Skill Mismatch of Indigenous Peoples in Canada: Findings from PIAAC*

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Abstract

Using the Programme for the International Assessment of Adult Competencies (Canadian sample) the paper examines the skill mismatch of Indigenous off-reserve peoples. Using several approaches to measuring skill mismatch we find that overskilling does not seem to be an issue for Aboriginal peoples of Canada. However, we do find significant differences in the underskilling rates between Indigenous populations and non-Aboriginal Canadian born. Specifically, First Nations females are more likely to be underskilled in numeracy, and First Nations males are more likely to be underskilled in literacy. Inuit peoples show the highest underskilling rates and are much more likely to be underskilled in literacy and numeracy in comparison to non-Aboriginal Canadian born. We also incorporate skill mismatch rates into the analysis of wages and conclude that it does not change previously documented differentials.

Keywords: Indigenous; Aboriginal; Skill Mismatch; Programme for the International Assessment of Adult Competencies (PIAAC)

JEL Codes: J15; J24; J71

1 Introduction

Technological progress, rampantly changing labor market, and the innate rigidity of skills have created an environment in which people's skills do not always match

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those required by their jobs. The literature on skill mismatch has documented that overskilling and underskilling has become a prevalent phenomenon existing in many countries (McGowan and Andrews (2015)). Due to matching mechanisms in the core of the labor market, some imbalances between demand and supply of skills are inevitable, but widespread mismatching may have pernicious economic consequences. It may also have negative impacts on social welfare and workers' productivity (Allen et al. (2013)). Overskilling is usually linked to lower wages and inefficient allocation of resources (McGuinness et al. (2018)), while underskilling may contribute to involuntary job loss during economic downturns (Nyström et al. (2018)).

As with many economic forces, skill mismatch may have a more profound effect on population groups that are already at a disadvantage in the labor market — one such group is the Aboriginal peoples of Canada. In addition to the challenges that these peoples face on Canadian labor market, they have historically retained strong ties with their reservations, so even those of them living off-reserves may experience a spatial constraint compelling them to choose jobs that do not match their skills. The differentials between the Aboriginal peoples of Canada and other Canadian born are not uniform and depend on many socio-demographic characteristics (see Pendakur and Pendakur (2011) for details), but on average, all groups of Indigenous peoples report lower wages, lower levels of educational attainment and lower labor participation rates than their non-Aboriginal Canadian-born counterparts. In the last decade there has been improvement in Aboriginal peoples' labor outcomes, but some disparities still persist.

Hu et al. (2019) show that after controlling for the skill level in literacy and numeracy, the earnings differential between off-reserve Indigenous peoples and non-Aboriginal Canadian born is substantially reduced. We expand upon their study by investigating whether First Nations, Metis, and Inuit peoples are more likely to be overskilled or underskilled in comparison to non-Aboriginal Canadian-born population. We do not find evidence that there is a statistically significant difference in the overskilling rates between Indigenous peoples and non-Aboriginal Canadian born. We also do not find any differences between First Nations and Metis. Unfortunately, the sample size for Inuit is too small to make sensible comparisons. As for the underskilling, we find that First Nations males are almost twice more likely to be underskilled in literacy in comparison to non-Aboriginal Canadian born, while First Nations females are twice more likely to be underskilled in numeracy, with the latter effect being stronger. We also find that Inuit males and females are much more likely to be underskilled in both literacy and numeracy. One of the main driving forces of underskilling is education, so our findings further solidify the importance of policies promoting the availability of education and heterogeneous training programs for the Indigenous peoples of Canada.

In addition to hazardous economic effects, both overskilling and underskilling may be a sign of workplace discrimination that requires different policy remedies. For example, overskilling may be tackled by policies aimed at removing barriers on the labor market and reforming institutions supporting inefficient structures of corporate governance. Underskilling, on the other hand, may be alleviated by provision of targeted training programs and further improvement of access to education. On the Canadian labor market workers with high educational attainment are more likely to be overskilled while recent immigrants, women and older workers are more likely to be underskilled (Mahboubi (2019)). The primary focus of this paper is on the Aboriginal peoples of Canada, but the results reveal that established immigrants are also prone to underskilling. The latter observation may be due to the conflicting effects of aging and time spent in Canada.

Finally, we incorporate mismatch rates into the analysis of wages and find that among all Indigenous peoples of Canada, First Nations males earn significantly less than their non-Aboriginal Canadian-born counterparts. The last observation is consistent with the previous findings (George and Kuhn (1994), Kuhn and Sweetman (2002)).

2 Literature Review

An extensive literature has documented that Indigenous peoples face challenges in the Canadian labor market. For example, George and Kuhn (1994), Kuhn and Sweetman

(2002), Pendakur and Pendakur (2011), Frenette et al. (2011) and Lamb (2013) find negative earnings differentials and lower rates of employment in comparison to the rest of the Canadian population[1]. All these papers point to education as the major impediment in the integration of Aboriginal peoples into the Canadian labor market. This situation is not unique to Canada. Similar tendencies have been documented for other countries, such as Australia (Jones (1993), Halchuk et al. (2006)) and the United States (Gitter and Reagan (2002)).

Education is undoubtedly an important factor contributing to the observed disparities in the labor market for Aboriginal peoples, but as noted by Hu et al. (2019), there are deeper reasons linked to information-processing skills, which affect labor market outcomes and which are not necessarily connected to formal education. Literacy and numeracy skills, for example, up until recently were hard to quantify, and they remained under the shroud of unobserved heterogeneity. Programme for the International Assessment of Adult Competencies (PIAAC) is aimed at measuring skills of individuals and helps to illuminate certain outcomes of Indigenous peoples from different angles. Previous surveys that measured skills (PISA, ALLS and IALS) are not as comprehensive. PIAAC encompasses adults 16-65 years old and measures their skills across three domains of information-processing skills (discussed below).

It is not surprising that skills are innately linked to earnings for most people. Finnie and Meng (2002) find that lower literacy levels account for a large income gap across many minority groups in Canada. Bonikowska et al. (2008) and Ferrer et al. (2006) show that the income gap between immigrants and the Canadian born is largely defined by differences in their literacy levels, even though the return on literacy is the same. Hanushek et al. (2015) show that for every population group earnings rise with an increase in information-processing skills. Mahboubi et al. (2017) find that Canadian Indigenous peoples have lower skills in comparison to non-Aboriginal populations, and this gap is largely defined by differences in attained education. Arriagada and Hango

[1] Additional evidence is provided by Drost (1994), De Silva (1999), Walters et al. (2004) Hossain and Lamb (2012) and Feir (2013).

(2016) argue that in some instances highly skilled representatives of First Nations are still less likely to be employed than low-skilled non-Aboriginal populations. Finally, Biswal (2008) shows that there is no gap in annual wages between high-skilled Aboriginal peoples and high-skilled non-Aboriginal Canadian born.

In the introduction we mentioned that overskilling and underskilling may serve as indirect measures of workplace discrimination. Previous research agrees that skill (and education) mismatch has pernicious consequences for the performance, productivity and rewards for workers and their employers (e.g. Leuven and Oosterbeek (2011), Sloane (2003), Erdogan et al. (2011)). There may be all sorts of constraints preventing a worker from getting a position matching his/her skills. Selective choices of employers are one of them. Rafferty (2019) shows that a variety of forms of workplace discrimination increases the probability of a person to be overskilled for his/her current position, and notes that some forms of discrimination may also be linked to underskilling. Hence, we provide results for both measures of skill mismatch. In addition, underskilling and overskilling influence the health of people via a variety of psychological factors documented by the vast psychological literature (e.g. Johnson and Johnson (1999), Wassermann and Hoppe (2019)).

