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From Engineer to Taxi Driver? Occupational Skills and the Economic Outcomes of Immigrants

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From Engineer to Taxi Driver? Occupational Skills and the Economic Outcomes of Immigrants

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Abstract

We examine the ability of male immigrants to transfer their occupational human capital 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 and skill accumulation to derive predictions about the cross-border transferability of occupational human capital. We then test the empirical implications 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. Regression analysis uncovers large returns to the analytical skill requirements of Canadian occupations, but no returns to source country skill requirements. Finally, our empirical findings suggests that occupational skill gaps are detrimental to immigrants' earnings.

JEL classification: D83, J24, J31, J61, J62, J71, J80

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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. 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 (2004) and Aydemir and Skuterud (2005)). Canada, like many Western countries, relies heavily on immigration to meet labour market needs and tries 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.[1] Ideally, the occupational human capital acquired prior to migration should be used and be compensated for in the host country economy. In this paper, we present theory and evidence on the transferability of occupational skills-based human capital from source country to host country labour markets.

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 (2010), Poletaev and Robinson (2008), Yamaguchi (2011) and others demonstrate that there

[1]Occupational skills are potentially a better measure of an immigrant's current human capital than educational variables. The highest level of educational attainment, in addition to being very broad, may not provide the most recent status of an immigrant's job-related human capital.

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 (2011) 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 that 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 the set of occupational skill requirements, rather than industries or occupations, is the most important source of human capital specificity in the determination of earnings for displaced workers. Robinson (2010) finds that a voluntary occupation switch is usually a lateral move or a progression in skill requirements. In contrast, involuntary occupation movers typically experience downward shifts in skill requirements. It is likely that some immigrants are voluntary switchers pursuing equal or better employment prospects in the host country. Others, however, may closely resemble displaced workers if

[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.

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? Perhaps more importantly, how essential is the cross-border transferability of occupational human capital for earnings?

We examine this issue using a unique data set 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 (2011) 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)). Using the O*NET, we construct two cognitive skills (interpersonal and analytical skills) and three manual skills (fine motor skills, visual skills, and physical strength). We then match these skills to the source and host country occupation information from the Longitudinal Survey of Immigrants to Canada (LSIC). We determine how well the skill requirements of pre- and post-immigration jobs match for male immigrants, and estimate the potential loss or gain in skill portfolios that resulted from immigration.[3] We then estimate the returns to source country job skills and Canadian occupation skills in terms of log weekly earnings.

We find that immigrants worked in source country occupations prior to migrating to 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 efforts and success of the Canadian immigration policy geared to attracting immigrants with high

[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.

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 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 they might be under-equipped.

We also construct a simple dynamic model of occupational choice and skill accumulation. It is similar to the skills-based models by Lazear (2009), Gathmann and Schönberg (2010) and Phelan (2010), but is explicitly dynamic in order to characterize the optimal occupational choice of forward looking immigrants. Furthermore, in contrast to the dynamic model of Yamaguchi (2010), it is simple enough that the occupational transitions can be characterized analytically and graphically. We find that the rich set of predictions of the model are consistent with our empirical findings, reaffirming our belief that a skills-based occupation model is a useful framework for understanding the labour market dynamics of immigrants.

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.

[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 Skilled Worker Principal Applicants.

2 The Model

The aim of this section is to develop an understanding of the transferability of immigrants' occupational skills to the host country labour market, and to investigate the implications for earnings. To do so, we present a theoretical model of the labour market in which immigrants differ in terms of the skill endowments they bring to the host country economy. Labour market frictions inhibit the efficient sorting of immigrants to occupations, so that some immigrants end up in less suitable occupations. This generates discrepancies between the skills required on the job and the ones with which immigrants are endowed. An important implication is a difference in skill requirements of pre- and post-immigration occupations. To align the theoretical and empirical parts of the paper, we focus on the skill gaps expressed in terms of differences in occupational skill requirements.[6] The skill gaps result in lower wages. Skill accumulation and on-the-job search both influence the persistence of skill gaps. To bring the theoretical framework in line with the immigration literature, we investigate the impact of language ability under the assumption that language difficulties reduce the transferability of skills between countries.

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. An important similarity between our environment and theirs is that workers' accumulation of an occupational skill is positively related to the importance of that skill in their current job.

[6] In the empirical part of the paper, skill endowments are unobservable, as we do not have objective skill measures in the data. Instead, we present a skill-based model with predictions about the skill requirements of immigrants' host country jobs. These theoretical implications are then analyzed empirically with the skill requirement variables generated with the O*NET data combined with the LSIC.

Perhaps a more relevant study is the work by Phelan (2010). His paper extends the Lazear (2009) model to include industries, which he models as a subset of firms with similar but not identical skill aggregation (production) functions. Workers choose to search for employment in a particular industry, but they cannot distinguish between firms within an industry ex ante. The author endorses the 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, but a similar mechanism 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 might have to accept a job with skill requirements that do not match his skill endowments. In addition to this, our model describes the subsequent dynamic labour market process, where immigrants accumulate skills at the new job, while waiting for the arrival of the job opportunity that closely matches their skill endowments. Our infinite horizon model is designed to trace out the above job transitions and skill accumulation dynamics, which earlier static models cannot.

2.1 Environment

Immigrants bring different levels and combinations of source country skills. Suppose there are two types of skills: let $m_i(t)$ and $c_i(t)$ denote the endowments of manual and cognitive skills of immigrant i at time t.

On the demand side of the labour market, firms use the skills of hired workers to produce output. They hire workers by making job offers to unemployed as well as employed workers. Jobs can be classified into occupations, which are heterogeneous in their use of skills; they combine skills in different proportions to produce output. For simplicity, assume that a firm can offer jobs only within a single occupation, so that firms and occupations are indistinguishable in the model. It is sufficient to consider only two types of occupations, $\{\alpha_1, \alpha_2\}$, with $0 < \alpha_1 < \alpha_2 < 1$. When worker i is hired by firm j, the output produced at time t is given by

$$y_{ij}(t) = \left(\frac{c_i(t)}{\alpha_j}\right)^{\alpha_j} \left(\frac{m_i(t)}{1-\alpha_j}\right)^{1-\alpha_j} \tag{1}$$

Workers are paid according to the output they produce:[7]

$$w_{ij}(t) = \delta y_{ij}(t) \tag{2}$$

The above setup means that workers are compensated for their skills, and for the quality of the occupation-worker match. Immigrant earnings vary according to how closely their source country skill portfolio aligns with the host country firm's demand for skills. Workers make job accept/reject decisions to maximize the discounted present value of wage earnings. Taking the first order condition of $y_{ij}(t)$ with respect to α_j yields

$$\frac{\alpha_j}{1-\alpha_j} = \frac{c_i(t)}{m_i(t)} \tag{3}$$

which defines the α_j that would give rise to the ideal match for an immigrant worker of type $\{m_i(t), c_i(t)\}$. Figure 1 displays the output that would be produced in a match with type 1 and type 2 firms over a range of $c_i(t)/m_i(t)$, normalized by dividing output by $c_i(t) + m_i(t)$. An immigrant with relatively high cognitive ability would be more productive in a type 2 occupation, while immigrants with more manual skills would prefer a type 1 job.

Immigrants continue to accumulate skills when they work in the host country. More specifically, suppose the accumulation of skills is governed by a pair of differential equations:

$$\dot{c}_i(t) = \sum_j \mathbb{1}_{ij}(t) g_j^c\left(c_i(t), m_i(t)\right) \tag{4}$$

$$\dot{m}_i(t) = \sum_j \mathbb{1}_{ij}(t) g_j^m\left(c_i(t), m_i(t)\right) \tag{5}$$

where $g_j^c(\cdot,\cdot)$ and $g_j^m(\cdot,\cdot)$ are job and skill specific functions of the worker's current skill

[7] For example, if Nash bargaining between the firm and the worker determines how revenue at a given point in time is divided between them, then δ can be thought of as the worker's relative bargaining strength.

portfolio and $\mathbb{1}_{ij}(t)$ is an indicator variable that equals 1 if worker i works at firm j at time t. Suppose g_j^c and g_j^m take the following function forms:

$$g_j^c(c_i(t), m_i(t)) = Ac_i(t) + \eta c_i(t)\left(\frac{c_i(t) + m_i(t)}{y_{ij}(t)} - 1\right)\left(\alpha_j - (1-\alpha_j)\frac{c_i(t)}{m_i(t)}\right)^{-1} \quad (6)$$

$$g_j^m(c_i(t), m_i(t)) = Am_i(t) + \eta m_i(t)\left(\frac{c_i(t) + m_i(t)}{y_{ij}(t)} - 1\right)\left((1-\alpha_j) - \alpha_j\frac{m_i(t)}{c_i(t)}\right)^{-1} \quad (7)$$

where $A, \eta > 0$ are global learning parameters. As in Gathmann and Schönberg (2010) and Phelan (2010), learning a skill on-the-job is related to the importance of that skill in their current occupation. The growth rates of skills $\{c(t), m(t)\}$ at a firm with a production technology characterized by α are given by

$$\frac{\dot{c}(t)}{c(t)} = A + \eta\left(\frac{c(t) + m(t)}{y(t)} - 1\right)\left(\alpha - (1-\alpha)\frac{c(t)}{m(t)}\right)^{-1} \quad (8)$$

$$\frac{\dot{m}(t)}{m(t)} = A + \eta\left(\frac{c(t) + m(t)}{y(t)} - 1\right)\left((1-\alpha) - \alpha\frac{m(t)}{c(t)}\right)^{-1} \quad (9)$$

The first term can be thought of as the long run growth rate of a given skill. The second term in the skill accumulation equation implies that the growth rate of a particular skill is more dramatic when the worker's skill mix is far from the optimal skill ratio. For example, if a former economics professor accepts a job as a construction worker, his cognitive skills will hardly improve at all with job tenure, while his manual skills will increase considerably. This has implications for the time path of output when a worker with skill endowments $c(0)$ and $m(0)$ at time $t = 0$ becomes employed at a firm with technology described by skill weights α and $1 - \alpha$. These implications are summarize in Proposition 1. All proofs are relegated to Appendix A.

