THE IMPACT OF SKILL MATCHING ON THE RETURNS TO FOREIGN HUMAN CAPITAL OF IMMIGRANTS IN CANADA

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ABSTRACT

Using the Longitudinal Survey of Immigrants in Canada for 2001-2005 the effects of matching pre-immigration and post-immigration occupational skills on immigrant entry earnings are analyzed, with a focus on the return to foreign experience. The main purpose of this research is to explore whether matching pre- and post-immigration skills can explain poor transferability of foreign work experience of recent immigrants in Canada.

We employ factor analysis and obtain three broad skill factors from 44 occupational characteristics provided in the HRSDC's Career Handbook. The survey contains rich information on immigrants' last occupation before immigration to Canada and employment history after immigration. Using occupational information we assign each immigrant a skill-portfolio, which contains pre- and post-immigration factor scores for "intelligence", "motor skills" and "strength" obtained in the factor analysis. A match for each of the three skill factors is constructed using normalized factor scores and is a dichotomous variable. We then use these match variables in regression analysis to examine direct and indirect effects of successful matching on immigrants' log weekly wages. The indirect effects are analyzed through returns to foreign work experience and foreign schooling for immigrants who match their pre- and post-immigration skill factors. As well the effects of ability in English and French on the returns to foreign human capital conditional on matching pre- and post-immigration skill factors are studied. We first conduct cross-sectional regression analysis. Then we expand the analysis and rerun regressions for a set of pair-wise immigrant sub-samples.

We reach a conclusion that controlling for pre- and post-immigration skill match does not help in explaining poor portability of foreign work experience of recent immigrants to Canada. Although, we find that immigrants who obtain a match in "intelligence" or "motor skills" receive substantially higher earnings than immigrants who do not obtain any match. Immigrants who

obtain a match in "strength" factor have a very small and often insignificant advantage in earnings. We also find that male immigrants who obtain a match in "intelligence" factor in wave 3 receive a moderate positive return to foreign experience, which together with the baseline return to foreign experience still results in zero total effect. The regression analysis gives some interesting insight into returns to foreign human capital for immigrant sub-samples in wave 3. Male immigrants employed in professional occupations as well as male immigrants who are not visible minorities have almost zero return to foreign experience instead of negative. The baseline return to foreign experience holds negative for other sub-samples. Matching some of the skills slightly improves the returns to foreign experience for some sub-samples, but the total effect is often negligible.

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Dedication

This research is dedicated to my parents, Galyna Lukashenko and Valerii Didkovskyi, who gave me love to learning and taught me to never stop reaching my dreams.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

Immigrant skills utilization is a major policy issue in Canada. The return to foreign work experience as well as foreign schooling is one of the measures of the extent to which immigrant skills are utilized in the Canadian labour market. It has been estimated that skills under-utilization results in an enormous economic loss and distracts foreign born from coming to Canada[1]. Hence, the recognition of immigrant skills has become one of the policy priorities for the government (HRSDC, 2011).

Strikingly, many studies in the literature on immigration find that recent immigrants in Canada receive a near zero return to foreign work experience (Schaafsma & Sweetman, 2001; Aydemir & Skuterud, 2005; Goldmann, Sweetman & Warman, 2009; Green and Worswick, 2010). Researchers attempted to find underlying causes of such low portability of foreign experience to the Canadian labor market. They studied the effects of age-at-immigration (Schaafsma & Sweetman, 2001), source-country composition (Aydemir & Skuterud, 2005), macroeconomic conditions (Green & Worswick, 2010), knowledge of official languages (Ferrer, Green & Riddell, 2006) and even occupational match (Goldmann, Sweetman & Warman, 2009). On the other hand, studies in the literature on specificity of human capital have shown that skill- specific experience plays a more important role in wage formation process than firm-, industry- or occupation-specific (Poletaev & Robinson, 2008). Using longitudinal data on immigrants in Canada for 2001-2005 this research explores the average log wage return to foreign

[1] The estimated loss of income associated with unrecognized skills/credentials of the foreign born is approximately 3.2 billion dollars (Conference Board of Canada, 2001). Reitz (2001) estimates that the annual loss due to under-utilization of immigrants' skills is about2.4 billion dollars.

human capital conditional on matching pre- and post-immigration skills with a focus on the return to foreign experience.

Remarkably, the return to pre-Canadian work experience is found to be discounted to almost zero and sometimes seen to be slightly negative for more recent immigrant cohorts (Schaafsma & Sweetman, 2001; Aydemir & Skuterud, 2005; Goldmann et al., 2009; Green & Worswick, 2010). Schaafsma and Sweetman (2001) conclude that “work experience in the source country is found to yield virtually no return in the host country.” (p.1069) Aydemir and Skuterud (2005) find that “the foreign experience of immigrant men from the east[2] is worthless by 1995 – 9” (p. 661) They find that for men from the east the return to foreign experience is somewhat negative by late 1990s. Green and Worswick (2010) conclude that “by the 1990s immigrants were effectively receiving a zero return to their foreign experience.” (p. 23) Goldmann et al. (2009) find that 2001 immigrants were receiving slightly negative return to foreign experience approximately four years after immigration to Canada.

In contrast, the return to foreign years of schooling has remained substantially positive, although lower than for both Canadian-born population and relative to immigrant schooling acquired in Canada (Schaafsma & Sweetman, 2001; Aydemir & Skuterud, 2005; Ferrer & Riddell, 2008).

Greater pre-immigration experience is found to be associated with poorer job-matches (Chiswick & Miller, 2008). It implies that the return to foreign experience may be associated with the transferability of occupation-specific skills (Goldmann et al., 2009). A substantial body of the literature on specificity of human capital has studied

[2] Aydemir and Skuterud (2005) define immigrants from the east as those born in Eastern Europe, Asia and Africa. The data suggests that the proportion of immigrants from the east rises to about 73% by late 1990s.

economic returns to work experience that is specific to a firm (Topel, 1991; Altonji & Williams, 1992), an industry (Neal, 1995; Parent, 2000), an occupation (Kamburov & Manovskii, 2009) and skills (Poletaev & Robinson, 2008). There is a unique study by Goldmann et al. (2009) in the literature on immigration that looks at effects of occupational match on the returns to foreign experience of immigrants in Canada. However, Poletaev and Robinson (2008) show that wage losses of displaced workers are associated with switching portfolios rather than switching industries or occupations.

In this research we follow an approach proposed by Poletaev and Robinson (2008) in construction of skills and skill-match, and a model proposed by Goldmann et al. (2009) in studying the effects of skill-match on the returns to foreign human capital with a focus on the returns to foreign work experience. Our data consist of two important parts. First, the Longitudinal Survey of Immigrants in Canada contains valuable information on immigrants' last pre-immigration occupation and current main occupation in Canada. Second, we use occupational characteristics from the Career Handbook provided by Human Resources and Skills Development Canada and factor analysis in order to construct skill portfolios for immigrant pre- and post-immigration occupations. These skill portfolios allow us to construct matches between immigrant pre- and post-immigration skills. Then we explore economic returns to foreign experience, foreign schooling, skill-matching, English and French ability and their interactions with a focus on the return to foreign experience. Then we expand our analysis focusing on immigrants who immigrated under Skilled Worker Principal Applicants immigration category, immigrants employed in regulated occupations and in professional occupations, as well as immigrants with a university degree and visible minorities.

We find that, although immigrants who match their skills on average obtain higher earnings, the baseline return to foreign work experience is still negligible. There is some moderate evidence of returns to immigrant experience acquired abroad conditional on skill-matching for male immigrants, but the total effect is still zero in most of the cases. The patterns of returns to foreign work experience conditional on skill matching differ across time and across immigrant sub-samples.

We add to several streams in the labor economics literature. First, we add to the literature on Canadian immigration by exploring economic outcomes and the returns to foreign human capital for recent immigrants in Canada. Second, we add to the literature on specificity of human capital exploring effects of matching pre- and post-immigration skills on the returns to foreign work experience in order to determine if skill matching can account for low returns to pre-immigration work experience.

This research is organized as follows. In the next chapter the literature review is presented. The theoretical background for the analysis is provided in the third chapter. The fourth chapter describes the data and methodology. The fifth chapter presents the descriptive results and the sixth chapter follows with a discussion of regression results. The last chapter concludes.

CHAPTER 2

LITERATURE REVIEW

The return to foreign experience has been found to be negligible for the most recent immigrant cohorts[3] (Schaafsma & Sweetman, 2001; Aydemir & Skuterud, 2005; Goldmann et al., 2009; Green & Worswick, 2010). Researchers, using different data and methodologies, have attempted to determine underlying conditions of these adverse economic outcomes of recent immigrants in Canada. They explored effects of source-country composition (Aydemir & Skuterud, 2005), labour market entry effects (Green & Worswick, 2010), literacy in English and French (Ferrer et al., 2006), as well as effects of occupational match between source- and host-country (Goldmann et al., 2009). However, they could not fully explain low portability of foreign experience. One more plausible issue that could explain poor transferability of foreign experience is a mismatch of job-skills (Chiswick & Miller, 2008). Moreover, Poletaev & Robinson (2008) show that greater wage loss after involuntary displacement is associated with switching skills rather than switching industry or occupation. To the best of our knowledge, there is no study in the literature on immigration that looks at effects of matching skills on the returns to foreign experience. We take into account the Poletaev and Robinson's (2008) finding and apply their approach for constructing a skill-match to determine if accounting for skill matching could explain poor transferability of foreign experience.

In the following section we review studies that find zero return to foreign experience for immigrants in Canada. A detailed review of the literature on the specificity of human capital is provided in section 2.2. In section 2.3 we present findings of a unique

[3] 1990s to early 2000s.

study in the literature on immigration that explores the effect of occupational match on the returns to foreign experience.

2.1 Returns to foreign human capital

The literature on immigration has found that the decline in immigrant entry earnings is strongly associated with deterioration of the returns to foreign human capital. Specifically, the economic return to foreign work experience for most recent immigrant cohorts is found to be around zero (Schaafsma & Sweetman, 2001; Aydemir & Skuterud, 2005; Green & Worswick, 2010). These studies still cannot fully explain low portability of foreign work experience of immigrants in Canada. The gap that I find in the previous literature is related to data construction used in these studies. The data they use do not contain any information on immigrants' pre-Canadian employment and, hence, does not allow them to account for job-skills mismatch.

Schaafsma and Sweetman (2001) study the decline in immigrant entry earnings over time using the Canadian Censuses of 1986, 1991, 1996 in the cross-sectional analysis. They report that average real annual earnings (in 1995 dollars) of immigrants between 1986 and 1991 exceeded earnings of Canadian born by $2000, but then fell short by $442 in 1996 as a result of a much bigger drop in average earnings of immigrants than of native born.

The authors explore the causes that led to the decline in immigrant earnings. They find that age at immigration is negatively correlated to immigrant earnings. For instance, adults who immigrated between 45 and 64 years have substantially lower earnings compared to infants who immigrated before the age of five. Schaafsma and Sweetman (2001) explore underlying factors of this correlation and find that it can be explained by the return to experience obtained in a sending country. The authors find that in the host-country there is "virtually no return" (p.1069) to potential years of foreign experience for all three cross-sectional years. On the other hand, the return to years of education is around 6% and is similar to the return to Canadian schooling that varies between 5.5% and 7% across years. Interestingly, that English as a mother tongue boosts up the return to total experience for older adults, unlike those who immigrated young.

Aydemir and Skuterud (2005) also explore causes of deterioration in immigrant entry earnings. They use the Censuses for the period of 1981-2001 and estimate flexible specification of the earnings regression including changes in immigrants' language abilities, region of birth, changes in returns to foreign experience and schooling, macroeconomic conditions and general labour market trends. Similarly to Schaafsma and Sweetman (2001), they find a clear deterioration in the return to foreign labour market experience, but not in the return to years of foreign education. Thus, when experience is separated into foreign and Canadian there is strong evidence that Canadian employers value the source-country experience less than the host-country work experience. For instance, in a regression specification when experience is the same across cohorts and when the squared term of the experience is included, the return to Canadian experience for immigrants declines from 3.1% to 1.8% between 1 and 10 years of experience. The return to foreign experience over the same period declines from 1.2% to 0.8% for men and mostly close to zero for women. Altogether, the authors find that about ¼ to ½ of the decline in immigrant entry earnings can be explained by the decline in the return to foreign experience.

Aydemir and Skuterud (2005) suggest that compositional shift from European to Asian countries or a shift from economic class of immigrants to refugees has to be tested in order to identify if they can explain the deterioration in the return to foreign experience. Interestingly, even when the sample is split into Western (North America, Northern, Western and Southern Europe) and Eastern (Eastern Europe, Africa, Asia) source-country regions, the results still suggest a strong deterioration for male immigrants from Eastern regions. The division into source-regions is less relevant for females. Hence, the authors rule out the hypothesis of compositional shift effect, however they note that shifts within regions still remain unknown.

Ferrer et al. (2006) using the 1998 Ontario Immigrant Literacy Survey and the Canadian version of the 1994 International Adult Literacy Survey to study effects of immigrant literacy skills on immigrant earnings. The data allow the authors to construct reliable measures of foreign work experience and foreign education. The sample is restricted to male individuals between the age of 16 and 60 with positive earnings. They find that although immigrant literacy skills have a significant positive influence on immigrant earnings and explains immigrant-native born gap in returns to education, controlling for literacy does not affect the returns to foreign experience.

Green and Worswick (2010) using the Immigrant Database for the 1981-2003 period, the Survey of Consumer Finances for 1981 to 1997 and the Survey of Labour and Income Dynamics (SLID) for 1997 through 2003 to investigate the causes of immigrant entry earnings deterioration over cohorts. They can explain about 25% of the deterioration between 1980-82 immigrant cohort and the 2000-02 cohort with flattening of the foreign experience profile, around 16% with the shift in source-country composition and 39% with general labour market entry effect totaling into roughly ¾ of the total deterioration. Thus for all levels of education and when the squared term of foreign experience is included immigrants receive a positive, but diminishing, return to years of foreign experience. Its interactions with cohort dummy variables suggest a downgrade of between 2.5% to 9% across cohorts, which means that the 2000-02 cohort has approximately 4% lower return to foreign experience than the 1983-86 cohort. This also suggests that the return to foreign experience is likely to become negative for more recent cohorts.

2.2 Specificity of human capital

The literature on specific human capital has focused on the extent of specificity of human capital with regard to firm tenure (Topel, 1991; Altonji & Williams, 1992), industry- (Neal, 1995; Parent, 2000), occupation- (Kamburov & Manovskii, 2009) and skill-specific experience (Poletaev & Robinson, 2008). There is a unique study that explores the effects of occupational match on the returns to foreign experience (Goldmann et al., 2009). However, Poletaev & Robinson (2008) show that skill-match is more important than industry- or occupational match for economic return to labour marker experience. There is no research in the literature on immigration that takes into account skill-match in studying return to foreign experience. We take this finding into account and explore effects of matching skills on the return to foreign experience of recent immigrants in Canada in order to determine if this can explain low portability of work experience acquired by immigrants prior to immigration.

Neal's (1995) work is the first to explore the importance of industry-specificity in worker's postdisplacement wage determination taking into account job tenure and potential work experience prior to displacement. His findings suggest that there is a substantial difference between wage patterns of displaced workers who find employment in the same industry and workers who switch their industry after displacement. Thus workers with predisplacement experience and job tenure who stay in the same industry after displacement have lower wage losses and greater wage returns to both their predisplacement experience and job tenure compared to workers who switch industry after displacement.

Neal (1995) uses the Displaced Workers Surveys from the 1990, 1988, 1986 and 1984 Current Population Surveys. The sample of the analysis is restricted to workers who were displaced after industry closing and does not include laid-off workers due to several reasons. The author notes it is plausible that workers are laid-off not randomly, but rather due to their lower productivity (as found by Gibbons and Katz, 1991). And second, there is a probability of a recall bias for laid-off workers (as found by Topel, 1990). In order to control for seasonality the agricultural sector is excluded. The other sample restrictions are applied to have individuals aged between 20 and 61 years old, who worked full-time (at least 35 hours a week) prior and after displacement; and currently have wages of at least $40 per week. The second part of the analysis is not presented for females as their potential work experience has a very low correlation with their actual industry tenure.

Neal (1995) uses several methods to study the importance of industry-specific factor in worker's wage profiles. First, he employs quasi-first difference approach. It consists of estimating a log wage difference between pre- and post-displacement wage separately for workers who switch their industry after displacement and workers who find employment in the same industry as their predisplacement one. This approach is undertaken due to data limitations that do not allow employing difference-in-difference estimation, which would be preferable having pure experimental data. One of the key data deficiencies is unavailability to construct actual industry tenure. Therefore, the log wage difference is run on potential predisplacement experience, predisplacement job tenure, years since displacement, weeks unemployed; and each regression controls for occupational dummies and year-of-displacement dummies, as well as demographic characteristics.

The results from quasi-first-difference estimation reveal a strong positive relationship between wage losses following displacement and both potential predisplacement experience and job tenure. The wage losses increase with potential predisplacement experience and job tenure twice as fast for industry switchers compared to industry stayers. Thus, for a male worker with 10 years of job tenure who switched industry after displacement the loss in log wages is around 0.27 log points higher than for a similar male who was displaced within his first year of employment and also switched industry. For males, an additional 10 years of experience with the same employer implies an increase in log wage losses after displacement of 0.27 for industry switchers after displacement but only 0.13 for stayers. In contrast, female predisplacement potential experience has a negligible and insignificant effect on wage losses. There is still a strong correlation between job tenure and wage losses for women. Excluding a square term, the loss in log wage after displacement increases with each additional year of job tenure by 0.015 for industry stayers and by 0.025 for industry switchers.

In the second part of his analysis Neal (1995) also employs Heckman's (1979) two-stage procedure to correct for selection bias as workers who possess low industry-specific skills are more likely to switch their industry after displacement. The first step lies in estimating probabilities of switching industry using factors that are not correlated with workers' wages directly, but are correlated with probability of switching their industry after displacement. The author argues that levels of employment in industries have no direct effect on wages, but has an effect on probability of switching industry. The second stage lies in the inclusion of transformed probabilities after the probit estimation in the wage equation as an additional control. In the same specification controlling for selection bias the results reveal even sharper difference between industry switchers and stayers. Thus, additional 10 years of potential work experience with the same employer increase the log wage loss by 0.31 for industry switchers and only by 0.10 for industry stayers respectively. After including additional controls, such as industry wage premium and union coverage rate, the effects are slightly weaker, but still indicate significant difference between industry switchers and stayers.

In the last part of the analysis Neal (1995) estimates the return to predisplacement experience and job tenure for male industry switchers and stayers using wages after displacement and compares to the return to predisplacement experience and job tenure for the full sample using wages prior to displacement. The results suggest that the predisplacement wages for the full sample and postdisplacement wages for the sample of stayers are both strongly and almost identically correlated to potential years of predisplacement experience and job tenure, unlike the sample of industry switchers. Thus, for 10 years of job tenure the predisplacement log wage return is 0.23 for the full sample and the postdisplacement log wage return is 0.20 for the sample of industry stayers in contrast to the postdisplacement log wage return of 0.07 for the sample of industry switchers. This indicates that firms of one industry should highly value predisplacement experience and job tenure in the same industry.

Parent (2000) uses data from both the National Longitudinal Survey of Youth (NLSY) that covers the period of 1979-96 and the Panel of Income Dynamics (PSID) that covers the period of 1981-92. In contrast to potential tenure that had to be constructed in Neal's (1995) work due to data deficiency, both surveys used in Parent (2000) allow constructing direct measures of firm and industry tenure. The sample from the NLSY is restricted to male and female workers of age 18-24 in the 1979, whereas the sample from the PSID only restricted to white male heads of households aged 18-64. The first sample is restricted to workers who worked at least 20 hours a week on a full-time basis and did not go back to full-time studies within six years from entering labour force; the sample includes temporary laid-off or actively searching for a job workers, and excludes respondents who were in military at any time, employed in a public sector or in a government programs. The second sample is restricted to workers who at least worked 500 hours and those who were not in the public sector.

Parent (2000) employed several different specifications and techniques to estimate direct log wage returns to firm and industry tenure controlling for total years of experience, as well as several methods to check the reliability of interpretation of the results. First he used GLS to account for heterogeneity and then he used IV-GLS to account for endogeneity issue as the error term is likely to be correlated with the variables of interest. The industry tenure variables are constructed in two ways. The first one is continuous and adds up years of industry tenure if industry stays the same when a worker changes employer and is reset to zero otherwise. In contrast, the second type of the industry tenure variable is non-continuous and when a worker changes industry when changing job is reset to the number of years that a worker had just prior to the change, instead of being reset to zero. The industry change is defined on the basis of both three- and one-digit code.

The results from both the GLS and the IV-GLS estimations suggest that once the industry tenure variable is included, either continuous or non-continuous, the effect of the firm tenure is reduced almost twice. For instance, in case of the GLS estimation for the sample from the NLSY the coefficient of the linear firm tenure variable is reduced from 3.7% to 1.6-2.2%, whereas the coefficient on the linear term of the industry tenure variable is approximately 4% for three-digit industry codes and around 3-4.4% for one-digit codes. The results for the sample from the PSID are qualitatively similar; however the estimated coefficient on the linear term of the firm tenure variable is initially very small; then it drops from 1.1% to almost zero and becomes insignificant when the industry tenure variables are included. The coefficients of the linear terms of the industry tenure variables are approximately 2.1-2.2%. Thus the industry tenure variable reduces the effect of the firm tenure by 40% to 57%.

The estimates of the IV-GLS in Parent (2000) reveal even bigger change in the effect of the firm tenure when controlling for industry tenure. Thus for the sample of the NLSY data the coefficient on industry tenure is between 2.2% and 4% for three-digit industry codes and is between 2.4% and 5% for one-digit codes, whereas the coefficient of firm tenure initially is around 2% and becomes insignificant when the industry tenure variable is included. And for the PSID sample the coefficients of the industry tenure are between 1.5% and 2.3% for both three- and one-digit industry codes and the coefficient of the firm tenure is initially low, around 0.6%, and becomes even smaller and insignificant after the inclusion of industry tenure. Thus, in the case of the IV-GLS all of the effect from firm tenure is eliminated by industry tenure variables.

In Parent's (2000) work, there are several important pitfalls in the interpretation of the results that have to be handled before any conclusion is drawn. The author combines several methods proposed in the literature in order to provide clear interpretation of the findings. Firstly, total experience, firm and industry tenure are likely to be correlated with corresponding error term components, such as individual specific effect, quality of job-match and industry-match. The first component is handled by using GLS under assumption that the error term contains person-specific components. Then using a methodology proposed by Altonji and Shakotko (1987) in Parent's (2000) IV-GLS the firm and industry tenure variables are respectively instrumented by their deviations from job-match and industry-match means. Hence the instruments by construction are uncorrelated with the components of the error term.

While instruments help to solve some endogeneity issues, there is still a potential correlation between experience and industry-tenure with the employer-match component of the error term. The correlation between experience and firm-tenure or industry seniority and firm-tenure "arise … as a result of job shopping over the course of a worker's career" (p.311). Thus, if longer industry-tenure helps to match employer better, then coefficients of the industry-tenure will be biased upward. Since firm tenure is highly correlated with industry tenure the coefficients of the firm tenure will be biased downward. Parent (2000) provides evidence of this concern by showing that quits with and without switching industry occur much more frequently compared to layoffs (for both sample and for both three- and one-digit industry codes).

Parent (2000) warns that another pitfall in the interpretation of his findings is a measurement error. It is important to understand whether a measurement error is driving a fall in tenure coefficients when industry tenure is included in the analysis. It is suggested that with inclusion of industry tenure, which is highly correlated to firm tenure measured with error, it is likely that the estimated firm tenure slope will be even more biased downward, because "the variance that is needed to identify the tenure coefficient is eliminated, thereby increasing the noise to signal ratio" (p. 318). First, the author replicates Neal's (1995) estimates using own samples by regressing postdisplacement log wage on predisplacement tenure separately for industry switchers and stayers, and finds quantitatively similar results. As in Neal's (1995) paper the postdisplacement log wage returns to predisplacement firm tenure for industry are much higher for industry stayers than for industry switchers.

Parent (2000) suggests that if all workers who quit stayed in the same industry while all laid-off workers switched their industry then positive effect of employer tenure for stayers "would merely reflect job match gains for those who located a better match and not really the effect of transferable industry-specific skills" (p.319). Firstly, the patterns of quits versus layoffs are very similar for both industry-switchers and stayers. This suggests this is not the issue of selection effects. Secondly, Parent (2000) uses higher moments as instruments and compares results with OLS estimates. Similarity of the results implies no evidence for a major role of the measurement errors in explaining the decrease in the tenure effect.

In conclusion, after checking results for robustness and ruling out measurement error effects, Parent (2000) finds that industry-specificity plays a more important role in wage determination compared to firm-specific factors.

Kamburov and Manovskii (2009) continue inspecting the extent of the specificity of human capital by studying the importance of occupation-specific factors in workers' wage determination process. They use data from the Panel Survey of Income Dynamics for 1968-93. For consistency with previous studies on specificity of human capital they restrict their sample to white male heads of households, aged 18-64, living in the continental US, with positive earnings (at least 1 dollar in constant 1979 dollars), who worked at least 500 hours in a given year. They exclude individuals who worked for the government, were self-employed, were in the military at any time, were farmers after 1975, or were simultaneously employed in several jobs.

In order to construct industry and occupation tenure variables Kamburov and Manovskii (2009) define industry and occupation switches on the basis of 1-, 2-, and 3-digit codes with the help of the Retrospective Occupation-Industry Supplemental Data Files[4] and using both "Employer_t" and "Position" partitions. The first partition identifies industry/occupation switches when a switch on the original PSID data is confirmed by an employer switch. And the second one identifies there is an industry/occupation switch when an employer or position switch is not a promotion. Following Parent (2000) they use "Partition T" suggested to be acceptable by Brown and Light (1992) in order to

[4] In 1999, the PSID released the Retrospective Occupation-Industry Supplemental Data Files that retrospectively assign 3-digit 1970 census codes to the reported occupations and industries of household heads and wives for the period 1968–80.

identify employer tenure. This partition identifies employer switch if the reported employment duration is smaller than the time elapsed since the last survey interview.

Kamburov and Manovskii (2009) use Parent's (2000) model as a base, but include occupation tenure variable in addition to employer and industry tenure. Other controls include total labour market experience and years of education, dummies for 1-digit occupations and industries, years, residence regions, marital status, a union dummy, an employment rate and its lag; as well as a dummy that equals to one if a person is not in the first year of employer tenure. Similar to Parent (2000) they decompose the error term into an unobserved individual-specific component, unobserved quality of job-match, industry-match and occupation-match. Therefore they estimate the model using both OLS and IV-GLS. For the latter they use instruments proposed by Altonji and Shakotko (1987) and used by Parent (2000). They instrument tenure variables and their square and cubic terms with respective deviations from their means. The IV-GLS is estimated under the assumption that the error term contains a serially correlated individual-specific component. They also make a series of checks and argue that their findings are driven neither by correlation of tenure variables with non-own components of the error term nor by any measurement errors.

The main finding of Kamburov and Manovskii (2009) is that occupation-specificity plays a major and the most important role in wage determination process. Their finding is consistent and robust across different specifications; and the estimations from OLS and IV-GLS are qualitatively similar. Thus for all digit classifications and the partition "Employer_t" when only employer tenure is included among all tenure variables, the coefficient of its linear term is around 1.7-1.8% in case of the OLS and around 6.6-8% in case of the IV-GLS. Consistently with Parent (2000) in case of the IV-GLS when both employer and industry tenure are included in the regressions the coefficient on the linear term of the employer tenure drops significantly. In Kamburov and Manovskii (2009) the industry tenure accounts for about 55% and 14% of the employer tenure for one-digit and three-digit classification respectively as compared to 40-45% in Parent (2000).

In Kamburov and Manovskii (2009)'s paper, when all tenure variables are included in the regression analysis, the coefficient of the linear term of the employer tenure variable becomes close to zero (or even negative) and/or insignificant for either OLS or IV-GLS estimation. The coefficients for industry tenure are significant in some cases, but are only around 12-14% and become smaller and less significant moving towards three-digit classification level. In contrast, the coefficients on the linear term of the occupation tenure increase towards three-digit classification level from 3.9% to 4.7% in case of the OLS and from 2% to 2.9% in case of the IV-GLS and are always significant at 5% significance level. Altogether, in case of the OLS estimation and 3-digit classification a worker with 5 year occupational tenure receives between 14% and 20% return, and the IV-GLS estimates suggest a total return of about 11-12% for the same worker. The total returns to either employer or industry 5 year tenure do not exceed 3% and are insignificant.

A paper of Poletaev and Robinson (2008) evaluates the relationship between wage losses after displacement and change in their skill-profiles using the Displaced Worker Survey for 1984-2000 and the Dictionary of Occupational Titles (DOT) for 1992. Their sample for the analysis is restricted to full-time private sector workers aged 61 and lower with wages of at least $40 in the past year, and excludes those who worked in agriculture or construction industry due to seasonality issue. The DOT provides detailed information on 12,741 unique occupations with 56 job-specific characteristics for each occupation. Using factor analysis to extract basic skill-factors from all 56 characteristics they construct a vector of four factor scores, so called skill-portfolio, that have zero mean and one standard deviation by construction: “intelligence” (40% of total variation), “fine motor skills” (20%), “physical strength” (12%) and “visual skills” (5%)[5]. Then they attach the skill-portfolios to 3-digit census occupations for workers from the sample.

Poletaev and Robinson (2008) use predicted factor scores for each of the four basic skills to define three groups of skill-portfolio switchers and stayers and compare them to industry, occupation and skill-portfolio switchers and stayers. First, for each occupation they define the “main” skill as the one that has the highest score. They define “main” skill stayers as those whose “main” skill order does not change in post-displacement job compared to pre-displacement. Second, for the “main” skill if there is a change in the order of the “main” skill, which is at least 0.5 of a standard deviation higher than the mean, they define that there is a change in portfolio one (PC1) if the change is at least half of a standard deviation in absolute value. Third, for the skills that are at least 0.6 of a standard deviation higher than the mean they define that the change in portfolio one (PC2) occurs if the change is not less than 0.3 of a standard deviation in absolute value. In addition, for PC2, those who initially were classified as stayers are reclassified as switchers if the change in the “main” skill is at least one standard deviation even if the order of the “main” skill is the same.

[5] In Poletaev and Robinson (2008) the factor called “visual skills” loads on color discrimination, color vision, far acuity, and field of vision.

In Poletaev and Robinson (2008), the results from investigating unconditional and conditional (on schooling, experience, pre-displacement tenure, years since displacement and weeks without work after displacement) mean log wage losses separately for industry, occupation and skill-portfolio reveal that losses for switchers are around twice higher than for stayers. Notably, while the mean log wage losses for industry and occupation are all approximately the same and range between 11% and 12% for switchers and between 5% and 6.3% for stayers the losses for skill-portfolio switchers and stayers are still greater accounting for about 15% for switchers and about 7% for stayers.

The study of Poletaev and Robinson (2008) motivates this research as their results indicate that wage losses of displaced workers are closer associated with skill-portfolio change than with industry or occupation change. However, while they study returns to skill-tenure of Canadian workers, in our research we study returns to foreign experience of immigrants conditional on skills matching. Moreover, unlike Poletaev and Robinson (2008), who study effects of skill-match based on a main skill of an occupation, we explore effects of matching each skill separately.

2.3 Returns to foreign human capital controlling for occupational match

There is a unique study in the literature on immigration that explores effects of occupational match on the return to foreign experience (Goldmann et al., 2009). However, Poletaev and Robinson (2008) show that skill match is more important than occupational (and industry-) match. Hence, there is still a gap in the literature on immigration as there is no study, to the best of our knowledge, that explores effects of skill-match on the returns to foreign experience.

Goldmann et al. (2009) account for findings of the previous literature on specific human capital and focus on occupational specificity to study economic returns to immigrant human capital. Using the Longitudinal Survey of Immigrants to Canada (LSIC) they investigate whether immigrants who match their source-country and host-country occupation are better able to transfer their foreign human capital then those who do not match. They use different occupational groupings to construct match variables between different combinations of source-, intended and host-country occupations. The sample is restricted to immigrants aged between 25 to 59 years old at the time of immigration, who reported they ever worked prior to immigrating to Canada; the sample excludes former temporary foreign workers and former international students in Canada for "cleaner measures". In their analysis of male Skilled Worker principal applicants[6] they also include the match between intended and host-country occupation, a match between source- and intended occupation and a match between all three of them together and their interactions with foreign experience and schooling.

Goldmann et al. (2009) first include a set of control variables and dummies for matching of source- and host-country occupation (and no interaction terms). They find that earnings for immigrants who obtain match are 33.2% and 38% higher for male and female respectively compared to those who don't match, whereas the returns to foreign work experience for both genders is -1% and are statistically significant at the 1% significance level and to the returns to years of schooling are close to zero or insignificant. When all interactions with foreign experience and schooling are included immigrant earnings for matchers are 29% and 33.5% higher for males and females

[6] Citizen and Immigration Canada (CIC) classifies immigrants by immigration categories: Skilled Workers, Family class, Provincial Nominees, Business Immigrants, and Refugees. All of these categories are subdivided into principal applicants and spouses or dependents.

respectively, the returns to foreign experience are still -1% and the returns to foreign experience and to schooling for matchers are not significantly different from zero for both genders.

Goldmann et al. (2009) extend their analysis by looking at the returns to foreign human capital for professional and non-professional occupations as well as licensed and non-licensed occupations and their interactions with matching source- and host-country occupation. For all specifications and both genders the returns to foreign experience are around -1% and are mostly statistically significant at the 1% significance level and the returns to foreign schooling are mostly statistically insignificant or close to zero. For male immigrants when all possible interactions of professional and non-professional occupations with match variable between source- and host-country are included the return to match variable alone is statistically insignificant anymore and any foreign human capital interactions receive no return with an exception of 5% return to each additional year of foreign school for matchers within non-professional occupations; however earnings are higher for those who obtain a match within professional occupations and within non-professional occupations by 41.8% and 37.5% respectively.

In Goldmann et al. (2009), the results for female immigrants for the same regression specification as above are somewhat striking. The returns to foreign experience and schooling alone are zero and insignificant, while the return to match alone and to its interaction with years of schooling turn negative, -35.8% and -10.2% respectively, and are statistically significant at all levels, the returns to school for professionals, for matchers within professional occupations and matchers within non-professional occupations are -5.8%, 16.2% and 16.9% respectively. Both professional matchers and non-professional matchers receive 85.1% and 59.1% higher earnings compared to non-matchers. For regressions with all possible interactions of match, foreign human capital and licensed and non-licensed occupations the earnings are higher by 30.5% and 37.7% for male and female matchers respectively. The returns to foreign experience for those immigrants who match their source- and host-country occupation are close to zero and insignificant for both genders, while the return to years of schooling is 2.6% and 5.1% for men and women respectively. Immigrant male and female matchers within licensed occupations have 12.3% and 29.1% lower earnings than those who don't match.

Goldmann et al. (2009) also look at the effects of combinations of matches between source-, intended and host-country occupations and their interactions with foreign experience and schooling for a sub-sample of male Skilled Worker principal applicants. Even for this sub-sample the return to years of foreign experience is negative and significant, -1.2%, and the return to years of education is zero and insignificant. Surprisingly, even for male Skilled Worker principal applicants, who obtain all combinations of matches between source-, intended and host-country occupations, the return to either foreign experience or schooling is statistically not different from zero at any significance level. In contrast, male Skilled Worker principal applicants who are able to match their source-, intended and host-country occupation receive positive and significant return to foreign schooling. Earnings are higher for Skilled Worker principal applicants who obtain a match between source- and host-country occupations, a match between intended and host-country occupation, and a match between source-, intended and host-country occupations by 26.45%, 30.3% and 18.5% respectively.

In this research we build on Goldman et al. (2009). We employ their model specifications; however, instead of occupational match, we explore returns to skill-match and its effect on the returns to foreign human capital with a focus on foreign experience.

CHAPTER 3

THEORETICAL BACKGROUND

This chapter reviews the theory of Investment in Human Capital. The review starts with introduction of most prominent and seminal academic works that pioneered in creation of the theory. The review includes works on investment in schooling and types of training on the job. Then theoretical foundations for the regression analysis are introduced, which includes the Mincerian log wage equation and the human capital equation. The chapter concludes with a review of findings on the specificity of human capital such as firm-, industry-, occupation- and skill-tenures.

3.1 Investment in human capital

The late 1950s to mid-1970s became a fruitful period for formation of investment in human capital. Becker (1964, 1994), Ben-Porath (1967) and Mincer (1974) provide rich and extensive theoretical ground in this matter. There are some remarkable economic works that have provided important empirical evidence.

