From Engineer to Taxi Driver? Language Proficiency and the Occupational Skills of Immigrants*

Susumu Imai[1] Derek Stacey[2] Casey Warman[†3]

[1]UTS Business School, University of Technology, Sydney
[2]Department of Economics, Ryerson University
[3]Department of Economics, Dalhousie University

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Abstract

We examine the ability of male immigrants to transfer the occupational human capital they acquired prior to immigration using information from the O*NET and a unique dataset that includes both the last source country occupation and the first four years of occupations in Canada. We first augment a model of occupational choice to study the implications of language proficiency on the cross-border transferability of occupational human capital. We then test the empirical predictions using the skill requirements of pre- and post-immigration occupations. We find that male immigrants to Canada were employed in source country occupations that required high levels of cognitive skills, but relied less intently on manual skills. Following immigration, they find initial employment in occupations that require the opposite. These discrepancies are both larger and more detrimental to earnings among immigrants with limited language fluency.

JEL classification: J24, J31, J61, J62, J71, J80

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†Corresponding author. Department of Economics, Dalhousie University, 6214 University Avenue, Halifax, Nova Scotia, Canada B3H 4R2. Phone: +1-902-494-4252. Email: warmanc@dal.ca

1 Introduction

Understanding the factors that determine the economic success of immigrants has become increasingly important as countries rely more heavily on immigration as a source of high-skilled workers, and as the economic outcomes of immigrants continue to decline.[1] Canada, like many Western countries, depends on immigration to meet labour market needs and strives to attract high skilled immigrants to benefit the domestic economy. Attracting high skilled immigrants is only meaningful, however, if the immigrants admitted are successful in finding employment in jobs that require these skills. Despite the large literature examining the economic integration of immigrants, which focuses on issues such as returns to foreign attained schooling, little is known about the occupational human capital that immigrants bring to the host country, and whether they find occupations that match their skills. Ideally, the occupational human capital acquired prior to migration should be used and compensated for in the host country economy. The objectives of this paper are to assess the human capital transferability of immigrants, and to understand specifically how language proficiency is related to skill mobility. The recently developed methodology using a skills-based approach to human capital enables us to accomplish these goals. We present theory and evidence on the transferability of occupational skills-based human capital from source country to host country labour markets, and show that dominant language proficiency is crucial for the efficient transfer of occupational human capital.

In the occupational mobility and immigration literatures, researchers often classify the numerous occupations into a few groups. A common classification system is the blue/white collar dichotomy based on skill requirements (i.e. primarily manual versus occupations relying more intently on cognitive skills) (Green, 1999; Cohen-Goldner and Eckstein, 2010). This approach potentially underutilizes important occupational information. Recent papers in occupational choice literature such as Ingram and Neumann (2006), Bacolod and Blum

[1]It is well established that recent cohorts of immigrants have had poor labour market outcomes. For evidence in the United States, see Borjas (1995) and Lubotsky (2007); and for evidence in Canada, see Baker and Benjamin (1994), Bloom, Grenier, and Gunderson (1995), Green and Worswick (2012) and Aydemir and Skuterud (2005).

(2010), Poletaev and Robinson (2008), Yamaguchi (2012) and others demonstrate that there are important differences in the skill requirements of occupations even within the broad occupational categories. For instance, a blue collar worker can switch to another blue collar job that has higher cognitive skill requirements. Unless these skill requirements are accounted for, the resulting wage increase would be inappropriately attributed to blue collar occupation tenure (see Yamaguchi (2012) for more details). This is particularly problematic in a study of immigrant outcomes since higher earnings resulting from occupational mobility could reflect switches to jobs that use the skills they acquired abroad rather than returns to years since migration.

Another approach common in the literature involves more finely partitioned classification systems.[2] Goldmann, Sweetman, and Warman (2011) use 10, 25, 47, and 139 occupation groupings to study the ability of immigrants to find employment that is directly related to the occupation they held prior to immigrating. There may be a loss or destruction of human capital if immigrants' new occupations are different from their source country employment. The evidence shows that occupational matching is an important determinant of immigrants' earnings, as well as the returns to years of foreign schooling. However, the incidence of occupational mismatch grows as the classification system becomes more finely defined. This is an undesirable feature, since immigrants who are unable to secure employment in the same occupation may be able to transfer human capital to a new job if it is similar in terms of the required skills.

Poletaev and Robinson (2008) find that occupational skill requirements, rather than industries or occupations, are the most important source of human capital specificity in the determination of earnings for displaced workers. Robinson (2011) finds that a voluntary occupation switch is usually a lateral move or a progression in skill requirements. In contrast, involuntary occupation movers typically experience a downward movement in skill requirements. It is likely that some immigrants are voluntary switchers pursuing equal or better

[2]Recent papers investigate the issue of human capital specificity. Neal (1995) and Parent (2000) examine the importance of industry-specific human capital, while Kambourov and Manovskii (2009) show that occupational tenure is an important determinant of wages among working age employed males in the US.

employment prospects in the host country. Others, however, may closely resemble displaced workers if having to find a new job is an inconvenient requisite following the move to the host country. Applying the notion of skill-specific human capital to the study of immigrant outcomes leads to a new set of questions: How drastic is the general shift in skill requirements encountered by immigrants? Does the transferability of certain skills rely more heavily on language fluency than others? Perhaps more importantly, how essential is the cross-border transferability of occupational human capital for earnings?

We examine these issues using a unique dataset that provides not only information on the labour market experiences of immigrants during the first four years after immigrating to Canada, but also information on the last occupation held in the source country prior to immigrating. We follow Ingram and Neumann (2006), Bacolod and Blum (2010), Poletaev and Robinson (2008), Yamaguchi (2012) and others, and derive a small set of fundamental skills requirements for each job from the detailed information in an occupation database (either the Dictionary of Occupational Titles (DOT) or Occupational Information Network (O*NET)). We construct a vector (portfolio) of skill measures that summarizes the skill requirements for each occupation listed in the O*NET. The vector consists of five variables; two of them correspond to cognitive skills (analytical and interpersonal skills) and the remaining three to manual skills (fine motor skills, visual skills and physical strength). By matching the source and host country occupations recorded in the Longitudinal Survey of Immigrants to Canada (LSIC) with those in the O*NET table and their corresponding vectors of skill requirements, we compare the skill requirements for all pre- and post-immigration jobs for male immigrants and estimate the gain or loss in required skill portfolios that resulted from immigration.[3] We show that these skill discrepancies vary systematically with English/French language fluency. We then estimate the potential gain or loss in earnings from impaired skill mobility.

We find that immigrants worked in source country occupations prior to migrating to

[3]We focus on male immigrants since, in addition to gender differences in labour market constraints that are beyond the scope of this paper, a large percentage of females had not worked prior to immigrating. While only 3 percent of male immigrants had not worked prior to immigrating, 20 percent of females do not report a source country occupation. In addition, a much larger percentage of males are directly assessed under the Canadian Point System, and therefore admitted based on human capital considerations.

Canada that generally required skill portfolios with higher levels of interpersonal skills and analytical skills relative to the occupations of the Canadian population, but lower motor skills, physical strength and visual skill requirements. This is an indication of the success of Canadian immigration policy geared towards attracting immigrants with high cognitive skills applicable to high technology, high knowledge economies.[4] After immigrating to Canada, however, our findings suggest that immigrants have difficulty finding suitable employment that utilizes the occupational human capital that they obtained abroad.[5] In the short term following migration to Canada, they work in occupations that not only require analytical skills and interpersonal skills that are on average similar to, or even lower than those of the Canadian population, but also require motor skills, strength, and visual skills that are similar to, and in some cases above the Canadian population averages. In other words, recent immigrants are working in jobs that do not utilize the cognitive skills that are sought after by immigrant receiving countries, but instead find jobs that require manual skills with which, given their source country work experience, they might be under-equipped.

We argue that these patterns emerge in the data because the transferability of occupational skills to a new labour market is conditional on dominant language proficiency. In particular, there is good reason to believe that the transfer of cognitive skills relies more heavily on language proficiency than the transfer of manual skills. Cognitive tasks tend to be carried out in environments that also require communication and interactions with others, while manual tasks can be performed in isolation or with minimum coordination and communication with clients and colleagues. In keeping with this line of reasoning, we find that the initial mismatch in skill requirements is markedly more severe among less fluent immigrants. Moreover, the fact that some evidence of convergence exists only for non-native speakers is consistent with the impact of language since dominant language proficiency presumably improves after migration.

[4]Two-thirds of our sample were directly assessed via the Canadian point system and admitted based on meeting a certain minimum level of human capital. We discuss this in greater detail in the data section.

[5]The results are almost identical when we restrict the sample to immigrants who are admitted under a human capital based point system (Skilled Worker Principal Applicants).

We conduct regression analysis to estimate the returns to the skill requirements of Canadian jobs, and then use the estimated coefficients to generate a set of predicted earnings under the counterfactual supposition that immigrants are successful in securing employment in occupations that match the skill requirements of their source country occupations. By comparing the predicted earnings under the assumption of perfect skill transfer and the actual earnings, we can measure the loss of earnings resulting from incomplete skill transfer. From this exercise, we find that Canadian immigrants suffer earnings losses in the range of 10 to 20 percent due to skill mismatch even four years after arrival, depending on their level of host country language proficiency.

The large literature examining the economic integration of immigrants has focused on a long list of specific issues: little or no returns to foreign attained schooling and foreign work experience (Friedberg, 2000; Schaafsma and Sweetman, 2001); the benefits of dominant language proficiency (Chiswick and Miller, 1995, 2012; Ferrer, Green, and Riddell, 2006; Skuterud, 2011); the consequences of an evolving source country composition (Aydemir and Skuterud, 2005); and the declining outcomes of all new labour market entrants (Green and Worswick, 2012). These studies share the broad view that immigrants have difficulty bringing their human capital to the host country labour market. Some studies view human capital as educational attainment, others consider foreign work experience, and still others focus on region-specific human capital such as language skills. In this regard, our analysis complements these strands of the literature, but differs in its adoption of the skills-based view of human capital.[6] Occupational skills, when combined with measures of language proficiency, potentially provide a better and more complete assessment of an immigrant's current human capital than other measures including educational and work experience variables. The highest level of educational attainment, for example, in addition to being very broad, may not provide the most recent status of an immigrant's job-related human capital.

[6]Several other recent papers in the immigration literature adopt a skill- or task-based approach to human capital; Peri and Sparber (2009) consider task specialization among immigrants and natives in the U.S., and Schuetze and Wood (2014) examine of the role social networks in the occupational choices of immigrants to Canada.

Of particular relevance are the recent studies identifying the importance of language skills for immigrant labour market employability and earnings. Ferrer, Green, and Riddell (2006) show that both self-assessed language ability and literacy test scores contribute to the earnings gap between immigrants to Canada and the Canadian born. Chiswick and Miller (1995) determine that dominant language fluency is associated with higher wages and increased probability of employment among foreign-born men in Australia. Berman, Lang, and Siniver (2003) find substantial returns to Hebrew proficiency among immigrants to Israel, and Bleakley and Chin (2004) report economic incentives associated with the English language skills of U.S. immigrants. In the analysis that follows, we also find that language fluency is a crucial determinant of an immigrant's labour market success, however, we focus specifically on role that language proficiency plays in the transfer of other skills to the host country economy.[7]

In the next section, we present the model that applies an occupational skill-based view of human capital to the analysis of immigrant labour market outcomes. In Section 3 we describe the data and outline our empirical methodology, in Section 4 we report our empirical results, and in Section 5 we conclude.

