The Labour Market Integration of Immigrants and Their Role on Innovation

by

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The thesis consists of materials of all which I authored or co-authored: see Statement of Contribution included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by examiners

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Statement of Contributions

Chapter 1 is sole authored. Chapters 2 and 3 are co-authored with Professor Joel Blit and Professor Mikal Skuterud. Professor Joel Blit and Professor Mikal Skuterud were responsible for developing original research questions and for the writing of these papers, while I was primarily responsible for the data analysis and model refinement.

Abstract

This thesis contains three chapters evaluating the role of labour market skills in determining immigrants' labour market integration and Canada's innovation rate.

In Chapter 1, I estimate how the impact of entry economic conditions on immigrants' labour market outcomes varies by the versatility of their skills. Skill versatility is measured using information on the sectoral concentration of native-born workers with a particular education field and level. Entry economic conditions are measured using city-level unemployment rates among native graduates from a similar education field and level. Since immigrants' location choices can be endogenous to geographic local economic conditions, I address the endogeneity of immigrants' location choices by exploiting the historical settlement patterns of immigrants from the same countries of origin.

I find that immigrants suffer a 5 to 8 percent decline in their annual earnings when there is a one percentage-point increase in entry unemployment rates. When I incorporate the skill versatility measure in the estimation, the earnings loss is mitigated by 1 to 3 percentage points, if there is a one standard deviation increase in immigrants' skill versatility level. This effect is less evident for highly educated immigrants and it may be due to their being more likely to have pre-arranged employment before landing. I also find that city-level onward migration is more likely for immigrants who face unfavourable labour market conditions at entry, and movers do fare better than stayers conditional on initial setbacks. Meanwhile, immigrants' geographical mobility is found to be strengthened to some extent by their skill versatility.

Chapter 2 examines the effect of changes in skilled-immigrant population shares in 98 Canadian cities between 1981 and 2006 on per capita patents. The Canadian case is of interest because its 'points system' for selecting immigrants is viewed as a model of skilled immigration policy. Our estimates suggest unambiguously smaller beneficial impacts of increasing the university-educated immigrant population share than comparable U.S. estimates, whereas our estimates of the contribution of Canadian-born university graduates are virtually identical in magnitude to the U.S. estimates. The modest contribution of Canadian immigrants to innovation is, in large part, explained by the low employment rates of Canadian STEM-educated immigrants in STEM jobs. Our results point to the value of providing employers with a role in the immigrant screening process.

Lastly, in Chapter 3, using inventors' names to identify their ethnicity and Canadian Census and NHS data to estimate ethnic populations, we estimate patenting rates for Canada's ethnic populations between 1986 and 2011. The results reveal higher patenting rates for Canada's ethnic minorities, particularly for Canadians with Korean, Japanese, and Chinese ancestry, and suggest that immigrants accounted for one-third of Canadian patents in recent years, despite comprising less than one-quarter of the adult population. Human capital characteristics, in particular the share with a PhD and the shares educated and employed in STEM fields, account for most of the ethnic-minority advantage in patenting. Our results also point to larger patenting contributions by foreign-educated compared to Canadian-educated immigrants, which runs counter to current immigrant selection policies favouring international students.

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Introduction

Canada consistently ranks among the world's largest immigrant-receiving countries measured as a proportion of its population. The Canadian *Immigration Act* of 1962 ended the historical practice of selecting immigrants on the basis of their country of origin and replaced it over the following decade with a 'points system' that emphasized the human capital of migrants. Between the mid-1980s and mid-1990s, both Canada's annual inflow of new permanent residents and the share of the inflow admitted under the 'points system' more than doubled. Consequently, the share of the Canadian working-age population comprised of university-educated immigrants increased from 2.6% in the early 1980s to 3.3% in the early 1990s and 6.7% by the mid-2000s.

Although the level of education for new immigrants has increased dramatically, little improvement is shown in their labour market performance over past decades (Aydemir and Skuterud, 2005; Picot and Hou, 2009; D. Green and Worswick, 2012; Ferrer, Picot, and Riddel, 2012; Warman and Worswick, 2015). For that reason, a criticism of the Canadian immigration system has emerged, with arguments that policymakers should not only address supply-side concerns, but also take the demand side into consideration. At the same time, a burgeoning economics literature examines that immigrants may not only serve to meet current labour needs in receiving countries, but also bring diversity to promote innovative ideas, which may improve firms' productivity and raise entrepreneurship. Given Canada's success at attracting skilled immigrants, this three-chapter dissertation contributes to an empirical understanding of how various types of skills that immigration brings affect the labour market integration of immigrants and innovation in Canada.

Chapter 1 examines how the effect of entry economic conditions on immigrants' labour market outcomes depends on the versatility of immigrants' skills. There is an ongoing debate regarding whether immigrants should be selected according to current labour market conditions or their own human capital characteristics, regardless of economic cyclical changes. It is true that macroeconomic entry conditions not only affect immigrants' labour market performance in the initial years after landing in the host-country, but they may also affect immigrants' performance in the long run (Aydemir, 2003). However, in practice, it is difficult to co-ordinate immigration levels with the business cycle, due to difficulties in predicting future labour market needs. Furthermore, labour market conditions may be localized and it is not possible to ensure that immigrants settle in geographic areas where labour market conditions are relatively strong. In this chapter, I construct a skill versatility measure using information on the sectoral concentration of workers with a particular education (field and level) and I measure entry economic conditions using unemployment rates at the city-education level. With these measures, I find that the skill versatility can buffer immigrants against adverse entry economic conditions.

To inform the innovation-enhancing potential of immigration in a setting in which a 'points system' is used to screen skilled immigrants, Chapter 2 examines the effect of changes in skilled-immigrant population shares within Canadian cities on per capita patents. By relating immigrant shares to patent rates at the city level, the result shows smaller beneficial impacts of increasing the university-educated immigrant population share than comparable U.S. estimates. The weaker contribution of Canadian immigrants to innovation is, is in large part, explained by the low employment rates of Canadian STEM-educated immigrants in STEM jobs.

Chapter 3 contributes further to the Canadian evidence on the human capital driving innovation. In this chapter, the attention is extended to the entire Canadian population. Rather than exploit spatial variation, as in Chapter 2, Chapter 3 explores ethnic variation of patenting rates in Canada. Chapter 3 investigates which educational and employment characteristics of the ethnic populations appear to drive innovation growth, as well as the relative role that immigrants play in contributing to Canadian innovation. The resulting annual time-series data reveal higher patenting rates among ethnic minority groups. Human capital characteristics, in particular the share with a PhD and the shares educated and employed in STEM fields, account for most of the ethnic-minority advantage in patenting.

According to the Labour Force Survey (LFS) in 2016, over 20% of Canadian labour force is accounted for by immigrants. The integration of immigrants into the labour market is important to Canadian economic growth. Results obtained from Chapter 1 reveal that immigrants with versatile skills are more resilient in the labour market. The skill versatility, thereby, should be accounted for when screening immigrants' skills under the 'points system'. Furthermore, there is a substantial evidence pointing to significant labour market challenges of Canadian university-educated immigrants, which suggests that the labour market skills of Canadian immigrants have not kept pace with the large increase in their educational levels (Clarke and Skuterud, 2013; Clarke and Skuterud, 2016; Clarke, Ferrer, and Skuterud, 2016). The labour market challenges faced by Canadian immigrants lead to a modest contribution of Canadian immigrants to innovation. For example, the relatively small Canadian estimates obtained from Chapter 2 appear to, in large part, reflect the relatively low employment rates of Canadian immigrants in STEM jobs, including among those educated in STEM fields. If governments are to lever education, training, and immigration policies to raise innovation, a first step is knowing what types of workers are contributing to Canadian innovation growth. Chapters 2 and 3 provide insights that the STEM education and STEM employment plays important role in raising Canada's patenting rates.

Chapter 1

The Effect of Skill Versatility on Immigrant Labour Market Integration

1.1 Introduction

There is an ongoing debate regarding whether immigrants should be selected according to current labour market conditions or their own human capital characteristics, regardless of economic cyclical changes. It is true that macroeconomic entry conditions not only affect immigrants' labour market performance in the initial years after landing in the host-country, but they may also affect immigrants' labour force participation rates and employment rates in the long run (Aydemir, 2003). However, in practice, it is difficult to co-ordinate immigration levels with the business cycle, due to difficulties in predicting future labour market needs. Furthermore, labour market conditions may be localized and it is not possible to ensure that immigrants settle in geographic areas where labour market conditions are relatively strong.

Immigrants have made up a considerable part of labour supply over the past decades and they will continue to be an important source of new workers (Kustec, 2012). According to the 2016 Labour Force Survey (LFS), over 20% of Canadian labour force is accounted for by immigrants. Therefore, the integration of immigrants into the labour market is important to Canadian economic growth. One primary goal of immigration policy is to select immigrants to meet economic demands in specific sectors and regions; the difficulty in predicting future economic fluctuation brings challenges to this policy goal. During the information and communications technology (ICT) boom in the late 1990s, Canada selected many postsecondary educated immigrants with computer science and engineering educational backgrounds to satisfy the demands of the high-tech sector. When the Dotcom bubble burst in the early 2000s, ICT employment growth decreased without a commensurate decline in labour supply, leading to poor labour market outcomes for ICT skilled immigrants who arrived in Canada in the early 2000s (Picot and Hou, 2009). Also, a report from Statistics Canada (Frenette, 2007) shows that Ottawa-Gatineau, a major high-tech cluster, registered the largest increase in its high-tech permanent layoff rate among major high tech centres during the ICT meltdown.[1] These facts together suggest that immigrants can be affected by sectoral economies specific to their skills and settlement places at entry. Since sectoral labour demands can shift more quickly than the immigration system can respond, it is important that immigrants possess versatile skills that transfer to different sectors. Accordingly, I raise the question: how does the versatility of immigrants' skills affect their ability in dealing with adverse entry economic conditions?

Instead of emphasizing how macroeconomic conditions at arrival affect immigrants' assimilation profiles, or what is referred to as the 'scarring effect'(Chiswick, Cohen, and Zach, 1997; McDonald and Worswick, 1998; Aydemir, 2003), this study stresses the role of versatile skills in helping immigrants adjust to adverse entry economic conditions. I have restricted my immigrant samples to those who are in their first ten years in Canada. Since immigrants who arrive during recessions have higher out-migration rates immediately after arrival (Aydemir and Robinson, 2008; Picot and Piraino, 2013), their successful labour market integration is critical in Canada's efforts to retain skilled immigrants.

Two major innovations are demonstrated in this paper. First, I use immigrants' educational field and level to approximate the skills they supply to the labour market and then characterize these skills using a quantitative measure of their versatility, which I construct. In particular, I construct a skill versatility measure (*vdex*) using information on the sectoral concentration of native-born workers with similar educational fields and levels. For example, university-educated workers graduating from the study field "Business" have a high skill versatility, because they are employed by a wide variety of sectors; whereas university-educated workers from the field "Education" have a low skill versatility, because they are

[1] The layoff rate increased from 2.2% in 2000 to 10.9% in 2001, compared with an increase from 2.1% to 5.3% between 2000 and 2001 in high-tech sector at the national level.

employed by a limited variety of sectors. The higher the versatility level of a skill, the broader the sectoral demand for that skill. Second, unlike the previous literature in which entry macroeconomic conditions are measured by national or regional unemployment rates, entry economic conditions are measured by unemployment rates at the region-education level. That is, entry economic conditions vary by immigrants' educational fields and levels, settlement cities, and landing years.

The reasons why the entry economic conditions are measured at the city-education level are well illustrated by the example of the ICT recession of the early 2000s. First, a particular education provides a set of skills tied to specific sectors and sectoral labour demand is often concentrated in a regional economy. Second, immigrants are free to choose where they live in Canada, but whether the local economy can absorb an increase in the supply of their skills is not well predicted. However, because immigrants may choose to settle in a city where they can access good job opportunities, the impact of entry economic conditions can be partly absorbed by such endogenous location choices. I therefore instrument entry economic conditions using their predicted location choices based on the historical settlement patterns of immigrants from a particular country of origin.

In this study, labour market outcomes are measured by either log annual employment earnings or employment status. My findings suggest that immigrants' labour market outcomes are sensitive to entry economic conditions and the impacts of initial conditions are more pronounced for females than for males. Male immigrants' annual earnings are decreased by about 5 log points if the entry unemployment rate increases by one percentage point. In comparison, females' are decreased by larger scales, ranging from 5 to 8 log points. When the labour market outcomes are measured by employment, the impact from entry economic conditions are not significant for males in most cases, while for females, their employment rates drop by 1% to 2%. Nonetheless, when the female samples are restricted to immigrants who are not married, women do not appear to fare worse than men in a weak labour market.

Furthermore, my results reveal that for below-graduate-level (College/Bachelor) educated immigrants, having versatile skills can buffer them against poor entry economic conditions. For example, when entry unemployment rates increase by one percentage point, a one standard deviation increase in a male's *vdex* level is expected to mitigate his earning loss by nearly 3 log points. However, such buffering effects are not evident for immigrants with graduate level education.

The discrepancy between the effects of skill versatility on College/Bachelor and Graduate educated immigrants is associated with immigrants' pre-arrival employment status. It is well recognized that highly educated immigrants are more likely to have pre-arrival job offers in Canada than less educated ones; therefore, highly educated immigrants' labour market integration process has more to do with maintaining rather than finding employment. My longitudinal analysis shows that skill versatility can affect individuals' job finding rates and job security in opposite directions.[2] On one hand, workers with a more versatile skills have higher job finding rates. On the other hand, workers with more versatile skills, face a lower level of job security which is driven by that fact that workers with less versatile skills are also more likely to be employed in the public sector or sectors with high unionization rates.[3] Because of this, highly educated immigrants with less versatile skills tend to have pre-arrival employment in the public sector or sectors with high unionization rates. In my main estimation, information on immigrants' union coverage status and public sector employment is not identified, so that the estimated buffer effects from skill versatility are diluted for a pooled sample of Graduate educated immigrants.

Finally, I relate immigrants' city-level mobility to economic conditions. Onward migration is more likely for immigrants who encounter poor initial labour market conditions. A further comparison between the samples who did move and who did not suggests that movers are less affected by the adverse initial conditions than the stayers. I also find some evidence indicating that immigrants' geographical mobility is strengthened by their skill versatility.

Concerned with the aging population and skill shortages that will potentially result from a flood of retirees, the Canadian government has committed to maintain a stable annual immigration level since the 1990s.[4] Meanwhile, more emphasis has been put on immigrants' educational attainment under the point-based immigration system. Although the level of education for new immigrants has increased dramatically, little improvement is shown in their labour market performance over recent decades (Aydemir and Skuterud, 2005; Picot and Hou, 2009; D. Green and Worswick, 2012; Ferrer, Picot, and Riddel,

[2] The longitudinal analysis are based on micro level longitudinal information provided by Survey of Labour and Dynamics (SLID), where sample size is small. To maintain statistical precision, I pool immigrants and natives in the longitudinal analysis.

[3] For example, workers that held graduate level degrees in 'Education' are more likely to work for public sectors than those held graduate level degrees in 'Business,' while a higher skill versatility level is assigned for workers graduated from the 'Business' field.

[4] The annual immigration level is about 0.8% of current population.

2012; Warman and Worswick, 2015). For that reason, a criticism of the immigration system has emerged, with arguments that policymakers should not only address supply-side concerns, but also take the demand side into consideration. Accordingly, the Express Entry program introduced in 2015, gives an important role to employers in assessing perspective immigrants. Screening immigrant applicants with the requisite skills demanded by specific sectors and occupations, can ensure a certain level of immigrant integration. However, these immigrants may find difficulty in responding to changing labour market conditions, because their skills are tightly tied to specific sectors. This study sheds some light on what types of immigrants should be admitted regarding their resilience in the labour market.

The remainder of this chapter is organized as follows: Section 2 reviews previous work relevant to my model and empirical results; Section 3 presents my data description and methodology; Section 4, presents empirical results; And section 5 concludes the paper.

1.2 Literature Review

Entry economic conditions play a critical role in an individual's careers. The importance of firm-, industry-, or occupation- specific skills are emphasized in one's career success (Neal, 1995; McDonald and Worswick, 1998; Gathmann and Schönberg, 2010). Bad economic shocks at the time of entry may lead to adverse subsequent placements for workers. Hence these workers have less time and opportunities to accumulate human capital. Asymmetric information also predicts a persistent effect of entry economic conditions (Katz and Gibbons, 1991). Firms tend to take workers' initial placements to infer their productivity. Hence, workers with unfavourable economic conditions at entry are locked in by their initial conditions. Moreover, an implicit contract model predicts that the conditions at the time of entry to the labour market can have a long-term impact if there is no occurrence of renegotiation on wages when economic conditions improve after recessions (Beaudry and DiNardo, 1991).

There is a wide perception that immigrants are fragile to macroeconomic conditions. The major barriers to labour market integration of new immigrants are: lack of networks (Åslund, Hensvik, and Skans, 2014), the recognition of foreign credentials (Ferrer and Riddell, 2008), the difficulty in transferring human capital to the labour market (Imai, D. Stacey, and Warman, 2014), and labour market discrimination towards immigrants with ethnic sounding names (Oreopoulos, 2011). If immigrants arrive in Canada in a period of high unemployment, their initial labour market outcomes tend to be further deteriorated. On one hand, employers lack immigrants' characteristic information and are likely use a unemployment history to screen their productivities (Kroft, Notowidigdo, and Lange, 2013). On the other hand, with regard to human capital, a longer spell of unemployment may be associated with a faster human capital deterioration. Consequently, a long unemployment spell caused by an economic downturn is likely to have a negative impact on an immigrant's career.

Early studies have provided empirical evidence on how entry economic conditions affect immigrants' labour market assimilation. Chiswick, Cohen, and Zach (1997) use U.S. Current Population Survey to show that poor economic conditions at arrival have no adverse long-term effect on the employment opportunities or the incidence of unemployment among foreign-born. McDonald and Worswick (1998) use public-use files of the Survey of Consumer Finances (SCF) between 1981 and 1992 to study the impact of macroeconomic conditions on earnings of immigrant men in Canada. They incorporate job tenure information to control for firm-specific human capital and find a negative, though insignificant, impact of entry unemployment rates on earnings. However, a different conclusion is drawn by Aydemir (2003) who uses the master files of the SCF, spanning the period from 1976 to 1997, to address the relationship between macroeconomic conditions and immigrants' labour market outcomes, which are measured as either a labour force participation rate or an employment rate. The master files of the SCF allow the author to measure entry unemployment rates at the year of the immigrant's arrival, whereas McDonald and Worswick (1998) can only measure entry unemployment rates over an extended period due to the limitation in public-use SCF files. With better data, Aydemir (2003) concludes that a higher unemployment rate at entry year has negative impacts on immigrants and that the impacts are permanent though small.

In this paper, I differentiate immigrants by their educational backgrounds and investigate how the effects of entry economic conditions differ among different types of immigrants. In this regard, my paper is closest to recent papers by Oreopoulos, Wachter, and Heisz (2012), Altonji, Kahn, and Speer (2016) and Liu, Salvanes, and Sørensen (2016). All of them focus on the effects of entry economic conditions on new college graduates. Oreopoulos, Wachter, and Heisz (2012) study the long-term effects of initial labour market conditions on Canadian college graduates. By tracking male college graduates' labour market performance for ten years by using Canadian longitudinal university-employer-employee data, they show that the magnitude of the long-term earnings loss associated with graduating from college during a recession varies across their labour market experience, as well as the skill levels attached to their major fields of study. The skill levels are approximated based on the estimated returns from major fields of study. The earnings loss suffered by the least advantaged graduates is more than four times the most advantaged graduates. Another related study is conducted by Altonji, Kahn, and Speer (2016), who measure career outcomes of U.S. college graduates from 1974 to 2011 associated with unemployment rates in one's graduation year. Similar to the former study, Altonji, Kahn, and Speer (2016) find that high-skilled graduates are less sensitive to economic conditions at graduation. Last, a paper from Liu, Salvanes, and Sørensen (2016) links the skills supplied by college graduates and skills demanded by hiring industries to study the mechanism driving persistent and heterogeneous career losses from graduating during recessions. They emphasize the importance of skill mismatch in explaining the short-term and long-term earning loss from graduating during a recession.

One noteworthy aspect of Altonji, Kahn, and Speer's analysis is that they stress the importance of the versatility of a major field of study. Using the census division unemployment rate in the year of college graduation as an indicator of entry conditions, their estimated results do show that compared to less concentrated majors, more occupational concentrated majors graduating in a large recession have more disadvantage in finding employment initially and are increasingly likely to be mismatched as they gain work experience. They state that majors with lower levels of occupational concentration have a more diverse set of options, thus are less prone to sectoral shocks.

Moreover, skill versatility can help immigrants recover after localized economic setbacks by reducing their job search costs or enhancing their outside options in the labour market. Workers entering the labour market in a recession are likely to be unemployed or face low wage job offer distributions. To recover from the initial setbacks, they need to take a costly job search process to find work or move from a low quality job to high quality one (Javanovic, 1979; Topel and Ward, 1992; Oreopoulos, Wachter, and Heisz, 2012). The search frictions are smaller for workers with higher versatile skills than those with less versatile skills, because the labour market, for them, is less tight. As a result, workers with more versatile skills receive more job opportunities in the labour market and search for higher paid jobs more intensely after initial setbacks. Under the search and bargaining mechanism, the shifts in industrial composition change the outside options for a worker bargaining with her employer, and the probability for an unemployed worker switching industries affects the intensity of her bargaining capability (Beaudry, D. Green, and Sand, 2012; Tschopp, 2015). Overall, having versatile skills is expected to enhance workers' outside options and allow them to negotiate a higher wage rate with employers after initial setbacks.

1.3 Data and Methodology

1.3.1 Variables from cross-sectional data

I use the master files of the data from Canadian Census for the years 1991, 1996, 2001 and 2006, together with the 2011 National Household Survey (NHS). These data files provide comprehensive demographic and statistical information. Critical information such as immigrant status, landing year, education, and industry are provided for persons listed in both Census files and the NHS. I pool a series of five cross-sectional data files taken from the Census, as well as the 2011 NHS file to build a pseudo-panel data set. I aim to examine the effect of skills that immigration brings at the time of landing, but post-immigration educational investments can change the skills. In order to avoid complications involving educational investments after immigration as well as attrition caused by death, I restrict my sample to immigrants whose landing ages are between 25 and 54 while not attending schools in reference years.[5]

Entry economic conditions are measured using entry unemployment rates at the city-education level, so that they vary by immigrants' educational fields and attainment, settlement cities and landing years. Since the field-of-study data was first available in the 1986 Census file, to construct an unemployment rate for a particular study field and examine its effects at entry, I further restrict my immigrant observations to those who landed in Canada between 1986 and 2011. Observations with postsecondary qualifications are assigned with a specific education field and level.[6] Twelve educational fields and five educational levels are identified. The education fields contain the following categories: 'Educational, Recreational and Counselling services,' 'Commerce, Management and Business Administration,'

[5]School attendance information is not available in the 1986 Census. I treat an individual whose total years of schooling is smaller than his or her age minus 6 as one without school attendance. The variable 'total years of schooling' is not available in the 2006 census and 2011 NHS, so I predict it from the sample in the 2001 census. The total years of schooling is regressed on variables such as highest degrees and birth regions, which are included in both the 2006 census and 2011 NHS.

[6]The field of study for some respondent is coded as 'No Specialization'. Two cases are related to that situation: first, those respondents whose highest degrees are below post secondary level; second, those respondents whose highest degrees are above secondary level but with an unspecified study field. I drop the respondents in the latter case.

'Fine and Applied Arts,' 'Humanities,' 'Social Science,' 'Agricultural, Biological, Nutritional, and Food Sciences,' 'ICT related,' 'Mining and Petroleum related,' 'Engineering and Applied Sciences,''Applied Science and Trade specific Technologies,' 'Mathematics and Physical Sciences,' and 'Health.'[7] The education levels, on the other hand, are 'Secondary and Lower', 'College Diploma', 'Bachelor's Degree', 'Master's Degree' and 'Ph.D..' For those who are without a field of study, that is, those from the 'Secondary and Lower' education level, I assign them the unemployment rates of natives with less than postsecondary education.

The master files of the Census provide 20% random samples of the Canadian population and obtained a approximately 94% response rate, while the 2011 NHS sampled one in three Canadian households and obtained a 68.6% response rate. The large sample size allows me to construct my key explanatory variables using only natives' information. I calculate the unemployment rates using the prime-aged (25-54) native sample living in Metropolitan and Agglomeration Areas (CMA/CA) with particular educational backgrounds. In addition, individuals' place of residence in the reference day and five years before the reference day are surveyed in each file. With samples composed of immigrants who are in their first 10 years after arriving in Canada, the data allows me to approximate their settlement cities at entry. Specifically, the initial settlement cities for immigrants landing in Canada within 5 years prior to the survey date are defined as their current residential CMA/CAs, whereas for immigrants landing between 6 to 10 years prior to the survey date, their initial settlement cities are identified as the CMA/CAs they lived in five years prior to the survey date. Ultimately, there are 541,205 recent immigrants in my sample, and 413,495 of them report positive annual earnings.[8]

One problem with my data set is that it is based on surveys conducted every five years. Consequently, it is impossible to calculate entry unemployment rates for immigrants annually. The Census files provide a large number of native samples with information on their field of study, educational attainment, and residential city, which are necessary to measure the city-education specific unemployment rate. To predict those entry economic conditions in the years that are missed in the non-consecutive surveys, I linearly interpolate

[7] Both the fields 'Engineering and Applied Sciences' and 'Applied Science and Trade specific Technologies' are exclusive to the 'ICT' and 'Mining and Petroleum related' fields.

[8] The annual earnings are the yearly employment income composed of wages and salaries, as well as net income from farming and non-farming self-employment.

the unemployment rates for a specific city and education combination over time.[9]

The key question of interest is: to what extent skill versatility mitigate adverse impact of initial economic conditions? To quantify the versatility level associated with immigrants' educational background, I construct a *vdex* using the sectoral distribution of natives:

$$vdex_e = 1 - \sum_{j=1}^{J} (s_{ej})^2, \tag{1.1}$$

where s_{ej} denotes the proportion of prime-aged natives with an education e that are employed in industry j.[10] The *vdex* of a particular education e ranges from 0 to 1, moving from 'least versatile' to 'most versatile'. Figure 1.4 illustrates the relationship between the sectoral employment distributions for the field of study 'Health' and 'ICT' and their corresponding *vdex* in a selected year (1991), respectively. The height of each bar represents the probability of a person being employed by an industry sector, conditional on her major field of study. There are 77 rectangles of equal width and each represents a specific industry defined by 2-digit 1980 Standard Industry Code (SIC). To save space, I only label the industry '01' and '99'. In the graph, the 'Health' associated *vdex* is less than that half of the size of 'ICT' associated (0.47 versus 0.95). The employment shares for people graduated from the 'Health' field are highly concentrated to a particular sector while the employment shares for people from the 'ICT' is widely dispersed among sectors. Figure 1.5 plots the the mean value of *vdex* by education levels over time. The graph suggests that the higher the education level, the lower the *vdex* value, while the value of *vdex* for a given education level varies little over time. Also, a slight upper trend is seen for the value

[9]Alternative interpolation methods are also examined. For example, by assuming that the change of the city-education specific unemployment rates follows the same movement pattern as the national level unemployment rates over time, I predict the missing entry unemployment rates based on the annual national level unemployment rates, which can be obtained from Labour Force Survey (LFS). Specifically, the unemployment rate ur in the missing year t is can be predicted by the equation $ur(t) = \frac{(ur(t5)-ur_{LFS}(t5))-(ur(t1)-ur_{LFS}(t1))}{t5-t1} \times (t-t1) + (ur(t5) - ur_{LFS}(t5)$, where t is a year missed between census year $t1$ and census year $t5$, i.e, $t5 - t1 = 5$; and $ur_{LFS}(t5)$ and $ur_{LFS}(t1)$ denote the unemployment rate obtained from LFS in year $t5$ and $t1$ respectively. Since the estimation results are not sensitive to what interpolation methods are chosen, I only present the estimates with linearly interpolated entry unemployment rates in this paper.

[10]The industry code systems selected for *vdex* measurement are as follows: two-digit SIC1980 for the Census between 1991 and 1996; three-digit NAICS1997 for the Census 2001; three-digit NAICS2003 for the Census 2006; and three-digit NAICS2007 for the NHS 2011. Since the total number of industries vary across census files, ranging from 77 to 100, the skill versatility measure used in the analysis is normalized by dividing $vdex_e$ by $(1 - \frac{1}{N})$, where N is the total number of industries.

of *vdex* over time, and such trend is likely to be caused by an adaptation on the change of technology. To capture the long-term trend and remove the cyclical influences on the skill versatility measure, I smooth the skill versatility measure over a quadratic time trend in the regression analysis that follows.[11] The standard deviation of *vdex* in the native sample is 0.1. To make the interpretations intuitive and meaningful, I estimate the effect of *vdex* by changing its value by one standard deviation.

1.3.2 Validity of *vdex*

The scale of *vdex* measures the versatility level of a skill set provided by an education. There are two possible notions of skill versatility that are of interest, that I want my measure of versatility to capture. The first is illustrated by Figure 1.1 – an education provides a person with one skill and that particular skill is demanded by a variety of industries. The second is illustrated by Figure 1.2 – an education provides a person with a broad set of skills, each of which is demanded by a particular industry.

However, there may exist a third case in which the high value of *vdex* is associated with skill heterogeneity instead of skill versatility. It is illustrated by Figure 1.3. In this case, an education provides each individual with a skill that is demanded by only one industry, so that the skill is extremely non-versatile and a low *vdex* value is expected for that particular education. Nonetheless, results can be contradictory to my expectation when multiple types of individuals are covered by this education category. Different types of persons under that particular education category can find employment in different sectors, and since *vdex* is calculated based on workers' sectoral distribution, I may observe a high rather than a low *vdex* value for that particular education. If the third case is the primary source of variation in my *vdex* measure, then my *vdex* fails to describe the skill versatility level.

If *vdex* is valid, individuals with a high *vdex* are expected to have a strong ability to bring their skills to different sectors. In the data, if individuals are observed to have changed employers, those with a high *vdex* are expected to be more likely to switch industries than others. Unfortunately, my cross-sectional data set does not allow me to follow an individual's working history over time. To verify my *vdex*, I make use of the individual's labour characteristics at a micro level using a longitudinal survey in Canada: the Survey

[11] I have replicated regression analysis using smoothed *vdex* based on a linear time trend, as well as unsmoothed *vdex*. The estimates are robust to different forms of *vdex* used in regressions.

of Labour and Income Dynamics (SLID). Six panels from the survey are used to build a longitudinal data set. The earliest panel starts from 1993, with a new panel being introduced every three years. In each panel, an individual is interviewed for six years. Consequently, an individual can be observed up to reference year 2010 in my longitudinal data. Since the sample size of SLID is small relative to the Census, I pool immigrants and natives in the following analysis to improve the precision of my estimates.