Proposition 1. *If the accumulation of skills is governed by the pair of differential equations* (8) *and* (9)*, then the following statements are true:*

1. *The worker's skill portfolio grows over time at constant rate A:*

$$\frac{d}{dt}\left[c(t)+m(t)\right]=A\left[c(t)+m(t)\right] \tag{10}$$

2. *Output at time t is given by*

$$y(t)=e^{(A-\eta)t}y(0)+\left(1-e^{-\eta t}\right)\left[c(t)+m(t)\right] \tag{11}$$

3. *The mix of skills is evolving such that the worker's skill portfolio converges over time to the optimal skill mix corresponding to the firm's technology.*

$$\lim_{t\to\infty}\frac{c(t)}{m(t)}=\frac{\alpha}{1-\alpha}, \quad \textit{which implies} \quad \lim_{t\to\infty}\frac{y(t)}{c(t)+m(t)}=1 \tag{12}$$

4. *The growth rates $\dot{c}(t)/c(t)$ and $\dot{m}(t)/m(t)$ tend to A as t goes to infinity.*

From Figure 1, it is clear that an immigrant would prefer employment in the occupation that provides the best match. In a Walrasian labour market, immigrants would simply choose to work for the firm that best suits their skill portfolio. As in Lazear (2009), Gathmann and Schönberg (2010), and Phelan (2010) however, labour market frictions prevent some workers from securing their most preferred job. To motivate this assumption in a model of immigrant labour market outcomes, a non-Walrasian market might arise because of search and matching frictions, or because immigrants have insufficient knowledge about the host country labour market.[8] This generates inefficient sorting of immigrant workers into occupations. To model this phenomenon, let μ_1 and μ_2 denote the poisson arrival rates of job offers for type 1 and type 2 occupations. Workers continue to receive job offers even after accepting employment, so a worker that prefers a type 1 job might accept temporary employment with a type 2

[8]Employers may face uncertainty about immigrants skills, creating additional matching frictions. For example, Oreopoulos (2011) compares callback rates using fake resumes with varying levels of foreign versus domestic work experience and educational qualifications, as well as English versus ethnic-sounding names. He finds that immigrants with Canadian work experience have higher callback rates than immigrants with only foreign experience. Moreover, employers appear to rely on the applicant's name as a signal of potential English language proficiency.

firm. As we will see, temporary employment can become permanent when job opportunities are scarce. If sufficient time passes without a type 1 offer, the worker's skill portfolio adjusts to match type 2 skill requirements, and the worker stops searching for a different job.

2.2 Deriving the Value Functions

Time is continuous and indexed by t, $r > A$ is the discount rate, and E_t is the expectations operator from a time t perspective. Consider an immigrant employed in a type 1 occupation and let τ denote the time at which the first type 2 job offer arrives. The value function for a type 1 job incumbent is[9]

$$v_1(t) = \mathrm{E}_t\left[\int_t^{\tau} e^{-r(s-t)} w_1(s)ds + e^{-r(\tau-t)}\max\{v_1(\tau), v_2(\tau)\}\right] \tag{13}$$

After differentiating with respect to time and rearranging, the value function can be rewritten as follows:[10]

$$rv_1(t) = w_1(t) + \mu_2 \max\{0, v_2(t) - v_1(t)\} + \dot{v}_1(t) \tag{14}$$

The analogous value function can be derived for a type 2 job incumbent:

$$rv_2(t) = w_2(t) + \mu_1 \max\{0, v_1(t) - v_2(t)\} + \dot{v}_2(t) \tag{15}$$

[9]Note that the skill endowments of the worker are also state variables in the value functions, but have been suppressed here for notational convenience.

[10]Alternatively, we can use an approximation of the value function to derive this expression. For small Δ,

$$v_1(t) = \frac{1}{1+r\Delta}\left[w_1(t)\Delta + \mu_2\Delta\max\{v_1(t+\Delta), v_2(t+\Delta)\} + (1-\mu_2)\Delta v_1(t+\Delta) + o(\Delta)\right]$$

This formulation provides some intuition: The first term is the flow value of working a type 1 job, the second term reflects the probability of receiving a type 2 job offer and the maximization takes into account the fact that the worker can decline the offer. The third term comes from the possibility that the worker might not receive a type 2 offer, and the final term arises from the approximation, with $o(\Delta)/\Delta \to 0$ as $\Delta \to 0$. Rearranging and taking the limit as $\Delta \to 0$ yields the value function in the main text.

Immigrants that successfully secure employment in their preferred occupation do not want to switch jobs. Their value functions simplify to

$$rv_1^*(t) = w_1(t) + \dot{v}_1^*(t), \quad \text{and} \quad rv_2^*(t) = w_2(t) + \dot{v}_2^*(t) \tag{16}$$

or

$$v_1^*(t) = \int_t^\infty e^{-r(\tau-t)} w_1(\tau) d\tau, \quad \text{and} \quad v_2^*(t) = \int_t^\infty e^{-r(\tau-t)} w_2(\tau) d\tau \tag{17}$$

Otherwise, immigrant workers continue to wait for job offers from the other type of firm, all the while accumulating skills according to their current occupation. For a type 1 job incumbent hoping for a type 2 offer, this means that $v_1(t)$ is increasing and $v_2^*(t)$ decreasing as skills are accumulated to bring the skill portfolio more in line with the type 1 production technology. At some point, the worker reaches an indifference point between the two jobs. Proposition 2 establishes this result.

Proposition 2. *Consider a type 1 job incumbent hoping for a type 2 offer. There exists a date $t = T$ at which $v_1(T) = v_1^*(T) = v_2^*(T)$, where the worker is indifferent between the two jobs. Moreover, the worker will remain in whatever occupation they choose at time T thereafter. With the skill accumulation equations* (8) *and* (9)*, time T is such that $w_1(T) = w_2(T)$, or equivalently, $y_1(T) = y_2(T)$.*

Workers are indifferent between type 1 and type 2 jobs when the current wages are equal. This is convenient because it allows us to identify the indifference point graphically. In Figure 1, it is the intersection of the type 1 and type 2 production functions.

2.3 Dominant Language Ability

An important issue in the immigration literature is the effect of language ability on immigrants' labour market outcomes in the host country.[11] A lack of dominant language ability

[11] 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

might impede immigrant workers fully utilizing their skills in host country jobs. To incorporate this into the model, let $l_i(t) \in [0,1]$ be an index of immigrant i's language ability at time t. Then define

$$c_i(t) = f^c\big(\hat{c}_i(t), l_i(t)\big) \tag{18}$$

$$m_i(t) = f^m\big(\hat{m}_i(t), l_i(t)\big) \tag{19}$$

as "host country usable" skills, where $\{\hat{c}_i(t), \hat{m}_i(t)\}$ are "home country usable" skills, and f^c and f^m are functions that convert home country usable skills into host country usable skills, conditional on the immigrant's proficiency in the host country's dominant language. Let f^s be increasing in both arguments, and satisfy $f^s(x,0) = 0$ and $f^s(x,1) = x$, for $s \in \{c, m\}$. Not only does a lack of language ability lower the absolute levels of skills $c_i(t)$ and $m_i(t)$, but it can also affect the skill ratio. For example, suppose f^c and f^m take the following multiplicatively separable form

$$f^c(\hat{c}, l) = l^{\xi^c}\hat{c}_i(t) \quad \text{and} \quad f^m(\hat{m}, l) = l^{\xi^m}\hat{m}_i(t) \tag{20}$$

with $\xi^c, \xi^m \geq 0$. Then,

$$\frac{c}{m} = \frac{f^c(\hat{c}, l)}{f^m(\hat{m}, l)} = l^{\xi^c - \xi^m}\left(\frac{\hat{c}}{\hat{m}}\right) \tag{21}$$

If, for example, $\xi^c > \xi^m$, then $l^{\xi^c - \xi^m} < 1$ for all $l \in (0,1)$, and an immigrant is more likely to be better suited to a type 1 occupation relative to their home country skill portfolio; that is, even if their closest home country match was a type 2 job. This result is easily understood by considering two closely related occupations that differ slightly in their use of manual and cognitive skills. 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.