2 The Model

In the empirical analyses that follow this section, we strive to understand the transferability of immigrant workers actual skill endowments, which are unobservable, by examining the skill requirement variables of pre- and post-immigration occupations. To guide the analysis, we first develop a skill-based model of the transferability of immigrants occupational skills to the host country labour market and derive testable predictions about the skill requirements of immigrants host country jobs. These theoretical implications are then analyzed empirically

[7]There are several other papers that study language skill complementarities with other forms of human capital. Berman, Lang, and Siniver (2003) find a positive interaction with occupational status, and Chiswick and Miller (2003) show that there exist complementarities between language skills and foreign schooling and experience. To our knowledge, this paper is the first to consider impact of language proficiency on occupational skill transferability.

with the skill requirement variables generated with the O*NET data combined with the LSIC.

We develop a model of the labour market in which immigrants differ in terms of the skill endowments they bring to the host country economy. In the model, proficiency in the dominant language of the host country is an important factor for the transferability of an immigrants portfolio of occupational skills. This generates discrepancies between the skills required on the job and the ones with which immigrants are endowed. An important implication for aligning the theoretical and empirical parts of the paper is a difference in skill requirements of pre- and post-immigration occupations, which we can observe in the data. Furthermore, we assume that the impact of language on skill transferability is asymmetric across skills; i.e., the lack of language proficiency has a stronger negative effect on skill transferability for cognitive skills than for manual skills, so that immigrants with language difficulties end up in less skill intensive and less suitable occupations. These skill gaps result in lower wages.

Our model is closely related to the two skill, two period model of skill-specific human capital proposed by Lazear (2009). His framework focuses on the human capital investment strategies of firms and the wage implications of layoffs and voluntary job separations. Another important contribution to the task-based approach to human capital is Gathmann and Schönberg (2010). In their model, each firm (or occupation) has a different production function, which aggregates the analytical and manual tasks performed by workers. Consequently, task-specific human capital is less transferable between occupations that are dissimilar in terms of the combination of tasks used as inputs in the production process. Perhaps a more relevant study is the work by Phelan (2011). His paper extends the Lazear (2009) skill-weights model as a means of reconciling the empirical finding that a non-negligible number of displaced workers end up accepting jobs in industries that differ from their pre-displacement industry. We abstract from the concept of industry in our framework, and instead show that the interaction between language ability and skill transferability leads to gaps in the skill requirements of pre- and post-migration jobs. Our model predicts that upon arrival in the host country, an immigrant worker with inadequate language skills might have to accept a job with skill requirements that do not match his skill endowments.

Immigrants bring different levels and combinations of source country skills. Suppose there are two types of skills: let M_i and C_i denote immigrant i's fixed endowments of manual and cognitive skills. On the demand side of the labour market, firms use the skills of hired workers to produce output. Immigrants sort into occupations, which are heterogeneous in their use of skills; they combine skills in different proportions. When worker i is hired by firm j, their wage is given by[8]

$$Y_{ij} = \left(\frac{C_i}{\alpha_j}\right)^{\alpha_j} \left(\frac{M_i}{1-\alpha_j}\right)^{1-\alpha_j} \tag{1}$$

where $\alpha_j \in [0, 1]$ is the characteristic of the firm.

The above setup means that workers are compensated for their skills and for the suitability of the occupation-worker match. In other words, a worker's earnings vary according to how closely their skill portfolio aligns with the firm's demand for skills. Immigrants therefore select the occupation that maximizes their wage earnings. Maximizing (1) with respect to α_j yields

$$\alpha_j^* = \frac{C_i}{C_i + M_i} \tag{2}$$

which defines the α_j^* that produces an ideal match for an immigrant worker of type $\{M_i, C_i\}$. For example, Figure 1 displays the wage for worker i at different firms (for any $\alpha_j \in [0, 1]$). The wage is normalized by dividing by the total endowment of skills, $y_{ij} = Y_{ij}/(C_i + M_i)$. An immigrant with relatively high cognitive ability would be more productive at an occupation with a correspondingly high α, while immigrants with more manual skills would be better suited for a low α job.

An important issue in the context of immigrant workers is the effect of language ability

[8]The choice of wage equation mirrors the skill aggregation function in Phelan's (2011) model of wage losses among displaced workers. The critical implication is that workers are more productive if their skill ratios align with the skill weights. In contrast, other papers in the skill- or task-based human capital literature assume functional forms that lead workers to choose occupations that rely the most on their best skill (Lazear, 2009; Gathmann and Schönberg, 2010).

on labour market outcomes in the host country.[9] A lack of dominant language ability might impede the full utilization of immigrants' skills in host country jobs. To incorporate this into the model, let $L_i \in [0, 1]$ be an index of immigrant i's language ability. Then define

$$C_i = [1 - \eta_C + \eta_C L_i)]\, \hat{C}_i, \qquad \eta_C \in [0, 1] \tag{3}$$

as "host country usable" cognitive skills, where $\hat{C}_i$ denotes "source country usable" cognitive skills. Converting source country usable skills into host country usable skills depends on the immigrant's fluency in the host country's dominant language. A host country usable skill is increasing in language ability and in the source country usable skill, and there is some minimum portion of source country usable skills, $(1 - \eta_C) \geq 0$, that can be transferred even without any dominant language ability ($L_i = 0$). With perfect language ability ($L_i = 1$), cognitive skills are perfectly transferable.

Similarly, define "host country usable" manual skills according to

$$M_i = [1 - \eta_M + \eta_M L_i)]\, \hat{M}_i, \qquad \eta_M \in [0, 1] \tag{4}$$

It is not necessarily the case that the impact of language proficiency on skill transferability is symmetric: i.e., that $\eta_M = \eta_C$. In fact, we will impose the restriction that $\eta_M < \eta_C$; manual skill transferability is less sensitive to language proficiency than cognitive skill transferability. There is reason to believe that performing manual-type tasks on-the-job does not typically necessitate a mastery of the dominant language, whereas activities that require cognitive ability are more likely to be carried out in the dominant language and thus require the job incumbent to communicate effectively. Language deficiencies not only lower the absolute

[9]For example Chiswick and Miller (2010) estimate positive returns to English language proficiency among US immigrants, and also find that earnings increase with occupational language skill requirements and the interaction between the two variables. Ferrer, Green, and Riddell (2006) find that differences in literacy explain the majority of the earnings differentials between immigrants and the native born in Canada.

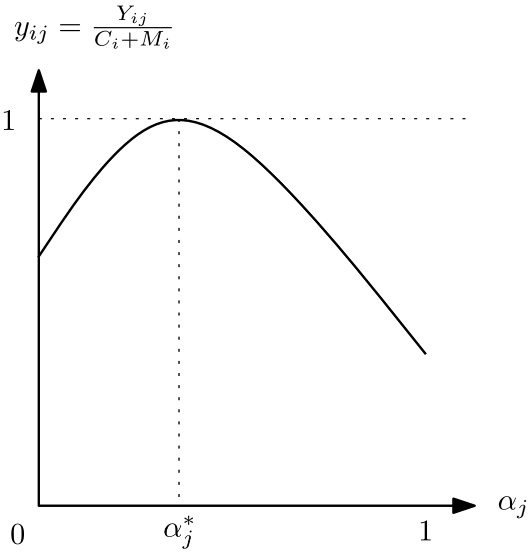

Figure 1: The wage paid to worker i.

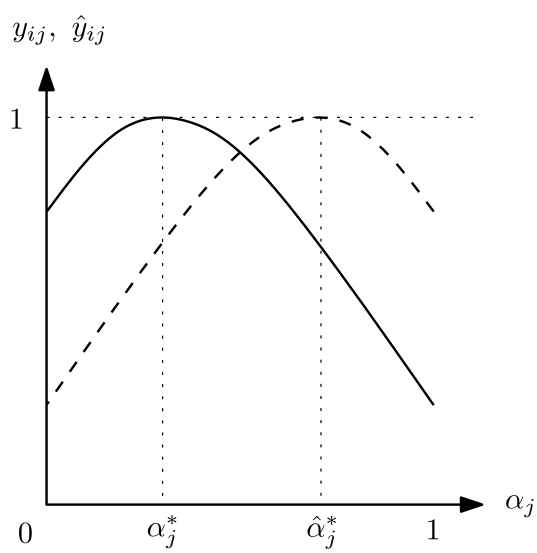

Figure 2: The source country wage (dashed line) and host country wage (solid line) for worker i when $L_i \in (0,1)$ and $\eta_M < \eta_C$.

levels of skills from $\{\hat{C}_i, \hat{M}_i\}$ to $\{C_i, M_i\}$, but can also affect the skill ratio:

$$\eta_M < \eta_C \quad \Leftrightarrow \quad \frac{C_i}{C_i + M_i} < \frac{\hat{C}_i}{\hat{C}_i + \hat{M}_i} \tag{5}$$

For example, a German marketing manager might be better suited for a position as a graphic designer in Canada if a lack of English/French language fluency affects his ability to convey information to clients without affecting his ability to develop graphics and illustrations. Figure 2 depicts this result for an immigrant with imperfect language ability, $L_i < 1$. $\hat{\alpha}_j^*$ pins down the ideal occupation in the source country, but $\alpha_j^* < \hat{\alpha}_j^*$ is the appropriate occupational choice in the host country because of the interaction between language fluency and skill transferability.

Language proficiency presumably improves with time spent in the host country. Appendix A describes the subsequent skill accumulation, occupational transitions and wage dynamics when immigrants' language proficiency improves with time spent in the host country. According to the theory, host country usable skills will increase along with language ability. Therefore, we expect skill gaps to diminish with time since migration to the extent that dominant language fluency develops over time. Skill gaps persist until an immigrant becomes perfectly fluent in the dominant language.

The empirical implications of the model are listed below.

1. Skill Gaps: Limited language proficiency gives rise to mismatches between the skill requirements of source country and host country occupations. Under the assumption that $\eta_M < \eta_C$, immigrants who lack fluency in the dominant language will be more productive in an occupation that differs from their source country occupation. In particular, language difficulties should cause wider cognitive skill gaps relative to the corresponding manual skill gaps.

2. Language Acquisition: To the extent that language proficiency improves with time since migration, the skill gaps for an immigrant cohort should diminish over time.

3. Earnings: Dominant language deficiencies adversely affect skill transferability and hence reduce an immigrant's earnings. The model predicts lower wages among recent immigrants with severe skill mismatches, conditional on the initial source country usable skill endowments.

In the subsequent sections, we inquire as to whether the predictions from the above simple model of immigrants' occupational choice are consistent with the data.

3 Occupation and Immigration Data

We use the recently developed methodology introduced by Ingram and Neumann (2006), Poletaev and Robinson (2008), Bacolod and Blum (2010), and Yamaguchi (2012) to reduce the abundant list of job characteristics in the Occupation Information Network (O*NET) into a small number of fundamental skill requirements. More specifically, we apply factor analysis techniques to the O*NET data in order to generate a vector of skills necessary to perform the job tasks associated with each occupation. The skill portfolios include both cognitive skills (analytical and interpersonal skills) as well as manual skills (fine motor skills, visual skills, and physical strength). We then match the source and host country occupations from the LSIC to the skill measures generated from the O*NET data in order to assign them skill requirements. Then, by comparing pre- and post-immigration occupations, we determine how well these jobs match in terms of the skills required to perform job tasks. We first document these discrepancies by plotting the distributions of source country and host country occupational skill requirements for immigrant males. We then estimate the mean gain or loss in skill requirements resulting from immigration for groups with different levels of language fluency. Finally, we conduct regression analysis of earnings data on host country occupational skill requirements and other individual controls to derive some counterfactual predicted earnings with different skill requirements. These estimation and prediction exercises demonstrate that the empirical results are consistent with the theoretical arguments.