My sampled individuals are restricted to prime-aged employer switchers, who did not attend schools. Using the information on individuals' job ID for their main job during the reference year (main job ID) and the date they first started working for an employer (starting date), an employer changer is defined as an individual whose main job ID[12] and the starting date corresponding to that job ID both changed between reference years.[13] The data is stacked by person ID and the measurement window, which closes when the person is observed with a new employer. For example, if a person is observed as having changed employers in 1994 and 1996 in the first panel (with reference year ranging from 1993 to 1996), respectively, then this person is split into two observations: the first is observed from 1993 ($t-1$) to 1994 (t); and the second is from 1994 ($t-1$) to 1996 (t). The skill versatility measure *vdex* is assigned to each individual. By restricting my sample to workers who have changed employers, the probability for them to switch industries is estimated as:

$$P_{iet} = \rho_0 + \rho_1 vdex_{et} + X_{iet}\lambda + \mu_{iet}, \tag{1.2}$$

where P_{iet} is a binary variable, taking value 1 if the individual with an education e has switched her industry, otherwise, 0; and μ_{iet} is the random error term. A vector of control variables are represented by X_{iet}, which includes an individual's gender, age, residential province, working experience, education, job duration, and experience associated with her

[12]The main job for the year is defined as the one with the most paid hours in the year. If hours are identical between two jobs, the main job is the one with the greatest earnings or the longest tenure (if earnings are identical). It is possible that a shift in a worker's main jobs is not driven by her job change behaviour but reallocated working schedule. In my sample, I only include those who have switched to a new job. That is, the main job they switched to should be with a identifier code that has never been observed prior to their job switching.

[13]The job ID is the unique identifier for a job or employment spell with an employer. According to the variables descriptions, two distinct employment spells with the same employer within the same reference year would each have a distinct "jobid". Therefore, simply comparing workers' job IDs can lead to a measurement error in my data. In the SLID, the date first started working for an employer (starting date) is provided for every person-jobid entry. Ultimately, the employer changers are defined as those who have changed not only their job IDs but also the starting date specific to their job IDs.

previous industry. Since one person may be observed more than once, the standard errors are clustered by an individual person.

The parameter ρ_1 is of my primary interest, estimating the impact of a change in skill versatility on the probability that an individual, who has switched employers, has also switched industry. I would expect a positive and significant estimate of ρ_1 if $vdex$ does capture an individual's skill versatility level (illustrated in Figures 1.1 and 1.2), as opposed to skill heterogeneity (illustrated in Figure 1.3). A linearly probability model is used to estimate the equation (1.2), and the results are presented in Table 1.1 for males and females, respectively.[14] All specifications include panel and year fixed effects. In column (2), I add a set of control variables including an individual's gender, age, residential province, working experience, education, and job duration. In column (3), I also control for an individual's experience associated with her previous industry. Estimated coefficients of $vdex$ reported in each column are positive and statistically significant at the 1% level, implying that a one standard deviation increase in $vdex$ is associated with a 1.5 to 2.5 percentage-point increase in the probability of an industry change for men and women, respectively. These findings provide evidence that my $vdex$ measure is indeed capturing the versatility of workers' skill, as opposed to skill heterogeneity across workers.

1.3.3 Main regressions with cross-sectional data

To address my main research question, I estimate the following baseline model

$$\begin{aligned} Y_{icet} = \alpha_0 + \alpha_1 ur^l_{ce} + f(ysm_{icet}, age\_imm_{icet}) + \alpha_2 vdex^l_e + \\ \alpha_3 ur^l_{ce} \times vdex^l_e + X_{icet}\gamma + city_c + year_t + \varepsilon_{icet}, \end{aligned} \tag{1.3}$$

where c represents an individual i's initial settlement city, e is her education in terms of an education level-field combination, t is the survey year, and ε_{icet} is the error term. The labour market outcomes Y_{icet} are measured by log annual earning or employment. Annual earnings are the employment income (including self-employment income) reported by individuals in the survey year t, and the value is adjusted by the 2002 Consumer Price Index. The employment variable takes the value 1 if annual earnings reported by an individual are positive, and otherwise, 0. The variable ur^l_{ce} denotes the unemployment rate at the entry year l. A quadratic function in the variable years since migration (ysm_{icet})

[14] A probit model is used to estimate the equation (1.2) as well. The signs of the point estimates predicted from the probit model are in the same direction as the signs predicted from the linearly probability model.

and age at migration (age_imm_{icet}) is denoted by $f(ysm_{icet}, age\_imm_{icet})$; the fixed effects from immigrants' first settlement cities and survey years are represented by $city_c$ and $year_t$ respectively. Other control variables include total years of schooling, mother tongue, region of origin, and education level, which are represented by X_{icet}. To assess how the effects of entry conditions vary by the skill versatility, I add the skill versatility measure for an education e at the landing year l, $vdex^l_e$, and the interaction between entry unemployment rates and skill versatility measure, $ur^l_{ce} \times vdex^l_e$ in equation (1.3). All the analysis is conducted for male and female immigrants separately and standard errors is clustered by education and year of immigration.

Although it is unlikely that newly landed immigrants have sophisticated knowledge about their host country, they still may choose their settlement places depending on local economic conditions. Their endogenous location choice can partially mitigate the impact of entry economic conditions. To purge the variation caused by immigrants' non-random location choice from the data, I instrument entry economic conditions using predicted location choices based on the historical city-level settlement patterns of immigrants from a specific country of origin. This approach is initially proposed by Card (2001). To be specific,

$$ivur^l_{re} = \sum_j \pi_{rj}(1981) \times ur^l_{je}, \tag{1.4}$$

where $ivur_{re}$ is the instrumented unemployment rate variable for immigrants from a origin area r with an education e landing in Canada in year l, and $\pi_{rj}(1981)$ is the probability for immigrants from that origin living in city j in the year of 1981. The intuition behind the instrument strategy is that, for example, if Chinese immigrants historically lived disproportionately in Vancouver, I would expect newly landed Chinese immigrant cohort to more significantly more likely to settle in Vancouver as well, not because these immigrants select themselves into Vancouver by the expectation of the favourable local economic conditions, but rather by the ethnic amenities and geographic proximity provided by the presence of previous immigrants from their community.

I begin my estimation with ordinary least square (OLS) regressions based on model (1.3). After the naive analysis, I replace the actual entry conditions with instrumented entry conditions. Two stage least square (2SLS) regressions are used for the estimation with instrumented variables (IV).

As described previously, the survey files provide information on the city where an individual lived five years prior to the survey date. By restricting my immigrant samples to those who arrived in Canada at least six years prior to the survey year, I am able to study their city-level onward migration. I replace the dependent variable with immigrants' city-level mobility status in equation (1.3), and the mobility variable takes a value of 1 if their current residential city is different from where they lived five years ago, otherwise, 0. In this extended analysis, I examine how immigrants' onward migration decisions are affected by labour market conditions, whether their geographical mobility can improve their resilience in the labour market, and finally see if their regional mobility is related to their skill versatility.

1.3.4 Skill versatility in the longitudinal analysis

To examine the mechanism through which *vdex* affects workers' employment transitions, I conduct a longitudinal analysis using micro-level information provided by the SLID. The SLID has been used to test the validity of *vdex* in the previous section. Again, to ensure a meaningful precision of my estimates, I pool immigrants and natives in the longitudinal analysis. Two types of labour market transitions are of particular interest: first, flows out of jobless spells; and second, exits jobs due to "layoff or business slowdown (not caused by seasonal conditions)." Respondents reporting their jobs came to an end because of a "layoff/business slowdown (not caused by seasonal conditions)" are defined as displaced workers. An exit rate from jobless spells indicates an individual's ability in finding new employment, whereas a job displacement rate reveals an individual's employment stability.

Longitudinal respondents are from six panels of the SLID data, between the age of 16 and 70. In the analysis that follows, I exclude the respondents who attended schools in any given reference year, as well as those who were self-employed. In each panel, the respondents are randomly selected from a stock at the beginning of the survey date and then interviewed after a time period has elapsed. In every interview, respondents are asked about their social-economic information in previous calendar years, changes since the previous interview, and working histories associated with dates. Ultimately, respondents are observed over windows of a six-year period. The sampling scheme can cause left truncation and right censoring in my data. The left truncation arises when an individual began her job/jobless spell at the time earlier than the reference periods. The right censoring arises if the displacement/job-finding event had not yet occurred within a fixed time frame. For example, when the entry time for a censored job spell reached the upper bound of a fixed-time observation window, one cannot say whether the censoring was due to a stable employment or only because the observation time was not long enough for the displacement event to occur. To handle the truncation and censoring issues, I use a hazard model to estimate the probability of the hazard or the failure event (represented by either displacement or job-finding) for individuals.

A year-to-year/month-to-month employment status transition is my primary focus. Therefore, the duration time is discretely distributed in my data. The conditional discrete hazard rate of a random duration time j for a person i can be written as:

$$h_{ij} = Prob(T_i = j | T_i >= j; X_{ij}), \tag{1.5}$$

where X_{ij} is a vector of covariates that can vary over time, and Ti represents the time at which the end of the spell occurs. The hazard rate measures the probability that a length of a job/jobless spell is j, given that they are no less than j. According to Jenkins (1995), a discrete-time hazard probability can be straightforwardly estimated via a logit hazard model. Specifically, the likelihood contribution for a censored spell can be written as:

$$L_i = Prob(T_i > j) = S_i(j) = \prod_{k=u_i+1}^{j} (1 - h_{ik}), \tag{1.6}$$

where $S_i(j)$ is a survivor function, and u_i denotes the left truncated periods. If a person entered the observation window five years after her spell was started, that is, she had been observed since the sixth year of her spell, then $u_i = 5$. If there is no left truncation, then $u_i = 0$. The likelihood contribution for a complete spell can be written as:

$$L_i = Prob(T_i = j) = f_i(j) = h_{ij} S_i(j - 1), \tag{1.7}$$

and consequently, the likelihood function for the whole sample can be written as:

$$log\ L = \sum_{i=1}^{n} \sum_{k=u_i+1}^{j} (y_{ik} log\ h_{ik} + (1 - y_{ik}) log(1 - h_{ik})), \tag{1.8}$$

where y_{ik} is a binary variable, taking value 1 if person i is displaced from her job in year j, otherwise, 0. A logistic function is chosen for h_{ik}:

$$h_{ik} = 1/(1 + exp(-\theta(k) - \beta' X_{ik})), \tag{1.9}$$

where $\theta(k)$ denotes the baseline hazard. I specify $\theta(k)$ as $log(k)$. Ultimately, I reorganize my data into person-period (which is person-year or person-month) format, and estimate the model using logit regressions for males and females separately. A set of covariates are included in X: the key variable is $vdex$, which can vary by education field and level, as well as calendar year; moreover, an individual's age, years of schooling, working experience, marital status, residential provinces, calendar year effects, and panel effects are included.

To examine the relation between skill versatility and job finding rates, I select individuals with jobless spells beginning at the time within their observation window. If a person encountered multiple jobless spells within her observation window, I choose the one with the earliest entry time. As a result, each individual is observed with one jobless spell and the jobless spell is not left truncated. A worker has a probability of ending her jobless spell at each value of j, which is the length of months between the starting month and ending month. Since my sampled workers have jobless spells that are not left truncated, I can easily identify what jobs they lost. In particular, the lost jobs are defined as the last job held by workers before they enter the jobless spells.

I find that workers with low skill versatility levels were more likely to have jobs in the public sector and in sectors with a high union coverage rate. For example, workers that graduated from the education field 'Health' were more likely to be unionized workers than those that graduated from 'Business.' It is possible that workers with more versatile skills sort into jobs differently than workers with less versatile skills. Moreover, Kuhn (1998) examines data sets on Canadian displaced workers and find that displaced unionized workers suffer a larger wage losses than displaced non-unionzed workers. These together lead one to suspect: when being unemployed, if workers with less versatile skills suffer greater subsequent earnings loss than workers with more versatile skills, the underlying mechanism may be driven by whether they have unionized jobs rather than whether they have versatile skills. With that concern, I extend my analysis to see whether the effect of skill versatility is entirely accounted for by workers' pre-jobless union status. A dummy variable *union* is added to my basic model. The variable *union* equals 1 if a worker held a unionized job prior to her jobless spell. Since unionized jobs and public-sector jobs share some characteristics in common, I replicate my analysis by incorporating a variable, *public*, in my basic model. The variable *public* equals 1 if a worker held a job in the public sector prior to her jobless spell. Finally, I incorporate both the variable *union* and *public* in my logit hazard regressions and compare their effects on workers' job finding rates.

Furthermore, I regroup my sampled individuals based on information on their lost jobs and I conduct an analysis for them separately. Specifically, my sampled individuals are categorized into three groups: individuals who lost non-unionized jobs are included in the first group, individuals who lost private-sector jobs are included in the second group, and individuals who lost jobs from non-unionized private sectors are included in the third group.

To investigate the relation between skill versatility and job displacement rates, I select individuals with valid job IDs from the survey. In the survey, an individual is assigned a job ID for her main job in a reference year. A displacement event occurs when an individual was laid off from her job that was the main job identified in her earliest reference year. A worker's job spell can be left truncated if her job started in the year earlier than being observed. The job spell is grouped by year. Although a job can lead to termination for multiple reasons, to simplify my model, a job spell can only be ended by an occurrence of a displacement event. That is, if a displacement is observed for a respondent, her job spell is complete, and otherwise, censored. Ultimately, a worker has the probability of being displaced from a job at each value of j, which is the length of years since she started that job. As discussed earlier, low skill versatility is associated with a higher probability of being a unionized or public-sector worker. And unionized workers or public-sector workers are less likely to become unemployed, even during recessions. Therefore, it is more interesting to analyse the effect of skill versatility on workers who are not associated with unions and/or public sectors. Therefore, I replicate my hazard analysis for the following subgroups of workers: non-union workers, non-public sector workers, and workers who were neither union members or public-sector workers.

1.4 Results

1.4.1 Effects of entry unemployment rates

Before proceeding to examine the effects of skill versatility, I estimate how immigrants' labour market outcomes are affected by entry economic conditions. The regressions are based on equation (1.3), but the variables $vdex_e^l$ and $ur_{ce}^l \times vdex_e^l$ are excluded. Corresponding results are provided in Tables 1.2 and 1.3 for male and female immigrants, respectively. In each table, the first five columns show the estimates from OLS analysis, and the rest show the estimates from IV(2SLS) analysis. Results with respect to earnings outcomes are illustrated in the upper panel, and the results concerning employment outcomes are in the lower panel.

I begin my regression analysis based on information collected from individuals for the complete male sample. OLS results presented in column 1 of Table 1.2 are estimated from the regressions where fixed effects of individuals' education levels are not included, whereas in column 2, the results are estimated from the regressions with the education level effects being controlled. A comparison between the point estimates of ur provided in column

1 and 2 show that the size of the effects from entry unemployment rates is sensitive to the education level controls. Immigrants' educational attainment has been emphasized in admission, therefore I am interested in studying the adjustment process for immigrants with different levels of education. I regroup my immigrant samples by their educational attainment, replicate analysis for every regrouped samples, and compare their resilience in dealing with poor economic conditions. Specifically, I restrict my immigrant sample to those who have postsecondary education and then divide the postsecondary educated sample into two groups: A Graduate group, comprised of individuals with postsecondary education above a Bachelor's degree, and a College/Bachelor's group, comprised of individuals with educational attainment at or below a Bachelor's level. The results from the OLS estimates show that a higher unemployment rate at the time of entry is associated with a decline in male immigrants' annual earnings. This is demonstrated through the fact that all the coefficients on ur in the earnings regressions are negative and statistically significant at the 1% level.

In Table 1.2, I also provide 2SLS estimates using the instrumented unemployment rate variable (IV). The first-stage regression results suggest that the actual unemployment rate, ur, is strongly correlated with an instrumented unemployment rate, $ivur$, which is based on the historical settlement patterns of immigrants from the same countries of origin.[15] At the end of the table, I present F-statistic under the null hypothesis that the instrument variable is irrelevant in the first stage. The results suggest the null hypothesis is rejected. Separated by a vertical line, the right area of Table 1.2 provides the IV(2SLS) estimates. The point estimates associated with ur are more negative in the IV analysis than in the OLS analysis. For example, the OLS estimates of ur associated with Graduate and College/Bachelor educated men are around -0.01 and -0.02 respectively, whereas the comparable IV estimators are roughly -0.05, for both Graduate and College/Bachelor educated men. This is consistent with my expectation that the impacts of initial economic conditions are mitigated by immigrants' endogenous location choices.

The same analysis that has been done for males has also been replicated for females, and the corresponding results are reported in Table 1.3. The findings indicate that the adverse impacts of entry economic conditions are more pronounced for females than males. In Table 1.3, I find that a one percentage-point increase in the entry unemployment rate results in a decrease in the earnings of immigrant women of roughly 8 log points. In comparison, the associated earnings loss for postsecondary educated males are about 5 log

[15] A full set of results from the first-stage least square regressions are available upon request.

points (see Table 1.2). Meanwhile, in terms of their employment outcomes, females are sensitive to entry conditions, and their employment rates are estimated to decline by 1% to 2% in response to a one percentage-point increase in the unemployment rate, whereas for males, the comparable estimates are small and not statistically different from zero.

One possible explanation why women are more affected by poor labour market conditions than men might be that women's careers are secondary to their husbands' careers within family. This is more likely for a married woman. For a married couple, the husband is usually the principle applicant as an immigrant, thus he tends to play a dominant role in making labour market related decisions and the wife follows his decision.[16] Therefore, if the local economy is bad, the household is likely to decide where to resettle depending on the husband's job opportunities, and the wife may choose to accompany her husband, rendering her less flexible to find employment that can optimize her own career development. As a result, women are affected more than men by economic shocks.

To assess a woman's labour market performance by her marital status closely, I replicate regression analysis for married and unmarried women. The results are presented in Table A.2 in the appendix. When the outcomes refer to annual earnings, the estimated coefficients for ur are more negative for married females than for their unmarried female counterparts. It is interesting to note that the point estimates of ur associated with unmarried female samples have magnitudes that are close to what are observed for their male counterparts. Although no significant differences are found between married and unmarried women, when the outcomes refer to their employment rates, the results associated with their earnings are consistent with my expectation. That is, compared to male immigrants, female immigrants are more vulnerable to the weak labour market conditions, which is consistent with married women being more constrained by their family roles.

[16]The household-level migration model suggests that the migration is a result of joint family utility maximization, but not all family members benefit equally. Based on this family migration model, Mincer (1978) brought the notion of ties, which exist when individual gains from migration have different signs for the different household members. For a family migration to occur, the net loss experienced by tied mover must be smaller than the net gain of the spouse. The model proposed by Mincer suggests that women are more likely than men to become tied movers, since they exhibit weak labour attachment and the returns to migration are smaller for individuals with weak labour attachment. As a result, migration tends to reduce men's unemployment but increases women's because they tend to be tied, having to give up their jobs when migrating with their partners, and are faced with uncertain employment prospects in the destination (Williams and Baláž, 2014).

1.4.2 Effects of skill versatility

To answer my primary research question, I add the skill versatility measure $vdex$ and its interaction with ur to the estimating equation. Estimated results are presented in Tables 1.4 and 1.5 for males and females, respectively. As demonstrated in Figure 1.5, $vdex$ is negatively correlated with an individual's educational attainment. To parse out the effect of an individual's educational attainment, I follow the steps that have been used in the previous section. I regroup my immigrant samples by their educational attainment and study the effect of skill versatility for each group separately.

The results suggest that when entry economic conditions are weak, the earnings loss suffered by the College/Bachelor educated immigrants can be mitigated by the versatility of their skills. This finding is implied by the IV estimates reported in Tables 1.4 and 1.5. When $vdex$ is set to its mean value (which is around 0.9), the sizes of the impact of the entry unemployment rate are closed to what have been presented in Tables 1.2 and 1.3. That is, a one percentage-point increase in the entry unemployment rate decreases earnings of immigrant men by about 5 log points. By comparison, earnings of immigrant women are declined by roughly 6 to 10 log points. When the value of $vdex$ increases by one standard deviation, the earnings loss suffered by a College/Bachelor educated male immigrant is mitigated by nearly 3 log points; for females, such mitigation effects are moderate, as shown by the positive but insignificant estimated coefficient for $ur \times vdex$.

In contrast to what is observed for College/Bachelor educated immigrants, Graduate educated immigrants are not shielded from initial setbacks by having versatile skills. This is in particular true for females, as suggested by the negative IV estimates of the interaction term between unemployment rate and $vdex$. For males, it is true that the IV estimate of this interaction term on earnings is positive, but the IV estimate based on Graduate educated immigrants' employment outcomes is negative (though insignificant at 10% level). Hence, the positive point estimate of $ur \times vdex$ observed with respect to a male's earnings may be partly due to sample selection caused by his labour market participation status.

Why does the skill versatility affect the labour market outcomes of university-educated immigrants with and without graduate degrees differently? To answer this question, one has to understand the underlying mechanism through which skill versatility affects workers' labour market resilience. As discussed earlier, skill versatility can buffer immigrants against adverse economic shocks by offering them broad employment opportunities. Therefore, I expect a positive relation between workers' job finding rates and the versatility of their skills. Using the longitudinal SLID data, I conduct a series of analyses based on a logit hazard model specified by equation (1.8). Average marginal/discrete effects of the variables I am interested in are reported in Tables 1.6 and 1.7 for males and females, respectively. An average marginal/discrete effect of x represents an average change in the probability of the outcome when x increases by one unit. The average marginal/discrete effect calculates the marginal/discrete effect for each individual and then averages the effect across the resulting estimates. Four panels are included in the tables, and each panel provides results estimated for workers with different education levels. Results reported in the first panel are for complete samples represented by males and females separately; in the second are for postsecondary educated males and females respectively; in the third are for Graduate educated males and females respectively; and in the fourth are for College/Bachelor educated males and females respectively.

In the first column of Table 1.6, the reported average marginal effects of *vdex* are positive, indicating a positive relation between the ability to find employment and the versatility of skills. This effect appears particularly large for College/BA male workers, whose probability of finding a new job increases by nearly 0.5 percent if there is a one standard deviation increase in their skill versatility level. For Graduate educated male workers, although the estimated average marginal effect of *vdex* is imprecise due to a small sample size, it is positive with value 0.02. From column 2 to column 4, I provide results estimated from extended specifications. In column 2, a variable *union* is added in the basic model. The value of the average discrete effect of *union* is around -0.01, meaning that for male workers, if the job they lost was covered by union contracts, the probability for them to find a new job is one percent lower than those who lost non-unionized jobs. In column 3, a variable *public* is added in the specification. The value of the average discrete effects of *public* is above -0.02, meaning that for male workers, if the job they lost were in the public sector, the probability for them to find a new job is more than two percent lower than those who lost private-sector jobs. In column 4, the results are estimated from regressions where both variables *union* and *public* are added to the basic model. The size of the effect associated with *union* is more than six times greater than the effect associated with *public*, indicating that the difficulty in finding new employment is most severe for workers who lost public-sector jobs. From column 1 to column 4, I find a slight decrease in the magnitude of the average marginal effects of *vdex* after controlling for *union* and/or *public* effects. This implies that the effect of the skill versatility, is to some extent driven by workers' union coverage and/or public sector employment status.

In the last three columns of Table 1.6, I report the estimates based on the basic specification for three sub-samples: males who lost non-unionized jobs, males who lost private sector jobs, and males who lost non-unionized private sector jobs. Corresponding results are shown in the last three columns of Table 1.6. The average marginal effects of *vdex* reported in the last three columns are positive, and most of them are statistically significant. Again, for the Graduate sample, the effects are not precisely estimated, due to a small sample size. Overall, I conclude that a one standard deviation increase in the level of a male worker's skill versatility would raise his job finding rate by about 0.4 to 0.5 percentage points.

In contrast to what is seen for male workers, female workers do not gain a significantly higher job finding rate by possessing versatile skills (see Table 1.7). This may be accounted for by a gender role difference in making labour market related decisions within households. A woman with a set of versatile skills can have broad career opportunities, but the necessity to take care of her families could cause her to give up some employment opportunities. Findings based on the longitudinal analysis are consistent with what has been shown in the cross-sectional analysis, where women modestly benefit from having versatile skills. Based on the basic model specification, the average marginal effects of *vdex* is small, with values ranging between 0.003 and 0.01. Furthermore, an interesting finding is observed for Graduate educated females. If I restrict these highly educated females to those who lost non-unionized and/or private sector jobs, the size of the average marginal effect of *vdex* is increased from sixfold to thirteenfold, with the estimated value ranging between 0.02 to 0.04. Although the estimates are not statistically significant, their large magnitudes imply that highly educated women, to some degree, do exploit their versatile skills to find new employment opportunities.

Thus far, I have found evidence that workers can gain new employment opportunities through having versatile skills. However, for highly educated immigrants who are likely to have pre-arranged employment in Canada, their ability to keep jobs rather than find jobs is more important for their successful labour market integration.[17] Accordingly, I examine how workers' job security is affected by their skill versatility. Corresponding results are

[17] Using the cross-sectional SLID data ranging between 1993 and 2010, I find that more than half of the master and doctoral level educated new immigrant arrivals land in Canada with arranged employment, compared a one fifth for their lower educated immigrant counterparts. The SLID survey reports each individual's annual labour force status in every reference year. Given the immigrants who land in Canada during the reference year, if their annual labour force status in that reference year is reported as "employed all year", I define them as those with arranged employment before their arrivals.

organized in a form that is comparable to what has been used for studying workers' job finding behaviours. Average marginal/discrete effects of variables are presented in Tables 1.8 and 1.9.

In columns 1 to 4 of Table 1.8, I find that a high level of skill versatility leads to unstable employment for men, but this effect is weakened after controlling for the effects associated with his union coverage status and/or public-sector employment. Based on the basic specification, the size of the average effect of *vdex* is between 0.03 and 0.04 for males belonging to certain education groups. With additional controls, especially when I add the variable *public*, the value of the average effect of *vdex* is reduced by, at most, one-half. In columns 2 through 4, I find the estimated average discrete effect of being employed in the public sector is more negative than the effect of unionization. These together imply that the impact of skill versatility on the job displacement rate can be explained by the fact that a man with less versatile skills is more likely to be employed in the public sector, where workers have a small chance of being displaced.[18]

More interestingly, the effect of skill versatility on male workers' displacement rates diminishes when I restrict my sample to non-unionized workers, private sector workers, or non-unionzed private sector workers. This finding is demonstrated through the fact that none of the estimated average marginal effects of *vdex* are statistically significant (see the last three column of Table 1.8).

The results for women are comparable to those of men. Similar to male workers, female workers have a low level of job security if their skills are more versatile. Nonetheless, two differences are found between males and females. First, males workers' employment stability is largely attributed to their employment in the public sector, whereas for women, their job security level is equally affected by unionization and public-sector employment (see column 4 of Table 1.9 for instance). Second, for males, the average marginal effect of *vdex*, reported in the last three columns of Table 1.8, is insignificant. But for women, the effect of *vdex* is still significant when the samples are separated into non-unionized workers, private sector workers, and non-unionzed private sector workers, respectively.

[18]Unionized male workers are associated with limited level of job security because their jobs are usually offered on a contract basis.For example, unionized male workers are highly concentrated in construction sectors.

In general, workers with more versatile skills have a higher probability of finding jobs. But, since highly educated immigrants are more likely to land in Canada with job offers, their labour market success has more to do with keeping a job rather than finding a job. Although I find that a low skill versatility results in a higher level of job security, this correlation diminishes, if the sampled workers, especially those of males, are restricted to non-union members and/or private sector employees. Unfortunately, I can not identify the union coverage and public-sector employment status for every individual in my main analysis where a cross-sectional data set is used. With a pooled sample of highly educated immigrants, I observe limited mitigation impacts from skill versatility on their outcome losses caused by poor economic conditions.

1.4.3 Entry unemployment rates, geographical mobility and skill versatility

Given that entry labour market conditions are localized, I argue one possibility for immigrants to recover from initial economic setbacks is through onward migration. To examine their geographical mobility, I restrict the sample to immigrants who became Canadian permanent residents at least six years prior to the Census survey date, and this allows me to compare an individual's current and past (five years prior to the survey date) cities of residence in Canada. Focusing on the results reported in the first four columns of Tables 1.10 and 1.11 respectively, I find both male and female immigrants' probabilities of city-level onward migration are slightly increased if there was an increase in the education-city specific unemployment rate five years ago. In addition, regarding the earlier discussion where I find that married women are particularly vulnerable to poor local economic conditions, I examine whether this is because married women are given less flexibility to seek employment elsewhere. To do this, I replicate the mobility analysis for married and unmarried immigrant women, respectively. No evidence is found that the mobility of married and unmarried women is different.[19]

As immigrants' city-level onward migration is indeed affected by localized initial labour market conditions, I then compare the labour market outcomes of movers and stayers. Tables 1.12 and 1.13 provide the corresponding results based on the male and female samples, respectively. In Table 1.12, a large difference in the effects associated with the entry unemployment rate on earnings is observed between movers and stayers who are Graduate educated. For example, Graduate educated male movers are not sensitive to the

[19] The results are available from author upon request.

initial labour market conditions. In contrast, Graduate educated male stayers suffer a 12% decline in their annual earnings in response to a one percentage-point increase in the entry unemployment rate. In comparison, results associated with female samples are reported in Table 1.13. Compared to female stayers, the adverse effects from initial setbacks are less severe for female movers in general, and similar to what is found for males. The contrast between stayers and movers is most significant among Graduate level educated females.

Last, I take one step further to examine the relation between immigrants' skill versatility and their geographical mobility. Corresponding results regarding males and females are shown in the last four columns of Tables 1.10 and 1.11 respectively. One potential mechanism I would expect skill versatility to play is that when there is a drop in the city-education specific labour demand, the affected workers with versatile skills are able to find employment in other sectors that might be located in other cities. As expected, the point estimate of the interaction of the entry unemployment rate and skill versatility based on the complete male sample is positive and statistically significant at the 10% level, suggesting that city-level onward migration is more likely for workers with high skill versatility facing poor initial economic conditions. But I do not find similar results for other male samples. Regarding the female samples, there is little evidence of the hypothesized mechanism through which skill versatility affects immigrants' geographical mobility. However, among College/University educated females, the estimated effect of skill versatility is positive and statistically significant at the 5% level. This implies that those who are with high skill versatility exhibit higher city-level mobility, when the initial unemployment rate is held at a certain level.

1.4.4 Robustness analysis

Since the cross-sectional data do not allow me to follow individuals over time, the non-random post-immigrant educational investments and sample attrition may cause a bias in my estimates. First, I am not able to rule out the possibility that immigrants may change their education after landing or leave Canada. The estimation bias may arise if immigrants' post-arrival education or outmigration decisions depend on economic conditions at entry. For example, immigrants who find their skills are not demanded by the Canadian labour market may choose to return to schooling to access new skills that are in need and immigrants who arrive during recession periods have higher out-migration rates (Aydemir and Robinson, 2008; Picot and Piraino, 2013). With these concerns, I select immigrants from the sample with additional criteria to see if the results are robust. To reduce the probability that the immigrants may further their education in Canada, I restrict my sample to immigrants who are foreign educated.[20] The analysis is replicated for the restricted samples. The estimates of the effect of the entry unemployment rate and its interaction with skill versatility is virtually identical in the magnitudes to the main estimates stated in the previous sections. To ensure my results are not biased by immigrants' outmigration decisions, I replicate my earning and employment regressions using the immigrant samples who are within their first two years after immigration. Although the variances of the point estimates increases significantly, due to the smaller sample size, the signs of the estimates of the effect of entry unemployment rate and its interaction with skill versatility do not alter compared to the main estimates.