Mincer (1958) derives a theoretical model for personal income distributions with respect to training differences and provides empirical evidence using the Census data on income and occupations. Training is subdivided into two types: (i) formal education, - years spent for schooling before an actual job; and (ii) informal education, - experience and skills received on the job. He suggests that total cost of training has two sources: opportunity cost, - the major source, and direct cost of training. The opportunity cost is a “deferral of earnings” during the training period. The direct costs are the costs of equipment, tuition and books. He focuses on inter- and intra-occupational life-time income differentials. The interoccupational are the differences in income streams between occupations, whereas the intra-occupational are the differences within occupations. He concludes that interoccupational differentials are a function of differences in (length of) training. On the other hand, the intra-occupational differentials arise from on-the-job experience differentials. In his analysis of dependence of earnings on age he finds that the relationship is steeper for occupations which require more skills, either in terms of years of schooling or years of experience on the job. He concludes that there is a rate of return to an amount of training: "… absolute differences in the length of training result in percentage differences in annual earnings." (p. 301)

Schultz (1961) provides an analysis of substance and formation of human capital. He states: "Although it is obvious that people acquire useful skills and knowledge, it is not obvious that these skills and knowledge are a form of capital, that this capital is in substantial part a product of a deliberate investment." (p. 1) He also suggests that "the quality of human effort" can be improved through such forms of investment in human capital as health, on-job-training, formal education and internal migration. Interestingly, he indirectly talks about "specific human capital". For instance, he says that farm people who switch to non-farm jobs earn substantially less than people with experience in these jobs of the same age, sex and race. In order to measure investment in human capital he proposes to distinguish between consumption and investment, and separates them into: pure consumption, pure investment and expenditure that have both characteristics.

Becker (1994) studied personal income differences of college graduates compared to high school graduates. He suggests that "social and private economic returns from college education would differ if a college education had different effects on earnings and productivity" (p.209).

Following Becker's (1962) theoretical framework on costs of training Mincer (1962) attempts to take into account both direct and indirect costs of schooling. He uses the 1939-1958 U.S. Census data and attempts to estimate costs and rates of return of investment in human capital. He denotes "training", both in school and on the job, as "investment in acquisition of skill or improvement of worker productivity". In his analysis such forms of informal training as apprenticeship and medical specialization are considered. In order to compute indirect cost of schooling he uses opportunity cost of students comparing them to similar individuals who are, instead, in the labor force. In his estimates opportunity costs constitute around one half of total costs (public and private), and around three quarters of private costs accrued by students. The data suggest that with lower level of education there is lower level of on-the-job training and with higher level of education the opposite is true. He finds that there is a strong positive correlation (86%) between formal and informal training. It is, however, much more difficult to separate direct and indirect cost of on-the-job training due to lack of data. Instead, he uses an approach proposed by Becker (1962), and compares income streams of individuals with different levels of schooling, assuming that the rate of return to additional year of schooling is the same for college and high-school graduates. He stresses that the rate of return found from equating present values of net earnings of college and high school graduates is not the rate of return to schooling, but rather some average of rates of return to formal and informal training. He estimates a range of rate of reruns using three different assumptions about comparative income stream groups. Essentially he equates a stream of value of cost of training to future stream of total return. The stream of value of cost of training is the difference between wage of a trainee and wage of an untrained person; and future stream of total return is the difference between wages of a trained person and untrained. He derives the following formula to determine a rate of return of investment in training:

$$(1 + r)^n = \frac{d}{c} \tag{3.1}$$

where r is the rate of return, n is number of training periods in years, d is the increment in earnings in the alternative job after training is completed, and c is forgone earnings during the training period. Interestingly, he finds that the rate of return to such investments in informal training as apprenticeship and medical specialization is essentially the same as the rate of return to total costs of college education. However, the private return is higher for formal education compared to the one for informal training. The estimated rates of return to investment in on-the-job training for medical specialization for males in 1950 are between 9% and 13% compared to Becker's (1960) estimates for college level education of 11%.

Ben-Porath (1967) proposed a model of optimal lifecycle investment in human capital implemented through a human capital production function. His model was an important building block in the theory of investment in human capital. The aim of the model was to explain growth of earnings with worker's age on the basis of production of human capital. He stated that individual "own abilities, innate or acquired, the quality of co-operating constraints and opportunities offered by institutional setup – all determine the "technology", or the production function" (p. 352). He asserts that the stock of human capital is similar to tangible capital, and also has a depreciation rate. Services of human capital can be traded in the labour market for a rental. The production of human capital increases its stock at decreasing rate and, hence, causes a down-ward-sloping demand.

An individual maximizes his/her life-time wealth through allocation of his/her time between earnings, i.e. through working, and production of human capital, i.e. through training.

Generally, Ben-Porath's (1967) human capital production function together with Becker's modification can be written as follows (Mincer, 1997):

$$Q_t = f(K_t,\ S_t,\ X_t; B_t) \tag{3.2}$$

where Q_t is the individual's gross investment in human capital in period t; K_t is the stock of human capital at time t; S_t is the gross additions to the stock or the fraction of time devoted to the production of Q_t; X_t are goods and services purchased for production of human capital at time t. Becker (1994) also adds a new term into the Ben-Porath (1967) production function, B_t, which stands for the "limited individual physical and intellectual capacity" and is added to rationalize the assumption of diminishing returns. Becker's (1994) modification aimed to analyze the optimal distribution of total accumulations of human capital across individuals.

3.2 On-the-job training

Becker's (1964) book "Investment in Human Capital" has become one the most well-known and most cited works in the field of Human Capital. He builds a seminal theoretical base of understanding of investment in general and specific human capital and its role in a worker's lifetime wage profile. In the chapter "Investment in Human Capital: Effects on Earnings" (pp. 31-58) he develops two important concepts that have become a focus of the vast empirical literature on human capital. First, assume that worker's productivity rises with accumulation of human capital. Human capital is perfectly general if accumulated worker's skills benefit one employer to the same extent as another employer. Thus an example of general human capital would be knowledge acquired during education period. On the other hand, employees also accumulate or master skills during on-job-training. Human capital is perfectly specific if one employer worker's productivity benefits one employer while another employer one does not receive any benefit from the same worker's skills. In other words, this worker cannot transfer accumulated skills across employers. Usually human capital is neither completely general nor completely specific.

Becker (1964) aims to determine the rates of return to general and specific human capital. First, assume that an individual starts work with a certain level of productivity. Assume also that firms operate in competitive markets. From the firm's profit-maximization problem the equilibrium in each period, *t*, occurs when worker's marginal product equals wages:

$$MP_t = W_t \tag{3.3}$$

If the firm makes a decision based on present value of future benefits and costs the equilibrium for such firm is when the stream of its future receipts, R_t, equals to the stream of its future expenditures, E_t, for period *t* from zero to *n*:

$$\sum_{t=0}^{n-1} \frac{R_t}{(1+i)^{t+1}} = \sum_{t=0}^{n-1} \frac{E_t}{(1+i)^{t+1}} \tag{3.4}$$

Suppose that t=0 is the period when the training to a worker is being provided at a direct cost of k, then the equation (3.4) could be rewritten in the following manner:

$$MP_0 + \sum_{t=1}^{n-1} \frac{MP_t}{(1+i)^t} = W_0 + k + \sum_{t=0}^{n-1} \frac{W_t}{(1+i)^{t+1}} \tag{3.5}$$

Let the firm's return, G, be the difference between the stream of future receipts, in terms of marginal products, and future expenditures, in terms of wages, after the training period.

$$G = \sum_{t=1}^{n-1} \frac{MP_t - W_t}{(1+i)^t} \tag{3.6}$$

Let k be direct costs of training, then the equation (3.5) can be rewritten as:

$$MP_0 + G = W_0 + k \tag{3.7}$$

Let the opportunity cost be measured as the difference between potential marginal product, MP_0', - when no training was provided -, and actual marginal product, MP_0. Denote C as the total of opportunity costs and direct costs of the training. Then the equation (3.7) can be rewritten as:

$$MP_0' + G = W_0 + C \tag{3.8}$$

Therefore, potential marginal product that could be produced, MP_0', can equal to the wage in the training period, W_0, only when the firm's return G is equal to the total costs that the firm accrues during the training period, C.

3.2.1 General training

Becker (1964) views completely general training as type of training that increases worker's marginal productivity in many firms, not only in the firm providing this training. Hence, a firm would only provide general training to a worker if it does not need to pay the costs of such training. Then the return to the firm, G, equals to zero:

$$G = \sum_{t=1}^{n-1} \frac{MP_t - W_t}{(1+i)^t} = 0 \tag{3.9}$$

It follows, that a trainee alone would be paying costs for general training and receiving consequent returns. Thus, worker's wage, W_0, in the period of his/her training would be lower than potential wage for his/her marginal product in case of no training, MP_0', exactly by the amount of the opportunity cost or, in other words, net of investment cost:

$$W_0 = MP_0' - C \tag{3.10}$$

Equally the worker's wage, W_0, would be lower than the wage paid for an actual marginal product during training, MP_0, by the amount of the direct costs of the training, k:

$$W_0 = MP_0 - k \tag{3.11}$$

Thus, "earnings" of the firm during the training period would be an income flow, in terms of potential marginal product, net of capital or stock term, in terms of training costs.

3.2.2 Specific training

In contrast to the general training, Becker (1964) suggests that specific training raises worker's productivity differently in different firms. For instance, perfectly specific training raises worker's marginal productivity exclusively in the firm providing the training and is virtually useless in other firms. In this extreme case a worker's wage in other firms is independent of (specific) training received with his/her employer.

Consider two cases. First, assume that an employer bears all the costs, *C*, associated with on-the-job training and collects all the return, *G*, from future higher productivity of a trained worker. Then using equation (3.8) it follows that this worker's wage, W_0, during the training period would be equal to potential marginal product, MP_0', that could be produced if no training was provided and is higher that his/her actual marginal product, MP_0. In contrast, assume that a trainee bears all the costs, *C*, by receiving a wage that is lower than the wage that would be paid in case of no training, as in equations (3.10) or (3.11). Then the firm's return, *G*, would be equal to zero and the worker would collect the future return by receiving higher future wages equaling to higher marginal productivity. In the first case, when a firm bears all costs of training, if the worker quits, the firm is worse off because it does not collect any return and only bears losses in terms of lost capital and investment. In the second case, when a trainee bears all costs, and if the trainee if laid-off or fired, he/she bears all the losses as he/she does not collect return from receiving higher future wages neither in this firm nor in other firms as the training is specific.

3.2.3 Training costs sharing

In order to split the costs and the return between an employer and its trainee Becker (1964) brings in likelihood of a quit. Consider turnover to be a function that is negatively related to wages. Thus, with higher wages the likelihood of a quit decreases. However, to balance demand and supply of workers who would want to get the job with higher wages, the costs of training have to be shared with trainees. If the training is neither completely specific nor completely general, but rather is a sum of both, then a firm is not willing to pay for the general part of it.

Let G'' be a sum of return collected by a firm, G, and by employees, G'. Let a share, α, of the total return collected by firms be $G = \alpha G''$, then a share of the total return collected by employees is $G' = (1 - \alpha)G''$. Using $G'' = C$ and equation (3.8) we obtain:

$$MP_0' + \alpha C = W_0 + C \qquad (3.12)$$

which becomes:

$$W = MP' - (1 - \alpha)C \tag{3.13}$$

The equation (3.13) is a generalization of training that consists of both types, when $0 < \alpha < 1$. Hence, in case of completely general training, when $\alpha = 0$, it reduces to the equation (3.10). In case of completely specific training, when $\alpha = 1$, it is reduced to $W_0 = MP_0'$.

The analysis leads to several important implications. First, firms pay higher wages to workers with specific training and lower wages to employers with general capital. And second, firms offer employees with specific training higher than market wages to decrease turnover as these firms pay part of the costs associated with such training.

3.3 Earnings function

In his seminal study Mincer (1974) builds a theoretical framework for understanding the relationship between schooling, experience and earnings. He specifically focuses on an econometric model for estimation of returns to schooling and on-the-job training.

Assume that an individual without education has earnings E_0 and they grow at a rate *r* with each year of schooling. Then the earnings in the next period can be written as:

$$E_1 = (1 + r)E_0 \tag{3.14}$$

Assuming r is constant over time, the individual's earnings after S years of schooling can be written as:

$$E_s = (1 + r)^s\, E_0 \tag{3.15}$$

Taking the natural logarithm of both sides we get:

$$lnE_s = S * ln(1 + r) + lnE_0 \tag{3.16}$$

where $ln(1 + r) \approx r$ for small r. Then equation (3.15) can be rewritten as:

$$lnE_s \approx S * r + lnE_0 \tag{3.17}$$

Regarding that individual's knowledge capacity is expanding while working, the post-schooling investment can be added to the schooling model:

$$lnE_{S,T} \approx lnE_0 + S * r + \beta_1 * T + \beta_2 * T^2 \tag{3.18}$$

where T stands for years of on-job-training or simply years of work experience, and the quadratic term T^2 captures the concavity of return to the training. Mincer (1974) and Becker (1994) believe that individual's capacity to learn is limited and has diminishing marginal returns. Hence, the coefficient on the quadratic term in equation (3.18) has a negative sign in Mincer's (1974) work.

Given, that individual earnings also depend on a vector of other characteristics, the standard equation in the literature on human capital can be written as:

$$lnY_i = a_i + b_1\ School_i + b_2\ Exp_i + b_3\ Exp_i^2 + b_4 X_i + e_i \tag{3.19}$$

where Y_i stands for earnings of an individual i, $School_i$ stands for years of schooling, Exp_i stands for years of work experience after completion of education and its square term Exp_i^2, X_i is a vector of other individual's characteristics (such as age, gender, race etc.), and e_i is an error term or a random shock to individual's earnings.

3.4 Degree of specificity of human capital

Becker (1964) mostly discusses specific training as specific to a firm. However, eventually he develops a talk around the extent of specificity. Thus specific training can be also specific "in a set of firms defined by a product, type of work, or geographical location" (p. 49), as well as industry, occupation, or country. The literature on specific human capital has attempted to investigate the extent and the importance of specificity of human capital in formation of workers' wage profiles. For instance, both Neal (1995) and Parent (2000) using different data surveys and different approaches find that industry-specificity plays a more important role than firm-specificity in wage determination of displaced workers.

The base for the specific human capital model is the following equation:

$$lnY_{ij} = a_i + b_1 \; School_i + b_2 \, f(Exp_i) + b_3 f(\, Ten_{ij}) + b_4 X_i + e_i \qquad (3.20)$$

where Y_{ij} stands for earnings of an individual i in firm j, $School_i$ is years of schooling, Exp_i stands for years of work experience after completion of education, f denotes a function that includes both linear and quadratic terms of a corresponding argument, Ten_{ij} stands for years of firm tenure, X_i is a vector of other individual's characteristics (such as age, gender, race etc.), and e_i is an error term or a random shock to individual's earnings. This equation can further be augmented by inclusion of different types of tenure.

Neal (1995) using the Displaced Workers Survey for the period of 1984-90 is the first to document the difference in postdisplacement log wage returns to predisplacement firm tenure and potential total experience between workers who switched industry after displacement and those who didn't. His main finding suggests that wage losses of male industry-switchers increase with experience at rates twice higher than for industry-stayers. For instance, the wage loss of an industry-switcher displaced male worker with 10 years tenure for the same employer is 0.27 log point higher than for a similar male worker who however was displaced in his first year of employment; whereas the wage loss of an industry-stayer displaced male worker with 10 years of firm seniority is 0.13 log points higher than for his counterpart that was however displaced within the first year of tenure.

Parent (2000) using both the National Longitudinal Survey of Youth for the 1979-96 period and the Panel Study of Income Dynamics for the 1981-92 period finds that the return to firm tenure is substantially reduced or virtually disappears when industry tenure is controlled. For instance, using the NLSY data and the GLS method the return to 10 years firm tenure is around 0.15, however it falls to between 0.02 and 0.07 when industry tenure is included and becomes insignificant; and in the case of IV-GLS from 0.02 it falls below zero and becomes insignificant. Using the PSID and GLS the return to 10 year employer tenure falls from 0.10 to between 0.03 and 0.05 after the industry experience is controlled and becomes insignificant; and in the case of IV-GLs it falls from 0.05 to between -0.03 and 0.03 and also becomes insignificant. The linear term of industry tenure is significant and indicates between 2 to 4% marginal return using the NLSY and between 1.5% and 2.3% with the PSID data.

Kamburov and Manovskii (2009) using the PSID for the 1968-93 period show that occupational tenure plays the most important role in wage determination. They find that occupation switchers experience 18% reduction in their weekly earnings, while occupation stayers only 6%. They include various combinations of employer, industry and occupation tenure in the regressions to see how the coefficients are affected. Consistently with Parent (2000) when they include industry tenure together with employer tenure the coefficients on the latter drops by half. However when all three types of tenure are included simultaneously, the coefficients on both employer and industry tenure become smaller and insignificant, whereas the coefficients on the occupation tenure are substantially bigger and always significant. For instance, the coefficient on the linear term of the occupation tenure is between 2% and 3%. Overall, the marginal effects suggest that the total returns to 5 years occupation tenure is 8% to 20% depending on the definition of variables and are significant and estimation method, while the returns to 5 years firm or industry tenure usually are at least twice smaller and often insignificant.

Poletaev and Robinson (2008) using the Displaced Worker Survey for 1984-2000 and the Dictionary of Occupational Titles (DOT) for 1992 construct skill portfolios and find that greater wage losses of workers after displacement are associated with switching skill-portfolios more than switching industry or occupation. The mean log wage losses for industry and occupation are all approximately the same and range between 11% and 12% for switchers and between 5% and 6.3% for stayers. However, the losses for skill-portfolio switchers and stayers are still greater and account for about 15% for switchers and about 7% for stayers.

CHAPTER 4

DATA

This chapter presents data used in the research as well as descriptive statistics of some key variables and characteristics. We begin with a description of the main sample of interest in section 4.1 and then proceed to sub-samples of wave 3 in section 4.2. Data on occupational characteristics is presented in section 4.3.

4.1 Main sample of interest

The Longitudinal Survey of Immigrants to Canada consists of three waves. The target population consists of immigrants that applied from abroad and landed between October 1st, 2000 and September 30th, 2001 and were ages 15 and older at the time of landing. In total, the target population accounts for 169,400 that constitutes around 67% of the immigrant cohort. The corresponding interviews were conducted in 2001, 2003 and 2005 approximately 6 months, 2 years and 4 years after landing respectively. The response rate is around 60% in the first wave and around 65% of them continued to respond through the 3rd wave. As a result, 7,716 immigrants are followed through the 3rd wave, which accounts for approximately 39% of those interviewed in the 1st wave.

The sample of interest taken for the analysis in this research has the following restrictions: (i) immigrants aged between 25 and 59 at the time of immigration; (ii) those who reported their last occupation prior to immigration and current occupation; (iii) those who receive positive earnings from wage and salaries. Consistently with previous studies, we apply the age restriction to capture population that is most likely to be in the labor force: likely to have completed full-time schooling as well as not to be retired. Unfortunately, it is impossible to determine whether an immigrant indeed worked in his/her last pre-immigration occupation or the length of time he/she worked in it. Goldmann et al. (2009) use the "Have you ever worked prior to immigrating to Canada?" question to sort out respondents who indicated their last pre-immigration occupation, but reported they had never worked. Similarly to Goldmann et al. (2009), we exclude former temporary foreign workers and former international students in Canada for clearer estimates of foreign work experience and schooling. For the same reason, we exclude respondents who reported they ever had refugee status, "Visitor" visa or "Other" reasons for living in Canada prior to immigrating as most of them lived in Canada for more than 1 year and may have different knowledge about Canadian labor market.

We use the natural logarithm weekly wages (log weekly wages) as a dependent variable in our regression analysis. In order for log weekly wages to be comparable across waves we adjust them to 1992 constant dollars using the core Consumer Price Index (CPI). Similarly to Goldmann et al. (2009), we use a moving average of the monthly CPI for each immigrant regarding his entry date and interview date. For instance, for an immigrant who immigrated in January 2001 and was interviewed in June 2001, we use an average CPI for the reference period of his/her 6 months.

The original occupational codes in the LSIC are coded under the Standard Occupational Classification (SOC). A measurement error often associated with the process of occupation coding in surveys is likely to be reduced due to the LSIC survey structure as the codes are derived from three open-ended questions. We use concordance tables from Human Resources and Skills Development Canada to translate these SOC codes into the National Occupational Classification (NOC) codes.

The LSIC is a sample survey with a complex longitudinal design. The final (post-stratification) probability weights must be used to ensure consistency between the estimates produced from the survey and population estimates. The variance is important for hypothesis tests in order to determine statistical significance of estimated coefficients. Due to its complex sample design and stratification stages it is hard to calculate the true variance for the LSIC. The bootstrap replication method is the one of the best ways to approximate the true variance for the survey and 1,000 bootstrap weights are provided with the survey by Statistics Canada. In brief, the "bootstrapping" consists of calculating the variance for each of 1,000 weights followed by calculating the variance of these 1,000 estimates.

A common issue when working with survey data is inability to track the exact same sample of immigrants over time either due to their changing employment status or due to missing observations for different reasons. Therefore, we start our analysis from comparison of means of economic and demographic characteristics across three waves. Descriptive statistics give a sense of the picture in general and may help to prevent some issues before using the data in regression analysis. We present means and standard errors of key variables. In order to make any inferences when comparing the means we use the test for equality of means with unequal variances. The null hypothesis of the test states that means are equal and the two-sided alternative hypothesis states that two means are not equal. Three common levels for rejection regions we use are the 1%, the 5% and the 10% significance level.

In table 4-1-1 we present means of key variables for male and female immigrants in each wave. The means of other variables can be found in Appendix A5. It is worth noting that while immigrant response rate falls over time the sample sizes used in our analysis increase dramatically due to increasing share of immigrants employed in each consequent wave. The sample size of male immigrants almost doubles in each wave compared to its previous wave. Female sample size almost triples in wave 2 compared to wave 1, and then doubles in wave 3 compared to wave 2.

Means of key variables for males are presented on the left hand side of Table 4-1. In general, means for males differ in several variables. Differences in age are expected as they are direct functions of time. Mean log weekly wage also grows over time, but we test the equality of its means across waves to have a sense of how big these changes are statistically. As a result, we reject the equality of mean log of weekly wages between wave 3 and both wave 2 and wave 1, but we cannot reject equality of means between wave 2 and wave 1. At the same time the number of years of foreign experience increases and number of years of foreign schooling decreases, however the null of equality cannot be rejected for these variables for all pair of waves. There is a tendency of decreasing average English score and increasing average French score over time. Using the mean equality test, we cannot reject the equality for these variables for wave 2 versus wave 1 at the 5% and the 1% level of significance.

Means of key characteristics for females are presented on the right hand side of Table 4-1. The means of the same variables for females have slightly different patterns than for men. Compared to men, women have lower average log weekly wages, age,

Table 4-1. Cross-sectional means of key variables

	Males			Females		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Log weekly wages	6.35 (0.030)	6.38 (0.019)	6.44 (0.014)	6.00 (0.043)	6.01 (0.030)	6.04 (0.019)
Age	36.17 (0.344)	37.73 (0.219)	39.58 (0.135)	34.87 (0.509)	36.82 (0.266)	38.32 (0.162)
Experience	14.62 (0.401)	14.51 (0.254)	14.27 (0.155)	13.52 (0.548)	13.88 (0.299)	13.54 (0.184)
School years	15.55 (0.154)	15.57 (0.097)	15.77 (0.065)	15.34 (0.220)	15.28 (0.125)	15.26 (0.077)
English	0.79 (0.012)	0.76 (0.007)	0.75 (0.005)	0.79 (0.016)	0.73 (0.010)	0.71 (0.007)
French	0.11 (0.013)	0.13 (0.009)	0.16 (0.006)	0.11 (0.017)	0.13 (0.011)	0.14 (0.007)
N-weighted	10,244	22,290	42,122	5,045	14,920	30,237

Note: All continuous variables have bootstrap standard errors in brackets.

foreign experience and schooling. Although female mean log weekly wage increases over time, the equality of means cannot be rejected across waves. Similarly to males, we cannot reject the equality of mean years of foreign experience and schooling. The average English score falls in wave 2 compared to wave 1, but the equality cannot be rejected in wave 3 compared to wave 2. The mean French score seems to rise over time, however we can only reject the equality at the 10% significance level in wave 3 compared to wave 1.

4.2 Sub-samples in wave 3

We then expand our analysis to sub-samples in wave 3. The third wave is chosen for the following two reasons: (1) wave 3 has the biggest sample size; (2) foreign born newcomers are most likely to return to their source-countries within the first year of immigration (Aydemir and Robinson, 2008), therefore wave 3 is also the most representative of immigrant population that is more likely to stay in Canada. Sub-samples considered are: (i) Skilled Worker principal applicants versus other immigration categories; (ii) regulated versus unregulated occupations; (iii) professional versus non-professional occupations; (iv) university educated immigrants versus other education levels; (v) visible minorities versus not visible minorities.

The first pair includes the Skilled Workers principal applicant sub-sample. The Skilled Worker is a federal immigration program[7]. Regarding that the target population of the LSIC are immigrants who arrived between in 2000/01, for that period an immigrant had to pass a minimum of 67 points and was assessed using the following criteria: age, education, length of work experience, job offer in Canada, knowledge of official languages and other. Its sample-mate includes the following immigration categories: Skilled Workers who were not principal applicants, all immigrants applied through

[7] For a review of immigration categories see Green and Green (1999).

Family class, Provincial Nominees, Business immigrants, Refugees and categories defined as “other”.

We use information provided in the HRSDC’s Career Handbook to classify immigrants’ main post-immigration occupations as regulated. Regulated requirements include licensing, certification and/or association membership (Career Handbook, 2001).

The NOC Matrix 2001 provides occupational classification structure based on Skill Levels and Skill types, which usually require a university degree. Using the matrix we include the following major groups in “Professionals” sub-sample: professional occupations in business and finance, professional occupations in natural and applied sciences, professional occupations in health, professional occupations in social science, education, government services and religion, professional occupations in art and culture.

We construct a sub-sample of university educated immigrants using information on their pre-immigration level of education that was obtained outside Canada. In this sub-sample we include immigrants who hold at least B.A. degree.

The survey contains information on immigrant visible minority status, which is used to construct a corresponding sub-sample. Initially we also constructed a sub-sample of immigrants on the basis of their country of origin into “Western” and “non-Western” region of origin. However, most immigrants who had visible minority status were sorted into “non-Western” sub-sample. The results for both “Visible minorities” and “non-Western” sub-samples were almost identical. We kept the “Visible minorities” sub-sample for the analysis regarding it had lower variance inflation factors.

In Table 4-2 the shares of sub-samples in wave 3 are presented for both genders. Information on shares for key sub-samples of the analysis is important for two reasons.

Firstly, in cross-sectional analysis it useful to have an idea of what immigrant groups represent the samples and how the representation of these groups changes over time. Second, in within-wave analysis it is useful to understand whether some immigrant groups sort into other groups. For instance, most of immigrants from non-Western countries sort into visible minorities group, which makes two groups almost identical, one of them is redundant in the analysis and not included thereof.

Table 4-2. Sub-sample shares across waves

	Males			Females		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
Skilled Workers PA	0.67	0.66	0.67	0.37	0.29	0.27
Regulated occupation	0.53	0.54	0.56	0.40	0.43	0.43
Professional	0.23	0.21	0.22	0.20	0.23	0.22
University degree	0.71	0.69	0.72	0.68	0.65	0.66
Visible minority	0.76	0.79	0.79	0.72	0.74	0.77
N-weighted	10,244	22,290	42,122	5,045	14,920	30,237

The left hand side of Table 4-2 contains shares of key sub-samples of male immigrants across waves. The equality cannot be rejected for all these shares across waves. Skilled Worker principal applicants, immigrants employed in regulated occupations, employed in professional occupations, immigrants who have university education, and visible minorities are each almost equally represented in full male samples across waves.

Similarly, we cannot reject equality of shares across waves for most of the sub-samples for females (the right hand side of Table 4-2). The exception is the sub-sample of female Skilled Worker principal applicants, for which the equality of shares is rejected between wave 2 and wave 1 at the 1% significance level; and between wave 3 and wave 1 at all of the significance levels. The share of female Skilled Worker principal applicants is half the share of those for males. It is also worth noting that although females on average have a lower share of Skilled Worker principal applicants compared to males, the shares of females and males employed in Professional occupations are almost identical.

Means of key characteristics by sub-sample are presented in table 4-3 for males and table 4-4 for females. An overview of means across sub-samples is important for two main reasons. First, it gives us preliminary understanding of differences in sub-samples compared to the full samples of males and females in wave 3. Second, it allows us to see some potential dependence patterns prior to the regression analysis. Appendix A6 and Appendix A7 contain means for the rest of variables and sample-mates.

Table 4-3. Means of key characteristics by sub-samples in wave 3, males

	Skilled Worker PA's	Regulated	Professional	University educated	Visible minority
Log weekly	6.54 (0.017)	6.50 (0.019)	6.76 (0.032)	6.51 (0.017)	6.39 (0.015)
Age	38.75 (0.135)	39.22 (0.193)	37.29 (0.262)	39.07 (0.157)	39.59 (0.156)
Experience	12.58	13.72	10.72	12.65	14.44

	(0.142)	(0.216)	(0.276)	(0.160)	(0.180)
Schooling	16.63 (0.066)	15.95 (0.083)	17.02 (0.126)	16.86 (0.061)	15.60 (0.075)
English	0.78 (0.005)	0.76 (0.007)	0.79 (0.010)	0.77 (0.006)	0.76 (0.006)
French	0.17 (0.008)	0.17 (0.009)	0.18 (0.016)	0.15 (0.008)	0.12 (0.007)
Share of full sample	0.67	0.56	0.22	0.72	0.79
N-weighted	28,387	23,739	9,329	30,341	33,377

Note: Experience stands for years of foreign work experience and schooling stands for years of foreign schooling. Bootstrap standard errors in brackets.

Table 4-4. Means of key characteristics by sub-samples in wave 3, females

	Skilled Worker PA's	Regulated	Professional	University educated	Visible minority
Log weekly	6.26 (0.037)	6.08 (0.032)	6.33 (0.05)	6.15 (0.026)	6.02 (0.021)
Age	38.17 (0.3)	38.10 (0.272)	37.32 (0.35)	37.85 (0.202)	38.16 (0.188)
Experience	12.51 (0.321)	13.07 (0.293)	11.32 (0.345)	11.93 (0.205)	13.55 (0.216)
Schooling	16.18 (0.137)	15.51 (0.102)	16.49 (0.147)	16.4 (0.075)	15.09 (0.081)
English	0.78 (0.011)	0.72 (0.01)	0.75 (0.013)	0.76 (0.007)	0.71 (0.008)
French	0.18 (0.017)	0.14 (0.013)	0.20 (0.02)	0.12 (0.009)	0.10 (0.008)
Share of full sample	0.27	0.43	0.22	0.66	0.77
N-weighted	8,235	13,082	6,694	19,943	23,239

See notes for table 4-2-1.

4.3 Occupational characteristics

The HRSDC's Career Handbook is used to obtain occupation characteristics for the National Occupational Classification 2001 using 4-digit codes. Ingram and Neumann (2006) note that "these characteristics' measure is a snapshot and cannot capture any skill-upgrading within jobs". The NOC that used in this research is dated as 2001, while the data used in the research cover 2001-2005 year. The original data in the Career Handbook contains a maximum of 26 indicators for five sets of characteristics: nine for aptitudes, five for interests, three for tasks related to working with data/people/things, six for physical activities, and three for environmental conditions. Poletaev and Robinson (2008) use the Dictionary of Occupational Titles in their study on US data. The authors exclude environmental conditions suggesting that they have the least to do with skills. We also exclude the set of environmental condition indicators and are left with a total of 23 indicators for four sets of characteristics. These 23 indicators represent 44 occupational characteristics. Similarly to Ingram and Neumann (2006), who employ the DOT, we presume that these job characteristics for the NOC potentially represent some dimensions of skill heterogeneity among workers.

Characteristic variables for some occupations were derived using guidelines on occupational coding provided in concordance tables. In most cases, means of characteristic scores were calculated if an original SOC occupation was classified into several occupations in the NOC. Although rare, if several SOC occupations had only one NOC code then the same characteristic scores were used for all of original codes.

4.3.1 Aptitudes

Each occupation is assigned scores, numerical or alpha codes for each set of characteristics. The first set of nine aptitudes consists of: "general learning ability", "verbal ability", "numerical ability", "spatial perception", "form perception", "clerical perception", "motor coordination", "finger dexterity" and "manual dexterity". An individual's overall capacity to learn the skills needed to perform job duties is based on his or her specific aptitudes for acquiring information and transforming it into action (Statistics Canada, retrieved on Jan 14, 2001). It is quite likely that "motor coordination", "finger dexterity" and "manual dexterity" are highly correlated and represent a similar skill dimension. The aptitudes are initially assigned an integer score between 5 and 1. The scale of the scores is based on the normal curve representing the Canadian labour force (Statistics Canada, retrieved on Jan 14, 2001). The scores "5" and "1" represents the lowest and the highest 10% of population respectively, "4" and "2" represent the lower and the upper third of population exclusive of the lowest and highest 10% respectively, and the score "3" represents the middle third of the population. For instance, "Economists and Economic Policy Researchers and Analysts" (further "Economists") occupation originally has the following nine scores for each corresponding aptitude: "121443444". Hence, the score "1" indicates that "Economists" have the level of both "general learning ability" and "numerical ability" that applies to the top 10 percent of the working population; "2" indicates that "Economists" have the level of "verbal ability" that applies to the upper third of the working population exclusive of the highest 10 percent etc. For simplicity of interpretation in this research the scores are reversed so that the score "1" is the lowest and the score "5" is the highest. In total, we have five variables for "Aptitudes" set.

4.3.2. Interests

The second set of characteristic indicators consists of five occupational interests: "Directive", "Innovative", "Methodological", "Objective" and "Social". Unlike the aptitudes that are all assigned a specific score, the interests have a more complicated code system. Each job is assigned a three-letter alpha-code in order of predominance (Career Handbook, 2001). Each letter in the code is the first letter of a specific interest. However, these letters also can be either capital of lower case. The lower case indicates a lower representation of a corresponding interest (Career Handbook, 2001). Hence, both "D" and "d" stand for "Directive", but their representation in an occupation is different. For instance, the "Economists" occupation is assigned an alpha-code "IDM", while "Letter Carriers" is assigned an alpha-code "Mos". In order to be able to use the letter-codes in the factor analysis we develop a scoring system to represent relevance of each interest regarding presence, order and the (upper/lower) case of each letter. The scores range between 0 and 1 with an interval of 0.2 for the following possibilities: (1) if a letter is in the first order (always capital) then the score for a corresponding interest is 1; (2) if a letter is in the second place and is either capital or lower case then the assigned score is 0.8 or 0.6 respectively; (3) if a letter is in the third place and is either capital or lower case then it is assigned a score of 0.4 or 0.2 respectively; (4) if a letter is not present in the three-letter alpha-code then it is assigned a score of 0. For instance, the "Economists" occupation, which originally has the alpha-code "IDM", in this analysis is assigned a score of "1" for "Innovative" interest, "0.8" for "Directive" interest and "0.4" for

"Methodological" interest; while "0" is assigned for both "Objective" and "Social" interests. Altogether, this leaves us with five variables for the "Interests" set.

4.3.3. Data-people-things

The third set of "Data-People-Things" characteristic indicators consists of three sub-sets of job tasks related to data, people and things. Each occupation is assigned a three-digit code using only one digit from each subset to represent relevant to a job characteristics. The first sub-set contains eight digits assigned to different types of data-related job tasks: "0" for synthesizing, "1" for coordinating, "2" for analyzing, "3" for compiling, "4" for computing, "5" for copying, "6" for comparing, and "8" for "Not significant" [8]. However we drop "8" due to zero observations. The second sub-set contains job tasks related to dealing with human beings and/or animals and contains nine types of tasks: "0" for mentoring, "1" for negotiating, "2" for instructing-consulting (including animals), "3" for supervising, "4" for diverting, "5" for persuading, "6" for speaking-signaling, "7" for serving-assisting and "8" for "not significant". And the third subset contains nine types of tasks related to working with things and objects: "0" for setting up, "1" for precision working, "2" for controlling, "3" for driving/operating, "4" for operating/manipulating, "5" for tending, "6" for feeding/off-bearing, "7" for handling and "8" for "not significant". For instance, the "Economists" occupation has a corresponding "Data-People-Things" three-digit code of "128". This indicates, that workers employed in "Economists" occupation perform such tasks as "Data co-ordination" (1), "Instructing-consulting" people (2), while things-related tasks are "not significant" (8). In our Analysis we separate each task into a dummy variable, which

[8] "7" is not used for coding.

leaves accounts for a total of 25 separate dummy variables related to “Data-People-Things”.

4.3.4. Physical activities

And the last set of occupational characteristics used in this analysis is related to physical activities. Each occupation is assigned a six-digit code related to the “Physical activities” set of occupational characteristics. Each digit in the code indicates a type or level of complexity of a specific physical activity: integers “1” through “4” for levels of visual field, “0” or “1” for color discrimination, integers “1” through “3” for hearing complexity including verbal interaction, integers “1” through “4” for body positions, integers “0” through “2” for levels of limb coordination, and “1” through “4” for strength levels. For instance, “Economists” is assigned a six-digit code “202101”. Hence, the first digit “2” indicates that workers employed in “Economists” occupation perform work activities that involve “near vision”; the second digit “0” indicates that color discrimination is irrelevant; the third digit “2” indicates that activities of this occupation involve “verbal interaction”; the fourth digit “1” indicates that work activities mostly involve “sitting” body position; the fifth digit “0” indicates that limb coordination is irrelevant in this occupation; and the last digit “1” indicates that “Economists” occupation work activities involve the lowest strength level.

All of these characteristics, except for strength and color discrimination, are separated into dummy variables. For instance, the visual field is separated into close visual acuity, near vision, near and far vision, total field of vision. The ‘hearing’ is divided into limited, verbal and other sound discrimination; the body position is separated into sitting, standing and/or walking, sitting-standing-walking, and other body position;

limb-coordination into ‘not relevant’, upper-limb coordination, and multiple limb coordination. Color discrimination is originally dichotomous, where it takes a value of one if color discrimination is relevant and zero if otherwise. As a result, we have 16 variables related to “Physical activities”. Altogether, we have 55 variables from all sets of 23 occupational characteristics for factor analysis.