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.

2.4 Empirical Implications

The theoretical framework provides a simple and intuitive way to interpret the labour market outcomes of immigrants. The model has specific implications for skill gaps, wages, and the impact of dominant language proficiency. Notice that it is the skill requirements of occupations that we derive from the data and not the actual skill endowments of immigrants. In the context of the model, the observed skill requirements roughly correspond to the α_j and $1 - \alpha_j$ parameters. The empirical implications of the model are listed below.

Skill Gaps

1. Labour market frictions give rise to mismatches between the skill requirements of home country and host country occupations.

2. Suppose $\mu_1 \geq \mu_2$, so that type 1 jobs opportunities are not overly scarce. If immigrants arrive in Canada with relatively high cognitive ability and relatively low manual skills, then labour market frictions imply that the average cognitive skill gap should be negative and the average manual skill gap should be positive.

3. Since workers can search for a new job while employed, there is a transitory element to skill gaps as a result of occupational mobility.

4. When skills are accumulated proportionately to the skill requirements of their job, immigrants may eventually find that their skills have become more suitable for a host country occupation that differs from their source country occupation. There is therefore a persistent element to skill gaps.

Consider an immigrant with a source country skill portfolio that aligns perfectly with a type 2 occupation. Figure 2 illustrates the labour market outcome of the immigrant when, due to frictions in the job market, he acquires a type 1 job upon arrival and never receives a type 2 offer in time to make a job switch worthwhile. The gap in skill requirements remains forever. Figure 3, on the other hand, shows the path of a similar immigrant who secures a type 1 job temporarily before moving to a type 2 occupation. There is an initial skill gap following migration that disappears after the job transition.

Wages

5. Skill gaps have a negative impact on wages. The output produced from a match and hence the wage depends on how well the skill endowments of the worker are aligned with the skill requirements of the firm. The model therefore predicts low wages for recent immigrants with skill mismatches.

6. Home country skills are poor predictors of host country wages if the pre- and post-migration occupations are dissimilar in terms of skill requirements. Host country skills are also poor predictors of host country wages if the worker is employed in an occupation that does not match their skill portfolio. In general, labour market frictions that lead to skill mismatches obscure the returns to skills in Mincer wage regressions.

Dominant Language Ability

7. Suppose $\xi^c > \xi^m$, so that for given language ability, manual skills are relatively more easily transferred to the host country labour market. Then, the model predicts larger positive manual skill gaps and cognitive skill gaps that are more negative for immigrants with language difficulties relative to their fluent counterparts.

8. Combining results 5 and 7 imply that the returns to skills are higher for the sample of immigrants proficient in the dominant language of the host country.

Figure 4 illustrates this outcome when dominant language deficiency prevents skills from being perfectly transferred to the host country labour market. Specifically, when cognitive skill transferability is relatively more affected by language ability, a smaller set of immigrants would accept a type 2 job over a type 1 job. The figure identifies the group of immigrants that are more productive at type 2 jobs in their home country, but more productive in manual type jobs in the host country as a consequence of language difficulties.

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

3 Occupation and Immigration Data

We use the recently developed methodology introduced by Ingram and Neumann (2006), Bacolod and Blum (2010), Poletaev and Robinson (2008), and Yamaguchi (2011) 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 (interpersonal skills and analytical skills) as well as manual skills (fine motor skills, visual skills, and physical strength). We then use the source and host country occupation information from the LSIC to determine how well these jobs match in terms of the skills required to perform job tasks. An advantage of this methodology over occupational classification is that in addition to identifying a mismatch, we can also measure the direction and degree of the mismatch. We first estimate the loss or gain in skill requirements resulting from immigration for males by comparing mean values and distributions of source country and host country occupational skill requirements in order to investigate the first group of four empirical implications of the model, as well as implication number seven pertaining to the impact of language proficiency. We then examine the remaining empirical implications of the model by examining the returns to skills with regression analysis.

3.1 Longitudinal Survey of Immigrants to Canada (LSIC)

The main data set 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. Individuals who applied and landed from within Canada are excluded from the survey, since they may have been in Canada for a considerable length of time before the official landing. Refugees claiming asylum from within Canada are also excluded. We drop a small percentage of immigrants who had previously been in Canada on a work or student visa, since some of them may have already established contact with employers in Canada prior to immigrating. We restrict our sample to immigrants aged 25 to 59 at the time of the first cycle to reduce any effects of educational or retirement decisions.

Although not the focus of the paper, another 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.[12] 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.[13,14] 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

[12] 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.

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

[14] 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 selection criteria of OECD countries.

Applicants.[15]

The LSIC provides three digit occupation codes for both source country occupation and the first four years of occupations since immigrating.[16] One shortcoming of the data is that source country employment information is incomplete, as we do not know how long the immigrant was employed in the source country occupation or how long since employment was terminated. For some immigrants, there may have been a lag between employment and immigration during which time the accumulated human capital may have deteriorated.

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. Moreover, there is no way of ranking the magnitude of an occupation switch between categories in terms of human capital requirements. Recently, researchers have characterized occupations based on the tasks required to perform 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 complete the job.

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 data set contains information on formal education, job training, and other qualifications necessary for each occupation, as well as different categories of knowledge required by its workers. It can be used to distinguish between occupations in terms of the abilities and knowledge they require.

[15] 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.

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

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 high 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 occupation information contained in the O*NET. Factor analysis assumes 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 used by Ingram and Neumann (2006), Bacolod and Blum (2010), and Poletaev and Robinson (2008). Methodological difficulties arise because determining the 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, called confirmatory factor analysis, which is similar to the approach used by Yamaguchi (2011). We separate the O*NET variables into groups of job characteristics that are associated with each *a priori* skill of interest. The relevant skills for this study include 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 in fact represented by the factor. 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. This procedure yields a portfolio of skills that 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.[17]

By construction, the resulting scores 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 to Canada contained in the LSIC data.[18]

3.3 The Returns to Skills

The theory predicts that returns to skills are adversely affected when immigrants are unable to find jobs in appropriate occupations given their particular skills. We therefore examine the "impact" of the five skills on earnings. We use log weekly earnings as the dependent variable expressed in real terms using the Consumer Price Index (CPI).[19] We estimate the regressions separately with home country and Canadian occupational skill requirements as independent variables. For instance, the earnings regression with Canadian skills on the right-hand side is:

$$Y_{it} = \gamma^j s_{it} + \beta X_{it} + \epsilon_{it} \tag{22}$$

where Y_{it} is the log weekly earnings of individual i in year t, and s_{it} is the vector of skill requirements for the individual's current occupation. X_{it} is a vector of individual control

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

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

[19] 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.

variables that includes months since migration, 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 B.1 in 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.

3.4 Methodological Remarks

It is important to acknowledge some of the caveats of the methodology described above. First, the O*NET is based on occupational skill requirements in the US. We apply the O*NET data to Canadian occupations because there is currently no equivalent data set for Canada. The assumption is that occupations in Canada require similar skills to those in the United States. A second assumption is that source country occupations also require the same skills as 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 source countries. Without similar O*NET data sets devised separately for every country, one must rely on the assumption that the differences are not too great.[20] Another potential problem arises from the fact that 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 far less compared to other broader occupation classifications.

[20] Differences in the same occupation's skill requirements within OECD countries are potentially smaller. As is noted in subsequent footnotes in the empirical section, we find smaller gaps between the source and host country skill requirements when we restrict the sample to OECD countries, but gaps exist nonetheless. Part of the reason for the smaller gaps may be due to differences in incentives to immigrate; i.e. a potential OECD emigrant might be less likely to immigrate unless there are similar economic opportunities in the potential host country. Given that 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.

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. That is, a skill gap reflects a mismatch in the Canadian economy more so than abroad. There are several reasons to believe that the skill content of source country occupations provide a reasonable reflection of a worker's actual skill endowments. As in the theoretical model, job-to-job transitions and skill acquisition imply that the worker's skills become more aligned with the skill requirements of their current occupation over time. The last job held by immigrants prior to migration is therefore the result of a lengthy process of learning occupational skills as well as matching and sorting into a suitable occupation. Moreover, information and matching frictions are likely less severe in a worker's home country labour market. Nevertheless, one should be cautious in interpreting mismatches in skill requirements in terms of the transferability of immigrants' actual skill endowments.