In addition, one may argue that education systems vary across countries, so that the results may not apply to immigrants from countries of origin where the skills provided by a specific education are different from Canada's. To see if the main results are robust to immigrants from particular country of origins, I replicate my analysis on those from 'non-traditional source' regions (such as Asia, Eastern Europe, Southern Europe and Africa) and those from 'traditional source' regions (such as United States, Britain, Western and Northern Europe, Australia and New Zealand). Although the estimates are less precise when I restrict my sample to immigrants from 'traditional source' origins, where the education system is similar to Canada's, the point estimates still suggest that immigrants are buffered against adverse entry labour market conditions at entry by having versatile skills. When I restrict the sample to immigrants of 'non-traditional' origins, I find that the estimates have the magnitudes that are virtually identical to what have been observed in the main estimates.

1.5 Conclusions

There are three main findings of my analysis. First, entry economic conditions do matter, and they matter more for immigrant women than men. I suspect this is due to a married woman's secondary role in making labour market related decisions within a household. For a married couple, the migration is a joint family decision but not all family members benefit equally (Mincer, 1978; Williams and Baláž, 2014). When the local economy is weak, the household is likely to decide where to resettle depending on the husband's job

[20] An immigrant is foreign educated if her total years of schoolings plus six is less than her age of migration.

opportunities, and the wife may choose to accompany her husband. As a result, women are less flexible to find employment and faced with uncertain employment prospects in the destination. My speculation is supported by the evidence that married women experience greater earnings loss as result of adverse entry conditions than single women. For a married couple, the husband is usually the principle applicant as an immigrant, thus he tends to play a dominant role in making labour market related decisions and the wife follows his decision.

Second, skill versatility does serve to mitigate the adverse effects of poor labour market conditions at the time of landing in Canada. But this conclusion should not be generalized to all immigrants, especially to those who have a degree above the Bachelor's level. The difference in the influence of skill versatility is related to different labour market integration processes faced by immigrants with different education levels. In particular, highly educated immigrants are more likely to have pre-arranged employment than their less educated counterparts. There is less evidence that skill versatility matters for workers who are employed in the public sector or in unionized jobs. This is because workers with little skill versatility are more likely to hold jobs within the public sector and/or sectors with high union coverage, where a high level of job security is offered.[21]

Last, geographical mobility, does mitigate the adverse impact of economic conditions faced by immigrants. I find immigrants' probabilities of city-level onward migration are slightly increased if the localized initial labour market conditions are weak. Furthermore, by comparing the labour market outcomes of immigrants who did move and who did not, I find movers are more affected than stayers by initial economic setbacks. Although the effects of skill versatility on regional mobility are mixed, this analysis extends my understanding on the role of skill versatility which plays into geographical flexibility and offers insight into future research.

This study provides direct policy implications regarding current immigration selection system. The importance of an immigrant's ability to adjust to uncertain labour market environments has been well recognized (Kustec, 2012), but the point-based Canadian immigration selection process has never explicitly taken this factor into consideration. Accounting for an individual's education level, variation in skill versatility reflects the skill

[21]Other methods, such as comparing similarity of the tasks that are used in the jobs held by a worker (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010), may assist in understanding the heterogeneity in the influences of skill versatility as well, but they are beyond the scope of this paper.

characteristics specific to various education fields. Policymakers should, therefore, should not only consider an immigrant's educational attainment, but also put some weight on their field-of-study related skill versatility level. In addition, this study has implication for the importance of geographic mobility. To prevent immigrants from being locked in by the local economic conditions, policymakers should not set implicit or explicit barriers for immigrants' mobility within Canada. The Canadian government has made some progress in addressing related concerns. For example, in April 2017, Canada has removed the two-year cohabitation requirements that applied to some sponsored spouses or partners of Canadian citizens and permanent residents, giving more physical flexibility to immigrant couples.

Figure 1.1: Skill versatility–scenario 1

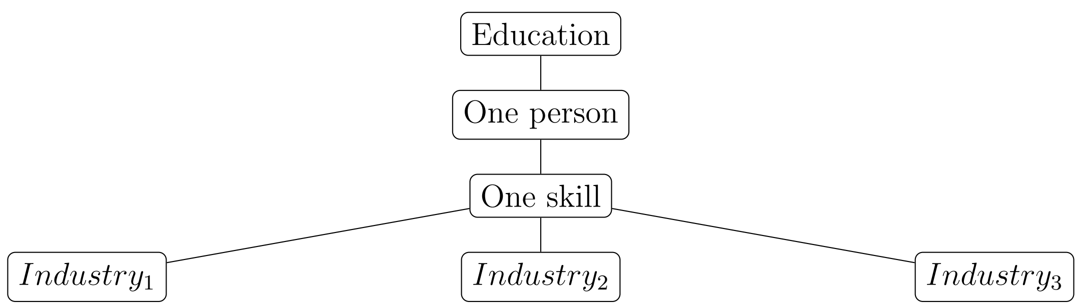


Figure 1.2: Skill versatility–scenario 2

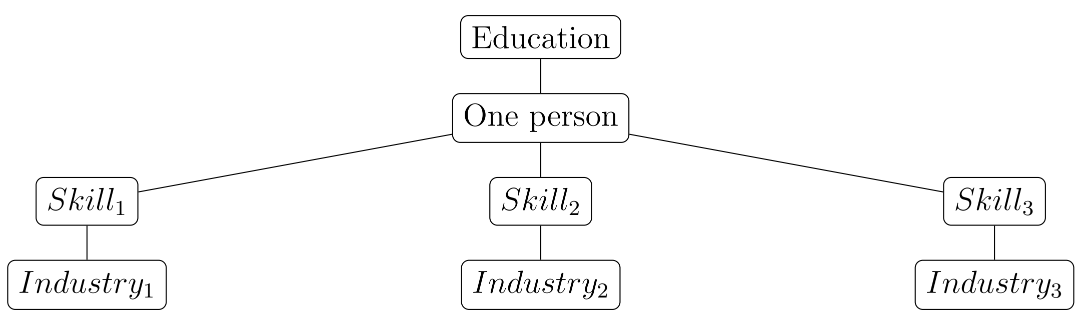


Figure 1.3: Skill heterogeneity–each person is with a skill that is demanded by one unique industry.

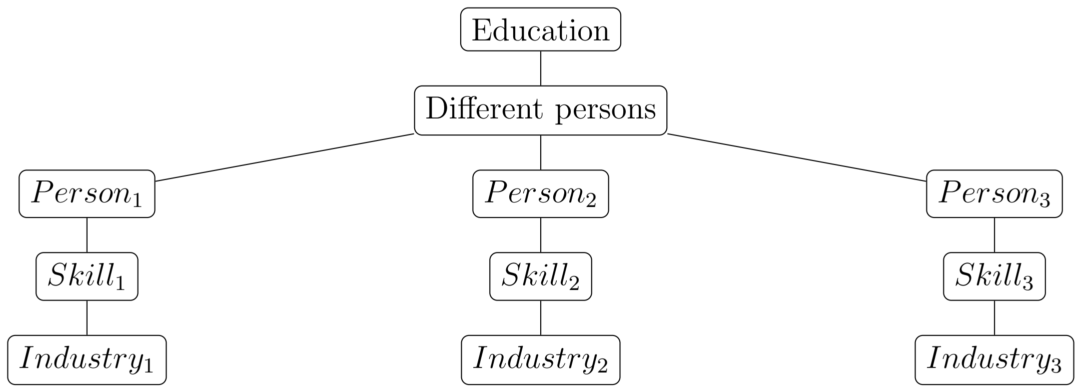


Figure 1.4: *vdex* and the sectoral employment distribution conditional on education fields, 1991 Census data

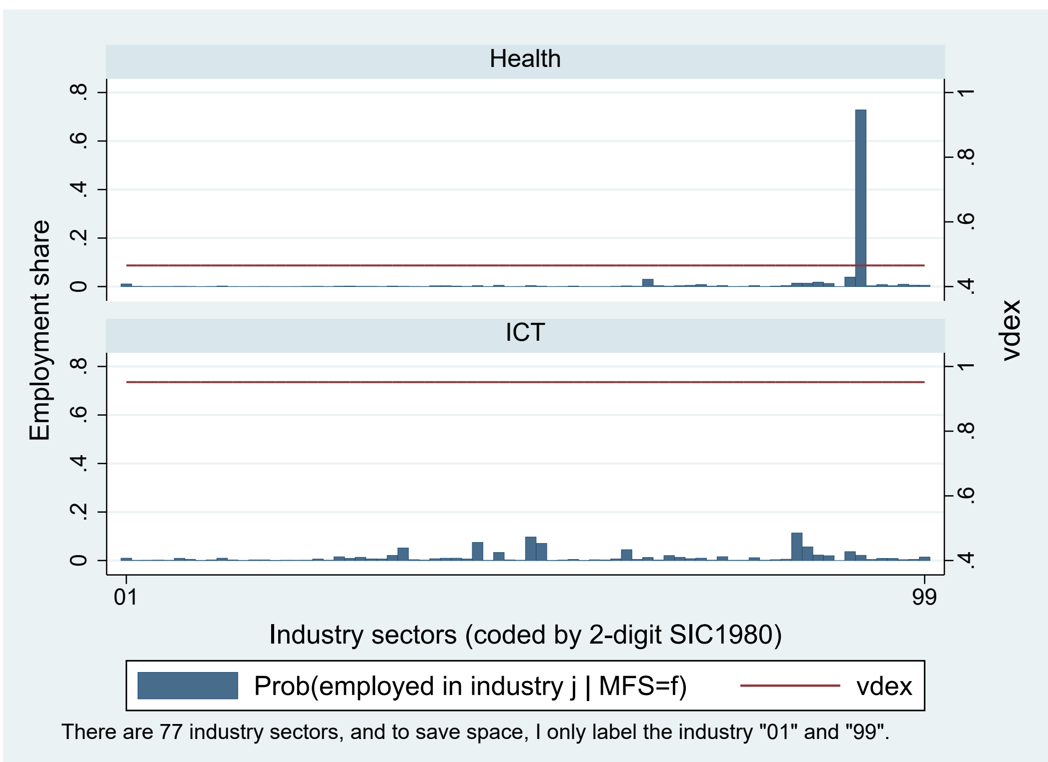


Figure 1.5: Mean of *vdex* taken for different education levels and years

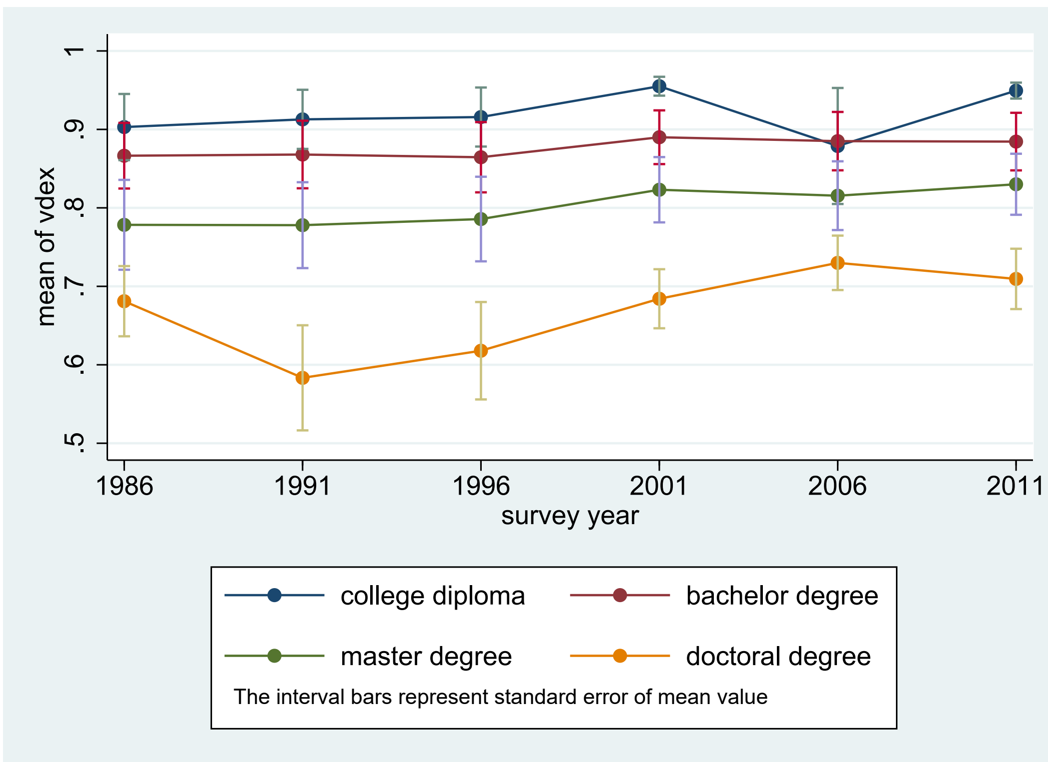


Table 1.1: OLS estimates of the effects of skill versatility on the probability for individuals to switch industry, conditional on workers who have changed employers.

	Male immigrants			Female immigrants		
Dependent variable: industry switch (= 1 if change industry)						
	(1)	(2)	(3)	(1)	(2)	(3)
vdex	0.131***	0.175***	0.165***	0.233***	0.271***	0.252***
	(0.048)	(0.059)	(0.058)	(0.035)	(0.041)	(0.039)
working experience		0.001	0.001		0.001	0.001
		(0.002)	(0.002)		(0.002)	(0.002)
working experience^2		-0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
years of schooling		0.000	0.000		-0.000	-0.000
		(0.001)	(0.001)		(0.001)	(0.001)
job tenure		0.000***	0.003***		-0.000	0.004***
		(0.000)	(0.001)		(0.000)	(0.000)
job tenure^2		-0.000	-0.000***		-0.000	-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)
age		-0.013***	-0.012***		-0.004***	-0.003
		(0.005)	(0.005)		(0.002)	(0.002)
age^2		0.000***	0.000***		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
industry experience			-0.003***			-0.004***
			(0.001)			(0.001)
industry experience^2			0.000***			0.000***
			(0.000)			(0.000)
Fixed effects:						
province		Yes	Yes		Yes	Yes
education level		Yes	Yes		Yes	Yes
panel survey	Yes	Yes	Yes	Yes	Yes	Yes
calendar year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,888	23,846	23,846	19,656	19,628	19,628
Adjusted R^2	0.138	0.208	0.214	0.139	0.219	0.231

Survey of Labour and Income Dynamics (SLID) data is used in the estimations. Standard errors in parentheses, clustered by individuals. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.2: Estimates of the effects of the entry unemployment rates on male immigrants' earnings and employment.

	OLS estimates					IV(2SLS) estimates			
Dependent variable: log annual earnings									
	Full sample	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	-0.024***	-0.016***	-0.015***	-0.009***	-0.021***	-0.045***	-0.050***	-0.049***	-0.045***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)	(0.006)	(0.011)	(0.009)
ysm	0.300***	0.300***	0.328***	0.370***	0.307***	0.299***	0.328***	0.372***	0.307***
	(0.013)	(0.013)	(0.012)	(0.019)	(0.014)	(0.013)	(0.012)	(0.019)	(0.015)
ysm^2	-0.016***	-0.016***	-0.018***	-0.018***	-0.017***	-0.016***	-0.017***	-0.018***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age_imm	0.032***	0.031***	0.029***	0.025***	0.029***	0.032***	0.028***	0.025***	0.028***
	(0.003)	(0.003)	(0.004)	(0.009)	(0.005)	(0.003)	(0.004)	(0.009)	(0.005)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.045***	0.020***	0.029***	0.033***	0.023***	0.019***	0.027***	0.032***	0.022***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
married	0.096***	0.095***	0.100***	0.114***	0.094***	0.094***	0.099***	0.112***	0.093***
	(0.008)	(0.008)	(0.009)	(0.014)	(0.011)	(0.008)	(0.009)	(0.014)	(0.011)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,625	225,625	166,545	54,945	111,600	225,540	166,490	54,935	111,555
Adjusted R^2	0.139	0.142	0.140	0.147	0.124				
F statistics for IV from first stage regression									
ivur						1815.292	1237.896	199.704	16598.821

Table1.2 – *Continued from previous page*

Dependent variable: employment (employment=1 if annual earning>0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	-0.002***	-0.001***	-0.001*	0.000	-0.001	-0.003***	-0.002	0.002	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.001)	(0.001)	(0.002)	(0.001)
ysm	0.043***	0.043***	0.039***	0.038***	0.040***	0.043***	0.039***	0.038***	0.040***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
ysm^2	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age_imm	0.014***	0.014***	0.017***	0.014***	0.017***	0.014***	0.017***	0.014***	0.017***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.008***	0.005***	0.003***	0.003***	0.002***	0.005***	0.003***	0.003***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
married	0.032***	0.031***	0.024***	0.015***	0.028***	0.031***	0.024***	0.015***	0.028***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264,965	264,965	190,505	62,305	128,200	264,855	190,440	62,290	128,150
Adjusted R^2	0.073	0.074	0.067	0.065	0.068				
F statistics for IV from first stage regression									
ivur						2459.307	1664.792	265.084	19322.123

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.3: Estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment.

	OLS estimates					IV(2SLS) estimates			
Dependent variable: log annual earnings									
	Full sample	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	-0.031***	-0.026***	-0.033***	-0.022***	-0.041***	-0.054***	-0.079***	-0.082***	-0.076***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.007)	(0.012)	(0.008)
ysm	0.254***	0.253***	0.254***	0.294***	0.238***	0.252***	0.252***	0.288***	0.237***
	(0.010)	(0.010)	(0.011)	(0.022)	(0.013)	(0.010)	(0.011)	(0.022)	(0.013)
ysm^2	-0.012***	-0.012***	-0.013***	-0.015***	-0.013***	-0.012***	-0.013***	-0.015***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.050***	0.051***	0.043***	0.040***	0.042***	0.051***	0.042***	0.039***	0.042***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.006)	(0.005)	(0.005)	(0.011)	(0.006)
age_imm^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.047***	0.031***	0.043***	0.051***	0.036***	0.030***	0.041***	0.047***	0.034***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
married	-0.208***	-0.209***	-0.245***	-0.238***	-0.237***	-0.208***	-0.245***	-0.240***	-0.236***
	(0.009)	(0.009)	(0.009)	(0.017)	(0.010)	(0.009)	(0.009)	(0.017)	(0.010)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	187,870	187,870	134,085	35,170	98,915	187,810	134,040	35,160	98,880
Adjusted R^2	0.095	0.097	0.094	0.117	0.079				
F statistics for IV from first stage regression									
ivur						9505.406	6894.596	718.434	31521.259

Table1.3 – *Continued from previous page*

Dependent variable: employment (employment=1 if annual earning>0)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	-0.010***	-0.007***	-0.008***	-0.002*	-0.012***	-0.018***	-0.019***	-0.005*	-0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
ysm	0.063***	0.063***	0.054***	0.057***	0.053***	0.062***	0.054***	0.057***	0.053***
	(0.004)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
ysm^2	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age_imm	0.033***	0.032***	0.026***	0.018***	0.028***	0.033***	0.026***	0.018***	0.028***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.016***	0.012***	0.008***	0.008***	0.008***	0.012***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
married	-0.097***	-0.097***	-0.112***	-0.095***	-0.113***	-0.097***	-0.111***	-0.096***	-0.113***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276,240	276,240	181,505	46,275	135,230	276,150	181,445	46,260	135,190
Adjusted R^2	0.089	0.091	0.060	0.058	0.062				
F statistics for IV from first stage regression									
$ivur$						11633.971	10065.907	927.021	37770.840

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.4: Estimates of the effects of the entry unemployment rates on male immigrants' earnings and employment conditional on skill versatility level.

	OLS estimates					IV(2SLS) estimates			
Dependent variable: log annual earnings									
	Full sample	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	0.031*	0.002	0.001	-0.046**	-0.081*	-0.173***	-0.149***	-0.187***	-0.289***
	(0.017)	(0.016)	(0.016)	(0.020)	(0.043)	(0.035)	(0.034)	(0.059)	(0.079)
$ur \times vdex$	-0.060***	-0.021	-0.019	0.043*	0.063	0.134***	0.103***	0.158**	0.253***
	(0.019)	(0.018)	(0.018)	(0.024)	(0.045)	(0.037)	(0.037)	(0.076)	(0.082)
$vdex$	-0.076	0.104	0.122	0.095	-0.177	-0.188	-0.075	-0.061	-0.670**
	(0.074)	(0.076)	(0.075)	(0.087)	(0.163)	(0.114)	(0.115)	(0.193)	(0.271)
ysm	0.300***	0.300***	0.328***	0.371***	0.307***	0.300***	0.329***	0.374***	0.307***
	(0.013)	(0.013)	(0.012)	(0.019)	(0.014)	(0.013)	(0.012)	(0.019)	(0.015)
ysm^2	-0.016***	-0.016***	-0.018***	-0.018***	-0.017***	-0.016***	-0.017***	-0.018***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age_imm	0.032***	0.031***	0.029***	0.025***	0.029***	0.031***	0.028***	0.025***	0.028***
	(0.003)	(0.003)	(0.004)	(0.009)	(0.005)	(0.003)	(0.004)	(0.009)	(0.005)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.040***	0.020***	0.029***	0.035***	0.023***	0.019***	0.027***	0.034***	0.022***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
married	0.096***	0.095***	0.100***	0.113***	0.093***	0.093***	0.098***	0.110***	0.092***
	(0.008)	(0.008)	(0.009)	(0.014)	(0.011)	(0.008)	(0.009)	(0.014)	(0.011)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,625	225,625	166,545	54,945	111,600	225,540	166,490	54,935	111,555

Table1.4 – *Continued from previous page*

Adjusted R^2	0.140	0.142	0.140	0.147	0.124				
F statistics for IV from first stage regression									
ivur						1492.134	738.099	396.729	7183.068
$ivur \times vdex$						2446.631	1460.233	361.503	7500.792
Dependent variable: employment (employment=1 if annual earning>0)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	0.018***	0.008**	0.005	-0.004	-0.009	0.023***	0.022***	0.012	-0.018
	(0.005)	(0.004)	(0.004)	(0.004)	(0.009)	(0.007)	(0.007)	(0.010)	(0.016)
$ur \times vdex$	-0.023***	-0.011**	-0.007	0.005	0.008	-0.029***	-0.027***	-0.016	0.017
	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.008)	(0.008)	(0.012)	(0.016)
vdex	0.104***	0.070***	0.054***	0.081***	-0.052	0.125***	0.112***	0.127***	-0.076
	(0.019)	(0.018)	(0.018)	(0.019)	(0.036)	(0.025)	(0.024)	(0.030)	(0.054)
ysm	0.043***	0.043***	0.039***	0.039***	0.040***	0.043***	0.039***	0.039***	0.040***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
ysm^2	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age_imm	0.015***	0.014***	0.017***	0.014***	0.017***	0.014***	0.017***	0.014***	0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.008***	0.006***	0.003***	0.004***	0.002***	0.005***	0.003***	0.004***	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
married	0.032***	0.031***	0.024***	0.015***	0.028***	0.031***	0.024***	0.015***	0.028***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	264,965	264,965	190,505	62,305	128,200	264,855	190,440	62,290	128,150
Adjusted R^2	0.073	0.074	0.067	0.066	0.068				
F statistics for IV from first stage regression									

Table1.4 – *Continued from previous page*

ivur	1492.134	738.099	396.729	7183.068
ivur × *vdex*	2446.631	1460.233	361.503	7500.792

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.5: Estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment conditional on skill versatility level.

	OLS estimates					IV(2SLS) estimates			
Dependent variable: log annual earnings									
	Full sample	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	-0.041**	-0.030	0.007	-0.076**	-0.046	-0.141***	-0.080***	-0.113	-0.172***
	(0.018)	(0.020)	(0.020)	(0.031)	(0.037)	(0.040)	(0.037)	(0.080)	(0.083)
$ur \times vdex$	0.011	0.003	-0.048**	0.060*	0.006	0.083*	-0.020	-0.011	0.096
	(0.019)	(0.022)	(0.022)	(0.036)	(0.039)	(0.043)	(0.039)	(0.111)	(0.087)
$vdex$	-0.089	0.008	0.178**	0.169*	-0.129	-0.078	0.309**	0.570**	-0.249
	(0.083)	(0.087)	(0.087)	(0.098)	(0.168)	(0.137)	(0.126)	(0.279)	(0.308)
ysm	0.254***	0.253***	0.255***	0.298***	0.237***	0.252***	0.254***	0.290***	0.238***
	(0.010)	(0.010)	(0.011)	(0.022)	(0.012)	(0.010)	(0.011)	(0.022)	(0.013)
ysm^2	-0.012***	-0.012***	-0.013***	-0.015***	-0.013***	-0.012***	-0.013***	-0.015***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.050***	0.051***	0.043***	0.041***	0.043***	0.051***	0.041***	0.039***	0.042***
	(0.005)	(0.005)	(0.005)	(0.011)	(0.006)	(0.005)	(0.005)	(0.011)	(0.006)
age_imm^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.046***	0.031***	0.043***	0.054***	0.035***	0.030***	0.041***	0.049***	0.034***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
married	-0.208***	-0.209***	-0.245***	-0.236***	-0.236***	-0.210***	-0.246***	-0.239***	-0.237***
	(0.009)	(0.009)	(0.009)	(0.017)	(0.010)	(0.009)	(0.009)	(0.017)	(0.010)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	187,870	187,870	134,085	35,170	98,915	187,810	134,040	35,160	98,880

Table1.5 – *Continued from previous page*

Adjusted R^2	0.095	0.097	0.094	0.119	0.079				
F statistics for IV from first stage regression									
ivur						3838.079	2536.790	651.338	10925.517
$ivur \times vdex$						5131.770	4402.297	647.806	11810.445
Dependent variable: employment (employment=1 if annual earning>0)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ur	0.036***	0.012**	0.021***	0.007	-0.001	0.002	0.015*	0.044**	-0.036**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.020)	(0.015)
$ur \times vdex$	-0.050***	-0.020***	-0.033***	-0.011	-0.011	-0.024***	-0.041***	-0.068**	0.011
	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)	(0.008)	(0.027)	(0.015)
vdex	0.136***	0.049**	0.087***	0.071***	0.005	0.105***	0.158***	0.223***	-0.010
	(0.020)	(0.019)	(0.018)	(0.025)	(0.035)	(0.030)	(0.027)	(0.067)	(0.053)
ysm	0.063***	0.062***	0.054***	0.057***	0.053***	0.062***	0.054***	0.056***	0.053***
	(0.004)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)	(0.003)
ysm^2	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
age_imm	0.033***	0.032***	0.026***	0.018***	0.028***	0.033***	0.026***	0.018***	0.027***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000***	-0.000	-0.000***	-0.000***	-0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.015***	0.012***	0.008***	0.008***	0.007***	0.012***	0.008***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
married	-0.097***	-0.097***	-0.111***	-0.095***	-0.113***	-0.097***	-0.111***	-0.095***	-0.113***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
Fixed effects:									
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	276,240	276,240	181,505	46,275	135,230	276,150	181,445	46,260	135,190
Adjusted R^2	0.090	0.091	0.060	0.058	0.063				
F statistics for IV from first stage regression									

Table1.5 – *Continued from previous page*

ivur	4302.783	3600.617	916.721	12592.247
ivur × *vdex*	5112.140	6191.835	911.128	13712.553

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.6: Average marginal/discrete effects of selected variables on males' probability of finding job.

Dependent variable: job finding (= 1 if jobless spell is ended)							
	Full sample				Subsets of full sample		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.045***	0.039***	0.026**	0.025**	0.051***	0.045**	0.042*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)	(0.020)	(0.023)
union		-0.010***		-0.004**			
		(0.002)		(0.002)			
public			-0.025***	-0.024***			
			(0.002)	(0.002)			
Observations	124,848	124,848	124,848	124,848	86,593	100,788	78,338
	Post sec.				Subsets of post sec.		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.043***	0.037***	0.026*	0.025*	0.048**	0.047**	0.044*
	(0.013)	(0.013)	(0.014)	(0.014)	(0.019)	(0.022)	(0.025)
union		-0.010***		-0.003			
		(0.003)		(0.003)			
public			-0.025***	-0.024***			
			(0.003)	(0.004)			
Observations	54,559	54,559	54,559	54,559	37,089	39,918	31,968
	Graduate				Subsets of Graduate		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.021	0.017	0.008	0.009	0.027	NA	0.025
	(0.016)	(0.016)	(0.017)	(0.017)	(0.025)		(0.041)
union		-0.009		0.003			
		(0.007)		(0.009)			
public			-0.021***	-0.023***			

Table1.6 – *Continued from previous page*

			(0.007)	(0.008)			
Observations	7,001	7,001	7,001	7,001	4,445		2,960
	College/Bachelor				Subsets of college/bachelor		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.048***	0.042**	0.031*	0.031	0.053**	0.052*	0.051*
	(0.018)	(0.019)	(0.019)	(0.019)	(0.027)	(0.028)	(0.031)
union		-0.010***		-0.004			
		(0.003)		(0.004)			
public			-0.026***	-0.024***			
			(0.004)	(0.004)			
Observations	47,598	47,598	47,598	47,598	32,644	36,587	29,008

Logit regression does not converge for Graduate male workers with last job in private sectors.
Survey of Labour and Income Dynamics (SLID) data is used in the estimations. Individuals' age, years of schooling, working experience, marital status, residential provinces, calendar year effects, and panel effects are controlled in the regressions.
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.7: Average marginal/discrete effects of selected variables on females' probability of finding job.

Dependent variable: job finding (= 1 if jobless spell is ended)							
	Full sample				Subsets of full sample		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.014**	0.009	0.008	0.007	0.008	0.010	0.010
	(0.007)	(0.006)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)
union		-0.007***		-0.002			
		(0.002)		(0.002)			
public			-0.011***	-0.010***			
			(0.002)	(0.002)			
Observations	169,076	169,076	169,076	169,076	133,706	133,610	121,071
	Post sec.				Subsets of post sec.		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.011	0.008	0.007	0.007	0.007	0.008	0.009
	(0.007)	(0.008)	(0.007)	(0.008)	(0.010)	(0.010)	(0.011)
union		-0.006***		-0.002			
		(0.002)		(0.003)			
public			-0.009***	-0.008***			
			(0.002)	(0.003)			
Observations	82,322	82,322	82,322	82,322	61,164	57,981	53,192
	Graduate				Subsets of Graduate		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.003	0.002	0.001	0.002	0.022	0.017	0.043
	(0.017)	(0.018)	(0.018)	(0.018)	(0.026)	(0.034)	(0.035)
union		-0.004		0.009			
		(0.008)		(0.011)			
public			-0.017**	-0.022***			

Table1.7 – *Continued from previous page*

			(0.008)	(0.010)			
Observations	5,603	5,603	5,603	5,603	3,371	2,412	2,308
	College/Bachelor				Subsets of college/bachelor		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.009	0.005	0.005	0.004	0.002	0.006	0.005
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.012)
union		-0.006**		-0.002			
		(0.003)		(0.003)			
public			-0.008***	-0.007**			
			(0.002)	(0.003)			
Observations	76,719	76,719	76,719	76,719	57,793	55,569	50,884

Survey of Labour and Income Dynamics (SLID) data is used in the estimations. Individuals' age, years of schooling, working experience, marital status, residential provinces, calendar year effects, and panel effects are controlled in the regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.8: Average marginal/discrete effects of selected variables on males' probability of being displaced.