CHAPTER 5

DEFINITIONS OF SKILLS AND SKILL MATCHES

In this chapter we present methodology used to obtain a set of potential skills specific to each of the NOC 2001 occupations and then we define skill matches. We also provide some descriptive statistics in order to have sense of whether the skill factors that we produced are plausible. Section 5.1 presents the methodology. Section 5.2 provides definitions of skills and summary statistics following with a discussion of potential variation in skill factors produced. Section 5.3 provides definitions of matches between pre- and post-immigration skills. Cross-sectional means of skill factor scores and means of skill factor scores for immigrant sub-samples in wave 3 are presented in section 5.4 and section 5.5 respectively. And section 5.6 presents matching patterns of pre- and post-immigration skill factors across waves and across sub-samples in wave 3.

5.1 Factor analysis

Each of the 23 characteristics described in section 4.3 is unlikely to represent a unique worker skill trait (Ingram & Neumann, 2006). Therefore both the exploratory and confirmatory factor analyses are employed to determine and construct broader skills for NOC occupations. The exploratory factor analysis is used to determine the number of common factors from given 23 characteristics and the strength of their relationship. For instance, “finger dexterity” and “manual dexterity” could be combined into a broader “motor coordination” skill etc. Then the confirmatory factor analysis is used to determine the ability of the factor model proposed after the exploratory factor analysis to fit an observed set of data.

After transformation of SOC occupations into NOC occupation the set contains 513 occupational units. Each unit is assigned a set of 51 characteristic variables on the basis of the Career Handbook profile summaries. From investigation of the correlation matrices for all characteristics we found that some of the characteristics had little or no correlation[9]. These were such components as computing data, diverting people, setting-up things, driving-operating things, tending things. These characteristics are still used in the factor analysis of this research; however their high "uniqueness" suggests potential independent sources of skills.

The original confirmatory factor analysis rests on several important assumptions. Firstly, the factors have to be orthogonal. And second, the factors should explain most of the covariance among given set of characteristics. The linear structural factor model of the following form is estimated for each job j ∈ [1;513]:

$$
\begin{aligned}
C_1 &= \mu_1 + \lambda_{11} f_1 + \cdots + \lambda_{1K} f_K + \varepsilon_1, \\
C_2 &= \mu_2 + \lambda_{21} f_1 + \cdots + \lambda_{2K} f_K + \varepsilon_2, \\
&\vdots \\
C_L &= \mu_L + \lambda_{L1} f_1 + \cdots + \lambda_{LK} f_K + \varepsilon_L,
\end{aligned}
\tag{5.1}
$$

where C_l is the observable rating for a characteristic l on job j; μ is a 55×1 vector of means, f_k is the amount of underlying skill k used in job j, λ_{lk} is the factor (skill) loading of a characteristic l on skill k. The model assumes that L characteristics are reflections of $K < L$ broader underlying factors (e.g. $f\ is\ a\ 3 \times 1$ vector of broader factors or basic skills with $\mathrm{E}[f] = 0$; $\varepsilon_l \sim N(0; \Sigma)$, Λ is a $55 \times k$ matrix of coefficients (factor loadings),

[9] The following levels of correlation are considered: 1-0.9 – high, 0.89-0.6-reasonably high, 0.59-0.4-moderate, 0.39-0.2-low, 0.19-0 –no correlation.

ε is a 51×1 vector of random variables that are uncorrelated with the factors. The assumption that matrix Σ is diagonal implies that all the correlations among characteristics are explained by the common basic factors f $(k \leq 55)$. Let $\mathrm{E}[ff'] = \Phi$, where Φ is $k \times k$, then the following is true:

$$\mathrm{E}(\mathrm{C} - \mu)(\mathrm{C} - \mu)' = \Lambda\Phi\Lambda' + \Sigma \qquad (5.2)$$

The underlying assumption of the model is that L characteristics can be explained by $K < L$ underlying basic skill factors. Note that the matrices Λ and Φ can be replaced by any other Λ^* and Φ^* such that $\Lambda\Phi\Lambda' = \Lambda^*\Phi^*\Lambda^{*\prime}$ without loss of generality. As elements of Λ and Φ are not separately identifiable usually the matrix Φ is restricted to be diagonal; hence its elements (factors) to be orthogonal. Furthermore, the diagonal elements of $\Lambda\Phi\Lambda'$ as well as diagonal elements of Σ are not separately identifiable. In order to resolve this indeterminacy the factors are normalized to have a zero mean and a standard deviation of one. The first factor is estimated to explain maximum amount of covariance among the characteristics; while the next one is estimated to explain the maximum amount of residual covariance among the characteristics conditional on the first factor etc. Hence, in our case up to 54 skill factors could be estimated. However, as long as most of the covariance among characteristics is explained by the first several factors all other factors have little explanatory power. One of the common rules of thumb to choose the number of broader factors is the Scree test. It consists of plotting the eigenvalues of the correlation matrix in descending order and then use a number of factors equal to the number of the eigenvalues that occur to the last major drop in eigenvalue magnitude[10]. Orthogonal rotation has to be performed to produce uncorrelated factors. After the rotation a factor solution is the same solution as an original but is supposed to have the simplest interpretation.

Initially factor analysis was employed for all 55 variables (representing 23 characteristics) simultaneously. Using the "Scree test" we retained five factors; these factors explained 47.36% of covariance among characteristics[11]. Then the orthogonal rotation was performed. In order to verify the robustness of factor analysis in this research a variety of orthogonal and oblique rotations were tested: varimax, orthomax, promax, and oblimin etc. All of the rotations produced similar results and suggested similar three to five factors. Eventually, we used a varimax rotation as it is widely believed to be the best option for orthogonal rotation. Thus, the first factor was highly correlated with "general learning ability", "verbal ability", "numerical ability", "clerical perception", "Directive" and "Social" interests, and had a high negative correlation with the "strength" variable. The second factor was highly correlated with "spatial perception" and "form perception", "motor coordination", "finger dexterity" and "manual dexterity", with "Innovative" interest and "Precision working" things-related task. However the rest of factors were hard to interpret. Specifically, often found in the literature of factor analysis for the DOT characteristics, "strength" does not appear as an independent factor in our analysis. In addition, it is often the case that several characteristics load on different factors.

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[10] Poletaev & Robinson (2008) chose a number of factors that equals a number of eigenvalues that are above two. Cain & Treiman (1981) suggested Kaiser criterion. The criterion consists of choosing a number of factors that equals a number of eigenvalues that are greater than one. In this analysis, in general, the Scree test solution coincides with the rule used in Poletaev & Robinson (2008).

[11] Adding more than five factors increases the amount of total explained variance by very little. For instance, to explain 100% of the variance among characteristics we would need to add around 25 more factors. This can be due to high uniqueness of some occupational characteristics, which do not load on our factors.

Cain and Treiman (1981) using confirmatory factor analysis for the DOT suggest that the "assumption of orthogonality in specifying the factor-analytic model is untenable and should be relaxed in future work" (p. 268). Following their suggestion we employ a method proposed by Ingram and Neumann (2006). In their analysis of the DOT they require only three factors (out of four) to be orthogonal. In this analysis the characteristics are split into two sub-samples and each sub-sample is required to produce orthogonal factors separately. Hence the upper left-hand two-by-two submatrix of Φ is diagonal and thus is the lower right-hand submatrix. Second, assume the matrix Λ has the following structure:

$$\Lambda = \begin{bmatrix} \Lambda_{11} & \cdots & 0_{12} \\ \vdots & \ddots & \vdots \\ 0_{21} & \cdots & \Lambda_{22} \end{bmatrix} \tag{5.3}$$

Here 0_{12} is a 39×2 vector of zeros and 0_{21} *is a* 22×1 vector of zeros[12]. Thus the first two factors are required to be orthogonal. However the third factor is not necessarily orthogonal to the first two factors and may have some common factor loadings. This implies that some characteristics contributing to factor 3 also load on factor 1 and factor 2.

In the factor analysis the occupations are weighted according to employment statistics by occupational grouping reported in the Labour Force Survey using a midpoint of the LSIC collection period for wave 3 (Appendix A). The employment statistics for both genders by NOC-S occupational grouping was adjusted for the NOC 2001. However, the employment statistics differs for males and females the aggregate is used as all three produce similar estimates. The weighting is important because some of

[12] These two sub-sets have six characteristics in common.

occupations may have plenty of labour employed while some may have few (Ingram and Neumann, 2006; Poletaev and Robinson, 2008). In this analysis we investigate immigrants' movement across occupational distribution of the Canadian labour market; therefore, the corresponding frequency weights are applied. The employment frequencies in the LFS are transformed for 3-digit NOC groupings and are equally distributed within each 3-digit group among 4-digit occupations. For instance, if there are five 4-digit occupations within a 3-digit occupational group, then each of the 4-digit unit group will receive a one-fifth of employment frequency of its corresponding 3-digit employment frequency.

5.2 Definition of skills

Following Ingram and Neumann (2006) we first perform factor analysis for a subset of characteristics including all aptitudes, interests (except for "objective"), data-related (except for "not significant"), people-related (except for "not significant"), one things-related ("precision work"), as well as some physical activities characteristics ("color discrimination", "visual field" and "hearing"). When we employ factor analysis the "Scree test" suggests three factors. Factor one and two explain 25% and 17% of the covariance respectively. Similarly to economic studies that use the DOT (Ingram and Neumann, 2006; Poletaev and Robinson, 2008), in our analysis of the NOC the first and the second factors are related to "intelligence" and "motor skills" respectively. However the third factor (8%) is difficult to interpret. It picks up such characteristics as "persuading" people together with "compiling" and "computing data" and negatively associated with "supervising" people and "coordinating" data. We therefore only retain the first two factors and proceed to the analysis of the second subset of characteristics.

Interestingly, from factor loadings in Table 5-1 it can be noticed that "people-related" tasks individually are not extremely useful in production of either "intelligence" or "motor skills" factor. Although, jointly they are important for "intelligence" factor production as suggested by a negation of the people-related characteristic called "not significant", which has a loading coefficient of -0.55 on the "intelligence" factor.

Table 5-1. Factor loadings for the first subset of characteristics, rotated

Characteristics	F1, intelligence	F2, motor skills	Uniqueness
<u>Aptitudes</u>			
General learning ability	**0.84**	0.27	0.22
Verbal ability	**0.87**	0.13	0.22
Numerical ability	**0.78**	0.19	0.36
Spatial ability	0.15	**0.79**	0.35
Form perception	0.15	**0.80**	0.34
Clerical perception	**0.61**	-0.13	0.60
Motor coordination	-0.38	**0.65**	0.44
Finger dexterity	-0.15	**0.67**	0.53
Manual dexterity	-0.44	**0.67**	0.36
<u>Interests</u>			
Directive interest	**0.65**	-0.24	0.52
Innovative interest	0.43	**0.54**	0.52
Methodological interest	-0.47	-0.37	0.64
Social interest	0.19	-0.40	0.80
<u>Data related</u>			
Data synthesis	0.29	0.36	0.79
Data coordination	**0.64**	-0.26	0.52
Data analysis	0.08	0.36	0.86
Data compilation	-0.13	0.10	0.97
Data computation	-0.10	-0.16	0.96
Data copying	-0.38	-0.10	0.85
Data comparison	**-0.56**	-0.14	0.67
<u>People related</u>			
Mentoring	0.20	0.13	0.94

Negotiating	0.44	-0.24	0.75
Instructing/consulting	0.38	0.10	0.85
Supervising	0.26	0.00	0.93
Diverting	0.01	0.08	0.99
Persuading	0.00	-0.22	0.95
Speaking/signaling	-0.19	0.09	0.96
Serving/assisting	-0.35	-0.19	0.85
"People-related" is not significant	**-0.55**	0.20	0.66
Things related			
Precision working	0.03	**0.71**	0.49
"Things-related" is not significant	**0.69**	-0.44	0.33
Physical activities			
Close vision only	-0.05	0.32	0.90
Near vision only	0.30	-0.07	0.91
Color discrimination	-0.15	0.41	0.81
Verbal interaction	**0.56**	-0.34	0.57
Sitting position only	0.48	-0.12	0.76
Standing/walking only	-0.26	-0.09	0.93
Limbs irrelevant	**0.70**	-0.32	0.41
Multiple limbs use	-0.36	0.08	0.86

When we employed factor analysis for the rest of characteristics, mostly related to tasks with "things" and to physical activities, the "Scree test" suggested two factors. The first factor explains 36% of covariance among given characteristics. This factor is strongly positively related to the level of "strength" and to body positions "other than sitting, standing and walking", "people-related is not significant", while negatively related to "verbal interaction" and "things not significant". This factor seems to pick up "strength" skills. The second factor explains another 15% of the covariance in the second subset of characteristics, however is difficult to interpret. Therefore, we only retain one factor from this subset.

From factor loadings in Table 5-2 it can be noticed that "things-related" tasks individually are not very useful in production of the "strength" factor. Although, jointly they are important for "strength" factor production as suggested by a negation of the characteristic called "things-related is not significant", which has a loading coefficient of -0.71.

Table 5-2. Factor loadings for the second subset of characteristics, rotated

Characteristics	F3, strength	Uniqueness
<u>Interests</u>		
Objective interest	**0.73**	0.47
<u>People related</u>		
"People-related" is not significant	**0.63**	0.60
<u>Things-related</u>		
Setting up things	0.12	0.99
Controlling things	0.12	0.98
Driving/operating	0.25	0.94
Operating/manipulating	0.31	0.90
Tending	0.04	1.00
Feeding equipment	0.16	0.97
Handling	0.08	0.99
"Things-related" is not significant	**-0.71**	0.50
<u>Physical activities</u>		
Near-far vision only	0.12	0.99
Total visual field	0.31	0.91
Limited hearing	**0.78**	0.38
Verbal interaction	**-0.85**	0.28
Other sound discrimination	0.22	0.95
Sitting position only	-0.46	0.79
Standing and/or walking	0.10	0.99
Sitting, standing, walking	-0.33	0.89
Other body positions	**0.80**	0.37
Upper limb coordination only	0.34	0.88
Multiple limb coordination	0.46	0.78
Strength	**0.83**	0.32

In our analysis we restricted only the first two factors to be orthogonal. Therefore, a correlation between them and the third factor is not exclusive. Indeed, from the correlation matrix in Table 5-3 it can be noticed that there is no correlation between factor one and two, but there is a fairly high negative correlation between "intelligence" and "strength", and a relatively low positive correlation between "motor skills" and "strength". The magnitude and the direction of the correlations is intuitive suggesting that we have chosen plausible factor loadings among all characteristics. As well the factors found in this analysis are consistent with factors found in studies that used the DOT (Ingram and Neumann, 2006; Poletaev and Robinson, 2008). However, while we produce three factors, economic studies using the DOT produce four factors and explain more variance among factors.

Table 5-3. Factors' correlation matrix

	F1, intelligence	F2, motor skills	F3, strength
F1, intelligence	1		
F2, motor skills	0.00	1	
F3, strength	-0.78	0.37	1

Factor summary (Table 5-4) confirms that all factors have zero mean and a standard deviation of one. Notably, the distributions of the factors are not normal and differ from each other. The "motor skills" factor score has the greatest maximum, while "intelligence" factor score has the biggest minimum. Moreover, while maximum and minimum of the "intelligence" factor are close in their magnitudes, magnitudes of "motor skills" and "strength" factors maximums are around four and two times bigger respectively than the corresponding magnitudes of their minimums.

Table 5-4. Factor summary

	Observations	Mean	Standard Deviation	Min	Max
F1, intelligence	16098	0.00	0.99	-1.87	1.92
F2, motor skills	16098	0.00	0.98	-1.22	4.00
F3, strength	16098	0.00	0.99	-1.02	2.24

Note: the observation number is in thousands

The following is the discussion of factor means by aggregate occupations presented in Table 5-5. The distributions of means factor scores across occupational groups indicate we produced plausible factors using occupational characteristics. It can be noticed that "intelligence" factor score declines almost monotonically across occupational groups, which are ordered from highest skill level to the lowest (except for "Managers" group). The exception is a shift up and a positive "intelligence" mean score of "Skilled primary industry" occupational group. "Managers" and "Professionals" group have very high "intelligence" factor scores relative to the mean of zero as well as to the maximum score value of 1.92. The mean "intelligence" factor scores for these two groups are the highest with a great lead compared to other groups. There is a symmetrical (opposite direction) pattern of mean scores for occupational groups within the "strength" factor. Its symmetry can be explained by its strong negative correlation to the "intelligence" factor. Hence, "Laborers" and "Operators" group has the highest mean "strength" scores with a great lead, while "Managers" group has the lowest. The "motor skills" factor has the most variation across occupational groups. Its highest mean score, with a great lead, is the score of "Skilled craft" group. Interestingly, while the "motor skills" factor has the greatest maximum value (Table 4-4), its biggest mean score across group means (1.01) is the lowest maximum among three factors compared to two other maximums of 1.34 and 1.69 for "intelligence" and "strength" factors respectively.

Interestingly, most of occupational groups have at least one factor with a positive mean factor score. This suggests that we produced enough factors to describe occupational "skill-profiles", although we were not able to explain all covariance among occupational characteristics.

Table 5-5. Factors' summary by occupational groups, for the LFS

	N	F1, intelligence	F2, motor skills	F3, strength
Managers	1459	1.34 (0.32)	-0.73 (0.35)	-.96 (0.29)
Professionals	2715	1.14 (0.38)	0.58 (1.13)	-0.55 (0.57)
Technicians	2623	0.15 (0.53)	0.36 (1.17)	-0.26 (0.74)
Intermediate sales and service	2920	-0.11 (0.64)	-0.70 (0.58)	-0.40 (0.64)
Elementary sales and service	2302	-0.71 (0.55)	-0.39 (0.43)	0.16 (0.71)
Skilled primary industry	521	0.23 (0.56)	0.04 (0.45)	-0.13 (0.92)
Skilled craft	1523	-0.50 (0.58)	1.01 (0.71)	0.95 (0.96)
Operators	1488	-1.31 (0.28)	0.12 (0.40)	1.40 (0.59)
Laborers	547	-1.63 (0.13)	-0.50 (0.31)	1.69 (0.10)
Total	16098			

Note: number of observations is the LFS midpoint total number of employed workers in thousands period of November, 2004 to November, 2005

The following tables (Table 5-6 to Table 5-9) present a potential variation in the factor. From the Table 5-6 it can be noticed that "Managers" group occupations have only positive "intelligence" scores, while occupations within "Operators" or "Laborers" group have only negative scores. All other occupational groups seem to have enough of variation in the "intelligence" factor.

Table 5-6. Variation in Factor 1 ("Intelligence") by occupational group

	Min	Occupation title	Max	Occupation title
Managers	0.28	Commissioned Officers, Armed Forces	1.85	Engineering, Science and Architecture Managers
Professionals	-0.25	Painters, Sculptors and Other Visual Artists	1.92	University Professors
Technical, associate professionals	-1.04	Nurse Aides and Orderlies	1.10	Administrative Officers
Intermediate sales and service	-1.41	Pet Groomers and Animal Care Workers	1.03	Funeral Directors and Embalmers
Elementary sales and service	-1.68	Dry Cleaning and Laundry Occupations	0.34	Production Clerks
Skilled primary industry	-1.58	Logging Machinery Operators	0.75	Landscaping and Grounds Maintenance Contractors and Managers
Skilled craft	-1.46	Plasterers, Drywall Installers and Finishers, and Lathers	0.70	Supervisors, Motor Transport and Other Ground Transit Operators
Operators	-1.79	Chain-saw and Skidder Operators	-0.31	Water and Waste Plant Operators

Laborers	-1.87	Landscaping and Grounds Maintenance Laborers	-1.43	Construction Trades Helpers and Laborers

Score intervals of the “motor skills” factor across occupational groups (Table 5-7) suggest all groups seem to have enough of variation in this factor, except for “Laborers” group, which only contains occupations with negative “motor skills” scores. Although not shown, “Dentists” occupation is an outlier in the “Professionals” group with 4.00 “motor skills” score, while the closest occupations with the second and third highest scores in this group are “Veterinarians” (3.16) and “Chemists” (3.14) respectively.

Table 5-7. Variation in Factor 2 (“Motor skills”) by occupational group

	Min	Occupation title	Max	Occupation title
Managers	-1.22	Accommodation Service Managers	0.25	Information Systems and Data Processing Managers
Professionals	-0.77	Probation and Parole Officers and Related Occupations	4.00	Dentists
Technical, associate professionals	-1.08	Supervisors, Library, Correspondence and Related Information Clerks	3.21	Artisans and Craftspersons
Intermediate sales and service	-1.19	Insurance Agents and Brokers	1.08	Other Ranks, Armed Forces
Elementary sales and service	-1.22	Other Elemental Sales Occupations	0.96	Typesetters and Related Occupations
Skilled primary industry	-0.76	Supervisors, Landscape and Horticulture	1.26	Petroleum, Gas and Chemical Process Operators

Skilled craft	-0.70	Railway Conductors and Brakemen/women	3.44	Jewelers, Watch Repairers and Related Occupations
Operators	-0.51	Automotive Mechanical Installers and Servicers	2.52	Electronics Assemblers, Fabricators, Inspectors and Testers
Laborers	-0.98	Railway and Motor Transport Laborers	-0.02	Harvesting Laborers

Similarly to "motor skills" factor, variation in "strength" factor (Table 5-8) is fairly big, except for "Laborers" group, which, unlike "motor skills" factor, only contains occupations with positive "strength" factor scores. Although not shown, many occupations have exactly the same predicted "strength" scores, especially those with negative values, which are mostly occupations with high "intelligence" scores (e.g. managerial occupations). We only report one occupation title for each minimum or maximum score as an example to have some sense of how plausible the predicted factors are.

Table 5-8. Variation in Factor 3 ("Strength") by occupational group

	Min	Occupation title	Max	Occupation title
Managers	-1.02	Facility Operation and Maintenance Managers	1.07	Commissioned Officers, Armed Forces
Professionals	-1.02	Financial and Investment Analysts	1.16	Registered Nurses
Technical, associate professionals	-1.02	Purchasing Agents and Officers	1.66	Landscape and Horticultural Technicians and Specialists

Intermediate sales and service	-1.02	Image, Social and Other Personal Consultants	1.61	Other Ranks, Armed Forces
Elementary sales and service	-0.97	Customer Service, Information and Related Clerks	1.67	Couriers and Messengers
Skilled primary industry	-0.92	Supervisors, Motor Vehicle Assembling	2.24	Logging Machinery Operators
Skilled craft	-0.97	Supervisors, Motor Transport and Other Ground Transit Operators	1.95	Drillers and Blasters - Surface Mining, Quarrying and Construction
Operators	-0.18	Lock and Cable Ferry Operators and Related Occupations	2.24	Chain-saw and Skidder Operators
Laborers	1.50	Railway and Motor Transport Laborers	1.89	Laborers in Fish Processing

5.3 Definition of matches

We define a skill match following guidelines of Poletaev and Robinson (2008) for their Skill Portfolio match (SP1) in analysis of displaced workers. However, we apply some modifications for our research purposes. Firstly, instead of grouping all skill matches, we construct a separate match variable for each skill to be able to separate effects of matching different skills on returns to foreign human capital. Secondly, we define “matchers”, however we do not define skill “switchers”. Hence, “switchers” and “indeterminate” cases are all classified as “non-matchers”. This modification is used in order to maximize the sample size for the regression analysis. This is crucial for two reasons. Firstly, sample size is important when using dummy variables and their interactions with other variables to minimize chances of multicollinearity. Secondly, we are interested in returns to foreign human capital "specific" to skills, but not the differences in returns between "matchers" and "switchers".

A skill factor score initially cannot be too small, and a change in a skill factor score cannot be too big (Poletaev and Robinson, 2008). The following two conditions have to be satisfied in order to obtain a match in each skill factor in this analysis: (1) the score of a pre-immigration occupation skill factor has to be at least a half of a standard deviation above the mean, (2) a difference between pre- and post-immigration occupation factor scores cannot exceed a half of a standard deviations in absolute value[13]. The first condition serves as an assumption that a pre-immigration skill level has to be big enough for a skill to be developed. The second condition assumes that a post-immigration skill level cannot be too far from its pre-immigration skill level. Both of these conditions imply that post-immigration factor score cannot be under the mean of zero to be considered for a match. Hence, each skill-match is a dichotomous variable that equals to one if a match in a specific skill occurs and equals zero otherwise.

Importantly, as the lower limit for a skill to be developed is a half of a standard deviation above the mean, all immigrants whose pre-immigration score of a specific factor is lower than the threshold are automatically classified as non-matchers within this specific skill factor. We do not remove this sub-set of immigrants from the analysis in order to keep our sample as big as possible. This implies that we compare immigrants who are able to match either of their skills to the rest of immigrants and not only to non-matchers. For simplicity, all immigrants other than matchers are called non-matchers. In

[13] Poletaev and Robinson (2008) in their analysis of displaced workers used 0.5/0.5 and 0.6/0.3 for the lowest predisplacement score/absolute difference in pre- and post-displacement scores and showed that their findings were robust. They also suggested that other values, as long as they are not extreme, produce similar results. In our analysis the following combination were verified and produced broadly similar results: 0.6/0.3, 0.0/0.3, and 0.0/0.5.

the following section (4.2.2) we provide information on matching patterns within each skill dimension.

5.4 Cross-sectional factor scores

The means of pre- and post-immigration factor scores for males are presented on the left hand side of Table 5-1-3. Comparing means of factors scores within each wave suggest that on average male immigrants worked in their (last) source country occupation with high “intelligence” and “motor skills” requirements, having skill factor score more than a half of a standard deviation above zero. The score of pre-immigration “strength” on average is lower than zero. This implies that on average male immigrants have lower likelihood to match their pre- and post-immigration “strength” factor regarding that we require the pre-immigration score level to be at least a half of a standard deviation.

In contrast, the patterns of post-immigration skill factor scores differ dramatically compared to those of pre-immigration skill factor scores. First, none of the post-immigration factor scores is above a half of a standard deviation on average. Moreover the post-immigration “intelligence” factor scores are on average below zero across all waves, while the “strength” factor scores are above.

The means of pre- and post-immigration factor scores for females are presented on the right hand side of Table 5-9. Similarly to males, prior to immigration females on average also worked in occupations with high requirements for “intelligence” factor and fairly high “motor skills” factor, while quite low “strength” factor requirements. All average pre-immigration factor scores for females are substantially lower than for males.

The patterns of post-immigration skill factor scores have the same direction as for males, but magnitudes for females are substantially lower, especially for “motors skills” and “strength”. All post-immigration factor scores are small or negative on average.

Table 5-9. Mean pre- and post-immigration factor scores

	Males			Females		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
<u>Pre-immigration scores:</u>						
Intelligence (F1)	0.66 (0.044)	0.64 (0.029)	0.70 (0.020)	0.55 (0.059)	0.63 (0.034)	0.62 (0.023)
Motor skills (F2)	0.67 (0.054)	0.63 (0.036)	0.70 (0.027)	0.32 (0.076)	0.37 (0.046)	0.34 (0.032)
Strength (F3)	-0.13 (0.040)	-0.15 (0.026)	-0.18 (0.019)	-0.27 (0.050)	-0.29 (0.028)	-0.29 (0.019)
<u>Post-immigration scores:</u>						
Intelligence (F1)	-0.17 (0.054)	-0.16 (0.034)	-0.10 (0.026)	-0.18 (0.064)	-0.23 (0.038)	-0.23 (0.027)
Motor skills (F2)	0.44 (0.053)	0.40 (0.035)	0.42 (0.025)	0.01 (0.66)	0.03 (0.040)	0.00 (0.026)
Strength (F3)	0.50 (0.050)	0.44 (0.032)	0.39 (0.025)	0.10 (0.059)	0.18 (0.035)	0.19 (0.025)

Note: Bootstrap standard errors in brackets.

5.5 Factor scores by sub-samples in wave 3

5.5.1 Skilled Workers principal applicants

The scores of pre-immigration “intelligence” and “motor skills” factor of Skilled Worker principal applicants have are all higher than a half of standard deviation, unlike other immigrants whose scores are positive, but lower than a half of a standard deviation (Table 5-10). In contrast, pre-immigration “strength” factor scores are quite low for both groups, and are negative for Skilled Worker principal applicants. Post-immigration factor scores are all positive for Skilled Worker principal applicants, however only "motor skills" factor score is higher than a half of a standard deviation. Post-immigration "intelligence" factor score for other immigrants is negative and big in magnitude, while "motor skills" and "strength" factor scores are both positive, and the last one is higher than a half of a standard deviation.

Table 5-10. Mean pre- and post-immigration factor scores, Skilled Worker PA's

	Males		Females	
	Skilled Worker PA's	Other categories	Skilled Worker PA's	Other categories
<u>Pre-immigration</u>				
Intelligence	0.92 (0.022)	0.24 (0.038)	0.88 (0.044)	0.53 (0.028)
Motor Skills	0.88 (0.032)	0.34 (0.045)	0.57 (0.065)	0.25 (0.035)
Strength	-0.29 (0.021)	0.05 (0.036)	-0.37 (0.031)	-0.25 (0.024)
<u>Post-immigration</u>				
Intelligence	0.16 (0.031)	-0.62 (0.037)	0.13 (0.053)	-0.37 (0.03)
Motor Skills	0.56 (0.032)	0.14 (0.036)	0.17 (0.058)	-0.06 (0.03)
Strength	0.20 (0.030)	0.77 (0.037)	-0.04 (0.047)	0.28 (0.029)
N	28,387	13,735	8,235	22,002

Both female sub-samples (Table 5-10) have higher than a half of a standard deviation pre-immigration "intelligence" scores and high "motor skills" factor scores, which is above a half of a standard deviation for Skilled Worker principal applicants; and both sub-samples have substantially negative pre-immigration "strength" score. None of the sub-samples have higher than a half of a standard deviation post-immigration factor scores.

5.5.2 Regulated occupations

Both male immigrants employed in regulated and unregulated occupations have pre-immigration "intelligence" and "motors skills" factor scores higher than a half of a standard deviation and slightly negative "strength" factor scores (Table 5-11). However, post-immigration factor scores differ dramatically for these two male sub-samples. Thus, on average both sub-samples have low post-immigration factor scores within "intelligence". Male immigrants in regulated occupations in wave 3 on average have high requirements for "motor skills". This is not true for male immigrants employed in unregulated occupations. Both sub-samples have higher than zero post-immigration "strength" factor scores.

Table 5-11. Mean pre- and post-immigration factor scores, Regulated occupations

	Males		Females	
	Regulated	Unregulated	Regulated	Unregulated
<u>Pre-immigration</u>				
Intelligence	0.74 (0.026)	0.65 (0.032)	0.70 (0.033)	0.57 (0.032)
Motor Skills	0.80 (0.035)	0.58 (0.040)	0.44 (0.046)	0.26 (0.042)
Strength	-0.17 (0.025)	-0.19 (0.028)	-0.29 (0.03)	-0.28 (0.025)
<u>Post-immigration</u>				
Intelligence	0.06 (0.032)	-0.30 (0.040)	0.03 (0.04)	-0.44 (0.035)
Motor Skills	0.78 (0.037)	-0.05 (0.028)	0.31 (0.048)	-0.24 (0.025)

Strength	0.39 (0.030)	0.39 (0.040)	0.11 (0.033)	0.25 (0.036)
N	23,739	18,383	13,082	17,155

All post-immigration factor scores are positive for females employed in regulated occupations, and only post-immigration "strength" factor score is positive for females in unregulated occupations (Table 5-11). None of post-immigration factor scores on average exceeds a half of a standard deviation.

5.5.3 Professional occupations

Both male sub-samples have higher than a half of a standard deviation pre-immigration scores for "intelligence" and "motor skills" factors and negative pre-immigration factor scores for "strength" (Table 5-12). However, post-immigration scores differ dramatically. For males immigrants employed in professional occupations in Canada, post-immigration scores for "intelligence" and "motor skills" factors are still higher than a half of a standard deviation, and even higher than corresponding pre-immigration scores. Male immigrants employed in non-professional occupations have negative post-immigration "intelligence" factor score and twice lower post-immigration, compared to pre-immigration, "motor skills" factor score. In contrast, average post-immigration "strength" factor score is negative for "professional" male immigrants, but it is higher than a half of a standard deviation for "non-professional" male immigrants.

Both female sub-samples have higher than a half of a standard deviation pre-immigration "intelligence" scores, positive "motor skills" scores and negative "strength" scores (Table 5-12). Female immigrants employed in professional occupations have high post-immigration "intelligence" scores on average, while female immigrants employed in unregulated occupations have negative. Neither female sub-sample on average has post-immigration “motor skills” or “strength” that exceed a half of a standard deviation.

Table 5-12. Mean pre- and post-immigration factor scores, Professional occupations

	Males		Females	
	Professional	Non-Professional	Professional	Non-Professional
Pre-immigration				
Intelligence	1.1 (0.032)	0.59 (0.024)	0.94 (0.037)	0.54 (0.028)
Motor Skills	0.88 (0.051)	0.65 (0.031)	0.47 (0.06)	0.30 (0.037)
Strength	-0.41 (0.026)	-0.11 (0.022)	-0.39 (0.039)	-0.26 (0.022)
Post-immigration				
Intelligence	1.25 (0.016)	-0.48 (0.024)	0.86 (0.04)	-0.54 (0.025)
Motor Skills	1.00 (0.049)	0.26 (0.027)	0.33 (0.059)	-0.09 (0.029)
Strength	-0.46 (0.020)	0.63 (0.028)	-0.30 (0.042)	0.33 (0.029)
N	9,329	32,794	6,694	23,543

5.5.4 University educated

From Table 5-13, the average pre-immigration “intelligence” and “motor skills” score is respectively 0.98 and 0.82 for the “university educated” group compared to -0.01 and 0.41 for other education levels; while the pre-immigration “strength” factor score is -0.39 for “university educated” compared to 0.29 for other education levels. Interestingly, the post immigration factor scores for “university educated” immigrants are all higher than zero, however none is higher than a half of a standard deviation. The post immigration "intelligence" factor score for immigrant with lower than BA degree is substantially low, while the "strength" factor score is substantially high.

Table 5-13. Mean pre- and post-immigration factor scores, University educated

	Males		Females	
	University	Other	University	Other
Pre-immigration				
Intelligence	0.98 (0.019)	-0.01 (0.040)	0.86 (0.026)	0.17 (0.042)
Motor Skills	0.82 (0.032)	0.41 (0.047)	0.48 (0.041)	0.07 (0.045)
Strength	-0.36 (0.018)	0.29 (0.043)	-0.41 (0.022)	-0.05 (0.036)
Post-immigration				
Intelligence	0.15 (0.030)	-0.72 (0.036)	-0.01 (0.035)	-0.66 (0.035)
Motor Skills	0.49 (0.031)	0.24 (0.039)	0.11 (0.035)	-0.21 (0.036)
Strength	0.20 (0.029)	0.88 (0.040)	0.07 (0.031)	0.43 (0.039)
N	30,341	11,781	19,943	10,294

Both female sub-samples (Table 5-13) have positive pre-immigration "intelligence" and "motor skills" factor scores and negative pre-immigration "strength" factor scores. The means of post-immigration "intelligence" and "motor skills" factor scores are substantially lower for both sub-samples compared to pre-immigration; however average post-immigration "strength" factor score is higher.

5.5.5 Visible minorities

From Table 5-14, while both sub-samples have higher than a half of a standard deviation pre-immigration "intelligence" and "motor skills" factor scores, visible minorities have negative and non-visible minorities have positive post-immigration score for this factor. On the other hand, both sub-samples have negative pre-immigration "strength" factor scores; however after immigration both sub-samples have positive scores of this factor, and visible minorities have twice as large as non-visible minorities do.

Table 5-14. Mean pre- and post-immigration factor scores, Visible minorities

	Males		Females	
	Visible minorities	Other	Visible minorities	Other
<u>Pre-immigration</u>				
Intelligence	0.70 (0.023)	0.69 (0.039)	0.61 (0.027)	0.67 (0.043)
Motor Skills	0.68 (0.031)	0.78 (0.052)	0.34 (0.036)	0.34 (0.062)
Strength	-0.19 (0.021)	-0.13 (0.039)	-0.28 (0.022)	-0.32 (0.036)
<u>Post-immigration</u>				
Intelligence	-0.16 (0.030)	0.16 (0.047)	-0.29 (0.031)	-0.04 (0.051)
Motor Skills	0.38 (0.029)	0.58 (0.050)	0.01 (0.032)	-0.03 (0.05)
Strength	0.44 (0.028)	0.19 (0.045)	0.24 (0.029)	0.02 (0.043)
N	33,377	8,705	23,239	6,981

We reject the null of equality for current "intelligence" and "strength" factor scores for females (Table 5-14). While both sub-samples have high and almost identical pre-immigration "intelligence" and "motor skills" factor scores and negative and similar "strength" factor scores, the patterns are more diverse after immigration. Both sub-samples have negative post-immigration "intelligence" factor score, which is bigger in magnitude for visible minorities. Average post-immigration "motor skills" factor score is close to zero for both sub-samples; and "strength" factor scores are positive, but much bigger for visible minorities.

5.6 Matching patterns

From results presented in Table 5-15 it can be noticed that matching patterns differ across skills. Regarding that we required a pre-immigration skill level to be at least a half of a standard deviation above the mean, among immigrants who match pre- and post-immigration occupation on the basis of 4-digit coding (12% of total male sample in wave 3) the shares of immigrants who match their (developed) skills are lower than that.