3.1 Longitudinal Survey of Immigrants to Canada (LSIC)

The main dataset used for the analysis of immigrant outcomes is the LSIC. This survey was designed to provide information on new immigrants' adjustment to life in Canada. The full survey sample consists of immigrants who arrived in Canada between October 1, 2000 and September 30, 2001, and were 15 years of age or older at the time of landing. It is a longitudinal survey with immigrants being interviewed at six months, two years, and four years after landing in Canada.[10] Individuals who applied and landed from within Canada are excluded from the original survey, since their arrival in Canada may have occurred far in advance of the official landing and the survey is designed to capture the initial social and economic integration of immigrants. Refugees claiming asylum from within Canada are also not surveyed. To create a sample representative of newcomers, we drop a small percentage

[10] For the sake of brevity, we present the estimates for six months and four years after landing. We find that the second year skill gap estimates tend to be between the six month and fourth year estimates.

of immigrants who had previously been in Canada on a work or student visa. We restrict our sample to immigrants of age 25 to 59 at the time of the first cycle to reduce any effects of educational or retirement decisions.

A unique feature of the LSIC data is that it contains information on entry class. While the majority of legal immigrants enter the US under the family reunification program, the majority of immigrants to Canada enter under the economic class.[11] Canada, like Australia and New Zealand, uses points-based selection criteria to admit the principal applicant (i.e., Skilled Worker Principal Applicant) of the family entering under the economic class.[12,13] We are able to identify the Skilled Worker Principal Applicants: the immigrants whose human capital was directly assessed by an immigration officer. The majority of our sample (67 percent) are Skilled Worker Principal Applicants.[14]

The LSIC provides three digit occupation codes for both source country occupation and the first four years of occupations since immigrating.[15] One shortcoming of the data is that source country employment information is incomplete, as we do not know the duration of source country employment or the date of termination. Human capital may depreciate with the passage of time between source country employment and migration.

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[11]Economic immigrants are also admitted under the Investor and Entrepreneur classes. See Beach, Green, and Worswick (2007) for an overview of the Canadian program and a description of the composition of immigrants' admission class.

[12]Canada has made recent changes to the immigration program to address the worsening outcomes of economic immigrants and to better meet regional needs. Skilled Worker applicants are now required to have at least one of the following: pre-arranged employment in Canada, work experience in an occupation that appears on a list of in-demand jobs, a recent PhD degree from a Canadian university, or current PhD student status in Canada. The Canadian Experience Class was introduced, under which former temporary foreign workers and international students are admitted, conditional on meeting certain criteria. The Provincial Nominee Program has also greatly expanded. Canadian provinces can select immigrants based on self-defined local needs and admit them as Provincial Nominees.

[13]While the US does not have a point system, there has been discussion about the possibility of adopting one (Beach, 2006). See Belot and Hatton (2008) for an overview of the immigrant selection criteria of OECD countries.

[14]Over the period covered by the data, around 60 percent of new immigrants enter under the Economic Class. Of these, only the Principal Applicant is assessed under the point system, so that Skilled Worker Principal Applicants typically represent only 20 to 25 percent of immigrants. Since most Skilled Worker Principal Applicants are working age males landing from abroad, we have a larger percentage of them in our sample.

[15]The LSIC contains information for all jobs in Canada. We focus our analysis on the main job as indicated by the respondent in each of the three cycles.

3.2 Constructing Skill Indices from the O*NET

Studies of the occupational mobility of immigrants (Green, 1999; Cohen-Goldner and Eckstein, 2010) have divided occupations into two or three broad categories: white collar, blue collar, and professional. Aggregating in this manner ignores the many differences between occupations within each category. While finer classification systems (Goldmann, Sweetman, and Warman, 2011) reduce within category variation, there is no conceivable method to rank the magnitude of an occupation switch between categories in terms of the human capital requirements. Recently, researchers have circumvented these shortcomings by characterizing occupations based on the tasks required to perform for the job. Ingram and Neumann (2006) and others have applied factor analysis to the Dictionary of Occupational Titles (DOT) in order to describe each occupation in terms of the skill set required to accomplish the job tasks.

The O*NET, which replaced the DOT, is a useful source of detailed and comprehensive information about hundreds of jobs (1,122 occupational units in total). The dataset contains information on formal education, job training, and other qualifications necessary for each occupation, as well as different abilities and categories of knowledge required by its workers. Much of this information can be used to determine the portfolio of skills needed for each job. For example, some jobs require numerical abilities, and knowledge of arithmetic, algebra, and statistics. One would expect workers in such jobs to possess advanced analytical skills. Other O*NET information includes aptitudes, temperaments, tasks, and environmental conditions, which can also imply certain skill requirements. For example, some occupations involve moving and handling objects and performing activities such as climbing and lifting, which suggest the need for physical strength.

We use factor analysis to reduce the dimensionality of the occupation information contained in the O*NET. The underlying assumption is that the large set of O*NET job characteristics can be summarized by a small number of fundamental skill requirements. Factor analysis and principal component analysis are the techniques that Ingram and Neumann (2006), Bacolod and Blum (2010), and Poletaev and Robinson (2008) applied to the DOT.

Methodological difficulties arise because determining the appropriate number of factors, and interpreting the factors as particular skills is somewhat arbitrary. Moreover, multivariate factor analysis reduces the large set of O*NET characteristics into a small number of orthogonal skills, which does not allow skill requirements to be correlated.

We propose a slight variation in the methodology, known as confirmatory factor analysis, which is similar to the approach used by Yamaguchi (2012). We separate the O*NET variables *a priori* into groups of job characteristics such that all attributes in each group are associated with a common skill component. Our polychotomy includes interpersonal skills, analytical skills, fine motor skills, physical strength, and visual skills. Then, we estimate the principal component of each group of variables separately, assuming that a single factor underlies each group. The output of this process provides a way to check which of the variables chosen from the O*NET are in fact contributing to the score associated with each skill: high factor loadings are needed to confirm that the variables selected *a priori* are represented by the principal component. Only variables with factor loadings above 0.8 are kept. While this is a somewhat arbitrary cutoff, it implies that for each of the O*NET variables used in the analysis, most (almost two thirds, or $0.8^2 = 0.64$) of the variance is explained by the factor. Iteratively dropping variables that fail to contribute to the factor of interest yields a score for each job that reflects the occupational requirement for the underlying skill. Online Appendix C contains descriptions of the relevant O*NET variables and the output from factor analysis. The resulting portfolio of skills is much easier to interpret than the principal component method used in some papers. Moreover, this methodology drops the unrealistic assumption that the underlying skills are orthogonal.[16]

By construction, the scores yielded have mean zero and unit variance. We use the occupational distribution of the Canadian population in the 2001 Census Masterfile as a weight for the factor analysis. This provides convenient intuition so that the unit of a derived factor score is equal to one standard deviation in the skill distribution for the Canadian population. The estimated factor scores are then applied to the occupations of recent immigrants

[16]This method of constructing skill requirements is also used as a robustness check in Bacolod and Blum (2010) as an alternative way of constructing skill indices.

to Canada contained in the LSIC data.[17]

3.3 Methodological Remarks

It is important to acknowledge some of the caveats of the methodology described above. First, skills may vary even within an occupation. For a given occupation, it is not possible for us to determine where a worker (immigrant or Canadian) is in the skill distribution. Fortunately, the O*NET contains information for over 1,100 jobs which are matched to almost 500 LSIC jobs, so the within occupation variation should be minute compared to other broader occupation classifications.

Potential methodological problems could arise when we apply the O*NET data to Canadian occupations when in fact the O*NET is based on occupational skill requirements in the United States. Doing so implicitly assumes that occupations in Canada require similar skills to those in the US. We then impose a second and perhaps more questionable assumption that all source country occupations are similar in skill requirements to the corresponding occupations in the US. Given the similarity between the American and Canadian economies, the first assumption seems plausible. In contrast, there are bound to be similarities and differences in the skill requirements of occupations in some countries.[18] Without similar O*NET datasets devised separately for every country, one must rely on the assumption that these differences are not too great. These asymmetries are potentially less severe among OECD countries. As noted in subsequent footnotes in the empirical section, we still find gaps between the source and host country skill requirements when we restrict the sample to OECD countries, but the gaps are smaller.[19] While there are other explanations for the

[17] We are able to successfully match over 95 percent of the LSIC occupations in our sample with the O*NET.

[18] A similar issue in the context of immigration policy is the absence of any distinction between credentials of different qualities among Canadian immigrants. To address this, Canada recently implemented policy changes to directly examine the quality of applicants credentials.

[19] Since less than 8 percent of our sample arrive from OECD countries, we cannot carry out extensive analysis for this subsample. As an additional robustness check, we investigate potential differences in the quality of occupational human capital by controlling for source country GDP in the earning regressions. We find that the overall results remain unaltered.

smaller gaps,[20] this could reflect less than perfectly comparable skill requirements for the same occupation in some non-OECD source countries relative to the US or Canada. For this reason, one might not expect the skill gaps to completely disappear even among immigrants with perfect language fluency. We return to this issue in Section 4.

Drawing conclusions about the transferability of immigrants' skills to the Canadian labour market relies on the additional assumption that a worker's skill endowments closely resemble their source country occupational skill requirements. Even in the source country where dominant language proficiency is an uncommon issue, we should acknowledge the possibility that other frictions prevent perfect matching between workers and occupations so that the skill requirements of the source country occupation does not altogether align with the immigrant's actual skills. On the other hand, the last job held by an immigrant prior to migration is likely the result of a lengthy process of human capital accumulation as well as matching and sorting into a suitable occupation. We therefore argue that the skill content of a source country occupation should provide a reasonable description of a worker's actual skill endowments, and the presence of a skill gap reflects a mismatch in the Canadian economy rather than abroad. In any case, the occupational information should provide a more up-to-date and complete assessment of an immigrants human capital than can be captured by means of education-related variables. Nevertheless, one should be cautious when interpreting mismatches in skill requirements as an incomplete transfer of immigrants actual skill endowments.

Occupational skill gaps could be driven by Canadian regulatory bodies that prevent immigrants from securing their most suitable occupation by not recognizing foreign credentials. Fortunately, LSIC respondents are asked "Do you have any professional or technical credentials that you received from outside Canada, such as a license required to practice your occupation? Some examples of these types of credentials include a mechanics license, a professional engineer accreditation, a plumbers certificate of qualification, a chartered pro-

[20] For example, the smaller gaps for the OECD subsample could be due to differences in incentives to immigrate; i.e., a potential OECD emigrant is unwilling to move unless they face similar economic opportunities in the host country.

fessional accountant designation and so on." To investigate the importance of unrecognized foreign credentials, we compute the skill gaps for immigrants with and without licensing requirements (results not shown but available from the authors). There are only slight differences between the two groups: not enough to alter the results when immigrants with license requirements are excluded from the sample.