Dependent variable: displacement (= 1 if job is ended as a result of lay-off/business slowdown)							
	Full sample				Subsets of full sample		
	(1)	(2)	(3)	(4)	Non-unionized (5)	In private sector (6)	Non-unionized and in private sector (7)
vdex	0.038***	0.037***	0.023*	0.024**	0.014	0.018	0.005
	(0.012)	(0.012)	(0.012)	(0.012)	(0.017)	(0.017)	(0.020)
union		-0.002		0.002			
		(0.001)		(0.001)			
public			-0.015***	-0.016***			
			(0.001)	(0.001)			
Observations	82,465	82,465	82,465	82,465	48,349	62,423	43,377
	Post sec.				Subsets of post sec.		
	(1)	(2)	(3)	(4)	Non-unionized (5)	In private sector (6)	Non-unionized and in private sector (7)
vdex	0.031***	0.030***	0.016*	0.017*	0.011	0.015	0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.013)	(0.015)	(0.016)
union		-0.002*		0.003**			
		(0.001)		(0.001)			
public			-0.015**	-0.016***			
			(0.001)	(0.001)			
Observations	47,699	47,699	47,699	47,699	27,384	32,494	23,632
	Graduate				Subsets of Graduate		
	(1)	(2)	(3)	(4)	Non-unionized (5)	In private sector (6)	Non-unionized and in private sector (7)
vdex	0.026*	0.021	0.018	0.017	0.025	0.024	0.010
	(0.015)	(0.015)	(0.015)	(0.015)	(0.026)	(0.04)	(0.044)
union		-0.008***		-0.003			
		(0.003)		(0.004)			
public			-0.012***	-0.010**			

Table1.8 – *Continued from previous page*

			(0.003)	(0.004)			
Observations	3,641	3,641	3,641	3,641	1,966	1,286	1,146
	College/Bachelor				Subsets of college/bachelor		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.028**	0.028**	0.012	0.012	0.001	0.010	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.018)
union		-0.002		0.004**			
		(0.001)		(0.001)			
public			-0.016***	-0.017***			
			(0.001)	(0.001)			
Observations	42,069	42,069	42,069	42,069	24,156	29,926	21,378

Survey of Labour and Income Dynamics (SLID) data is used in the estimations. Individuals' age, years of schooling, working experience, marital status, residential provinces, calendar year effects, and panel effects are controlled in the regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.9: Average marginal/discrete effects of selected variables on females' probability of being displaced.

Dependent variable: displacement (= 1 if job is ended as a result of lay-off/business slowdown)							
	Full sample				Subsets of full sample		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.031***	0.023***	0.023***	0.021***	0.020**	0.024***	0.014
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.010)
union		-0.009***		-0.005***			
		(0.001)		(0.001)			
public			-0.011***	-0.009***			
			(0.001)	(0.001)			
Observations	83,996	83,996	83,996	83,996	49,502	53,122	43,540
	Post sec.				Subsets of post sec.		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.025***	0.017***	0.019***	0.016***	0.019***	0.024***	0.015*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.009)
union		-0.008***		-0.005***			
		(0.001)		(0.001)			
public			-0.009**	-0.007***			
			(0.001)	(0.001)			
Observations	53,837	53,837	53,837	53,837	27,914	28,790	23,373
	Graduate				Subsets of Graduate		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.005	-0.001	0.000	-0.002	-0.026	-0.016	-0.038
	(0.009)	(0.009)	(0.009)	(0.009)	(0.027)	(0.027)	(0.039)
union		-0.012***		-0.007*			
		(0.004)		(0.005)			
public			-0.015***	-0.010**			

Table1.9 – *Continued from previous page*

			(0.005)	(0.005)			
Observations	2,530	2,530	2,530	2,530	728	703	471
	College/Bachelor				Subsets of college/bachelor		
					Non-unionized	In private sector	Non-unionized and in private sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
vdex	0.028**	0.020**	0.022***	0.019***	0.027***	0.030***	0.023**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.008)	(0.010)
union		-0.008***		-0.005***			
		(0.001)		(0.001)			
public			-0.010***	-0.007***			
			(0.001)	(0.001)			
Observations	49,356	49,356	49,356	49,356	26,102	27,354	22,231

Survey of Labour and Income Dynamics (SLID) data is used in the estimations. Individuals' age, years of schooling, working experience, marital status, residential provinces, calendar year effects, and panel effects are controlled in the regressions. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.10: OLS estimates of the effects of the entry unemployment rates and skill versatility on male immigrants' city-level onward migrations.

Dependent variable: mob (mob=1 if city changes)								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ur	0.002***	0.001***	0.001***	0.004***	-0.015**	-0.004	-0.005	0.042**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.007)	(0.008)	(0.010)
$ur \times vdex$					0.020**	0.006	0.007	-0.039**
					(0.009)	(0.008)	(0.011)	(0.019)
$vdex$					-0.104***	-0.063**	-0.043	0.055
					(0.028)	(0.027)	(0.032)	(0.058)
ysm	-0.049***	-0.057***	-0.052**	-0.056***	-0.049***	-0.057***	-0.052**	-0.056***
	(0.011)	(0.012)	(0.023)	(0.015)	(0.011)	(0.012)	(0.023)	(0.015)
ysm^2	0.002***	0.003***	0.002	0.003***	0.002***	0.003***	0.002	0.003***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	-0.005***	-0.006***	-0.007*	-0.006***	-0.005***	-0.006***	-0.007*	-0.006***
	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)
age_imm^2	0.000	0.000*	0.000	0.000*	0.000	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	0.000**	0.000	0.000	0.000	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.002**	0.007***	0.014***	0.004*	0.002*	0.006***	0.014***	0.003*
	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
married	-0.030***	-0.029***	-0.023***	-0.031***	-0.030***	-0.029***	-0.023***	-0.031***
	(0.004)	(0.004)	(0.007)	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88,570	68,515	23,410	45,105	88,570	68,515	23,410	45,105
Adjusted R^2	0.191	0.178	0.193	0.168	0.191	0.178	0.193	0.169

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.11: OLS estimates of the effects of the entry unemployment rates and skill versatility on female immigrants' city-level onward migrations.

Dependent variable: mob (mob=1 if city changes)								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ur	0.004***	0.003***	0.003**	0.003**	0.004	0.012**	-0.001	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.006)	(0.010)	(0.011)
$ur \times vdex$					0.001	-0.011	0.004	-0.038***
					(0.008)	(0.007)	(0.011)	(0.012)
$vdex$					-0.008	0.027	0.012	0.102***
					(0.026)	(0.023)	(0.027)	(0.038)
ysm	-0.051***	-0.038***	-0.065***	-0.028**	-0.051***	-0.038***	-0.065***	-0.029**
	(0.009)	(0.011)	(0.023)	(0.011)	(0.009)	(0.011)	(0.023)	(0.011)
ysm^2	0.002***	0.002**	0.003**	0.001	0.002***	0.002**	0.003**	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	-0.009***	-0.008***	-0.011***	-0.006***	-0.009***	-0.008***	-0.011***	-0.006***
	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)
age_imm^2	0.000***	0.000***	0.000**	0.000*	0.000***	0.000***	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	0.000***	0.000	0.000	0.000	0.000***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	-0.001	0.002	0.013***	-0.002	-0.001	0.002	0.013***	-0.002
	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
married	-0.006**	-0.004	-0.018***	0.002	-0.006**	-0.003	-0.018***	0.002
	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,775	65,125	17,050	48,075	91,775	65,125	17,050	48,075
Adjusted R^2	0.188	0.170	0.171	0.173	0.188	0.170	0.171	0.173

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.12: Estimates of the effects of the entry unemployment rates on male immigrants' earnings and employment: stayers versus movers.

	OLS estimates for stayers				OLS estimates for movers			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ur	-0.013***	-0.014***	-0.012***	-0.018***	-0.011***	-0.011***	-0.003	-0.031***
	(0.002)	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)	(0.010)
ysm	0.117**	0.157**	0.182	0.144**	-0.016	0.005	-0.130	0.093
	(0.053)	(0.064)	(0.123)	(0.072)	(0.102)	(0.118)	(0.178)	(0.152)
ysm^2	-0.005	-0.007*	-0.007	-0.007	0.001	0.003	0.011	-0.002
	(0.004)	(0.004)	(0.008)	(0.005)	(0.007)	(0.008)	(0.012)	(0.010)
age_imm	0.026***	0.035***	0.045**	0.030***	0.072***	0.088***	0.095**	0.085***
	(0.007)	(0.009)	(0.017)	(0.009)	(0.018)	(0.021)	(0.037)	(0.026)
age_imm^2	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.001	-0.001	-0.001	-0.000	0.001	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
years of schooling	0.032***	0.041***	0.048***	0.031***	0.045***	0.043***	0.041***	0.038***
	(0.004)	(0.005)	(0.010)	(0.006)	(0.006)	(0.009)	(0.012)	(0.012)
married	0.126***	0.137***	0.134***	0.134***	0.111***	0.101***	0.085	0.119***
	(0.013)	(0.014)	(0.023)	(0.017)	(0.027)	(0.031)	(0.052)	(0.038)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,895	53,500	17,840	35,665	10,005	8,190	3,475	4,715
Adjusted R^2	0.119	0.097	0.089	0.081	0.152	0.105	0.058	0.094
Dependent variable: employment (employment=1 if annual earning>0)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Table1.12 – *Continued from previous page*

ur	-0.000	-0.000	-0.000	0.001	-0.001	-0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
ysm	0.032***	0.037***	0.033	0.037**	0.004	-0.011	0.041	-0.044
	(0.012)	(0.014)	(0.024)	(0.017)	(0.026)	(0.029)	(0.040)	(0.038)
ysm^2	(0.000)	-0.001	-0.000	-0.001	0.001	0.002	-0.001	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
age_imm	0.028***	0.031***	0.032***	0.030***	0.018***	0.018***	0.015*	0.020***
	(0.002)	(0.003)	(0.005)	(0.003)	(0.005)	(0.006)	(0.009)	(0.008)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001**	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.007***	0.003*	0.002	0.003	0.009***	0.006***	0.005*	0.008***
	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
married	0.041***	0.033***	0.027***	0.035***	0.045***	0.041***	0.035**	0.048***
	(0.004)	(0.004)	(0.007)	(0.004)	(0.009)	(0.009)	(0.014)	(0.011)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,230	59,485	19,670	39,815	11,340	9,030	3,745	5,285
Adjusted R^2	0.063	0.049	0.047	0.049	0.076	0.051	0.021	0.065

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.13: Estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment: stayers versus movers.

	OLS estimates for stayers				OLS estimates for movers			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ur	-0.038***	-0.045***	-0.029***	-0.060***	-0.011	-0.013*	-0.006	-0.033***
	(0.005)	(0.006)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.012)
ysm	0.236***	0.214**	0.185	0.223**	0.133	0.231	0.507*	0.171
	(0.070)	(0.083)	(0.156)	(0.095)	(0.142)	(0.162)	(0.275)	(0.197)
ysm^2	-0.008*	-0.007	-0.002	-0.009	-0.008	-0.016	-0.037**	-0.010
	(0.005)	(0.006)	(0.011)	(0.007)	(0.009)	(0.011)	(0.019)	(0.013)
age_imm	0.097***	0.093***	0.089***	0.095***	0.053**	0.044	0.080	0.037
	(0.008)	(0.009)	(0.018)	(0.011)	(0.024)	(0.027)	(0.057)	(0.031)
age_imm^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.002***	-0.003***	-0.002***	0.000	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
years of schooling	0.058***	0.064***	0.071***	0.056***	0.031***	0.038***	0.095***	0.012
	(0.005)	(0.007)	(0.012)	(0.008)	(0.010)	(0.012)	(0.021)	(0.015)
married	-0.146***	-0.171***	-0.129***	-0.178***	-0.220***	-0.195***	-0.217***	-0.183***
	(0.012)	(0.013)	(0.025)	(0.015)	(0.036)	(0.042)	(0.082)	(0.050)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	60,050	45,850	12,225	33,630	7,210	5,630	1,785	3,845
Adjusted R^2	0.087	0.056	0.046	0.045	0.086	0.063	0.056	0.030
Dependent variable: employment (employment=1 if annual earning>0)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)

Table1.13 – *Continued from previous page*

ur	-0.009***	-0.010***	-0.003**	-0.016***	-0.005**	-0.005**	-0.002	-0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ysm	0.068***	0.055**	0.047	0.059**	0.036	-0.014	0.057	-0.041
	(0.018)	(0.022)	(0.033)	(0.025)	(0.041)	(0.049)	(0.085)	(0.058)
ysm^2	-0.001	-0.001	0.001	-0.001	0.000	0.002	0.000	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.004)
age_imm	0.056***	0.053***	0.046***	0.054***	0.040***	0.031***	0.022	0.034***
	(0.004)	(0.003)	(0.005)	(0.003)	(0.007)	(0.009)	(0.018)	(0.010)
age_imm^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001	-0.002*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
years of schooling	0.020***	0.013***	0.013***	0.012***	0.020***	0.018***	0.029***	0.013***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)	(0.007)	(0.004)
married	-0.056***	-0.063***	-0.048***	-0.066***	-0.056***	-0.072***	-0.040*	-0.076***
	(0.004)	(0.004)	(0.008)	(0.005)	(0.010)	(0.012)	(0.021)	(0.014)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	81,430	57,650	14,795	42,860	10,345	7,475	2,260	5,215
Adjusted R^2	0.085	0.037	0.027	0.040	0.088	0.031	0.056	0.024

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees. Standard errors in parentheses, clustered by education and year of immigration. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 2

Immigrants and Patents: Evidence from Canadian Cities

2.1 Introduction

An important consequences of the economic turmoil brought about by the financial crisis of 2008 was a decrease in voters' support of immigration. This development, which has been particularly evident in the U.S. and the U.K., has put increasing pressure on pro-immigration politicians to justify the economic benefits of continued large-scale immigration. To do so, increasing reference has been made in policy discussions to the burgeoning economics literature exploring the 'wider' benefits of immigration, including effects on international trade flows, entrepreneurship, and, perhaps most significantly, given the growing consensus of its importance to long-term economic growth, on innovation. Although the precise theoretical mechanisms through which diversity increases innovation are less well developed, the empirical literature provides remarkably consistent evidence of the productivity-enhancing benefits of increasing ethnic diversity within workplaces, cities, and countries.[1]

For government policymakers responsible for immigration, the critical question is how to harness this growth-enhancing potential of ethnic diversity. In this respect, the eco-

[1]The notion of 'wider effects' of immigration is due to Nathan (2014b). The literature linking ethnic diversity and innovation is interdisciplinary with papers in psychology (van Knippenberg, Dreu, and Homan, 2004), sociology (Herring, 2009), management studies (Ely and Thomas, 2001; Richard et al., 2003), and economics.

nomics literature linking skilled immigration with higher patenting rates is arguably not only the most relevant, but also the most compelling. Beginning with U.S. studies by Peri (2007), Chellaraj, Maskus E., and Mattoo (2008), Hunt and Gauthier-loiselle (2010), and Kerr and Lincoln (2010), but now also including a number of European studies (Ozgen, Nijkamp, and Poot, 2012; Parrotta, Pozzoli, and Pytlikova, 2014; Nathan, 2014a), this literature has attracted considerable attention in the policy world. The results from these studies consistently suggest that increasing skilled immigration, particularly of immigrants educated in science, technology, engineering, and mathematics (STEM) fields, has a significant positive impact on the numbers of patents that are created. For example, Hunt and Gauthier-loiselle (2010) find that a one percentage-point increase in the share of a state's population who are college-educated immigrants can be expected to increase state-level patents per capita by $9-18\%$. Comparing the magnitude of this effect to what is implied by the differential patenting rate of immigrants observed in individual-level data, they conclude that an important part of this effect reflects a positive externality of immigrants on the patenting rates of native-born Americans. The potential of immigrants to raise innovation levels not only directly through their own patents, but also making natives more innovative, makes a strong economic case for immigration.

In this paper, we examine the Canadian case in order to inform the innovation-enhancing potential of immigration in a setting in which a 'point system' is used to screen skilled immigrants. Canada's 'point system' is seen by many as a model of effective skilled immigration policy; the U.K. adopted a point system in 2008 and it is regularly pointed to as an option in ongoing U.S. immigration reform discussions. The Canadian case is also important because Canada consistently ranks among the world's largest immigrant-receiving countries measured as a proportion of its population. Between the mid-1980s and mid-1990s, both Canada's annual inflow of new permanent residents and the share of the inflow admitted under the 'point system' more than doubled. Consequently, the share of the Canadian working-age population comprised of university-educated immigrants increased from 2.6% in the early 1980s to 3.3% in the early 1990s and 6.7% by the mid-2000s.

Given Canada's success at attracting skilled immigrants, there is the potential for exceptionally large effects of immigration on innovation in the Canadian case. However, there is also substantial evidence pointing to significant labour market challenges of Canadian university-educated immigrants, which suggest that the labour market skills of Canadian immigrants have not kept pace with the large increase in their education levels (Clarke and Skuterud, 2013; Clarke and Skuterud, 2016; Clarke, Ferrer, and Skuterud, 2016). It is an open question whether the poor earnings performance of Canadian immigrants, possibly resulting from the crudeness of the criteria used by the 'point system' to screen human capital, is mirrored in their contributions to innovation. In particular, while the Canadian 'point system' gives considerable weight to foreign sources of education and work experience, there is evidence that foreign sources of human capital are devalued by Canadian employers (D. Green and Worswick, 2012; Skuterud and Su, 2012).

The primary challenge in examining the Canada case is its relatively small population, which limits the geographic variation in immigrant population shares. Nonetheless, relating changes in university-educated immigrant shares within 98 Canadian cities between 1981 and 2006 to changes in patenting rates, we obtain estimates that are unambiguously smaller than those found by Hunt and Gauthier-loiselle (2010) (hereafter HGL) using U.S. data. This remains true even when we restrict attention to university-educated immigrants who were educated in a STEM field. On the other hand, the estimated effect of Canadian-born university graduates on patenting rates is larger and virtually identical in magnitude to the HGL estimate for U.S. natives, suggesting that the smaller magnitude of our immigrant estimates does not reflect greater measurement error in our data or something intrinsic to the Canadian economy or innovation sectors. Overall, our analysis suggests that increasing the university-educated immigrant population share in Canada may have contributed to raising patenting rates, but only modestly, and any spillover effects of immigrants on native patenting are likely minimal.

An important policy question is to what extent the weaker contribution of Canadian immigrants to innovation that we identify is related to the broader labour market challenges of Canadian immigrants identified elsewhere. Indeed, when we isolate the effect of university-educated immigrants who were educated in a STEM field and are currently employed in a STEM occupation, our estimates become much larger and statistically significant. The relatively small Canadian estimates therefore appear to, in large part, reflect the relatively low employment rates of Canadian immigrants in STEM jobs, including among those educated in STEM fields. While we provide no direct evidence on why Canadian STEM-educated immigrants face greater employment barriers than their U.S. counterparts, the difference is consistent with U.S. immigrants being relatively positively selected owing to a greater role of employers in immigrant selection and higher economic returns to skill in U.S. labour markets.

The remainder of the paper is organized as follows. In the following section, we discuss the relevance of the Canadian context. In section 3, we describe our methodological approach, including the data that we employ. In section 4, we discuss our results in detail. In the final section, we summarize our main findings and discuss their policy relevance.

2.2 The Canadian context

The Canadian *Immigration Act* of 1962 ended the historical practice of selecting immigrants on the basis of their country of origin and replaced it over the following decade with a 'point system' that emphasized the human capital of migrants. The success of the Canadian 'point system' in raising the average education levels of its immigrant population has led a number of countries, including Australia and the U.K., to follow its approach, and has received much attention in recent immigration reform discussions in the United States. The key rationale underlying the Canadian approach is that human capital is a stronger predictor of long-run economic success than the extent to which an immigrants' skills match current labour market need. Moreover, current local labour market needs are difficult to identify empirically and, are often short-lived, and the approach is in practice impractical, since immigrants are free to choose where they settle. However, within Canada there has been growing criticism of this approach in response to evidence of a deterioration in the ability of Canada's skilled immigrants to obtain jobs commensurate with their levels of education and experience obtained abroad (see Picot and Sweetman (2012) for a review of this literature).[2]

The level of innovation in Canada has historically been lower than that of the United States. The economy invests a smaller fraction of GDP on research and development (2.0% in Canada versus 2.5% in the U.S. in 2006) and generates fewer patents per capita (19.9 patents per $100,000$ in Canada versus 48.0 patents per $100,000$ in the U.S. in 2006). Prevailing explanations for this gap include differences in the industrial mix (in particular, Canada's historical reliance on natural resources), a higher degree of foreign ownership in Canada, and the relatively smaller size of Canadian firms. However, the two countries do not differ in the fraction of their workforces employed in STEM. As reported by Beckstead

[2]This has led the Canadian government to make significantly policy shifts in recent years towards giving employers a greater role in immigrant selection. In particular, a sufficient condition for obtaining an invitation for permanent residency under the new Express Entry system for processing application, introduced in January 2015, is a job offer from a Canadian employer. Job offers for foreign workers must, however, clear a labour market test intended to ensure that the employer was unable to fill the job domestically.

and Gellatly (2006), the share of employment in science, engineering and related occupations was, for Canada and the U.S. respectively, 9.8% and 9.6% in 1981/80, 11.7% and 11.3% in 1991/90, and 13.6% for both in 2001/00.

Given the lower level of patenting activity in Canada, we might expect lower patenting rates among Canadian skilled immigrants and that they generate less patenting spillovers on native. However, the focus of our analysis is whether Canada's 'point system' for screening skilled immigrants, in particular on the basis of their educational attainment levels, has resulted in Canadian immigration having a larger proportional impact on patenting rates. To provide some initial sense of the magnitudes of these changes, in Figure 2.1 we plot both national-level patents per capita in Canada and the U.S. between 1980 and 2006 and the shares of their populations aged 25 and over comprised of university-educated immigrants. In both countries, the university-educated immigrant share increased consistently over the entire period. Given the Canadian system's emphasis on skilled immigration, the Canadian share in 1980 was more than twice the U.S. share (2% compared to 0.7%). Over the following 25 years, Canada continued to attract more skilled immigrants as a fraction of its population, so that by the mid-2000s nearly 6.4% of its working-age Canadian population were university-educated immigrants, compared to 4.2% in the United States.

Given the evidence in HGL, this increase should have served to raise patenting rates proportionally more in Canada than in the United States. Interestingly, the Canadian patenting rate did, in fact, increase more over this period than the U.S. rate.[3] Whereas patents per capita ($\times 100,000$) nearly tripled in Canada (from about 6.9 in 1980 to 19.9 in 2006), they only doubled in the U.S. (25.9 in 1980 to 48.0 in 2006). Of course, the increase in patenting rates implied by even the upper bound estimate of HGL (an 18 log point increase in patents per capita from a 1 percentage-point increase in the university-educated immigrant share) are much smaller than the log point increase that either Canada or the U.S. actually experienced. Of course, there are many other factors serving to raise patenting rates besides immigration. Moreover, these national-level correlations could be entirely misleading. To plausibly identify the causal impact of Canada's skilled immigration

[3]Both countries exhibit upward trending patenting rates up to the dot-com bubble bursting in 2001. For the U.S., in particular, this increase was followed by a large decline, which may have been due, in part, to a drop in the success rate of patent applications at the USPTO, particularly in the "drugs and medical instruments" and "computers and communication" fields (Carley, Hedge, and Marco, 2013). It is important to note that, because we have collected patents granted up to November 2014, and that among patents granted in 2013 only 1.8% of them took 8 years or longer to be granted from the date of application, which we use in the figure, data truncation likely explains only a small fraction of this decrease.

on its patenting rate, we need a strategy to isolate a source of increases in skilled immigrant population shares that are plausibly independent of increases in patenting rates that would have occurred even in the absence of any changes in skilled immigrant population shares.

2.3 Methodology

We focus on comparisons to the results of HGL for three reasons. First, their results are the most general, as they are focused on college-educated shares in the overall population, as opposed to international students or H-1B visa holders. This makes it possible to conduct more direct comparisons. Second, HGL has attracted the most interest.[4] Third, they find evidence of large direct and spillover effects of immigration on U.S. patenting rate.[5] However, rather than examine state-level (or province-level) immigration shares, as HGL do, we relate immigrant shares to patent rates at the city level.[6] Specifically, we construct a 1981–2006 balanced panel of Canadian Census Metropolitan and Agglomeration Areas (CMA/CAs) with observations on skilled immigrant population shares in 98 cities every 5 years.[7] Our cities range in population (age 15-70)in 2006 from a low of $8,488$ to a high of $3,684,831$, with 66 cities above $25,000$ individuals, 46 above $50,000$, 26 above $100,000$, and 7 above $500,000$.

We estimate the skilled immigrant shares of the population using the master files of the 1981, 1986, 1991, 1996, 2001 and 2006 Canadian Censuses, which provide 20% random samples of the Canadian population. Skilled immigrants are defined in four alternative ways: (i) university-educated; (ii) university-educated in a STEM field; (iii) university-educated and employed in a STEM occupation; or (iv) university-educated in a STEM field and employed in a STEM occupation. The appendix provides details on how we define STEM fields of study and occupations in the various Census years. In addition, we distinguish between STEM-educated immigrants with Canadian and foreign degrees, which we estimate using information on years of schooling and age at immigration.[8] In

[4]Citation counts for HGL in Google Scholar are 417 and 56 in Web of Science as of May 2016. In comparison, the second most cited paper, Kerr and Lincoln (2010), has 291 and 48 citations, respectively.

[5]Kerr and Lincoln (2010) do not find strong evidence of spillover effects.

[6]With only 10 Canadian provinces, two of which account for roughly 60% of the national population, an analysis at the province level is not available.

[7]A CMA is defined as one or more adjacent municipalities centred on a population core with at least $100,000$. A CA must have a core population of at least $10,000$.

[8]Specifically, we assume schooling is strictly continuous, so that years of schooling plus 6 identifies the age of school completion. Comparing this age to the age at immigration identifies whether the terminal

cases where the population shares are defined using field of study, we lose the first year of data in our panel because field of study was not identified in the 1981 Census.

Skilled immigrant population shares in Census years are related to the number of patent applications (per capita) within cities over the following 5 years. The five-year lag is not only convenient for maximizing our sample size using the quinquennial Canadian Censuses, but is also justified by a separate analysis we conducted suggesting that the impact of changes in the composition of the population on patent application counts peaks four years after the change.[9] We construct patent counts at the level of the city and year using United States Patent and Trademark Office (USPTO) data on patents granted to inventors residing in Canada. Alternatively, we could have examined patents granted by the Canadian Intellectual Property Office (CIPO) to Canadian inventors. However, this would have resulted in us observing only a small subset of patented Canadian inventions, since Canadian inventors tend to patent in the U.S. and forego patenting in Canada altogether, due to the much larger size of the U.S. market.[10]

Patents are assigned to cities by linking the address of inventors to Canadian CMA/CAs. Where patents contained multiple inventors, we assigned fractions of patent to cities, so that each patent received equal weight. For example, a patent with two inventors from Toronto and one from Kitchener-Waterloo is counted as two-thirds of a patent for Toronto and one-third for Kitchener-Waterloo. Patents are assigned a year based on the application date of the patent (not the grant date), since this coincides most closely to the actual date that the innovation took place. Because we only observe patents granted up to November 2014, our patent counts for the five-year window following 2006 (the years 2007-2011) will

degree was obtained in Canada or abroad. The resulting variable contains some measurement error where schooling is not continuous and where international students obtain Canadian schooling prior to landing. Skuterud and Su (2012) show that the consequences of this measurement error are negligible in estimating earnings to foreign and Canadian schooling.

[9] We related changes in a city's population from a given ethnicity with changes in the number of future patent applications by members of that ethnicity residing in that city. We thank Bill Kerr for generously providing us with data on the predicted ethnicity of patent inventors based on their names (see Kerr and Lincoln, 2010).

[10] We conducted a separate search on the websites of the CIPO and the USPTO for patents filed in the year 2000 with at least one Canadian inventor and found 1,136 CIPO and 5,195 USPTO patents meeting the criteria. To further test the premise that CIPO patents are largely a subset of USPTO patents, we manually searched the USPTO database for the first 100 Canadian-inventor CIPO patents applied for in 2000 and found 93 unambiguous USPTO matches and 2 additional probable ones. These data are available from the authors upon request.

be lower due to data truncation. However, among patents granted in 2013, we find that 58% of patents were granted within 3 years of application, 75% within 4 years, 85% within 5 year, 93% within 6 years, and 96% within 7 years. Our estimated patent counts will, therefore, be roughly 18% lower in this window than they should, but this variation should be absorbed in the 2006 year fixed effect.

Our baseline empirical model estimates a specification as close as possible to the first-difference (FD) weighted least squares (WLS) specification of HGL. We then extend this specification, by including a richer set of controls intended to address the possible endogeneity of within-city changes in skilled immigrant population shares. Specifically, we estimate the equation:

$$\begin{aligned}\Delta log\Big(\frac{\sum_{j=1}^{5} patent_c(t+j)}{pop_c(t)}\Big) = \beta_m \Delta\Big(\frac{sm_c(t)}{pop_c(t)}\Big) + \beta_n \Delta\Big(\frac{sn_c(t)}{pop_c(t)}\Big) + \\ \Delta X_c(t)\sigma + Z_c(1981)\theta + y(t) + \epsilon_c(t)\end{aligned} \tag{2.1}$$

where $patent_c(t+j)$ is the total number of patents granted to inventors residing in city c that were filed in year $t+j$; $pop_c(t)$ is the population aged 15 and over; $sm_c(t)$ and $sn_c(t)$ are the number of skilled immigrants and natives (age 15 and over), respectively; $X_c(t)$ is a vector of time-varying control variables; $Z_c(1981)$ is a vector of controls measured in 1981, intended to capture the influence of initial conditions; $y(t)$ is a set of Census year fixed effects; $\epsilon_c(t)$ is a random error potentially correlated across years within cities; and Δ is the first-difference between Census years. The parameter β_m identifies the proportional effect of increasing the skilled immigrant population share by one percentage point on patents per capita, both directly and through possible spillovers on the patents of natives.

Following HGL, we begin by estimating equation (2.1) including log mean age in $X_c(t)$ and both log mean income and log population in $Z_c(1981)$. We then extend the model by adding to $X_c(t)$: (i) the employment rate; and (ii) the expected number of log patents per capita based on the distribution of a city's patents between 1972–1980 across patent classes and the national-level number of patents within those patent classes across Census years. This latter control variable, which we borrow from Kerr and Lincoln (2010), is intended to capture spurious correlations between historical sectoral distributions of innovation across cities and subsequent immigration flow. In the extended version of the model, we also include a set of region-year fixed effects, where regions include the Maritimes, Quebec, Ontario, the Prairies, and British Columbia. Finally, we allow the log mean income control variable to vary across Census years. Given the considerable variation in city sizes in our sample of 98 Canadian cities, the variance of the error term across city observations will vary considerably. To improve the efficiency of the FD estimator we therefore weight all the regressions by city population size.[11]

It is, of course, possible to estimate equation (2.1) using a fixed-effects (FE) estimator instead. With more than two time periods, the FE estimator produces different estimates than the FD estimator, although both estimators are consistent under the strict exogeneity assumption that the right-hand-side variables in equation(2.1) are uncorrelated with $\epsilon_c(t)$ across all Census years. Obtaining substantially different point estimates using FE, that is not due to sampling error, provides evidence against the strict exogeneity assumption. We have estimated all the specifications we report using a FE estimator and none of our main findings are substantively altered.