Table 5-15. Male immigrants' matching patterns by skill factors within 4-digit occupational match, wave 3

4-digit occupation			
Matched (12%)		Not Matched (88%)	
Intelligence		Intelligence	
Matched	Not matched	Matched	Not matched
62%	38%	16%	84%
Motor Skills		Motor Skills	
Matched	Not matched	Matched	Not matched
76%	24%	13%	87%
Strength		Strength	
Matched	Not matched	Matched	Not matched
21%	79%	9%	91%

Among 4-digit occupation matchers the share of “intelligence” and “motor skills” matchers is respectively 62% and 76%, while the share of “strength” factor matchers is only 21%. These shares can be explained by the fact that most of male immigrants prior to immigration worked in occupations with high “intelligence” and/or “motor skills” factor, however low “strength” factor. Also, among male immigrants who do not match pre- and post-immigration 4-digit occupation (88%) the share of immigrants who still match their pre- and post-immigration “intelligence”, “motor skills” and “strength” factor is 16%, 13% and 9% respectively. Matching patterns for females are similar, but matching occurs less frequently.

Matching patterns across waves for both genders are presented in Table 5-16. It can be noted, that the shares of immigrants who match either of their skill factors slightly decreases overtime (across waves). The share of male immigrants that match their pre- and post-immigration “intelligence” factor or motor skills factor drops in wave 2 compared to wave 1, although the wave 3 and wave 2 shares for these types of match are almost identical, both within skills and across skills. The share of male immigrants who match their pre- and post-immigration “strength” factor in wave 1 is twice smaller than the first two types of matches, it stays the same in wave 2 and drops slightly in wave 3. The shares of female immigrants who match their pre- and post-immigration “intelligence” or “motor skills” factor are substantially smaller than for males. Interestingly, the share of female immigrants who match their pre- and post-immigration “intelligence” factor does not change overtime, while there is a slight decline in the share of female immigrants who match shares of female immigrants who match their pre- and post-immigration “motor skills” or “strength” factor. In all cases the absolute number of both male and female immigrants who match their pre- and post-immigration skill factors increases overtime.

Table 5-16. Cross-sectional immigrant matching patterns

	Males			Females		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
"Intelligence" match	0.26	0.22	0.21	0.16	0.16	0.16
"Motor skills" match	0.27	0.21	0.21	0.15	0.12	0.10
"Strength" match	0.13	0.13	0.11	0.12	0.10	0.09

Matching patterns for sub-samples of wave 3 are presented in Table 5-17 for males and in Table 5-18 for females. For both genders, the share of immigrants who match their pre- and post-immigration "intelligence" as well as "motor skills" factor is the biggest for those employed in professional occupations and the smallest for visible minorities.

Table 5-17. Matching patterns by key sub-samples of wave 3, males

	Skilled Worker PA's	Regulated	Professional	University educated	Visible minority
"Intelligence" match	0.27	0.24	0.70	0.27	0.21
"Motor skills" match	0.25	0.27	0.45	0.24	0.19
"Strength" match	0.07	0.11	.	0.04	0.10

Note: "." means that the number could not be disclosed due to Statistics Canada regulations.

The shares of both male and female immigrants who match their pre- and post-immigration "strength" factor are quite low compared to the first two factors. The share of male "strength" matchers is the highest for those employed in regulated occupations in wave 3 as well as visible minorities (Table 5-17). The share of female "strength" matchers is the highest for visible minorities (Table 5-18).

Table 5-18. Matching patterns by key sub-samples of wave 3, females

	Skilled Worker PA's	Regulated	Professional	University educated	Visible minority
"Intelligence" match	0.25	0.23	0.53	0.23	0.15
"Motor skills" match	0.14	0.16	0.27	0.12	0.09
"Strength" match	0.05	0.08	0.08	0.06	0.10

CHAPTER 6

ECONOMETRIC SPECIFICATIONS

We use regression specifications proposed in Goldmann et al. (2011). The base of the model is the Mincerian log-wage equation. However, specifications of the model have some important features. The main features are the following multiple-way interaction terms: (1) skill-match variables interacted with foreign human capital variables; (2) language scores interacted with foreign human capital variables; (3) skill-match variables interacted with interaction of language scores and human capital variables. This section introduces and explains model specifications and construction of variables used for the regression analysis.

6.1 Specification 1

Specification 1 is a standard model in the literature that includes human capital variables and controls for demographic characteristics.

$$lnWages_{it} = \alpha_t + \beta_{1t}Exp_{it}^{For} + \beta_{2t}School_{it}^{For} + \gamma_t X_{it} + e_{it} \tag{6.1}$$

where $\ln Wages_{it}$ is a natural logarithm of weekly wage of the i^{th} immigrant interviewed in wave t earned in his/her main job; Exp_{it}^{For} is years of potential foreign experience calculated as (age at immigration - years of schooling – 6); $School_{it}^{For}$ is years of successfully completed schooling prior to immigration as reported by a respondent. For consistency with Goldmann et al. (2009, 2011), X_{it} includes the following set of control variables: months since immigration measured as number of months between landing and interview date; immigration class (Family (default); Skilled (PA); Skilled (not PA); Bus/Nom/Ref/Other); birth region (US/W Europe/ UK/ Other Northern Europe/ Oceania (default); C & S America/Caribbean & Bermuda; E Europe; S Europe; Africa; WC Asia

& M East; E Asia; SE Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under age 18; marital status (single (default); married/common law).

We do not include a square term of foreign experience variable for two reasons. First, similarly to Goldmann et al (2009; 2011), we find that foreign experience squared is irrelevant in most specifications: its magnitude is zero and it is (strongly) statistically insignificant. Second, the squared term interactions with match variables and language scores are highly correlated with other variables.

6.2 Specification 2

The variables for immigrants' English and French language abilities are added in Specification 2:

$$lnWages_{it} = \alpha_t + \beta_{1t}Exp_{it}^{For} + \beta_{2t}School_{it}^{For} + \\ +\beta_{3\ t}^{Eng}Eng_{it} + \beta_{3\ t}^{Fre}Fre_{it} + \gamma_t X_{it} + e_{it} \tag{6.2}$$

where Eng_{it} and Fre_{it} are language scores for immigrant i in wave t, normalized to vary between 0 and 1. These scores capture effects of immigrant's language ability on his/her wages as literature on immigrant economic assimilation suggests that knowledge of official languages is important determinant of immigrant assimilation in a host-country (Ferrer et al., 2008). See section 6.1 for the description of other parameters.

6.3 Specification 3

Specification 3 expands the previous model by adding factor match dummy variables.

$$lnWages_{it} = \alpha_t + \beta_{1t}Exp_{it}^{For} + \beta_{2t}School_{it}^{For} +$$

$$+\beta_3^{Eng}{}_t Eng_{it} + \beta_3^{Fre}{}_t Fre_{it} + \beta_4^j{}_t mF_{it}^j + \gamma_t X_{it} + e_{it} \tag{6.3}$$

where a dummy variable $mF_{it_{it}}^j$ equals to 1 if the i^{th} immigrant in t^{th} wave matched pre- and post-immigration j^{th} skill factor, where $j \epsilon [1;3]$ for "intelligence", "motor skills" and "strength" respectively; and equals to zero otherwise (see section 5.3 for a definition of match). The role of these match variables is to capture the differences in intercept of immigrants' earnings function compared to baseline intercept for earnings of immigrants who do not match any of these factors. See section 6.1 and 6.2 for the description of other parameters.

6.4 Specification 4

Specification 4 builds on the previous model by introduction of interaction terms between match variables and foreign human capital variables as well as match variables and language scores.

$$lnWages_{it} = \alpha_t + \beta_{1t}Exp_{it}^{For} + \beta_{2t}School_{it}^{For} +$$

$$+\beta_3^{Eng}{}_{it} Eng_{it} + \beta_3^{Fre}{}_{it} Fre_{it} + \beta_4^j{}_{it} mF_{it}^j +$$

$$+\beta_{5k_t}^j mF_{it}^j (Exp_{it}^{For} + School_{it}^{For} + Eng_{it} + Fre_{it}) + \gamma_t X_{it} + e_{it} \tag{6.4}$$

where $k \in [1;4]$ for each interaction of the j^{th} ($j \epsilon [1;3]$) factor match variable and foreign experience, foreign schooling, English score and French score. For instance, for $k = 1$ (for foreign experience variable) and $j = 1$ (for "intelligence" factor match dummy) the interaction coefficient is $\beta_{51_{it}}^1$. This coefficient shows the return to foreign experience for immigrant i in wave t who matched his pre- and post-immigration "intelligence" factor. Hence, interacting match variables with foreign human capital variables as well as with language scores is introduced to capture log wage returns to this variables for immigrants who match their pre- and post-immigration factors (each separately) in addition to baseline returns to foreign human capital and language ability for immigrants who do not match any of their factors. See section 6.1-6.3 for the description of other parameters.

6.5 Specification 5

In addition to variables of the previous model interactions of language scores and foreign human capital variables are included in Specification 5.

$$
\begin{gathered}
lnWages_{it} = \alpha_t + \beta_{1t} Exp_{it}^{For} + \beta_{2t} School_{it}^{For} + \\
+ \beta_{3\ t}^{Eng} Eng_{it} + \beta_{3\ t}^{Fre} Fre_{it} + \beta_{4\ t}^{j} mF_{it}^{j} + \\
+ \beta_{5k_t}^{j} mF_{it}^{j} (Exp_{it}^{For} + School_{it}^{For} + Eng_{it} + Fre_{it}) + \\
+ \beta_{6m_t} Eng (Exp_{it}^{For} + School_{it}^{For}) + \\
+ \beta_{7m_t} Fre (Exp_{it}^{For} + School_{it}^{For}) + \gamma_t X_{it} + e_{it}
\end{gathered}
\tag{6.5}
$$

where $m \in [1;2]$ for foreign experience and foreign schooling variables respectively. The interaction of language scores and foreign human capital variables are included to capture effects of language ability of the i^{th} immigrant in wave t on his/her returns to foreign experience and foreign schooling. Regarding that literature finds knowledge of official languages to have a large impact on labour market outcomes (Ferrer et al., 2008), this interaction variables show if English and/or French proficiency can mediate the transferability of immigrant foreign human capital into Canadian labour market. See section 6.1-6.4 for description of other parameters.

6.6 Specification 6

Finally, Specification 6 also includes three-term interactions of match dummy variables, language scores and foreign human capital variables in addition to the variables introduced in previous models.

$$\begin{gathered}
lnWages_{it} = \alpha_t + \beta_{1t}Exp_{it}^{For} + \beta_{2t}School_{it}^{For} + \\
+\beta_{3t}^{Eng}Eng_{it} + \beta_{3t}^{Fre}Fre_{it} + \beta_{4\,t}^{j}mF_{it}^{j} + \\
+\beta_{5k_t}^{j}mF_{it}^{j}(Exp_{it}^{For} + School_{it}^{For} + Eng_{it} + Fre_{it}) + \\
+\beta_{6m_t}Eng_{it}(Exp_{it}^{For} + School_{it}^{For}) + \\
+\beta_{7m_t}Fre_{it}(Exp_{it}^{For} + School_{it}^{For}) \\
\beta_{8m_t}^{j}mF^{j} \times Eng_{it} \times (Exp_{it}^{For} + School_{it}^{For}) + \\
\beta_{9m_t}^{j}mF^{j} \times Fre_{it} \times (Exp_{it}^{For} + School_{it}^{For}) + \gamma_t X_{it} + e_{it}
\end{gathered} \tag{6.6}$$

where $m \in [1;2]$ for foreign experience and foreign schooling variables respectively. The three-term interactions are assumed to capture whether English or French language ability of the i^{th} immigrant in wave t who match a pre- and post-immigration j^{th} skill factor in wave t, where $j \epsilon [1;3]$ for "intelligence", "motor skills" and "strength" respectively. See section 6.1-6.5 for description of other parameters.

6.7 Error term

The error term, e_{it}, is a deviation of the dependent variable, $lnWages_{it}$, from its mean value given all explanatory variables. It is important for the error term to be independently identically distributed with zero mean and finite variance in order for Ordinary Least Squares (OLS) to be best linear unbiased estimator (BLUE).

Another important assumption is that the error term has to be uncorrelated with explanatory variables. It is plausible that the error term in our analysis contains immigrants' unobserved characteristics, e.g. motivation. Usually longitudinal data are suitable for controlling individual unobserved characteristics, which are assumed to be constant over time. However, individual fixed effects are perfectly collinear with foreign experience and foreign schooling variables, which are also constant over time after immigration; while Hausman test rejects random effects.

6.8 Multicollinearity

When working with dichotomous variables in regressions and their interactions with other variables, it is likely that some of these variables will be near perfectly correlated. The first step is to detect the source of collinearity. This can be done by investigation of correlation matrices of independent variables. However, in case of larger sets of variables and higher number of model specifications investigating correlation matrices can be not the best choice. In this research, we use variance inflation factors (VIF's) in order to determine effects of correlation on estimation of standard errors. Under conditions of high collinearity of variables standard errors are magnified and the corresponding estimated coefficients are often insignificant. When collinearity is too high it may not only cause false inferences on significance of coefficients, but also flip signs of collinear coefficients. A common rule of thumb is that the VIF's should not exceed 10 (Kutner et al., 2004).

When original regressions were run, the VIF's suggested high multicollinearity. The remedies for multicollinearity include: (i) obtaining more data; (ii) dropping some of collinear variables; (iii) grouping dummy variables; (iv) centering or demeaning of collinear variables. We first dropped age variable as it is highly collinear to foreign experience variable, which is in fact a linear transformation of age variable. However, other variables, such as foreign experience, foreign schooling, English and French scores, could not be dropped from the regression analysis as they are of a great interest in this research. Therefore, we employ the centering[14] method.

The method of centering data (i.e. Kromney et al, 1998) consists of subtracting its own mean from a collinear variable before its transformation (i.e. obtaining a square or a cube) or its interaction with a dummy variable. This procedure minimizes the multicollinearity as transformed or interacted centered variables are then not correlated with initially collinear variables, but still are highly correlated with their corresponding original (non-centered) variables. Echambadi and Hess (2007) suggest that mean-centering data does not remove collinearity itself; however, it may be employed for interpretive purposes.

We employed centering over several stages. First, we center foreign experience, schooling and language scores for the two-term interactions. Then, for the three-term interactions, their previous two-term interactions are also centered. For instance, in order to reduce collinearity between Exp^{For} variable and a two-term interaction $Exp^{For} * mF^{j}$, the foreign experience is centered before interacting it with a skill match variable. Hence, the corresponding regressions will include Exp^{For} and $centered(Exp^{For}) * mF^{j}$. Furthermore, in order to treat collinearity between the two-term interaction $centered(Exp^{For}) * mF^{j}$ and the three-term interactions $centered(Eng) * centered(Exp^{For}) * mF^{j}$, the mean of the two-term interaction is subtracted from it just before interacting it with a skill match variable. As a result, the following variables will

[14] Also called "demeaning"

be included in corresponding regressions: Exp^{For}, $centered(Exp^{For}) * mF^{j}$, and $centered(centered(Eng) * centered(Exp^{For})) * mF^{j}$.

CHAPTER 7

REGRESSION RESULTS

In this chapter we present and discuss regression results of log wage equations for different specifications for both genders. We start with cross-sectional analysis and then follow with detailed analysis of immigrant sub-samples of wave 3. The cross-sectional analysis is done for the full sample of each wave. The analysis for wave 3 is expanded for five pairs of sub-samples, sometimes endogenous: (i) Skilled Worker principal applicants versus other immigration classes; (ii) regulated occupations versus unregulated; (iii) professional occupations versus non-professional; (iv) university educated immigrants versus other education levels; (v) visible minorities versus not visible minorities.

7.1 Cross-sectional analysis

This section mainly discusses results from regression specifications (1) and (4). The discussion includes the returns to foreign human capital as well as direct and indirect effects of matching pre- and post-immigration skill factors on immigrant entry earnings. We leave the results for other variables and regression specifications (2), (3), (5) and (6) in Appendix B1 and B2. Section 7.1.1 discusses the log wage returns to foreign experience and section 7.1.2 discusses the results for the log wage returns to foreign schooling; direct effect of matching skills are discussed in section 7.1.3; and a discussion of results' sensitivity to the inclusion of additional controls (i.e. specifications (5) and (6)) can be found in section 7.1.4.

7.1.1 Returns to foreign experience

The baseline return to foreign experience for males is negligible in all waves (Table 7-1-1-1). In fact, the coefficient is slightly negative and significant across waves regardless of regression specification. The coefficients on the returns to foreign experience conditional on any type of skill-match differ across waves. The return to foreign experience for male immigrants who match their pre- and post-immigration "intelligence" factor is positive, but insignificant in wave 1 and 2. In wave 3, the return to foreign work experience interacted with the "intelligence"-match dummy becomes statistically significant at the 10% level. Its magnitude, however, is very moderate. The total effect of baseline foreign experience and foreign experience conditional on matching the "intelligence" factor still suggests ($-0.013 + 0.011 = -0.002$) zero return to foreign work experience. Neither matching the "motor skills" nor the "strength" factor is beneficial for male immigrant returns to foreign experience in any of the waves. Interestingly, even the negative and significant coefficient on the return to foreign experience conditional on "motor skills" factor match (specification (4), wave 1 in Table 7-1-1-1) is not helpful in explaining the negative return to the baseline foreign work experience.

Similarly to males, the baseline return to foreign experience for females is negligible regardless of regression specification and wave (Table 7-1-1-2), but is slightly smaller in magnitude. Only female immigrants who match their pre- and post-immigration "strength" factor in wave 2 receive a fairly substantial and statistically significant return to years of experience acquired abroad, which allows them to overcome the negative effect of baseline foreign experience ($-0.009 + 0.043 = 0.034$). However, this advantage disappears completely in wave 3. The return to foreign experience for females who match pre- and post-immigration "intelligence" factor is initially positive and insignificant in wave 1, then it is twice smaller in wave 2 and insignificant, and

Table 7-1-1-1. Cross-sectional log wage returns to foreign experience, males

	Wave 1		Wave 2		Wave 3	
	(1)	(4)	(1)	(4)	(1)	(4)
Experience	-0.011**	-0.007*	-0.012**	-0.011**	-0.012**	-0.013**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Experience × "Intelligence" match		0.016		0.008		0.011+
		(0.011)		(0.007)		(0.005)
Experience × "Motor skills" match		-0.030**		-0.004		0.005
		(0.009)		(0.006)		(0.005)
Experience × "Strength" match		0.007		0.009		0.004
		(0.008)		(0.006)		(0.005)
School	+	+	+	+	+	+
Language scores		+		+		+
Match dummies		+		+		+
Match dummies × school		+		+		+
Match dummies × language scores		+		+		+
R^2	0.24	0.43	0.23	0.36	0.17	0.26
N-weighted	10,244	10,244	22,291	22,291	42,122	42,122

Note: All samples restricted to age-at-immigration between 25 and 59. Experience and School stand for years of foreign experience and schooling. Match dummies (e.g. "Intelligence" match) equal to 1 if there is a match and zero otherwise. All regressions control for months since immigration (msm), immigration category (Family (default); Skilled Workers principal applicants (PA's); Skilled Workers not PA's; Business/Nominees/Refugees/Others); birth region (US/Western Europe/ UK/ Other Northern Europe/ Oceania (default); Central & South America/Caribbean & Bermuda; Eastern Europe; Southern Europe; Africa; West Central Asia & Middle East; Eastern Asia; Southeastern Asia; Southern Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in a household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. **-significant and 1%; *-significant at 5%; +-significant at 10%.

Table 7-1-1-2. Cross-sectional log wage returns to foreign experience, females

	Wave 1		Wave 2		Wave 3	
	(1)	(4)	(1)	(4)	(1)	(4)
Experience	-0.007	-0.001	-0.007+	-0.009*	-0.010**	-0.007*
	(0.005)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
Experience × "Intelligence" match		0.025		0.013		0.000
		(0.024)		(0.015)		(0.008)
Experience × "Motor skills" match		-0.039		-0.032		0.012
		(0.029)		(0.021)		(0.009)
Experience × "Strength" match		-0.008		0.043+		0.000
		(0.025)		(0.022)		(0.006)
School	+	+	+	+	+	+
Language scores		+		+		+
Match dummies		+		+		+
Match dummies × school		+		+		+
Match dummies × language scores		+		+		+
R^2	0.26	0.51	0.15	0.30	0.11	0.22
N-weighted	5,045	5,045	14,920	14,920	30,237	30,237

See notes for Table 7-1-1-1.

disappears in wave 3 completely. The sign of the coefficient on the interaction of foreign experience and "motor skills" factor match is negative in wave 1 and 2, but not significant; then it becomes positive in wave 3, but is still small and remains insignificant.

7.1.2 Returns to foreign schooling

The baseline return to foreign schooling is mostly negligible and insignificant for male immigrants across waves (Table 7-1-2-1). While Canadian studies in the literature on immigration usually find a substantial return to foreign schooling for males, in our analysis even in the standard model (specification (1) in each wave, Table 7-1-2-1) the return is negligible in all waves and is only statistically significant at the 10% level in wave 3. Goldmann et al. (2009, 2011) use the same data (LSIC) and also find a very moderate return to foreign schooling. Goldmann et al. (2009) suggest that studies that use other data (e.g. Census) do not have a direct measure of foreign schooling; that is, potential years of foreign schooling in those studies may contain some years of schooling received in Canada prior to immigrating to Canada.

From Table 7-1-2-1, male immigrants who match their pre- and post-immigration "intelligence" factor on average receive a positive return to foreign schooling, but the return is only significant in wave 2 and only at the 10% level. The return to foreign schooling for "motor skills" male matchers is initially negative and insignificant in wave 1, then it grows in wave 2, but still is insignificant, and becomes significant at the 1% level in wave 3. The return to foreign schooling for male immigrants who match their pre- and post-immigration "strength" factor is statistically insignificant across waves; moreover, its coefficient drops in wave 2 and becomes slightly negative in wave 3. Note,

Table 7-1-2-1. Cross-sectional log wage returns to foreign schooling, males

	Wave 1		Wave 2		Wave 3	
	(1)	(4)	(1)	(4)	(1)	(4)
Schooling	0.016	0.013	0.008	-0.003	0.008+	0.000
	(0.010)	(0.013)	(0.006)	(0.008)	(0.005)	(0.006)
Schooling × "Intelligence" match		0.009		0.028+		0.009
		(0.025)		(0.015)		(0.012)
Schooling × "Motor skills" match		-0.016		0.014		0.030**
		(0.025)		(0.016)		(0.011)
Schooling × "Strength" match		0.019		0.006		-0.014
		(0.026)		(0.016)		(0.012)
Experience	+	+	+	+	+	+
Language scores		+		+		+
Match dummies		+		+		+
Match dummies × experience		+		+		+
Match dummies × language scores		+		+		+
R^2	0.24	0.43	0.23	0.36	0.17	0.26
N-weighted	10,244	10,244	22,291	22,291	42,122	42,122

See notes for Table 7-1-1-1.

Table 7-1-2-2. Cross-sectional log wage returns to foreign schooling, females

	Wave 1		Wave 2		Wave 3	
	(1)	(4)	(1)	(4)	(1)	(4)
Schooling	0.048*	0.009	0.037**	0.002	0.019*	0.002
	(0.021)	(0.021)	(0.014)	(0.012)	(0.009)	(0.011)
Schooling × "Intelligence" match		0.122		0.035		-0.023
		(0.077)		(0.039)		(0.025)
Schooling × "Motor skills" match		-0.063		0.030		0.059*
		(0.082)		(0.040)		(0.025)
Schooling × "Strength" match		-0.049		0.029		-0.004
		(0.079)		(0.064)		(0.023)
Experience	+	+	+	+	+	+
Language scores		+		+		+
Match dummies		+		+		+
Match dummies × experience		+		+		+
Match dummies × language scores		+		+		+
R^2	0.26	0.51	0.15	0.30	0.11	0.22
N-weighted	5,045	5,045	14,920	14,920	30,237	30,237

See notes for Table 7-1-1-1.

the magnitude of the baseline return to foreign schooling for males in wave 2 and 3 first decreases with the inclusion of language scores (specification (2), Appendix B1) and then decreases again with the inclusion of the two-term interactions of match variables and foreign human capital variables (specification (4), Table 7-1-2-1 or Appendix B1).

Surprisingly, for females the baseline return to foreign schooling is bigger than for males in the standard model waves (specification (1)) and is statistically significant in all, but its coefficient decreases towards wave 3 (Table 7-1-2-2). Goldmann et al. (2009) also find an advantage in the returns to foreign schooling for women. Unlike male immigrants, for females the coefficient is sensitive to the inclusion of skill-match dummies in each wave (specification (3), Appendix B2). It drops almost twice and becomes insignificant once the match variables are included and then drops even more and is insignificant once interactions of match variables and human capital are included (specification (4), Table 7-1-2-2 or Appendix B2). The return to foreign schooling for female immigrants who are able to match their pre- and post-immigration "intelligence" factor is insignificant in all waves and specifications; moreover its coefficient is initially positive in wave 1, but drops in wave 2 and becomes negative in wave 3. In contrast, the coefficient on the interaction of foreign schooling and "motor skills" match is initially negative and insignificant in wave 1; then it turns positive, but is still insignificant in wave 2, and finally becomes substantially positive and significant at the 5% level in wave 3. The return to foreign schooling for "strength" matchers is never statistically significant. Its coefficient is initially negative in wave 1, then becomes positive in wave 2, but drops again in wave 3.

7.1.3 Direct effect of skill-match

Male immigrants who match their pre- and post-immigration “intelligence” or “motor skills” factor receive substantially higher earnings than those who do not obtain any match (Table 7-1-3-1). The effect of matching “strength” factor is smaller and usually is statistically insignificant.

Matching “intelligence” or “motor skills” factor usually has a large and statistically significant effect on earnings for females (Table 7-1-3-1); the effect is also bigger for females than for males, especially in wave 2. Also, in wave 3 females who are able to match their “strength” factor receive higher earnings than those who do not match any skill, but the effect is around three times smaller than matching the other two skill factors.

7.1.4 Controlling for higher order interactions

In the specification (5) we also include interactions of language scores and foreign experience and interactions of language scores and foreign schooling; and in the specification (6) we add the three-term interactions of match variables, language scores and foreign human capital variables. The cross-sectional regression results for the specifications (5) and (6) are presented in Appendix B1 and B2. The corresponding VIF’s for cross-sectional regressions are provided in Appendix C1 and C2. Usually the VIF’s for these specifications are higher than for the specifications (1) through (4). In the specification (6) many of the VIF’s for both males and females in wave 1 are higher than the threshold of 10. Therefore, we must be careful when interpreting the results as the standard errors of the regression coefficients that have high VIF’s are magnified.

The results for males are presented in Appendix B1. For males, the inclusion of

Table 7-1-3-1. Direct effect of skill-match on earnings, males

	Wave 1	Wave 2	Wave 3
	(4)	(4)	(4)
"Intelligence" match	0.235**	0.139*	0.241**
	(0.078)	(0.055)	(0.040)
"Motor skills" match	0.260**	0.246**	0.262**
	(0.064)	(0.044)	(0.031)
"Strength" match	0.052	0.046	0.032
	(0.094)	(0.051)	(0.038)
Experience and School (HC)	+	+	+
Language scores	+	+	+
Match dummies	+	+	+
Match dummies × HC	+	+	+
Match dummies × language scores	+	+	+
R^2	0.43	0.36	0.26
N-weighted	10,244	22,291	42,122

See notes for Table 7-1-1-1.

Table 7-1-3-2. Direct effect of skill-match on earnings, females

	Wave 1	Wave 2	Wave 3
	(4)	(4)	(4)
"Intelligence" match	0.563**	0.211+	0.349**
	(0.162)	(0.117)	(0.062)
"Motor skills" match	0.111	0.502**	0.388**
	(0.208)	(0.103)	(0.056)
"Strength" match	-0.032	0.055	0.123+
	(0.201)	(0.167)	(0.072)
Experience and School (HC)	+	+	+
Language scores	+	+	+
Match dummies	+	+	+
Match dummies × HC	+	+	+
Match dummies × language scores	+	+	+
R^2	0.51	0.30	0.22
N-weighted	5,045	14,920	30,237

See notes for Table 7-1-1-1.

additional interactions in the specifications (5) and (6) affects neither the baseline return to foreign experience nor the baseline return to foreign schooling. The returns to foreign experience and foreign schooling conditional on skill-match variables are more sensitive to the inclusion of the new interactions. The coefficient on the interaction of foreign experience and "intelligence" match in wave 3 becomes insignificant in the specification (6); and the coefficient on the interaction of foreign schooling and "intelligence" match in wave 2 becomes insignificant in the specifications (5) and (6). Other interaction coefficients of foreign schooling or foreign experience with match variables can change in magnitude but their significance does not change. It is also worth noting that in wave 1 and 3 in the specification (5) and (6) male immigrants receive a substantial positive and statistically significant return to foreign schooling with higher proficiency in English. While male immigrants who are able to match their pre- and post-immigration "intelligence" factor also receive a substantial positive and statistically significant return to foreign schooling with higher proficiency in French.

The results for females are presented in Appendix B2. Similarly to males, the inclusion of additional interactions in the specifications (5) and (6) does not affect either the females' baseline return to foreign experience or the baseline return to foreign schooling. Most of the effects of interactions between the skill-match variables and foreign human capital variables remain unchanged. In wave 2, the coefficient on the interaction of foreign experience and the "strength" match variables becomes smaller and statistically not significant in wave 2. We do not find any statistically significant coefficients among additional interaction terms in specifications (5) and (6) for females.

7.1.5 Months since immigration effect

The cross-sectional regression results for the months since immigration variable are presented in Appendix B1 and B2. Interestingly, for males, the effect of months since migration is positive, but not statistically significant across all specifications in wave 1. In wave 2 and wave 3, it drops to zero and is statistically not significant. In contrast, for females, the coefficient for months since migration is negative in wave 1 and wave 2, but statistically insignificant. In wave 3, however, the coefficient becomes positive and statistically significant across all specifications. For females in wave 3, the effect of months since migration is also economically significant and suggests about 4.6% to 5.2% increase in weekly wages with each additional month lived in Canada after immigration. This implies that in a year and a half after immigration earnings for females almost double.

7.2 Returns to foreign experience of sub-samples

We expand our analysis and present regression results for sub-samples within wave 3. We focus our discussion on the returns to foreign experience while full tables with results from log wage regressions are provided in Appendix B3 to B12. The sample of wave 3 has the most observations and the most reliable coefficients regarding the corresponding VIF's (Appendix C3 to C12). Also Aydemir and Robinson (2008) find that new immigrants are most likely to leave in their first year (80% of all immigrants who leave within first five years), therefore wave 3 is also the most representative and informative of immigrant population that is more likely to stay in Canada. We subdivide the sample of immigrants of each gender in wave 3 into five main sub-samples and compare them with the corresponding rest of immigrants. These sub-samples are: (i)

Skilled Worker principal applicants (PA's) versus other immigration classes; (ii) regulated versus unregulated occupations; (iii) professional versus non-professional occupations; (iv) university educated immigrants versus other education levels; (v) visible minorities versus non-visible minorities.

7.2.1 Skilled Worker PA's vs. other immigration categories

Both male sub-samples, Skilled Worker principal applicants and other immigration categories, receive a negative and statistically significant return to foreign experience (Table 7-2-1-A). However the return to foreign experience for male Skilled Worker principal applicants who matched their pre- and post-immigration "intelligence" or "strength" factor is positive and statistically significant. The total effect from general foreign experience and foreign experience conditional on either "intelligence" factor match $(-0.017 + 0.016 = -0.001)$ or "strength" factor match $(-0.017 + 0.023 = 0.006)$ is still negligible for male Skilled Worker principal applicants. Immigrants from other immigration categories who match their pre- and post-immigration "motor skills" factor receive a positive and significant return to foreign work experience, however this return only covers the negative baseline effect $(-0.013 + 0.016 = 0.003)$, and together they result into zero return. Interestingly, while the inclusion of language scores (specification (2), Appendix B3) and skill-match variables (specification (3), Appendix B3) slightly reduces the baseline return to foreign experience in magnitude for male Skilled Worker principal applicants, the inclusion of interactions between foreign work experience and match variables (specification (4), Table 7-2-1-A or Appendix B3) increases the magnitude of this return again.

Table 7-2-1-A. Return to foreign experience for Skilled Worker principal applicants vs. Other immigration categories, males, wave 3

	Skilled Worker principal applicants		Other immigration categories	
	(1)	(4)	(1)	(4)
Experience	-0.015***	-0.017***	-0.014***	-0.013***
	(0.003)	(0.004)	(0.002)	(0.002)
Experience × “Intelligence” match		0.016**		-0.001
		(0.007)		(0.010)
Experience × “Motor skills” match		0.002		0.016**
		(0.006)		(0.008)
Experience × “Strength” match		0.023**		-0.008
		(0.009)		(0.006)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.10	0.22	0.20	0.29
N-weighted	28,387	28,387	13,735	13,735

Note: All samples restricted to age-at-immigration between 25 and 59. Experience and School stand for years of foreign experience and schooling. Match dummies (e.g. “Intelligence” match) equal to 1 if there is a match and zero otherwise. All regressions control for months since immigration (msm), birth region (US/Western Europe/ UK/ Other Northern Europe/ Oceania (default); Central & South America/Caribbean & Bermuda; Eastern Europe; Southern Europe; Africa; West Central Asia & Middle East; Eastern Asia; Southeastern Asia; Southern Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in a household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets.***-significant and 1%; **-significant at 5%; *-significant at 10%.

Table 7-2-1-B. Return to foreign experience for Skilled Worker principal applicants vs. Other immigration categories, females, wave 3

	Skilled Worker principal applicants		Other immigration categories	
	(1)	(4)	(1)	(4)
Experience	-0.010*	-0.011*	-0.011***	-0.006**
	(0.006)	(0.007)	(0.003)	(0.003)
Experience × "Intelligence" match		0.014		-0.007
		(0.013)		(0.011)
Experience × "Motor skills" match		-0.007		0.020*
		(0.019)		(0.012)
Experience × "Strength" match		-0.023		-0.005
		(0.062)		(0.006)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.09	0.31	0.09	0.18
N-weighted	8,235	8,235	22,002	22,002

See notes for Table 7-2-1-A.

Similarly, both female sub-samples (Skilled Worker principal applicants and other immigration categories) receive a negative and mostly statistically significant return to foreign work experience (Table 7-2-1-B). Unlike males, female Skilled Worker principal applicants do not receive any statistically significant return to foreign work experience conditional on any type of skill-match. Although, females from other immigration categories who match their pre- and post-immigration "motor skills" receive positive and statistically significant return to experience acquired abroad. The total effect of the baseline return and the return conditional on matching "motor skills" is quite moderate ($-0.006 + 0.020 = 0.014$), but it still suggests a positive influence on earnings.

Interestingly, in the most expanded specifications (i.e. (5) and (6)), we find that the return to foreign work experience interacted with French score is between 0.026 and 0.029 for male immigrants who immigrated through categories other than Skilled Worker principal applicants (Appendix B3). In these model specifications, the return to foreign experience for different types of skill-match are robust in magnitude, but sometimes become statistically insignificant. That is, in specification (6) for male Skilled Worker principal applicants the return to foreign experience lowers from 0.016 to 0.013 among "intelligence" matchers and becomes statistically insignificant.

7.2.2 Regulated versus unregulated occupations

The baseline return to foreign experience for both male immigrant sub-samples is negative and statistically significant across all waves and all specifications (Table 7-2-2-A). Male immigrants employed in regulated occupations who obtain a match in their pre- and post-immigration "intelligence" factor receive a positive and significant return to foreign work experience that slightly overcomes the baseline negative return. But the

Table 7-2-2-A. Return to foreign experience for Regulated vs. Unregulated occupations, males, wave 3

	Regulated occupations		Unregulated occupations	
	(1)	(4)	(1)	(4)
Experience	-0.010***	-0.013***	-0.015***	-0.012***
	(0.003)	(0.004)	(0.002)	(0.002)
Experience × "Intelligence" match		0.020***		-0.001
		(0.007)		(0.009)
Experience × "Motor skills" match		0.003		0.008
		(0.006)		(0.010)
Experience × "Strength" match		0.007		-0.001
		(0.007)		(0.007)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.13	0.21	0.23	0.37
N-weighted	23,739	23,739	18,383	18,383

Note: Immigrants 25 to 59 at the time of immigration. Experience and School stand for years of foreign experience and schooling. Match dummies (e.g. "Intelligence" match) equal to 1 if there is a match and zero otherwise. All regressions control for months since immigration (msm), immigration category (Family (default); Skilled Workers principal applicants (PA's); Skilled Workers not PA's; Business/Nominees/Refugees/Others); birth region (US/Western Europe/ UK/ Other Northern Europe/ Oceania (default); Central & South America/Caribbean & Bermuda; Eastern Europe; Southern Europe; Africa; West Central Asia & Middle East; Eastern Asia; Southeastern Asia; Southern Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in a household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant and 1%; **-significant at 5%; *-significant at 10%.