The longitudinal analysis focusing on occupations gives rise to a further complication due to the possibility of measurement error. Respondents may change the label of their occupation from year to year, which can be misinterpreted as an occupational switch. Our analysis circumvents this problem to a large degree for several reasons. First, respondents are asked to specify their source country job and their occupations during the first six months in Canada in the same interview. Moreover, the two subsequent interviews are only a year and a half, and three and a half years later. If immigrants happen to mislabel their occupations, it is likely that they will report an occupation that is similar in terms of skill requirements, which reduces measurement error relative to analyses that identify switches using occupation codes.

4 Sample Statistics and Estimation Results

4.1 Skill Gaps

Column 1 of Table 1 displays the skill content of cycle 1 occupations (six months after landing in Canada), which is compared to that of source country occupations for immigrant men. Recall that each factor is constructed such that zero represents the average for the Canadian population, and the units are standard deviations of the Canadian skill requirement distribution. The data show that immigrants work in source country jobs that require interpersonal skills that are on average 0.70 standard deviations above the average for the Canadian workforce. Similarly, the analytical skill requirement is 1.13 standard deviations above the Canadian average. In other words, prior to moving to Canada, immigrants worked in jobs that require very high cognitive skills. After landing in Canada, immigrants acquire jobs that require interpersonal skills that are on average 0.35 standard deviations below the Canadian average, resulting in a drop in skill requirement of 1.05 standard deviations. The analytical skill requirement also decreases from 1.13 standard deviations above the Canadian population average to 0.07 standard deviations below: a 1.20 standard deviation drop.

In contrast, the manual skill requirements of immigrants' jobs after landing in Canada have dramatically increased relative to their source country jobs. The requirement for motor skills increases from 0.28 standard deviations below the Canadian average for source country occupations to 0.25 standard deviations above average; this is a move of more than half a standard deviation up the skill distribution. The visual skill requirement increases from 0.09 standard deviations below the Canadian average to 0.10 above, while the strength requirement increases from 0.49 standard deviations below to 0.22 above the Canadian average. Overall, we can conclude that immigrants work in jobs after landing that require much lower cognitive skills but much higher manual skills compared to their source country occupations.

To check for signs of convergence in skill requirements among immigrants to Canada, we report the skill gap between source country occupations and cycle 3 Canadian occupations (four years after landing) in column 2. The decline in cognitive skill gaps is particularly noteworthy: the interpersonal skill gap decreases from 1.05 to 0.71 standard deviations, and the analytical skill gap drops from 1.20 to 0.82 standard deviations. Even though cognitive skill gaps persist, there is evidence that immigrants gradually move to jobs that utilize their interpersonal and analytical skills. In contrast, there appears to be only slight improvement or no change at all in manual skill gaps: the strength gap falls from 0.72 to 0.55 standard deviations, while there is very little change in the gaps for visual and fine motor skills.[21] Changes in Canadian skill requirements between cycles 1 and 3 can manifest as a result of changes in the composition of the sample studied; the sample increases from $1,476$ to $1,927$

[21] Immigrants from OECD countries experience smaller gaps in terms of interpersonal and analytical skill requirements. The differences are around half of a standard deviation at six months after arrival, and only 0.25 and 0.34 standard deviations for interpersonal and analytical skill requirements by the fourth year in Canada. They also experience smaller increases in manual skill requirements. These results are available from the authors upon request.

due to delays in entering the workforce. Despite the large jump in sample size between cycles, there is very little change in average source country occupational skill requirements.

We re-estimate the means separately for Skilled Worker Principal Applicants and non-Economic class immigrants (defined as Family and Humanitarian class immigrants[22]). We find that the Skilled Worker Principal Applicants worked in source country occupations with much higher cognitive skill requirements, and much lower manual skill requirements. However, despite being admitted based on economic criteria, they are no more successful in terms of the skill requirement gaps. While some of the gaps between the source and host county occupational skill requirements are similar to non-Economic class immigrants, the Skilled Worker Principal Applicants suffer much larger gaps in terms of the analytical skill and strength requirements.[23] In results not presented here but available upon request, we find that the small group of immigrants with pre-arranged employment in our data tend to closely match source country skill requirements. This might support the policy changes in 2013 that made pre-arranged employment a key component for admittance for Skilled Worker Principal Applicants, although we do not know how long it took each applicant to find and arrange employment from abroad prior to landing in Canada.

In Figure 3, we present the density estimates for the various skill requirements of source country occupations and the occupations six months and four years after arrival. We also include the densities for the overall Canadian population, which are calculated using the 2001 Canadian Census Masterfile.[24]

The densities of the cognitive skill requirements of the source country occupations lie above those for the domestic born population at higher values of the cognitive skill measure. Strength and other manual skill requirements for immigrants' occupations in Canada, in

[22]We exclude other Economic class immigrants, such as the spouse of the Principal Applicant, in these calculations.

[23]Given the similarity in the results for Skilled Worker Principal Applicants to those presented in the paper, we do not present these results separately, but instead include them in the online Appendix (see Table 6). The results for the non-Economic class immigrants are also included in this table.

[24]We do not calculate the Canadian population densities separately based on gender since the overall densities provide the various distributions of skill requirements for the entire set of Canadian occupations faced by immigrants when they first arrive.

contrast, have distributions that are more concentrated at lower values of skill requirements than those of the domestic born population. Comparing the distributions of immigrant occupational skill requirements in Canada to those of the Canadian population suggests that immigrants converge to the Canadian population in terms of cognitive skill requirements within four years after arrival. Note, however, that immigrants are observably different in terms of their human capital endowments. For example, a much higher percentage of immigrants have obtained a university degree relative to the domestic-born population.[25] In terms of occupational skill requirements, the densities in Figure 3 reveal that immigrants' pre-migration occupations were much more cognitive skill intensive than the occupations of the domestic-born population. Convergence merely to the Canadian population distributions therefore implies that immigrants' cognitive skills are underutilized.

In the context of the skill-based model, a lack of fluency in the dominant language impedes immigrants from transferring their human capital to the domestic labour market. The sample statistics and density estimates discussed above reveal that immigrants are arriving in Canada with high cognitive to manual skill ratios. The conjectured asymmetric effect of language proficiency on the transferability of different types of skills should result in large cognitive skill gaps and smaller manual skill gaps. This is consistent with the skill requirement gaps reported in column 1 of Table 1, except that the model does not predict positive manual skill gaps. Rather, the negative gaps for manual skills should be smaller than those for cognitive skills. The positive manual skill gaps in the data could arise because of a negative correlation between the cognitive and manual skill requirements of occupations for labour market demand side reasons, which are not modelled in Section 2. If occupations that require low levels of Canada usable cognitive skills tend to involve excessive manual tasks, then the detrimental effect of language fluency on cognitive skill transferability could lead to the observed positive gaps in the requirements of manual skills. The covariance matrix of the skill requirements, which is available from the authors upon request, affirms

[25]The percentage of the domestic born university degree holders (with positive earnings) in the 2001 Census is 20.0 percent compared to 64.5 percent in the sample of immigrants in the LSIC (with positive earnings in cycle 3). Similarly, in the 2001 Census data, 60.3 percent of male immigrants with positive earnings who immigrated in 2000 have a university degree.

the presence of strong negative correlations between cognitive and manual skills.

To the extent that dominant language proficiency improves with time in the host country, we expect skill gaps to diminish with time since arrival. The smaller skill requirement gaps reported in column 2 align well with the theory.[26] The incomplete convergence results in Figure 3 suggest that skill transferability is less than perfect even four years after migration. Note that the documented skill gaps may also partly reflect differences between the occupational skill requirements documented in the O*NET and those associated with some source country occupations, as noted earlier.[27]

To investigate whether the skill gap results are related by dominant language fluency, we present mean skill requirements for subsamples based on self-assessed language fluency in English or French in Table 2.[28,29] All three language groups experience declines in occupational cognitive skill requirements. However, the gaps are much smaller for immigrants with better language ability. We also re-estimate the densities in Figure 3 for the sample of immigrants whose native language is the dominant language of the local labour market. These densities (see Figure 4) reveal that the mismatch is less severe relative to the full

[26]Moreover, the change over time is more dramatic for cognitive skills than for manual skills, which is consistent with the assertion in the model that the mobility of certain skills (namely, cognitive skills) is more sensitive to language fluency.

[27]We use occupation information reported at the time of landing, yet immigrants would likely have experienced career progression in the source country had they not emigrated. The correct counterfactual would be the skills in the source country at the time of interview in Canada had the immigrant not emigrated. Consequently, our estimates may overstate convergence.

[28]We determine language fluency using the following LSIC questions: "How well can you speak English?" and "How well can you speak French?". We generate language categories as follows: 1 if "cannot speak this language", "poorly", "fairly well" or "well"; 2 if "very well"; and 3 if "native tongue". The choice of language to determine fluency is based on the dominant language of the place of residence of the immigrant (English, French, or bilingual location). For bilingual locations, we use the language in which the immigrant has the highest ability.

[29]A large fraction of immigrants change their assessment of their own language ability. Although some of these changes are likely due to immigrants improving their language ability with time in Canada, we also find that a non-negligible number of immigrants indicate a lower language ability in the later cycles, with most changes occurring between cycles 1 and 2. For example, nearly a quarter of people who were categorized as speaking very well in cycle 1 were categorized as less fluent in cycle 2. This suggests that immigrants are reassessing their language ability with time spent in Canada and adjusting their responses accordingly. We use cycle 2 responses to avoid the possibly inaccurate initial language self-assessments in cycle 1. A disadvantage of this approach is the possible overestimation of language ability at the time of entry for some other respondents. A very small fraction of the cycle 1 to cycle 2 changes is instead due to immigrants moving from one location to another where the other official language is dominant.

sample. This lends support to the hypothesis that the transferability of skills relies critically on dominant language proficiency, particularly for cognitive skills. Language ability may be correlated with the quality of source country human capital. However, the gaps for different language groups are very similar to the simple means presented in Table 2 when we control for source region and source country GDP with regression analysis.[30] Furthermore, there is very little change between the skill gaps six months and four years after arrival among native speakers, which is not the case for the other language groups. These results can be interpreted as evidence that language proficiency is the source of the skill mismatch; if some other labour market friction were causing skill gaps, we should see convergence for native speakers as well. Instead, convergence exists only for non-native speakers as dominant language fluency presumably improves with time since migration.

4.2 Earnings

Thus far we have presented evidence of a misalignment of immigrants' skill endowments and the skill requirements of their Canadian occupations. It is of equal importance to investigate the impact of the human capital mismatch on earnings. The theory predicts an adverse wage effect when the transferability of occupational skills is incomplete. We therefore examine the "impact" of the five skills on earnings in the data. To do so, we begin by estimating the returns to the skill requirements of Canadian jobs, while controlling for source country skill requirements:

$$Y_{it} = \gamma s_{it} + \beta X_{it} + \epsilon_{it} \tag{6}$$

where Y_{it} is the log weekly earnings of individual i in year t expressed in real terms using the Consumer Price Index[31], and s_{it} is the vector of skill requirements for the individual's current occupation. X_{it} is a vector of individual control variables that includes the vector of skill requirements for the individual's source country occupation, months since migration,

[30] Estimates not shown but available upon request.

[31] We use the weekly wage instead of the hourly wage for two reasons: First, it is likely a better measure of overall labour force success since the weekly wage is a function of both hourly wages and weekly hours. Second, the weekly wage is less prone to measurement error.

age, region of origin, region of residence, language ability, marital status and number of children (summary statistics of the main variables are presented in Table 5 of the online Appendix). To correct the standard errors, we cluster based on the three digit occupation. All models use sampling weights provided by the LSIC. We present the results for cycles 1 and 3 (interviewed approximately six months and four years after arrival) in Table 3.