The key challenge in identifying the causal impact of immigration on patents using an area-level analysis is that we would expect skilled migration flows to be higher to cities that are experiencing relatively large increases in innovation activity for reasons that are entirely independent of immigration. For example, skilled immigration in the U.S. is driven in large part by the recruiting activities of employers, through the H-1B visa program. If unobserved technology shocks simultaneously lead to increases in both patents and the demand for H-1B workers, the estimates of β_m will tend to be upward biased estimates of the causal impact of immigrants. Employer labour demand has, however, historically played little role in the Canadian 'point system', which is used to screen the vast majority of economic class applicants. Moreover, the system has historically been characterized by significant processing bottlenecks, making it arguably less likely that supply-drive changes in immigration flows to Canadian cities are correlated with latent city-level changes in patenting activity. Nonetheless, even in Canada, immigrants ultimately decide in which city they will reside. To the extent that skilled immigrants choose to settle in cities where increases in patenting rates are already happening, there is still reason to be concerned that the results from the naive estimates of equation (2.1) are upward biased.

[11] Specifically, we weight the first-differenced observations by $(pop_c(t+1)^{-1} + pop_c(t)^{-1})^{-1}$. A concern with the WLS approach is the influence of Toronto on the estimates, given its relatively large population. This is also a concern in the IV estimation described below, in which the instruments are based on historical distributions of immigrants across cities. To assure ourselves that our findings are not driven by the Toronto observation alone, we have also estimated all our models excluding Toronto. Although these naive FD-WLS estimates do suggest substantially larger beneficial impacts of immigration, our IV estimates are almost identical to those reported in Table 2.5.

A common solution to this inference problem, initially proposed by Card (2001), is to isolate the supply-push component of immigration flows to a particular city using attributes of cities that are plausibly unrelated to latent innovation trends. The standard approach, which we follow, is to instrument local skilled immigrant populations using predicted immigrant populations based on the historical city-level settlement pattens of immigrants from particular origin countries and national-level population of immigrants from those countries. That is, we instrument the skilled immigrant share $sm_c(t)$ in equation (2.1) using the constructed variable:

$$sm_c(t) = \sum_j \lambda_{ij}(1976) sm_j(t) \tag{2.2}$$

where $\lambda ij(1976)$ is the share of 1976 Canadian immigrants born in country j living in city c and $sm_j(t)$ is the national-level population of skilled immigrants from country j living in Canada in year t.[12] Using first-difference of the skilled immigrant shares, the intuition behind the instrumental variables (iv) strategy is that, for example, if the increase in the skilled immigrant population originating from Germany is exceptionally high at the national level between two Census years, we would expect the city of Kitchener-Waterloo (KW) to receive a disproportionately large share of this increase, not because these immigrants were attracted by the expectation of heightened innovation activity in KW, but because the historical population of German migrants residing in KW and the associated cultural amenities they offer attracts them.

2.4 Results

Before examining the results of our regression analysis, in Table 2.1 we report sample means of the variables used in the regressions separately by Census year. The means are

[12] To obtain 1976 immigrant city population by origin country we used mobility information in the previous five years contained in the 1981 Census, but restricted the sample to immigrants who landed in 1976 or earlier. We did not, however, restrict the sample to skilled immigrants, since cultural amenities that attract immigrants are likely to be shared across education groups. We also grouped countries into regions with shared cultures, in order to reduce measurement error in the estimates of $\lambda ij(1976)$. The groups are the Caribbean and Bermuda (French and non-French are separate groups), Central America, South America (French and non-French), Germany, France, Western Europe (excluding Germany and France), Eastern Europe, Scandinavia, Southern Europe, Australia/New Zealand/U.K. and colonies, Sub-Saharan Africa (French and non-French), other Africa (French and non-French), Oceania (French and non-French), Western Asia and Middle East, India/Bangladesh/Pakistan, China/Hong-Kong/Taiwan, Singapore/Malaysia/Indonesia, Korea, South Asia (excluding India, Pakistan, and Bangladesh), and rest of the world.

weighted by city populations, so that they are representative of the Canadian population residing within one of Canada's largest 98 cities. Note that the patent rates in Table 2.1 are roughly five times larger than those in Figure 2.1 because they are cumulative sums of patents in the 5 years following the Census year (the dependent variable in equation (2.1)). Consistent with the national-level Canadian patenting rate in Figure 2.1, the first row of Table 2.1 indicates that average patenting rates in Canada's cities increased consistently between the early 1980s and 2000s, resulting in a near threefold increase. The question is, to what extent did skilled immigration contribute to this increase?

In the following rows of Table 2.1, we report skilled population shares separately for immigrants and natives. The overall immigrant share within Canada's largest cities increased by 4.6 percentage points between 1981 and 2006, which is larger than in change in the national-level share, reflecting the increasing concentration of new immigrants in Canada's three largest cities–Toronto, Montreal, and Vancouver. More important, all of this increase appears to be accounted for by university-educated immigrants, as their share alone increased by 5 percentage points (from 2.7% to 7.6%). Given that the Canadian 'point system' has never discriminated on the basis of field of study, it is possible that this increase is accounted for primarily by immigrants who were educated and employed in sectors where patenting activity is rare. In that case, their effect on patent rates may have been much smaller than the HGL estimates would predict. However, not only did the STEM-university-educated share increase by about 2 percentage points between 1986 and 2006, accounting for close to half of the overall increase in the university-educated share, but by the early 2000s the share of university-educated Canadian immigrants who were educated in a STEM field exceeded the comparable share for U.S. immigrants. Defining STEM fields of study similarly using the U.S. National Survey of College Graduates (NSCG), 33.6% of U.S. college-educated immigrants in 2003 were educated in a STEM field, compared to 37.4% and 38.7% of Canadian university-educated immigrants in 2001 and 2006, respectively. The Canadian 'point system' appears, therefore, to have been successful in not only raising the education levels of Canada's immigrants, but also in selecting immigrants educated in STEM fields.

Nonetheless, the Canadian research on the labour market performance of new immigrants reveals significant job-education mismatch. Foreign-trained engineers driving taxis is more than a cliche in Canada (Xu, 2012). Given that the vast majority of patenting happens through corporate research and development activities, challenges of STEM-educated immigrants in obtaining jobs in STEM occupations may have limited the impact of STEM-educated immigrants on Canadian patenting. There is, in fact, some evidence of this possibility in Table 2.1, as the population share comprised of university-educated immigrants from STEM fields increased by 2 percentage points between 1986 and 2006, but the share are employed in a STEM occupation increased by less than 1 percentage points.

In Table 2.2, we examine this education-job mismatch more closely by reporting conditional probabilities of employment in a STEM occupation separately for immigrants and native. The results reveal that not only are Canadian immigrants more likely more likely to hold a university degree than their native-born counterparts, but this advantage has grown significantly over time. Moreover, university-educated immigrants in Canada have always been more likely to be educated in a STEM field than their native-born counterparts and this difference has also become larger over time. By 2006, nearly 4-in-10 university-educated Canadian immigrants were trained in a STEM field, compared to 2-in-10 natives. However, the probability of a STEM-university-educated immigrant being employed in a STEM occupation has tended to decrease over time, whereas it has increased for natives. Consequently, by 2006 there was nearly a 5 percentage point gap in the STEM-employment rate of Canadian STEM-educated immigrants (0.37 for natives, compared to 0.32 for immigrants). In comparison, data from the NSCG indicate that one-half of STEM-educated immigrants in the U.S. were employed in STEM jobs in both 1993 and 2003. In contrast, the comparable rate for Canadian and the U.S. natives is similar (roughly 0.4 in both countries).[13] We would clearly expect this shortfall in the STEM-employment-rates of Canadian immigrants to have limited, in a significant way, the potential of Canada's growing STEM-university-educated immigrant population to boost Canadian innovation.

A possible explanation for the low STEM-employment rates of STEM-educated Canadian immigrants is that foreign sources of education, which the Canadian 'point system' values highly, may result in barriers to employment, perhaps because the quality of schooling is lower on average or because employers have more difficulty evaluating foreign credentials. Distinguishing between immigrants educated in Canadian and foreign universities provides some limited support for this possibility. Rows 6 and 7 of Table 2.2 show that the probability of being employed in a STEM job among STEM-educated immigrants with Canadian degrees has consistently been about 3 percentage points higher than for STEM-educated immigrant with foreign degrees (the only exception being the end of the dot

[13] Although the field of study and occupation classification systems in our Census data and the NSCG are different, the fact that the estimated STEM-employment-rate of STEM-educated natives are similar suggests to us that the much lower employment rate of Canadian STEM-educated immigrants is not being drive in how STEM fields and occupations are being classified in the two data sources or by a different industrial mix across the two countries.

com bubble in 2001, when the rates were identical). However, the impact of this employment gap has become magnified as the share of STEM-university-educated immigrants who graduated from a foreign university increased from about 50% in 1986 to 57% in 2006, presumably reflecting the growing importance of the 'point system' in immigrant selection. Once again, we would expect this trend to have limited the potential of Canadian skilled immigration to raise patent rates.

Finally, in the remaining rows of Table 2.1 we report the weighted sample means of city-level average age, nominal income, and employment rates, as well as the expected patents per capita variable described above. Simple correlations with the sample means in Table 2.1 appear to suggest that patenting rates tend to be higher in older populations and tend to increase in recessions (based, in particular, on the large increase in the patenting rate between 1991 and 1996 when employment rates fell). More compelling evidence of these effects is, however, provided by regression analyses that control for unobserved period effects.

The results from estimating equation (2.1) using both the HGL specification (1) and a richer set of controls (2) are reported in Table 2.3. The first column indicates that increasing the Canadian university-educated immigrant share by 1 percentage point is expected to increase patents per capita by about 1.1 log points. The comparable U.S. estimate (see specification (1) of Table 5 in HGL) is 14.7 log points, which falls far outside the confidence interval of our estimate. The coefficient on the native share is, however, almost identical to the HGL estimate (4.5 compared to the HGL estimate of 4.1) and is statistically significant at the 10% level. This suggests that the large difference in our immigrant share estimated does not reflect greater measurement error in our population shares, structural economic difference between the two countries, or other differences in our methodological differences, such as our focus on cities, as opposed to states. In fact, if we use an alternative specification and variable definitions that most closely match that of HGL, that is, using 10-year first-differences (instead of 5) and counting patents only for the one year following the census year based on the residence of only the first inventor, the difference in the impact of university-educated immigrants across the two countries becomes even larger. Although the variances of the estimated coefficients increase substantially, presumably due to the smaller sample size and noisier dependent variable, the point estimates suggest even smaller beneficial impacts of skilled immigration in Canada, and a slightly larger impact of skilled natives.[14]

[14]These results are available from the authors upon request.

The second column of Table 2.3 presents our results using a richer set of controls. Although the university-educated immigrant coefficient increases to 3.5, on par with the effect of university-educated natives, this coefficient is still statistically insignificant and much smaller than the HGL benchmark estimate. In the next two columns of Table 2.3 we instead define the skilled population as university-educated individuals who are employed in a STEM occupation. As expected, the point estimates increase substantially, but more for immigrants than natives. Using the HGL controls, the estimated effects of increasing the skilled immigrant population share are now 7.3 and 6.3 for immigrants and natives, respectively, but neither estimate is statistically significant. However, using the richer set of controls increases these estimates to 21.7 and 19.0, and both coefficients are statistically significant at the 10% level. Taken as a whole, the results in Table 2.3 appear to suggest that the impact of university-educated immigration on Canadian patenting has been modest and, that this is in large part due to the low employment rates of STEM-educated Canadian immigrants in STEM jobs.

In Table 2.4, we explore this issue in more detail by redefining the skilled population using information on field of study. Since we are forced to drop the 1986-1981 differences, we re-estimate the first two columns of Table 2.3 using the smaller sample (columns 1 and 2). The key result is that refining our definition of skilled to mean university educated in a STEM field has essentially no impact on the immigrant coefficient, but increases the native coefficient substantially. Both immigrant coefficients remain close to zero and are insignificant, whereas the native coefficients increase to 16.8 and 19.1 in specifications (2.1) and (2.2), respectively (compared to 5.4 and 4.2 in columns 1 and 2) and are both significant. The difference in the impact of STEM-educated immigrants and natives is stark. An obvious question is to what extent the difference reflects the foreign educational credentials of immigrants. In the fifth and sixth columns of Table 2.4, we distinguish between Canadian- and foreign-educated immigrant. Although the estimates for Canadian-educated immigrants are larger, they are still much smaller than the comparable coefficients for natives, suggesting that the difference reflects, at least in part, something other than schooling quality. One possible explanation is employer discrimination against Canadian-educated immigrants with ethnic names, consistent with the Canadian audit study of Oreopoulos (2011).

Finally, in the last two columns of Table 2.4 we examine the impact of increasing the population share of immigrants and natives that are not only university-educated in a STEM field, but also employed in a STEM occupation. Here we see a substantial increase in the coefficient on the immigrant population share to 9.3 and 36.3 in specifications (2.1) and (2.2), respectively. The latter coefficient is statistically significant at the 10% level and comparable in magnitude to the 52.4 for the immigrant scientists and engineers share in HGL (Table 6 panel C). Taken as a whole, the estimates appear to suggest that the relatively small contribution of skilled immigrants to innovation in Canada does not reflect the educational backgrounds of Canadian immigrants, in terms of either their relative concentration in STEM fields or the quality of their schooling. Rather, it seems that barriers to employment in STEM jobs are the primary source of their modest contribution to innovation.

It is, of course, possible that our naive FD estimates are downard biased, perhaps as a consequence of measurement error in the Canadian population shares. In Table 2.5, we examine the robustness of our estimates to instrumenting immigration to Canadian cities. As described in Section 3, we instrument changes in skilled immigrant populations using stock populations based on Census data. Our first stage estimates are significant at the 1% level.

Using our complete sample, we define skilled workers as: (i) the university educated; or (ii) university-educated and employed in a STEM job. The IV estimates of the effect of raising the university-educated immigrant share change little and continue to suggest small positive and statistically insignificant effects. This is in sharp contrast to HGL, whose estimates based on the same instrument nearly double in magnitude (see Panel A of Table 8). Isolating the effect of increasing the population share comprised of university-educated immigrants who are employed in a STEM job continues to produce substantially larger estimates. Using the richer controls (specification (2.2)) the point estimate goes from 1.1 to 10.4 and is statistically insignificant, although the latter is now half what it was in Table 2.3.[15]

2.5 Conclusions

We argue that Canada is an important case study because its 'point system' for screening prospective immigrants is seen by many as a model of how to raise the average skill levels of

[15]A further concern is that the inclusion of endogenous control variables could bias our results. We ran the IV specifications in table 2.5 with only fixed effects and obtained similar coefficients for the share of university-educated immigrants and somewhat larger but still insignificant coefficients on university-educated STEM-employed immigrant shares.

immigration inflow. The main finding from our analysis is that Canadian STEM-educated immigrants who are successful in obtaining jobs in STEM areas do appear to raise patenting rates in a significant way. However, with little more than one-third of STEM-educated immigrants finding employment in STEM jobs, the impact Canadian skilled immigration on patent rates has been relatively modest in comparison to the United States. The fact that the employment rates of Canadian STEM-educated immigrants in STEM job has, if anything, tended to decrease over time, while the comparable rate for Canadian natives has been increasing, should be cause for concern among policymakers contemplating introducing 'point systems' for immigrant selection. Given the modest magnitude of our estimated effects, it appears that, for Canada, any spillover effects of immigrants on native patenting are minimal.

What is the policy relevance of these findings? It would appear that adopting a 'point system' so as to put more weight on STEM educational backgrounds is unlikely to have the desired effect of boosting innovation. Rather, our evidence emphasizes that selecting immigrants with STEM skills is not sufficient, given the challenges that Canadian STEM-educated immigrants appear to face in obtaining STEM jobs. The critical question for policy is whether the employment barriers that STEM-educated immigrants appear to face reflect differences in their skills and abilities or labour market inefficiencies arising from information frictions in job search, foreign credential assessment, or racial discrimination. In this regard, it is noteworthy that STEM-educated immigrants find STEM employment less frequently than natives even when they were educated in Canadian universities and that the contribution of STEM-educated immigrants from Canadian universities appears to also fall far short of the comparable contribution to innovation of native-born Canadians. This suggests to us that more than information frictions around the value of immigrants' educational credentials is responsible.

An alternative explanation is that the employment challenges of Canadian STEM-educated immigrants primarily reflect differences in Canadian and U.S. skilled immigration policy. In particular, whereas the vast majority of skilled immigrants in the U.S. are admitted via temporary work permits from sponsoring employers, H-1B visas in particular, skilled-stream immigrants arriving in Canada as new permanent typically do not have pre-arranged employment.[16] Instead, the Canadian 'point system' grants permanent residency to foreign applicants solely on the basis of their foreign educational credentials and years

[16] Administrative data from the U.S. Office of Immigration Statistics indicate that somewhere between 75% and 90% of new skill-stream permanent residents in the U.S. between 2001 and 2011 transitioned from a temporary work permit or student visa (see Yearbook of Immigration Statistics, Homeland Security,

of work experience. To the extent that U.S. employers have richer information regarding the productivity of foreign workers, STEM-educated immigrants in U.S. are not only be more likely to "hit the ground running" with a job, but may also be of higher "quality" on dimensions unobservable to the 'point system.' This suggests that it would be beneficial for Canada to put greater emphasis on pre-arranged employment in its skilled immigrant selection policy. Indeed, in January 2015, Canada introduced the Express Entry (EE) system for processing applications for permanent residency, which gives priority to applicants with job offers from Canadian employers. Our evidence suggests that this should serve to raise the employment of Canada's STEM-educated immigrants in STEM jobs and, in turn, the contribution of Canada's immigrants to Canadian innovation.

various years). In contrast, over the same period, between 10% and 25% of Canadian skilled-stream immigrants transitioned from a work or student visa (see *Facts and Figures*, Immigration, Refugee, and Citizenship Canada, various years).

Figure 2.1: University-educated immigrant population shares and patent per capita, Canada and the USA, 1980–2006

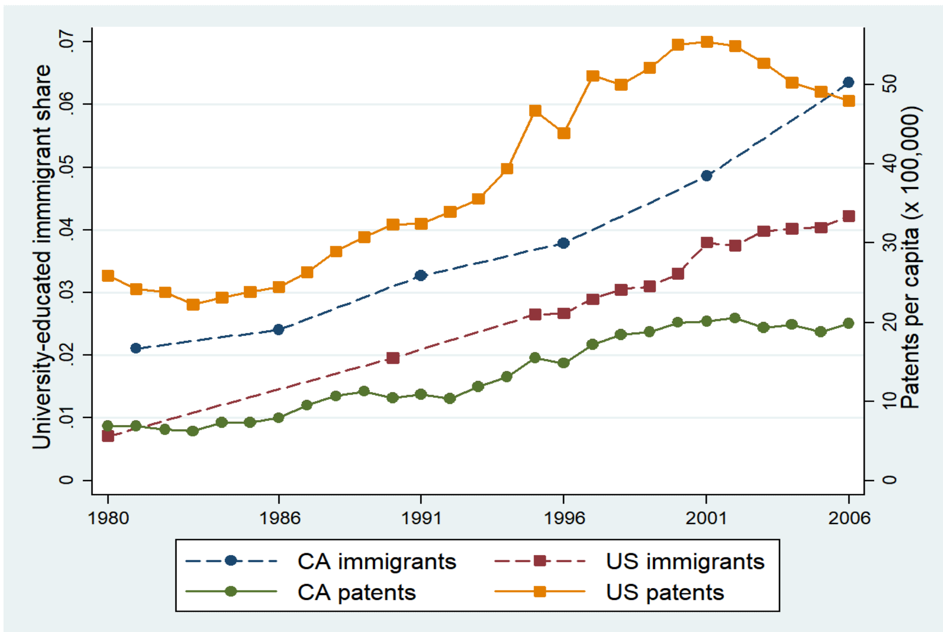


Table 2.1: Population-weighted sample means by Census year

	1981	1986	1991	1996	2001	2006	2006–1981/6 difference
Patents	489.7	744.2	1055.2	1553.1	1755.9	1668.7	1179.0***
Patents per capita (x 100,000)	42.2	58.5	74	105.8	113.2	103	60.8***
Population	971,384	1,074,428	1,169,049	1,277,834	1,383,794	1,504,691	533,307***
Immigrant population share	0.223	0.219	0.231	0.247	0.255	0.268	0.046**
Univ. edu.	0.027	0.03	0.037	0.047	0.06	0.076	0.050***
Univ. STEM edu.		0.01	0.012	0.016	0.022	0.03	0.020***
Canadian-univ. STEM edu.		0.005	0.006	0.008	0.1	0.013	0.008***
Foreign-univ. STEM edu.		0.005	0.006	0.008	0.012	0.017	0.012***
Univ. edu. & STEM emp.	0.004	0.004	0.005	0.006	0.009	0.011	0.007***
Univ. STEM edu. & STEM emp.		0.003	0.004	0.005	0.008	0.01	0.006***
Native-born population share	0.777	0.781	0.769	0.753	0.745	0.732	-0.046**
Univ. edu.	0.073	0.087	0.102	0.115	0.128	0.142	0.069***
Univ. STEM edu.		0.019	0.021	0.022	0.025	0.027	0.008***
Univ. edu. & STEM emp.	0.007	0.008	0.009	0.01	0.013	0.014	0.007***
Univ. STEM edu. & STEM emp.		0.006	0.007	0.008	0.009	0.01	0.004***
Mean age	32.6	33.7	34.6	35.4	36.7	38	5.3***
Mean income	9222	13,398	18,385	19,430	24,032	28,947	19,725***
Employment rate	0.659	0.657	0.672	0.652	0.688	0.7	0.041***
Expected patents per capita (x 100,000)	42.2	58.4	73.9	105.7	113.1	102.9	60.7***
Observations	98	98	98	98	98	98	196

Patents are the cumulative sum of annual patents in the five years following the Census year. The 1981 Canadian Census does not report field of study. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.2: Conditional probabilities of STEM education & STEM employment for immigrants & natives

	1986	1991	1996	2001	2006	2006–1986 difference
Immigrants						
Pr[Univ. educated]	0.138	0.16	0.188	0.233	0.285	0.165
Pr[STEM educated $\mid$ univ. educated]	0.324	0.328	0.337	0.374	0.387	0.062
Pr[Canadian education $\mid$ STEM univ. educated]	0.505	0.519	0.5	0.447	0.429	-0.076
Pr[Foreign education $\mid$ STEM univ. educated]	0.495	0.481	0.5	0.553	0.571	0.076
Pr[STEM employed $\mid$ STEM univ. educated]	0.348	0.338	0.311	0.345	0.322	-0.026
Pr[STEM employed $\mid$ Canadian STEM univ. educated]	0.363	0.355	0.322	0.343	0.343	-0.019
Pr[STEM employed $\mid$ Foreign STEM univ. educated]	0.333	0.32	0.301	0.347	0.307	-0.027
Natives						
Pr[Univ. educated]	0.112	0.132	0.153	0.172	0.194	0.101
Pr[STEM educated $\mid$ univ. educated]	0.214	0.202	0.193	0.195	0.191	-0.023
Pr[STEM employed $\mid$ STEM univ. educated]	0.342	0.355	0.355	0.37	0.37	0.028

These probabilities are constructed using the mean population shares (weighted by population size) across Canadas largest 98 cities. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: WLS-FD estimates of the effect of university-educated & university-educated-STEM-employed immigrant population shares on log patents per capita

	Univ.-edu.		Univ.-edu. & STEM-emp.	
	(1)	(2)	(1)	(2)
Immigrant population share	1.118	3.508	7.276	21.743*
	(1.677)	(2.992)	(7.915)	(12.887)
Native population share	4.457*	3.315	6.328	19.007*
	(2.391)	(3.303)	(9.318)	(11.415)
Log mean age	0.494	-0.589	0.772	-0.431
	(1.257)	(1.507)	(1.228)	(1.452)
Log population (1981)	0.003	-0.006	0.006	-0.009
	(0.008)	(0.012)	(0.008)	(0.013)
Log mean income (1981)	0.053		0.005	
	(0.112)		(0.113)	
Log mean income		-0.028		-0.521
		(0.607)		(0.630)
Employment rate		-0.094		-0.034
		(1.266)		(1.275)
Log expected patents per capita		0.202*		0.231*
		(0.116)		(0.118)
Year fixed effects	Yes	No	Yes	No
Year-region fixed effects	No	Yes	No	Yes
R-squared	0.285	0.332	0.284	0.340
Number of observations	490	490	490	490

Observations are weighted using population sizes. Standard errors are clustered by city. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.4: WLS-FD estimates of the effect of university-educated, university-STEM-educated, and university-education-STEM-employed immigrant population shares on log patents per capita

	Univ.-edu.		Univ.-STEM-edu.		Univ.-STEM-edu.		Univ.-STEM-edu. & STEM-emp.	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Immigrant population share	-1.026	0.511	-3.342	1.093			9.265	36.341*
	(1.800)	(3.417)	(3.628)	(4.855)			(13.658)	(19.855)
Immigrant Canadian univ.					4.295	3.406		
					(29.814)	(42.164)		
Immigrant foreign univ.					-5.686	0.309		
					(8.282)	(13.952)		
Native population share	5.389*	4.156	16.784*	19.109*	16.525*	19.013*	17.563	26.522
	(3.096)	(4.210)	(9.148)	(10.661)	(9.112)	(10.340)	(16.666)	(20.611)
Log mean age	-.260	-1.814	-0.452	-1.825	-0.357	-1.817	0.456	-1.331
	(1.476)	(1.801)	(1.397)	(1.709)	(1.349)	(1.676)	(1.428)	(1.714)
Log population (1981)	0.020**		0.020*	0.007	0.018	0.007	0.016	-0.013
	(0.010)	(0.014)	(0.11)	(0.013)	(0.015)	(0.019)	(0.010)	(0.016)
Log mean income (1981)	0.072		0.072		0.066		-0.034	
	(0.119)		(0.120)		(0.122)		(0.126)	
Log mean income		-0.166		-0.258		-0.261		-0.874
		(0.649)		0.608		(0.597)		(0.697)
Employment rate		-0.929		-1.045		-1.027		-0.632
		(1.314)		(1.307)		(1.251)		(1.337)
Log expected patents per capita		0.147		0.154		0.153		0.181
		(0.117)		(0.119)		(0.116)		(0.123)
Year fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Year-region fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.253	0.284	0.253	0.287	0.254	0.287	0.250	0.297
Number of observations	392	392	392	392	392	392	392	392

Samples are restricted to 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first-differences, since field of study information is not available in the 1981 Census. Observations are weighted using population sizes. Standard errors are clustered by city. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.5: IV (2SLS) estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	Univ.-edu.		Univ.-edu. & STEM-emp.	
	(1)	(2)	(1)	(2)
Immigrant population share	2.870	1.060	8.730	10.404
	(4.393)	(5.656)	(11.347)	(13.912)
Native population share	5.350	2.006	5.964	20.388*
	(3.650)	(4.288)	(8.981)	(11.115)
Log mean age	0.733	-0.725	0.828	-0.549
	(1.409)	(1.451)	(1.294)	(1.400)
Log population (1981)	-0.002	0.004	0.006	-0.001
	(0.015)	(0.022)	(0.009)	(0.011)
Log mean income (1981)	0.027		-0.001	
	(0.107)		(0.113)	
Log mean income		0.121		-0.259
		(0.613)		(0.580)
Employment rate		-0.235		-0.212
		(1.251)		(1.257)
Log expected patents per capita		0.202*		0.221**
		(0.111)		(0.109)
Year fixed effects	Yes	No	Yes	No
Year-region fixed effects	No	Yes	No	Yes
R-squared	0.285	0.331	0.284	0.338
Number of observations	490	490	490	490
First stage:				
Exp. Immigrant Share	0.622***	0.588***	0.943***	0.908***
	(0.157)	(0.144)	(0.327)	(0.194)
F statistic	64.90	345.39	32.01	189.69

Table 2.5 – *Continued from previous page*

Estimates are from two-stage least squares. Observations are weighted using population sizes. Standard errors are clustered by city. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Sample without Toronto - FD estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	Univ.-educated		Univ.-educated & STEM-employed	
	(1)	(2)	(1)	(2)
Immigrant population share	2.838	7.733*	26.339*	42.861***
	(2.956)	(4.518)	(15.077)	(15.573)
Native population share	3.831	2.917	-5.397	10.906
	(2.789)	(3.281)	(12.961)	(13.532)
Log mean age	0.305	-0.212	0.665	-0.082
	(1.222)	(1.448)	(1.157)	(1.391)
Log population (1981)	0.008	-0.008	0.015	-0.006
	(0.010)	(0.014)	(0.010)	(0.011)
Log mean income (1981)	0.031		-0.046	
	(0.122)		(0.121)	
Log mean income		-0.490		-1.130
		(0.688)		(0.764)
Employment rate		0.746		1.094
		(1.313)		(1.253)
Log expected patents per capita		0.167		0.196*
		(0.109)		(0.109)
Year fixed effects	Yes	No	Yes	No
Year-region fixed effects	No	Yes	No	Yes
R-squared	0.259	0.305	0.263	0.318
Number of observations	485	485	485	485

Observations are weighted using population sizes. Standard errors are clustered by city. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: Sample of cities with a population of at least 40,000 in 1981 Unweighted FD estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	Univ.-educated		Univ.-educated & STEM-employed	
	(1)	(2)	(1)	(2)
Immigrant population share	7.146	8.788	38.742*	30.638
	(6.062)	(6.527)	(19.393)	(20.571)
Native population share	8.605**	5.191	20.399	29.476
	(4.256)	(5.473)	(23.722)	(26.300)
Log mean age	-0.330	-1.782	0.113	-1.495
	(1.898)	(2.035)	(1.931)	(2.119)
Log population (1981)	-0.004	-0.024	0.007	-0.013
	(0.022)	(0.023)	(0.017)	(0.014)
Log mean income (1981)	-0.260		-0.299	
	(0.244)		(0.237)	
Log mean income		1.004		0.760
		(0.825)		(0.880)
Employment rate		-1.027		-0.995
		(2.300)		(2.243)
Log expected patents per capita		0.116		0.146
		(0.140)		(0.144)
Year fixed effects	Yes	No	Yes	No
Year-region fixed effects	No	Yes	No	Yes
R-squared	0.241	0.346	0.243	0.352
Number of observations	265	265	265	265

Observations are weighted using population sizes. Standard errors are clustered by city. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

An Analysis of the Patenting Rates of Canada's Ethnic Populations

3.1 Introduction

Canada's persistently poor productivity performance relative to the U.S. has arguably been its most significant national economic policy issue for the past two decades. It is an issue of critical concern because there is a growing consensus that productivity, and more specifically the innovative activity that gives rise to it, is the primary driver of economic growth and determinant of living standards in the long-run. However, despite Canadian 15-year-olds ranking among the world's best performers in science and mathematics (OECD, 2016), a world-renowned 'points system' for screening skilled immigrants, and significant government support for research and development (R&D), Canadian corporations continue to lag behind their global peers on innovation and productivity measures (Coucil of Canadian Academincs, 2013).