Due to the specific nature of the information required to analyze skill mismatch, education mismatch is encountered more frequently in the literature. Leuven and Oosterbeek (2011), Rubb (2003) and Groot and Van Den Brink (2000) provide a comprehensive review of that topic, and Hartog (2000) discusses existing methodologies in detail. Skill mismatch, on the other hand, is different, because nominal education does not always reflect actual abilities. Education is frequently used as a proxy for unobserved skills, but there is much more variation in the skill level of individuals working for positions with the same educational requirements. This heterogeneity rises with the complexity of tasks at jobs demanding higher skill levels. Quintini (2011) provides a good overview of the existing literature on education and skill mismatch concluding that the former is by no means synonymous to the latter.

Unlike education mismatch, skill mismatch is scarcer in the literature, especially for Canada. To the best of our knowledge, there are only two papers that examine skill mismatch in the Canadian labor market and provide results for all Aboriginal peoples: Calhoun (2015) and Mahboubi (2019) (the latter study is based on the data analysis from the former study). These papers find that Indigenous peoples are more likely to be underskilled in numeracy in comparison to non-Aboriginal Canadian born, but not in literacy. Our research extends this analysis in two directions. Firstly, we investigate differences between skill mismatch rates for each unique group of Indigenous populations: First Nations, Metis and Inuit. Secondly, we perform our analysis by gender and provide separate results for males and females. We find that First Nations females are more likely to be underskilled in numeracy, while First Nations males are more likely to be underskilled in literacy. This adds a layer of nuance to the findings of Calhoun (2015).

We identify skill mismatch using adapted versions of several methods found in the literature. Perry et al. (2014) provide a good overview of the existing methodology based on PIAAC. Allen et al. (2013) study skill mismatch using these data across a large number of OECD countries concluding that higher skill utilization (i.e. lower skill mismatch) is always positive for economies. The authors also document a weak relationship between education and skill mismatch.[2] Quintini (2014) analyzes the same data and shows that skill mismatch is pervasive and affects just over one in seven workers, with young people being especially prone to overskilling. Pellizzari and Fichen (2013) find that on average, across OECD countries, there is a higher percent of overskilled rather than underskilled employees, but that the matching rate (using the authors' methodology) is quite high: 80-85%. Within this sample, men are more likely to be overskilled than women, and foreign workers are substantially more likely to be underskilled[3]. In addition, there is strong overlap in skill mismatch between literacy and numeracy.

This paper is organized as follows. The next section discusses the data. Section 4 develops the relevant methodology. Section 5 provides results for our mismatch

[2]Desjardins and Rubenson (2011) provide similar analysis based on ALLS survey and arrive to the same conclusions.

[3]We observe the same effect for Canadian immigrants.

analysis. Section 6 examines how skill mismatch affects wage differentials among different population groups, and section 7 concludes.

3 Data Description

We employ microdata from the Canadian sample of the 2012 PIAAC survey, which was developed by the OECD and was conducted in more than 30 countries. PIAAC belongs to the family of surveys measuring competencies, e.g. the Program for International Student Assessment (PISA), International Adult Literacy Survey (IALS) and Adult Literacy and Lifeskills Survey (ALLS). It combines the best practices of the previous designs and measures adults' (16-65 years old) competencies across three information-processing domains: literacy, numeracy and problem-solving in technologically rich environments (PTRE). The survey defines literacy as "understanding, evaluating, using and engaging with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential"; numeracy as "the ability to access, use, interpret and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life"; and PTRE as "the ability to use digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks". Respondents were able to choose paper- or computer-based tests in literacy and numeracy, but PTRE was administered only on computers. Hence, people who refused computer-based testing or did not have any computer experience did not participate in PTRE testing.[4]

Each domain of the information-processing skills is represented by ten plausible values measuring the skills of participating individuals on the scale from 0 to 500[5]. It is common in the design of competency tests to have an algorithm guiding each respondent

[4]Around 80% of non-Aboriginal populations have participated in computer-based testing. For Aboriginal peoples this indicator is lower (65-70% depending on the group).

[5]More information on the type of questions and scores interpretation is available from the PIAAC Reader's Companion.

through a subset of the test items, which helps to reduce the length of the assessment and increase participation. All answers are used to estimate a psychometric model based on Item Response Theory (IRT) (De Ayala (2013), Jakubowski (2013)). The purpose of the IRT model is to estimate respondents' unobserved abilities in each domain (literacy, numeracy and PTRE) using information on their observed performance in tasks that are associated with each domain. The number of potential tasks is infinite, and only their finite subset may be tested in practice. Hence, competency scores are imputed for respondents in tasks that they did not directly participate in, and plausible variables are designed to account for potential errors due to the imputation process. This methodology is meaningful for the whole population, but not for any single individual.

The survey contains information on 27,285 Canadians, which, combined with the implemented weights, represent around 24 million individuals aged 16-65 years. Oversampling of Indigenous peoples and immigrants allowed for the creation of representative samples of these groups (5,378 and 4,389 respectively). In addition to the information on latent plausible variables measuring competencies across the three domains, the survey also includes a rich background questionnaire comprising information on a large array of socio-demographic characteristics of respondents. The design of the survey utilizes the jackknife replication method with one unit removed to derive appropriate weights and variance estimates (with 80 replicate weights for each individual). To account for the sampling method, jackknife standard errors are calculated and reported throughout the paper.

We exclude students from the analysis and include only those respondents who currently work either full-time or part-time. We also restrict the age of respondents to 25-65 years. This decreases variation in the potential interaction between skills and professions, but also excludes young workers with innately higher overskilling rates (Desjardins and Rubenson (2011)). We further separate immigrants from the non-Aboriginal Canadian-born population by dividing them into two groups: recent (5 years or less from the landing date) and established (more than 5 years since landing). The test results of immigrants in literacy and numeracy differ significantly from the

Canadian born (Xu et al. (2017)). As shown in this paper and other studies, this also holds true for overskilling and underskilling rates (Calhoun (2015), Mahboubi (2019)). When analyzing wage, we include only respondents who reported hourly earnings between 5$ and 1000$. Self-employed individuals did not report any earnings, so they were excluded from this analysis.

We do not include PTRE domain into our analysis by two reasons. First, the methodology for the employed methods of measuring skill mismatch in this paper has been developed only for literacy and numeracy. Second, around one third of Aboriginal peoples did not participate in computer-based testing, which would further decrease the statistical power of the analysis. We found that underskilling rates in literacy are higher for respondents who refused to take computer-based testing, so it is possible that the overskilling rates in literacy are slightly overestimated.

Finally, one of the main limitations of the PIAAC data is that Indigenous peoples of Canada are represented by Metis, Inuit and First Nations who live exclusively off-reserve. According to the 2011 National Household Survey only around 25% of Indigenous peoples live on reserves. However, it is exactly those people, who account for a large share of socio-economic discrepancies observed in the labor market (Pendakur and Pendakur (2011)). This should be kept in mind when interpreting the results of this analysis.

4 Methodology

There are no ideal measures of skill mismatch. Each method has its own advantages and disadvantages. Our methodology builds on Verdugo and Verdugo (1989) and research on skill mismatch discussed in the introduction. Any employed individual possesses certain skills, and a job has certain skill requirements. The difficulty with measuring skill mismatch is that there are no perfect measures of either, so comparing them is even more challenging. Skill mismatch occurs when a worker's skills do not match the skills required by the job. PIAAC provides a measure of a worker's skills in three information-processing domains (by no means ideal), but the skills required by the job need to be derived from some observable information. PIAAC has two questions where respondents self-identify whether they are skill mismatched or not. For example, in one of the questions, individuals are asked to evaluate whether their skills are enough to cope with more demanding duties, while another question asks whether they feel that they need further training to cope well with their present duties. Following Pellizzari and Fichen (2013), an answer of "no" to both questions would indicate that the worker is matched. An answer of "yes" to at least one of the questions would indicate a mismatch.

As with any self-reported assessments the results are prone to a considerable bias. Hence, we employ direct methods of measuring skill mismatch (Perry et al. (2014)). The first method uses only objective observable information on any worker while the other two methods partially rely on certain self-reported parameters.