Given the large gaps between the skill requirements of pre- and post-immigration occupations, the source country skills are not important determinants of earnings in Canada. In other words, immigrants who experience difficulty converting their source country skill portfolios into usable skills in the Canadian economy may end up in unrelated jobs, which curbs their ability to earn a return on skills acquired previously. We therefore report only the coefficients for the Canadian skill requirements.[32] These earnings regression coefficients provide a basis for the potential returns to occupational skills in Canada, which we will use to determine the potential impact of the skill mismatch on earnings later in this section.

Analytical skill requirements have a large positive impact on earnings. A one standard deviation increase in the occupational analytical skill requirement increases earnings by around 32 percent both at six months and four years after arrival. In contrast, interpersonal skill requirements have a negative impact on earnings, with a one standard deviation increase lowering earnings by around 15 percent. Working in occupations that require a large amount of interpersonal skills likely reduces productivity if the immigrant is not fully fluent in the host country language. For immigrants with very good local language proficiency (langVG = 1) or who are native speakers (langN = 1), interpersonal skill requirements do not affect earnings. [33,34] It is interesting to note that most education variables are insignificant. This supports the occupational skills-based view of human capital; the vector of skill requirements provides a more complete and up-to-date assessment of the human capital that an immigrant worker is using and being compensated for in the Canadian labour market.

[32]We find small positive returns to source country analytical skill requirements only.

[33]For example, as shown in column 6 of Table 3, the return to interpersonal skills for immigrants with very good local language ability is $-0.016 = -0.176 + 0.160$.

[34]The P-values from the F-tests on the overall significance of the interpersonal skills for "Very good" and "Native Speakers" are between 0.297 and 0.829.

When we again restrict the sample to Skilled Worker Principal Applicants, the results are very similar to the full sample results presented in Table 3. Despite being directly chosen for economic characteristics, Skilled Worker Principal Applicants do not earn noticeably higher returns to either their source country or Canadian occupational skill requirements. Even non-economic class immigrants earn returns to Canadian occupational skill requirements that are similar to the full sample.[35]

We next examine the potential loss in earnings resulting from the incomplete transfer of skills as reflected by a mismatch in the occupational skill requirements. To do so, we make use of the computed returns to immigrants' Canadian occupational skill requirements (i.e., the coefficients from the earnings regressions). We generate a set of predicted earnings, $\hat{Y}$, using the same coefficients but substituting in the source country occupational skill variables instead of the Canadian variables. In Table 4 we present the predicted gain in earnings at six months and four years after arrival had immigrants been able to match their source country occupational skill requirements, which is calculated as $E[\hat{Y} - Y]$. We estimate the predicted values for the full sample, as well as for immigrants with poor/moderate language ability, very good language ability, native speakers, Skilled Worker Principal Applicants and non-Economic class immigrants. We present results without and with additional covariates. The additional covariates are set to their mean values.

Under the assumption that the returns to Canadian occupational skill requirements provide a reasonable portrayal of the value of an immigrant's occupational skill, immigrants face a substantial loss in earnings. Without controlling for additional variables, predicted mean earnings may have been 43 percent higher at 6 months after arrival; with controls this drops slightly to around 39 percent.[36] Although the potential loss is still sizeable at four years after arrival, the loss declines sharply over the period studied to somewhere between 21 and 23 percent, depending on the inclusion of additional covariates.

We re-estimate the predicted values for different language groups (see rows 2 to 4 of

[35]The results for the Skilled Worker Principal Applicants are shown in Table 7, while the results for the non-Economic class immigrants are shown in Table 8 of the online Appendix.

[36]This is calculated as $e^{E[\hat{Y}-Y]} - 1$.

Table 4). Consistent with the theory, the gap between the actual earnings and the predicted earnings using source country skill requirements is smallest for native speakers. Once again the values are similar in cycles 1 and 3 for native speakers, but there is notable improvement for the less proficient language groups. Immigrants with language proficiency ranging from poor to very good lose up to twenty percent of their earnings due to the incomplete transferability of their occupational human capital even after four years in Canada.

In rows 5 and 6 of Table 4, we compare the predicted values for the subsamples of Skilled Worker Principal Applicants and non-economic class immigrants. Skilled Worker Principal Applicants do much worse than their non-economic class counterparts in terms of the potential loss in earnings. As previously discussed, Skilled Worker Principal Applicants are specifically selected by an immigration officer according to human capital considerations. This high skill subsample has much more to lose in the conversion of source country usable skills into Canada usable skills as a result of English/French language deficiencies. The bottom rows of Table 4 lend further support to our result that Skilled Worker Principal Applicants are not immune to the difficulties of transferring their source country occupational human capital despite being admitted to Canada based on their general human capital and potential for economic integration.

5 Conclusion

In this paper we analyze the skill requirements of immigrants' source country occupations and determine the transferability of these skills to the Canadian economy. Canada, like many immigrant-receiving countries, favour highly educated workers, and there is an expectation that immigrants will therefore contribute to high skill sectors. Using a skills-based model of human capital with cross-border skill conversion, we argue that limited language proficiency foments an incomplete transfer of occupational human capital from the source country to the host country. Some immigrants end up in occupations that do not align well with their source country skills, which generates discrepancies between the skills required on the job and the ones accrued prior to immigrating.

Our empirical analysis confirms that Canada is successful in admitting workers that have experience in occupations that should require high cognitive skills, and hence tend to require low manual skills. Upon entering the Canadian labour market, however, they settle for occupations that require not only lower cognitive skills but also higher manual skills. Consistent with the theory, skill gaps are particularly large among immigrants with poor language ability. Immigrants fluent in English/French experience minimal skill discrepancies after coming to Canada, and these remain unchanged even after four years in Canada. On the other hand, the large skill gaps of immigrants with limited English/French proficiency improve substantially with time spent in the Canadian labour market, presumably because of language acquisition. Even Skilled Worker Principal Applicants have very similar outcomes to non-screened immigrants despite having been directly chosen based on the human capital that should help them readily attain economic and occupational success in Canada. How important are these skill gaps for the economic integration of immigrants? We learn from the earnings regressions that economic outcomes would improve substantially if immigrants to Canada were able to find employment that required similar skills to their source country jobs. This is especially true for Skilled Worker Principal Applicants. Clearly, selecting immigrants based on their skills and qualifications is not enough to ensure that immigrants' occupational human capital is fully employed.

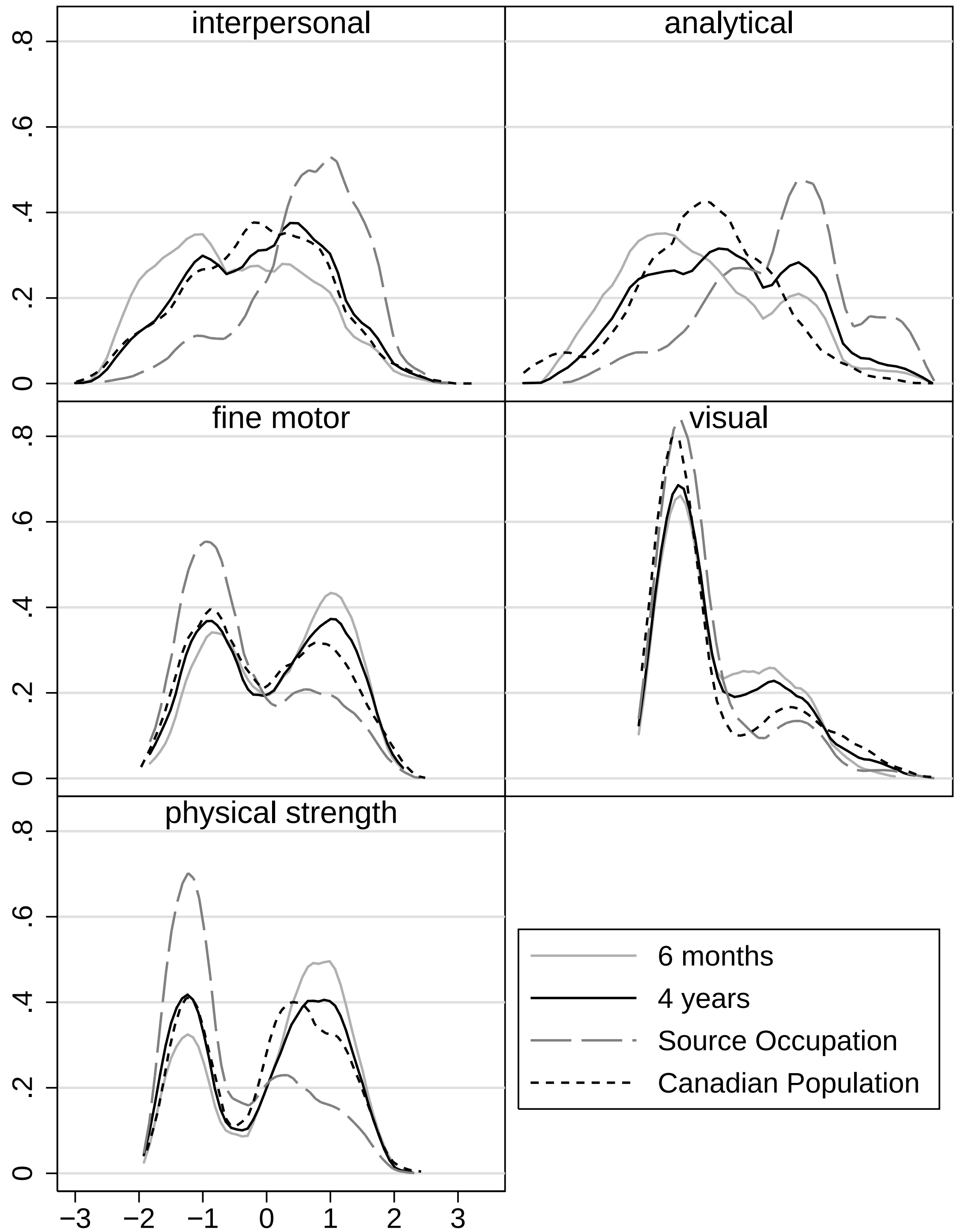

Figure 3: The density estimates for the skill requirements of source country occupations and Canadian occupations of immigrants. Also included is the density estimate for the overall Canadian population.