While the root causes of Canada's productivity gap remain elusive, the solution is increasingly being framed in terms of labour market skills, and in particular the need to increase the proportion of the workforce with advanced skills in science, technology, engineering and mathematics (STEM). For example, the government of Ontario recently announced a commitment to increase the annual number of STEM graduates from $40,000$ to $50,000$.[1] STEM workers are seen as having not only the cutting-edge knowledge necessary

[1] See Clark, 2017

to augment and expand existing technologies, but are believed to also have the potential to create knowledge spillovers on neighbouring workers within cities, regions, and countries. Harnessing the economic growth potential of STEM workers is central to the current Liberal government's innovation agenda: plans to invest in the digital and coding skills of school-age children: skills training for the unemployed and underemployed; and policies to ease the recruitment of foreign workers within 10 designated occupation, all of which fall within the information and communications technology (ICT) sector.[2]

Notwithstanding the government's policy efforts, the reality is that we know almost nothing about who is driving innovation in Canada. If governments are to lever education, training, and immigration policies to raise innovation, a first step is knowing what types of workers are contributing to Canadian innovation growth. While immigrants comprise less than one-quarter of the adult population, they represent 41% of individuals educated in STEM, 53% of individuals with a PhD degree, and 66% of STEM-employed PhDs, suggesting that they play an important role.[3] To what extent are immigrants contributing to innovation, and are there differences between the contributions of immigrants educated in Canada and immigrants educated abroad? Is innovation primarily being generate by workers employed in STEM occupations? What are the education levels of our most innovative workers and to what extent are they educated in STEM fields? And are workers educated in STEM fields being employed in STEM jobs?

In this article, we provide evidence on the human capital driving Canadian innovation by relating changes in the patenting rates of 11 ethnic populations over the 1986-2011 period to changes in the educational and employment characteristics of these populations. To estimate patenting rates for ethnic groups, we use the first and last names of inventors recorded in patent applications to infer inventors' ethnic backgrounds, and ancestry data from the Census and National Household Survey (NHS) to estimate ethnic populations. The resulting annual time-series data reveal higher patenting rates among ethnic minority groups, particularly Korean-, Japanese-, and Chinese-Canadians, and suggest that immigrants, while less than one-quarter of the population, account for roughly one-third of

[2]The list includes computer and information systems manager (0213), computer engineers (2157), information systems analysts and consultants (2171), database analysis and data administrators (2172), software engineers and designers (2173), computer programmers and interactive media developers (2174), web designers and developers (2175), electrical and electronics engineering technologists and technicians (2241), information systems testing technicians (2283), and digital media designers (subset of 5241).

[3]Figures are the estimated share of the Canadian population aged 18-70 in each category that are immigrants or temporary residents from the 2011 National Household Survey.

Canadian patents in recent years. The educational and employment characteristics of ethnic minorities, in particular the share with a PhD, with a STEM education, and employed in a STEM job, account in large part for these differences. Lastly, our results suggest larger contributions to patenting among the foreign-educated, than Canadian-educated, immigrants. This difference, which runs counter to the current direction of Canadian immigrant selection policy favouring former international students, is also evident in substantially lower STEM employment rates of Canadian-educated immigrant with a STEM education (particularly among Master's and PhD educated immigrants).

The remainder of the paper is organized as follows. In the following section, we briefly review the current literature and the Canadian evidence. In section 3, we describe our methodological approach, including the data that we employ. In Section 4 we discuss our main findings and their policy relevance. Section 5 concludes.

3.2 Existing Literature

Innovation is notoriously difficult to measure. On the one hand, we can measure inputs into innovation activities, such as R&D expenditures or the number of engineers and scientists. Alternatively, we can measure innovation outputs like the intensity of high-tech exports, the number of publications, or the number of patents. Much of the literature has focused on patents, because the data is objective, plentiful, and widely available. Moreover, because patents are costly, they are more likely to represent innovations with commercial value than are publications. Certainly, not all innovations are presented and not all patents represent valuable innovations, but there is a consensus among researchers that as a body, they provide a useful measure of innovation and technological progress (Griliches, 1990).

Patenting in Canada has historically been low, particularly relative to the United States. Figure 3.1 presents patents per capita for Canada and the U.S. between 1986 and 2011. There is a clear and persistent gap between the two countries. While some of the gap is undoubtedly explained by structural differences, such as Canada's relative industrial mix, degree of firm foreign ownership, and small firm size, identifying the human capital factors underlying the gap remains a first-order policy question.

Knowledge of the human capital characteristics of inventors (patent creators) can provide useful insights to inform both innovation and immigration policy. The most direct way to examine inventor characteristics is to analyse patent data, which, among other things, provide information on the geographic residence of inventors (Jaffe, Trajtenberg, and Henderson, 1993), the firms they work for (Song, Almeida, and Wu, 2003), and their gender, since first names in most cultures are gender-specific (Frietsch et al., 2009; Kugele, 2010). Patents, however, provide no information on the educational or other human capital characteristics of inventors. To obtain richer information, researchers have relied on surveys of inventors using patent databases for sampling frames. The first such study by Schmooker (1957), surveyed 87 inventors who were granted U.S. patents in 1953. Since then, numerous inventor surveys have been conducted including Amesse et al. (1991) who surveyed 374 Canadian individual inventors, Giuri et al. (2007) who surveyed 9,017 European inventors, and No and Walsh (2010), who examined 3,658 inventors residing in Japan and 1,919 inventors residing in the United States. Typical findings in these studies are: a significant underrepresentation of women (they represent 1.1% of Canadian, 2.8% of European, 1.7% of Japanese, and 5.2% of U.S. inventors); a large fraction of inventors with tertiary education (58%, 76.9%, 87.9%, and 93.6%, respectively); and an important overrepresentation of individuals with doctoral degrees (26.0%, 12.9%, and 45.2% of Japanese, European, and U.S. inventors, respectively).

The obvious concern with surveying inventors directly is low response rates with selective non-response. In their 2006 review of 8 studies using inventor surveys, Mattes, M. C. Stacey, and Marinova (2006) find response rates ranging from 23% to 55%. In addition, samples are often unrepresentative of the populations of interest, because for example, addresses are only available in Unite States Patent and Trademark Office (USPTO) patents for individual assignees. A more recent paper by Jung and Ejermo (2014) applies a higher degree of sophistication by matching 81,386 Swedish inventors who filed patents at the European Patent Office between 1978 and 2009 to population register data from Statistic Sweden, achieving a match rate of 79.3%. They find that between 1985 and 2007, the share of inventors with at least two years of post-secondary education increased from 44% to 76%, the share of inventors with a doctoral degree more than doubled from 14% to 29%, and by 2007, 90% of inventors had at least some post-secondary education in a STEM field. In addition, the share of female inventors rose over this period from 2.4% to 9.1%, while their average age dropped from a high of 46.3 in 1996 to 43.4 in 2007.

An alternative to relying on patent data itself is to exploit broader population surveys with information on the characteristics of individuals and whether they have ever patented. For example, Stephan et al. (2007) use the 1995 U.S. Survey of Doctoral Recipients to examine the extent of patenting activity of 10,962 doctoral students and find that patenting is related to field of study and publications output. Hunt and Gauthier-loiselle (2010) examine data from the 2003 National Survey of College Graduates and find that U.S. immigrants patent at twice the rate of U.S. natives and that this difference can be entirely attributed to a higher incidence of immigrants holding science and engineering degrees. Using the same survey, Hunt, Garant, et al. (2013) examine why women are underrepresented among patent inventors and find that the gap primarily reflects low employment rate of STEM-educated women in STEM jobs.

Finally, a third strategy is to aggregate patent counts on some dimension that is observed in the patent data, such as the geographic residence of inventors, and relate the variation in these counts to the characteristics of the underlying populations. Kerr and Lincoln (2010), for example, relate patent counts within U.S. cities to H-1B skilled immigrant inflows into cities. Hunt and Gauthier-loiselle (2010) relate patenting rates within U.S. states to the share of state populations comprised of college-educated immigrants and, similar to Kerr and Lincoln (2010), find that immigrants contribute significantly to U.S. innovation. Moreover, in contrast to Kerr and Lincoln (2010), the magnitude of their estimates suggest large spillover effects of immigrants on the patenting rates of natives. Finally, Skuterud, Blit, and Zhang (2017) examine patenting rates within Canadian cities, closely following the methodology of Hunt and Gauthier-loiselle (2010), and find relatively modest impacts of Canadian university-educated immigrants on patenting rates, but much larger effects when attention is restricted to university-educated immigrants who are employed in STEM jobs.

As noted above, there is a dearth of research on the human capital characteristics that are associated with patenting in Canada. The 1991 paper of Canadian inventors by Amasse et al., described above, is the most recent Canadian study prior to Skuterud, Blit, and Zhang (2017). Moreover, it only examines the characteristics of the minority of inventors that patent as as individuals (and not as employees of a firm). The dearth of Canadian evidence presumably reflects the dearth of data. Most notably, Canada's survey of university graduates – the National Graduate Survey (NGS) – does not identify the patenting activity of respondents. We are, in fact, unaware of any large nationally representative Canadian survey that queries patenting activity. To contribute further to the Canadian evidence, in this article we examine aggregated patent rates, but rather than exploit spatial variation, as in our previous study, we use the names of Canadian inventors provided in patent applications to estimate patenting rates within ethnic population.[4] We then inves-

[4]We thank Bill Kerr for providing us with these data.

tigate which educational and employment characteristics of these populations appear to drive innovation growth, as well as the relative role that immigrants play in contributing to Canadian innovation.

3.3 Methodology

We collected data on all patents granted by the USPTO between January 1986 and November 2014 and identified the subset of patents in which one or more inventors have a Canadian residential address. We use USPTO patents because they are a better measure of innovation by Canadians than Canadian Intellectual Property Office (CIPO) patents.[5] In total, we have 85,658 Canadian patents with an application year between 1986 and 2011.

While we do not directly observe the ethnicity of patent inventors, we can estimate probable ethnicities based on inventors' names reported in full in patent citations for all inventors involved in the innovation. Our data use two commercial ethnic name databases and an associated name-matching algorithm, developed and customized by Kerr (2007) for USPTO data, to match inventors to one of 9 groups: English, European (including French), Chinese, Indian, Japanese, Korean, Vietnamese, Russian, and Hispanic.[6] The matching procedure, uses first, middle, and last names, and has been used in Kerr (2007) and Kerr and Lincoln (2010).[7] The algorithm places the largest emphasis on the surname. For example, the inventor "James Wong" is assigned to the Chinese ethnic group and "John Rodriguez" to the Hispanic group, despite both inventors having English first names. First and middle names are influential when the surname is either ambiguous or does not correspond to one of the nine groups. Kerr (2007) provides further details on the procedure, as well as summary statistics and robustness checks.[8] The match rate for our sample of

[5]Not only do Canadian inventors patent at much higher rates at the USPTO than they do at CIPO, there is also some evidence that CIPO patents are largely a subset of USPTO patents. As reported in Blit (2017), Canadian residents applied for 1,129 CIPO patents and 4,300 USPTO patents in 2000, and 2,937 CIPO patents and 8,903 USPTO patents in 2015. In addition, among 100 CIPO patents sampled, 93 had a corresponding USPTO patent.

[6]The Hispanic group includes Filipino, since the most common Filipino surnames are all of Spanish origin.

[7]We wish to thank Bill Kerr for conducting this matching procedure on our data.

[8]For example, he shows that 85% of UK inventors are assigned to the English group, 74% of inventors in Hispanic countries to the Hispanic group, 88% of Indian inventors to the Indian group, 88% of Chinese and Singapore inventors to the Chinese group, 81% of Russians to the Russian group, 84% of South Korean inventors to the Korean group, and 100% of Japanese inventors to the Japanese group. The one surprise is that only 36% of Vietnamese inventors are assigned to the Vietnamese group.

Canadian inventors is 98.9%. The small fraction of unmatched names is assigned to the group "Others."

For the purpose of our analysis of Canadian inventors, we further subdivided the European group into French and non-French patents using historical records of baptismal certificates from Quebec Catholic parishes from the years 1621-1849[9] and a listing of the family names of individuals born in France between 1890 and 2015.[10] We classified any inventor whose last name either appeared in a Quebec historical baptismal certificate or was in the $25,000$ most common surnames in France as French. To be sure, this aggressive classification likely results in some non-Franco European names, such as Schmitt, being classified as French. However, we prefer to, if anything, overestimate French patenting rates, which we find to be exceptionally low relative to other Canadian ethnic groups.

In order to avoid giving more weight to patents with more inventors, we divide fractions of patents equally across inventors where there are multiple inventors on a single patent. Moreover, the names of some inventors results in them being probabilistically mapped to more than one ethnic group. In these cases, patent counts are further divided. For example, a patent with two inventors, one of whom is English with 100% certainty, and the other is French with 50% probability and Hispanic with 50% probability, would yield half a patent count to the English group, a quarter to the French group, and a quarter to the Hispanic group. We obtain patent counts by ethnic group and patent application year by adding these counts across all patents.

In constructing our time-series of ethnic patenting rates, we assign patent years according to the year of the initial application, rather than the year in which the patent was granted, since applications will be closer in time to the creation of the intellectual property underlying the patent. However, since patten applications typically take multiple years to process and we only observe patents granted up to November 2014, our patent counts for the later application years will tend to be lower due to data truncation. Within our sample of patents granted in 2013, 58% of patents were granted within 3 years after application, 75% within 4 years, 86% within 5 years, 93% within 6 years, and 96% within 7 years. Our

[9]We wish to thank Bertrand Desjardins and the Programme de Recherche en Demographie Historique for giving us access to these data.

[10]This data is from the Repertoire National d'Identification des Personnes Physiques de l'Insee. It is available at from the genealogie.com website at http://www.genealogie.com/nom-de-famille/classesment-general-1

estimated patent counts should, therefore, be roughly 42%, 25%, 14%, 7%, and 4% lower for 2011, 2010, 2009, 2008 and 2007, respectively.

This truncation is evident in the decline in the national-level patenting rates in Figure 3.1. To account for this truncation in the empirical estimation, we control for quadratic time trends in all of our models. Our models also include a time trend for each ethnic group. These trend terms should absorb any differential growth in patenting due to ethnic groups that are concentrated in sectors with higher patenting growth, as well as the effects of institutional changes in the USPTO, which have resulted in the granting of more, and possibly lower value, patents (Jaffe and Lerner, 2004).

To estimate patents per capita for each ethnic group, we divide our ethnic patent counts by estimates of the underlying ethnic populations aged 18-70. To estimate these populations, we use data from the 1986, 1991, 1996, 2001 and 2006 long-form Censuses and the 2011 National Household Survey (NHS), which asked all respondents: "To which ethnic or cultural group(s) did this person's ancestor belong?". Where individuals claim multiple ethnicities, we count fractions of individuals. The full concordance between the large number of ethnicities in the Census/NHS responses and the 11 groups in our patent data, and the resulting estimated ethnic populations of individuals aged 18-70, are presented in appendix C.1.

The Census data files provide 20% random samples of the Canadian population. However, in 2011 the long-form Census was replaced with a voluntary survey, the NHS, which sampled one-in-three Canadian households and obtained a 68.6% response rate. We use the sampling weights provided in the NHS and Census data, which are designed to ensure the national representativeness of the samples. Table 3.1 shows the estimated population of individuals aged 18-70 by ethnic group for each of the Census years, in addition to the fraction of the group that are immigrants and the group's unconditional patenting rate. The growth rates in the estimated populations between 2006 and 2011 do not suggest any significant biases owing to selective non-response in the 2011 NHS. Finally, to obtain annual population estimates to combine with our annual patent counts, we linearly interpolate populations in the years between the quinquennial Census and NHS years.

Our final sample is a panel of annual patenting rates from 1986 through 2011 for 11 ethnic groups, providing a pooled sample of 286 observations. We examine the determinants of these rates by regressing them on the educational and employment characteristics of ethnic groups, which are also estimated using the Census and NHS data. Specifically, we estimate the following linear regression model:

$$\frac{patents_{et}}{pop_{et}} = \alpha + \bar{x_{et}}'\beta + \bar{z}'_{et}\gamma + \phi_e + \lambda_e t + t^2 + \epsilon_{et} \tag{3.1}$$

where the dependent variable is the number of granted patents with application year t filed by inventors from ethnic group e divided by the group's population in year t; $\bar{x}_{et}$ is a vector of group means that we expect to influence the propensity to patent; $\bar{z}_{et}$ is a vector of control variables; ϕ_e are fixed effects for ethnic groups; t is a time trend equal to 1 in 1986; and ϵ_{et} is a random error. The vector of explanatory variables includes the shares of group e in year t who: hold a doctoral degree, a master's degree, a bachelor's degree, and a non-university post-secondary diploma or certificate; are educated in a STEM field; are employed in a STEM occupation; are born in Canada, are born abroad but educated in Canada, and are born and educated abroad; and are self-employed. Appendix C.2 outlines in detail which fields are included in the STEM category. Our education source variables measure the share of foreign-born individuals who are educated in Canada and educated abroad (the omitted group is Canadian born individuals), which we estimate using information on years of schooling and age at immigration.[11] Finally, STEM employment is captured by the share that are STEM professionals and, separately, the share that are employed in technical STEM occupation. Appendix C.3 gives a detailed discussion of the STEM occupation classification. The vector of control variables includes the male population share, average age, and the population share between 40 and 54 years of age[12] Finally, note that we restrict the quadratic term of the time trends, intended to capture the truncation in the patent rates after 2006, to be the same across ethnic groups.

We estimate the parameters of equation (3.1) using a feasible generalized least squares (FGLS) estimator assuming group specific heteroskedasticity and autocorrelation (an AR(1) process) and contemporaneous correlations across groups. We have also estimated equation (3.1) by OLS with standard errors clustered by ethnic groups. While the standard errors roughly double, the findings on which we draw our main conclusions do not change.

[11] We assume that schooling is strictly continuous, so that years of schooling plus 6 identifies the age of school completion. We then identify whether the last completed degree was obtained in Canada or abroad by comparing this age to the age at immigration. While the resulting variable contains some measurement error due to cases where schooling is not continuous or where international students obtain Canadian schooling prior to landing, the consequences of this measurement error are unlikely to be significant (Skuterud and Su, 2012).

[12] The latter "middle aged" variable was included because Amesse et al. (1991) found a disproportionate number of Canadian inventors in this age group.

This is also true when we assume a different error structure in the FGLS estimation. Given the considerable variation in the size of ethnic groups (see Table 3.1), the variance of the error term across ethnic group observations will vary considerably. We, therefore, weight our regressions by the unweighted group sizes in the Census/NHS data to improve the efficiency of the FGLS estimator.

Of primary interest are the differences in patenting intensities across ethnic groups, captured by ϕ_e, and to what extent can be accounted for by the human capital characteristics in $\bar{x}_{et}$. The interpretation of the estimates of β are worth emphasizing. Most important, they do not capture differences in patenting rates between individuals with varying educational and employment characteristics. Rather, they identify how marginal changes over time in these characteristics within ethnic groups are related to changes in the patenting rates of these groups. However, because the variables are population shares, they implicitly involve a tradeoff between types of workers. For example, the coefficient on the PhD population share variable tells us how a one percentage point increase in the share of the population with a PhD, achieved by reducing the share with a high school diploma or less (the omitted group), is related to patents per capita produced in that population (conditional on the other variables in the model). These marginal effects are more arguably more policy relevant than the levels in patenting rates, since it is at the margin that policy can affect these shares.

A complication in the analysis is that the patenting rates and the ethnic minority shares, as well as many of the explanatory variables in the model, such as the PhD population shares, are trending upwards over the sample period. To limit the possibility that our estimates are capturing spurious correlations over time, we control for group-specific time trends. Using a Levin, Lin, and Chu (2002) unit root test with group-specific intercepts and linear time trends, we are able to reject the null hypothesis that the patent rates time-series contain a unit root over the years with no truncation (1986-2006).[13] Nonetheless, in the absence of valid instrumental variables for the population shares in the vector $\bar{x}_{et}$, the estimated marginal effects cannot be given a causal interpretation. Some caution should therefore be exercised when inferring what the effect might be of, for example, a policy

[13]The Levin, Lin, and Chu (2002) test is appropriate for panels of "moderate size," described as having between 10 and 250 panels and 25 to 250 observations per panel. The value of the LLC test statistic is -2.5203 with a p-value of 0.0059. If we include post-2006 years, where truncation leads to declining patenting rates, the test statistic is no longer significant. However, this is because the test does not allow for a higher-order polynomial time trend to capture the curvature in the trend.

directed at raising the share of Canadians with a STEM education on Canadian patenting rate.

Finally, it turns out that the ethnic fixed effects alone account for 74% of the variation in our pooled sample of 286 ethnic patenting rate. When we also add the year fixed effects, the R-squared statistic rises to 0.88[14]. Consequently, the remaining variation used to identify the marginal effects of the education and employment characteristics is limited. Moreover, the human capital variables tend to be highly collinear over time within ethnic groups. Therefore, although we would like to identify the effects of interaction of the elements in $\bar{x}_{et}$, such as the differential influence of a STEM credential obtained in Canada and abroad on patenting rates, we are unable to do so with enough precision using our aggregated data, and therefore focus on estimating more parsimonious specifications.

3.4 Results

We begin our data analysis by examining the sample means of our dependent, explanatory, and control variables by Census/NHS year. The means, reported in Table 3.2 are weighted by the number of individuals in each group, so that they are representative of the Canadian population. Canada's patenting rate per capita nearly doubled between 1986 and 2011 (in spite of the undercounting of patents in 2011 due to data truncation). A number of factors, beyond changes to the institutional setting within which patents are granted and governed in the U.S., likely contributed to this large increase. First, the educational attainment of Canadians increased substantially over the period. The share of Canadians with a high school diploma or less decreased from 65% to 41%, while the share with a doctoral degree more than doubled. In addition, the share of the population with postsecondary credentials in STEM fields increased substantially, particularly among immigrants, as did the share of the population in professional STEM occupations (which increased from 1.7% to 3.2%).

The extent to which individuals educated in a STEM field are employed in STEM sectors, where R&D is concentrated, is potentially also an important determinant of patenting rates. Table 3.3 presents conditional probabilities of being employed in a STEM occupation given a STEM education, by educational attainment, and for three groups: natives, immigrants whose highest degree was obtained in Canada, and immigrants whose highest degree is

[14]Calculated as the square of the correlation between the actual and fitted values of the ethnic patenting rates.

foreign. The estimates indicate that STEM-educated natives experienced the lowest rates of education-job mismatch in recent years, followed by immigrants who obtained their STEM degree abroad (first and third rows). While some of this mismatch is clearly voluntary, we would expect Canadian-born STEM-educated individuals to be most likely to opt for jobs outside STEM, since these jobs typically require stronger language and culturally-specific interpersonal skills. Thus, if anything, voluntary mismatch is likely to be masking even bigger differences in labour market mismatch between STEM-educated immigrants and native.

The results in Table 3.3 also indicate that natives and immigrants educated abroad have experienced substantial improvements in matching over time, while the same is not true for Canadian-educated immigrants. The divergent experience of foreign- and Canadian-educated immigrants is most apparent at higher levels of educational attainment. Most striking is the fact that 32.9% of immigrants with foreign PhDs in a STEM field were employed in STEM jobs in 2011, compared to only 21.7% of immigrants with Canadian STEM PhDs (and 23.4% of native STEM PhDs). This is as much explained by the improving education-job match rates of immigrants with foreign PhDs as by the increasing mismatch of immigrants with Canadian PhDs. In fact, in the mid-1980s, Canadian-educated immigrants with STEM PhDs had the highest job-education match rates of the three groups, but they seem to have been especially adversely affected by the dot-com crash of the early 2000s.[15] An important consideration in our analysis is to what extent the apparent labour market challenges of immigrants with Canadian STEM education are reflected in their relative contribution to patenting.

Table 3.1 presents our estimated patenting rates for each ethnic group and each Census year, and Figure 3.2 plots our estimated annual patenting rates for Canada's ethnic groups (we exclude the European and Other group as they are the most heterogeneous and therefore least interesting). The results reveal markedly different patenting intensities across groups, with Canada's ethnic minorities making larger contributions to Canadian patenting. Almost all of the minority ethnic groups have higher patenting rates than French and English Canadians, with Koreans and Chinese having particularly high rates, especially in the most recent years.

[15]See (Picot and Hou, 2009) for evidence of the impact of the dot-com market crash on the deteriorating entry earnings of Canadian immigrants, particularly male immigrants who arrived in Canada through the 1990s with the intention of working in information technology (IT) and engineering occupations.

These ethnic patenting rates, while interesting in and of themselves, also offer a glimpse into the relative contribution of immigrants to patenting in Canada. In 2011, immigrants outnumbered natives in 7 of our 11 ethnic groups, with the English-, French-, European-, and Russian-Canadians being the exceptions (see Table 3.1). Together, the seven majority-immigrant groups accounted for 29.1% of all Canadian patents, even though they represent only 19.6 of the population. We can obtain a different (and potentially more accurate) estimate of the fraction of patents that are generated by immigrants if we assume that within ethnic groups, immigrants and natives patent at the same rate. This would be true if, for example, the differences in ethnic patenting rates are driven by cultural factors that are passed across the generations, as opposed to the higher concentration of immigrants within some groups. As some suggestive evidence of the importance of cultural factors, South Korea consistently ranks as one of the most innovative countries in the world, just as Canadians with Koreans ancestry do within Canada.[16] Multiplying our ethnic patenting rates by the number of immigrants in the ethnic group, and summing the results across all groups, suggest that immigrants contributed 32.3% of Canadian patents in 2011, even though they represented only 24.8% of the population. The fact that the majority of our groups are either largely immigrants or natives implies that this estimate should be reasonably accurate even if immigrants and natives within the same group have somewhat different patenting rates. And to the extent that even within ethnic groups immigrants patent at somewhat higher rates than natives, our estimate of 32.3% will understate the actual fraction of patents that are generated by immigrants.[17]

[16] For example, the Martin Prosperity Institute (2015) ranks South Korea first in their Global Technology index. South Korea also ranks first in R&D expenditures as a fraction of GDP (authors' own calculation for 2011) and fourth behind Japan, the U.S., and Israel in granted USPTO patents per capita (authors' own calculation for 2008).

[17] An alternative assumption, consistent with the view that cultural differences across groups are unimportant for driving innovation and what matters is whether individuals are immigrants (and the skills and attitudes that immigrants bring with them), is that within each group the relative patenting rate of immigrants and natives is the same as the national relative patenting rates between immigrants and natives. We can then compute the immigrant share of national patenting by initially assigning equal patenting rates to all individuals within a group and computing the ensuing relative patenting rates of immigrants and natives at the national level. We then assign this relative patenting rate between immigrants and natives to each group (instead of assuming equal patenting rates) and compute a new relative patenting rate at the national level. We continue iterating in this way until the national relative patenting rate reaches a steady state (a fixed point). It should be noted that this procedure can overestimate the national patenting contributions of immigrants if the relative patenting rates of immigrants and natives within groups are on average lower than the national relative rate. This approach yields the estimate that immigrants account for 41.4% of all Canadian patents in the year 2011.

Several factors could explain the higher patenting rates of Canada's ethnic minorities (and immigrants). First, as shown in Figure 3.3, ethnic minorities are more likely to have university degrees at all levels. The education levels of Canadians with Korean, Japanese and Chinese ancestry are especially high in the most recent years, with nearly one-half of all Korean-Canadians and 40% of Japanese- and Chinese-Canadians being university educated. These levels reflect a substantial acceleration in educational attainment observed after 1996, which has been linked to the effects of a 1993 reform of Canada's 'point system' used for screening skilled migrants, which put greater weight on university education and less on short-run occupational needs (Beach, A. G. Green, and Worswick, 2007). In addition, Figure 3.4 reveals that the postsecondary credentials of ethnic minorities are more likely to be in STEM fields. While the fraction of individuals with a STEM education is increasing over time for most groups, the rise is particularly stark for the Chinese-, Indian-, and Korean-Canadians. By 2011, almost one-quarter of Chinese-Canadians were STEM educated and nearly 20% of Indian- and Korean-Canadians. This appears to be an unintended consequence of the 1993 policy reform, since the revised 'point system' did not give preference to STEM-educated migrants. The share of Chinese individuals with a STEM occupation is also exceptionally large, reaching almost 10% by 2011. As it turns out, this steep rise in STEM degrees and occupations for Chinese-Canadians after 1996 (and a similar rise in educational attainment) closely matches for the increase in Chinese-Canadian patenting rates after that year.

While the above descriptive statistics suggest a relationship between education, occupation, and patenting rates, we now turn to a formal regression analysis of our data. The first column of Table 3.4 shows the results when we estimate equation (3.1) with ethnic fixed effects, time trends, and control variables, but without the explanatory variables. Rather than report the ethnic-specific intercepts and time trends separately, we report the difference in the (conditional) mean patenting rates of each ethnic group relative to the English group over the 1986-2011 sample period. For each ethnic group e, this is calculated as $\hat{\phi}_e + 13\hat{\lambda}$. Consistent with Figure 3.2, the results point to larger contributions of Canada's ethnic minorities on Canadian innovation. Six of the seven majority-immigrant groups (the only exception being the "Other" group) are estimated to have higher patenting rates than English-Canadians, though the difference is not significant for the Vietnamese group. The Korean estimate is the largest and indicates that, after accounting for four controls, over our sample period Korean-Canadian produced 22.14 more patents per $100,000$ adults than Anglo-Canadian reference group. This is a substantial difference given that the national-level Canadian patenting rate never exceed 22 patents per $100,000$ adults aged 18-70 in the 1986-2011 period. The estimates also point to a significant patenting advantage for

Japanese- and Chinese-Canadians.

Column 2 presents the results when we add the educational attainment, education field, occupation, immigrant status, source of education, and self-employment explanatory variables to the baseline specification. Most striking is the large coefficient on the PhD population share. The estimate implies that a one-tenth of a percentage point increase in the share of the population with a PhD (and offsetting reduction in the share with high school diploma or less) is associated with an increase of 2.02 patents per $100,000$ individuals. At the national level, this implies that an increase in the PhD share from its current value of 0.8% to 0.9% would increase patents per adult aged 18-70 by 9.4% in 2002 (the year that patents per adult peaked at 21.39).

Also of significance, though perhaps less surprising, are the coefficients on STEM educations and STEM occupation variables. The latter estimate implies that a one percentage-point increase in the share of individuals employed in a professional STEM occupation (and equivalent decline in the share not employed in STEM) is associated with an increase in patents per capita of 4.86 per $100,000$ individuals (for technical STEM occupations the coefficient is of a similar magnitude, but is estimated less accurately). The coefficient on STEM education, on the other hand, implies that a one percentage-point increase in the share of the population educated in a STEM field, holding the remaining shares constant, including the share employed in a STEM occupation, increases patents per capita by 1.65 per $100,000$ individuals. This suggests that STEM education may contribute to innovation not just directly by preparing workers for STEM occupations, but also indirectly by teaching important critical thinking and problem-solving skills that can be used to innovate in any occupation.

In addition to the PhD and STEM employment shares, marginal increases in the share of the population who are self-employed is associated with higher patenting rates. Specifically, the point estimates suggest that a one percentage-point increase in the self-employment share, which increased from 7.3% to 9.4% between 1986 and 2006 at the national level, but then fell to 8.4% in 2011, is expected to increase patents per $100,000$ individuals by 2.77.

Lastly, there is an unexpected result worth considering. The point estimates on the Master's degrees (with an equivalent decline in the high-school-or-less share) is associated with lower patenting rates. While the result may seem surprising, it is not clear, for example, that individuals with MBAs or law degrees (both of which are classified as Master's degrees in our data) contribute more, on average, to patenting than individuals with high school diplomas, many of whom might be interested in technology, but did not have the opportunity to further their studies. If we distinguish the Master's degree variable by whether or not it was obtained in a STEM field, we obtain a large negative (and strongly significant) coefficient for the share of the population with a Master's in a non-STEM field, but a large positive coefficient (though insignificant due to a large standard error) for the share of the population with a Master's in a STEM field.