In the survey, there are 10 plausible values and 80 replicate weights for each observation resulting in $10 \times 80 = 800$ additional estimates. The standard errors accounting for the variability in those estimates are calculated as follows (see Wu (2005) for details):

$$SE_{\theta_p} = \sqrt{\left[\sum_{p=1}^{P} \underbrace{\left(f\sum_{r=1}^{R}(\hat{\theta}_{r,p} - \overline{\theta}_{0,P})^2\right)}_{\text{Sampling Error}} \frac{1}{P}\right] + \left[(1+\frac{1}{P}) \underbrace{\frac{\sum_{p=1}^{P}(\hat{\theta}_{0,p} - \overline{\theta}_{0,P})^2}{P-1}}_{\text{Measurement Error}}\right]}$$

where $\overline{\theta}_{0,P} = \frac{\sum_{p=1}^{P}\theta_{0,p}}{P}$, P is the number of plausible values, $\hat{\theta}_{r,p}$ is the estimate for replicate weight r and plausible value p, $\hat{\theta}_{0,P}$ is the estimate for the final sample weight for plausible value p.

4.1 Realized Matches

This method is a variant of approaches used in Perry et al. (2014) and Calhoun (2015), although in both papers it is not clear whether the authors used sample or survey weights to compute means and standard deviations. We compute both moments using jackknife weights. The greatest advantage of this method is that it does not rely on any self-reported information. It is constructed by calculating an average skill level of workers in literacy and numeracy by each occupational category and then considering all workers with a skill level higher (lower) than one standard deviation from the mean to be overskilled (underskilled). Figure 1 provides an exposition of this method. Occupational groups are identified according to 2-digit National Occupational Classification of Canada[6]. Perry et al. (2014) and Calhoun (2015) use 1.5 standard deviations in their analysis, which makes the conditions for mismatch more stringent. Due to a more detailed level of our analysis engendering lower statistical power we decreased this value to 1. Higher (lower) standard deviations will inevitably lead to lower (higher) mismatch rates.

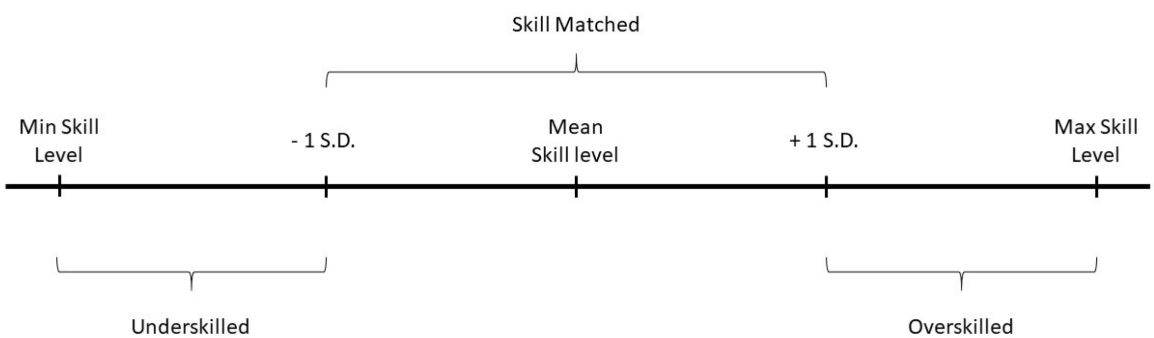

Figure 1: Identifying skill-mismatched workers

The major shortcoming of this method is that it does not capture heterogeneity of skills within same occupation groups, but it allows for a relatively detailed decomposition of industry skills into various categories serving as a proxy for the required skill levels (which are unobserved). It was not feasible to use three- or four-digit occupation codes due to the restrictions imposed by the sample size.

We calculate an individual's skill mismatch score for each of his/her ten plausible values for literacy and numeracy. Then, we estimate logistic regressions for males and females in literacy and numeracy separately, where the dependent variables are overskilling and underskilling, and the independent variables include the variable of

[6] https://www.canada.ca/en/employment-social-development/services/noc.html

interest discerning between different population groups and a set of controls. The final estimates are produced by averaging out the results among ten regression equations:

$$OS_{i,j}(US_{i,j}) = \beta_0 + \beta_1^a A_i + \beta_2^b I_i + \gamma X_i + \epsilon_i \tag{1}$$

where $OS_{i,j}(US_{i,j})$ is a set of ten dummy variables of being either overskilled (underskilled) or not for each of the plausible values[7]. β_1^a is a set of dummy variables for three Indigenous groups (A), i.e. Metis, Inuit and First Nations. β_2^b is a set of dummies for immigrants (I), including recent immigrants who landed in Canada five or less years before the survey, and established immigrants, who landed in Canada more than five years before the survey. The reference group is non-Aboriginal Canadian born. γ is a vector of coefficients for controls including age, education, marital status, number of children, parents' education, province, full- or part-time employment, and self-reported language ability.

We also run separate regressions for a subsample including only Indigenous peoples, which allows us to compare groups of Aboriginal populations amongst themselves.

$$OS_{i,j}^A(US_{i,j}^A) = \beta_0 + \beta_1 I_i + \beta_2 M_i + \alpha X_i + \epsilon_i \tag{2}$$

where I_i defines Inuit, M_i — Metis, and First Nations is the reference group. For overskilling, we do not run another set of regressions for a different reference group (Metis), because there are almost no overskilled Inuit in the sample, so that exercise would be redundant. For underskilling, we provide additional results for a different reference group (Metis).

4.2 OECD method

The OECD method is based on Pellizzari and Fichen (2013) and is similar to the previous approach, because it aims at identifying variation in the skill requirements

[7]Note that in this case the reference group is the people who are matched, which does not include underskilled individuals.

across industries by establishing a range of values around a central tendency measure. It employs a hybrid approach where the matched population is derived from the following two questions of the survey:

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? Yes/No

2. Do you feel that you need further training in order to cope well with your present duties? Yes/No

An answer of "no" to both questions indicates that the worker is matched. An answer of "yes" to the first question and "no" to the second question suggests that the worker is overskilled. An answer of "no" to the first question and "yes" to the second question suggests that the worker is underskilled. Then, for matched workers within each 1-digit International Standard Classification of Occupations (ISCO) categories,[8] we calculate 5^{th} and 95^{th} percentiles for literacy and numeracy. Workers with scores outside this range are identified as mismatched (overskilled if higher than the 95^{th} percentile and underskilled if lower than the 5^{th} percentile). As previously, decreasing (increasing) the percentile range will lead to an increase (decrease) in skill mismatch rates.

We estimate the same regression equations as in the previous method (for the whole sample and a subsample of Aboriginal peoples) with the exception that overskilling and underskilling are now calculated according to the OECD method discussed above. Similar to the realized matches approach, the OECD method has its shortcomings. It shares the problem of the former method in that it does not account well for the heterogeneity of skills used across each of the occupation groups. Despite that, it still provides a measure of the central tendency for skill levels across occupation categories, which serves as a proxy for the average required skills.

Another problem with this method is that questions 1 and 2 do not specify which skills exactly workers need to identify when answering them. Hence, it is implied that workers are matched on literacy and numeracy, when in reality their answers may

[8]Following Pellizzari and Fichen (2013) we exclude armed forces (ISCO code 10) and skilled agricultural and fishery workers (ISCO code 6) due to the shortage of observations. We also combine managers (ISCO code 1) and professionals (ISCO code 2).

be much broader. Finally, this method assumes that the skill distributions among underskilled, matched and overskilled workers are non-overlapping, when in practice it is hardly the case. In fact, Allen et al. (2013) shares these concerns indicating that relying on well-matched workers is redundant in practice.

4.3 Krahn and Lowe Method

In this section we develop a measure of skill mismatch based on Krahn and Lowe methodology (Krahn and Lowe (1998)). We identify skills required by a job based on how frequently individuals carry out different tasks in literacy and numeracy at their workplaces. The latter information is contained in the survey: the respondents are asked how frequently they perform various activities in one of the information-processing domains. For literacy, an example would be reading (and writing) reports, journals, financial statements, diagrams, maps or schematics and other publications; for numeracy — using a calculator, preparing charts, applying simple algebra or advanced math/statistics etc. There are around 15 questions in total.

