.256)	-0.993***	(0.307)	-0.399	(0.224)
Health	0.979**	(0.334)	0.176	(0.337)	0.097	(0.240)
Ed., Law, Gov. Serv.	0.896***	(0.279)	-0.556*	(0.253)	-0.321	(0.233)
Art, Culture, Rec.	1.126***	(0.336)	-1.041	(0.937)	-0.327	(0.470)
Trades, Trans., Equip.	0.762**	(0.253)	-0.483	(0.280)	0.008	(0.201)
Nat. Res., Agric.	1.075*	(0.442)	0.141	(0.628)	-0.217	(0.484)
Mfg., Utilities	0.617	(0.358)	0.087	(0.376)	-0.241	(0.305)
Constant	-3.462***	(0.324)	-3.283***	(0.423)	-2.537***	(0.246)
N	12,580		12,589		12,580	
Pseudo-R^2	0.071		0.107		0.037	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001.

APPENDIX E

COMPARISON OF DIFFERENT SKILL MISMATCH BOUNDARIES IN LITERACY: UNDER-SKILLED RELATIVE TO SKILL-MATCHED

	2 SDs		1.5 SDs		1 SD	
Variable	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Regions						
Other Canada (ref.)						
Atlantic	0.185	(0.349)	0.122	(0.201)	0.140	(0.132)
Territories	1.042**	(0.378)	0.853*	(0.349)	0.663*	(0.262)
Population density						
Non-urban (ref.)						
Urban	0.094	(0.389)	0.090	(0.192)	0.050	(0.134)
Gender						
Male (ref.)						
Female	0.150	(0.254)	0.143	(0.187)	0.187	(0.125)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	-0.118	(0.582)	0.040	(0.375)	0.060	(0.222)
Age 25 to 34	-0.298	(0.443)	-0.341	(0.294)	-0.201	(0.191)
Age 45 to 54	0.521	(0.364)	0.495*	(0.229)	0.403*	(0.160)
Age 55 to 65	0.978*	(0.403)	0.721**	(0.258)	0.593***	(0.158)
Immigrant status						
Non-immigrant (ref.)						
Immigrant	2.889***	(0.389)	2.232***	(0.291)	1.695***	(0.196)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	-0.04***	(0.012)	-0.029**	(0.010)	-0.022**	(0.007)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	0.475	(0.345)	0.384	(0.251)	0.314	(0.179)
Mother tongue						
Non-French (ref.)						
French	0.129	(0.267)	0.240	(0.182)	0.168	(0.133)
Education levels						
< PSE (ref.)						
PSE < bach.	-0.889***	(0.277)	-0.747***	(0.168)	-0.602***	(0.127)
PSE >= bach.	-1.587***	(0.316)	-1.341***	(0.267)	-1.104***	(0.179)
Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	-0.852**	(0.278)	-0.595***	(0.185)	-0.453***	(0.121)

Parent PSE >= bach.	-0.854*	(0.336)	-0.727***	(0.217)	-0.609***	(0.136)
Occupational groups						
Sales and serv. (ref.)						
Mgmt.	0.157	(0.452)	0.342	(0.315)	0.370	(0.212)
Business, Fin., Adm.	-0.037	(0.408)	0.156	(0.251)	0.088	(0.198)
Sciences	0.509	(0.427)	0.628*	(0.308)	0.399	(0.224)
Health	0.332	(0.590)	0.575	(0.404)	0.54*	(0.267)
Ed., Law, Gov. Serv.	0.395	(0.455)	0.570	(0.324)	0.576**	(0.220)
Art, Culture, Rec.	-1.091	(1.258)	-0.570	(0.761)	-0.447	(0.612)
Trades, Trans., Equip.	-0.293	(0.406)	-0.120	(0.277)	-0.016	(0.189)
Nat. Res., Agric.	0.128	(0.591)	-0.211	(0.419)	-0.338	(0.507)
Mfg., Utilities	-0.392	(0.548)	-0.176	(0.339)	-0.179	(0.245)
Constant	-3.908***	(0.500)	-2.853***	(0.348)	-1.727***	(0.250)
N	12,589		12,589		12,589	
Pseudo-R^2	0.153		0.108		0.085	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001. SD = Standard Deviation. 2 SDs, 1.5 SDs, and 1 SD each represent the different boundaries for defining skill-matched, under-skilled and over-skilled individuals.