To what extent can these estimated effects of human capital characteristics account for the higher patenting rates of ethnic minorities identified in Figure 3.2 and column 1 of Table 3.4? For all of our ethnic groups, with the exception of Hispanics, we observe a decrease in the ethnic patenting rates differences when we include the explanatory variables in the model. The large patenting advantage of Korean- relative to Anglo-Canadians almost entirely disappears, suggesting that the human capital characteristics of Korean-Canadians fully account for their higher patenting rates. In the case of Chinese-Canadians, on the other hand, we now find appreciably lower conditional patenting rates compared to Anglo-Canadians, though the difference is not statistically significant. Only Japanese- and Hispanic-Canadians now exhibit substantially higher (but not statistically significant) conditional patenting rates than Anglo-Canadians.

Given the strong correlation between the PhD population shares and patenting rates identified in Table 3.4, we examine the patent contributions of the PhD population further by estimating separate marginal effects of PhDs with STEM education and STEM jobs, as well as for foreign- and Canadian-educated doctorate. The results are presented in Table 3.5. Not surprisingly, the estimates in column (1) suggest that the exceptional contribution of PhDs is entirely due to PhDs educated in STEM fields. Specifically, a one-tenth of a percentage point increase in the STEM-PhD share (which was 0.4% in 2011) is associated with an additional 2.95 patents per $100,000$ individuals (an increase of 14% from the peak rate of 21.39 in 2002), conditional on the remaining population shares in the regression. Interestingly, the magnitude of the coefficient on "STEM educated" drops drastically relative to that reported in Table 3.4, suggesting that the relationship between patents per capita and the STEM-educated share is largely driven by STEM-educated PhDs, an not by STEM-educated individuals with lower educational attainments.

The effect of PhDs also appears to be almost driven entirely by PhDs employed in a STEM occupation. The point estimate in column (2) suggests that a one-tenth of a percentage point increase in the share of PhDs employed in STEM jobs (which was 0.12% in 2011) is associated with an additional 3.76 patents per 100,000 (a 18% increase in the 2011 national rate). The coefficient on "STEM professional" is substantially smaller than it was in Table 3.4, suggesting that an appreciable portion of the relationship between patents per capita and the share of STEM professionals is due to STEM professionals with a PhD.

Finally, the estimates in column (3) of Table 3.5 suggest that Canadian-born PhDs are contributing the most to Canadian patenting, with a one-tenth of a percentage point increase in the share being associated with an additional 5.18 patents per $100,000$. Foreign-educated immigrants with doctorate also make large and significant contributions to Canadian patenting. Conversely, the effect of Canadian-educated immigrants with PhDs is statistically indiscernible from zero. We note, as well, that the coefficient on "Foreign educated" (pertaining to immigrant with all levels of educational attainment) is also positive and significant, suggesting that the superior performance of foreign-educated immigrants also holds for lower levels of educational attainment than doctorates. This result is observed consistently across all specification and is unexpected, given that Canadian-educated immigrants are less likely to experience credential recognition issues. Across all specifications, a large share of the population comprised of Canadian-educated immigrants is associated with a decline in patents per capita (although the coefficient is never significant), while an equivalent trade-off between foreign-educated immigrants and native Canadians appears to have a positive impact on patents per capita (and is always significant).

This could be explained by the fact that, as shown in Table 3.3, the share of Canadian-educated immigrants with STEM degrees who are employed in STEM jobs declined significantly through the 2000s, while at the same time, the STEM-employment rates of foreign-educated immigrants were stable. The difference in education-job mismatch is particularly stark at the PhD level where in 2006 and 2011 the STEM employment rate of foreign-STEM-educated immigrants was more than 50% higher than that of Canadian-STEM-educated immigrants. This suggests that migrant selectivity, particularly at higher levels of education, may be more important than credential recognition issues. That is, migrants who are motivated to study in Canada by the pathway to permanent residency that a Canadian PhD education provides, may be very different from migrants who complete their doctorates abroad, are then recruited by a Canadian high-tech company or university, and arrive in Canada with pre-arranged employment.

Finally, we note that in our specifications which condition on separate STEM and non-STEM PhD population shares (column 1) and with separate STEM and non-STEM occupation PhD shares (column 2), there is little to no evidence of higher patenting rates among Canada's ethnic-minority populations. This is consistent with the view that the cultural factors, emphasized elsewhere in the literature, and which could produce persistent differences across generations of Canadians with varying ethnic ancestries, are not nearly as important as human capital factors in explaining ethnic differences in the innovativeness.[18]

3.5 Conclusion

We estimate patenting rates for eleven ethnic groups in the Canadian population and find that Canada's ethnic minorities, including both immigrants and their Canadian-born descendants, make important contributions to Canadian innovation. Given the high concentration of immigrants in these ethnic-minority populations, we infer that immigrants generate at least one-third of Canada's patents, despite comprising less than one-quarter of its population. Relating changes over time in ethnic patenting rates to human capital characteristics of the underlying ethnic populations, we find a large role for increases in STEM education and employment, and in particular, increases in the share of the population with doctoral degrees. Although we are unable to identify the precise causal links between these variables, our findings do suggest that the higher patenting rates of Canadian ethnic minorities largely reflect their education and employment characteristics, suggesting that ethnic and cultural traits, emphasized elsewhere in the literature, are relatively unimportant.

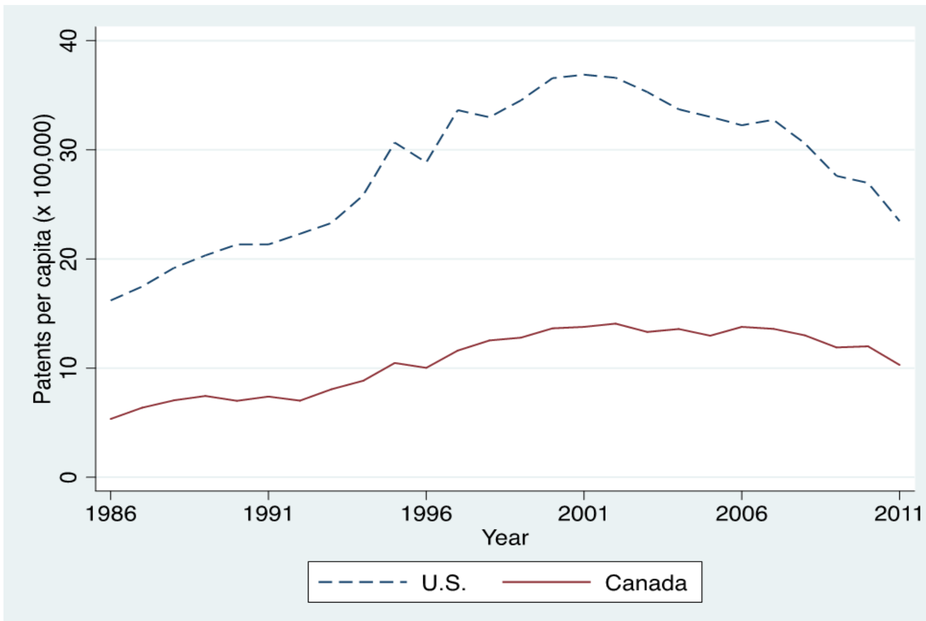
An important finding of our analysis is that Canadian-educated immigrants appear to be contributing less to Canadian patenting than their foreign-educated counterparts. This is consistent with our finding of lower STEM employment rates among STEM-educated immigrants with Canadian, as opposed to foreign, educational credentials. This difference appears especially large for individuals with a PhD and in the years following the dot-com

[18] There are a number of different threads of research pointing to a role for ethnic or cultural factors affecting the contributions of individuals to innovation. For example, there is evidence that ethnic identities and norms affect the economic behaviour of individuals, including risk preferences (Benjamin, Choi, and Strickland, 2010). There is also growing discussion, within both business and political spheres, of a possible link between ethnic diversity and innovation within workplaces, as the ideas and knowledge of minority-group workers, which are scarce, interact with those of the majority population to produce new ideas and knowledge (eg., Page, 2007).

crash of the early 2000s. These findings suggest that credential recognition issues may be less important than differences in the types of immigrants selected under various immigration programs. For example, programs that emphasize employer job offers, as opposed to Canadian educational credentials, may be more successful in identifying the types of highly educated immigrants in STEM fields that contribute most to innovation. Moreover, these findings suggest that the preference given to Canadian-educated immigrants in the Federal government's Express Entry system, and the Provincial Nominee Programs of all ten provinces, may be unwarranted.

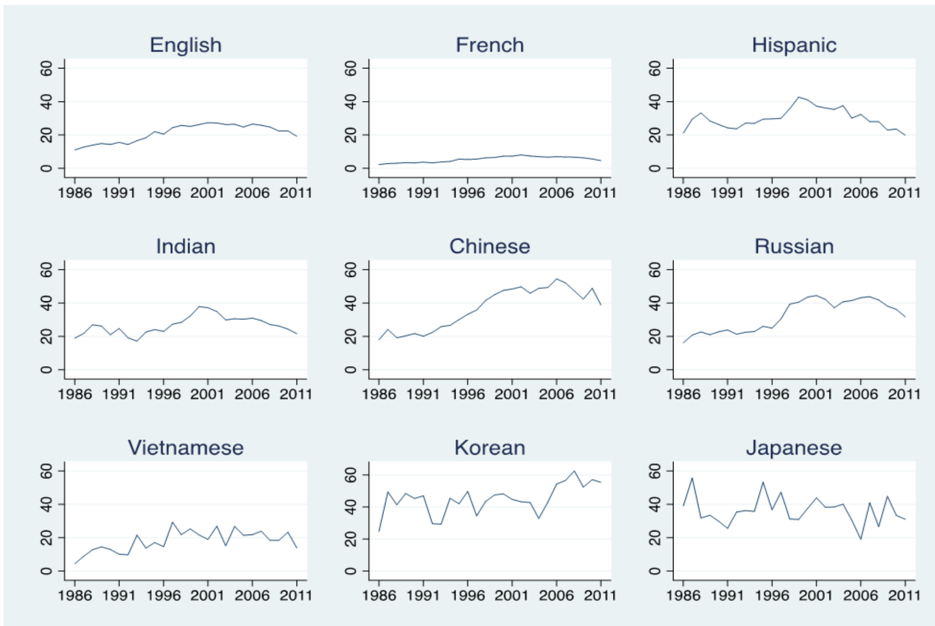
Finally, we note that our findings contrast, to some extent, with the results of our earlier research (Skuterud, Blit, and Zhang, 2017), which found a relatively modest impact of university-educated immigrants on Canadian patenting rates, when compared to both Canadian-born educated immigrants and skilled immigrants in the United States (Hunt and Gauthier-loiselle, 2010). There are, however, important methodological differences in our two studies. Most important, our earlier study identifies the effect of marginal changes in skilled-immigrant population shares within 98 Canadian cities on the number of patents generated in those cities over the subsequent five years. In contrast, the current study identifies differences in the average patenting rates of existing ethnic populations, which include both immigrants and subsequent generations of Canadians. It may be that immigrants' contributions to Canadian innovation take more than five years to surface. Alternatively, it could be that earlier immigrant cohorts were more innovative than more recent cohorts; an explanation that can reconcile the findings of both papers and is consistent with the larger literature documenting a long-term deterioration in the labour market performance of Canadian immigrants (Picot and Sweetman, 2005). As such, this paper's finding that ethnic minorities have higher patenting rates is at best suggestive of the impact that future immigration might have on innovation. Perhaps the most important take-away of this study, and our previous one, is that we find relatively low and worsening rates of STEM employment among STEM-educated immigrants, suggesting that there remains significant potential for improving how Canada selects its immigrants and supports their labour market integration.

Figure 3.1: Patents per 100,000 population, Canada and the U.S., 1986–2011[19].



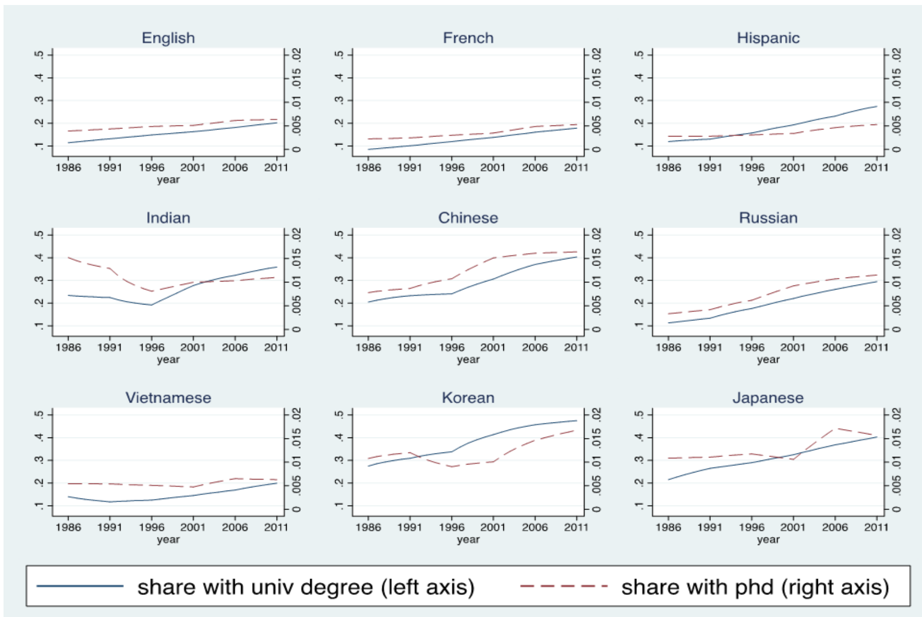
Notes: Number of USPTO patents granted to inventors residing in Canada and the U.S. per 100,000 population, by patent application year. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Population data was obtained from the World Bank World Development Indicators. Only patents granted up to November 2014 were tabulated. This truncation of the data explains the observed drop in patents per capita since 2007.

Figure 3.2: Patents per $100,000$ individuals by ethnic group, 1986–2011[20].



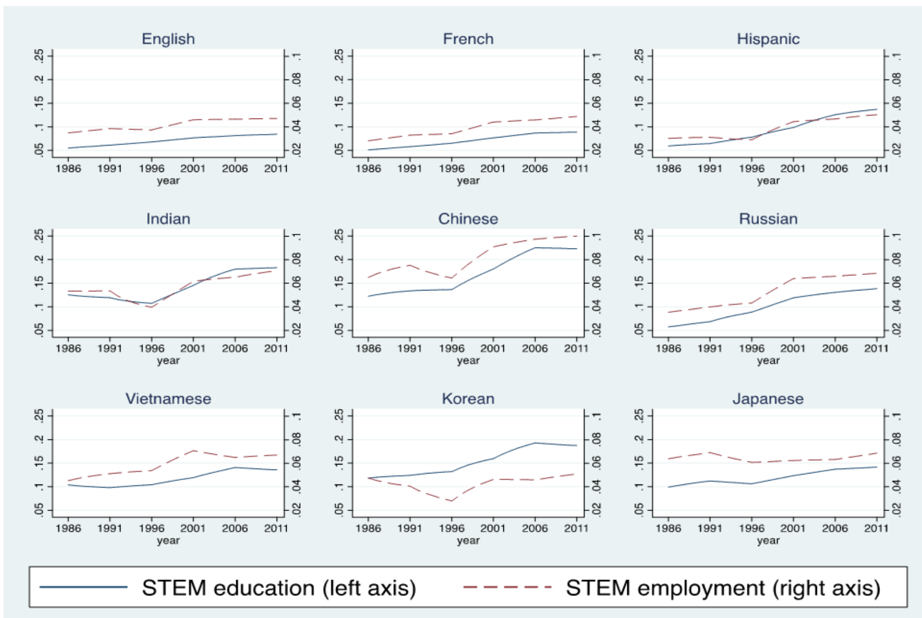
Notes: Number of USPTO patents granted to inventors residing in Canada and the U.S. per 100,000 population, by patent application year. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Population data was obtained from the World Bank World Development Indicators. Only patents granted up to November 2014 were tabulated. This truncation of the data explains the observed drop in patents per capita since 2007.

Figure 3.3: Educational attainment by ethnic group, 1986–2011[21].



Notes: Number of USPTO patents granted to inventors residing in Canada and the U.S. per 100,000 population, by patent application year. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Population data was obtained from the World Bank World Development Indicators. Only patents granted up to November 2014 were tabulated. This truncation of the data explains the observed drop in patents per capita since 2007.

Figure 3.4: Share of individuals with STEM education and STEM employment by ethnic group, 1986–2011[22].



Notes: Number of USPTO patents granted to inventors residing in Canada and the U.S. per 100,000 population, by patent application year. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Population data was obtained from the World Bank World Development Indicators. Only patents granted up to November 2014 were tabulated. This truncation of the data explains the observed drop in patents per capita since 2007.

Table 3.1: : Ethnic group population, immigrant share, and patenting rate per 100,000 individuals

	1986	1991	1996	2001	2006	2011
English	7,802,939	8,117,804	7,956,656	8,341,782	8,405,577	8,887,691
	(0.125)	(0.118)	(0.093)	(0.100)	(0.093)	(0.085)
	[11.11]	[15.63]	[20.53]	[27.45]	[26.51]	[19.27]
French	4,998,735	5,180,095	5,045,584	5,113,238	5,135,302	5,250,895
	(0.027)	(0.026)	(0.028)	(0.028)	(0.030)	(0.034)
	[2.30]	[3.70]	[5.33]	[7.35]	[6.98]	[4.62]
European	2,520,096	2,754,033	3,441,931	3,474,174	3,812,260	3,818,533
	(0.448)	(0.422)	(0.344)	(0.320)	(0.285)	(0.252)
	[6.82]	[7.94]	[9.91]	[10.99]	[10.66]	[8.88]
Hispanic	291,655	447,178	541,978	651,089	812,818	1,074,072
	(0.911)	(0.892)	(0.851)	(0.823)	(0.797)	(0.799)
	[21.18]	[24.25]	[29.70]	[37.28]	[32.41]	[19.87]
Indian	188,680	305,513	599,785	617,698	844,928	1,032,611
	(0.965)	(0.949)	(0.884)	(0.886)	(0.874)	(0.863)
	[18.87]	[24.70]	[22.94]	[37.19]	[30.95]	[21.61]
Chinese	250,384	418,028	616,455	741,139	898,024	999,725
	(0.874)	(0.897)	(0.896)	(0.882)	(0.862)	(0.843)
	[17.96]	[20.08]	[33.18]	[48.45]	[54.45]	[38.83]
Russian	378,992	386,208	514,058	552,123	637,492	668,062
	(0.134)	(0.136)	(0.128)	(0.164)	(0.199)	(0.227)
	[16.17]	[23.81]	[24.92]	[44.50]	[43.21]	[31.77]
Vietnamese	38,066	59,083	81,559	92,647	107,566	132,832
	(0.989)	(0.991)	(0.983)	(0.954)	(0.898)	(0.838)
	[4.49]	[10.11]	[14.59]	[18.94]	[21.81]	[13.87]
Korean	17,789	29,949	46,546	71,391	102,067	119,807
	(0.988)	(0.955)	(0.918)	(0.911)	(0.915)	(0.918)
	[24.69]	[46.99]	[49.78]	[44.70]	[54.37]	[55.43]

Table 3.1 – *Continued from previous page*

Japanese	34,454	41,714	46,548	48,534	52,928	53,590
	(0.281)	(0.382)	(0.455)	(0.483)	(0.512)	(0.535)
	[38.88]	[25.60]	[36.73]	[43.91]	[19.10]	[31.06]
Other	517,012	754,744	562,846	665,436	901,996	1,128,498
	(0.348)	(0.446)	(0.683)	(0.701)	(0.717)	(0.755)
	[2.85]	[3.33]	[8.51]	[12.79]	[12.84]	[8.95]

For each ethnic group and each Census Year, the table lists the number of individuals aged 18-70, the fraction of that population that were born outside of Canada (in parentheses), and the groups patenting rate per 100,000 individuals aged 18-70 (in square brackets).

Table 3.2: Population-weighted sample means and standard errors by Census year

	1986		1991		1996		2001		2006		2011	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Patents	460.2	(118.7)	652.0	(173.1)	818.4	(215.5)	1134.7	(305.0)	1072.4	(291.5)	816.0	(224.5)
Patents per capita (x 100,000)	8.17	(1.56)	11.3	(2.08)	15.29	(2.60)	21.01	(3.81)	20.67	(3.93)	15.25	(2.90)
Educ. Attainment												
High school or less	0.646	(0.006)	0.600	(0.006)	0.555	(0.008)	0.512	(0.008)	0.441	(0.008)	0.406	(0.009)
College	0.247	(0.004)	0.273	(0.006)	0.297	(0.008)	0.314	(0.011)	0.355	(0.013)	0.362	(0.015)
Bachelor's degree	0.072	(0.005)	0.083	(0.006)	0.099	(0.006)	0.114	0.008)	0.132	(0.011)	0.150	(0.011)
Master's degree	0.032	(0.002)	0.039	(0.003)	0.045	(0.003)	0.054	(0.005)	0.065	(0.007)	0.075	(0.008)
Doctoral degree	0.004	(0.001)	0.004	(0.001)	0.005	(0.001)	0.006	(0.001)	0.007	(0.001)	0.008	(0.001)
STEM Edu.												
Canadian-born	0.042	(0.003)	0.046	(0.004)	0.052	(0.005)	0.059	(0.006)	0.063	(0.007)	0.065	(0.007)
Immigrant educated in Canada	0.007	(0.003)	0.011	(0.005)	0.013	(0.005)	0.015	(0.006)	0.019	(0.008)	0.020	(0.008)
Immigrant educated abroad	0.008	(0.003)	0.009	(0.003)	0.011	(0.005)	0.015	(0.007)	0.022	(0.010)	0.024	
STEM Emp.												
Professional	0.017	(0.001)	0.021	(0.002)	0.021	(0.002)	0.029	(0.003)	0.030	(0.003)	0.032	(0.004)
Technical	0.017	(0.001)	0.018	(0.000)	0.017	(0.000)	0.021	(0.000)	0.022	(0.001)	0.023	(0.001)
Canadian born	0.812	(0.067)	0.794	(0.075)	0.784	(0.083)	0.776	(0.084)	0.762	(0.087)	0.752	(0.092)
Foreign born educated in Canada	0.071	(0.021)	0.091	(0.030)	0.095	(0.033)	0.100	(0.033)	0.107	(0.034)	0.114	(0.037)
Foreign born educated abroad	0.116	(0.047)	0.115	(0.045)	0.121	(0.050)	0.124	(0.051)	0.131	(0.054)	0.134	(0.055)
Self-Emp.	0.073	(0.006)	0.078	(0.006)	0.094	(0.006)	0.094	(0.006)	0.094	(0.005)	0.084	(0.005)
Age	39.4	(0.4)	40.2	(0.4)	40.9	(0.3)	41.8	(0.4)	42.6	(0.4)	43.3	(0.5)
Middle aged	0.243	(0.005)	0.273	(0.003)	0.309	(0.005)	0.342	(0.005)	0.348	(0.005)	0.328	(0.003)
Male	0.494	(0.003)	0.495	(0.003)	0.494	(0.003)	0.493	(0.003)	0.491	(0.003)	0.492	(0.004)
Observations	11		11		11		11		11		11	

Sample means and standard errors (in parenthesis) of variables used in the regressions by Census year. The means are weighted by ethnic group population so that they are representative of the Canadian population. Population shares are calculated as the fraction of individuals aged 18-70 that fall in each category.

Table 3.3: Conditional probabilities of STEM employment given STEM education for native and immigrants by educational attainment

	1986	1991	1996	2001	2006	2011	2011 1986 difference
All Edu. Levels							
Canadian-born	0.218	0.290	0.274	0.294	0.306	0.311	0.093
Immigrant edu. in Canada	0.262	0.307	0.279	0.304	0.275	0.276	0.014
Immigrant edu. abroad	0.218	0.270	0.246	0.293	0.284	0.298	0.080
College Degree							
Canadian-born	0.179	0.238	0.222	0.247	0.264	0.273	0.094
Immigrant edu. in Canada	0.209	0.250	0.220	0.249	0.222	0.225	0.016
Immigrant edu. abroad	0.163	0.194	0.162	0.177	0.169	0.182	0.019
Bachelors Degree							
Canadian-born	0.301	0.399	0.379	0.390	0.388	0.379	0.078
Immigrant edu. in Canada	0.315	0.371	0.331	0.355	0.329	0.315	0.000
Immigrant edu. abroad	0.281	0.329	0.286	0.320	0.308	0.320	0.039
Master's Degree							
Canadian-born	0.232	0.319	0.319	0.333	0.343	0.343	0.111
Immigrant edu. in Canada	0.296	0.323	0.307	0.320	0.294	0.303	0.007
Immigrant edu. abroad	0.303	0.374	0.357	0.415	0.406	0.405	0.102
Doctoral Degree							
Canadian-born	0.248	0.309	0.318	0.307	0.256	0.234	-0.014
Immigrant edu. in Canada	0.288	0.335	0.338	0.332	0.225	0.217	-0.071
Immigrant edu. abroad	0.250	0.339	0.354	0.394	0.349	0.329	0.079

Conditional probabilities constructed using the mean population shares (weighted by population size) for individuals aged 18-70. STEM employment is defined as both having a STEM occupation and being employed (see Appendix C.3 for more details). Overall, the fractions of STEM educated individuals that are STEM employed has increased over time for both Canadian-born individuals and for immigrants whose highest degree was obtained abroad. The same overall trend is not apparent for immigrants that are educated in Canada. The extent of education-job mismatch for immigrants changes markedly by source of education as a function of educational attainment. While immigrants with Canadian college STEM degrees are significantly more likely to be employed in STEM than those educated abroad, the opposite is true at higher levels of educational attainment. The difference and trend is particularly striking for individuals holding doctoral degrees. In 1986, immigrants with Canadian PhDs had, among the three groups, the highest rate of being STEM employed (28.8%) and this dropped to the lowest (21.7%) by 2011. For immigrants with foreign PhDs, the rate increased from 25.0% to 32.9%. Immigrants holding a Canadian PhD seem to be experiencing a significant, and growing, education-job mismatch, while the opposite is true for immigrants who obtained their PhDs abroad.

Table 3.4: FGLS estimates of patents-per-capita regression

Dependent variable: *Patents per capita* $\times 100,000$

	(1)		(2)	
Ethnic dummies				
French	-14.89***	(1.29)	-13.38***	(2.83)
European	-11.01***	(1.04)	-23.64***	(5.42)
Hispanic	8.61**	(3.46)	15.99	(14.55)
Indian	8.27**	(3.26)	4.49	(12.96)
Chinese	15.35***	(2.49)	-14.09	(16.34)
Russian	8.63***	(2.23)	6.08	(4.20)
Vietnamese	2.75	(2.55)	-34.36**	(13.45)
Korean	22.14***	(3.10)	1.27	(27.38)
Japanese	15.65***	(2.78)	13.29	(16.35)
Other	-7.75***	(2.05)	-25.80***	(7.07)
Educational attainment				
Doctorate			1820.49***	(377.13)
Masters			-385.04***	(78.32)
Bachelors			-153.14**	(70.86)
College			-85.54***	(22.43)
STEM edu.			271.29***	(64.81)
STEM occ.				
Professional			337.91*	(181.62)
Technical			-423.78	(305.61)
Immigrant				
Canadian-edu.			-71.61***	(15.59)
Foreign-edu.			-2.18	(13.45)
Self-emp.				
Controls				
Age	0.56	(0.57)	-1.41	(1.06)
Middle-aged	71.73***	(11.83)	-10.62	(17.82)

Table 3.4 – *Continued from previous page*

Male	-29.80	(47.68)	137.03	(95.98)
Constant	-12.83	(34.57)	-21.76	(56.59)
Ethnic group time trends	Yes		Yes	
Time trend squared	Yes		Yes	
Number of observations	286		286	

FGLS estimates weighted by population. The number reported for each ethnic group is their mean patenting rate (conditional) deviation from the patenting rate of the English group across all years, taking into account both the dummy for that ethnic group and its time trend, but not other variables. The dependent variable is patents per capita x 100,000. All specifications include ethnic group specific time trends and the square of the time trend. The panel consists of 11 ethnic groups for the years 1986, 1991, 1996, 2001, 2006, and 2011. We estimate the model allowing an AR(1) autocorrelation structure within groups (that is group-specific) and a heteroskedastic and correlated error structure across groups. Standard errors are normalized by N-k instead of by N. *p ¡ .10, **p ¡ .05, ***p ¡ .01.

Table 3.5: FGLS estimates of patents-per-capita regression with doctoral degree interactions

Dependent variable: *Patents per capita* $\times 100,000$	(1)		(2)		(3)	
Ethnic dummies						
French	-12.46***	(2.91)	-12.40***	(2.91)	-11.21***	(2.56)
European	-26.67***	(5.70)	-27.43***	(5.94)	-24.08***	(5.51)
Hispanic	5.41	(15.64)	1.85	(15.87)	16.99	(15.23)
Indian	-4.72	(14.06)	-5.73	(14.09)	1.07	(13.52)
Chinese	-26.70	(17.91)	-26.86	(17.92)	-9.51	(16.18)
Russian	6.07	(4.23)	2.95	(4.48)	4.30	(3.87)
Vietnamese	-43.59***	(14.50)	-37.97**	(14.03)	-39.30***	(13.48)
Korean	-13.19	(28.22)	-20.74	(29.13)	1.84	(26.96)
Japanese	5.30	(17.06)	4.96	(16.70)	22.71	(15.21)
Other	-28.21***	(7.34)	-24.99***	(7.19)	-24.66***	(7.68)
Doctorate						
STEM PhD	2948.17***	(677.37)				
Non-STEM PhD	-189.91	(1156.56)				
STEM occ.			3755.44***	(666.70)		
Non-STEM occ.			296.97	(787.62)		
Canadian-born					5183.04***	(1666.46)
Immigrant edu. in Canada					-1505.82	(1043.18)
Immigrant edu. abroad					3022.98***	(612.10)
Educational attainment						
Masters	-674.19***	(72.49)	-574.97***	(83.45)	-579.92***	(75.92)
Bachelors	-22.00	(100.27)	5.96	(102.41)	-163.29*	(92.45)
College	7.04	(24.44)	7.71	(23.36)	-39.52	(24.89)
STEM edu.	38.19	(104.18)	130.64*	(78.93)	154.15*	(81.85)
STEM occ.						
Professional	525.15***	(156.41)	291.71*	(164.46)	501.76***	(167.83)
Technical	663.73**	(322.16)	806.32***	(303.98)	478.62*	(289.10)
Foreign born						
Canadian edu.	-24.60	(25.25)	-12.32	(25.08)	-17.74	(24.81)
Foreign edu.	52.20**	(24.79)	46.42*	(25.41)	51.79**	(21.93)
Self-emp.	313.72***	(66.45)	302.47***	(68.68)	324.63***	(60.28)
Controls						
Age	-1.85*	(1.10)	-1.02	(1.10)	-1.94*	(1.06)

Table 3.5 – *Continued from previous page*

Middle-aged	-4.46	(17.76)	3.77	(18.83)	-40.24**	(17.32)
Male	126.44	(93.39)	94.70	(98.22)	182.28**	(91.88)
Constant	-7.32	(56.65)	-32.78	(58.48)	-16.09	(57.66)
Ethnic group time trends	Yes		Yes	Yes	Yes	Yes
Time trend squared	Yes		Yes	Yes	Yes	Yes
Number of observations	286		286	286	286	286

FGLS estimates weighted by population. The number reported for each ethnic group is their mean patenting rate (conditional) deviation from the patenting rate of the English group across all years, taking into account both the dummy for that ethnic group and its time trend, but not other variables. The dependent variable is patents per capita x 100,000. All specifications include ethnic group specific time trends and the square of the time trend. The panel consists of 11 ethnic groups for the years 1986, 1991, 1996, 2001, 2006, and 2011. We estimate the model allowing an AR(1) autocorrelation structure within groups (that is group-specific) and a heteroskedastic and correlated error structure across groups. Standard errors are normalized by N-k instead of by N. *p ¡ .10, **p ¡ .05, ***p ¡ .01.