In addition to search and information frictions in the Canadian labour market, the occupational skill gap results could be driven primarily 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 would be a license to be a mechanic, engineer, plumber, chartered accountant and so on." To investigate the importance 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. Another somewhat related issue is the relevance of the information technology bubble given the time period covered by the LSIC. To examine the impact of the IT bubble on our results, we re-estimate the results excluding immigrants in computer related occupations. The overall results are unchanged.

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 Mean Skills

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 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 work 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 home country jobs. The requirement for motor skills increases from 0.28 standard deviations below the Canadian average for home 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, there appears to be a trend that immigrants work in jobs after landing that require much lower cognitive skills but much higher manual skills compared to their source country occupations. As noted earlier, these skill gaps may partly reflect differences between the occupational skill requirements found in the O*NET and in some of the source country occupations.

In the context of the skill-based model, labour market frictions prevent immigrants from transferring their human capital to the domestic labour market. The sample statistics discussed above reveal that immigrants are arriving in Canada with high cognitive to manual skill ratios. Securing employment in occupations that make inadequate use of their skills should therefore result in negative cognitive skill gaps and positive manual skill gaps. This is consistent with the skill requirement gaps reported in column 1.

To check for signs of partial convergence in skill gaps among immigrants to Canada, we report the skill gap between source country occupations and cycle 3 Canadian occupations (four years after landing) in column 3. The first thing to notice is the decrease in cognitive skill gaps: the interpersonal skill gap decreases from 1.05 to 0.71 standard deviations, and the analytical skill gap drops to 0.82 from 1.20 standard deviations. Even though cognitive skill gaps persist, there is evidence that immigrants slowly 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]

[21]Immigrants from OECD countries experience smaller declines in terms of interpersonal and analytical

There exists the potential for changes in Canadian skill requirements between cycles 1 and 3 to manifest as a result of changes in the composition of the sample employed; the sample increases from $1,476$ to $1,927$. However, despite the large jump in the sample size, there is very little change in average source country occupational skill requirements.[22] We when re-estimate the means separately for Skilled Worker Principal Applicants and non-Economic class immigrants (defined as family and Humanitarian class immigrants[23]), 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.[24]

In Table 2, we present subsamples based on self-assessed language fluency in English or French to investigate whether the skill gap results are driven by language ability.[25,26] All

skill requirements, with declines of around half a standard deviation at six months after arrival. By four years after landing this difference further declines to .25 and .34 standard deviations for interpersonal and analytical skill requirements. Immigrants from OECD countries also experience smaller increases in manual skill requirements. These results are available from the authors upon request.

[22]We do not find much impact of the source country skills on the probability of employment when we estimate probit models. Results are not shown here but are available from the authors.

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

[24]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 B.2). The results for the non-Economic class immigrants are also included in this table.

[25]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.

[26]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 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

three language groups experience declines in the occupational cognitive skill requirements. However, the gaps are smaller for immigrants with better language ability. This lends support to our supposition in the theoretical section that the transferability of skills relies critically on dominant language ability, particularly for cognitive skills (recall the assumption that $\xi^c > \xi^m$, so that manual skills are relatively more transferable to the host country labour market for a given language ability).[27]

4.2 Distribution of Skills

In Figure 5, we present the density estimates for the various skill requirements for the source country occupations and the occupations six months and four years after arrival.[28] We also include the densities for the overall Canadian population, which are calculated using the 2001 Canadian Census Masterfile. 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.

The densities of the cognitive skill requirements of the source country occupations are weighted to the right of the densities of the domestic born population. However, within four years after arrival, the immigrant densities tend to converge towards those of the Canadian population. The densities of the manual skills tend to show a bimodal distribution where occupations either require a large amount, or very little strength, fine motor or visual skills. The densities of the source country occupational manual skill requirements are more heavily weighted towards the left relative to the domestic born population. The distribution of

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.

[27] 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 (estimates not shown but available upon request).

[28] For ease of presentation, we do not display the densities for two years after landing. These densities are distributed between the six month and four year densities for each of the five skills. These additional plots are available upon request.

strength requirements for immigrants' occupations in Canada, in contrast, is more weighted towards the right relative to 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. However, immigrants are observably different in terms of their educational attainment; a much higher percentage of immigrants have obtained a university degree relative to the domestic-born population and one would expect that higher education leads to occupations requiring a greater amount of cognitive skills.[29] Convergence merely to the Canadian population distributions is therefore suggestive that the source country skills of immigrants are underutilized. To investigate further, we re-estimate the densities of the various skills separately for the university educated. Once the sample is restricted to people with a university degree (Figure 6), the convergence result vanishes. The distributions of source country interpersonal skill requirements for immigrants with a university degree and for the domestic born population with a university degree are very similar. The distribution of analytical skill requirements for immigrants has more weight in the right-hand tail. Even though the distributions of cognitive skill requirements of Canadian jobs held by male immigrants shift to the right over the first four years in Canada, these densities remain more weighted to the left of the domestic born university educated population and of the source country occupation densities. These results do not support conditional convergence. It could be that labour market frictions prevent conditional convergence even four years after migration.[30] Alternatively, it could be skill accumulation at Canadian occupations that explains the persistent element of the gaps in skill requirements as in the theoretical model. This occurs when an immigrant becomes adept at performing the tasks of the new occupation.

[29]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 who immigrated in 2000 (and had positive earnings in 2001) have a university degree.

[30]Skuterud and Su (2010) find that immigrants get trapped in low-wage jobs even in the long term following migration, so the partial convergence in occupational skill requirements we observe over the first four years since migration in the LSIC data may never lead to full convergence.

4.3 Earnings Regressions

Thus far we have presented evidence that suggests 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. We estimate earnings regression models to determine the returns to source and host country occupational skill requirements. As shown in equation (22), the dependent variable is the log of weekly earnings for immigrants and the independent variables are various controls, including source country occupational skill requirements (shown in Table 3) and Canadian occupational skill requirements (shown in Table 4). We present the results for cycles 1 and 3 (interviewed approximately six months and four years after arrival).

The regression results in Table 3 reveal that source country skills are insignificant predictors of earnings in Canada, with only a few exceptions. We first control for only source country skills and basic controls (age at arrival and age at arrival squared, months since migration and indicators for very good language ability and native speaker). We find that in the first six months after arrival, the source country occupational skills are not important in determining earnings (column 1 of Table 3). We also allow the returns to source country cognitive skills to vary based on language ability by interacting interpersonal skills and analytical skills with the language ability dummies, since language ability likely affects how well immigrants are able to transfer their cognitive skills. For people who speak the local language very well, a very modest return to source country occupational analytical skill requirements is observed. For native speakers, this return is larger in magnitude, but is not statistically significant in most specifications due to large standard errors. With time in Canada, analytical skills are linked to slightly higher weekly earnings (see column 4 of Table 3). The coefficient on the source country interpersonal skill requirement is negative four years after landing and statistically significant. For people who are either very good speakers or native speakers, the interpersonal skills coefficients are not statistically significant (P-values from an F-test are 0.280 and 0.990 in column 6). The negative impact of source country interpersonal skill requirements on earnings for workers with poor/moderate host country language ability fits with the model as long as interpersonal skills are relatively more difficult to bring to the Canadian labour market for immigrants with low English/French language ability.

In Table 4, we examine the returns to the occupational skill requirements of immigrants' Canadian occupations. 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 people with very good local language ability or who are native speakers, interpersonal skill requirements do not affect earnings.[31]

One important difference between the results when we control for host country rather than source country skills is the impact of educational attainment. Most education variables are insignificant once we control for host country skill requirements. This is not the case when source country skill requirements are included. Source country skills are poor predictors of immigrants' wages in Canada, but perhaps educational background acts as a signal of high cognitive skill endowments to employers, allowing immigrants to secure higher paying employment. Given that the skill requirements of Canadian occupations are better indicators of earnings, this would explain why including them among the regressors causes foreign educational achievement to lose explanatory power.

When we again restrict the sample to Skilled Worker Principal Applicants, the results are very similar to the full sample results presented in Tables 3 and 4. Therefore, 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

[31] 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.

requirements. Even non-Economic class immigrants earn returns to Canadian occupational skill requirements that are similar to the full sample.[32]

Given the large gaps in skill requirements between pre- and post- immigration occupations reported in Table 1 and Figure 5, source country skills should not be important determinants of Canadian earnings.[33] If immigrants have difficulty acquiring jobs in Canada that match the skill portfolios of their source country occupations, they may settle for unrelated jobs, which hinders their ability to earn a return on skills acquired previously. Moreover, immigrants may rely on educational attainment to convey qualification information to Canadian employers, an imperfect and potentially incomplete signal of skill endowments.

4.4 Predicted Values

We next examine the potential loss in earnings resulting from the inability of new immigrants to find employment in an occupation that matches their source country occupational skill requirements. In the previous section we computed the returns to immigrants' Canadian occupational skill requirements (i.e. coefficients from the earnings regressions when Canadian occupational skill requirements are used as controls). Here, 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 5 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 immigrants. We present results without and with additional covariates. The additional covariates are set to their mean values.