COMPARISON OF DIFFERENT SKILL MISMATCH BOUNDARIES IN LITERACY: OVER-SKILLED RELATIVE TO SKILL-MATCHED

Variable	2.0 SDs Coef.	2.0 SDs S.E.	1.5 SDs Coef.	1.5 SDs S.E.	1.0 SD Coef.	1.0 SD S.E.
Regions						
Other Canada (ref.)						
Atlantic	0.013	(0.380)	-0.045	(0.159)	-0.139	(0.102)
Territories	0.340	(0.871)	0.110	(0.499)	-0.202	(0.345)
Population density						
Non-urban (ref.)						
Urban	0.182	(0.355)	0.055	(0.218)	0.023	(0.122)
Gender						
Male (ref.)						
Female	-0.627	(0.399)	-0.533**	(0.191)	-0.367**	(0.138)
Age groups						
Age 35 to 44 (ref.)						
Age 16 to 24	-0.205	(0.796)	-0.039	(0.343)	0.044	(0.190)
Age 25 to 34	0.376	(0.384)	0.274	(0.222)	0.147	(0.145)
Age 45 to 54	-0.176	(0.429)	-0.204	(0.226)	-0.145	(0.150)
Age 55 to 65	-0.476	(0.822)	-0.439	(0.294)	-0.394*	(0.185)
Immigrant status						
Non-immigrant (ref.)						
Immigrant	-1.858*	(0.802)	-1.627***	(0.362)	-1.414***	(0.227)
Immigrant duration						
Non-immigrant (ref.)						
Years since immigration	0.040	(0.033)	0.033	(0.018)	0.027**	(0.010)
Aboriginal status						
Non-Aboriginal (ref.)						
Aboriginal	-0.280	(0.918)	-0.106	(0.312)	0.025	(0.191)
Mother tongue						
Non-French (ref.)						
French	-0.225	(0.361)	-0.232	(0.160)	-0.278*	(0.113)
Education levels						
< PSE (ref.)						
PSE < bach.	0.924	(0.601)	0.495	(0.285)	0.516**	(0.169)
PSE >= bach.	2.05**	(0.663)	1.292***	(0.281)	1.133***	(0.169)
Parental education levels						
Parent < PSE (ref.)						
Parent PSE < bach.	0.694	(0.525)	0.610*	(0.243)	0.422**	(0.152)
Parent PSE >= bach.	1.105*	(0.524)	0.889***	(0.233)	0.657***	(0.151)
Occupational groups						

Sales and serv. (ref.)						
Mgmt.	-0.476	(0.733)	-0.489	(0.304)	-0.535**	(0.207)
Business, Fin., Adm.	0.193	(0.624)	-0.003	(0.266)	-0.100	(0.182)
Sciences	-0.629	(0.781)	-0.658	(0.340)	-0.646**	(0.243)
Health	0.427	(0.722)	0.057	(0.372)	-0.202	(0.236)
Ed., Law, Gov. Serv.	-0.489	(0.666)	-0.515	(0.293)	-0.482*	(0.197)
Art, Culture, Rec.	-3.669	(10.249)	-0.679	(0.873)	-0.413	(0.407)
Trades, Trans., Equip.	-0.133	(0.572)	-0.246	(0.297)	-0.122	(0.196)
Nat. Res., Agric.	-1.519	(8.205)	0.307	(0.715)	0.343	(0.367)
Mfg., Utilities	0.649	(0.948)	0.480	(0.427)	0.213	(0.237)
Constant	-5.78***	(0.827)	-3.405***	(0.393)	-1.807***	(0.221)
N	12,589		12,589		12,589	
Pseudo-R^2	0.153		0.108		0.085	

Note. Sample is restricted to employees that work at least 30 hours per week, that are non-apprentices, and are non-students. All results abide by the publishing requirements for PIAAC data. *p < 0.05, **p < 0.01, ***p < 0.001. SD = Standard Deviation. 2 SDs, 1.5 SDs, and 1 SD each represent the different boundaries for defining skill-matched, under-skilled and over-skilled individuals.

Results from the other domains of numeracy and problem-solving are available upon request.

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Calhoun, J., Holtmann, C., & Haan, M. (2014). Developing Infrastructure to Assess New Brunswick's Labour Market and Economic Competitiveness. *Sourcing the Trends in Increasing Dependency Ratios in New Brunswick.* Working Paper.

Haan, M., Calhoun, J., Calhoun, A., & Holtmann, C. (2014). *Report on Population Dynamics in New Brunswick and the Implications for the Province's Labour Market*. Working Paper.

Conference presentations:

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