Conclusion

The three chapters of my dissertation shed light on what types of labour market skills can improve workers' resilience in the labour market and drive innovation growth in Canada. In Chapter 1, I stress the role of versatile skills to help immigrants deal with adverse entry economic conditions. Studying labour market outcomes for immigrants who are in their first 10 years after landing, I obtain three main findings. First, entry economic conditions do matter, and they matter more for women than men. I suspect this is due to a married woman's secondary role in making labour market related decisions within a household. Second, skill versatility does serve as a cushion to help prevent the sharp decline in immigrants' earning outcomes after initial economic setbacks. But this conclusion should not be generalized to highly educated immigrants, who are more likely to have pre-landing employment arrangements than their less educated counterparts. Because workers with more versatile skills are more likely to work in the private sector or in sectors with low union coverage, a low level of job security is seen for highly educated immigrants with versatile skills. Last, I relate immigrants' city-level mobility to economic conditions and find that moving to other cities does mitigate the impact of initial economic setbacks. I also find that immigrants' geographical mobility, to some extent, is strengthened by their skill versatility.

Turning to economic impacts of skilled immigration, the main finding in Chapter 2 is that Canadian STEM-educated immigrants who are successful in obtaining jobs in STEM areas do appear to raise patenting rates in a significant way. However, with little more than one-third of STEM-educated immigrants finding employment in STEM jobs, the impact Canadian skilled immigration on patent rates has been relatively modest in comparison to the United States. The fact that the employment rates of Canadian STEM-educated immigrants in STEM job has, if anything, tended to decrease over time, while the comparable rate for Canadian natives has been increasing, should be cause for concern among policymakers contemplating introducing 'point systems' for immigrant selection. Given the modest magnitude of our estimated effects, it appears that, for Canada, any spillover effects of immigrants on native patenting are minimal.

In Chapter 3, We estimate patenting rates for eleven ethnic groups in the Canadian population and find that Canada's ethnic minorities, including both immigrants and their Canadian-born descendants, make important contributions to Canadian innovation. Given the high concentration of immigrants in these ethnic-minority populations, we infer that immigrants generate at least one-third of Canada's patents, despite comprising less than one-quarter of its population. Relating changes over time in ethnic patenting rates to human capital characteristics of the underlying ethnic populations, we find a large role for increases in STEM education and employment, and in particular, increases in the share of the population with doctoral degrees. Although we are unable to identify the precise causal links between these variables, our findings do suggest that the higher patenting rates of Canadian ethnic minorities largely reflect their education and employment characteristics, suggesting that ethnic and cultural traits, emphasized elsewhere in the literature, are relatively unimportant.

These studies provide direct policy implications for the immigrant selection system. The key rationale underlying the Canadian approach is that human capital is a stronger predictor of long-run economic success than the extent to which an immigrants' skills match current labour market needs. Although the level of education for new immigrants has increased dramatically, the labour market skills of Canadian immigrants have not kept pace with the large increase in their educational levels (Clarke and Skuterud, 2013; Clarke and Skuterud, 2016; Clarke, Ferrer, and Skuterud, 2016). For that reason, a criticism on the immigration system has emerged, with arguments that policymakers should not only address supply-side concerns, but also take the demand side into consideration. The Express Entry (EE) system introduced in 2015, indeed, gives a greater role to employers in screening perspective immigrants. Screening immigrant applicants with the requisite skills demanded by specific sectors and occupations, can ensure a certain level of immigrant integration; these immigrants may still find difficulty in responding to changing labour demands, because their skills are tightly tied to specific sectors. Policymakers should, therefore, not only consider an immigrant's educational attainment, but also put some weight on their field-of-study related skill versatility level.

In addition, geographic mobility plays an important role in improving immigrants' resilience in the labour market. To prevent immigrants from being locked in by the local economic conditions, policymakers should not set implicit or explicit barriers for immigrants' mobility within Canada. The Canadian government has made some progress in addressing related concerns. For example, in April 2017, Canada has removed the two-year cohabitation requirements that applied to some sponsored spouses or partners of Canadian citizens and permanent residents, giving more physical flexibility to immigrant couples.

Moreover, it would appear that adopting a 'points system' so as to put more weight on STEM educational backgrounds is unlikely to have the desired effect of boosting innovation. Rather, our evidence emphasizes that selecting immigrants with STEM skills is not sufficient, given the challenges that Canadian STEM-educated immigrants appear to face in obtaining STEM jobs. The critical question for policy is whether the employment barriers that STEM-educated immigrants appear to face reflect differences in their skills and abilities or labour market inefficiencies arising from information frictions in job search, foreign credential assessment, or racial discrimination. An alternative explanation is that the employment challenges of Canadian STEM-educated immigrants primarily reflect differences in Canadian and U.S. skilled immigration policy. Our evidence suggests that it would be beneficial to put greater emphasis on pre-arranged employment in skilled immigration policy.

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APPENDICES

Appendix A

The Appendix for Chapter 1

Table A.1: OLS estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment: married versus unmarried.

	OLS estimates for married women				OLS estimates for unmarried women			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ur	-0.028***	-0.034***	-0.021***	-0.045***	-0.019***	-0.029***	-0.028***	-0.031***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.008)	(0.006)
ysm	0.262***	0.262***	0.294***	0.247***	0.236***	0.243***	0.314***	0.220***
	(0.010)	(0.012)	(0.024)	(0.014)	(0.014)	(0.017)	(0.033)	(0.019)
ysm^2	-0.013***	-0.014***	-0.015***	-0.014***	-0.011***	-0.012***	-0.015***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.049***	0.041***	0.038***	0.041***	0.054***	0.044***	0.036*	0.046***
	(0.005)	(0.006)	(0.014)	(0.007)	(0.007)	(0.009)	(0.018)	(0.010)
age_imm^2	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
years of schooling	0.031***	0.049***	0.060***	0.041***	0.030***	0.025***	0.028***	0.019***
	(0.003)	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.011)	(0.005)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,735	103,395	27,750	75,645	44,135	30,690	7,420	23,270
Adjusted R^2	0.093	0.092	0.113	0.078	0.109	0.094	0.113	0.072
Dependent variable: employment (employment=1 if annual earning>0)								
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ur	-0.007***	-0.008***	-0.002**	-0.013***	-0.006***	-0.005***	0.001	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)

Table A.1 – *Continued from previous page*

ysm	0.068***	0.060***	0.064***	0.057***	0.044***	0.040***	0.034***	0.041***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)
ysm^2	-0.004***	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
age_imm	0.034***	0.029***	0.019***	0.031***	0.026***	0.015***	0.010	0.016***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000*	-0.000**	-0.000***	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.010***	0.009***	0.009***	0.009***	0.018***	0.003**	0.005*	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217,610	144,495	37,470	107,025	58,630	37,010	8,800	28,205
Adjusted R^2	0.082	0.054	0.053	0.056	0.120	0.054	0.045	0.059

Standard errors in parentheses, clustered by education and year of immigration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees.

Table A.2: IV(2SLS) estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment: married versus unmarried.

	IV(2SLS) estimates for married women				IV(2SLS) estimates for unmarried women			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
ur	-0.062***	-0.085***	-0.085***	-0.084***	-0.031***	-0.056***	-0.065***	-0.054***
	(0.007)	(0.007)	(0.014)	(0.009)	(0.007)	(0.007)	(0.015)	(0.009)
ysm	0.261***	0.259***	0.286***	0.246***	0.236***	0.242***	0.313***	0.221***
	(0.010)	(0.012)	(0.024)	(0.014)	(0.014)	(0.016)	(0.032)	(0.019)
ysm^2	-0.013***	-0.014***	-0.015***	-0.013***	-0.011***	-0.012***	-0.015***	-0.010***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.049***	0.040***	0.035**	0.040***	0.054***	0.043***	0.037**	0.045***
	(0.005)	(0.006)	(0.014)	(0.007)	(0.007)	(0.009)	(0.018)	(0.010)
age_imm^2	-0.001***	-0.001***	-0.000**	-0.001***	-0.001***	-0.001***	-0.000*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.001***	-0.001**	-0.001***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
years of schooling	0.030***	0.046***	0.055***	0.039***	0.030***	0.024***	0.025**	0.018***
	(0.003)	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.011)	(0.005)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,695	103,365	27,740	75,625	44,115	30,675	7,420	23,255
Adjusted R^2	0.093	0.092	0.113	0.078	0.109	0.094	0.113	0.072
F statistics for IV from first stage regression								
ivur	9494.769	6251.432	667.677	24280.676	4599.153	3506.491	305.779	12121.113
Dependent variable: employment (employment=1 if annual earning>0)								
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)

Table A.2 – *Continued from previous page*

ur	-0.018***	-0.020***	-0.005*	-0.026***	-0.015***	-0.011***	-0.002	-0.014***
	(0.002)	-0.002	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
ysm	0.068***	0.059***	0.064***	0.057***	0.044***	0.039***	0.034***	0.041***
	(0.004)	-0.003	(0.006)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)
ysm^2	-0.004***	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
age_imm	0.034***	0.028***	0.019***	0.031***	0.027***	0.015***	0.011*	0.015***
	(0.002)	-0.002	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000*	-0.000**	-0.000***	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.010***	0.008***	0.008***	0.008***	0.017***	0.003**	0.005*	0.002
	(0.001)	-0.001	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217,550	144,455	37,460	106,995	58,600	36,990	8,800	28,190
F statistics for IV from first stage regression								
ivur	12094.568	8766.124	810.358	31907.822	5355.897	5486.413	464.838	13742.749

Standard errors in parentheses, clustered by education and year of immigration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees.

Table A.3: OLS estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment conditional on skill versatility level: married versus unmarried.

	OLS estimates for married women				OLS estimates for unmarried women			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	
ur	-0.026	0.013	-0.088***	-0.041	-0.034	0.008	-0.031	-0.052
	(0.022)	(0.022)	(0.034)	(0.040)	(0.029)	(0.030)	(0.049)	(0.056)
$ur \times vdex$	-0.003	-0.054**	0.075*	-0.000	0.015	-0.043	-0.004	0.028
	(0.024)	(0.024)	(0.040)	(0.043)	(0.031)	(0.033)	(0.061)	(0.059)
$vdex$	0.029	0.198**	0.124	-0.094	-0.017	0.181	0.392**	-0.211
	(0.092)	(0.092)	(0.108)	(0.176)	(0.116)	(0.123)	(0.171)	(0.219)
ysm	0.263***	0.262***	0.298***	0.246***	0.236***	0.243***	0.317***	0.220***
	(0.010)	(0.012)	(0.024)	(0.014)	(0.014)	(0.017)	(0.033)	(0.019)
ysm^2	-0.013***	-0.014***	-0.015***	-0.014***	-0.011***	-0.012***	-0.015***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.049***	0.041***	0.039***	0.041***	0.054***	0.044***	0.036*	0.046***
	(0.005)	(0.006)	(0.014)	(0.007)	(0.007)	(0.009)	(0.019)	(0.010)
age_imm^2	-0.001***	-0.001***	-0.000***	-0.001***	-0.001***	-0.001***	-0.000*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
years of schooling	0.031***	0.049***	0.063***	0.041***	0.030***	0.025***	0.030***	0.019***
	(0.003)	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.011)	(0.005)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,735	103,395	27,750	75,645	44,135	30,690	7,420	23,270
Adjusted R^2	0.093	0.092	0.115	0.078	0.109	0.094	0.116	0.073

TableA.3 – *Continued from previous page*

Dependent variable: employment (employment=1 if annual earning>0)

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ur	0.009	0.021***	0.004	-0.003	0.021***	0.022***	0.014	0.005
	(0.006)	(0.005)	(0.008)	(0.010)	(0.007)	(0.007)	(0.011)	(0.010)
$ur \times vdex$	-0.017***	-0.034***	-0.009	-0.010	-0.029***	-0.030***	-0.017	-0.014
	(0.006)	(0.006)	(0.010)	(0.011)	(0.007)	(0.008)	(0.014)	(0.011)
vdex	0.040*	0.092***	0.071**	0.001	0.085***	0.083***	0.066	0.027
	(0.022)	(0.021)	(0.028)	(0.040)	(0.028)	(0.029)	(0.042)	(0.042)
ysm	0.068***	0.059***	0.065***	0.057***	0.044***	0.039***	0.034***	0.041***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)
ysm^2	-0.004***	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
age_imm	0.034***	0.029***	0.019***	0.031***	0.026***	0.015***	0.010	0.016***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000*	-0.000**	-0.000***	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.010***	0.009***	0.009***	0.008***	0.018***	0.003**	0.006*	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217,610	144,495	37,470	107,025	58,630	37,010	8,800	28,205
Adjusted R^2	0.082	0.054	0.053	0.056	0.120	0.054	0.045	0.059

Standard errors in parentheses, clustered by education and year of immigration.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-

New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees.

Table A.4: IV(2SLS) estimates of the effects of the entry unemployment rates on female immigrants' earnings and employment conditional on skill versatility level: married versus unmarried.

	IV(2SLS) estimates for married women				IV(2SLS) estimates for unmarried women			
Dependent variable: log annual earnings								
	Full sample	Post sec.	Graduate	College/ Bachelor	Full sample	Post sec.	Graduate	College/ Bachelor
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ur	-0.156***	-0.090**	-0.124	-0.184**	-0.092**	-0.033	-0.102	-0.127
	(0.045)	(0.041)	(0.094)	(0.091)	(0.045)	(0.044)	(0.096)	(0.083)
$ur \times vdex$	0.089*	-0.018	-0.007	0.099	0.060	-0.039	0.010	0.080
	(0.048)	(0.044)	(0.131)	(0.095)	(0.049)	(0.048)	(0.124)	(0.087)
$vdex$	-0.063	0.328**	0.574*	-0.231	-0.092	0.293*	0.499	-0.289
	(0.144)	(0.135)	(0.327)	(0.328)	(0.164)	(0.163)	(0.308)	(0.316)
ysm	0.261***	0.261***	0.287***	0.247***	0.236***	0.243***	0.315***	0.220***
	(0.011)	(0.013)	(0.024)	(0.014)	(0.014)	(0.017)	(0.032)	(0.019)
ysm^2	-0.012***	-0.014***	-0.015***	-0.013***	-0.011***	-0.011***	-0.015***	-0.010***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
age_imm	0.049***	0.039***	0.035**	0.040***	0.054***	0.043***	0.038**	0.046***
	(0.005)	(0.006)	(0.014)	(0.007)	(0.007)	(0.009)	(0.018)	(0.010)
age_imm^2	-0.001***	-0.000***	-0.000**	-0.001***	-0.001***	-0.001***	-0.000*	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.002***	-0.001***	-0.001**	-0.001***	-0.002***	-0.002***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
years of schooling	0.030***	0.047***	0.058***	0.040***	0.030***	0.024***	0.027**	0.019***
	(0.003)	(0.004)	(0.007)	(0.004)	(0.004)	(0.005)	(0.011)	(0.005)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,695	103,365	27,740	75,625	44,115	30,675	7,420	23,255
F statistics for IV from first stage regression								
$ivur$	3881.657	2224.034	483.303	7944.291	1954.916	1369.726	382.875	4219.777

Table A.4 – *Continued from previous page*

$ivur \times vdex$	5189.4	3625.295	500.152	8708.606	2598.267	2267.323	338.416	4654.779
Dependent variable: employment (employment=1 if annual earning>0)								
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ur	-0.001	0.016*	0.038*	-0.039**	0.016	0.021*	0.064**	-0.014
	(0.010)	(0.009)	(0.022)	(0.018)	(0.012)	(0.012)	(0.027)	(0.017)
$ur \times vdex$	-0.021**	-0.044***	-0.061**	0.012	-0.035***	-0.037***	-0.088**	-0.001
	(0.010)	(0.010)	(0.030)	(0.018)	(0.013)	(0.012)	(0.034)	(0.018)
$vdex$	0.097***	0.171***	0.211***	-0.010	0.140***	0.130***	0.244***	0.011
	(0.032)	(0.030)	(0.075)	(0.061)	(0.042)	(0.042)	(0.086)	(0.064)
ysm	0.068***	0.059***	0.063***	0.057***	0.044***	0.039***	0.033***	0.041***
	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)
ysm^2	-0.004***	-0.003***	-0.004***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
age_imm	0.034***	0.028***	0.018***	0.031***	0.027***	0.015***	0.010	0.015***
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)
age_imm^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$ysm \times age\_imm$	-0.000***	-0.000***	-0.000*	-0.000**	-0.000***	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
years of schooling	0.010***	0.008***	0.009***	0.008***	0.017***	0.003**	0.006*	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Fixed effects:								
mother tongue	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
birth region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
survey year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
education level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
initial city	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217,550	144,455	37,460	106,995	58,600	36,990	8,800	28,190
F statistics for IV from first stage regression								
$ivur$	4622.524	3122.558	684.456	10554.228	2105.469	2064.355	422.8	4542.485
$ivur \times vdex$	5649.229	5150.523	712.43	11581.415	2359.025	3182.967	392.041	4937.733

Standard errors in parentheses, clustered by education and year of immigration.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Earnings are adjusted by the 2002 consumer price index. Six types of mother tongues are identified: English only, French only, English and French only, English and other non-French language(s), French and other non-English language(s), English and French with other language(s), and Neither English nor French. Nine regions of origins are specified: Africa, Central and South America, Eastern Asia, South and South East Asia, South and East Europe, United Kingdom-Australia-New Zealand-North America, West Asia and Middle East, West and North Europe, and other Areas. Education levels categorized into five groups: less than post secondary, college diploma, bachelor degrees, degrees above bachelor or master, and doctoral degrees.

Appendix B

The Appendix for Chapter 2

STEM fields of study in the Canadian Census data are identified using information on major field of study (MFS), which is identified for all individuals who have completed a post-secondary program of study. Major field of study is coded using a MFS classification system during the census years 1986, 1991, 1996 and 2001, while in 2006 it is coded according Classification of Instructional Program (CIP) Canada 2000. Therefore, we use the MFS classification as the master code and map the CIP to MFS, and then select the study fields from MFS to identify STEM fields.

To construct a concordance between MFS and CIP, we make use of the empirical concordances from CIP to MFS provided by Statistics of Canada (http://www12.statcan.ca/census-recensement/2006/ref/dict/app-ann020-eng.cfm). The empirical concordances provide mappings of the distributional relationships between the two classifications. The details are described on the website. There are three levels of MFS and CIP groupings respectively, correspondingly, three concordances are provided for each group level: CIP primary groupings-MFS major level (level 1), CIP subseries (4 digit) and MFS minor level (level 2), and CIP instructional programs (6 digit) and MFS unit level (level 3). In these concordances, a share variable is calculated as the percentage of total CIP that is accounted for by the specific MFS code. Thus for each CIP, the shares add up to 1. A higher share value indicates a more frequent occurring of a MFS in a CIP.

Our strategy is to take the share variable for each CIP and apply the mode method. In particular, we start from the level 3 concordance (the least aggregated categories), and map a CIP to a MFS which returns a highest share value given that particular CIP. If there are some CIP categories not mapped to MFS in level 3 concordances, we then use the level 2 concordances and apply the same method, and then level 1 (At last, there are quite few CIP categories not being mapped, we then read the descriptions on those CIP variables and map them to MFS manually.). A list of the concordance is provided in Table 3. Consequently, the STEM field is made up by four major MFS categories: 'Agricultural, biological, nutritional and food sciences,' 'Engineering and applied sciences,' 'Applied sciences technologies and trade; Mathematics,' and 'Computer and physical sciences.'

The STEM occupation variable is constructed based on the occupation information in each census file. To be specific, 1980 standard occupational classification (occ81) system is used in 1981 and 1986 census files respectively, and 1991 standard occupational classification (soc91) system is used in 1991, 1996, 2001 and 2006 census files respectively. Accordingly, in 1981 and 1986 census files, the STEM occupation is identified if the variable occ81 falls into the category 'Major Group 21 Occupations in Natural sciences, engineering and mathematics;' while in the rest census files, the STEM occupation is identified if the variable soc91 falls into the category 'C-Natural and Applied Sciences and Related Occupations.'

Appendix C

The Appendix for Chapter 3

C.1 Ethnic Populations

In order to obtain sensible estimates of a group's patenting rate per capita, it is crucial that the name matching algorithm and the census ethnicity data map as closely as possible. Thus, the overarching objective of our classification of census respondents into one of our 11 ethnic groups is the mapping of individuals whose names are likely to be assigned to a particular ethnic group by the algorithm used to identify the ethnicity of inventors' names.

Our ethnic population estimates for Census year is reported in Table 3.1. The estimates are based on Census and NHS questions on ethnicity and mother-tongue. The exact ethnicity question varies slightly by Census year. From 1986 to 2001 the question was "To which ethnic or cultural group(s) did this person's ancestors belong?"[1] For 2006 and the 2011 NHS, it was "What were the ethnic or cultural origins of this person's ancestors?" Table C.1 shows which ancestral ethnicity reported in the Census are mapped to each of our 11 ethnic groups.

Some ancestral origins are too ambiguous to be classified to one of the 11 ethnic groups (see the last row of Table C.1. For example, many individual list their ethnic origins as

[1]Prior to 1996, respondents were given a list of possible ethnicities and were asked to mark any that applied to them. They were, in addition, given blank spaces to provide any additional ethnicities. Starting in 1996, the list of options was abandoned and instead respondents were asked to write down their ethnic origin in blank spaces. This modification to the format in which the ethnicity question was presented could affect comparability across Census years.

being "Canadian." For these ambiguous cases, we use the reported mother tongue. Table C.2 provides details on which mother tongues are mapped to each of the ethnic groups. For example, individuals of Canadian origin are grouped into the English group if their mother tongue is English, and are grouped into the French group if their mother tongue is French.

Another complexity arises when individuals respond with multiple ethnic origins (which the Census and NHS surveys allow). In such cases, we assign equal fractions to each reported ethnicity. For example, a respondent who reports British, Chinese, and French ethnic origins is counted as 1/3 English, 1/3 Chinese and 1/3 French.

Table C.1: Mapping of Census ancestral ethnicities to the 11 ethnic groups

Ethnic group	Ancestral ethnicities as reported in the Census and NHS
ENGLISH	English, Irish, Scottish, Welsh, British, American, Cornish, Manx, Australian, New Zealander, Bahamian, Bermudan, St. Lucian, Grenadian, Caribbean, Caribbean Black, West Indian, Trinidadian, Tobagonian, Vincentian, Belizean, Kittitian/Nevisian, Jamaican, Antiguan, Montserrantan, St.Lucian
CHINESE	Chinese, Taiwanese
HINDI	Bengali, Gujarati, Punjabi, Tamil, Sinhalese, Bangladeshi, Indian, Pakistani, Sri Lankan, Indo-Pakistani, East Indian, Sinhalese, Goan, Hindu, Kashmiri, Nepali, Khmer, Kashmiri, South Asian, Sikh
RUSSIAN	Ukrainian, Russian, Byelorussian
HISPANIC	Spanish, Hispanic, Portuguese, Filipino, Argentinean, Chilean, Cuban, Dominican, Ecuadorian, Peruvian, Brazilian, Mexican, Puerto Rican, Colombian, Salvadorean, Latin/Central/South American, Central/South American Indian, Aboriginal Central/South American, Nicaraguan, Guatemalan, Uruguayan, Paraguayan, Uruguayan, Venezuelan, Honduran, Panamanian, Costa Rican, Bolivian, Other
FRENCH	French, Acadian, Franco-Ontarian, Franco-Manitoban, French Canadian, Haitian, Martinique, Martinican
EUROPEAN	European, Belgian, Dutch, Danish, Icelandic, Norwegian, Swedish, Scandinavian, Finnish, German, Austrian, Magyar(Hungarian), Swiss, Czech, Slovak, Slav, Kosovar, Czechoslovakian, Estonian, Lettish, Lithuanian, Polish, Romanian, Hungarian, Croatian, Serbian, Slovenian, Albanian, Macedonian, Bulgarian, Italian, Greek, Other European, Bulgar, Latvian, Maltese, Flemish, Yugoslav, Cypriot, Basque, Luxembourger, Frisian, Hutterite, Sicilian, Bosnian, Montenegrin, Afrikaner, Mennonite, Doukhobor, Gypsy
JAPANESE	Japanese
KOREAN	Korean
VIETNAMESE	Vietnamese
OTHER	Palestinian, Egyptian, North African Arab, Syrian,Cambodian, Laotian, Malaysian, Burmese, Thai, East/Southeast Asian, Singaporean, Mongolian, Turk, Armenian, Tibetan, Indonesian, Fijian, Polynesian, Other Pacific Islanders, Lebanese, Israeli, Guyanese, Ghanaian, Ethiopian, Somali, Maghrebi, Iraqi, Moroccan, Afghan, Kurdish, Berber, Algerian, Tunisian, Jordanian, Kurd, Ismaili Muslim, East African, South African, Tanzanian, Ugandan, Eritrean, Mauritian, Sudanese, African (Black), Nigerian, Kenyan, Rwandan, Zairian, Burundian, Assyrian, Kuwaiti, Libyan, Georgian, Tartar, Pashtun, Barbadian, Hmong, Maori, Hawaiian, Ugandan, Gambian,

Table C.1 – *Continued from previous page*

	Angolan, Yoruba, Khmer, Samoan, Oromo, Seychellois, Sundanese, Cameroonian, Senegalese, Akan, Ashanti, Congolese, Guinean, Ivorian, Malagasy, Malian, Sierean Leonean, Togolese, Zimbabwean, Burundian, Afrikaner, Amhara, Bantu, Chadian, Dinka, Gabonese, Harari, Pashtun, Ibo, Ivorian, Peulh, Sierra Leonean, Tigran, Zambian, Zulu, Kuwaiti, Maghrebi, Azerbaijani, Tatar
AMBIGUOUS ETHNICITIES	Canadian, New Brunswicker, Newfoundlander, Nova Scotian, Ontarian, Quebecois,Black, Jewish, Other provincial or regional origins, Other North American origins, First Nations, Inuit, Metis

Table C.2: Mapping of ambiguous ethnicities by mother tongue

Ethnicities	Mother tongues as reported on Census and NHS
ENGLISH	English, Welsh, Irish, Scottish;
FRENCH	French;
HINDI	Punjabi, Gujarati, Marathi, Sinhalese, Hindi, Urdu, Bengali, Malayalam, Tamil, Pashto, Indo-Iranian,Telugu, Dravidian, Kannada, Konkani;
CHINESE	Chinese, Mandarin, Cantonese, Chaochow, Fukien, Hakka, Shanghainese, Taiwanese;
RUSSIAN	Ukrainian, Russian, Byelorussian;
HISPANIC	Spanish, Portuguese, Pilipino, Tagalog;
JAPANESE	Japanese;
KOREAN	Korean;
VIETNAMESE	Vietnamese;
EUROPEAN	Italian, Romanian, Catalan, Romance, Dutch, Flemish, Frisian, German, Yiddish, Danish, Icelandic, Norwegian, Swedish, Afrikaans, Germanic, Gaelic, Celtic, Bosnian, Bulgarian, Croatian, Czech, Macedonian, Polish, Serbian, Serbo-Croatian, Slovak, Slovenian, Slavic, Latvian, Lithuanian, Greek, Armenian, Albanian, Georgian, Estonian, Finnish, Hungarian, Azerbaijani, Turkish, Turkic.
OTHER	Mother tongues that are not listed above.

C.2 STEM Field of Study

STEM field of study is identified based on the field-of-study questions in the Canadian Census and NHS files. The field-of-study questions are coded according to the predominant discipline or area of learning or training of a person's highest completed postsecondary certificate, diploma, or degree.

The major field of study (MFS) classification system is used during the census years of 1986, 1991, 1996 and 2001. In the 2006 census year, the field-of-study questions are coded by two separate classification systems: MFS classification and Classification of Instructional Program (CIP) Canada 2000. In the 2011 NHS, the questions are coded according to Classification of Instructional Program (CIP) Canada 2011. We classify as STEM-educated all individuals whose field-of-study is matched to the CIP 2011 STEM categories, which are available through a variant of CIP 2011-STEM groupings provided by Statistics of Canada (http://www23.statcan.gc.ca/imdb/p3VD.pl?Function=getVDTVD=139116).

Since the CIP 2011 classification system is only available for the observations in 2011 NHS, we need a concordance of the CIP to the MFS classification, as well as CIP 2000. Since the 2011 NHS uses both the CIP 2011 and CIP 2000, we use it to construct a probabilistic concordance between the two classifications. Specifically, a CIP 2000 category is probabilistically mapped to a CIP 2011 STEM field using the percentage of individuals with that CIP 2000 category that had that particular CIP 2011 STEM field. Consequently, each CIP 2000 code is mapped to either STEM or non-STEM, with the shares adding up to 1. A similar approach is used to convert the MFS to CIP, given that both MFS and CIP codes are provided in the 2006 census file.

C.3 STEM Employment

The 1986 Census uses the 1980 Standard Occupational Classification (SOC 1980) to classify occupations; the 1991, 1996 and 2001 Censuses use the 1991 Standard Occupational Classification (SOC 1991); the 2006 Census uses the National Occupational Classification for Statistics 2001 (NOC-S 2001); and the NHS uses the National Occupational Classification for Statistics 2001 (NOC-S 2006). The STEM occupation variable is constructed based on the occupation information in each census file. To make the STEM occupation comparable across years, we take the STEM occupation definition based on NOC-S 2001 code system as the master code and map other classifications to it.

The STEM occupation includes professional and technical occupations. According to Table C.3, STEM professional occupations include those in the category 'C0- Professional Occupations in Natural and Applied Sciences,' 'A12 Managers in Engineering, Architecture, Science and Information Systems.' STEM technical occupations include 'C1 -Technical Occupations Related to Natural and Applied Sciences.'

We combine the above with the individuals' labour force activity in the reference week to generate the STEM employment variable. Individuals are classified as either STEM professionals, STEM technicians, or non-STEM employed (if they are either unemployed, or employed but not in a STEM occupation).

Table C.3: STEM occupation: National Occupational Classification for Statistics 2001 (NOC-S 2001)

STEM Professional Occupation		
A1	Specialist Managers	
	A12	Managers in Engineering, Architecture, Science and Information Systems
C0	Professional Occupations in Natural and Applied Sciences	
	C01	Physical Science Professionals
	C02	Life Science Professionals
	C03	Civil, Mechanical, Electrical and Chemical Engineers
	C04	Other Engineers
	C05	Architects, Urban Planners and Land Surveyors
	C06	Mathematicians, Statisticians and Actuaries
	C07	Computer and Information Systems Professionals
STEM Technician Occupation		
C1	Technical Occupations Related to Natural and Applied Sciences	
	C11	Technical Occupations in Physical Sciences
	C12	Technical Occupations in Life Sciences
	C13	Technical Occupations in Civil, Mechanical and Industrial Engineering
	C14	Technical Occupations in Electronics and Electrical Engineering
	C15	Technical Occupations in Architecture, Drafting, Surveying and Mapping
	C16	Other Technical Inspectors and Regulatory Officers
	C17	Transportation Officers and Controllers
	C18	Technical Occupations in Computer and Information Systems