Table 7-2-2-B. Return to foreign experience for Regulated vs. Unregulated occupations, females, wave 3

	Regulated occupations		Unregulated occupations	
	(1)	(4)	(1)	(4)
Experience	-0.009**	-0.005	-0.010***	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Experience × “Intelligence” match		0.001		-0.008
		(0.013)		(0.011)
Experience × “Motor skills” match		0.016		0.005
		(0.014)		(0.016)
Experience × “Strength” match		-0.011		0.003
		(0.016)		(0.008)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.13	0.24	0.11	0.25
N-weighted	13,082	13,082	17,155	17,155

See notes for Table 7-2-2-A.

total effect is still close to zero.

Similarly, female immigrants from both sub-samples receive a slightly negative and usually significant return to general foreign experience (Table 7-2-2-B). Moreover, matching any of the skill factors does not help in transferring their foreign work experience to Canada either for immigrant women employed in regulated or in unregulated occupations.

In the most expanded specification (i.e. (6), Appendix B5) male immigrants employed in unregulated occupations who match their "strength" factor also receive a positive and significant return to foreign experience interacted with English score. This three-term interaction affects neither the baseline return to foreign experience nor returns to foreign experience conditional on any type of skill-match.

7.2.3 Professional versus non-professional occupations

Male immigrants employed in professional occupations in Canada receive zero return to their general foreign work experience, while male immigrants employed in non-professional occupations have a negative and statistically significant return (Table 7-2-3-A). Matching pre- and post-immigration skills do not help in transferability of foreign work experience for either male sub-sample.

In Table 7-2-3-B, the baseline return to foreign experience for female immigrants employed in professional occupations is slightly negative, but statistically insignificant in the standard model (i.e. (1)), and even when we control for language scores (specification (2), Appendix B8) and add skill-match variables (specification (3), Appendix B8). However, when we add the interaction terms between foreign experience and skill-match variables (specification (4), Table 7-2-3-B) the return to foreign experience becomes

Table 7-2-3-A. Returns to foreign experience for Professional vs. Non-professional occupations, males, wave 3

	Professional occupations		Non-professional occupations	
	(1)	(4)	(1)	(4)
Experience	0.000	-0.003	-0.012***	-0.012***
	(0.005)	(0.009)	(0.002)	(0.002)
Experience × "Intelligence" match		-0.002		0.011
		(0.012)		(0.009)
Experience × "Motor skills" match		0.010		0.002
		(0.011)		(0.005)
Experience × "Strength" match		-0.049		0.003
		(0.320)		(0.005)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.11	0.19	0.17	0.24
N-weighted	9,329	9,329	32,794	32,794

See notes for Table 7-2-2-A.

Table 7-2-3-B. Returns to foreign experience for Professional vs. Non-professional occupations, females, wave 3

	Professional occupations		Non-professional occupations	
	(1)	(4)	(1)	(4)
Experience	-0.013	-0.021*	-0.008***	-0.006*
	(0.008)	(0.011)	(0.003)	(0.003)
Experience × "Intelligence" match		0.023		-0.015
		(0.017)		(0.011)
Experience × "Motor skills" match		0.003		0.020
		(0.023)		(0.017)
Experience × "Strength" match		0.008		0.001
		(0.031)		(0.006)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.17	0.29	0.10	0.16
N-weighted	6,694	6,694	23,543	23,543

See notes for Table 7-2-2-A.

more negative and statistically significant at the 5% level. Interestingly, although none of the coefficients on the interactions of foreign experience and skill-match dummies is significant for females employed in professional occupations, the return to foreign work experience for immigrant women employed in professional occupations who match their pre- and post-immigration “intelligence” factor is positive and has approximately the same magnitude as the baseline coefficient. If the return to foreign experience for the “intelligence” factor for female matchers employed in professional occupations was significant[15] it would cover $(-0.021 + 0.023 \approx 0)$ the negative return to general foreign work experience. Moreover, it suggests that the baseline effect of foreign work experience on earnings is sensitive to the inclusion of the two-term interactions as its magnitude changes in specification (4) compared to previous specifications (Appendix B8). Interestingly, in the most expanded specification (i.e. (6), Appendix B8) the return to foreign experience interacted with French score for female immigrants in non-professional occupations who match their “intelligence” factor is negative and significant. However, it still does not help in explaining the negative baseline return to foreign work experience as well as it does not affect the returns to foreign experience interacted with match variables alone.

7.2.4 University degree versus other education levels

Both male immigrant sub-samples receive slightly negative and statistically significant return to general foreign work experience (Table 7-2-4-A). Although, male immigrants with university degrees who obtain a match in the “intelligence” factor receive a moderate positive and statistically significant return to experience acquired abroad. The total effect of general foreign experience and the interaction of foreign

[15] It is quite close to the significance level of 10%.

experience and "intelligence" match for immigrant men with university degree is still negligible ($-0.016 + 0.011 = -0.005$). The returns to foreign experience for immigrant men without university degrees who match any of the skill factors are not statistically significant. However, the effect of the foreign experience interacted with "intelligence" match is positive and fairly close to the significance region of 10%.

The baseline return to foreign experience for female immigrants with either type of education is slightly negative and mostly significant (Table 7-2-4-B). The return to general foreign work experience for immigrant women with a university degree slightly goes up and becomes statistically insignificant when we add the skill-match dummies (specification (3), Appendix B10) and also when we add their interactions with the foreign human capital variables (specification (4), Appendix B10). Immigrant women with a university degree who match their pre- and post-immigration "motor skills" factor obtain a positive and statistically significant return to pre-immigration work experience. Moreover, this return is big enough to overcome the negative baseline return. The total effect is moderate ($-0.007 + 0.026 \approx 0.020$), but still suggests that female immigrants with a university degree obtained prior to immigration who match their "motor skills" factor are able to transfer some portion of their foreign work experience after immigration to Canada. We do not find any benefits for the returns to foreign experience from matching any type of skill factors for female immigrants without a university degree.

In the most expended specification (i.e. (6)) we find that male immigrants with university education who match their "intelligence" skill factor receive a positive and

Table 7-2-4-A. Returns to foreign experience for University educated vs. Other education levels, males, wave 3

	University educated		Other education levels	
	(1)	(4)	(1)	(4)
Experience	-0.015***	-0.016***	-0.009***	-0.009***
	(0.003)	(0.003)	(0.002)	(0.003)
Experience × “Intelligence” match		0.011*		0.020
		(0.006)		(0.013)
Experience × “Motor skills” match		0.008		0.008
		(0.006)		(0.009)
Experience × “Strength” match		0.014		-0.005
		(0.012)		(0.005)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.12	0.23	0.28	0.33
N-weighted	30,341	30,341	11,781	11,781

See notes for Table 7-2-2-A.

Table 7-2-4-B. Returns to foreign experience for University educated vs. Other education levels, females, wave 3

	University educated		Other education levels	
	(1)	(4)	(1)	(4)
Experience	-0.012***	-0.007	-0.009***	-0.007*
	(0.004)	(0.004)	(0.003)	(0.004)
Experience × "Intelligence" match		0.002		-0.027
		(0.009)		(0.052)
Experience × "Motor skills" match		0.026*		0.001
		(0.015)		(0.016)
Experience × "Strength" match		-0.007		-0.001
		(0.016)		(0.007)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.09	0.21	0.12	0.19
N-weighted	19,943	19,943	10,294	10,294

See notes for Table 7-2-2-A.

statistically significant return to foreign experience interacted with French score (Appendix B9). From the same specification for females with university education who match their “motor skills” the return to foreign experience interacted with French score is negative and significant (Appendix B10). However, this three-term interaction does not affect the baseline return to foreign experience. Moreover, in the specification (6) the effect of matching “motor skills” on the return to foreign experience alone becomes smaller and insignificant compared to the specifications (4) and (5) (Appendix B10).

7.2.5 Visible minorities versus non-visible minorities

Both visible-minority and non-visible minority male and female immigrants receive a negligible return to general foreign work experience (Table 7-2-5-A and Table 7-2-5-B). However, while the baseline return to foreign experience for male/female visible minorities is negative and significant, for immigrants who are not visible minorities it is closer to zero and is statistically insignificant. Neither of the male/female sub-samples receives any additional return to foreign work experience conditional on skill-match.

From the most expanded specification (i.e. (6)) we also find that visible minority female immigrants receive a positive and significant return to foreign work experience interacted with French score (Appendix 12). This two-term interaction does not affect other coefficients for this sub-sample discussed earlier in the sub-section.

7.2.6 Other possible sub-samples

From the descriptive statistics for males (Table 5-2-1) and females (Table 5-2-2) in section 5.2 it can be noticed that source countries sorting into

Table 7-2-5-A. Returns to foreign experience for Visible minorities vs. Non-visible minorities, males, wave 3

	Visible minorities		Non-visible minorities	
	(1)	(4)	(1)	(4)
Experience	-0.014***	-0.015***	-0.004	-0.004
	(0.002)	(0.002)	(0.004)	(0.005)
Experience × “Intelligence” match		0.008		0.010
		(0.006)		(0.009)
Experience × “Motor skills” match		0.009		-0.004
		(0.006)		(0.008)
Experience × “Strength” match		0.005		0.005
		(0.006)		(0.011)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.13	0.23	0.16	0.32
N-weighted	33,377	33,377	8,705	8,705

Note: All samples restricted to age-at-immigration between 25 and 59. Experience and School stand for years of foreign experience and schooling. Match dummies (e.g. “Intelligence” match) equal to 1 if there is a match and zero otherwise. All regressions control for months since immigration (msm), immigration category (Family (default); Skilled Workers principal applicants (PA’s); Skilled Workers not PA’s; Business/Nominees/Refugees/Others); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in a household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant and 1%; **-significant at 5%; *-significant at 10%.

Table 7-2-5-B. Returns to foreign experience for Visible minorities vs. Non-visible minorities, females, wave 3

	Visible minorities		Non-visible minorities	
	(1)	(4)	(1)	(4)
Experience	-0.010***	-0.009***	-0.008	-0.007
	(0.003)	(0.003)	(0.006)	(0.007)
Experience × "Intelligence" match		0.000		0.006
		(0.010)		(0.019)
Experience × "Motor skills" match		0.012		0.014
		(0.013)		(0.022)
Experience × "Strength" match		0.000		0.010
		(0.007)		(0.030)
School	+	+	+	+
Language scores		+		+
Match dummies		+		+
Match dummies × school		+		+
Match dummies × language scores		+		+
R^2	0.09	0.24	0.12	0.19
N-weighted	23,239	23,239	6,981	6,981

See notes for Table 7-2-5-A.

non-visible minorities are the US, the UK, Australia, New Zealand and the like (so called "traditional" source-countries). We also ran regressions for regions within the "non-traditional" region and found that results were broadly similar to those of visible minority sub-sample. Splitting the regions into countries produced unreliable coefficients regarding high VIF's for many variables of interest, which suggested high collinearity. Similarly, splitting the samples by Census Metropolitan Areas (CMA's) produced unreliable coefficients regarding high VIF's. A sub-sample that only includes immigrants living in large CMA's or a sub-sample that excludes immigrants living in Quebec produces results broadly similar to those of the full sample.

7.2.7 Months since immigration

The returns to months since immigration can be useful in understanding differences in assimilation processes of immigrant sub-samples in Canada. Interestingly, the returns to months since immigration for males are usually weaker than for males across all sub-samples and all specifications. For instance, the returns to months since immigration are not statistically significant for either male Skilled Worker principal applicants or for males from other immigration categories (Appendix 3). However, the returns are statistically significant for females from other immigration categories and are between 4% and 4.6% across specifications, while the returns to months since immigration for females from other immigration categories are only statistically significant in the standard model (specification (1)) (Appendix 4).

Similarly, the return to months since immigration for both males employed either in regulated or unregulated occupations are not statistically significant (Appendix 5);

whereas, female immigrants employed in regulated occupations in wave 3 receive between 7.3% and 8% marginal return (Appendix 6).

Both males employed in professional and males employed in non-professional occupations receive statistically insignificant returns to months since immigration (Appendix 7). For females, the returns are sensitive to the inclusion of skill match dichotomous variables (Appendix 8). Thus, in specifications (1) and (2) our data suggest that females immigrants employed in professional occupations receive around 10% marginal return, while the magnitude is three times smaller and statistically insignificant for females employed in non-professional occupations. In specifications (3) though (6), the magnitudes are similar for these two female sub-samples, but the significance disappears for professionals and the coefficients become statistically significant to non-professionals.

The returns to months since immigration are not statistically significant for male immigrants both with and without a university degree (Appendix 9). In contrast, both female sub-samples receive substantial and statistically significant returns to months since immigration across all specifications (Appendix 10). The returns range between 4% and 5.2% for females with a university degree and between 6% and 6.9% for females without university degree.

The sub-division into visible minorities and not visible minorities provides some interesting insight in assimilation differences (Appendix 11). The data suggest that only males who are not visible minorities receive substantial and statistically highly significant return to months since immigration that ranges between 7.5% and 9.9% across specifications. In contrast, only female immigrants who are visible minorities receive 6% to 7.1% marginal return to months since immigration (Appendix 12).

CHAPTER 8

CONCLUSION

Using longitudinal survey data on immigrants in Canada for 2001-2005 years and data on occupational characteristics from the Career Handbook, we construct occupational skill factors and explore direct and indirect effects of pre- and post-immigration skill matching on immigrant earnings. We focus on how successful matching of immigrant pre- and post-immigration “intelligence”, “motors skills” or “strength” factor affects immigrant log wage returns to foreign experience.

Consistently with the previous literature we find that the return to foreign work experience for recent immigrants is negligible. In fact, our data suggest that it is mostly slightly negative. The exception is the (endogenous) sub-sample of male immigrants employed in professional occupations and the sub-sample of males who are not visible minorities. For them, the return to foreign experience is zero return, instead of being negative.

Although immigrants receive some moderate returns to foreign experience when matching their pre- and post-immigration skill factors, the total effect with the baseline return to foreign experience is still negligible. First we employ a cross-sectional analysis and then follow with an analysis of sub-samples in wave 3. In the cross-sectional analysis we find that male immigrants who match their “intelligence” factor receive significant, but moderate return to foreign experience. For them, the return to foreign experience conditional on “intelligence” factor match of 1.1% still does not completely compensate the negative baseline return to foreign experience of -1.4%. We also find that in wave 1 males who match their “motor skills” factor receive substantially negative return to foreign experience of -3%. However, even substantially negative return to “motor skills”-specific foreign experience does not explain negative baseline return to foreign experience 0f -0.7%. Females who match their “strength” factor in wave 2 also receive a substantial positive return to foreign experience; moreover, it overcomes the baseline return, although the effect is lost in wave 3.

We find that males receive negligible baseline return to foreign schooling. Moreover, the return to foreign schooling for males is only statistically significant in the standard model in wave 3. Goldmann et al. (2009) also find a negligible return to foreign schooling for male immigrants; they suggest that the LSIC, unlike other data sets used in most other studies on immigrants, allows sorting out immigrants who had ever received any of their schooling in Canada prior to immigrating to Canada. Similarly to Goldmann et al. (2009), we find that the return to foreign schooling in the standard model is bigger for females. Interestingly, it decreases over time. However, in more expanded models, the return to foreign schooling for females becomes smaller and eventually statistically insignificant with the inclusion of language scores, skill-match variables as well as the interactions of skill-matches and foreign human capital variables. Goldmann et al. (2009) also find that the return to foreign schooling for females is sensitive to language scores, occupational match dummies and their interactions with foreign human capital variables.

We find evidence that males who match “intelligence” factor in wave 2 and males who match “motor skills” factor in wave 3 receive significant positive return to foreign schooling of around 3%. Female immigrants who match “motor skills” factor in wave 3 also receive substantial positive return to foreign schooling.

We then proceed to the analysis of sub-samples in wave 3. For many male and female sub-samples we find significant positive, but mostly moderate, returns to foreign experience conditional on matching different skills. We find a significant positive return to potential foreign work experience for “intelligence” factor matchers within the sub-sample of males who immigrated through Skilled Worker principal applicant category (0.016), the sub-sample of males who are employed in regulated occupations (0.020) and the sub-sample of males who received university education prior to immigrating (0.011). We also find a moderate return to foreign work experience for both male and female “motor skills” matchers who immigrated through categories other than Skilled Worker principal applicant (0.016 and 0.020 respectively), and university educated females (0.026). In the case of the third skill factor, only the sub-sample of male Skilled Worker principal applicants who match their “strength” factor receives a significant positive, but moderate, return to foreign experience (0.023). Notably, most of the returns to foreign experience conditional on skill-match together with (slightly negative) baseline return to foreign work experience result in zero total return. The only exception is the sub-sample of university educated females. For them, the total effect from baseline return and the return to foreign work experience conditional on matching their “motor skills” is around 2%.

It can be concluded that controlling for foreign experience conditional on skill matching does not help in explaining poor transferability of general foreign experience of recent immigrants in Canada. Moreover, in most cases, even a moderate positive return to foreign experience conditional on matching different skills together with the baseline return to foreign experience result in zero total effect.

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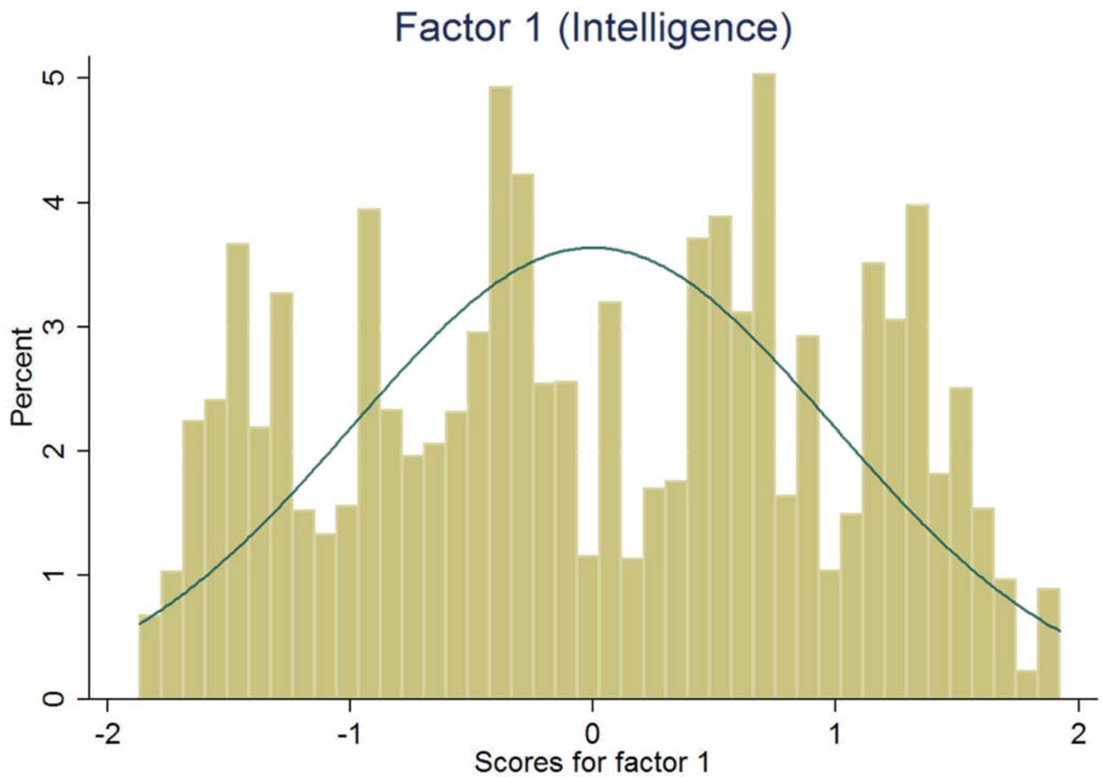
Appendix A1. Average LFS employment, November, 2004 to November, 2005

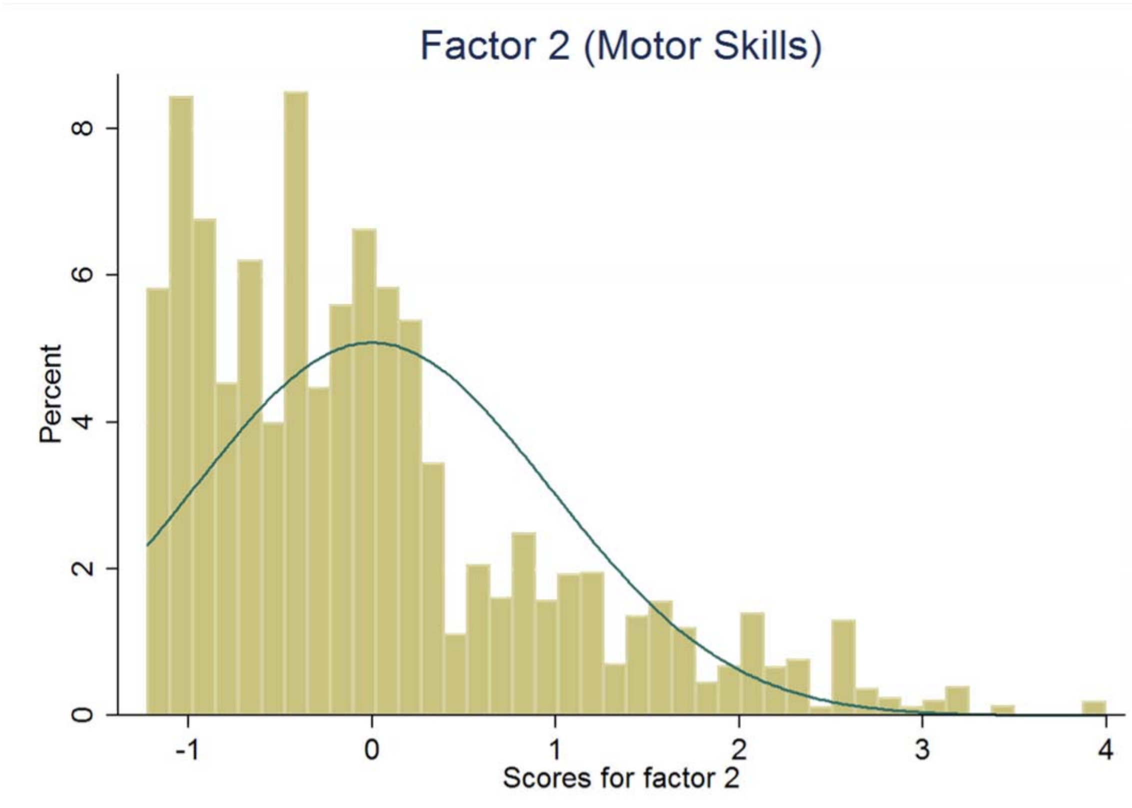
NOC group (3-digit grouping)	Total	Males	Females	Ratio
Senior management occupations	91.82	70.23	21.59	3.25
Other management occupations	1352.12	857.77	494.35	1.74
Professional occupations in business and finance	474.22	224.99	249.22	0.90
Financial, secretarial and administrative occupations	796.08	129.37	666.71	0.19
Clerical occupations, including supervisors	1611.83	464.90	1146.93	0.41
Natural and applied sciences and related occupations	1097.65	869.62	228.02	3.81
Professional occupations in health, nurse supervisors and registered nurses	448.21	98.18	350.03	0.28
Technical, assisting and related occupations in health	500.50	77.52	422.98	0.18
Occupations in social science, government service and religion	692.71	201.55	491.15	0.41
Teachers and professors	633.45	222.11	411.34	0.54
Occupations in art, culture, recreation and sport	490.32	227.46	262.85	0.87
Wholesale, technical, insurance, real estate sales specialists, and retail, wholesale and grain buyers	526.19	343.22	182.98	1.88
Retail salespersons, sales clerks, cashiers, including retail trade supervisors	1027.62	322.45	705.17	0.46
Chefs and cooks, and occupations in food and beverage service, including supervisors	501.41	190.01	311.40	0.61
Occupation in protective services	227.07	182.25	44.82	4.07

Childcare and home support workers	189.19	15.48	173.72	0.09
Sales and service occupations not elsewhere classified, including occupations in travel and accommodation, attendants in recreation and sport as well as supervisors	1377.93	623.30	754.63	0.83
Contractors and supervisors in trades and transportation	245.35	232.72	12.64	18.41
Construction trades	340.15	327.18	12.97	25.23
Other trades occupations	885.86	836.39	49.47	16.91
Transport and equipment operators	590.10	545.66	44.44	12.28
Trades helpers, construction, and transportation laborers and related occupations	330.11	290.85	39.26	7.41
Occupations unique to primary industry	572.84	458.58	114.26	4.01
Machine operators and assemblers in manufacturing, including supervisors	885.63	632.63	253.00	2.50
Laborers in processing, manufacturing and utilities	209.40	129.22	80.18	1.61
Total	16097.74	8573.63	7524.11	1.14

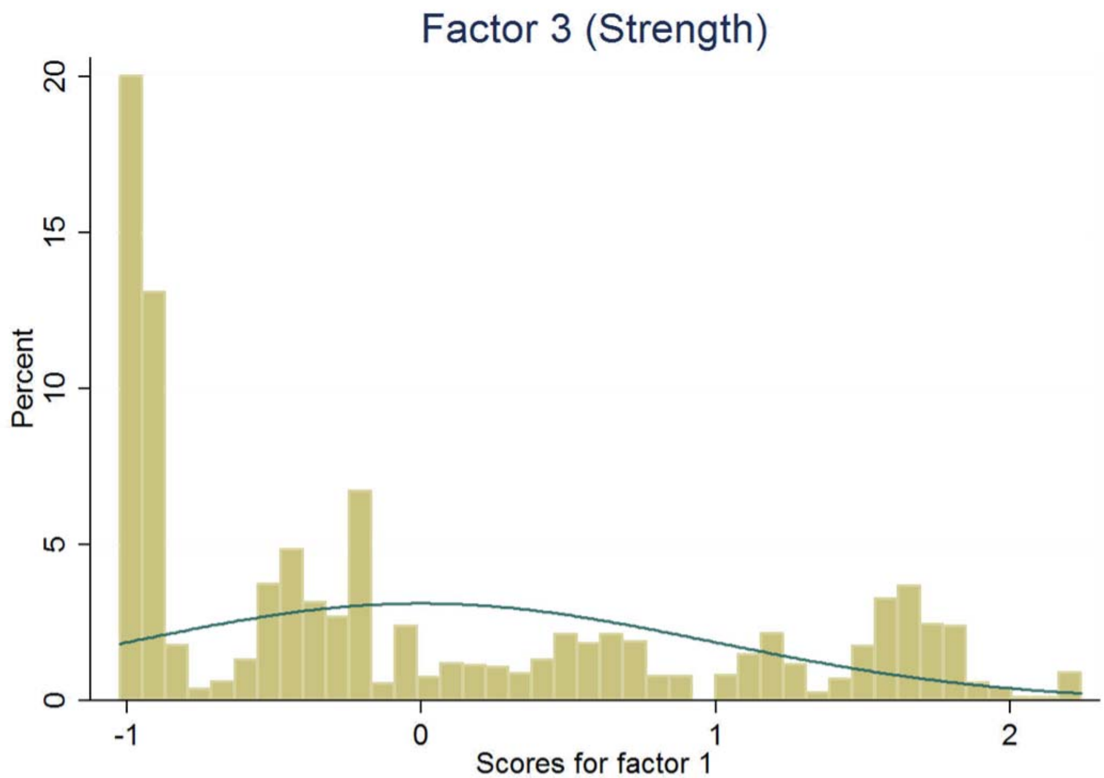
Appendix A2. Distribution of scores for "Intelligence" factor



Appendix A3. Distribution of scores for "Motor Skills" factor



Appendix A4. Distribution of scores for "Strength" factor



Appendix A5. Cross-sectional means of variables

	Males			Females		
	Wave 1	Wave 2	Wave 3	Wave 1	Wave 2	Wave 3
<u>Dependent variable</u>						
Log weekly wages	6.35 (0.030)	6.38 (0.019)	6.44 (0.014)	6.00 (0.043)	6.01 (0.030)	6.04 (0.019)
<u>Independent variables</u>						
Experience	14.62 (0.401)	14.51 (0.254)	14.27 (0.155)	13.52 (0.548)	13.88 (0.299)	13.54 (0.184)
School years	15.55 (0.154)	15.57 (0.097)	15.77 (0.065)	15.34 (0.220)	15.28 (0.125)	15.26 (0.077)
English	0.79 (0.012)	0.76 (0.007)	0.75 (0.005)	0.79 (0.016)	0.73 (0.010)	0.71 (0.007)
French	0.11 (0.013)	0.13 (0.009)	0.16 (0.006)	0.11 (0.017)	0.13 (0.011)	0.14 (0.007)
“Intelligence” match = 1 (mF1)	0.26	0.22	0.21	0.16	0.16	0.16
“Motor skills” match = 1 (mF2)	0.27	0.21	0.21	0.15	0.12	0.10
“Strength” match = 1 (mF3)	0.13	0.13	0.11	0.12	0.10	0.09
<u>Other key characteristics</u>						
Age	36.17 (0.344)	37.73 (0.219)	39.58 (0.135)	34.87 (0.509)	36.82 (0.266)	38.32 (0.162)
Months since landing	6.91 (0.051)	19.68 (0.040)	22.91 (0.022)	6.79 (0.076)	19.84 (0.050)	22.84 (0.026)

Married/common law = 1	0.85	0.88	0.90	0.80	0.89	0.90
Children18	0.90 (0.048)	0.96 (0.032)	1.06 (0.023)	0.79 (0.068)	0.90 (0.034)	1.05 (0.025)
"Traditional" origin = 1	0.19	0.18	0.17	0.25	0.23	0.20
Eastern Canada = 1	0.75	0.72	0.73	0.78	0.74	0.74
N-weighted	10,244	22,290	42,122	5,045	14,920	30,237

Note: All continuous variables have bootstrap standard errors in brackets.

Appendix A6. Means of variables by sub-samples of wave 3, males

	Full sample	**Skilled Worker PA's**		**Regulated**		**Professional**		**University educated**		**Visible minority**	
		1	0	1	0	1	0	1	0	1	0
Log weekly wages	6.44 (0.014)	6.54 (0.017)	6.25 (0.020)	6.50 (0.019)	6.36 (0.019)	6.76 (0.032)	6.35 (0.015)	6.51 (0.017)	6.27 (0.020)	6.39 (0.015)	6.65 (0.026)
Age	39.58 (0.135)	38.75 (0.135)	41.30 (0.306)	39.22 (0.193)	40.05 (0.247)	37.29 (0.262)	40.23 (0.169)	39.07 (0.157)	40.91 (0.340)	39.59 (0.156)	39.56 (0.310)
Experience	14.27 (0.155)	12.58 (0.142)	17.77 (0.348)	13.72 (0.216)	14.98 (0.285)	10.72 (0.276)	15.27 (0.191)	12.65 (0.160)	18.42 (0.389)	14.44 (0.180)	13.59 (0.330)
Schooling	15.77 (0.065)	16.63 (0.066)	13.99 (0.132)	15.95 (0.083)	15.54 (0.111)	17.02 (0.126)	15.42 (0.075)	16.86 (0.061)	12.98 (0.123)	15.60 (0.075)	16.44 (0.143)
Months since landing	22.91 (0.022)	22.93 (0.028)	22.88 (0.036)	22.89 (0.029)	22.95 (0.032)	22.91 (0.045)	22.92 (0.024)	22.90 (0.026)	22.94 (0.037)	22.91 (0.025)	22.93 (0.041)
English score	0.75 (0.005)	0.78 (0.005)	0.68 (0.011)	0.76 (0.007)	0.73 (0.009)	0.79 (0.010)	0.73 (0.006)	0.77 (0.006)	0.68 (0.012)	0.76 (0.006)	0.71 (0.010)
French score	0.16 (0.006)	0.17 (0.008)	0.12 (0.010)	0.17 (0.009)	0.14 (0.010)	0.18 (0.016)	0.15 (0.007)	0.15 (0.008)	0.17 (0.014)	0.12 (0.007)	0.30 (0.019)
mF1 = 1	0.21	0.27	0.11	0.24	0.19	0.70	0.08	0.27	0.06	0.21	0.24
mF2 = 1	0.21	0.25	0.11	0.27	0.12	0.45	0.14	0.24	0.13	0.19	0.28
mF3 = 1	0.11	0.07	0.19	0.11	0.11	.	0.13	0.04	0.27	0.10	0.11
Skilled Worker PA's = 1	0.67	1	0	0.72	0.62	0.85	0.62	0.82	0.30	0.66	0.71
Regulated = 1	0.56	0.6	0.49	1	0	0.64	0.54	0.59	0.50	0.54	0.66
Professional = 1	0.22	0.28	0.10	0.25	0.18	1	0	0.29	0.04	0.22	0.23

University = 1	0.72	0.87	0.40	0.75	0.68	0.94	0.66	1	0	0.72	0.71
Visible minority = 1	0.79	0.78	0.82	0.76	0.84	0.79	0.8	0.80	0.79	1	0
“Traditional” origin = 1	0.17	0.17	0.16	0.20	0.13	0.18	0.17	0.17	0.18	0.01	0.78
Eastern Canada = 1	0.73	0.80	0.60	0.74	0.73	0.76	0.73	0.77	0.65	0.73	0.76
Married/common law = 1	0.90	0.91	0.90	0.91	0.90	0.91	0.90	0.92	0.86	0.91	0.90
Children18	1.06 (0.023)	1.11 (0.029)	0.96 (0.037)	1.09 (0.030)	1.03 (0.035)	1.00 (0.045)	1.08 (0.027)	1.09 (0.027)	0.99 (0.043)	1.09 (0.027)	0.95 (0.043)
pre-imm. F1 score	0.70 (0.020)	0.92 (0.022)	0.24 (0.038)	0.74 (0.026)	0.65 (0.032)	1.1 (0.032)	0.59 (0.024)	0.98 (0.019)	-0.01 (0.040)	0.70 (0.023)	0.69 (0.039)
pre-imm. F2 score	0.70 (0.027)	0.88 (0.032)	0.34 (0.045)	0.80 (0.035)	0.58 (0.040)	0.88 (0.051)	0.65 (0.031)	0.82 (0.032)	0.41 (0.047)	0.68 (0.031)	0.78 (0.052)
pre-imm. F3 score	-0.18 (0.019)	-0.29 (0.021)	0.05 (0.036)	-0.17 (0.025)	-0.19 (0.028)	-0.41 (0.026)	-0.11 (0.022)	-0.36 (0.018)	0.29 (0.043)	-0.19 (0.021)	-0.13 (0.039)
post-imm. F1 score	-0.10 (0.026)	0.16 (0.031)	-0.62 (0.037)	0.06 (0.032)	-0.3 (0.040)	1.25 (0.016)	-0.48 (0.024)	0.15 (0.030)	-0.72 (0.036)	-0.16 (0.030)	0.16 (0.047)
post-imm. F2 score	0.42 (0.025)	0.56 (0.032)	0.14 (0.036)	0.78 (0.037)	-0.05 (0.028)	1.00 (0.049)	0.26 (0.027)	0.49 (0.031)	0.24 (0.039)	0.38 (0.029)	0.58 (0.050)
post-imm. F3 score	0.39 (0.025)	0.20 (0.030)	0.77 (0.037)	0.39 (0.030)	0.39 (0.040)	-0.46 (0.020)	0.63 (0.028)	0.20 (0.029)	0.88 (0.040)	0.44 (0.028)	0.19 (0.045)
N-weighted	42,122	28,387	13,735	23,739	18,383	9,329	32,794	30,341	11,781	33,377	8,705

Appendix A7. Means of variables by sub-samples of wave 3, females

	Full sample	Skilled Worker PA's		Regulated		Professional		University educated		Visible minority	
		1	0	1	0	1	0	1	0	1	0
Log weekly wages	6.04 (0.019)	6.26 (0.037)	5.96 (0.022)	6.08 (0.032)	6.02 (0.023)	6.33 (0.05)	5.96 (0.019)	6.15 (0.026)	5.84 (0.025)	6.02 (0.021)	6.14 (0.039)
Age	38.32 (0.162)	38.17 (0.3)	38.38 (0.201)	38.10 (0.272)	38.49 (0.233)	37.32 (0.35)	38.6 (0.198)	37.85 (0.202)	39.24 (0.337)	38.16 (0.188)	38.85 (0.354)
Experience	13.54 (0.184)	12.51 (0.321)	13.92 (0.228)	13.07 (0.293)	13.89 (0.266)	11.32 (0.345)	14.17 (0.226)	11.93 (0.205)	16.65 (0.379)	13.55 (0.216)	13.49 (0.378)
Schooling	15.26 (0.077)	16.18 (0.137)	14.92 (0.089)	15.51 (0.102)	15.07 (0.11)	16.49 (0.147)	14.91 (0.086)	16.4 (0.075)	13.07 (0.115)	15.09 (0.081)	15.84 (0.186)
Months since landing	22.84 (0.026)	22.91 (0.051)	22.81 (0.03)	22.83 (0.04)	22.85 (0.033)	22.9 (0.057)	22.82 (0.029)	22.87 (0.033)	22.79 (0.043)	22.83 (0.03)	22.89 (0.05)
English score	0.71 (0.007)	0.78 (0.011)	0.69 (0.008)	0.72 (0.01)	0.71 (0.009)	0.75 (0.013)	0.70 (0.008)	0.76 (0.007)	0.62 (0.013)	0.71 (0.008)	0.71 (0.012)
French score	0.14 (0.007)	0.18 (0.017)	0.12 (0.008)	0.14 (0.013)	0.13 (0.009)	0.20 (0.02)	0.12 (0.008)	0.12 (0.009)	0.16 (0.014)	0.10 (0.008)	0.25 (0.02)
mF1 = 1	0.16	0.25	0.12	0.23	0.10	0.53	0.05	0.23	0.03	0.15	0.18
mF2 = 1	0.10	0.14	0.08	0.16	0.05	0.27	0.05	0.12	0.06	0.09	0.12
mF3 = 1	0.09	0.05	0.10	0.08	0.09	0.08	0.09	0.06	0.15	0.1	0.06
Skilled Worker PA's = 1	0.27	1	0	0.26	0.28	0.37	0.24	0.35	0.12	0.27	0.29
Regulated = 1	0.43	0.41	0.44	1	0	0.75	0.34	0.45	0.39	0.42	0.47
Professional = 1	0.22	0.30	0.19	0.38	0.1	1	0	0.28	0.10	0.21	0.26