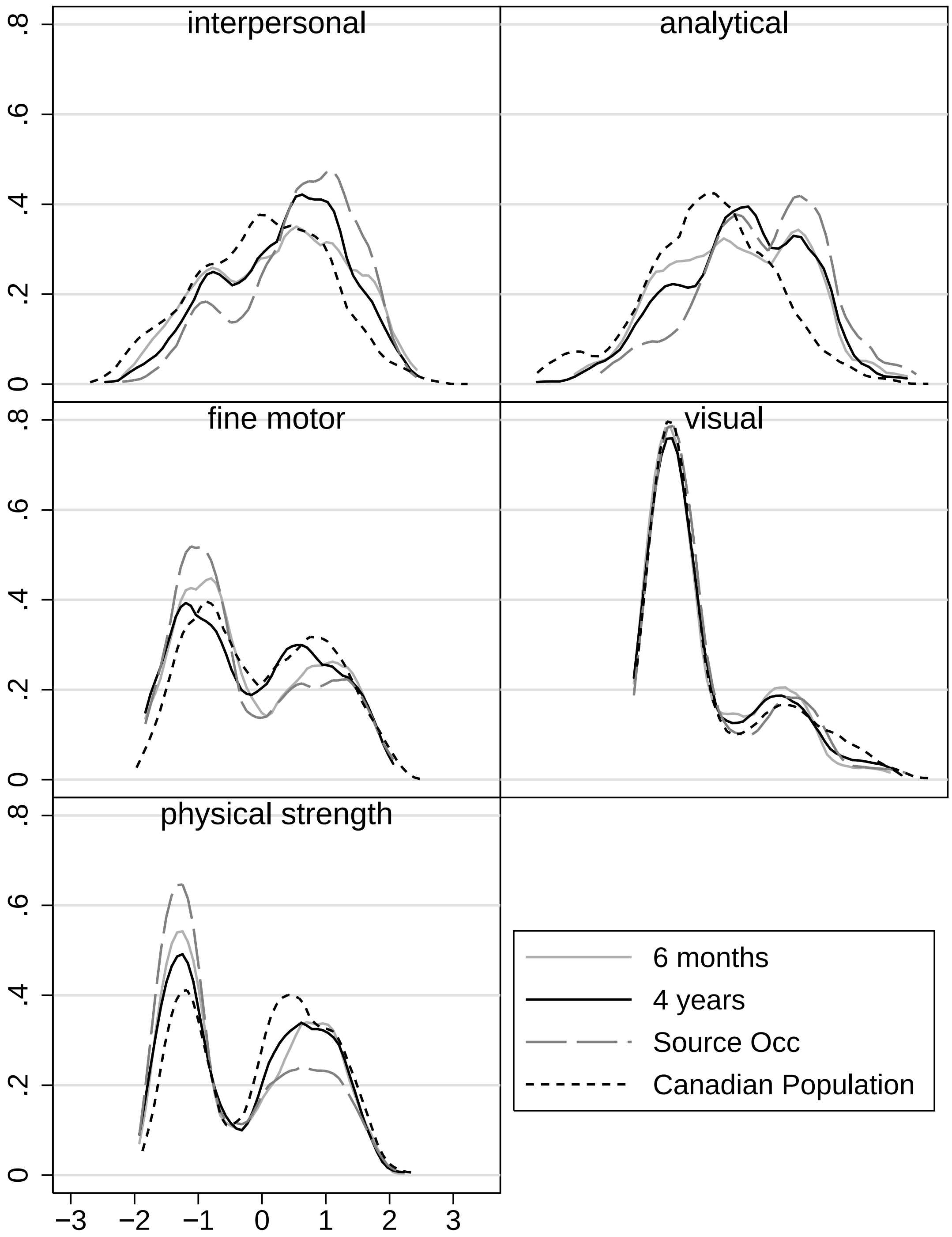

Figure 4: The density estimates for the skill requirements of source country occupations and Canadian occupations of immigrants who are native English/French speakers. Also included is the density estimate for the overall Canadian population.

Table 1: Skill Requirements of the Source Country Occupation, Immigrants' Occupation in Canada, and the Difference

	6 months		4 years	
	Mean	S.E.	Mean	S.E.
Interpersonal Skill				
Source Country	0.70	0.02	0.71	0.02
Canadian	-0.35	0.03	0.00	0.02
Difference	-1.05	0.03	-0.71	0.02
Analytical Skill				
Source Country	1.13	0.03	1.14	0.02
Canadian	-0.07	0.03	0.32	0.03
Difference	-1.20	0.03	-0.82	0.03
Fine Motor Skill				
Source Country	-0.28	0.02	-0.32	0.02
Canadian	0.25	0.02	0.13	0.02
Difference	0.53	0.03	0.45	0.02
Visual Skill				
Source Country	-0.09	0.02	-0.12	0.02
Canadian	0.10	0.02	0.09	0.02
Difference	0.20	0.02	0.21	0.02
Physical Strength				
Source Country	-0.49	0.02	-0.53	0.02
Canadian	0.22	0.03	0.02	0.02
Difference	0.72	0.03	0.55	0.02
Observations	1476		1927	

Sample based on workers who had positive earnings and non-missing source country and host country occupation codes. Sample restricted to people aged 24 to 59 at the time of cycle 1.

Table 2: Difference Between Source Country and Canadian Occupational Skill Requirements, by Language Group

	6 months		4 years	
	Mean	S.E.	Mean	S.E.
Poor Language Ability				
Interpersonal	-1.29	0.04	-0.87	0.03
Analytical	-1.47	0.05	-1.01	0.04
Fine Motor	0.61	0.04	0.52	0.03
Visual	0.19	0.04	0.24	0.03
Physical Strength	0.85	0.04	0.64	0.04
Observations	714		989	
Good Language Ability				
Interpersonal	-0.94	0.04	-0.62	0.04
Analytical	-1.08	0.05	-0.69	0.05
Fine Motor	0.54	0.04	0.43	0.04
Visual	0.23	0.04	0.22	0.03
Physical Strength	0.68	0.04	0.50	0.04
Observations	603		758	
Native Speaker				
Interpersonal	-0.34	0.07	-0.31	0.06
Analytical	-0.42	0.08	-0.39	0.07
Fine Motor	0.12	0.07	0.17	0.06
Visual	0.04	0.07	0.01	0.06
Physical Strength	0.22	0.07	0.27	0.07
Observations	159		180	

Sample based on workers who had positive earnings and non-missing source country and host country occupation codes. Sample restricted to people aged 24 to 59 at the time of cycle 1.

Table 3: Log Weekly Earnings Regressions, Controlling for Canadian Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.142^{+}	-0.146^{+}	-0.168*	-0.160**	-0.173**	-0.176**
	(0.0814)	(0.0807)	(0.0795)	(0.0586)	(0.0587)	(0.0576)
analytic	0.322**	0.320**	0.323**	0.323**	0.320**	0.316**
	(0.0660)	(0.0653)	(0.0626)	(0.0475)	(0.0472)	(0.0455)
motor	0.0707	0.0735	0.0772	0.0346	0.0315	0.0359
	(0.0681)	(0.0681)	(0.0660)	(0.0533)	(0.0523)	(0.0457)
visual	0.0874^{+}	0.0896^{+}	0.0842^{+}	0.0704^{+}	0.0764^{+}	0.0720^{+}
	(0.0479)	(0.0480)	(0.0456)	(0.0394)	(0.0391)	(0.0372)
strength	-0.119	-0.124	-0.127	-0.0911^{+}	-0.0932^{+}	-0.0873^{+}
	(0.0873)	(0.0873)	(0.0844)	(0.0528)	(0.0520)	(0.0472)
langVG × interpers[1]	0.0850	0.0852	0.107	0.143**	0.145**	0.160**
	(0.0748)	(0.0749)	(0.0708)	(0.0519)	(0.0521)	(0.0489)
langN × interpers[2]	0.0289	0.0325	0.135	0.190*	0.190*	0.216**
	(0.109)	(0.110)	(0.107)	(0.0860)	(0.0859)	(0.0827)
langVG × analytic[3]	0.0348	0.0370	0.0141	-0.0667	-0.0623	-0.0773^{+}
	(0.0584)	(0.0581)	(0.0573)	(0.0416)	(0.0415)	(0.0399)
langN × analytic[4]	0.104	0.104	0.00710	-0.0817	-0.0865	-0.0929
	(0.0917)	(0.0919)	(0.0896)	(0.0744)	(0.0739)	(0.0703)
high school		-0.0388	-0.0828		0.0469	-0.0215
		(0.0672)	(0.0761)		(0.0664)	(0.0654)
some post secondary		-0.00257	-0.0685		0.0948	0.00921
		(0.0884)	(0.0938)		(0.0643)	(0.0662)
trade or college		0.0550	-0.0146		0.121*	0.0132
		(0.0793)	(0.0878)		(0.0528)	(0.0586)
bachelor degree		0.0215	-0.0559		0.113^{+}	0.0165
		(0.0750)	(0.0815)		(0.0583)	(0.0640)
graduate degree		0.0478	-0.0610		0.154*	0.0372
		(0.0795)	(0.0848)		(0.0615)	(0.0695)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	1476	1476	1476	1927	1927	1927
R-squared	0.332	0.333	0.375	0.344	0.348	0.402
P-value[1]	0.507	0.478	0.436	0.762	0.620	0.767
P-value[2]	0.297	0.297	0.747	0.709	0.829	0.591
P-value[3]	0.000	0.000	0.000	0.000	0.000	0.000
P-value[4]	0.000	0.000	0.000	0.001	0.001	0.000

All regressions include controls for months since migration, age and age squared and dummy variables for very good language ability, and native speaker. Additional controls include: region of origin, region of residence, marital status, number of children, continuous controls for English and French language ability variables constructed with factor analysis using a series of subjective questions by Statistics Canada. Robust standard errors clustered on the Canadian occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 4: Predicted Values

	6 months			4 years		
	(1)	(2)	Obs.	(1)	(2)	Obs.
Full Sample	0.43	0.39	1476	0.23	0.21	1927
Poor/Moderate Language Ability	0.40	0.37	714	0.25	0.21	989
Very Good Language Ability	0.43	0.40	603	0.20	0.18	758
Native Speakers	0.17	0.12	159	0.13	0.11	180
Skilled Worker Principal Applicants	0.47	0.44	938	0.24	0.22	1137
Non-Economic Class	0.31	0.16	334	0.20	0.13	538
Additional Controls	NO	YES		NO	YES	

All regressions control for months since migration and the immigrants' Canadian occupational skill requirements (interpersonal, analytical, physical strength, visual and fine motor). Predicted values are then calculated using the source country occupational skill requirements with other variables at their mean values. Additional controls include: age, age squared, marital status, number of children, region of origin and region of residence.

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A Model Dynamics

Let $t \geq 0$ denote time since migration. Suppose an immigrant's language deficiency at time t, $1 - L(t)$, is subject to exponential decay:

$$\frac{d\left[1 - L(t)\right]}{dt} = -\lambda \left[1 - L(t)\right], \qquad \lambda > 0 \tag{7}$$

The solution to this differential equation is

$$L(t) = e^{-\lambda t} L(0) + \left(1 - e^{-\lambda t}\right) \tag{8}$$

where $L(0) \in [0, 1]$ is the index of dominant language fluency at the time of arrival. Combining (8) with the measures of host country usable skills, (3) and (4), yields

$$C(t) = C(0) + \eta_C \left(1 - e^{-\lambda t}\right) \left[1 - L(0)\right] \hat{C} \tag{9}$$

$$M(t) = M(0) + \eta_M \left(1 - e^{-\lambda t}\right) \left[1 - L(0)\right] \hat{M} \tag{10}$$

The skill gaps, $\hat{C} - C(t)$ and $\hat{M} - M(t)$, therefore diminish over time from their initial values to zero as $t \to \infty$. In other words, immigrants accumulate host country usable occupational skills as they become more familiar with the dominant language. Since language ability affects cognitive and manual skill gaps asymmetrically, this implies that the ideal occupation match (α_j^* from equation (2)) is constantly shifting. If immigrant workers can costlessly and constantly shift to a new and more suitable occupation, their wage at every point in time will satisfy $Y(t) = C(t) + M(t)$. Wages will evolve according to

$$Y(t) = e^{-\lambda t} Y(0) + \left(1 - e^{-\lambda t}\right) \hat{Y} \tag{11}$$

where $\hat{Y}$ is the wage that an immigrant would earn in the host country labour market if their source country usable skills were perfectly transferable. Of course, continuously shifting from one occupation to another is infeasible in an actual labour market.[37] It might be more reasonable to expect wage growth to approximate (11) but with discrete jumps in wages at every occupational switch.