The frequency of using each of the activities is measured on a scale from 1 (never use) to 5 (use every day). We subdivide activities into three categories: reading, writing, and numeracy and then calculate the average among the answers within each of the groups rounding it to the lowest integer. As a result, we derive 4 skill levels required by the job with 1 being the lowest required skill level and 4 being the highest required skill level. The received values for reading and writing groups are averaged to produce a literacy index. Without any further alterations, the value for the numeracy group is transformed into a numeracy index.

Using calculated literacy and numeracy indices as a proxy for the required skill level, we then compare these with the respondents' actual skills as measured by the test scores, which are also grouped into 4 classes based on the suggested categories from the survey. The following ranges of test scores for literacy and numeracy are used: 0-225 for skill level 1, 226-275 for skill level 2, 276-325 for skill level 3, and 326-500 for skill level

4[9]. A two-level difference between the required and the actual skill level constitutes a skill mismatch.[10] For example, if a respondent has a skill level 1 in literacy, and the required skill level in literacy for the job is 3 or 4, then this worker will be deemed as underskilled. Likewise, if a worker's skill in numeracy is 4, and the job requirement in numeracy is skill level 2 or 1, then he/she will be deemed as overskilled.

As previously, we estimate two regressions — one for the whole sample and a second for subsample of Aboriginal peoples using the developed measures of overskilling and underskilling in this section. The main shortcoming of this approach is that it equalizes the frequency with which a worker uses skills at the job with the skills actually required by his/her job. However, the particular skills of the worker have most likely selected him/her into the position requiring a different frequency for using those skills. Allen et al. (2013) show that there is indeed positive correlation between the two. In addition, the way calculated literacy and numeracy indices are matched to respondents' skill levels is somewhat arbitrary, because they are measured on different scales.

5 Results

Tables 1 and 2 present summary statistics for the sample revealing a stark difference in the observed distributions of socio-demographic characteristics between Inuit and other population groups. In particular, we see that Inuit education is significantly skewed toward lower levels (Hu et al. (2019) also point this out), and most of the sample is concentrated in the territories. They are younger, and more than 60% do not have a single parent who attained upper secondary education. Other Indigenous peoples are to a larger extent in line with non-Aboriginal Canadian born, with the exception of their location across provinces and the presence of a spouse.

Table 3 provides average unconditional scores in literacy and numeracy for

[9] The PIAAC separates test scores for literacy and numeracy into 6 skill levels: below level 1: 0-175, level 1: 176-225, level 2: 226-275, level 3: 276-325, level 4: 326-375, and level 5: 376-500.

[10] Quintini (2014) defines skill mismatch as one-level difference, which results in higher mismatch rates.

different population groups. It is not clear if there is significant difference between the scores of Aboriginal females and males in literacy and numeracy due to the size of the standard errors. It can be inferred, however, that Indigenous males and females (First Nations and Inuit in particular) score lower in literacy and numeracy in comparison to non-Aboriginal Canadian born. Hu et al. (2019) provide further details on what socio-demographic factors affect this outcome, and to what extent.

Examining unconditional over- and underskilling rates in tables 4 and 5 we can see that males seem to have higher overskilling rates than females across all population groups and methods used. One exception to this is the Krahn and Lowe method, in which males have the same or lower overskilling rates than females. Notice that, on average, Canadian born seem to have higher (lower) rates of overskilling (underskilling) than other population groups (except Metis). This observation is reflected in the odds from the subsequent regression analysis. There are almost no overskilled Inuit in the sample, so the results for this group are not reported.

Tables 6 and 7 are pivotal for this paper. They provide the odds of being overskilled or underskilled for different population groups in comparison to non-Aboriginal Canadian born. An odds ratio less than 1 indicates a lower probability for the corresponding group to be under- or overskilled in comparison to the reference group (Canadian born). An odds ratio higher than 1 means that the probability is higher. Neither of the methods has revealed significant differences in the odds of being overskilled except the realized matches approach, which found a weak effect for First Nations males to be less likely to be overskilled in numeracy than their non-Aboriginal Canadian-born counterparts. As for the underskilling, there are some important implications. First Nations males are almost twice as likely to be underskilled in literacy in comparison to non-Aboriginal Canadian-born males, and First Nations females are twice as likely to be underskilled in numeracy. The latter effect seems to drive the results of Calhoun (2015) for all Aboriginal peoples of Canada, although the ratios for Inuit peoples may have also played a part in it. Interestingly, if we restrict the sample only to respondents who participated in computer-based testing, the estimate for First Nations males becomes insignificant. While the coefficients are to some extent similar across the employed methods, only the realized matches approach shows significant differences. Additionally, we find that Inuit males and females are significantly more likely to be underskilled in literacy and numeracy in comparison to non-Aboriginal Canadian born, and the coefficients are substantive (5-7 times more likely).

Table (8) presents the odds ratios of being overskilled for the sample of Aboriginal peoples, where the reference group is First Nations. We can see that there are no significant differences in overskilling rates between Metis and First Nations. In addition, none of the controls have a significant impact on the odds as well. The fact that education does not have a significant impact on the probability of being overskilled is puzzling. We have run a separate regression for the subsample of non-Aboriginal Canadian born and we found that education is a strong predictor of being overskilled (this also drives results for the whole sample in Calhoun (2015)). A possible explanation may lie in different distributions of educational attainment across Aboriginal peoples and non-Aboriginal Canadian born, but this question requires further investigation.

The next tables (9 and 10) report the odds ratios of being underskilled for the sample of Aboriginal peoples with two sets of estimates. The first set uses First Nations as the reference group, and the other uses Metis. This allows for comparison between each of the groups of Aboriginal peoples. We can see that, on average, there is no statistically significant effect, but it is quite likely that those differences may exist across provinces. A spatial factor is important in the analysis of Indigenous populations, because even if they choose not to reside on a reservation, it is quite likely that the ties with their land will remain strong. While the sample size is not enough to provide detailed analysis by province, we present two tables (11 and 12) illustrating the differences in unconditional over- and underskilling rates among Aboriginal peoples across Canadian provinces. We can see that Metis peoples have higher rates of overskilling in numeracy in the provinces where these peoples historically had strong representation. To link these numbers to a spatially-compelled skill mismatch would require further research and different type of data, but we believe it may indeed be the case. First Nations, on the other hand, have the highest underskilling rates in Territories (more than twice as much as in Ontario), which may also be facilitated by the same underlying processes.

It is important to note that even despite the insignificance of many coefficients for overskilling, which may be due to a relatively small sample size, these odds are well below 1, which provides evidence that overskilling is most likely not an issue for First Nations. For Metis, on the other hand, it may potentially be a problem requiring further investigation. The results for underskilling suggest that this direction of skill mismatch may be an important issue for First Nations and Inuit, so correcting policies should prioritize these groups of Indigenous populations. Based on the analysis of this paper, these programs should be targeted and vary by gender. In addition, we cross-referenced underskilling rates of Aboriginal peoples with their occupation categories (under NOC) and found some heterogeneity. Specifically, Inuit peoples have higher underskilling rates in occupations belonging to C-level (intermediate jobs that usually call for high school and/or job-specific training) and D-level (labor jobs that usually give on-the-job training) jobs. This outcome may also be related to province-specific factors, such as relatively lower number of A- and B-level jobs in Territories in comparison to other provinces. Either way, providing training to Indigenous populations is one of the potential remedies to the issues outlined in this paper, and Canada has already taken steps in this direction.[11]

6 Skill Mismatch and Wages

Skill mismatch on its own may capture some workplace discrimination, but it does not tell us much about its economic consequences. One of the salient indicators of economic discrimination is wage — specifically, the wage differentials between different population groups. The goal of this section is to estimate the differences in wages across examined population groups controlling for both skills and skill mismatch in addition

[11] For details, see a report on Indigenous Employment and Skills Strategies in Canada.

to socio-demographic characteristics. To do that, we estimate an adapted version of the regression specified by Hu et al. (2019), where we gradually add ancillary controls:

$$\ln w_i = \beta_0 + \beta_1^a A_i + \beta_2^b I_i + \psi^c S_{ij}^{l,n} + \phi^d OS_{ijk}^{l,n} + \gamma X_i + \epsilon_i \tag{3}$$

where $\ln w_i$ is the natural logarithm of hourly wage. In addition to dummies for Aboriginal peoples (A_i) and immigrants (I_i) as well as controls for socio-demographic variables, this regression also includes a respondent's skill level in both literacy and numeracy ($S_i^{l,n}$) and whether he/she is over- or underskilled in literacy and numeracy ($OS_i^{l,n}$). Subscript i indicates the unique observation; $j = 1, \ldots, 10$ stands for plausible values, and $k = \{RM, OECD, K\&L\}$ represents measures of overskilling calculated based on the discussed methods: realized matches, OECD, and Krahn and Lowe.