University = 1	0.66	0.85	0.59	0.69	0.63	0.85	0.61	1	0	0.66	0.65
Visible minority = 1	0.77	0.75	0.78	0.75	0.78	0.73	0.78	0.77	0.76	1	0
"Traditional" origin = 1	0.20	0.20	0.20	0.23	0.17	0.23	0.19	0.20	0.20	0.01	0.83
Eastern Canada = 1	0.74	0.73	0.74	0.74	0.73	0.75	0.73	0.77	0.68	0.73	0.75
Married/common law = 1	0.90	0.79	0.94	0.91	0.89	0.90	0.90	0.90	0.90	0.90	0.89
Children18	1.05	0.91	1.11	1.07	1.05	1.01	1.07	1.06	1.05	1.09	0.94
	(0.025)	(0.052)	(0.028)	(0.037)	(0.034)	(0.055)	(0.028)	(0.031)	(0.042)	(0.029)	(0.052)
pre-imm. F1 score	0.62	0.88	0.53	0.7	0.57	0.94	0.54	0.86	0.17	0.61	0.67
	(0.023)	(0.044)	(0.028)	(0.033)	(0.032)	(0.037)	(0.028)	(0.026)	(0.042)	(0.027)	(0.043)
pre-imm. F2 score	0.34	0.57	0.25	0.44	0.26	0.47	0.3	0.48	0.07	0.34	0.34
	(0.032)	(0.065)	(0.035)	(0.046)	(0.042)	(0.06)	(0.037)	(0.041)	(0.045)	(0.036)	(0.062)
pre-imm. F3 score	-0.29	-0.37	-0.25	-0.29	-0.28	-0.39	-0.26	-0.41	-0.05	-0.28	-0.32
	(0.019)	(0.031)	(0.024)	(0.03)	(0.025)	(0.039)	(0.022)	(0.022)	(0.036)	(0.022)	(0.036)
post-imm. F1 score	-0.23	0.13	-0.37	0.03	-0.44	0.86	-0.54	-0.01	-0.66	-0.29	-0.04
	(0.027)	(0.053)	(0.03)	(0.04)	(0.035)	(0.04)	(0.025)	(0.035)	(0.035)	(0.031)	(0.051)
post-imm. F2 score	0	0.17	-0.06	0.31	-0.24	0.33	-0.09	0.11	-0.21	0.01	-0.03
	(0.026)	(0.058)	(0.03)	(0.048)	(0.025)	(0.059)	(0.029)	(0.035)	(0.036)	(0.032)	(0.05)
post-imm. F3 score	0.19	-0.04	0.28	0.11	0.25	-0.3	0.33	0.07	0.43	0.24	0.02
	(0.025)	(0.047)	(0.029)	(0.033)	(0.036)	(0.042)	(0.029)	(0.031)	(0.039)	(0.029)	(0.043)
N-weighted	30,237	8,235	22,002	13,082	17,155	6,694	23,543	19,943	10,294	23,239	6,981

Appendix B1. Cross-sectional results from log wage regressions, males

	Wave 1						Wave 2						Wave 3					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.011**	-0.010**	-0.007*	-0.007*	-0.007*	-0.008*	-0.012**	-0.010**	-0.008**	-0.011**	-0.011**	-0.011**	-0.012**	-0.011**	-0.010**	-0.013**	-0.014**	-0.014**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
School	0.016	0.009	0.011	0.013	0.014	0.013	0.008	0.002	0.002	-0.003	-0.002	-0.002	0.008+	0.004	0.005	0	0.001	0.002
	(0.010)	(0.010)	(0.009)	(0.013)	(0.014)	(0.015)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
msm	0.027	0.032	0.037	0.033	0.035	0.038	-0.007	-0.009	-0.001	-0.002	-0.002	-0.003	0.002	0.001	0	0.001	0	0
	(0.030)	(0.029)	(0.025)	(0.025)	(0.024)	(0.024)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.014)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Eng		0.450**	0.318**	0.242	0.363*	0.397*		0.359**	0.276**	0.178+	0.252*	0.263*		0.307**	0.217**	0.181*	0.237**	0.240**
		(0.126)	(0.113)	(0.155)	(0.177)	(0.189)		(0.080)	(0.076)	(0.093)	(0.107)	(0.112)		(0.065)	(0.061)	(0.075)	(0.080)	(0.082)
Fre		0.182	0.24	0.277	0.324	0.331		-0.076	-0.032	-0.162	-0.139	-0.13		-0.108	-0.103	-0.14	-0.137	-0.141
		(0.202)	(0.202)	(0.264)	(0.273)	(0.293)		(0.103)	(0.097)	(0.100)	(0.102)	(0.102)		(0.079)	(0.075)	(0.087)	(0.088)	(0.090)
mF1			0.335**	0.235**	0.268**	0.141			0.272**	0.139*	0.152**	0.122			0.259**	0.241**	0.253**	0.265**
			(0.064)	(0.078)	(0.082)	(0.137)			(0.044)	(0.055)	(0.056)	(0.091)			(0.035)	(0.040)	(0.040)	(0.042)
mF2			0.309**	0.260**	0.260**	0.274**			0.275**	0.246**	0.255**	0.257**			0.260**	0.262**	0.268**	0.259**
			(0.062)	(0.064)	(0.065)	(0.077)			(0.039)	(0.044)	(0.045)	(0.058)			(0.031)	(0.031)	(0.031)	(0.032)
mF3			0.074	0.052	0.065	0.071			0.055	0.046	0.049	0.049			0.060+	0.032	0.046	0.055
			(0.060)	(0.094)	(0.095)	(0.654)			(0.042)	(0.051)	(0.052)	(0.056)			(0.034)	(0.038)	(0.038)	(0.040)
Exp×mF1				0.016	0.017	0.014				0.008	0.009	0.01				0.011+	0.010+	0.009
				(0.011)	(0.011)	(0.017)				(0.007)	(0.007)	(0.007)				(0.005)	(0.006)	(0.006)
Exp×mF2				-0.030**	-0.030**	-0.030**				-0.004	-0.003	-0.003				0.005	0.005	0.004
				(0.009)	(0.009)	(0.010)				(0.006)	(0.006)	(0.006)				(0.005)	(0.005)	(0.005)
Exp×mF3				0.007	0.008	0.006				0.009	0.008	0.007				0.004	0.004	0.007
				(0.008)	(0.008)	(0.118)				(0.006)	(0.006)	(0.010)				(0.005)	(0.005)	(0.005)
School×mF1				0.009	0	0.022				0.028+	0.025	0.034				0.009	0	-0.006
				(0.025)	(0.026)	(0.057)				(0.015)	(0.016)	(0.027)				(0.012)	(0.012)	(0.015)
School×mF2				-0.016	-0.018	-0.034				0.014	0.012	0.01				0.030**	0.029*	0.026*
				(0.025)	(0.029)	(0.033)				(0.016)	(0.016)	(0.020)				(0.011)	(0.011)	(0.012)
School×mF3				0.019	0.022	0.009				0.006	0.006	0.002				-0.014	-0.009	-0.003
				(0.026)	(0.026)	(0.270)				(0.016)	(0.016)	(0.023)				(0.012)	(0.011)	(0.013)
mF1×Eng				1.282**	1.075*	1.468*				1.115**	1.028**	1.111**				0.377+	0.3	0.245
				(0.394)	(0.422)	(0.577)				(0.225)	(0.233)	(0.329)				(0.194)	(0.195)	(0.199)
mF2×Eng				0.049	-0.05	0.011				0.187	0.11	0.101				-0.119	-0.18	-0.148
				(0.281)	(0.302)	(0.335)				(0.207)	(0.216)	(0.233)				(0.153)	(0.152)	(0.148)
mF3×Eng				-0.187	-0.016	0.1				-0.07	0.003	-0.136				0.069	0.212	0.135
				(0.237)	(0.226)	(0.308)				(0.169)	(0.174)	(0.231)				(0.134)	(0.132)	(0.169)
mF1×Fre				0.509+	0.487	0.759				0.384**	0.353*	0.359+				0.128	0.106	0.065
				(0.291)	(0.297)	(0.503)				(0.140)	(0.149)	(0.210)				(0.125)	(0.126)	(0.151)
mF2×Fre				-0.191	-0.157	-0.29				0.074	0.058	0.065				0.033	0.006	0.051

				(0.249)	(0.258)	(0.433)				(0.124)	(0.125)	(0.174)				(0.110)	(0.109)	(0.118)
mF3×Fre				-0.633	-0.586	-0.316				-0.028	-0.002	0.029				0.012	0.059	0.081
				(0.771)	(0.772)	(5.745)				(0.200)	(0.203)	(0.253)				(0.109)	(0.111)	(0.134)
Exp×Eng					0.002	0.012					-0.008	-0.005					0.007	0.002
					(0.012)	(0.015)					(0.008)	(0.009)					(0.006)	(0.007)
Exp×Fre					0.017	0.011					0.003	0.005					0	-0.008
					(0.017)	(0.024)					(0.008)	(0.009)					(0.009)	(0.012)
School×Eng					0.067+	0.100*					0.019	0.037					0.068**	0.054**
					(0.038)	(0.048)					(0.023)	(0.026)					(0.017)	(0.021)
School×Fre					0.034	0.008					0.013	0.012					0.019	0.002
					(0.041)	(0.061)					(0.019)	(0.024)					(0.016)	(0.019)
mF1×Exp×Eng						0.031						-0.008						0.012
						(0.082)						(0.035)						(0.029)
mF1×Exp×Fre						0.028						-0.013						0.024
						(0.076)						(0.027)						(0.021)
mF1×School×Eng						-0.158						-0.078						0.065
						(0.274)						(0.117)						(0.068)
mF1× School ×Fre						-0.099						-0.03						0.077+
						(0.211)						(0.056)						(0.043)
mF2×Exp×Eng						-0.015						-0.002						0.027
						(0.045)						(0.032)						(0.021)
mF2×Exp×Fre						-0.002						0.006						0.01
						(0.061)						(0.021)						(0.018)
mF2×School×Eng						-0.043						0.004						0.021
						(0.138)						(0.101)						(0.049)
mF2× School ×Fre						0.101						0.004						0
						(0.138)						(0.061)						(0.041)
mF3×Exp×Eng						-0.045						-0.009						0.008
						(0.030)						(0.023)						(0.016)
mF3×Exp×Fre						0.033						-0.013						0.026
						(1.050)						(0.064)						(0.020)
mF3×School×Eng						-0.101						-0.065						0.01
						(0.092)						(0.062)						(0.044)
mF3× School ×Fre						0.012						0.023						0.053
						(2.403)						(0.127)						(0.047)
R^2	0.24	0.26	0.39	0.43	0.44	0.45	0.23	0.24	0.33	0.36	0.36	0.36	0.17	0.18	0.25	0.26	0.27	0.27
N	10,244	10,244	10,244	10,244	10,244	10,244	22,291	22,291	22,291	22,291	22,291	22,291	42,122	42,122	42,122	42,122	42,122	42,122

Note: Immigrants' age is 25 to 59. mF1, mF2, mF3 indicates a match between pre- and post-immigration "intelligence", "motor skills" and "strength" factor respectively. All regressions control for months since immigration (msm). Additional controls: immigration category (Family (default); Skilled Workers principal applicants (PA's); Skilled Workers not PA's; Business/Nominees/Refugees/Others); birth region (US/Western Europe/ UK/ Other Northern Europe/ Oceania (default); Central & S America/Caribbean & Bermuda; E Europe; S Europe; Africa; W Central Asia & Middle East; E Asia; Southeastern Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. **-significant at 1%; *-significant at 5%; +-significant at 10%.

Appendix B2. Cross-sectional results from log wage regressions, females

	Wave 1						Wave 2						Wave 3					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.007	-0.006	-0.002	-0.001	-0.002	-0.001	-0.007+	-0.005	-0.004	-0.009*	-0.009*	-0.009*	-0.010**	-0.008**	-0.006*	-0.007*	-0.007*	-0.007*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
School	0.048*	0.044+	0.019	0.009	0.014	0.014	0.037**	0.031*	0.017	0.002	0.005	0.005	0.019*	0.013	0.006	0.002	0.004	0.004
	(0.021)	(0.023)	(0.017)	(0.021)	(0.023)	(0.025)	(0.014)	(0.014)	(0.012)	(0.012)	(0.013)	(0.013)	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)	(0.011)
msm	-0.042	-0.041	-0.045	-0.055	-0.052	-0.050	-0.020	-0.022	-0.022	-0.017	-0.018	-0.019	0.052**	0.050**	0.046**	0.048**	0.048**	0.047**
	(0.039)	(0.040)	(0.035)	(0.037)	(0.038)	(0.044)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.020)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
Eng		0.561*	0.420+	0.45	0.503	0.513		0.471**	0.417**	0.240+	0.286+	0.303*		0.453**	0.390**	0.337**	0.392**	0.380**
		(0.260)	(0.220)	(0.276)	(0.311)	(0.357)		(0.165)	(0.160)	(0.143)	(0.149)	(0.153)		(0.090)	(0.087)	(0.094)	(0.100)	(0.103)
Fre		-0.103	-0.12	-0.209	-0.17	-0.215		0.116	0.107	-0.116	-0.111	-0.073		0.167	0.166	0.151	0.155	0.135
		(0.255)	(0.206)	(0.278)	(0.297)	(0.338)		(0.203)	(0.193)	(0.182)	(0.184)	(0.186)		(0.121)	(0.115)	(0.127)	(0.125)	(0.126)
mF1			0.674**	0.563**	0.582**	0.613			0.334**	0.211+	0.217+	0.269			0.364**	0.349**	0.354**	0.407**
			(0.106)	(0.162)	(0.165)	(0.567)			(0.085)	(0.117)	(0.118)	(0.205)			(0.056)	(0.062)	(0.064)	(0.084)
mF2			0.269*	0.111	0.122	0.068			0.558**	0.502**	0.508**	0.389*			0.403**	0.388**	0.396**	0.399**
			(0.125)	(0.208)	(0.213)	(4.381)			(0.109)	(0.103)	(0.106)	(0.182)			(0.059)	(0.056)	(0.057)	(0.069)
mF3			-0.006	-0.032	-0.043	-0.004			0.056	0.055	0.048	-0.054			0.120+	0.123+	0.109	0.107
			(0.120)	(0.201)	(0.221)	(4.302)			(0.122)	(0.167)	(0.169)	(0.212)			(0.062)	(0.072)	(0.074)	(0.078)
Exp×mF1				0.025	0.03	0.039				0.013	0.013	0.018				0	-0.001	0.003
				(0.024)	(0.025)	(0.099)				(0.015)	(0.015)	(0.020)				(0.008)	(0.008)	(0.008)
Exp×mF2				-0.039	-0.038	-0.054				-0.032	-0.031	-0.044				0.012	0.015	0.012
				(0.029)	(0.030)	(0.774)				(0.021)	(0.021)	(0.034)				(0.009)	(0.010)	(0.011)
Exp×mF3				-0.008	-0.009	-0.008				0.043+	0.043+	0.027				0	-0.001	-0.002
				(0.025)	(0.027)	(0.506)				(0.022)	(0.023)	(0.027)				(0.006)	(0.006)	(0.007)
School×mF1				0.122	0.118	0.145				0.035	0.033	0.028				-0.023	-0.028	-0.031
				(0.077)	(0.079)	(0.378)				(0.039)	(0.039)	(0.048)				(0.025)	(0.027)	(0.032)
School×mF2				-0.063	-0.065	-0.083				0.03	0.023	0.038				0.059*	0.060*	0.053+
				(0.082)	(0.083)	(0.642)				(0.040)	(0.040)	(0.073)				(0.025)	(0.026)	(0.032)
School×mF3				-0.049	-0.061	0.033				0.029	0.033	0.006				-0.004	0	0.005
				(0.079)	(0.086)	(1.508)				(0.064)	(0.064)	(0.122)				(0.023)	(0.023)	(0.024)
mF1×Eng				0.328	0.262	0.294				1.157*	1.056*	0.897				0.434	0.356	0.197
				(0.812)	(0.843)	(1.592)				(0.520)	(0.519)	(0.788)				(0.285)	(0.287)	(0.347)
mF2×Eng				-0.209	-0.329	0.239				-1.186*	-1.166*	-1.220*				-0.207	-0.245	-0.34
				(1.025)	(1.047)	(1.994)				(0.514)	(0.507)	(0.568)				(0.241)	(0.243)	(0.269)
mF3×Eng				0.191	0.324	-0.386				1.044	1.094+	1.364				0.238	0.369	0.514
				(0.634)	(0.694)	(10.234)				(0.652)	(0.665)	(0.943)				(0.244)	(0.252)	(0.327)
mF1×Fre				0.489	0.578	-0.208				0.809**	0.819**	0.543				0.183	0.068	0.007
				(0.573)	(0.575)	(6.119)				(0.286)	(0.304)	(0.497)				(0.210)	(0.239)	(0.346)
mF2×Fre				-0.509	-0.388	-1.888				-0.51	-0.484	-0.638				-0.19	-0.193	-0.173

				(0.880)	(0.910)	(73.983)				(0.482)	(0.491)	(1.284)				(0.221)	(0.228)	(0.361)
mF3×Fre				-0.098	-0.053	-0.617				0.306	0.332	-1.196				0.034	0.061	0.098
				(1.056)	(1.202)	(22.481)				(0.733)	(0.762)	(1.513)				(0.266)	(0.272)	(0.337)
Exp×Eng					-0.015	-0.015					0.002	-0.009					-0.011	-0.003
					(0.025)	(0.030)					(0.013)	(0.012)					(0.007)	(0.009)
Exp×Fre					-0.006	0.004					0.001	-0.002					0.012	0.019
					(0.032)	(0.036)					(0.016)	(0.018)					(0.014)	(0.018)
School×Eng					-0.003	0.007					0.04	0.028					0.031	0.035
					(0.078)	(0.106)					(0.040)	(0.039)					(0.025)	(0.029)
School×Fre					-0.077	-0.045					-0.001	-0.009					0.067	0.081
					(0.073)	(0.088)					(0.051)	(0.056)					(0.047)	(0.058)
mF1×Exp×Eng						-0.076						0.008						-0.036
						(0.389)						(0.076)						(0.038)
mF1×Exp×Fre						-0.196						0.01						-0.023
						(0.655)						(0.048)						(0.031)
mF1×School×Eng						-0.314						0.136						0.086
						(1.191)						(0.331)						(0.159)
mF1× School ×Fre						-0.213						0.144						0.01
						(3.052)						(0.182)						(0.133)
mF2×Exp×Eng						0.096						0.077						-0.016
						(0.375)						(0.146)						(0.049)
mF2×Exp×Fre						-0.161						0.069						-0.064
						(6.668)						(0.144)						(0.040)
mF2×School×Eng						-0.056						-0.079						-0.114
						(1.306)						(0.198)						(0.095)
mF2× School ×Fre						0.006						0.11						-0.174
						(5.371)						(0.434)						(0.161)
mF3×Exp×Eng						0.022						0.065						-0.019
						(0.689)						(0.064)						(0.019)
mF3×Exp×Fre						0.117						-0.196						0.002
						(4.042)						(0.196)						(0.039)
mF3×School×Eng						0.001						0.185						0.028
						(2.674)						(0.186)						(0.061)
mF3× School ×Fre						1.094						-0.485						-0.029
						(10.419)						(0.828)						(0.108)
R^2	0.26	0.29	0.47	0.51	0.52	0.54	0.15	0.16	0.26	0.3	0.31	0.32	0.11	0.13	0.21	0.22	0.23	0.23
N	5,045	5,045	5,045	5,045	5,045	5,045	14,920	14,920	14,920	14,920	14,920	14,920	30,237	30,237	30,237	30,237	30,237	30,237

See notes for Appendix B1.

Appendix B3. Log wage regressions for Skilled Worker principal applicants vs. Other immigration categories, males, wave 3

	Skilled Worker principal applicants						**Other immigration categories**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.015***	-0.014***	-0.012***	-0.017***	-0.017***	-0.016***	-0.014***	-0.013***	-0.012***	-0.013***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
School	0.009	0.008	0.008	0	-0.005	-0.002	0.004	0	-0.002	-0.002	0.002	0.003
	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.011)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
msm	-0.001	-0.003	-0.010	-0.007	-0.008	-0.009	0.014	0.012	0.022	0.026	0.028	0.029
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)
Eng		0.498***	0.351***	0.296***	0.219*	0.241*		0.186**	0.122	0.122	0.216*	0.237*
		(0.102)	(0.096)	(0.113)	(0.124)	(0.124)		(0.092)	(0.089)	(0.111)	(0.127)	(0.126)
Fre		-0.039	-0.054	-0.071	-0.118	-0.122		-0.151	-0.154	-0.209	-0.193	-0.203
		(0.104)	(0.098)	(0.115)	(0.121)	(0.120)		(0.129)	(0.120)	(0.135)	(0.133)	(0.136)
mF1			0.203***	0.198***	0.213***	0.220***			0.421***	0.385***	0.382***	0.374***
			(0.040)	(0.053)	(0.053)	(0.075)			(0.067)	(0.073)	(0.072)	(0.075)
mF2			0.293***	0.303***	0.302***	0.295***			0.176***	0.212***	0.196***	0.219***
			(0.036)	(0.041)	(0.040)	(0.061)			(0.056)	(0.060)	(0.061)	(0.076)
mF3			0.001	0	-0.003	0.006			0.106**	0.052	0.103	0.117
			(0.048)	(0.054)	(0.053)	(0.077)			(0.046)	(0.068)	(0.070)	(0.088)
Exp×mF1				0.016**	0.016**	0.013				-0.001	-0.004	-0.008
				(0.007)	(0.007)	(0.010)				(0.010)	(0.010)	(0.013)
Exp×mF2				0.002	0.001	-0.001				0.016**	0.017**	0.015
				(0.006)	(0.006)	(0.008)				(0.008)	(0.008)	(0.010)
Exp×mF3				0.023**	0.024***	0.021*				-0.008	-0.006	-0.007
				(0.009)	(0.009)	(0.011)				(0.006)	(0.006)	(0.009)
School×mF1				0.014	0.004	-0.004				0.009	-0.004	-0.015
				(0.014)	(0.015)	(0.022)				(0.029)	(0.029)	(0.037)
School×mF2				0.019	0.022	0.017				0.036*	0.034*	0.032
				(0.015)	(0.015)	(0.019)				(0.019)	(0.018)	(0.025)
School×mF3				0.01	0.014	0.017				-0.026	-0.013	-0.009
				(0.022)	(0.022)	(0.028)				(0.017)	(0.016)	(0.026)
mF1×Eng				0.416	0.391	0.355				0.385	0.262	0.282
				(0.259)	(0.260)	(0.286)				(0.342)	(0.332)	(0.379)
mF2×Eng				-0.311	-0.334*	-0.295				-0.088	-0.076	-0.127
				(0.201)	(0.202)	(0.231)				(0.253)	(0.256)	(0.327)
mF3×Eng				0.375	0.479	0.365				-0.05	0.053	-0.037
				(0.297)	(0.300)	(0.331)				(0.155)	(0.157)	(0.240)
mF1×Fre				0.121	0.099	0.101				0.257	0.213	0.144
				(0.154)	(0.153)	(0.187)				(0.240)	(0.248)	(0.325)
mF2×Fre				-0.054	-0.082	0.02				0.089	0.018	0.102

				(0.131)	(0.129)	(0.150)				(0.239)	(0.239)	(0.445)
mF3×Fre				0.233	0.281	0.28				-0.156	-0.154	0.027
				(0.170)	(0.177)	(0.215)				(0.176)	(0.185)	(0.354)
Exp×Eng					0.008	-0.008					0.007	0.008
					(0.015)	(0.018)					(0.007)	(0.008)
Exp×Fre					-0.013	-0.027					0.026**	0.029**
					(0.013)	(0.017)					(0.011)	(0.013)
School×Eng					0.096**	0.051					0.064***	0.077***
					(0.040)	(0.056)					(0.021)	(0.024)
School×Fre					0.023	-0.003					0.023	0.013
					(0.023)	(0.028)					(0.027)	(0.031)
mF1×Exp×Eng						0.02						0.009
						(0.047)						(0.051)
mF1×Exp×Fre						0.018						0.015
						(0.028)						(0.046)
mF1×School×Eng						0.074						-0.067
						(0.105)						(0.162)
mF1×School×Fre						0.042						0.095
						(0.054)						(0.142)
mF2×Exp×Eng						0.041						0.036
						(0.040)						(0.037)
mF2×Exp×Fre						0.037						-0.056
						(0.025)						(0.072)
mF2×School×Eng						0.061						0
						(0.096)						(0.097)
mF2×School×Fre						0.047						-0.148
						(0.060)						(0.149)
mF3×Exp×Eng						0.031						-0.012
						(0.060)						(0.019)
mF3×Exp×Fre						0.035						0.009
						(0.039)						(0.052)
mF3×School×Eng						0.052						-0.048
						(0.142)						(0.054)
mF3×School×Fre						0.027						0.083
						(0.092)						(0.136)
R^2	0.10	0.12	0.20	0.22	0.22	0.23	0.20	0.21	0.28	0.29	0.31	0.31
N-weighted	28,387	28,387	28,387	28,387	28,387	28,387	13,735	13,735	13,735	13,735	13,735	13,735

Note: The sample is restricted to age between 25 and 59 at the time of immigration. mF1, mF2, mF3 indicates a match between pre- and post-immigration “intelligence”, “motor skills” and “strength” factor respectively. All regressions control for months since immigration (msm). Additional controls are:; birth region (US/W Europe/ UK/ Other N Europe/ Oceania (default); Central & South America/Caribbean & Bermuda; E Europe; S Europe; Africa; West central Asia & Middle East; E Asia; Southeastern Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant at 1%; **-significant at 5%; *-significant at 10%.

Appendix B4. Log wage regressions for Skilled Worker principal applicants vs. Other immigration categories, females, wave 3

	Skilled Worker principal applicants						**Other immigration categories**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.010*	-0.01	-0.006	-0.011*	-0.012	-0.012	-0.011***	-0.008***	-0.006**	-0.006**	-0.006*	-0.005
	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
School	0.021	0.018	0.003	-0.013	-0.014	-0.02	0.023**	0.011	0.008	0.01	0.015	0.015
	(0.024)	(0.024)	(0.020)	(0.024)	(0.030)	(0.031)	(0.009)	(0.009)	(0.009)	(0.011)	(0.012)	(0.012)
msm	0.078*	0.078*	0.050	0.045	0.047	0.044	0.040*	0.036	0.041*	0.045*	0.046**	0.044*
	(0.040)	(0.041)	(0.038)	(0.038)	(0.039)	(0.040)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)
Eng		0.483**	0.432*	0.485*	0.477*	0.470*		0.516***	0.448***	0.354***	0.417***	0.390***
		(0.240)	(0.223)	(0.254)	(0.262)	(0.270)		(0.096)	(0.093)	(0.102)	(0.111)	(0.114)
Fre		-0.058	-0.005	-0.017	-0.022	-0.053		0.396**	0.352**	0.286*	0.272*	0.27
		(0.183)	(0.179)	(0.183)	(0.187)	(0.192)		(0.159)	(0.154)	(0.172)	(0.164)	(0.168)
mF1			0.350***	0.418***	0.427***	0.268			0.346***	0.342***	0.364***	0.411***
			(0.065)	(0.092)	(0.097)	(0.173)			(0.080)	(0.089)	(0.089)	(0.115)
mF2			0.444***	0.287**	0.296**	0.369			0.382***	0.407***	0.416***	0.409***
			(0.080)	(0.124)	(0.127)	(0.784)			(0.083)	(0.079)	(0.080)	(0.100)
mF3			0.102	-0.675	-0.67	-2.343			0.108	0.116	0.105	0.109
			(0.202)	(1.410)	(1.415)	(27.655)			(0.068)	(0.080)	(0.083)	(0.087)
Exp×mF1				0.014	0.016	0.021				-0.007	-0.007	-0.003
				(0.013)	(0.014)	(0.016)				(0.011)	(0.011)	(0.012)
Exp×mF2				-0.007	-0.008	-0.011				0.020*	0.023*	0.018
				(0.019)	(0.019)	(0.134)				(0.012)	(0.012)	(0.015)
Exp×mF3				-0.023	-0.025	-0.005				-0.005	-0.005	-0.006
				(0.062)	(0.062)	(5.894)				(0.006)	(0.006)	(0.009)
School×mF1				-0.008	-0.005	0.077				-0.052*	-0.065**	-0.071*
				(0.062)	(0.061)	(0.071)				(0.030)	(0.031)	(0.040)
School×mF2				0.073	0.066	0.012				0.052	0.05	0.037
				(0.060)	(0.061)	(0.360)				(0.033)	(0.034)	(0.048)
School×mF3				-0.07	-0.075	0.807				-0.003	0.003	0.006
				(0.240)	(0.236)	(8.597)				(0.023)	(0.024)	(0.026)
mF1×Eng				-0.495	-0.535	-0.176				0.786**	0.663*	0.508
				(0.369)	(0.399)	(0.580)				(0.385)	(0.382)	(0.493)
mF2×Eng				0.008	0.019	0.009				-0.082	-0.1	-0.265
				(0.501)	(0.510)	(0.696)				(0.313)	(0.323)	(0.406)
mF3×Eng				3.81	3.795	5.641				0.125	0.281	0.457
				(4.924)	(4.907)	(63.865)				(0.248)	(0.256)	(0.344)
mF1×Fre				-0.143	-0.106	0.469				0.395	0.253	-0.089
				(0.254)	(0.269)	(0.500)				(0.295)	(0.333)	(0.792)
mF2×Fre				-0.127	-0.106	-0.773				0.079	0.138	-0.11

				(0.414)	(0.424)	(7.769)				(0.291)	(0.307)	(0.575)
mF3×Fre				2.376	2.408	5.469				-0.183	-0.153	-0.112
				(2.870)	(2.840)	(85.387)				(0.263)	(0.301)	(0.385)
Exp×Eng					0.008	0.016					-0.01	0
					(0.030)	(0.037)					(0.008)	(0.009)
Exp×Fre					-0.006	0					0.022	0.03
					(0.019)	(0.025)					(0.016)	(0.021)
School×Eng					0.018	0.051					0.04	0.042
					(0.111)	(0.132)					(0.026)	(0.031)
School×Fre					-0.032	0.009					0.104*	0.117
					(0.071)	(0.081)					(0.063)	(0.078)
mF1×Exp×Eng						-0.041						-0.059
						(0.082)						(0.054)
mF1×Exp×Fre						-0.046						-0.028
						(0.048)						(0.061)
mF1×School×Eng						-0.62						0.042
						(0.420)						(0.237)
mF1×School×Fre						-0.505*						0.113
						(0.262)						(0.211)
mF2×Exp×Eng						-0.025						-0.027
						(0.160)						(0.068)
mF2×Exp×Fre						0.018						-0.087
						(0.911)						(0.073)
mF2×School×Eng						0.467						-0.126
						(0.414)						(0.127)
mF2×School×Fre						0.466						-0.195
						(2.442)						(0.273)
mF3×Exp×Eng						0.145						-0.025
						(19.985)						(0.020)
mF3×Exp×Fre						0.608						-0.01
						(7.390)						(0.048)
mF3×School×Eng						-4.71						0.025
						(19.781)						(0.065)
mF3×School×Fre						-2.638						-0.098
						(57.737)						(0.127)
R^2	0.09	0.11	0.27	0.31	0.31	0.33	0.09	0.11	0.17	0.18	0.20	0.20
N-weighted	8,235	8,235	8,235	8,235	8,235	8,235	22,002	22,002	22,002	22,002	22,002	22,002

See notes for Appendix B3.

Appendix B5. Log wage regressions for Regulated vs. Unregulated occupations, males, wave 3

	Regulated						Unregulated					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.010***	-0.008***	-0.008**	-0.013***	-0.015***	-0.015***	-0.015***	-0.014***	-0.011***	-0.012***	-0.012***	-0.013***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
School	0.008	0.004	0.004	-0.003	-0.007	-0.007	0.007	0.005	0.006	0.005	0.007	0.009
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)	(0.009)
msm	-0.012	-0.014	-0.010	-0.006	-0.009	-0.009	0.026	0.026	0.015	0.015	0.017	0.016
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.022)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)
Eng		0.384***	0.308***	0.247**	0.327***	0.323***		0.224**	0.133	0.084	0.093	0.116
		(0.097)	(0.094)	(0.118)	(0.122)	(0.124)		(0.090)	(0.086)	(0.097)	(0.107)	(0.111)
Fre		-0.083	-0.084	-0.181	-0.197*	-0.206*		-0.171	-0.147	-0.153	-0.129	-0.139
		(0.099)	(0.092)	(0.116)	(0.118)	(0.125)		(0.139)	(0.138)	(0.143)	(0.147)	(0.151)
mF1			0.208***	0.191***	0.201***	0.245***			0.327***	0.291***	0.300***	0.250***
			(0.047)	(0.057)	(0.056)	(0.063)			(0.052)	(0.062)	(0.063)	(0.083)
mF2			0.214***	0.202***	0.213***	0.191***			0.346***	0.405***	0.410***	0.447***
			(0.039)	(0.040)	(0.040)	(0.041)			(0.055)	(0.070)	(0.070)	(0.122)
mF3			0.046	0.054	0.059	0.084*			0.085*	0.011	0.018	-0.04
			(0.045)	(0.047)	(0.047)	(0.049)			(0.050)	(0.075)	(0.076)	(0.092)
Exp×mF1				0.020***	0.019**	0.023*				-0.001	-0.002	-0.005
				(0.007)	(0.008)	(0.012)				(0.009)	(0.009)	(0.011)
Exp×mF2				0.003	0.004	0.004				0.008	0.008	0.011
				(0.006)	(0.006)	(0.006)				(0.010)	(0.011)	(0.016)
Exp×mF3				0.007	0.006	0.006				-0.001	0	0.013
				(0.007)	(0.007)	(0.007)				(0.007)	(0.007)	(0.014)
School×mF1				0.012	0.009	0.01				0.009	0	0.004
				(0.017)	(0.018)	(0.023)				(0.016)	(0.018)	(0.025)
School×mF2				0.035**	0.033**	0.034**				0.016	0.013	0.002
				(0.017)	(0.017)	(0.017)				(0.022)	(0.022)	(0.036)
School×mF3				-0.006	0	0.012				-0.033*	-0.031*	-0.026
				(0.018)	(0.018)	(0.020)				(0.019)	(0.018)	(0.030)
mF1×Eng				0.508*	0.392	0.294				0.369	0.328	0.467
				(0.284)	(0.282)	(0.287)				(0.305)	(0.312)	(0.374)
mF2×Eng				0.024	-0.089	-0.062				-0.616*	-0.594*	-0.723
				(0.205)	(0.203)	(0.196)				(0.357)	(0.358)	(0.487)
mF3×Eng				-0.157	0.035	0.096				0.264	0.350**	-0.062
				(0.249)	(0.225)	(0.247)				(0.164)	(0.168)	(0.270)
mF1×Fre				0.245	0.208	0.157				-0.028	-0.006	-0.035
				(0.173)	(0.174)	(0.206)				(0.196)	(0.205)	(0.335)
mF2×Fre				0.08	0.023	0.093				-0.034	-0.04	0.161

				(0.141)	(0.139)	(0.150)				(0.242)	(0.243)	(0.442)
mF3×Fre				-0.071	0.042	0.081				0.097	0.043	-0.176
				(0.163)	(0.155)	(0.204)				(0.205)	(0.210)	(0.336)
Exp×Eng					0.007	0.009					0.007	-0.004
					(0.010)	(0.012)					(0.007)	(0.008)
Exp×Fre					0	-0.005					-0.002	-0.01
					(0.014)	(0.022)					(0.013)	(0.014)
School×Eng					0.098***	0.084**					0.038	0.028
					(0.029)	(0.038)					(0.024)	(0.029)
School×Fre					0.050**	0.04					-0.014	-0.031
					(0.023)	(0.030)					(0.022)	(0.026)
mF1×Exp×Eng						-0.038						0.048
						(0.055)						(0.050)
mF1×Exp×Fre						0.004						0.024
						(0.037)						(0.039)
mF1×School×Eng						0.052						-0.009
						(0.117)						(0.102)
mF1×School×Fre						0.08						0.067
						(0.070)						(0.084)
mF2×Exp×Eng						0.024						0.014
						(0.026)						(0.076)
mF2×Exp×Fre						0.004						0.06
						(0.023)						(0.073)
mF2×School×Eng						-0.063						0.172
						(0.077)						(0.144)
mF2×School×Fre						-0.062						0.101
						(0.054)						(0.193)
mF3×Exp×Eng						-0.004						0.036**
						(0.027)						(0.018)
mF3×Exp×Fre						0.024						0.072
						(0.026)						(0.080)
mF3×School×Eng						0.078						-0.007
						(0.080)						(0.058)
mF3×School×Fre						0.062						0.099
						(0.066)						(0.165)
R^2	0.13	0.14	0.19	0.21	0.22	0.22		0.23	0.24	0.36	0.37	0.37	0.38
N-weighted	23,739	23,739	23,739	23,739	23,739	23,739		18,383	18,383	18,383	18,383	18,383	18,383

Note: Immigrants' age is 25 to 59. mF1, mF2, mF3 indicate a match between pre- and post-immigration "intelligence", "motor skills" and "strength" factor respectively. All regressions control for months since immigration (msm). Additional controls: immigration category (Family (default); Skilled Workers principal applicants (PA's); Skilled Workers not PA's; Business/Nominees/Refugees/Others); birth region (US/W Europe/ UK/ N Europe/ Oceania (default); C & S America/Caribbean & Bermuda; E Europe; S Europe; Africa; W C Asia & M East; E Asia; SE Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under 18; marital status (single; married/common law). Bootstrap standard errors in brackets. ***-significant at 1%; **-significant at 5%; *-significant at 10%.