[32]The results for the Skilled Worker Principal Applicants are shown in Tables B.3 and B.4, while the results for the non-Economic class immigrants are shown in Tables B.5 and B.6 in the online appendix.

[33]When we re-estimate Table 3 adding in the Canadian occupational requirements, source country occupational analytical skill requirements are no longer statistically significant.

Assuming 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.[34] 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.

Re-estimating the predicted values for different language groups (see rows 2 to 4 of Table 5) reveals the anticipated trends, with one surprising result. As expected, the gap between the actual earnings and the predicted earnings using their source country endowment is the smallest for native speakers. Furthermore, there is very little change between the six months and four years after arrival values. In contrast, immigrants who classify themselves as having very good language ability experience larger gaps than immigrants who are classified in the poor/moderate language category. While initially a puzzling result, this stems from the fact that fluent immigrants earn high returns to Canadian skills (at least interpersonal skills), so the same skill gap will have a bigger impact on predicted earnings.

In row 5 of Table 5, we examine the predicted values for the subsample of Skilled Worker Principal Applicants. As previously discussed, Skilled Worker Principal Applicants earn similar returns to Canadian occupational skill requirements as non-Economic class immigrants. Moreover, there are only slight differences in the skill gaps experienced by Skilled Worker Principal Applicants relative to those exhibited by the rest of the sample. It is thus not surprising that when we compare row 1 (full sample) to row 5 (Skilled Worker Principal Applicants), we find that there is very little difference in the magnitude of the predicted values, both six months and four years after arrival. This could be partly due to the fact that Skilled Worker Principal Applicants make up around two thirds of the total weighted sample of employed males. If we restrict the sample to immigrants who do not enter under the Economic Class (row 6 of Table 5), we find the magnitude of the predicted values are

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

smaller. This is not surprising, since as previously discussed the non-Economic class immigrants face smaller analytical and strength gaps. This lends further support to our result that Skilled Worker Principal Applicants also have difficulty 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 in Canada. Using a dynamic model of occupational choice and skill accumulation, we argue that search and information frictions in the labour market foment an incomplete transfer of occupational human capital from the source country to the host country. Some immigrants end up in unbefitting occupations, 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. Although skill gaps are particularly large among immigrants with poor language ability, the misallocation cannot be fully explained by fluency in English/French. Immigrants with very good language skills and whose source country jobs required high levels of cognitive skills also experience skill discrepancies after coming to Canada. 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 immigrants are not being compensated for the skills of their source country employment. Moreover, even the skill requirements of their Canadian jobs are not always translating into higher earnings for recent immigrants. If immigrants to Canada were able to find employment that requires similar skills to their source country jobs, we would expect higher estimates of the returns to skills. Although there are slight improvements over the four years after arrival, the skill gaps persist. More work needs to be done in order to fully understand the causes of occupational mismatches and develop effective policies to address them. Clearly, selecting immigrants based on their skills and qualifications is not enough to ensure that immigrants' occupational human capital are being employed.

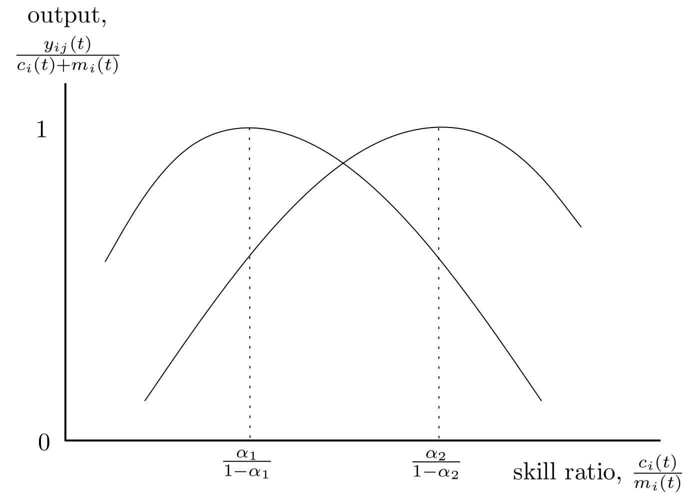

Figure 1: The output produced by worker i matched with firm j at time t, $y_{ij}(t)$.

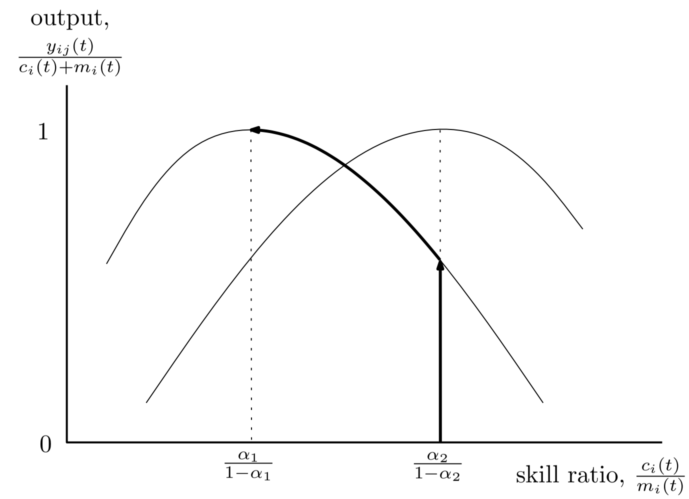

Figure 2: Skill gap persistence for an immigrant with skill endowments suitable for a type 2 job at the time of migration.

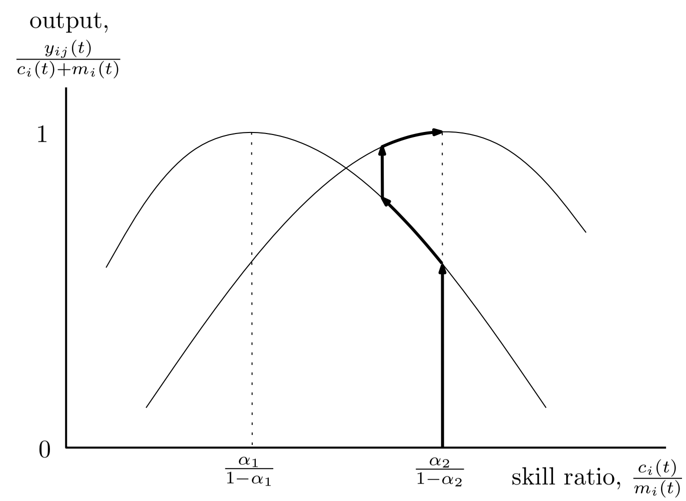

Figure 3: Skill gap convergence for an immigrant with skill endowments suitable for a type 2 job at the time of migration.

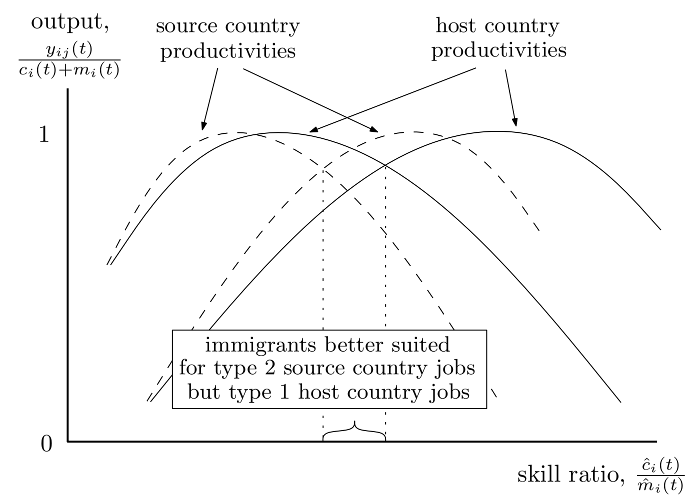

Figure 4: The effect of dominant language ability on productivity when $\xi^c > \xi^m$.