Table 13 presents the results. It includes over- and underskilling calculated only according to the realized matches approach. Other methods lead to similar results, and are available on request. We can see that the wage differentials decrease for each group of Aboriginal peoples with the addition of more controls, but in most of the specifications only the First Nations males earn significantly less than the other Canadian born. There is also a small positive effect for Inuit females. Education, skills, occupation and skill mismatch account only for about five-ten percentage points of the difference in the wage differential identified with the basic controls. Interestingly, the wage gap is higher for overskilled First Nations males than the underskilled ones. On the other hand, for females, the wage disparities are much lower. This phenomenon has already been documented in the literature, e.g. George and Kuhn (1994), Kuhn and Sweetman (2002). We can also see that the same trend extends to immigrants (both recent and established). Again, these results underestimate the overall gap, because the sample does not include Aboriginal peoples living on reserves.

7 Conclusion

An extensive literature has documented that the Aboriginal peoples of Canada face challenges on the labor market. In addition to a potentially larger impact of economic forces on their well-being, Indigenous populations are unique in their ties with home reservations. The combination of those two factors may contribute to a more prevalent skill mismatch. The focus of this paper is on the skill mismatch rates among the Indigenous peoples of Canada. Using the PIAAC survey we have constructed several measures of skill mismatch and compared over- and underskilling rates across different population groups. We showed that there is a large degree of variation in over- and underskilling rates for Canadian Aboriginal peoples, especially across different provinces. We have also tested whether Aboriginal peoples were more likely to be over- or underskilled than non-Aboriginal Canadian born and we did not find any significant differences in the overskilling rates (except for a small effect for First Nations males in numeracy). For underskilling, however, we find that First Nations males are almost twice as likely to be underskilled in literacy, and First Nations females are twice as likely to be underskilled in numeracy. Inuit peoples are significantly more likely to be underskilled in both literacy and numeracy unconditional of the gender.

Each of the three measures of skill mismatch that was used in this analysis has advantages and disadvantages. Both those skills required by a profession and those skills possessed by an individual are unobservable and difficult to measure. Identifying a mismatch between the two is an even greater challenge. We have employed several methods to measure skill mismatch, and they all showed some variation in the over- and underskilling rates among the groups of Aboriginal peoples. While not all significant, the estimates produced by these various methods were similar. We believe that despite the discussed shortcomings of each of the methods individually, together they provide compelling evidence that underskilling is serious issue for the Aboriginal peoples of Canada. This issue can be addressed through policies aimed at further improving access to education and providing various training programs. The latter should take into account the revealed gender differences in literacy and numeracy.

Lastly, we have examined the wage differentials among different population groups controlling for the skill mismatch. Previous research has shown that wage differentials are larger for Aboriginal peoples' males than females. Controlling for over- and underskilling in literacy and numeracy did not change the picture. First Nations males and females were still found to earn lower wages in comparison to non-Aboriginal Canadian born. These gaps were larger for males who were overskilled, and for females who were underskilled.

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Table 1: Summary statistics, males

	First Nations	Metis	Inuit	Rec. imm.	Est. imm.	Can. born
Education						
Less than high school diploma	23.54	16.32	54	2.47	6.28	12.33
High school diploma	24.67	22.16	10.67	11.78	13.21	21.26
Below bachelor's degree	39.55	45.81	32	22.47	29.78	42.52
Bachelor's degree	8.85	12.13	2.67	35.34	28.96	16.33
First prof. degree, master's or PhD	3.39	3.59	0.67	27.95	21.77	7.55
Official Language Ability						
Poor or can't speak	0	0	0	5.48	3.91	0
Fair	0	0	0	15.07	11.55	0
Good	0	0	0	26.85	23.91	0
Very good	100	100	100	52.6	60.64	100
Spouse						
No spouse	20.88	12.46	21.37	11.62	10.03	11.5
Has a spouse	79.12	87.54	78.63	88.38	89.97	88.5
Age group						
25-34 years	22.41	20.81	28	34.79	16.45	19.69
35-44 years	30.13	26.65	29.33	42.74	31.09	23.53
45-54 years	27.31	31.74	30.67	18.63	30.64	31.5
55-65 years	20.15	20.81	12	3.84	21.82	25.29
Children						
No children	25.09	22.75	19.46	30.14	21.2	25.8
Youngest child $\leq$ 12 years	39.25	31.74	59.06	56.99	42.58	29.47
Youngest child $>$ 12 years	35.66	45.51	21.48	12.88	36.21	44.73
Parents' education						
Neither attained upper secondary	42.86	33.99	74.55	22.22	28.42	30.58
One attained post-sec. non-tertiary	34.92	39.41	13.64	30.56	29.27	38.89
At least one attained tertiary	22.22	26.6	11.82	47.22	42.3	30.52
Province						
Atlantic provinces	7.72	2.99	1.33	4.66	3.55	28.23
Quebec	2.45	4.49	0.67	21.64	23.45	28.34
Ontario	30.13	25.45	2.67	27.67	37.55	13.47
Prairies	22.98	48.2	0	18.9	14.55	18.27
British Columbia	13.56	12.57	0.67	24.66	15.09	4.42
Territories	23.16	6.29	94.67	2.47	5.82	7.26
Average Total Obs.:	531	668	150	365	1100	5232

Notes: The sample includes working males from 25 to 65 years old and excludes students. Numbers are given in percentages with the average sample size across subgroups.

Table 2: Summary statistics, females

	First Nations	Metis	Inuit	Rec. imm.	Est. imm.	Can. born
Education						
Less than high school diploma	11.89	8.39	46.94	2.66	6.44	6.92
High school diploma	20.06	21.7	15.65	10.36	12.77	19.7
Below bachelor's degree	45.62	47.67	29.93	23.67	27.62	43.18
Bachelor's degree	17.83	17.44	7.48	38.17	33.86	22.31
First prof. degree, master's or PhD	4.61	4.79	0	25.15	19.31	7.89
Official language ability						
Poor or can't speak	0	0	0	3.25	3.86	0
Fair	0	0	0	13.91	10.19	0
Good	0	0	0	27.22	23.74	0
Very good	100	100	100	55.62	62.22	100
Spouse						
No spouse	32.83	23.82	31.65	15.71	14.18	16.01
Has a spouse	67.17	76.18	68.35	84.29	85.82	83.99
Age group						
25-34 years	21.69	22.77	39.19	47.63	16.62	21.41
35-44 years	30.76	29.03	31.76	37.28	32.54	24.55
45-54 years	31.5	29.96	17.57	12.43	30.27	32.4
55-65 years	16.05	18.24	11.49	2.66	20.57	21.63
Children						
No children	14.29	21.17	10.14	36.09	18.02	22.1
Youngest child ≤ 12 years	35.86	31.03	60.81	45.56	36.44	28.86
Youngest child > 12 years	49.85	47.8	29.05	18.34	45.54	49.04
Parents' education						
Neither attained upper secondary	39.08	30.18	64.35	17.47	23.26	31.27
One attained post-sec. non-tertiary	33.04	41.27	20	31.63	32.99	36.91
At least one attained tertiary	27.89	28.55	15.65	50.9	43.75	31.82
Province						
Atlantic provinces	7.73	3.46	4.05	3.55	6.03	30.38
Quebec	2.53	2.4	0.68	17.75	18	28.28
Ontario	28.53	24.77	2.03	33.14	38.48	14.02
Prairies	23.63	48.6	0	17.75	14.34	17.56
British Columbia	12.18	14.25	0.68	24.85	16.72	3.82
Territories	25.41	6.52	92.57	2.96	6.43	5.95
Average Total Obs.:	673	751	148	338	1011	5478

Notes: The sample includes working females from 25 to 65 years old and excludes students. Numbers are given in percentages with the average sample size across subgroups.