Appendix B6. Log wage regressions for Regulated vs. Unregulated occupations, females, wave 3

	Regulated occupations						Unregulated occupations					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.009**	-0.007*	-0.004	-0.005	-0.006	-0.006	-0.010***	-0.008**	-0.007*	-0.007*	-0.007	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
School	0.030**	0.023*	0.018	0.027*	0.030*	0.028*	0.011	0.006	-0.004	-0.011	-0.009	-0.009
	(0.013)	(0.013)	(0.012)	(0.014)	(0.016)	(0.016)	(0.013)	(0.014)	(0.012)	(0.015)	(0.015)	(0.016)
msm	0.080**	0.080**	0.073**	0.080**	0.083**	0.075**	0.038	0.035	0.035	0.032	0.030	0.031
	(0.033)	(0.033)	(0.031)	(0.033)	(0.033)	(0.033)	(0.025)	(0.025)	(0.023)	(0.023)	(0.023)	(0.024)
Eng		0.584***	0.524***	0.365**	0.377**	0.378**		0.387***	0.334***	0.339***	0.405***	0.401***
		(0.159)	(0.157)	(0.177)	(0.188)	(0.190)		(0.119)	(0.108)	(0.122)	(0.129)	(0.133)
Fre		0.074	0.16	0.038	0.04	-0.032		0.263	0.222	0.252	0.29	0.299
		(0.195)	(0.194)	(0.213)	(0.215)	(0.226)		(0.171)	(0.153)	(0.169)	(0.179)	(0.190)
mF1			0.248***	0.266***	0.275***	0.525***			0.583***	0.521***	0.524***	0.526***
			(0.081)	(0.089)	(0.089)	(0.120)			(0.062)	(0.081)	(0.084)	(0.129)
mF2			0.459***	0.457***	0.464***	0.472**			0.264***	0.205**	0.209**	0.228
			(0.088)	(0.091)	(0.094)	(0.226)			(0.079)	(0.091)	(0.096)	(0.143)
mF3			0.145	0.183	0.166	0.142			0.107	0.096	0.078	0.089
			(0.121)	(0.146)	(0.145)	(0.453)			(0.067)	(0.076)	(0.086)	(0.121)
Exp×mF1				0.001	0.002	0.006				-0.008	-0.008	-0.007
				(0.013)	(0.012)	(0.014)				(0.011)	(0.011)	(0.013)
Exp×mF2				0.016	0.02	0.023				0.005	0.009	0.008
				(0.014)	(0.015)	(0.028)				(0.016)	(0.017)	(0.025)
Exp×mF3				-0.011	-0.013	-0.018				0.003	0.003	0.002
				(0.016)	(0.017)	(0.081)				(0.008)	(0.008)	(0.018)
School×mF1				-0.053	-0.06	-0.117**				0	-0.002	-0.008
				(0.037)	(0.039)	(0.049)				(0.036)	(0.038)	(0.045)
School×mF2				0.021	0.02	-0.006				0.067**	0.071**	0.073
				(0.042)	(0.043)	(0.106)				(0.032)	(0.034)	(0.051)
School×mF3				-0.01	-0.004	-0.002				0.002	0.005	0.016
				(0.046)	(0.048)	(0.369)				(0.026)	(0.028)	(0.043)
mF1×Eng				0.748*	0.690*	-0.226				0.134	0.058	0.101
				(0.412)	(0.414)	(0.493)				(0.308)	(0.319)	(0.471)
mF2×Eng				-0.041	-0.065	-0.194				-0.282	-0.306	-0.263
				(0.428)	(0.432)	(0.463)				(0.343)	(0.358)	(0.601)
mF3×Eng				0.165	0.287	0.474				0.127	0.272	0.351
				(0.651)	(0.656)	(0.810)				(0.230)	(0.237)	(0.318)
mF1×Fre				0.318	0.285	0.069				-0.016	-0.169	-0.404
				(0.293)	(0.302)	(0.502)				(0.245)	(0.295)	(0.545)
mF2×Fre				-0.287	-0.259	0.278				-0.082	-0.132	-0.254

				(0.403)	(0.429)	(1.631)				(0.292)	(0.315)	(0.612)
mF3×Fre				0.617	0.603	0.718				-0.385	-0.326	-0.304
				(0.425)	(0.421)	(3.819)				(0.274)	(0.335)	(0.728)
Exp×Eng					-0.022	-0.006					-0.002	0.003
					(0.016)	(0.017)					(0.009)	(0.011)
Exp×Fre					0.013	0.014					0.016	0.027
					(0.013)	(0.014)					(0.027)	(0.033)
School×Eng					0.021	0.028					0.045	0.046
					(0.052)	(0.059)					(0.028)	(0.034)
School×Fre					0.027	0.03					0.094	0.114
					(0.037)	(0.040)					(0.083)	(0.098)
mF1×Exp×Eng						-0.038						-0.022
						(0.062)						(0.049)
mF1×Exp×Fre						-0.002						-0.058
						(0.046)						(0.056)
mF1×School×Eng						0.595**						-0.029
						(0.265)						(0.183)
mF1×School×Fre						0.155						-0.03
						(0.174)						(0.178)
mF2×Exp×Eng						-0.03						0.034
						(0.094)						(0.116)
mF2×Exp×Fre						-0.04						-0.06
						(0.171)						(0.094)
mF2×School×Eng						-0.18						0.029
						(0.315)						(0.158)
mF2×School×Fre						-0.508						-0.038
						(0.595)						(0.246)
mF3×Exp×Eng						-0.088						-0.021
						(0.074)						(0.021)
mF3×Exp×Fre						0.009						-0.025
						(0.570)						(0.122)
mF3×School×Eng						-0.143						0.007
						(0.239)						(0.067)
mF3×School×Fre						0.122						-0.127
						(2.525)						(0.250)
R^2	0.13	0.15	0.23	0.24	0.25	0.26	0.11	0.13	0.24	0.25	0.26	0.27
N-weighted	13,082	13,082	13,082	13,082	13,082	13,082	17,155	17,155	17,155	17,155	17,155	17,155

See notes for Appendix B5.

Appendix B7. Log wage regressions for Professional vs. Non-Professional occupations, males, wave 3

	Professional						Non-Professional					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	0	0	0	-0.003	-0.006	0.001	-0.012***	-0.011***	-0.010***	-0.012***	-0.013***	-0.013***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.010)	(0.010)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
School	0.005	0.006	0.011	0.008	0.002	0.01	0.003	-0.001	0	-0.004	-0.003	-0.003
	(0.010)	(0.010)	(0.011)	(0.020)	(0.022)	(0.021)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
msm	-0.023	-0.021	-0.042	-0.044	-0.049	-0.055	0.008	0.006	0.011	0.010	0.011	0.010
	(0.057)	(0.057)	(0.056)	(0.062)	(0.064)	(0.063)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Eng		0.016	-0.062	-0.104	-0.257	-0.458		0.299***	0.256***	0.243***	0.295***	0.304***
		(0.195)	(0.193)	(0.323)	(0.401)	(0.477)		(0.067)	(0.065)	(0.075)	(0.085)	(0.086)
Fre		-0.166	-0.116	-0.067	-0.245	-0.369		-0.109	-0.133	-0.146	-0.137	-0.137
		(0.168)	(0.159)	(0.261)	(0.356)	(0.442)		(0.089)	(0.089)	(0.095)	(0.095)	(0.098)
mF1			0.092	0.072	0.09	0.014			0.274***	0.161**	0.173**	0.176**
			(0.061)	(0.097)	(0.100)	(0.105)			(0.059)	(0.068)	(0.068)	(0.077)
mF2			0.275***	0.326***	0.321***	0.351*			0.267***	0.254***	0.256***	0.250***
			(0.053)	(0.075)	(0.079)	(0.178)			(0.032)	(0.032)	(0.032)	(0.036)
mF3			0.26	0.411	0.553	-1.157			0.061*	0.024	0.035	0.044
			(0.180)	(7.413)	(5.768)	(0.985)			(0.034)	(0.039)	(0.039)	(0.041)
Exp×mF1				-0.002	-0.002	-0.017				0.011	0.011	0.016
				(0.012)	(0.012)	(0.011)				(0.009)	(0.009)	(0.012)
Exp×mF2				0.01	0.01	0.014				0.002	0.002	0.001
				(0.011)	(0.011)	(0.016)				(0.005)	(0.005)	(0.006)
Exp×mF3				-0.049	-0.039	-0.228**				0.003	0.003	0.006
				(0.320)	(0.253)	(0.092)				(0.005)	(0.005)	(0.005)
School×mF1				0.007	-0.001	-0.017				0.026*	0.016	0.022
				(0.024)	(0.026)	(0.025)				(0.015)	(0.016)	(0.031)
School×mF2				0	0.003	0.002				0.050***	0.047***	0.047***
				(0.029)	(0.030)	(0.042)				(0.013)	(0.013)	(0.015)
School×mF3				-0.082	-0.082	-0.078				-0.026**	-0.022*	-0.017
				(1.468)	(1.140)	(0.061)				(0.012)	(0.012)	(0.014)
mF1×Eng				0.102	0.128	0.388				0.835**	0.774**	0.780**
				(0.361)	(0.393)	(0.522)				(0.339)	(0.346)	(0.392)
mF2×Eng				-0.137	-0.136	-0.201				-0.075	-0.138	-0.085
				(0.367)	(0.368)	(0.613)				(0.151)	(0.152)	(0.158)
mF3×Eng				1.438	0.209	10.239*				0.081	0.183	0.042
				(11.784)	(9.380)	(5.793)				(0.130)	(0.130)	(0.178)
mF1×Fre				-0.202	-0.154	0.03				0.362*	0.344	0.462
				(0.216)	(0.241)	(0.397)				(0.217)	(0.220)	(0.292)
mF2×Fre				0.253	0.268	0.15				-0.168	-0.205*	-0.101

				(0.223)	(0.223)	(0.330)				(0.116)	(0.119)	(0.161)
mF3×Fre				-0.279	-0.582	2.565				0.159	0.183	0.207
				(13.096)	(10.193)	(1.737)				(0.119)	(0.121)	(0.148)
Exp×Eng					0.012	-0.05					0.005	0.003
					(0.032)	(0.060)					(0.006)	(0.007)
Exp×Fre					0.004	-0.032					-0.006	-0.011
					(0.019)	(0.044)					(0.011)	(0.013)
School×Eng					0.130*	0.068					0.049***	0.049**
					(0.073)	(0.134)					(0.018)	(0.021)
School×Fre					0.063	0.022					0.004	0.003
					(0.044)	(0.085)					(0.019)	(0.022)
mF1×Exp×Eng						0.119						-0.035
						(0.082)						(0.050)
mF1×Exp×Fre						0.083						0.018
						(0.056)						(0.039)
mF1×School×Eng						0.174						-0.05
						(0.175)						(0.125)
mF1×School×Fre						0.113						-0.021
						(0.117)						(0.089)
mF2×Exp×Eng						-0.03						0.032
						(0.101)						(0.023)
mF2×Exp×Fre						-0.036						0.018
						(0.053)						(0.028)
mF2×School×Eng						-0.057						0.05
						(0.209)						(0.067)
mF2×School×Fre						-0.031						-0.033
						(0.113)						(0.061)
mF3×Exp×Eng						0.867**						0.002
						(0.352)						(0.017)
mF3×Exp×Fre						-						0.025
												(0.022)
mF3×School×Eng						-						-0.024
												(0.046)
mF3×School×Fre						-						0.063
												(0.057)
R^2	0.11	0.12	0.18	0.19	0.20	0.21	0.17	0.18	0.22	0.24	0.24	0.25
N-weighted	9,329	9,329	9,329	9,329	9,329	9,329	32,794	32,794	32,794	32,794	32,794	32,794

Note: immigrants' age is 25 to 59 at the time of immigration. mF1, mF2, mF3 indicate a match between pre- and post-immigration "intelligence", "motor skills" and "strength" factor respectively. All regressions control for months since immigration. Additional controls: immigration category (Family (default); Skilled Workers (PA's); Skilled Workers not PA's; Bus/Nomin/Refug/Others); birth region (US/W Europe/ UK/ Other N Europe/ Oceania (default); C& S America/Caribbean & Bermuda; E Europe; S Europe; Africa; W C Asia & M East; E Asia; SE Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); No of children in household < 18 y.o.; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant at 1%; **-significant at 5%; *-significant at 10%.

Appendix B8. Log wage regressions for Professional vs. Non-Professional occupations, females, wave 3

	Professional occupations						**Non-Professional occupations**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.013	-0.01	-0.006	-0.021*	-0.025*	-0.024	-0.008***	-0.007**	-0.006**	-0.006*	-0.005	-0.005
	(0.008)	(0.008)	(0.008)	(0.011)	(0.013)	(0.016)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
School	0.03	0.028	0.02	0.02	0.026	0.022	0.009	0.002	0.001	-0.001	0.002	0.001
	(0.024)	(0.024)	(0.021)	(0.033)	(0.039)	(0.043)	(0.010)	(0.010)	(0.010)	(0.012)	(0.013)	(0.013)
msm	0.099*	0.104*	0.084	0.087	0.094	0.083	0.031	0.028	0.035*	0.037*	0.038*	0.036*
	(0.057)	(0.056)	(0.054)	(0.060)	(0.062)	(0.064)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.020)
Eng		0.538*	0.476	0.386	0.294	0.254		0.415***	0.379***	0.368***	0.424***	0.401***
		(0.306)	(0.297)	(0.422)	(0.448)	(0.479)		(0.091)	(0.089)	(0.098)	(0.107)	(0.109)
Fre		0.198	0.335	0.238	0.332	0.271		0.064	0.068	0.063	0.076	0.07
		(0.243)	(0.235)	(0.324)	(0.345)	(0.368)		(0.142)	(0.135)	(0.138)	(0.139)	(0.141)
mF1			0.217*	0.276**	0.274**	0.415**			0.493***	0.477***	0.481***	0.521***
			(0.118)	(0.139)	(0.138)	(0.199)			(0.066)	(0.088)	(0.087)	(0.147)
mF2			0.486***	0.495***	0.512***	0.34			0.272***	0.313***	0.315***	0.338
			(0.127)	(0.141)	(0.147)	(0.253)			(0.083)	(0.079)	(0.078)	(0.702)
mF3			0.162	0.349	0.32	-0.103			0.083	0.081	0.071	0.081
			(0.191)	(0.652)	(0.675)	(2.776)			(0.068)	(0.081)	(0.085)	(0.094)
Exp×mF1				0.023	0.024	0.024				-0.015	-0.014	-0.015
				(0.017)	(0.017)	(0.020)				(0.011)	(0.011)	(0.014)
Exp×mF2				0.003	0.007	-0.001				0.02	0.022	0.026
				(0.023)	(0.024)	(0.031)				(0.017)	(0.017)	(0.082)
Exp×mF3				0.008	0.014	0.031				0.001	0	-0.001
				(0.031)	(0.032)	(0.342)				(0.006)	(0.007)	(0.011)
School×mF1				-0.028	-0.031	-0.065				-0.022	-0.025	-0.052
				(0.074)	(0.076)	(0.089)				(0.034)	(0.033)	(0.050)
School×mF2				0.042	0.04	0.06				0.078**	0.076**	0.088
				(0.074)	(0.076)	(0.107)				(0.036)	(0.035)	(0.307)
School×mF3				-0.117	-0.127	0.354				-0.003	0.001	0.007
				(0.150)	(0.157)	(2.682)				(0.024)	(0.025)	(0.029)
mF1×Eng				0.459	0.512	0.017				0.089	0.013	-0.164
				(0.608)	(0.618)	(0.757)				(0.379)	(0.374)	(0.464)
mF2×Eng				-0.855	-0.952	-0.166				-0.189	-0.214	-0.141
				(0.686)	(0.720)	(1.051)				(0.298)	(0.292)	(0.372)
mF3×Eng				0.207	0.433	0.061				0.186	0.319	0.493
				(1.531)	(1.575)	(3.034)				(0.256)	(0.269)	(0.348)
mF1×Fre				0.267	0.284	0.002				0.098	-0.018	-1.294
				(0.389)	(0.391)	(0.540)				(0.287)	(0.329)	(0.816)
mF2×Fre				-0.365	-0.323	0.225				0.05	0.031	-0.11

				(0.421)	(0.449)	(0.938)				(0.312)	(0.314)	(6.183)
mF3×Fre				0.214	0.057	-4.244				0.058	0.096	0.176
				(3.774)	(3.983)	(23.811)				(0.314)	(0.334)	(0.500)
Exp×Eng					-0.022	-0.008					-0.008	-0.003
					(0.038)	(0.056)					(0.008)	(0.009)
Exp×Fre					0.023	0.033					0.015	0.022
					(0.024)	(0.040)					(0.020)	(0.023)
School×Eng					-0.004	0.027					0.033	0.023
					(0.125)	(0.176)					(0.027)	(0.031)
School×Fre					-0.022	-0.002					0.086	0.096
					(0.084)	(0.114)					(0.065)	(0.074)
mF1×Exp×Eng						-0.044						-0.029
						(0.087)						(0.051)
mF1×Exp×Fre						-0.011						-0.138*
						(0.058)						(0.076)
mF1×School×Eng						0.233						0.354
						(0.426)						(0.251)
mF1×School×Fre						0.163						0.088
						(0.224)						(0.271)
mF2×Exp×Eng						0.167						-0.024
						(0.176)						(0.076)
mF2×Exp×Fre						-0.09						-0.034
						(0.097)						(0.551)
mF2×School×Eng						-0.245						0.051
						(0.508)						(0.117)
mF2×School×Fre						-0.422						0.134
						(0.403)						(2.144)
mF3×Exp×Eng						-0.1						-0.019
						(0.673)						(0.020)
mF3×Exp×Fre						0.21						-0.027
						(1.952)						(0.069)
mF3×School×Eng						-0.442						0.031
						(3.860)						(0.065)
mF3×School×Fre						2.839						-0.108
						(16.405)						(0.141)
R^2	0.17	0.18	0.27	0.29	0.30	0.32	0.10	0.11	0.16	0.16	0.17	0.18
N-weighted	6,694	6,694	6,694	6,694	6,694	6,694	23,543	23,543	23,543	23,543	23,543	23,543

See notes for Appendix B7.

Appendix B9. Log wage regressions for University educated vs. Other education levels, males, wave 3

	University educated						Other education levels					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.015***	-0.015***	-0.012***	-0.016***	-0.016***	-0.016***	-0.009***	-0.009***	-0.009***	-0.009***	-0.007***	-0.007***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
School	0.004	0.001	0.002	-0.006	-0.01	-0.007	-0.002	-0.002	0.001	0.005	0.012	0.012
	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)
msm	-0.008	-0.008	-0.009	-0.008	-0.009	-0.011	0.022	0.018	0.02	0.017	0.023	0.023
	(0.024)	(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)
Eng		0.516***	0.372***	0.303***	0.235**	0.241*		0.063	0.038	0.011	0.057	0.114
		(0.098)	(0.092)	(0.104)	(0.119)	(0.124)		(0.087)	(0.086)	(0.111)	(0.145)	(0.144)
Fre		-0.065	-0.057	-0.089	-0.142	-0.153		-0.209**	-0.225**	-0.212*	-0.201*	-0.201*
		(0.109)	(0.102)	(0.118)	(0.130)	(0.133)		(0.103)	(0.102)	(0.112)	(0.119)	(0.118)
mF1			0.237***	0.223***	0.230***	0.251***			0.267***	0.169*	0.168**	0.197
			(0.038)	(0.047)	(0.048)	(0.059)			(0.073)	(0.087)	(0.084)	(0.150)
mF2			0.280***	0.300***	0.295***	0.293***			0.154***	0.263***	0.249***	0.248***
			(0.037)	(0.040)	(0.041)	(0.057)			(0.058)	(0.077)	(0.074)	(0.086)
mF3			0.053	0.024	0.024	-0.021			0.071	0.009	0.022	0.02
			(0.063)	(0.065)	(0.067)	(0.116)			(0.043)	(0.055)	(0.056)	(0.060)
Exp×mF1				0.011*	0.011*	0.01				0.02	0.014	-0.002
				(0.006)	(0.006)	(0.008)				(0.013)	(0.013)	(0.033)
Exp×mF2				0.008	0.007	0.006				0.008	0.006	0.008
				(0.006)	(0.006)	(0.007)				(0.009)	(0.009)	(0.010)
Exp×mF3				0.014	0.015	0.012				-0.005	-0.003	-0.002
				(0.012)	(0.013)	(0.017)				(0.005)	(0.005)	(0.007)
School×mF1				0.017	0.014	0.002				-0.009	-0.029	-0.06
				(0.014)	(0.014)	(0.018)				(0.047)	(0.049)	(0.119)
School×mF2				0.019	0.023	0.019				0.050**	0.040*	0.045
				(0.015)	(0.016)	(0.018)				(0.023)	(0.022)	(0.030)
School×mF3				0	0.004	-0.001				-0.026*	-0.021	-0.022
				(0.030)	(0.031)	(0.047)				(0.015)	(0.015)	(0.018)
mF1×Eng				0.341	0.312	0.197				0.385	0.277	0.015
				(0.222)	(0.227)	(0.254)				(0.442)	(0.434)	(0.733)
mF2×Eng				-0.294	-0.307	-0.276				-0.009	0.079	0.078
				(0.192)	(0.195)	(0.247)				(0.250)	(0.234)	(0.453)
mF3×Eng				1.096***	1.100***	1.060*				-0.017	0.024	-0.194
				(0.356)	(0.367)	(0.554)				(0.152)	(0.151)	(0.211)
mF1×Fre				0.102	0.086	0.221				0.072	0.011	0.097
				(0.147)	(0.149)	(0.214)				(0.231)	(0.238)	(0.354)
mF2×Fre				-0.015	-0.036	-0.115				0.112	0.168	0.3

				(0.132)	(0.131)	(0.177)				(0.216)	(0.212)	(0.384)
mF3×Fre				0.432**	0.465**	0.494				-0.173	-0.204	-0.043
				(0.197)	(0.212)	(0.406)				(0.149)	(0.147)	(0.250)
Exp×Eng					-0.002	-0.011					0.020***	0.021***
					(0.012)	(0.014)					(0.007)	(0.008)
Exp×Fre					-0.008	-0.021					0.015*	0.014
					(0.013)	(0.017)					(0.009)	(0.010)
School×Eng					0.059	0.033					0.069***	0.092***
					(0.042)	(0.056)					(0.025)	(0.028)
School×Fre					0.023	0.003					0.014	-0.002
					(0.025)	(0.031)					(0.023)	(0.025)
mF1×Exp×Eng						0.007						0.103
						(0.037)						(0.145)
mF1×Exp×Fre						0.051*						0.004
						(0.027)						(0.070)
mF1×School×Eng						0.088						0.144
						(0.088)						(0.522)
mF1×School×Fre						0.051						0.221
						(0.051)						(0.302)
mF2×Exp×Eng						0.026						0.007
						(0.038)						(0.033)
mF2×Exp×Fre						-0.004						0.06
						(0.024)						(0.047)
mF2×School×Eng						0.033						-0.02
						(0.090)						(0.139)
mF2×School×Fre						0.034						-0.012
						(0.061)						(0.139)
mF3×Exp×Eng						0.031						-0.012
						(0.083)						(0.017)
mF3×Exp×Fre						0.03						0.013
						(0.062)						(0.036)
mF3×School×Eng						-0.139						-0.084*
						(0.271)						(0.048)
mF3×School×Fre						-0.055						0.087
						(0.210)						(0.093)
R^2	0.12	0.14	0.22	0.23	0.24	0.24	0.28	0.28	0.31	0.33	0.34	0.36
N-weighted	30,341	30,341	30,341	30,341	30,341	30,341	11,781	11,781	11,781	11,781	11,781	11,781

Note: Immigrants are 25 to 59 at the time of immigration; mF1, mF2, mF3 indicate a match between "intelligence", "motor skills" and "strength" factor respectively. All regressions control for months since immigration (msm). Additional controls: immigration class (Family (default); Skilled Workers (PA); Skilled Workers (not PA); Bus/Nom/Ref/Other); birth region (US/W Europe/ UK/ Other Northern Europe/ Oceania (default); C & S America/Caribbean & Bermuda; E Europe; S Europe; Africa; WC Asia & M East; E Asia; SE Asia; S Asia); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant at 1%; **-significant at 5%; *-significant at 10%.

Appendix B10. Log wage regressions for University educated vs. Other education levels, females, wave 3

	University educated						**Other education levels**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.012***	-0.009**	-0.004	-0.007	-0.004	-0.003	-0.009***	-0.008**	-0.008**	-0.007*	-0.008**	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
School	0.014	0.011	0.005	-0.003	-0.002	-0.002	0.002	-0.005	-0.006	-0.009	-0.004	-0.005
	(0.017)	(0.017)	(0.014)	(0.017)	(0.020)	(0.021)	(0.011)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)
msm	0.051*	0.052**	0.043*	0.045*	0.042*	0.040	0.066**	0.060*	0.062**	0.066**	0.066**	0.069**
	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)	(0.031)	(0.031)	(0.031)	(0.032)	(0.032)	(0.034)
Eng		0.606***	0.534***	0.476***	0.454***	0.455***		0.336***	0.295***	0.244**	0.361**	0.369**
		(0.138)	(0.131)	(0.142)	(0.156)	(0.159)		(0.113)	(0.112)	(0.119)	(0.150)	(0.156)
Fre		0.172	0.149	0.168	0.092	0.048		0.069	0.129	0.142	0.164	0.184
		(0.163)	(0.158)	(0.197)	(0.190)	(0.211)		(0.146)	(0.141)	(0.140)	(0.155)	(0.161)
mF1			0.320***	0.265***	0.260***	0.388***			0.495***	0.399	0.403	0.882
			(0.063)	(0.077)	(0.077)	(0.112)			(0.180)	(0.357)	(0.359)	(23.952)
mF2			0.444***	0.495***	0.489***	0.359***			0.261**	0.334	0.305	0.298
			(0.068)	(0.081)	(0.085)	(0.109)			(0.121)	(0.255)	(0.262)	(0.871)
mF3			0.183*	0.155	0.147	0.508			0.111	0.113	0.117	0.113
			(0.101)	(0.246)	(0.249)	(0.901)			(0.080)	(0.119)	(0.120)	(0.147)
Exp×mF1				0.002	0	0.003				-0.027	-0.025	0.077
				(0.009)	(0.010)	(0.011)				(0.052)	(0.053)	(2.630)
Exp×mF2				0.026*	0.026*	0.018				0.001	0.003	0.003
				(0.015)	(0.015)	(0.017)				(0.016)	(0.016)	(0.136)
Exp×mF3				-0.007	-0.005	0.007				-0.001	0	-0.001
				(0.016)	(0.016)	(0.096)				(0.007)	(0.007)	(0.015)
School×mF1				0.013	0.009	-0.018				-0.109	-0.118	-0.003
				(0.037)	(0.038)	(0.046)				(0.174)	(0.177)	(3.784)
School×mF2				0.028	0.034	0.066				0.04	0.032	0.041
				(0.040)	(0.042)	(0.056)				(0.054)	(0.053)	(0.488)
School×mF3				-0.008	0.001	-0.178				0	0.006	0.003
				(0.072)	(0.071)	(1.302)				(0.031)	(0.031)	(0.038)
mF1×Eng				0.459	0.466	0.025				0.188	0.138	-0.643
				(0.317)	(0.329)	(0.426)				(1.724)	(1.754)	(117.000)
mF2×Eng				-0.303	-0.307	-0.057				0.466	0.484	1.023
				(0.334)	(0.343)	(0.422)				(0.493)	(0.476)	(1.032)
mF3×Eng				0.459	0.454	-0.089				0.233	0.298	0.311
				(0.618)	(0.619)	(1.042)				(0.293)	(0.298)	(0.464)
mF1×Fre				-0.021	-0.06	-0.187				-0.033	0.058	4.565
				(0.264)	(0.274)	(0.389)				(2.207)	(2.216)	(191.765)
mF2×Fre				-0.349	-0.319	-0.305				0.668	0.665	0.885

				(0.273)	(0.288)	(0.572)					(1.552)	(1.595)	(6.406)
mF3×Fre				0.423	0.366	1.005					-0.108	-0.06	-0.076
				(1.336)	(1.361)	(11.102)					(0.310)	(0.316)	(0.750)
Exp×Eng					-0.019	-0.009						-0.001	0.006
					(0.017)	(0.018)						(0.010)	(0.012)
Exp×Fre					0.017	0.042						0.003	0.004
					(0.021)	(0.033)						(0.015)	(0.016)
School×Eng					0.002	0.009						0.043	0.05
					(0.074)	(0.078)						(0.035)	(0.042)
School×Fre					0.077	0.106						0.006	0.011
					(0.083)	(0.107)						(0.040)	(0.045)
mF1×Exp×Eng						-0.027							-0.124
						(0.045)							(21.282)
mF1×Exp×Fre						-0.048							0.632
						(0.043)							(30.461)
mF1×School×Eng						0.262							-0.597
						(0.236)							(63.347)
mF1×School×Fre						0.035							0.756
						(0.172)							(114.398)
mF2×Exp×Eng						-0.024							0.017
						(0.077)							(0.095)
mF2×Exp×Fre						-0.112**							-0.051
						(0.053)							(0.960)
mF2×School×Eng						-0.384							0.174
						(0.235)							(0.247)
mF2×School×Fre						-0.3							0.218
						(0.242)							(3.410)
mF3×Exp×Eng						-0.125							-0.025
						(0.137)							(0.023)
mF3×Exp×Fre						-0.058							0.005
						(0.644)							(0.094)
mF3×School×Eng						0.509							-0.035
						(0.724)							(0.082)
mF3×School×Fre						-0.56							-0.065
						(9.275)							(0.169)
R^2	0.09	0.11	0.20	0.21	0.22	0.23		0.12	0.13	0.17	0.19	0.19	0.21
N-weighted	19,943	19,943	19,943	19,943	19,943	19,943		10,294	10,294	10,294	10,294	10,294	10,294

See notes for Appendix B9.

.

Appendix B11. Log wage regressions for Visible minorities vs. Not visible minorities, males, wave 3

	Visible minorities						Not visible minorities					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.014***	-0.013***	-0.011***	-0.015***	-0.017***	-0.017***	-0.004	-0.003	-0.001	-0.004	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
School	0.001	-0.004	-0.002	-0.007	-0.004	-0.004	0.024**	0.017*	0.015	0.01	0.015	0.014
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.014)	(0.014)	(0.014)
msm	-0.009	-0.014	-0.014	-0.013	-0.013	-0.012	0.099***	0.080***	0.080***	0.079***	0.075***	0.076***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.030)	(0.030)	(0.029)	(0.029)	(0.028)	(0.028)
Eng		0.336***	0.293***	0.267***	0.331***	0.335***		0.725***	0.550***	0.413**	0.450**	0.487**
		(0.067)	(0.064)	(0.075)	(0.081)	(0.083)		(0.148)	(0.141)	(0.182)	(0.185)	(0.193)
Fre		-0.055	-0.005	-0.027	-0.028	-0.036		0.13	0.069	0.003	-0.017	-0.034
		(0.084)	(0.083)	(0.096)	(0.101)	(0.106)		(0.141)	(0.127)	(0.146)	(0.146)	(0.155)
mF1			0.250***	0.239***	0.255***	0.241***			0.316***	0.234***	0.222***	0.243***
			(0.041)	(0.048)	(0.048)	(0.066)			(0.057)	(0.066)	(0.065)	(0.087)
mF2			0.255***	0.265***	0.276***	0.265***			0.212***	0.217***	0.214***	0.209***
			(0.039)	(0.040)	(0.039)	(0.044)			(0.049)	(0.052)	(0.052)	(0.060)
mF3			0.110***	0.083*	0.093**	0.095**			0.006	-0.015	-0.024	-0.017
			(0.038)	(0.046)	(0.046)	(0.048)			(0.070)	(0.079)	(0.080)	(0.109)
Exp×mF1				0.008	0.009	0.007				0.01	0.013	0.017
				(0.006)	(0.006)	(0.009)				(0.009)	(0.009)	(0.010)
Exp×mF2				0.009	0.010*	0.008				-0.004	-0.005	-0.007
				(0.006)	(0.006)	(0.007)				(0.008)	(0.008)	(0.008)
Exp×mF3				0.005	0.006	0.008				0.005	0.001	0
				(0.006)	(0.005)	(0.006)				(0.011)	(0.011)	(0.015)
School×mF1				0.007	-0.003	-0.003				0.009	0.021	0.021
				(0.016)	(0.016)	(0.023)				(0.020)	(0.023)	(0.031)
School×mF2				0.039***	0.036**	0.034*				0.004	-0.002	0.005
				(0.015)	(0.015)	(0.018)				(0.019)	(0.020)	(0.023)
School×mF3				-0.008	-0.007	-0.008				0.012	-0.003	0.002
				(0.014)	(0.014)	(0.016)				(0.025)	(0.027)	(0.039)
mF1×Eng				0.25	0.158	0.205				1.114***	1.222***	1.121***
				(0.240)	(0.239)	(0.236)				(0.316)	(0.333)	(0.401)
mF2×Eng				-0.007	-0.101	-0.053				-0.378	-0.375	-0.408
				(0.185)	(0.182)	(0.172)				(0.257)	(0.268)	(0.322)
mF3×Eng				0.043	0.258*	0.177				-0.059	-0.167	-0.332
				(0.143)	(0.145)	(0.200)				(0.340)	(0.361)	(0.509)
mF1×Fre				0.085	0.073	0.017				0.310**	0.313**	0.467**
				(0.177)	(0.176)	(0.198)				(0.149)	(0.158)	(0.221)
mF2×Fre				0.08	0.034	0.082				-0.075	-0.08	-0.047

				(0.172)	(0.172)	(0.181)				(0.132)	(0.136)	(0.188)
mF3×Fre				0.018	0.112	0.087				0.01	0.02	0.096
				(0.140)	(0.148)	(0.172)				(0.231)	(0.239)	(0.382)
Exp×Eng					0.006	-0.001					-0.014	-0.009
					(0.006)	(0.007)					(0.021)	(0.031)
Exp×Fre					-0.006	-0.016					-0.019	-0.02
					(0.013)	(0.018)					(0.013)	(0.017)
School×Eng					0.075***	0.059***					-0.073	-0.084
					(0.018)	(0.023)					(0.057)	(0.078)
School×Fre					0.014	-0.003					-0.021	-0.01
					(0.020)	(0.024)					(0.028)	(0.037)
mF1×Exp×Eng						0.031						-0.045
						(0.042)						(0.057)
mF1×Exp×Fre						0.025						0.002
						(0.031)						(0.030)
mF1×School×Eng						0.043						0.009
						(0.105)						(0.153)
mF1×School×Fre						0.088						-0.051
						(0.082)						(0.073)
mF2×Exp×Eng						0.031						0.055
						(0.027)						(0.052)
mF2×Exp×Fre						0.031						0.003
						(0.028)						(0.030)
mF2×School×Eng						0.055						0.075
						(0.068)						(0.133)
mF2×School×Fre						0.067						-0.073
						(0.076)						(0.071)
mF3×Exp×Eng						0.011						-0.029
						(0.017)						(0.065)
mF3×Exp×Fre						0.023						0.007
						(0.027)						(0.064)
mF3×School×Eng						0.01						-0.021
						(0.049)						(0.176)
mF3×School×Fre						-0.002						0.149
						(0.069)						(0.144)
R^2	0.13	0.15	0.22	0.23	0.23	0.24	0.16	0.21	0.30	0.32	0.33	0.34
N-weighted	33,377	33,377	33,377	33,377	33,377	33,377	8,705	8,705	8,705	8,705	8,705	8,705

Note: The sample is restricted to age between 25 and 59 at the time of immigration; immigrants who worked before immigration; three indicators for a match between each skill of a source-country occupation and a corresponding skill of a main job in Canada in the current wave. All regressions control for months since immigration (msm). Additional controls are: immigration class (Family (default); Skilled Worker (PA); Skilled Worker (not PA); Bus/Nom/Ref/Other); residence region (Toronto (default); Montreal; QB; ON; AB; BC; Other); number of children in household under the age of 18; marital status (single (default); married/common law). Bootstrap standard errors in brackets. ***-significant at 1%; **-significant at 5%; *-significant at 10%.