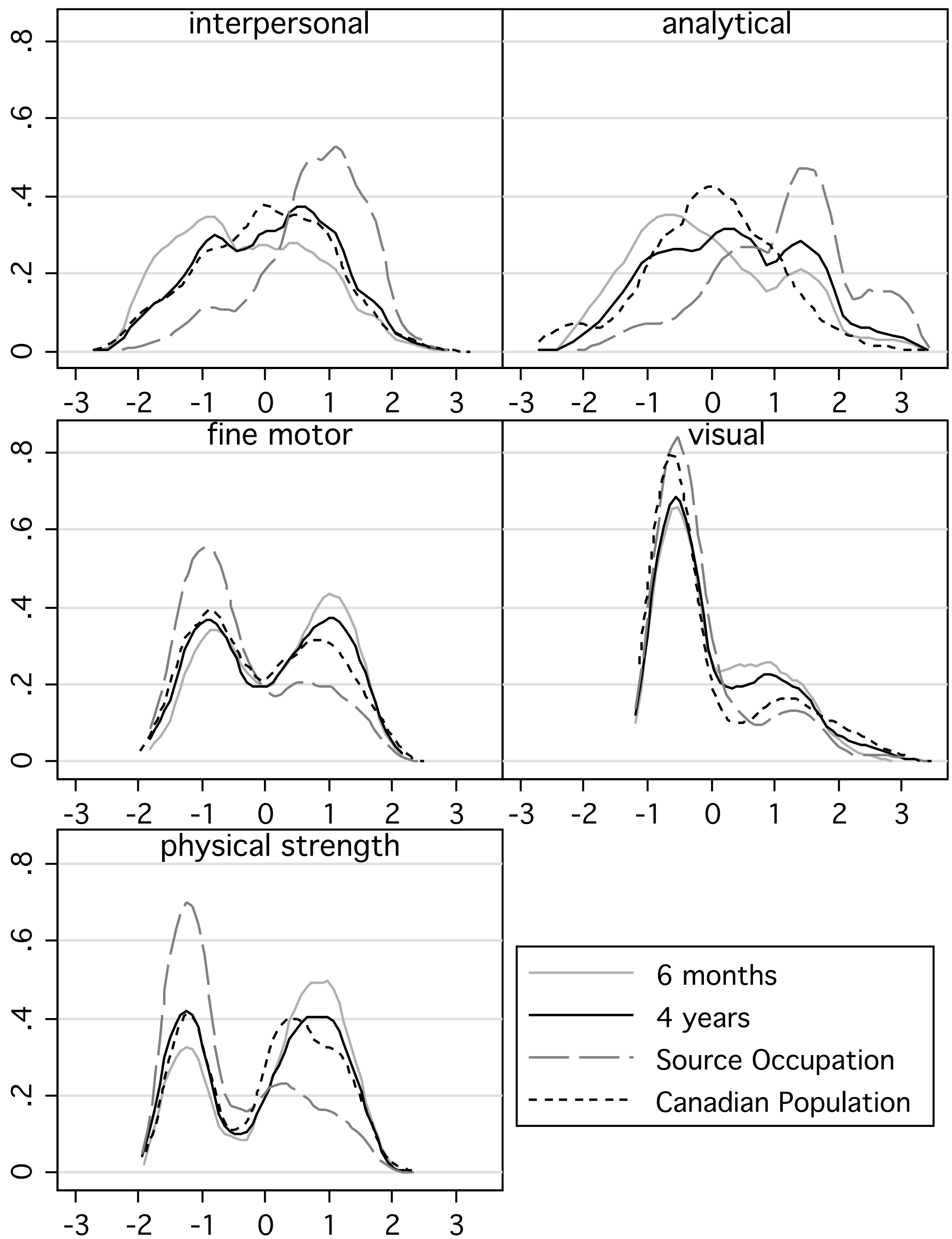

Figure 5: The density estimates for the skill requirements of source country occupations and Canadian occupations of immigrants. Also included is the density estimate for the overall Canadian population.

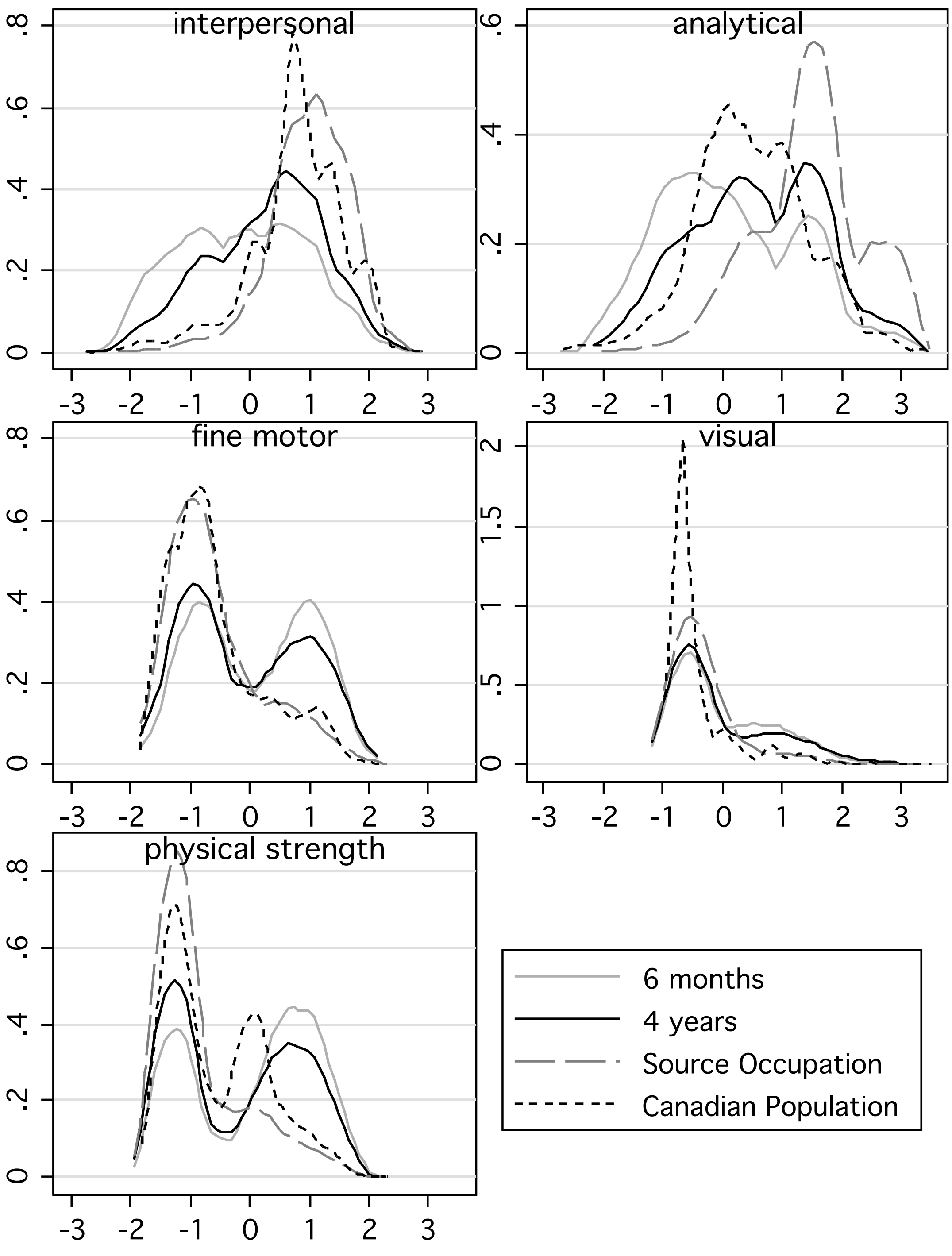

Figure 6: The density estimates for the skill requirements of source country occupations and Canadian occupations of university educated immigrants. Also included is the density estimate for the university educated Canadian population.

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 nonmissing 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 Source Country Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.0369	-0.0730	-0.0777	-0.0601	-0.108*	-0.103*
	(0.0676)	(0.0701)	(0.0673)	(0.0454)	(0.0419)	(0.0415)
analytic	0.0470	0.0422	0.0356	0.0992**	0.0890**	0.0813**
	(0.0393)	(0.0378)	(0.0391)	(0.0298)	(0.0276)	(0.0270)
motor	0.0266	0.00887	0.00694	0.0743	0.0454	0.0510
	(0.0521)	(0.0522)	(0.0525)	(0.0451)	(0.0414)	(0.0419)
visual	-0.0224	-0.00282	0.00481	-0.0110	0.0174	0.0306
	(0.0353)	(0.0352)	(0.0357)	(0.0275)	(0.0256)	(0.0268)
strength	-0.0411	-0.0352	-0.0258	-0.103*	-0.0876*	-0.0911*
	(0.0626)	(0.0606)	(0.0585)	(0.0482)	(0.0438)	(0.0443)
langVG × interpers[1]	-0.0493	-0.0472	-0.0350	0.0284	0.0197	0.0415
	(0.0694)	(0.0687)	(0.0637)	(0.0514)	(0.0486)	(0.0463)
langN × interpers[2]	0.006	-0.004	0.113	0.0609	0.0379	0.104
	(0.117)	(0.114)	(0.102)	(0.0790)	(0.0785)	(0.0708)
langVG × analytic[3]	0.0970$^+$	0.107$^+$	0.105$^+$	-0.0177	9.60e-05	-0.0234
	(0.0570)	(0.0567)	(0.0551)	(0.0377)	(0.0354)	(0.0325)
langN × analytic[4]	0.188	0.202$^+$	0.163	0.0742	0.0967	0.0752
	(0.116)	(0.110)	(0.102)	(0.0740)	(0.0726)	(0.0629)
high school		-0.0200	-0.129		0.0585	-0.0409
		(0.0786)	(0.0832)		(0.0519)	(0.0529)
some post secondary		0.0131	-0.123		0.0993	-0.0140
		(0.0871)	(0.0976)		(0.0660)	(0.0686)
trade or college		0.136$^+$	-0.00350		0.146*	0.0130
		(0.0781)	(0.0856)		(0.0580)	(0.0600)
bachelor degree		0.139$^+$	-0.0138		0.238**	0.105$^+$
		(0.0812)	(0.0909)		(0.0597)	(0.0624)
graduate degree		0.226*	0.0115		0.370**	0.199**
		(0.0935)	(0.101)		(0.0647)	(0.0694)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	1476	1476	1476	1927	1927	1927
R-squared	0.081	0.090	0.171	0.125	0.150	0.227
P-value[1]	0.311	0.160	0.153	0.615	0.128	0.280
P-value[2]	0.778	0.483	0.718	0.993	0.415	0.990
P-value[3]	0.007	0.004	0.004	0.036	0.016	0.094
P-value[4]	0.032	0.020	0.048	0.017	0.012	0.023