Table 3: Mean literacy and numeracy scores for different population groups

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Mean	**SE**	**Mean**	**SE**	**Mean**	**SE**	**Mean**	**SE**
First Nations	258.1	(4.659)	262.4	(5.348)	248.1	(5.225)	240.5	(6.848)
Metis	274.6	(4.879)	282.4	(4.406)	269.2	(5.103)	262.9	(4.747)
Inuit	226.1	(12.14)	225.7	(10.70)	215.1	(12.87)	203.2	(10.33)
Recent Immigrants ($\leq$ 5 years since landing)	261.6	(4.227)	259.5	(3.821)	263.8	(4.651)	245.4	(3.847)
Established Immigrants ($>$ 5 years since landing)	262.1	(2.222)	257.0	(2.635)	264.3	(2.351)	245.7	(2.582)
Non-Aboriginal Canadian Born	284.6	(1.128)	285.8	(1.162)	282.9	(1.106)	272.2	(1.263)

Notes: the table provides survey-weighted means averaged across ten plausible values. Jackknife standard errors are in parenthesis.

Table 4: Overskilling rates for different population groups

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Percent	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**
Realized Matches								
First Nations	11.803	(4.003)	10.691	(3.353)	10.415	(2.682)	7.201	(2.807)
Metis	21.102	(5.621)	17.301	(5.853)	21.810	(5.413)	11.391	(4.046)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	14.757	(2.925)	11.977	(3.335)	20.419	(4.301)	11.323	(2.870)
Established Immigrants ($>$ 5 years since landing)	11.973	(1.741)	9.019	(1.967)	15.873	(1.977)	9.042	(2.045)
Non-Aboriginal Canadian Born	20.957	(1.005)	16.741	(0.978)	21.740	(1.047)	14.222	(1.033)
OECD Method								
First Nations	3.525	(1.487)	3.734	(1.651)	3.315	(1.272)	1.619	(0.968)
Metis	11.112	(4.427)	5.592	(2.993)	12.035	(4.530)	3.447	(2.407)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	5.469	(1.732)	3.880	(1.634)	9.126	(2.724)	3.482	(1.410)
Established Immigrants ($>$ 5 years since landing)	4.010	(1.401)	2.746	(1.245)	6.994	(1.632)	3.084	(1.031)
Non-Aboriginal Canadian Born	8.731	(1.243)	6.311	(0.910)	10.241	(1.221)	4.474	(0.858)
Krahn and Lowe Method								
First Nations	8.703	(3.003)	8.682	(2.768)	12.004	(3.204)	9.001	(2.795)
Metis	8.967	(2.819)	13.588	(4.200)	12.460	(2.704)	11.982	(3.825)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	6.408	(2.501)	7.811	(2.744)	12.858	(2.962)	9.938	(2.281)
Established Immigrants ($>$ 5 years since landing)	6.310	(1.430)	6.231	(1.323)	12.633	(1.583)	11.847	(1.722)
Non-Aboriginal Canadian Born	9.781	(0.883)	11.496	(0.806)	15.450	(1.071)	18.141	(0.955)

Notes: the table provides survey-weighted percentages of overskilling averaged across ten plausible values. Jackknife standard errors are in parenthesis.

Table 5: Underskilling rates for different population groups

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Percent	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**
Realized Matches								
First Nations	24.110	(4.261)	27.334	(4.504)	28.195	(5.662)	35.508	(5.396)
Metis	20.026	(5.354)	14.649	(3.345)	21.852	(5.876)	18.249	(3.948)
Inuit	49.352	(11.83)	54.917	(9.578)	55.167	(11.26)	59.950	(8.018)
Recent Immigrants ($\leq$ 5 years since landing)	28.483	(4.328)	27.977	(4.415)	26.190	(3.637)	30.593	(4.215)
Established Immigrants (> 5 years since landing)	28.396	(2.075)	32.450	(2.868)	25.473	(2.655)	32.278	(2.574)
Non-Aboriginal Canadian Born	14.143	(0.874)	14.952	(0.955)	13.624	(1.041)	16.903	(0.961)
OECD Method								
First Nations	4.386	(2.592)	5.605	(2.981)	5.617	(2.700)	8.473	(3.723)
Metis	1.979	(1.354)	1.231	(0.684)	1.706	(0.948)	2.293	(1.281)
Inuit	11.178	(3.469)	21.436	(7.397)	13.231	(4.181)	28.062	(9.342)
Recent Immigrants ($\leq$ 5 years since landing)	6.027	(2.200)	5.170	(1.809)	3.344	(1.283)	5.665	(1.907)
Established Immigrants (> 5 years since landing)	6.566	(1.300)	6.320	(1.672)	5.678	(1.490)	6.455	(1.900)
Non-Aboriginal Canadian Born	1.734	(0.355)	1.809	(0.504)	1.898	(0.500)	2.662	(0.647)
Krahn and Lowe Method								
First Nations	10.124	(2.951)	10.905	(3.981)	9.136	(2.866)	13.145	(3.687)
Metis	5.901	(2.079)	5.574	(1.649)	5.942	(2.130)	6.792	(1.900)
Inuit	12.208	(3.903)	17.732	(7.014)	16.305	(11.49)	18.228	(7.396)
Recent Immigrants ($\leq$ 5 years since landing)	8.801	(2.296)	8.920	(2.260)	9.411	(2.946)	14.455	(2.770)
Established Immigrants (> 5 years since landing)	10.707	(1.448)	10.895	(1.816)	11.552	(1.688)	15.124	(2.152)
Non-Aboriginal Canadian Born	6.032	(0.644)	4.601	(0.568)	6.744	(0.653)	7.962	(0.823)

Notes: the table provides survey-weighted percentages of underskilling averaged across ten plausible values. Jackknife standard errors are in parenthesis.

Table 6: Odds of being overskilled, full sample, different methods

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Odds	SE	Odds	SE	Odds	SE	Odds	SE
Realized Matches								
First Nations	0.672	(0.506)	0.722	(0.428)	0.536*	(0.366)	0.563	(0.497)
Metis	1.349	(0.404)	1.029	(0.558)	1.248	(0.406)	0.806	(0.463)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	0.524*	(0.336)	0.422*	(0.440)	0.629	(0.319)	0.446*	(0.466)
Established Immigrants ($>$ 5 years since landing)	0.469***	(0.218)	0.448**	(0.342)	0.564**	(0.258)	0.416**	(0.414)
OECD Method								
First Nations	0.528	(0.543)	0.768	(0.493)	0.465	(0.539)	0.401	(0.873)
Metis	2.018	(0.515)	0.980	(0.722)	1.722	(0.554)	0.735	(1.114)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	0.533	(0.457)	0.547	(0.597)	0.663	(0.409)	0.530	(0.740)
Established Immigrants ($>$ 5 years since landing)	0.477*	(0.375)	0.505	(0.556)	0.571*	(0.321)	0.554	(0.628)
Krahn and Lowe Method								
First Nations	1.347	(0.555)	0.974	(0.448)	1.206	(0.423)	0.662	(0.425)
Metis	1.173	(0.476)	1.507	(0.534)	0.903	(0.328)	0.918	(0.449)
Inuit	—	—	—	—	—	—	—	—
Recent Immigrants ($\leq$ 5 years since landing)	0.612	(0.624)	0.497	(0.495)	0.840	(0.341)	0.333***	(0.326)
Established Immigrants ($>$ 5 years since landing)	0.550	(0.401)	0.582	(0.342)	0.772	(0.237)	0.627**	(0.227)

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference group is non-Aboriginal Canadian born. Jackknife standard errors are in parenthesis. Controls include age, education, children, self-assessed language ability, parents' education, spouse, full- or part-time employment, and province of residence.