Appendix B12. Log wage regressions for Visible minorities vs. Not visible minorities, females, wave 3

	Visible minorities						**Not visible minorities**					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Exp	-0.010***	-0.010***	-0.008***	-0.009***	-0.009***	-0.009***	-0.008	-0.004	-0.003	-0.007	-0.008	-0.009
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
School	0.011	-0.003	-0.01	-0.016	-0.014	-0.015	0.032	0.031	0.027	0.026	0.022	0.022
	(0.010)	(0.010)	(0.009)	(0.011)	(0.011)	(0.011)	(0.020)	(0.020)	(0.019)	(0.022)	(0.018)	(0.018)
msm	0.071***	0.064***	0.061***	0.062***	0.062***	0.060**	0.019	0.011	0.011	0.01	0.017	0.014
	(0.025)	(0.024)	(0.023)	(0.023)	(0.023)	(0.024)	(0.034)	(0.033)	(0.033)	(0.033)	(0.035)	(0.035)
Eng		0.544***	0.503***	0.442***	0.481***	0.468***		0.371*	0.381**	0.303	0.231	0.192
		(0.083)	(0.080)	(0.087)	(0.094)	(0.095)		(0.203)	(0.193)	(0.220)	(0.244)	(0.254)
Fre		0.148	0.158	0.045	0.068	0.058		0.371	0.375*	0.393	0.293	0.247
		(0.140)	(0.129)	(0.141)	(0.145)	(0.150)		(0.229)	(0.223)	(0.251)	(0.233)	(0.240)
mF1			0.393***	0.376***	0.383***	0.404***			0.259**	0.311**	0.313**	0.476**
			(0.067)	(0.078)	(0.079)	(0.114)			(0.117)	(0.143)	(0.149)	(0.228)
mF2			0.458***	0.491***	0.498***	0.526			0.249**	0.176	0.152	0.203
			(0.069)	(0.070)	(0.074)	(0.569)			(0.122)	(0.173)	(0.177)	(0.314)
mF3			0.131*	0.149*	0.136*	0.095			0.135	0.115	0.114	0.138
			(0.068)	(0.080)	(0.082)	(0.110)			(0.133)	(0.180)	(0.182)	(0.680)
Exp×mF1				0	0.001	0.004				0.006	-0.002	0.007
				(0.010)	(0.010)	(0.010)				(0.019)	(0.019)	(0.027)
Exp×mF2				0.012	0.014	0.013				0.014	0.015	0.033
				(0.013)	(0.013)	(0.061)				(0.022)	(0.023)	(0.038)
Exp×mF3				0	0	0.003				0.01	0.013	0.028
				(0.007)	(0.007)	(0.014)				(0.030)	(0.032)	(0.117)
School×mF1				-0.011	-0.014	-0.005				-0.054	-0.073	-0.13
				(0.028)	(0.029)	(0.037)				(0.073)	(0.075)	(0.116)
School×mF2				0.060**	0.056*	0.019				0.075	0.09	0.147
				(0.031)	(0.031)	(0.258)				(0.073)	(0.074)	(0.142)
School×mF3				0.007	0.009	0.021				0.004	0.01	0.039
				(0.026)	(0.025)	(0.033)				(0.084)	(0.092)	(0.304)
mF1×Eng				0.503*	0.424	0.262				0.066	0.034	-0.409
				(0.304)	(0.305)	(0.408)				(0.948)	(0.968)	(1.110)
mF2×Eng				-0.31	-0.323	-0.45				0.422	0.38	-0.202
				(0.275)	(0.275)	(0.323)				(0.810)	(0.837)	(1.551)
mF3×Eng				0.274	0.369	0.643*				0.123	0.229	0.647
				(0.280)	(0.288)	(0.388)				(0.735)	(0.756)	(1.482)
mF1×Fre				0.463*	0.386	0.008				-0.029	-0.091	-0.431
				(0.242)	(0.256)	(0.516)				(0.470)	(0.486)	(0.802)
mF2×Fre				0.061	0.094	0.456				0.145	0.084	-0.053

				(0.370)	(0.396)	(4.764)				(0.431)	(0.468)	(1.099)
mF3×Fre				0.084	0.078	-0.027				0.217	0.369	0.446
				(0.336)	(0.341)	(0.632)				(0.625)	(0.602)	(4.425)
Exp×Eng					-0.011	-0.005					0.001	0.01
					(0.009)	(0.010)					(0.024)	(0.026)
Exp×Fre					0.005	0.004					0.034	0.054*
					(0.013)	(0.015)					(0.026)	(0.033)
School×Eng					0.015	0.004					0.109	0.109
					(0.028)	(0.034)					(0.079)	(0.087)
School×Fre					0.031	0.028					0.123	0.134
					(0.032)	(0.038)					(0.095)	(0.106)
mF1×Exp×Eng						-0.03						-0.048
						(0.047)						(0.179)
mF1×Exp×Fre						0.003						-0.061
						(0.044)						(0.076)
mF1×School×Eng						0.119						0.365
						(0.180)						(0.786)
mF1×School×Fre						0.163						0.181
						(0.159)						(0.363)
mF2×Exp×Eng						0.015						-0.173
						(0.062)						(0.276)
mF2×Exp×Fre						-0.019						-0.113
						(0.422)						(0.117)
mF2×School×Eng						-0.072						-0.295
						(0.107)						(0.833)
mF2×School×Fre						-0.391						-0.207
						(1.791)						(0.456)
mF3×Exp×Eng						-0.013						0.004
						(0.021)						(0.328)
mF3×Exp×Fre						0.055						-0.041
						(0.090)						(0.728)
mF3×School×Eng						0.082						0.107
						(0.072)						(0.970)
mF3×School×Fre						0.015						-0.057
						(0.180)						(1.817)
R^2	0.09	0.12	0.23	0.24	0.24	0.25	0.12	0.14	0.18	0.19	0.21	0.23
N-weighted	23,239	23,239	23,239	23,239	23,239	23,239	6,981	6,981	6,981	6,981	6,981	6,981

See notes for Appendix B11.

Appendix C1. Cross-sectional Variance inflation factors, males

	Wave 1						Wave 2						Wave 3					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.83	1.86	1.88	2.82	3.05	3.19	1.6	1.63	1.64	2.34	2.41	2.44	1.43	1.46	1.47	2.09	2.15	2.18
School	1.76	1.84	1.89	3.68	3.75	3.9	1.73	1.83	1.9	2.88	2.9	2.92	1.59	1.64	1.71	2.46	2.52	2.56
Eng		1.77	1.84	2.85	3.34	3.5		1.91	1.94	2.69	3.16	3.25		1.93	1.97	2.73	3	3.06
Fre		2.67	2.69	3.53	3.69	3.74		3.36	3.38	4.32	4.52	4.62		4.46	4.47	5.36	5.56	5.69
mF1			1.35	2.24	2.35	6.19			1.22	2.06	2.13	4.36			1.19	1.81	1.83	2.88
mF2			1.4	1.78	1.8	2.14			1.21	1.6	1.62	2.38			1.18	1.46	1.46	1.75
mF3			1.29	1.94	1.95	2.18			1.22	1.66	1.67	1.76			1.21	1.53	1.54	1.63
Exp×mF1				2.35	2.5	5.33				1.99	2.03	2.47				1.83	1.89	2.74
Exp×mF2				2.48	2.52	2.84				1.86	1.89	2.06				1.79	1.81	2.05
Exp×mF3				3.06	3.17	6.06				2.45	2.54	3.99				2.37	2.43	2.91
School×mF1				2.96	3.24	11				2.17	2.29	3.97				2.07	2.17	3.13
School×mF2				2.4	3.04	4.04				1.82	1.84	2.24				1.81	1.81	2
School×mF3				4	4.12	4.7				3.24	3.32	4.02				2.92	2.97	3.43
mF1×Eng				2.34	2.49	3.95				1.99	2.11	3.14				2.03	2.08	2.67
mF2×Eng				1.86	2.02	2.27				1.7	1.75	1.97				1.67	1.71	1.78
mF3×Eng				2.12	2.34	5.01				2.15	2.26	3.75				2.09	2.24	3.68
mF1×Fre				2.27	2.34	4.65				1.8	1.86	2.88				1.84	1.86	2.69
mF2×Fre				2.15	2.3	5.08				1.62	1.63	2.59				1.68	1.72	2.52
mF3×Fre				1.45	1.49	2.22				1.55	1.65	2.12				1.73	1.83	2.36
Exp×Eng					3.94	5.73					2.58	3.54					2.52	3.5
Exp×Fre					2.2	3.16					1.55	2.25					1.64	2.28
School×Eng					4.96	7					3.07	4.29					2.94	4.16
School×Fre					2.66	5.67					1.72	2.54					1.88	2.52
mF1×Exp×Eng						5.08						2.18						2.76
mF1×Exp×Fre						6.39						2.46						2.65
mF1×School×Eng						13.43						4.08						3.41
mF1× School ×Fre						17.67						3.53						3.03
mF2×Exp×Eng						2.44						2.04						2.08
mF2×Exp×Fre						6.29						1.88						2.8
mF2×School×Eng						3.7						2.2						2.57
mF2× School ×Fre						14.37						2.53						3.08
mF3×Exp×Eng						11.25						5						5.44
mF3×Exp×Fre						3.76						3.81						2.5
mF3×School×Eng						13.56						7.15						7.1
mF3× School ×Fre						3.11						4.17						3.47

Appendix C2. Cross-sectional Variance inflation factors, females

	Wave 1						Wave 2						Wave 3					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.41	1.48	1.5	2.05	2.39	2.48	1.33	1.38	1.39	1.87	1.89	1.91	1.34	1.38	1.39	1.86	1.88	1.89
School	1.52	1.56	1.67	2.62	2.84	2.9	1.43	1.48	1.56	2.12	2.28	2.32	1.44	1.49	1.52	2	2.04	2.05
Eng		2.14	2.15	2.84	3.29	3.47		2.09	2.11	2.59	2.89	2.93		2	2.01	2.41	2.57	2.6
Fre		2.51	2.58	3.63	3.94	4.2		3.44	3.47	4.05	4.09	4.2		3.49	3.52	4.1	4.1	4.22
mF1			1.32	2.41	2.45	7.14			1.19	2.03	2.06	4.13			1.14	1.81	1.84	3.44
mF2			1.4	2.51	2.57	4.8			1.23	1.67	1.7	2.51			1.13	1.44	1.45	1.59
mF3			1.35	1.6	1.67	2.06			1.25	1.54	1.55	1.89			1.14	1.32	1.33	1.38
Exp×mF1				2.55	2.64	9.42				1.71	1.76	2.42				1.72	1.75	2.05
Exp×mF2				2.72	2.75	8.19				1.99	2.05	3.62				1.83	1.85	2.56
Exp×mF3				3.53	3.69	4.18				2.39	2.44	3.3				2.12	2.15	2.52
School×mF1				8.77	8.85	11.13				3.58	3.62	4.16				2.92	2.96	3.85
School×mF2				8.38	8.47	9.98				3.03	3.14	4.32				2.42	2.45	2.83
School×mF3				3.17	3.67	10.7				2.75	2.78	3.92				2.5	2.55	2.85
mF1×Eng				2.22	2.34	4.33				1.47	1.58	3.37				1.53	1.6	2.49
mF2×Eng				2.24	2.42	3.36				1.8	1.84	2.18				1.59	1.6	1.77
mF3×Eng				2.21	2.46	6.57				2.5	2.56	4.02				1.92	2	2.7
mF1×Fre				3.08	3.16	29.85				1.81	2.04	3.93				1.67	1.79	3.55
mF2×Fre				2.03	2.1	40.92				1.52	1.53	2.91				1.37	1.37	2.02
mF3×Fre				1.63	1.69	6.79				1.49	1.55	2.82				1.38	1.39	1.49
Exp×Eng					2.96	4.56					2.27	3.03					2.04	2.73
Exp×Fre					3.42	4.19					2.21	2.94					1.73	2.32
School×Eng					2.92	5.44					2.38	3.07					2.35	3.14
School×Fre					2.53	3.35					2.19	2.75					1.86	2.4
mF1×Exp×Eng						8.33						3.06						2.23
mF1×Exp×Fre						22.26						3.26						2.77
mF1×School×Eng						6.48						4.8						4.35
mF1× School ×Fre						12.25						6.84						5.23
mF2×Exp×Eng						2.49						4.74						2.43
mF2×Exp×Fre						34.73						2.68						2.2
mF2×School×Eng						3.34						3.2						2.41
mF2× School ×Fre						9.78						4.18						2.74
mF3×Exp×Eng						7.86						4.49						3.65
mF3×Exp×Fre						7.97						3.36						1.86
mF3×School×Eng						7.3						5.47						5.05
mF3× School ×Fre						9.79						2.71						1.79

Appendix C3. Variance inflation factors for Skilled Worker principal applicants and Other immigration categories, males, wave 3

	Skilled Worker principal applicants						Other immigration categories					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.2	1.21	1.22	1.74	1.89	1.97	1.59	1.66	1.67	2.28	2.64	2.81
School	1.16	1.16	1.19	1.94	2.29	2.46	1.52	1.77	1.86	2.46	2.54	2.58
Eng		2.22	2.27	3.03	3.33	3.53		1.9	1.95	2.75	3.63	3.91
Fre		5.36	5.39	6.7	7.42	7.96		3.22	3.24	3.68	3.73	3.79
mF1			1.17	2.16	2.22	4.79			1.19	1.35	1.35	1.72
mF2			1.16	1.8	1.81	3.53			1.18	1.34	1.36	1.82
mF3			1.12	1.27	1.28	1.77			1.25	2.58	2.73	3.84
Exp×mF1				2.05	2.1	3.53				1.78	1.89	2.72
Exp×mF2				2	2.01	2.89				1.81	1.81	2.32
Exp×mF3				1.32	1.33	1.67				3.04	3.13	6.25
School×mF1				2.32	2.5	4.22				1.88	1.94	2.33
School×mF2				1.98	1.99	2.58				1.9	1.91	2.09
School×mF3				1.37	1.38	1.67				4.92	5.12	8.89
mF1×Eng				2.41	2.46	3.96				1.37	1.41	1.69
mF2×Eng				1.99	2	2.88				1.44	1.47	1.8
mF3×Eng				2.23	2.28	2.55				2.55	2.68	5.8
mF1×Fre				2.08	2.1	3.59				1.45	1.49	1.77
mF2×Fre				1.9	1.93	3.43				1.53	1.55	1.75
mF3×Fre				2.31	2.42	2.79				1.92	2.06	4.55
Exp×Eng					2.13	3.03					3.27	4.49
Exp×Fre					2.34	3.37					1.72	2.33
School×Eng					2.77	4.46					3.94	5.34
School×Fre					3.11	4.93					1.74	2.17
mF1×Exp×Eng						4.21						2.05
mF1×Exp×Fre						4						1.76
mF1×School×Eng						5.26						1.93
mF1× School ×Fre						4.11						1.96
mF2×Exp×Eng						3.36						2.27
mF2×Exp×Fre						3.53						3.7
mF2×School×Eng						3.28						4.53
mF2× School ×Fre						3.73						4.66
mF3×Exp×Eng						3.49						7.69
mF3×Exp×Fre						3.63						6.84
mF3×School×Eng						2.63						11.87
mF3× School ×Fre						3.24						11.09

Appendix C4. Variance inflation factors for Skilled Worker principal applicants and Other immigration categories, females, wave 3

	Skilled Worker principal applicants						Other immigration categories					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.17	1.17	1.18	1.58	2.29	2.48	1.39	1.44	1.45	1.93	1.96	1.98
School	1.2	1.23	1.26	1.89	2.91	3.18	1.41	1.52	1.55	2.01	2.11	2.15
Eng		1.97	1.98	2.44	2.83	3.02		1.97	1.99	2.41	2.64	2.69
Fre		3.89	3.99	4.68	4.95	5.08		3.42	3.44	4.08	4.11	4.24
mF1			1.31	2.43	2.48	6.95			1.09	1.71	1.73	2.99
mF2			1.31	2.63	2.71	9.49			1.12	1.32	1.32	1.47
mF3			1.12	6.45	6.49	72.04			1.17	1.41	1.42	1.5
Exp×mF1				1.99	2.09	3.4				1.81	1.84	2.06
Exp×mF2				1.95	2.05	3.21				2.17	2.2	3.01
Exp×mF3				1.8	1.83	37.75				2.34	2.37	2.87
School×mF1				7.43	7.51	12.78				2.26	2.31	2.93
School×mF2				6.32	6.54	28.76				2.11	2.12	2.28
School×mF3				1.65	1.67	44.94				2.66	2.71	3.16
mF1×Eng				2.23	2.34	4.9				1.36	1.41	2.05
mF2×Eng				1.95	1.96	2.85				1.56	1.59	2.05
mF3×Eng				7.01	7.04	18.67				1.96	2.05	2.95
mF1×Fre				2.48	2.65	6.05				1.48	1.58	3.18
mF2×Fre				1.9	1.92	19.2				1.33	1.35	2.08
mF3×Fre				2.79	2.8	83.63				1.38	1.4	1.58
Exp×Eng					2.38	3.13					2.21	2.95
Exp×Fre					2.76	3.52					1.71	2.24
School×Eng					3.6	4.57					2.61	3.54
School×Fre					3.91	5.02					1.76	2.26
mF1×Exp×Eng						3.87						2.32
mF1×Exp×Fre						6.24						2.27
mF1×School×Eng						18.05						3.23
mF1× School ×Fre						17.72						4.04
mF2×Exp×Eng						2.85						2.97
mF2×Exp×Fre						2.39						3.33
mF2×School×Eng						11.96						2.64
mF2× School ×Fre						21.79						2.92
mF3×Exp×Eng						19.25						4.05
mF3×Exp×Fre						22.36						1.98
mF3×School×Eng						145.8						5.79
mF3× School ×Fre						144.63						1.86

Appendix C5. Variance inflation factors for Regulated occupations and Unregulated occupations, males, wave 3

	Regulated occupations						Unregulated occupations					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.34	1.38	1.38	2.08	2.13	2.18	1.57	1.6	1.63	2.14	2.24	2.27
School	1.46	1.5	1.54	2.24	2.35	2.39	1.8	1.9	1.99	2.87	2.94	2.98
Eng		1.95	1.99	2.78	2.91	2.96		1.98	2.03	2.84	3.31	3.42
Fre		4.58	4.59	5.82	6.03	6.26		4.4	4.45	5.19	5.44	5.54
mF1			1.16	1.89	1.9	2.85			1.29	1.87	1.89	3.27
mF2			1.18	1.4	1.41	1.65			1.27	2.47	2.47	7.8
mF3			1.19	1.31	1.32	1.41			1.29	2.39	2.46	2.91
Exp×mF1				1.82	1.9	3.06				2	2.07	2.79
Exp×mF2				1.86	1.88	2.18				2.73	2.75	4.86
Exp×mF3				2.17	2.21	2.41				2.76	2.9	7.21
School×mF1				2.22	2.29	2.96				2.09	2.28	4.25
School×mF2				2.23	2.23	2.48				1.75	1.76	3.19
School×mF3				2.39	2.41	2.68				4.51	4.64	7.56
mF1×Eng				2.22	2.29	2.98				2.07	2.12	2.86
mF2×Eng				1.88	1.94	1.99				2	2.02	4.58
mF3×Eng				2.3	2.44	3.3				2.17	2.34	5.01
mF1×Fre				1.88	1.9	2.48				2.01	2.07	3.71
mF2×Fre				1.88	1.93	2.66				1.79	1.81	4.57
mF3×Fre				2.15	2.27	2.87				1.48	1.59	2.52
Exp×Eng					2.19	3.13					2.99	4.08
Exp×Fre					1.62	2.51					1.84	2.2
School×Eng					2.59	3.74					3.53	4.83
School×Fre					1.97	2.75					1.98	2.52
mF1×Exp×Eng						3.33						2.75
mF1×Exp×Fre						2.46						3.99
mF1×School×Eng						2.99						5.04
mF1× School ×Fre						2.48						4.54
mF2×Exp×Eng						2.45						5.04
mF2×Exp×Fre						2.51						8.02
mF2×School×Eng						3.76						3.92
mF2× School ×Fre						3.85						4.79
mF3×Exp×Eng						5.69						6.63
mF3×Exp×Fre						2.52						7.15
mF3×School×Eng						7.14						9.13
mF3× School ×Fre						4.06						6.56

Appendix C6. Variance inflation factors for Regulated occupations and Unregulated occupations, females, wave 3

	Regulated occupations						Unregulated occupations					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.33	1.36	1.38	1.96	1.99	2.01	1.4	1.45	1.46	1.89	1.92	1.93
School	1.4	1.44	1.46	2.04	2.12	2.14	1.53	1.58	1.63	2.07	2.1	2.12
Eng		2	2.02	2.56	2.68	2.73		2.06	2.06	2.43	2.66	2.69
Fre		3.4	3.48	4.61	4.69	5.06		3.68	3.68	3.95	3.98	4.07
mF1			1.15	1.71	1.76	4.04			1.23	2.12	2.15	3.6
mF2			1.22	1.95	1.96	2.57			1.2	1.61	1.62	2.32
mF3			1.26	1.47	1.48	1.74			1.1	1.33	1.34	1.42
Exp×mF1				1.72	1.77	2.19				2.03	2.04	2.29
Exp×mF2				1.99	2.04	3.32				2.53	2.55	4.61
Exp×mF3				2.36	2.43	3.48				2.23	2.25	2.51
School×mF1				2.49	2.6	3.85				4.43	4.44	5.23
School×mF2				1.99	2.05	3.63				3.98	4	4.72
School×mF3				1.88	1.92	2.19				3.4	3.45	3.86
mF1×Eng				1.62	1.71	3.1				1.62	1.67	2.46
mF2×Eng				1.85	1.86	2.02				1.68	1.7	2.77
mF3×Eng				2.06	2.09	2.34				2.31	2.43	3.61
mF1×Fre				1.8	1.93	3.75				1.9	2.04	5.56
mF2×Fre				1.77	1.77	3				1.57	1.58	2.94
mF3×Fre				1.41	1.42	1.62				1.57	1.58	1.8
Exp×Eng					1.93	2.55					2.26	2.99
Exp×Fre					1.86	2.71					1.82	2.27
School×Eng					2.04	2.73					2.77	3.58
School×Fre					1.97	2.81					1.96	2.38
mF1×Exp×Eng						2.39						2.51
mF1×Exp×Fre						2.74						4.42
mF1×School×Eng						5.64						5.46
mF1× School ×Fre						4.99						9.94
mF2×Exp×Eng						2.05						5.79
mF2×Exp×Fre						2.83						2.92
mF2×School×Eng						2.71						4.46
mF2× School ×Fre						3.13						4.02
mF3×Exp×Eng						4.84						4.23
mF3×Exp×Fre						2.53						2.2
mF3×School×Eng						3.86						7.29
mF3× School ×Fre						1.65						2.52

Appendix C7. Variance inflation factors for Professional occupations and Non-professional occupations, males, wave 3

	Professional occupations						Non-professional occupations					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.33	1.33	1.33	4.55	4.98	5.75	1.43	1.47	1.47	1.95	2.03	2.05
School	1.22	1.23	1.26	2.85	3.99	5.02	1.64	1.71	1.8	2.38	2.4	2.41
Eng		2.38	2.4	5.74	6.88	10.18		1.92	1.95	2.62	2.97	3.08
Fre		5.11	5.17	9.39	12.37	19.01		4.44	4.48	5.16	5.29	5.41
mF1			1.21	2.73	2.95	5.58			1.06	1.59	1.6	2.4
mF2			1.18	2.44	2.5	5.06			1.12	1.22	1.22	1.46
mF3			1.21	21.78	22.05	291.76			1.23	1.68	1.7	1.8
Exp×mF1				5.44	5.6	8.03				1.33	1.37	2.39
Exp×mF2				3.48	3.53	5.43				1.44	1.46	1.65
Exp×mF3				6.16	6.22	132.42				2.47	2.55	3.08
School×mF1				4.1	4.47	5.46				1.74	1.84	4.07
School×mF2				3.33	3.5	4.41				1.54	1.56	1.71
School×mF3				12.98	13.03	14.64				3.43	3.5	4.1
mF1×Eng				5.64	5.71	12.09				1.82	1.85	2.15
mF2×Eng				2.95	2.95	5.62				1.42	1.46	1.52
mF3×Eng				9.42	9.71	228.74				2.22	2.39	4.04
mF1×Fre				4.81	4.93	11.09				1.4	1.42	2.08
mF2×Fre				2.44	2.45	4.86				1.61	1.64	2.39
mF3×Fre				13.15	13.32	148.47				1.96	2.1	2.7
Exp×Eng					2.98	8.82					2.66	3.58
Exp×Fre					2.74	8.3					1.55	2.01
School×Eng					3.53	7.72					3.11	4.24
School×Fre					4.59	11.62					1.72	2.2
mF1×Exp×Eng						11.19						2.65
mF1×Exp×Fre						8.99						1.77
mF1×School×Eng						7.97						4.24
mF1× School ×Fre						7.6						2.52
mF2×Exp×Eng						5.88						1.84
mF2×Exp×Fre						5.01						2.77
mF2×School×Eng						5.54						2.8
mF2× School ×Fre						4.54						3.38
mF3×Exp×Eng						98.14						5.78
mF3×Exp×Fre						.						2.77
mF3×School×Eng						.						8.06
mF3× School ×Fre						.						4.03

Appendix C8. Variance inflation factors for Professional occupations and Non-professional occupations, females, wave 3

	Professional occupations						Non-professional occupations					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.14	1.18	1.2	2.96	3.24	3.59	1.38	1.42	1.42	1.77	1.8	1.81
School	1.26	1.26	1.29	2.86	3.33	3.9	1.47	1.53	1.55	1.88	1.94	1.97
Eng		2	2.01	3.73	3.93	4.09		2.07	2.08	2.38	2.58	2.61
Fre		3.58	3.66	6.48	6.99	7.92		3.53	3.54	3.72	3.74	3.85
mF1			1.31	2.46	2.56	4.68			1.05	1.81	1.84	3.1
mF2			1.59	3.12	3.16	7.13			1.03	1.23	1.23	1.31
mF3			1.86	5.15	5.18	24.71			1.08	1.29	1.3	1.32
Exp×mF1				3.28	3.32	4.09				1.68	1.69	2.21
Exp×mF2				3.73	3.84	5.31				1.95	1.96	2.84
Exp×mF3				3.16	3.21	7.17				2.18	2.22	2.65
School×mF1				7.29	7.31	9.99				2.08	2.09	2.44
School×mF2				5.88	6.12	13.24				2.03	2.05	2.41
School×mF3				1.66	1.68	27.78				2.78	2.84	3.28
mF1×Eng				2.85	3.1	5.61				1.5	1.52	1.92
mF2×Eng				2.67	2.71	7.17				1.41	1.42	1.91
mF3×Eng				6.66	6.72	9.43				1.86	1.94	2.68
mF1×Fre				3.52	3.66	6.65				1.63	1.75	7.16
mF2×Fre				1.6	1.61	4				1.39	1.4	1.72
mF3×Fre				1.7	1.78	32.49				1.45	1.46	1.53
Exp×Eng					1.88	3.32					2.14	2.75
Exp×Fre					2.29	5.29					1.83	2.09
School×Eng					3	5.34					2.49	3.22
School×Fre					2.91	6.41					1.85	2.17
mF1×Exp×Eng						3.84						2.5
mF1×Exp×Fre						5.08						7.28
mF1×School×Eng						12.39						4.04
mF1× School ×Fre						10.38						8.69
mF2×Exp×Eng						4.66						2.62
mF2×Exp×Fre						2.66						2.58
mF2×School×Eng						13.73						2.71
mF2× School ×Fre						4.86						2.54
mF3×Exp×Eng						5.73						3.83
mF3×Exp×Fre						5.07						2
mF3×School×Eng						15.01						5.51
mF3× School ×Fre						30.01						2.11

Appendix C9. Variance inflation factors for University educated and Other education levels, males, wave 3

	University educated						Other levels of education					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.17	1.18	1.19	1.69	1.8	1.83	1.74	1.8	1.82	2.48	2.77	2.87
School	1.17	1.17	1.18	1.82	2.07	2.18	1.78	1.9	1.94	2.9	3.02	3.1
Eng		2	2.03	2.6	2.97	3.13	1.06	1.07	1.08	1.13	1.15	1.17
Fre		4.63	4.67	5.6	6.58	6.92		2.21	2.27	3.38	5.35	6.28
mF1			1.17	2.09	2.14	3.84		4.58	4.61	5.56	6	6.32
mF2			1.16	2.01	2.02	3.44			1.17	2.06	2.07	3.19
mF3			1.09	1.29	1.3	1.91			1.24	2.32	2.34	2.6
Exp×mF1				1.99	2.05	3.04			1.23	2.48	2.55	2.87
Exp×mF2				1.94	1.95	2.61				2.35	2.4	7.08
Exp×mF3				1.38	1.38	1.57				1.88	1.92	2.29
School×mF1				2.46	2.62	3.67				3.19	3.25	5.02
School×mF2				2.15	2.2	2.62				2.65	2.7	10.31
School×mF3				1.48	1.5	1.76				2.99	3.14	4.42
mF1×Eng				2.18	2.22	3.64				5.73	5.84	7.27
mF2×Eng				1.79	1.8	3.03				2.18	2.2	3.33
mF3×Eng				1.77	1.8	2.68				1.96	1.99	5.29
mF1×Fre				2.03	2.05	4.12				2.94	2.98	6.2
mF2×Fre				1.69	1.71	3.55				1.96	2.01	2.76
mF3×Fre				1.6	1.63	1.94				2.24	2.29	5.29
Exp×Eng					1.68	2.29				2.57	2.62	5.01
Exp×Fre					1.84	2.66					3.72	5.21
School×Eng					2.74	4.06					1.79	2.23
School×Fre					3.2	4.73					5.31	8.1
mF1×Exp×Eng						3.29					2.18	3.04
mF1×Exp×Fre						3.16						8.32
mF1×School×Eng						4.43						4.62
mF1× School ×Fre						4.12						15.66
mF2×Exp×Eng						2.88						5.28
mF2×Exp×Fre						3.02						2.54
mF2×School×Eng						3.35						4.33
mF2× School ×Fre						3.63						8.99
mF3×Exp×Eng						2.41						8.94
mF3×Exp×Fre						2.78						7.45
mF3×School×Eng						3.33						4.92
mF3× School ×Fre						3.03						11.8

Appendix C10. Variance inflation factors for University educated and Other education levels, females, wave 3

	University educated						Lower levels of education					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.16	1.2	1.22	1.67	1.85	1.95	1.48	1.52	1.53	1.98	2.13	2.17
School	1.21	1.21	1.22	1.73	1.86	1.92	1.58	1.67	1.67	2.23	2.39	2.44
Eng		1.72	1.73	2.12	2.61	2.74		2.35	2.37	2.83	3.94	4.2
Fre		3.18	3.21	4.25	5.3	6.17		4.61	4.64	4.72	5.28	5.66
mF1			1.15	2.22	2.28	4.66			1.08	1.46	1.46	23.01
mF2			1.14	2.21	2.22	3.76			1.19	1.95	1.98	2.19
mF3			1.13	2.64	2.67	13.45			1.21	1.95	1.96	2.31
Exp×mF1				1.96	2.07	2.51				1.45	1.47	55.64
Exp×mF2				2.08	2.11	2.86				1.85	1.93	14.18
Exp×mF3				1.32	1.33	3.51				2.86	2.94	3.64
School×mF1				4.18	4.24	5.78				1.73	1.74	8.47
School×mF2				3.29	3.35	7.26				2.58	2.62	3.41
School×mF3				1.41	1.43	53.22				3.94	4.05	5.27
mF1×Eng				1.71	1.75	3.55				2.63	2.64	4.33
mF2×Eng				1.59	1.6	2.83				1.94	1.97	5.64
mF3×Eng				2.14	2.14	3.34				2.38	2.46	4.46
mF1×Fre				2.02	2.04	4.99				2.44	2.47	76.98
mF2×Fre				1.32	1.33	2.98				1.94	1.94	2.32
mF3×Fre				1.46	1.5	45.1				1.88	1.92	2.13
Exp×Eng					1.6	1.98					2.85	3.82
Exp×Fre					1.83	3.27					1.9	2.17
School×Eng					2.49	3.12					3.96	5.51
School×Fre					3	4.4					2.36	2.99
mF1×Exp×Eng						2.63						3.29
mF1×Exp×Fre						3.96						116.4
mF1×School×Eng						7.48						4.62
mF1× School ×Fre						8.02						9.49
mF2×Exp×Eng						2.26						4.86
mF2×Exp×Fre						2.15						14.73
mF2×School×Eng						6.34						6.52
mF2× School ×Fre						3.72						5.26
mF3×Exp×Eng						2.96						5.24
mF3×Exp×Fre						2.58						2.12
mF3×School×Eng						4.68						8.87
mF3× School ×Fre						76.98						2.49

Appendix C11. Variance inflation factors for Visible minorities and Not visible minorities, males, wave 3

	Visible minorities						Not visible minorities					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.44	1.45	1.47	2.01	2.22	2.29	1.36	1.37	1.38	2.24	2.42	2.51
School	1.7	1.75	1.81	2.48	2.55	2.59	1.27	1.3	1.38	2.4	2.74	2.86
Eng		1.45	1.45	2.14	2.35	2.4		1.7	1.82	2.81	2.88	2.98
Fre		2.97	2.98	3.72	3.9	4.04		4.13	4.23	5.45	5.91	6.22
mF1			1.2	1.93	1.95	3.77			1.16	1.92	1.96	3.2
mF2			1.17	1.57	1.58	2			1.14	1.47	1.5	1.79
mF3			1.17	1.58	1.59	1.65			1.27	1.56	1.57	1.91
Exp×mF1				1.82	1.85	2.85				2.06	2.26	4.16
Exp×mF2				1.8	1.83	2.26				2.15	2.21	2.36
Exp×mF3				2.56	2.6	3.17				1.71	1.84	2.39
School×mF1				2.06	2.12	2.76				2.43	2.74	6.72
School×mF2				1.78	1.79	2.1				2.15	2.21	2.59
School×mF3				3.27	3.3	3.89				2.09	2.39	3.38
mF1×Eng				2.04	2.1	3.07				2	2.09	3.06
mF2×Eng				1.66	1.71	1.85				1.83	1.85	2.03
mF3×Eng				2.08	2.3	4.21				2.2	2.39	4.13
mF1×Fre				1.83	1.84	2.37				2.29	2.37	4.28
mF2×Fre				1.76	1.81	2.41				2.08	2.15	3.46
mF3×Fre				1.79	1.93	2.64				1.64	1.72	2.39
Exp×Eng					2.66	3.61					2.27	3.73
Exp×Fre					1.66	2.32					2.39	3.8
School×Eng					3.12	4.34					2.95	4.21
School×Fre					1.83	2.33					2.47	3.87
mF1×Exp×Eng						3.07						3.91
mF1×Exp×Fre						2.82						4.23
mF1×School×Eng						2.94						7.75
mF1× School ×Fre						3.2						4.84
mF2×Exp×Eng						2.18						2.81
mF2×Exp×Fre						2.69						3.88
mF2×School×Eng						2.7						3.64
mF2× School ×Fre						3.64						3.32
mF3×Exp×Eng						5.86						3.79
mF3×Exp×Fre						2.85						2.36
mF3×School×Eng						7.77						5.3
mF3× School ×Fre						4.64						2.38

Appendix C12. Variance inflation factors for Visible minorities and Not visible minorities, females, wave 3

	Visible minorities						Not visible minorities					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Exp	1.37	1.37	1.39	1.92	1.96	1.97	1.3	1.38	1.39	1.86	1.96	1.99
School	1.5	1.59	1.64	2.21	2.26	2.28	1.31	1.31	1.34	1.68	1.73	1.74
Eng		1.37	1.38	1.79	1.91	1.95		1.88	1.88	2.28	2.44	2.48
Fre		2.73	2.75	3.39	3.45	3.57		2.78	2.85	3.48	3.64	3.78
mF1			1.14	2.01	2.04	4.14			1.14	2.1	2.14	4.39
mF2			1.13	1.95	1.96	2.38			1.17	1.64	1.67	2.16
mF3			1.14	1.48	1.51	1.94			1.15	1.32	1.32	1.64
Exp×mF1				1.78	1.8	2.13				2.06	2.13	2.85
Exp×mF2				1.96	1.98	5.82				2.06	2.1	3.05
Exp×mF3				2.19	2.21	3.05				3.16	3.27	7.27
School×mF1				2.59	2.62	3.38				5.53	5.67	9.53
School×mF2				1.92	1.95	3.88				5.09	5.18	8.35
School×mF3				2.75	2.78	3.12				2.5	2.6	5.17
mF1×Eng				1.47	1.54	2.72				2.4	2.48	3.66
mF2×Eng				1.59	1.6	1.93				2.2	2.25	3.33
mF3×Eng				1.96	2.07	2.96				2.14	2.22	3.38
mF1×Fre				1.53	1.72	4.57				3.01	3.04	5.06
mF2×Fre				1.91	1.92	3.17				1.6	1.65	4.34
mF3×Fre				1.48	1.53	2.14				1.91	1.94	2.74
Exp×Eng					2.19	3.08					1.65	1.94
Exp×Fre					1.8	2.4					1.82	2.48
School×Eng					2.66	3.65					1.91	2.19
School×Fre					1.98	2.65					2.12	2.49
mF1×Exp×Eng						2.15						3.81
mF1×Exp×Fre						2.31						5.06
mF1×School×Eng						3.86						14.04
mF1× School ×Fre						5.96						10.85
mF2×Exp×Eng						2.64						4.42
mF2×Exp×Fre						6.08						2.45
mF2×School×Eng						2.2						10.64
mF2× School ×Fre						4.62						8.27
mF3×Exp×Eng						4.04						4.4
mF3×Exp×Fre						2.85						3.47
mF3×School×Eng						6.12						5.24
mF3× School ×Fre						1.87						4.82