Under the assumption that language proficiency improves with time spent in the host country, the above equations describe the evolution of occupational skills and wages. Figure 5 provides a graphical representation of the evolution of language proficiency, wages, and host country usable skills relative to source country counterparts for a numerical example with $\hat{C} = \hat{M} = 1$, $L(0) = 1/4$, $\eta_M = 1/10$, $\eta_C = 9/10$ and $\lambda = 1/3$. According to the theory, skill gaps diminish over time as enhanced dominant language ability allows more source country usable skills to be applied in the host country economy. As a consequence, immigrants experience wage growth. The model also implies occupational transitions to jobs that more closely resemble source country occupations in terms of their occupational skill requirements.

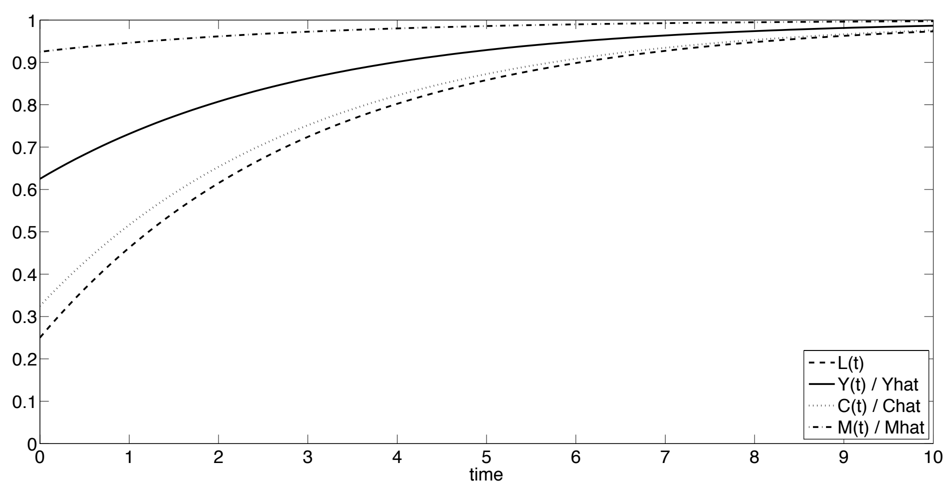

Figure 5: Language proficiency, wages, and host country usable skills relative to source country counterparts. For this example, $\hat{C} = \hat{M} = 1$, $L(0) = 1/4$, $\eta_M = 1/10$, $\eta_C = 9/10$ and $\lambda = 1/3$).

[37]For evidence of frictions in the job search process of immigrants see Skuterud and Su (2012) and Bowlus, Miyairi, and Robinson (2013).

B Supplementary Tables

Table 5: Summary Statistics

	Mean
Age at Cycle 1	36.12
Highest Level of Education (Pre Landing)	
High School	0.07
Some Post Secondary	0.07
Trade/College	0.10
Bachelor Degree	0.47
Graduate Degree	0.25
Language Ability (at Cycle 2)	
English Proficiency	0.73
French Proficiency	0.15
Immigrant Class	
Skilled Worker Principal Applicant	0.67
Skilled Worker Dependant	0.10
Family Class	0.14
OECD Emigrant	0.08
Region of Origin	
Asia	0.60
US/UK/Australia/NZ	0.02
Other Europe	0.12
Africa	0.10
Middle East	0.07
Observations	1927

Sample based on workers who had positive earnings in cycle 3 and non-missing source country and host country occupation codes. Sample restricted to people aged 24 to 59 at the time of cycle 1.

Table 6: Skill Requirements of the Source Country Occupation, Immigrants Occupation in Canada, and the Difference

	Skilled Worker Principal Applicants				Non-Economic Immigrants			
	6 months		4 years		6 months		4 years	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Interpersonal Skill								
Source Country	0.93	0.02	0.92	0.02	0.01	0.05	0.03	0.04
Canadian	-0.11	0.03	0.24	0.03	-0.97	0.05	-0.75	0.04
Difference	-1.03	0.04	-0.68	0.03	-0.97	0.06	-0.77	0.05
Analytical Skill								
Source Country	1.45	0.03	1.45	0.03	0.20	0.06	0.18	0.04
Canadian	0.18	0.04	0.61	0.03	-0.71	0.05	-0.55	0.04
Difference	-1.26	0.05	-0.84	0.04	-0.90	0.06	-0.73	0.05
Fine Motor Skill								
Source Country	-0.47	0.03	-0.49	0.03	0.26	0.05	0.22	0.04
Canadian	0.11	0.03	-0.02	0.03	0.59	0.04	0.58	0.04
Difference	0.58	0.03	0.47	0.03	0.34	0.06	0.36	0.05
Visual Skill								
Source Country	-0.24	0.02	-0.25	0.02	0.36	0.06	0.35	0.05
Canadian	0.03	0.03	0.00	0.02	0.27	0.05	0.40	0.04
Difference	0.26	0.03	0.25	0.03	-0.09	0.07	0.06	0.06
Physical Strength								
Source Country	-0.72	0.03	-0.75	0.02	0.17	0.05	0.13	0.04
Canadian	0.05	0.03	-0.19	0.03	0.60	0.04	0.60	0.04
Difference	0.77	0.04	0.56	0.03	0.43	0.06	0.47	0.05
Observations	938		1137		334		538	

Table 7: Log Weekly Earnings Regressions for Skilled Worker Principal Applicants, Controlling for Canadian Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.157	-0.158	-0.170^{+}	-0.189**	-0.197**	-0.206**
	(0.104)	(0.103)	(0.100)	(0.0703)	(0.0709)	(0.0679)
analytic	0.319**	0.318**	0.316**	0.344**	0.343**	0.348**
	(0.0809)	(0.0805)	(0.0786)	(0.0512)	(0.0512)	(0.0498)
motor	0.0775	0.0744	0.0875	0.0184	0.0148	0.0216
	(0.0829)	(0.0839)	(0.0775)	(0.0648)	(0.0638)	(0.0549)
visual	0.109^{+}	0.118^{+}	0.110^{+}	0.0914*	0.0961*	0.0894*
	(0.0607)	(0.0613)	(0.0594)	(0.0388)	(0.0384)	(0.0389)
strength	-0.163	-0.166	-0.169	-0.0935	-0.0978^{+}	-0.0906
	(0.104)	(0.105)	(0.102)	(0.0586)	(0.0577)	(0.0562)
langVG × interpers[1]	0.0885	0.0899	0.112	0.151*	0.147*	0.161**
	(0.1000)	(0.0989)	(0.0899)	(0.0584)	(0.0589)	(0.0551)
langN × interpers[2]	0.0337	0.0343	0.113	0.183^{+}	0.195^{+}	0.213*
	(0.136)	(0.136)	(0.139)	(0.106)	(0.108)	(0.104)
langVG × analytic[3]	0.0385	0.0353	0.00223	-0.0745	-0.0701	-0.0965*
	(0.0785)	(0.0772)	(0.0736)	(0.0456)	(0.0458)	(0.0429)
langN × analytic[4]	0.100	0.101	0.0109	-0.0367	-0.0474	-0.0651
	(0.111)	(0.111)	(0.118)	(0.0879)	(0.0874)	(0.0842)
high school		-0.185	-0.185		0.112	0.0229
		(0.346)	(0.283)		(0.325)	(0.294)
some post secondary		-0.336	-0.279		0.121	0.105
		(0.379)	(0.323)		(0.287)	(0.258)
trade or college		-0.131	-0.118		0.181	0.139
		(0.328)	(0.275)		(0.295)	(0.264)
bachelor degree		-0.192	-0.184		0.111	0.100
		(0.325)	(0.271)		(0.294)	(0.262)
graduate degree		-0.157	-0.184		0.172	0.137
		(0.326)	(0.272)		(0.293)	(0.262)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	938	938	938	1137	1137	1137
R-squared	0.322	0.325	0.378	0.326	0.331	0.397
P-value[1]	0.476	0.476	0.504	0.525	0.405	0.456
P-value[2]	0.330	0.327	0.651	0.942	0.981	0.936
P-value[3]	0.000	0.000	0.000	0.000	0.000	0.000
P-value[4]	0.000	0.000	0.00272	0.000	0.000	0.000

All regressions include controls for months since migration, age and age squared and dummy variables for very good language ability, and native speaker. Additional controls include: region of origin, region of residence, marital status, number of children, continuous controls for English and French language ability variables constructed with factor analysis using a series of subjective questions by Statistics Canada. Robust standard errors clustered on the Canadian occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 8: Log Weekly Earnings Regressions for Non-Economic Class Immigrants, Controlling for Canadian Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.121	-0.119	-0.181	-0.187+	-0.206+	-0.131
	(0.110)	(0.111)	(0.114)	(0.109)	(0.110)	(0.0918)
analytic	0.330*	0.326*	0.390**	0.265**	0.273**	0.209*
	(0.132)	(0.131)	(0.128)	(0.0964)	(0.0996)	(0.0832)
motor	0.132	0.169+	0.116	-0.0237	-0.0205	0.0497
	(0.0946)	(0.0960)	(0.0817)	(0.0937)	(0.0975)	(0.0835)
visual	0.0261	0.0105	-0.0477	0.126	0.130+	0.0792
	(0.0685)	(0.0673)	(0.0622)	(0.0761)	(0.0759)	(0.0664)
strength	-0.0162	-0.0138	0.0477	-0.128	-0.134	-0.117
	(0.0952)	(0.0963)	(0.0886)	(0.0932)	(0.0934)	(0.0766)
langVG $\times$ interpers[1]	0.200	0.207	0.114	0.154	0.165	0.169
	(0.155)	(0.151)	(0.129)	(0.128)	(0.124)	(0.112)
langN $\times$ interpers[2]	0.418	0.459	0.304	0.344+	0.334+	0.140
	(0.293)	(0.293)	(0.227)	(0.187)	(0.192)	(0.186)
langVG $\times$ analytic[3]	-0.126	-0.113	-0.0868	-0.0495	-0.0528	-0.0641
	(0.172)	(0.165)	(0.140)	(0.110)	(0.107)	(0.0967)
langN $\times$ analytic[4]	-0.130	-0.137	-0.150	-0.234	-0.236	-0.115
	(0.291)	(0.288)	(0.222)	(0.164)	(0.168)	(0.158)
high school		-0.0374	0.00512		0.0467	-0.00817
		(0.0762)	(0.0963)		(0.0813)	(0.0801)
some post secondary		-0.0408	-0.0466		0.0835	0.00892
		(0.113)	(0.124)		(0.0925)	(0.0880)
trade or college		0.0943	0.130		0.0852	-0.0354
		(0.0926)	(0.108)		(0.0699)	(0.0858)
bachelor degree		-0.0272	-0.0412		0.112	0.0334
		(0.0872)	(0.101)		(0.0808)	(0.0863)
graduate degree		0.198	-6.50e-05		0.0264	-0.0809
		(0.141)	(0.162)		(0.124)	(0.120)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	334	334	334	538	538	538
R-squared	0.343	0.353	0.478	0.249	0.253	0.356
P-value[1]	0.592	0.546	0.574	0.779	0.723	0.689
P-value[2]	0.281	0.222	0.556	0.463	0.559	0.960
P-value[3]	0.120	0.108	0.00509	0.0118	0.0107	0.0463
P-value[4]	0.435	0.464	0.198	0.856	0.833	0.538

All regressions include controls for months since migration, age and age squared and dummy variables for very good language ability, and native speaker. Additional controls include: region of origin, region of residence, marital status, number of children, continuous controls for English and French language ability variables constructed with factor analysis using a series of subjective questions by Statistics Canada. Robust standard errors clustered on the Canadian occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^+$ $p < 0.1$

C Principal Component Factor Analysis

The information in the O*NET can be used to construct skill indices associated with each job, so that every occupation can be described by a vector of basic skill requirements. The O*NET contains a large number of characteristic ratings including aptitudes, abilities, environmental conditions, and knowledge. Many of them correlated, and might in fact be measures of the same underlying skill category. It is therefore convenient to reduce a group of characteristics in the O*NET into one variable. For example, "performing general physical activities" and "handling and moving objects" likely reflect the requirement for physical strength on-the-job. Similarly, "oral expression" and "written expression" are both indicators of broad communication/interpersonal skills; "mathematical reasoning" and "number facility" are both related to analytical skills; and "manual dexterity" and "finger dexterity" both reflect fine motor skills.