Table 7: Odds of being underskilled, full sample, different methods

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Odds	**SE**	**Odds**	**SE**	**Odds**	**SE**	**Odds**	**SE**
Realized Matches								
First Nations	1.821**	(0.290)	1.570	(0.279)	1.744	(0.407)	2.059***	(0.270)
Metis	1.310	(0.471)	0.852	(0.361)	1.224	(0.424)	1.015	(0.374)
Inuit	5.963*	(0.960)	5.002***	(0.539)	7.525**	(0.980)	5.153***	(0.550)
Recent Immigrants ($\leq$ 5 years since landing)	2.585**	(0.371)	3.381***	(0.273)	2.835***	(0.360)	3.770***	(0.265)
Established Immigrants ($>$ 5 years since landing)	2.288***	(0.216)	2.680***	(0.255)	2.479***	(0.247)	2.414***	(0.223)
OECD Method								
First Nations	1.797	(1.204)	1.671	(1.038)	2.303	(0.998)	2.071	(0.671)
Metis	0.956	(1.018)	0.857	(0.721)	0.958	(0.995)	0.859	(0.651)
Inuit	3.069	(0.695)	6.078	(1.156)	3.936*	(0.779)	5.187**	(0.807)
Recent Immigrants ($\leq$ 5 years since landing)	4.105*	(0.750)	4.200**	(0.698)	2.914	(0.766)	3.795*	(0.771)
Established Immigrants ($>$ 5 years since landing)	3.530**	(0.559)	3.439**	(0.522)	3.751**	(0.614)	3.107**	(0.495)
Krahn and Lowe Method								
First Nations	1.610	(0.530)	2.047	(0.435)	1.539	(0.481)	1.394	(0.296)
Metis	0.933	(0.531)	1.218	(0.403)	0.819	(0.501)	0.927	(0.351)
Inuit	1.346	(0.600)	4.466***	(0.539)	4.210	(1.612)	1.047	(0.528)
Recent Immigrants ($\leq$ 5 years since landing)	1.464	(0.407)	3.847***	(0.423)	1.871	(0.419)	3.178***	(0.393)
Established Immigrants ($>$ 5 years since landing)	1.661*	(0.296)	3.561***	(0.342)	2.093***	(0.276)	2.372***	(0.265)

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference group is non-Aboriginal Canadian born. Jackknife standard errors are in parenthesis. Controls include age, education, children, self-assessed language ability, parents' education, spouse, full- or part-time employment, and province of residence.

Table 8: Odds of being overskilled, subsample of Aboriginal peoples

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Odds	**SE**	**Odds**	**SE**	**Odds**	**SE**	**Odds**	**SE**
Realized Matches								
Intercept	0.245	(1.974)	0.778	(1.745)	0.191	(1.618)	0.215	(1.551)
Metis	1.493	(0.747)	1.534	(0.820)	1.479	(0.615)	1.580	(0.602)
Inuit	—	—	—	—	—	—	—	—
25-34 years	1.206	(1.199)	0.465	(1.244)	1.795	(0.760)	1.906	(0.737)
45-54 years	1.634	(1.156)	0.663	(0.762)	1.171	(0.974)	1.142	(0.962)
55-65 years	1.706	(1.079)	1.118	(1.072)	1.427	(1.083)	1.268	(1.159)
No children	1.252	(0.891)	1.177	(0.848)	1.030	(0.896)	1.097	(0.916)
Youngest child > 12 years	0.608	(0.973)	0.710	(0.757)	0.748	(0.932)	0.803	(0.992)
Less than high school diploma	0.138	(1.714)	0.136	(1.844)	0.112	(1.462)	0.136	(1.528)
High school diploma	0.543	(1.163)	0.436	(0.979)	0.153	(1.156)	0.166	(1.181)
Below bachelor's degree	0.590	(0.983)	0.381	(0.640)	0.402	(0.839)	0.409	(0.824)
First prof. degree, master's or PhD	0.723	(1.868)	0.559	(1.001)	0.220	(1.701)	0.350	(1.589)
Employment type	0.741	(0.847)	0.670	(0.745)	0.788	(1.096)	0.639	(1.022)
Neither attained upper secondary	0.480	(0.861)	0.345	(0.893)	0.537	(0.910)	0.592	(0.841)
One attained post-sec. non-tertiary	0.657	(0.787)	0.703	(0.717)	1.048	(0.694)	0.978	(0.686)
Atlantic provinces	1.119	(1.204)	0.994	(1.036)	0.730	(1.506)	0.724	(1.465)
Quebec	1.460	(1.628)	0.876	(1.508)	1.135	(1.453)	0.945	(1.448)
Prairies	1.943	(1.019)	0.900	(0.838)	2.142	(0.664)	1.790	(0.739)
British Columbia	2.044	(1.082)	0.858	(1.082)	2.393	(0.934)	1.937	(0.982)
Territories	0.922	(1.394)	0.590	(1.301)	0.710	(1.345)	0.705	(1.324)
Has a spouse	0.852	(0.863)	1.021	(0.958)	1.470	(1.079)	1.495	(1.073)
Urban status	1.904	(1.054)	0.871	(1.084)	2.514	(0.892)	2.260	(0.877)
OECD Method								
Metis	0.890	(0.721)	0.944	(0.739)	1.334	(0.709)	1.334	(0.709)
Inuit	—	—	—	—	—	—	—	—
Krahn and Lowe Method								
Metis	0.892	(0.672)	0.873	(0.682)	1.021	(0.502)	1.211	(0.565)
Inuit	—	—	—	—	—	—	—	—

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference groups are as follows: Aboriginal peoples — First Nations, age — 35-44 years old, children — youngest child ≤ 12 years, education — bachelor's degree, parents' education — at least one parent has attained tertiary, province — Ontario, spouse — no spouse, employment type — full-time, urban status — rural. OECD and Krahn and Lowe Methods include the same controls. Jackknife standard errors are in parenthesis.