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 source country occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^+$ $p < 0.1$

Table 4: 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 5: 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 Omitted Proofs

Proof of Proposition 1

Proof. Part 1: The growth rate of the skill portfolio is

$$\frac{\dot{c}(t)+\dot{m}(t)}{c(t)+m(t)} = \left(A+\eta\left(\frac{c(t)+m(t)}{y(t)}-1\right)\left[\alpha-(1-\alpha)\frac{c(t)}{m(t)}\right]^{-1}\right)\frac{c(t)}{c(t)+m(t)}$$
$$+\left(A+\eta\left(\frac{c(t)+m(t)}{y(t)}-1\right)\left[(1-\alpha)-\alpha\frac{m(t)}{c(t)}\right]^{-1}\right)\frac{m(t)}{c(t)+m(t)}$$
$$= A+\eta\left(\frac{c(t)+m(t)}{y(t)}-1\right)\left(\alpha-(1-\alpha)\frac{c(t)}{m(t)}\right)^{-1}\left((1-\alpha)-\alpha\frac{m(t)}{c(t)}\right)^{-1}$$
$$\times\left(\left[(1-\alpha)-\alpha\frac{m(t)}{c(t)}\right]\frac{c(t)}{c(t)+m(t)}+\left[\alpha-(1-\alpha)\frac{c(t)}{m(t)}\right]\frac{m(t)}{c(t)+m(t)}\right) = A$$

Thus, the skill portfolio grows at constant rate A. □

Proof. Part 2: Differentiating the production function yields

$$\frac{\dot{y}(t)}{y(t)} = \alpha\frac{\dot{c}(t)}{c(t)}+(1-\alpha)\frac{\dot{m}(t)}{m(t)} \tag{A.1}$$

After substituting for the growth rates of skills from (8) and (9), this becomes

$$\frac{\dot{y}(t)}{y(t)} = A+\eta\left(\frac{c(t)+m(t)}{y(t)}-1\right)\left[\frac{\alpha}{\alpha-(1-\alpha)c(t)/m(t)}+\frac{1-\alpha}{(1-\alpha)-\alpha m(t)/c(t)}\right] \tag{A.2}$$

which simplifies to

$$\dot{y}(t) = (A-\eta)y(t)+\eta\,[c(t)+m(t)] \tag{A.3}$$

The solution to this differential equation is

$$y(t) = e^{(A-\eta)t}y(0)+(1-e^{-\eta t})\,[c(t)+m(t)]$$

□

Proof. Part 3: The limit $\lim_{t\to\infty} y(t)/(c(t)+m(t)) = 1$ follows directly from part 2 of the

Proposition. Then, given a skill portfolio with a given size, $c(t)+m(t)=\mathcal{S}$, the first order condition of output $y(t)$ with respect to $c(t)$ determines the optimal skill ratio:

$$\frac{c(t)}{m(t)}=\frac{\alpha}{1-\alpha} \tag{A.4}$$

Then, if $y^*(t)$ denotes firm output at time t when the worker has the ideal mix of skills, then

$$y^*(t)=c(t)+m(t) \quad \text{or} \quad \frac{y^*(t)}{c(t)+m(t)}=1 \tag{A.5}$$

The only way for $\lim_{t\to\infty} y(t)/(c(t)+m(t))=1$ given (A.5) and part 1 of the Proposition is if the portfolio evolves such that $\lim_{t\to\infty} c(t)/m(t)=\alpha/(1-\alpha)$. In other words, if (normalized) output converges to the level of production when the ideal worker is employed, and if the incumbent's skill portfolio grows at a constant rate, then the worker's skill ratio must converge to the optimal mix of skills given the firm's production technology. □

Proof. Part 4: The limit of (8) as t goes to infinity is

$$\lim_{t\to\infty}\frac{\dot{c}(t)}{c(t)}=A+\eta\lim_{t\to\infty}\left(\frac{c(t)+m(t)}{y(t)}-1\right)\left[\alpha-(1-\alpha)\frac{c(t)}{m(t)}\right]^{-1} \tag{A.6}$$

Applying L'Hôpital's rule, the limit on the right hand side can be written

$$\begin{aligned}\lim_{t\to\infty}\frac{\frac{c(t)+m(t)}{y(t)}-1}{\alpha-(1-\alpha)\frac{c(t)}{m(t)}} &= \lim_{t\to\infty}-\frac{\frac{\dot{c}(t)+\dot{m}(t)}{y(t)}-\frac{c(t)+m(t)}{y(t)}\frac{\dot{y}(t)}{y(t)}}{(1-\alpha)\frac{c(t)}{m(t)}\left[\frac{\dot{c}(t)}{c(t)}-\frac{\dot{m}(t)}{m(t)}\right]} && \text{(A.7)}\\ &= \lim_{t\to\infty}\frac{\frac{c(t)+m(t)}{y(t)}\left(\frac{\dot{y}(t)}{y(t)}-A\right)}{(1-\alpha)\frac{c(t)}{m(t)}\left[\frac{\dot{c}(t)}{c(t)}-\frac{\dot{m}(t)}{m(t)}\right]} && \text{(A.8)}\\ &= \lim_{t\to\infty}\frac{\frac{\dot{y}(t)}{y(t)}-A}{\alpha\left[\frac{\dot{c}(t)}{c(t)}-\frac{\dot{m}(t)}{m(t)}\right]} && \text{(A.9)}\end{aligned}$$

where the second line uses the fact that $\dot{c}(t)+\dot{m}(t)=A[c(t)+m(t)]$ from part 1, and the last line uses part 3 of the Proposition. Substituting for the growth rate of output from (A.1) yields

$$\lim_{t\to\infty} \frac{\frac{\dot{m}(t)}{m(t)} + \alpha\left(\frac{\dot{c}(t)}{c(t)} - \frac{\dot{m}(t)}{m(t)}\right) - A}{\alpha\left[\frac{\dot{c}(t)}{c(t)} - \frac{\dot{m}(t)}{m(t)}\right]} = 1 - \lim_{t\to\infty} \frac{A - \frac{\dot{m}(t)}{m(t)}}{\alpha\left[\frac{\dot{c}(t)}{c(t)} - \frac{\dot{m}(t)}{m(t)}\right]} \tag{A.10}$$

Substituting from (8) and (9), this becomes

$$1 + \frac{1}{\alpha}\lim_{t\to\infty}\left(\frac{\eta\left(\frac{c(t)+m(t)}{y(t)} - 1\right)}{1-\alpha-\alpha\frac{m(t)}{c(t)}}\right)\left(\frac{\eta\left(\frac{c(t)+m(t)}{y(t)} - 1\right)}{\alpha-(1-\alpha)\frac{c(t)}{m(t)}} - \frac{\eta\left(\frac{c(t)+m(t)}{y(t)} - 1\right)}{1-\alpha-\alpha\frac{m(t)}{c(t)}}\right)^{-1} \tag{A.11}$$

or, after some manipulation,

$$1 + \frac{1}{\alpha}\lim_{t\to\infty}\frac{\frac{\alpha}{1-\alpha} - \frac{c(t)}{m(t)}}{1 - \frac{\alpha}{1-\alpha} - \frac{\alpha}{1-\alpha}\frac{m(t)}{c(t)} + \frac{c(t)}{m(t)}} \tag{A.12}$$

Another application of L'Hôpital's rule yields

$$1 - \frac{1}{\alpha}\lim_{t\to\infty}\frac{\frac{m(t)\dot{c}(t)-c(t)\dot{m}(t)}{m(t)^2}}{\frac{m(t)\dot{c}(t)-c(t)\dot{m}(t)}{m(t)^2} - \frac{\alpha}{1-\alpha}\frac{c(t)\dot{m}(t)-m(t)\dot{c}(t)}{c(t)^2}} = 1 - \frac{1}{\alpha}\lim_{t\to\infty}\frac{1}{1+\frac{\alpha}{1-\alpha}\frac{m(t)^2}{c(t)^2}} \tag{A.13}$$