The statistical method used to collapse several job characteristics into one variable is factor analysis. The principal component method of factor analysis chooses the vector of factor loadings to maximize the part of the observed variances in O*NET variables that can be explained by the underlying skill. Estimating the principal component thus allows us to reduce each group of variables into one index that is easily interpretable given that each group of O*NET variables is specifically selected *a priori* to reflect a basic skill of interest. We generate five basic skills: interpersonal skills, analytical skills, fine motor skills, physical strength, and visual skills.

Interpersonal Skills

We construct an index of interpersonal skills using ten O*NET variables. The first six are analyst-based ratings in the Abilities section of the O*NET database. The last four are job incumbent ratings of the level of performance required for generalized work activities related to communication. For example, 4A4a2 was generated from a question that asked respondents, "What level of COMMUNICATING WITH SUPERVISORS, PEERS, OR SUBORDINATES is needed to perform your current job?" The answer is a seven point scale, where an answer of 1 indicates that the job incumbent must be capable of "writ[ing] brief notes to others," an answer of 4 implies that the incumbent must be able to, for example, "report the results of a sales meeting to a supervisor," and an answer of 6 means that the occupation requires a worker who can "create a videotaped presentation of a company's internal policies." Table 10 contains the results of the factor analysis of the ten O*NET variables. The first principal component explains 78.6 percent of the variation in the interpersonal skill-related O*NET ratings. Each variable is important for the first factor, with loadings between 0.81 and 0.93.

Analytical Skills

We construct an index of analytical skills using nine O*NET variables. The first six are analyst-based ratings in the Abilities section of the O*NET database. The variable 1C7b is a job incumbent rating of the importance of analytical thinking, while 4A2b1 is an incumbent's response to "what level of MAKING DECISIONS AND SOLVING PROBLEMS is needed to perform your current job?" The last one is a job incumbent rating of the level of mathematical knowledge required for their particular occupation. Table 12 contains the results of the factor analysis of the nine O*NET variables. The first principal component explains 74.6 percent of the variation in the numeracy-related O*NET ratings. Each variable is important for the first factor, with loadings between 0.80 and 0.94.

Physical Strength

We construct an index of physical strength using six O*NET variables. The first four are analyst-based ratings in the Abilities section of the O*NET database. The last two are job incumbent ratings of the level of performance required for carrying out physical activities and handling objects. Table 14 contains the results of the factor analysis of the six O*NET variables. The first principal component explains 90.6 percent of the variation in the strength-related O*NET ratings. Each variable is important for the first factor, with loadings above 0.92.

Visual Skills

We construct an index of visual skills using five O*NET variables. All are analyst-based ratings in the Abilities section of the O*NET database. Table 16 contains the results of the factor analysis of the five O*NET variables. The first principal component explains 86.9 percent of the variation in the visual-related O*NET ratings. Each variable is important for the first factor, with loadings between 0.82 and 0.97.

Fine Motor Skills

We construct an index of motor skills skills using eight O*NET variables. All are analyst-based ratings in the Abilities section of the O*NET database. Table 18 contains the results of the factor analysis of the eight O*NET variables. The first principal component explains 82.5 percent of the variation in the motor skill-related O*NET ratings. Each variable is important for the first factor, with loadings between 0.86 and 0.93.

Table 9: Variables Included in the Interpersonal Skill Category

Variable ID	Variable Name	Description
1A1a1	Oral Comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.
1A1a2	Written Comprehension	The ability to read and understand information and ideas presented in writing.
1A1a3	Oral Expression	The ability to communicate information and ideas in speaking so others will understand.
1A1a4	Written Expression	The ability to communicate information and ideas in writing so others will understand.
1A4b4	Speech Recognition	The ability to identify and understand the speech of another person.
1A4b5	Speech Clarity	The ability to speak clearly so others can understand you.
4A4a1	Interpreting the Meaning of Information for Others	Translating or explaining what information means and how it can be used.
4A4a2	Communicating with Supervisors, Peers, or Subordinates	Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person.
4A4a3	Communicating with Persons Outside	Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.
4A4a4	Establishing and Maintaining Interpersonal Relationships	Developing constructive and cooperative working relationships with others, and maintaining them over time.

Table 10: Factor Analysis for the Interpersonal Skill

Variables	Factor Loadings				Uniqueness
	1	2	3	4	
1A1a1	0.9332	-0.1291	-0.2069	0.0204	0.0693
1A1a2	0.9285	-0.1727	-0.1949	-0.0513	0.0674
1A1a3	0.9244	0.0781	-0.2047	-0.0136	0.0972
1A1a4	0.9338	-0.0928	-0.2054	-0.0253	0.0766
1A4b4	0.8091	0.5188	-0.0531	0.0800	0.0670
1A4b5	0.8970	0.2781	-0.0552	0.0963	0.1057
4A4a1	0.8442	-0.4325	0.0448	-0.0543	0.0953
4A4a2	0.8519	-0.2217	0.3041	0.3001	0.0426
4A4a3	0.8600	0.0967	0.2794	-0.3903	0.0208
4A4a4	0.8754	0.1107	0.3546	0.0451	0.0937
Eigenvalue	7.8629	0.6656	0.4691	0.2669	
% of variance	0.7863	0.0666	0.0469	0.0267	

Table 11: Variables Included in the Analytical Skill Category

Variable ID	Variable Name	Description
1A1b4	Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense.
1A1b5	Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
1A1b6	Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).
1A1b7	Category Flexibility	The ability to generate or use different sets of rules for combining or grouping things in different ways.
1A1c1	Mathematical Reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.
1A1c2	Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.
1C7b	Analytical Thinking	Job requires analyzing information and using logic to address work-related issues and problems.
4A2b1	Making Decisions and Solving Problems	Analyzing information and evaluating results to choose the best solution and solve problems.
2C4a	Mathematics	Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.

Table 12: Factor Analysis for the Analytical Skill

Variables	Factor Loadings				Uniqueness
	1	2	3	4	
1A1c1	0.8682	0.4437	-0.1103	0.0504	0.0346
1A1c2	0.8029	0.5344	-0.1872	0.0674	0.0302
2C4a	0.8183	0.2849	0.4179	0.0518	0.0720
4A2b1	0.8347	-0.2738	-0.2432	0.3311	0.0595
1C7b	0.8334	-0.2562	0.3750	0.1500	0.0767
1A1b4	0.9373	-0.1964	-0.1013	-0.0212	0.0721
1A1b5	0.8782	-0.3422	-0.1197	-0.0775	0.0912
1A1b6	0.9091	-0.0999	0.0252	-0.1206	0.1484
1A1b7	0.8830	-0.0339	-0.0319	-0.3897	0.0662
Eigenvalue	6.7153	0.8711	0.4478	0.3148	
% of variance	0.7461	0.0968	0.0498	0.0350	

Table 13: Variables Included in the Physical Strength Category

Variable ID	Variable Name	Description
1A3a1	Static Strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.
1A3a3	Dynamic Strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
1A3a4	Trunk Strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.
1A3b1	Stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.
4A3a1	Performing General Physical Activities	Performing physical activities that require considerable use of your arms and legs and moving your whole body, such as climbing, lifting, balancing, walking, stooping, and handling of materials.
4A3a2	Handling Moving Objects	Using hands and arms in handling, installing, positioning, and moving materials, and manipulating things.

Table 14: Factor Analysis for Physical Strength

Variables	Factor Loadings				Uniqueness
	1	2	3	4	
1A3a1	0.9735	-0.0626	-0.1046	-0.1107	0.0251
1A3a3	0.9685	-0.0524	-0.1862	-0.0501	0.0221
1A3a4	0.9355	-0.2444	0.2425	0.0317	0.0053
1A3b1	0.9674	-0.1613	-0.0417	0.0334	0.0352
4A3a1	0.9424	0.2124	-0.0264	0.2540	0.0016
4A3a2	0.9238	0.3206	0.1305	-0.1570	0.0021
Eigenvalue	5.4382	0.2403	0.1239	0.1060	
% of variance	0.9064	0.0400	0.0206	0.0177	

Table 15: Variables Included in the Visual Skill Category

Variable ID	Variable Name	Description
1A1f1	Spacial Orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.
1A4a4	Night Vision	The ability to see under low light conditions.
1A4a5	Peripheral Vision	The ability to see objects or movement of objects to one's side when the eyes are looking ahead.
1A4a6	Depth Perception	The ability to judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.
1A4a7	Glare Sensitivity	The ability to see objects in the presence of glare or bright lighting.

Table 16: Factor Analysis for the Visual Skill

Variables	Factor Loadings				Uniqueness
	1	2	3	4	
1A1f1	0.9661	-0.0752	-0.1139	-0.2188	0.0002
1A4a4	0.9643	-0.1851	-0.0637	0.1136	0.0188
1A4a5	0.9615	-0.1905	-0.1090	0.0908	0.0192
1A4a6	0.8199	0.5689	-0.0519	0.0374	0.0000
1A4a7	0.9398	-0.0342	0.3392	-0.0172	0.0002
Eigenvalue	4.3432	0.4010	0.1467	0.0707	
% of variance	0.8686	0.0802	0.0293	0.0141	

Table 17: Variables Included in the Fine Motor Skill Category

Variable ID	Variable Name	Description
1A2a1	Arm-Hand Steadiness	The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.
1A2a2	Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
1A2b1	Control Precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
1A2b2	Multilimb Coordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
1A2b3	Response Orientation	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
1A2b4	Rate Control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
1A2c1	Reaction Time	The ability to quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.
1A2c3	Speed of Limb Movement	The ability to quickly move the arms and legs.

Table 18: Factor Analysis for the Fine Motor Skill

Variables	Factor Loadings				Uniqueness
	1	2	3	4	
1A2a1	0.8705	0.4524	-0.0083	0.1301	0.0207
1A2a2	0.8964	0.3980	-0.0602	0.1094	0.0225
1A2b1	0.9290	0.1807	-0.1267	-0.2339	0.0335
1A2b2	0.9339	-0.0118	0.1912	-0.2419	0.0325
1A2b3	0.9168	-0.3158	-0.0762	0.0998	0.0440
1A2b4	0.9307	-0.2365	-0.1907	0.0151	0.0412
1A2c1	0.9211	-0.2999	-0.1582	0.0492	0.0342
1A2c3	0.8660	-0.1403	0.4542	0.0937	0.0152
Eigenvalue	6.6017	0.6611	0.3298	0.1635	
% of variance	0.8252	0.0826	0.0412	0.0204	