Table 9: Odds of being underskilled, subsample of Aboriginal peoples

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Odds	**SE**	**Odds**	**SE**	**Odds**	**SE**	**Odds**	**SE**
Realized Matches								
Intercept	0.107	(1.442)	0.176*	(0.934)	0.344	(1.246)	0.268	(1.055)
Metis	0.725	(0.607)	0.621	(0.482)	0.725	(0.608)	0.544	(0.479)
Inuit	3.032	(1.275)	1.306	(0.719)	4.413	(1.411)	1.365	(0.737)
25-34 years	1.211	(0.984)	0.900	(0.672)	1.152	(0.962)	1.388	(0.618)
45-54 years	1.754	(0.958)	1.310	(0.703)	1.045	(0.844)	1.074	(0.622)
55-65 years	1.471	(0.886)	1.467	(0.843)	1.515	(0.925)	1.345	(0.801)
No children	0.484	(0.789)	0.572	(0.903)	0.585	(0.799)	0.377	(0.687)
Youngest child $>$ 12 years	0.625	(0.855)	1.170	(0.657)	0.596	(0.793)	1.606	(0.510)
Less than high school diploma	4.401*	(0.763)	4.933**	(0.803)	2.352	(0.731)	4.455**	(0.779)
High school diploma	5.158*	(0.927)	1.053	(0.683)	1.546	(0.829)	0.989	(0.675)
Below bachelor's degree	1.529	(0.734)	0.929	(0.619)	0.897	(0.711)	0.812	(0.524)
First prof. degree, master's or PhD	1.931	(1.557)	0.331	(1.073)	0.407	(1.521)	1.858	(1.025)
Employment type	0.665	(0.770)	1.162	(0.535)	0.473	(0.710)	0.976	(0.577)
Neither attained upper secondary	4.004**	(0.570)	1.334	(0.554)	3.375	(0.862)	2.160	(0.514)
One attained post-sec. non-tertiary	2.105	(0.746)	1.085	(0.588)	1.880	(0.989)	1.367	(0.488)
Atlantic provinces	1.238	(0.987)	0.829	(0.812)	1.325	(0.931)	0.809	(0.773)
Quebec	1.669	(1.184)	0.961	(0.942)	0.779	(1.395)	0.701	(0.825)
Prairies	0.666	(0.567)	1.282	(0.584)	0.678	(0.602)	1.186	(0.604)
British Columbia	0.527	(0.809)	0.927	(0.904)	0.570	(0.714)	0.586	(0.682)
Territories	1.180	(1.020)	4.396**	(0.585)	0.753	(1.069)	2.708*	(0.571)
Has a spouse	0.523	(0.937)	0.641	(0.472)	0.760	(0.834)	0.662	(0.437)
Urban status	0.819	(1.395)	0.620	(0.662)	0.613	(1.180)	0.429	(0.682)
OECD Method								
Metis	0.658	(0.891)	—	—	0.628	(0.898)	0.522	(0.787)
Inuit	0.763	(0.954)	—	—	0.985	(1.706)	1.900	(1.602)
Krahn and Lowe Method								
Metis	0.603	(0.738)	0.629	(0.760)	0.698	(0.635)	0.766	(0.597)
Inuit	0.567	(0.970)	0.650	(0.953)	3.442	(2.253)	1.063	(1.698)

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference groups are as follows: Aboriginal peoples — First Nations, age — 35-44 years old, children — youngest child $\leq$ 12 years, education — bachelor's degree, parents' education — at least one parent has attained tertiary, province — Ontario, spouse — no spouse, employment type — full-time, urban status — rural. OECD and Krahn and Lowe Methods include the same controls. Jackknife standard errors are in parenthesis.

Table 10: Odds of being underskilled, subsample of Aboriginal peoples, different reference group

	Literacy				Numeracy			
	Male		Female		Male		Female	
	Odds	**SE**	**Odds**	**SE**	**Odds**	**SE**	**Odds**	**SE**
Realized Matches								
First Nations	0.598	(0.321)	1.609	(0.482)	1.378	(0.608)	1.837	(0.479)
Inuit	0.285	(1.430)	2.103	(0.714)	6.082	(1.428)	2.508	(0.755)
OECD Method								
First Nations	1.519	(0.891)	1.519	(0.891)	1.590	(0.898)	1.913	(0.787)
Inuit	1.160	(1.170)	1.160	(1.170)	1.567	(1.734)	3.638	(1.736)
Krahn and Lowe Method								
First Nations	1.657	(0.738)	1.588	(0.760)	1.431	(0.635)	1.303	(0.597)
Inuit	0.940	(0.999)	1.033	(0.999)	4.928	(2.152)	1.385	(1.728)

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference group for Aboriginal peoples — Metis. Controls include age, education, children, self-assessed language ability, parents' education, spouse, full- or part-time employment, and province of residence. Jackknife standard errors are in parenthesis.

Table 11: Overskilling rates by province of residence

	Atlantic Region		Quebec		Ontario		Prairies		British Columbia		Territories	
	Percent	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**
Literacy												
First Nations	13.191	(6.119)	13.223	(12.020)	12.899	(4.258)	7.882	(4.569)	13.692	(6.607)	5.408	(3.633)
Metis	6.867	(5.518)	15.294	(9.304)	15.922	(8.883)	23.055	(6.940)	21.046	(7.143)	14.128	(7.997)
Inuit	—	—	—	—	—	—	—	—	—	—	—	—
Numeracy												
First Nations	8.411	(4.761)	10.476	(8.954)	10.220	(3.718)	7.264	(3.563)	12.887	(7.871)	4.707	(2.727)
Metis	9.587	(6.647)	10.677	(7.066)	12.923	(3.981)	21.765	(6.972)	15.812	(5.635)	9.112	(5.531)
Inuit	—	—	—	—	—	—	—	—	—	—	—	—

Table 12: Underskilling rates by province of residence

	Atlantic Region		Quebec		Ontario		Prairies		British Columbia		Territories	
	Percent	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**	**Percent**	**SE**
Literacy												
First Nations	22.952	(6.045)	21.633	(10.872)	22.359	(5.889)	31.360	(7.375)	16.083	(4.896)	52.308	(6.651)
Metis	20.546	(7.891)	40.784	(16.169)	10.445	(3.021)	14.681	(3.886)	13.636	(6.838)	29.410	(8.861)
Inuit	—	—	—	—	—	—	—	—	—	—	59.475	(4.837)
Numeracy												
First Nations	30.127	(6.957)	18.775	(10.676)	29.927	(7.100)	40.438	(7.844)	22.144	(6.253)	52.754	(8.187)
Metis	22.683	(8.539)	35.920	(15.823)	13.406	(4.277)	20.501	(5.738)	12.099	(4.523)	31.530	(7.614)
Inuit	—	—	—	—	—	—	—	—	—	—	63.267	(4.442)

Notes: the tables provide survey-weighted percentages of over- and underskilling by province averaged across ten plausible values. Only estimates received by the realized matches approach are reported. Jackknife standard errors are in parenthesis.

Table 13: Differences in Log Hourly Wages

	Basic Controls		+ Education		Skills + Noc WorkExp		+ Overskilling		+Underskilling (-Overskilling)	
	Est.	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
Males										
First Nations	-0.220***	(0.038)	-0.138***	(0.033)	-0.129***	(0.041)	-0.153***	(0.048)	-0.127***	(0.048)
Metis	-0.088***	(0.032)	-0.038	(0.035)	-0.017	(0.040)	-0.030	(0.048)	-0.003	(0.041)
Inuit	-0.115	(0.137)	0.036	(0.147)	0.130	(0.123)	0.203	(0.208)	0.075	(0.141)
Recent Immigrants	-0.251***	(0.044)	-0.388***	(0.047)	-0.258***	(0.043)	-0.269***	(0.054)	-0.286***	(0.050)
Established Immigrants	-0.037	(0.039)	-0.111***	(0.040)	-0.067*	(0.039)	-0.075*	(0.041)	-0.084*	(0.048)
R^2	0.274		0.380		0.464		0.488		0.459	
Observations	5952		5559		5202		4195		4027	
Females										
First Nations	-0.170***	(0.033)	-0.110***	(0.033)	-0.078**	(0.031)	-0.057*	(0.035)	-0.084***	(0.035)
Metis	0.018	(0.061)	0.082	(0.072)	0.113	(0.079)	0.090	(0.092)	0.139	(0.097)
Inuit	-0.124	(0.082)	0.029	(0.078)	0.093*	(0.053)	0.170*	(0.095)	0.079	(0.057)
Recent Immigrants	-0.101**	(0.043)	-0.259***	(0.046)	-0.101**	(0.042)	-0.121**	(0.054)	-0.089*	(0.046)
Established Immigrants	0.014	(0.033)	-0.068**	(0.031)	0.019	(0.028)	0.022	(0.035)	0.030	(0.032)
R^2	0.229		0.382		0.449		0.464		0.443	
Observations	6487		6047		5294		4004		4491	

Notes: statistical significance is represented by * for 10%, ** for 5% and *** for 1%. Reference group is non-Aboriginal Canadian born. Jackknife standard errors are in parenthesis. Basic controls include age, children, self-assessed language ability, parents' education, spouse, full- or part-time employment, and province of residence. Skills, overskilling, and underskilling include both literacy and numeracy. The results for over- and underskilling are presented only for the realized matches approach. Other methods provide similar estimates, and are available on request.