Finally, evaluating the limit reveals that

$$\lim_{t\to\infty}\frac{\dot{c}(t)}{c(t)} = A + \eta\left[1 - \frac{1}{\alpha}\left(\frac{1}{1+\frac{1-\alpha}{\alpha}}\right)\right] = A \tag{A.14}$$

A similar exercise confirms that $\lim_{t\to\infty}\dot{m}(t)/m(t) = A$. □

Proof of Proposition 2

Proof. Substitute the wage equation (2) into the value function (17) for $t \geq T$:

$$v_j^*(t) = \int_t^\infty e^{-r(\tau-t)}\delta y_j(\tau)d\tau$$

Using part 2 of Proposition 1, we can write the output of a worker with skill portfolio $\{c(t), m(t)\}$ in job $j \in \{1, 2\}$ at time $t \geq T$ as

$$y_j(t) = e^{(A-\eta)(t-T)} y_j(T) + (1 - e^{-\eta(t-T)}) e^{A(t-T)} (c(T) + m(T))$$

The value function can then be written

$$\begin{aligned} v_j^*(t) = & \int_t^{\infty} e^{(A-\eta-r)(\tau-t)} e^{(A-\eta)(t-T)} \delta y_j(T) d\tau \\ & + \int_t^{\infty} \left[e^{(A-r)(\tau-t)} e^{A(t-T)} - e^{(A-\eta-r)(\tau-t)} e^{(A-\eta)(t-T)} \right] \delta(c(T) + m(T)) d\tau \end{aligned} \tag{A.15}$$

Solving these integrals yields

$$v_j^*(t) = \frac{e^{(A-\eta)(t-T)} \delta y_j(T) + \left[\frac{r-(A-\eta)}{r-A} - e^{-\eta(t-T)} \right] e^{A(t-T)} \delta \left(c(T) + m(T) \right)}{r - (A - \eta)} \tag{A.16}$$

Recall from part 1 of Proposition 1 that $c(t) + m(t)$ grows at a constant rate regardless of which job is accepted at time T. A worker's indifference at time T thus requires $y_1(T) = y_2(T)$. Since $w_j(t) = \delta y_j(t)$, it follows that $v_1^*(T) \gtreqless v_2^*(T) \iff w_1(T) \gtreqless w_2(T)$. $\square$

B Supplementary Tables

Table B.1: 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 B.2: 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 B.3: Log Weekly Earnings Regressions for Skilled Worker Principal Applicants, Controlling for Source Country Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.00655	-0.0131	0.0259	-0.0769	-0.104$^+$	-0.104$^+$
	(0.0904)	(0.0964)	(0.0886)	(0.0575)	(0.0565)	(0.0583)
analytic	-0.00132	0.00695	-0.0116	0.0568	0.0649$^+$	0.0755*
	(0.0435)	(0.0434)	(0.0457)	(0.0356)	(0.0344)	(0.0359)
motor	0.0115	0.0266	0.0225	0.0448	0.0421	0.0309
	(0.0694)	(0.0698)	(0.0645)	(0.0549)	(0.0529)	(0.0541)
visual	-0.0816	-0.0660	-0.0610	-0.0391	-0.0216	-0.00241
	(0.0525)	(0.0540)	(0.0543)	(0.0368)	(0.0362)	(0.0400)
strength	0.0119	-0.0182	-0.00468	-0.0674	-0.0810	-0.0797
	(0.0764)	(0.0792)	(0.0776)	(0.0555)	(0.0523)	(0.0548)
langVG × interpers[1]	-0.0877	-0.0916	-0.150*	0.0168	0.00666	0.00896
	(0.0783)	(0.0778)	(0.0722)	(0.0620)	(0.0581)	(0.0577)
langN × interpers[2]	0.00998	0.0145	0.0488	0.0414	0.0411	0.0730
	(0.151)	(0.146)	(0.148)	(0.111)	(0.112)	(0.106)
langVG × analytic[3]	0.121$^+$	0.120$^+$	0.133*	0.0111	0.0212	-0.0253
	(0.0648)	(0.0636)	(0.0625)	(0.0431)	(0.0398)	(0.0407)
langN × analytic[4]	0.298$^+$	0.300*	0.226	0.172	0.172$^+$	0.112
	(0.154)	(0.147)	(0.145)	(0.105)	(0.103)	(0.0915)
high school		-0.334	-0.393		0.00978	-0.240
		(0.460)	(0.354)		(0.407)	(0.367)
some post secondary		-0.387	-0.358		0.0859	-0.0550
		(0.440)	(0.331)		(0.385)	(0.343)
trade or college		-0.0736	-0.0936		0.164	-0.000140
		(0.426)	(0.314)		(0.390)	(0.341)
bachelor degree		-0.236	-0.247		0.127	-0.0167
		(0.429)	(0.321)		(0.380)	(0.336)
graduate degree		-0.138	-0.226		0.273	0.0923
		(0.424)	(0.317)		(0.385)	(0.341)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	938	938	938	1137	1137	1137
R-squared	0.059	0.069	0.171	0.072	0.090	0.190
P-value[1]	0.358	0.322	0.184	0.386	0.141	0.168
P-value[2]	0.981	0.992	0.583	0.761	0.587	0.787
P-value[3]	0.0430	0.0310	0.0240	0.111	0.0360	0.199
P-value[4]	0.0490	0.0310	0.137	0.0323	0.0260	0.0618

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 source country occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^+$ $p < 0.1$

Table B.4: 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 B.5: Log Weekly Earnings Regressions for Non-Economic Immigrants, Controlling for Source Country Occupational Skill Requirements

	6 months			4 years		
	(1)	(2)	(3)	(4)	(5)	(6)
interpers	-0.188*	-0.195*	-0.187*	-0.0525	-0.0714	-0.00165
	(0.0827)	(0.0881)	(0.0858)	(0.0604)	(0.0578)	(0.0509)
analytic	0.128*	0.128+	0.144*	0.0394	0.0458	-0.00412
	(0.0639)	(0.0668)	(0.0676)	(0.0478)	(0.0462)	(0.0424)
motor	-0.105	-0.115	-0.0394	0.0555	0.0514	0.128+
	(0.0724)	(0.0755)	(0.0884)	(0.0765)	(0.0749)	(0.0739)
visual	0.0741*	0.0752*	0.0454	0.0221	0.0281	0.0147
	(0.0346)	(0.0356)	(0.0423)	(0.0376)	(0.0371)	(0.0329)
strength	0.0261	0.0417	0.0211	-0.0670	-0.0491	-0.0584
	(0.0702)	(0.0717)	(0.0768)	(0.0615)	(0.0597)	(0.0621)
langVG × interpers[1]	0.198	0.201+	0.137	0.0826	0.0851	0.0843
	(0.122)	(0.115)	(0.108)	(0.0829)	(0.0819)	(0.0763)
langN × interpers[2]	0.414+	0.431+	0.447*	0.212	0.205	0.0915
	(0.230)	(0.229)	(0.185)	(0.164)	(0.164)	(0.153)
langVG × analytic[3]	-0.0443	-0.0570	-0.0446	0.0577	0.0349	0.0311
	(0.117)	(0.108)	(0.105)	(0.0852)	(0.0871)	(0.0720)
langN × analytic[4]	-0.103	-0.111	-0.199	-0.00300	-0.00706	0.0176
	(0.197)	(0.197)	(0.174)	(0.140)	(0.140)	(0.124)
high school		0.0367	0.0607		0.0663	-0.00735
		(0.0932)	(0.0901)		(0.0534)	(0.0522)
some post secondary		-0.00805	-0.0597		0.0861	-0.000628
		(0.112)	(0.114)		(0.0793)	(0.0825)
trade or college		0.00344	0.0504		0.0622	-0.0655
		(0.103)	(0.119)		(0.0714)	(0.0743)
bachelor degree		0.0742	0.0356		0.207*	0.125
		(0.104)	(0.111)		(0.0895)	(0.0803)
graduate degree		0.173	-0.0357		0.163	-0.0532
		(0.187)	(0.161)		(0.123)	(0.122)
Additional Controls	NO	NO	YES	NO	NO	YES
Observations	334	334	334	538	538	538
R-squared	0.168	0.173	0.373	0.138	0.149	0.304
P-value[1]	0.929	0.958	0.636	0.709	0.862	0.274
P-value[2]	0.337	0.314	0.147	0.325	0.405	0.528
P-value[3]	0.431	0.455	0.253	0.171	0.265	0.637
P-value[4]	0.903	0.932	0.751	0.792	0.777	0.910

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 source country occupation are in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table B.6: Log Weekly Earnings Regressions for Non-Economic 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 schoole		-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 companys internal policies." Table C.2 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 incumbents 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 C.4 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 C.6 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 C.8 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 C.10 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 C.1: 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 C.2: 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 C.3: 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 C.4: 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 C.5: 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 C.6: 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 C.7: 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 C.8: 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 C.9: 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 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.
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 C.10: 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	