Can Skilled Immigration Raise Innovation? Evidence from Canadian Cities

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July 2018

Abstract

We examine the effect of changes in skilled-immigrant population shares in 98 Canadian cities 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 that the impact of increasing the share of university-educated immigrants on patenting rates is smaller than the impact that both native-borns have in Canada and immigrants have in the U.S.. The modest contribution of Canadian immigrants appears to be primarily explained by the fact that only one-third of Canadian STEM-educated immigrants find employment in STEM jobs, compared to two-fifths of the Canadian-born and one-half of U.S. immigrants. Consistent with this, we find a large and significant effect of Canadian STEM-educated immigrants when we also condition on STEM employment. Our results suggest benefits from giving employers a greater role in the selection of skilled immigrants.

Keywords: Immigration; innovation; immigration policy
JEL Classifications: J61, J18, O38

1   Introduction

Canada, and its `points system' in particular, is widely seen as a model of effective skilled immigration policy; the U.K. adopted a points system in 2008 and it is regularly pointed to as an option in ongoing U.S. immigration reform discussions. It has been so successful in shifting the mix of Canadian immigration toward high skilled immigrants, that the share of immigrants in Canada holding university degrees more than doubled from 14% in 1986 to 29% in 2006, and the share of those with science, engineering, technology, and mathematics (STEM) degrees increased from 32% to 39%.

Yet behind this success lies the uncomfortable truth that Canada's immigration system may not be performing as well as is widely believed. Recent studies have found that foreign sources of education and work experience are devalued by Canadian employers (Green and Worswick 2012; Skuterud and Su 2012). Moreover, newer cohorts of immigrants are not faring as well as cohorts from times past (Picot and Sweetman 2005).

In this paper, we examine the contributions of immigrants to Canada, not by examining their labour market earnings, as in previous studies, but by examining the extent to which they foster innovation in the cities in which they settle. The Canadian case is important, not just because it is a model of skilled immigration policy, but also because it ranks among the world's largest immigrant-receiving countries measured as a proportion of its population. We find the impact of skilled (university-educated) immigrants on patenting rates to be surprisingly small, compared to both skilled Canadian-born individuals and skilled immigrants in the United States. We present evidence suggesting that this is in large part due to STEM-educated Canadian immigrants struggling to find jobs in STEM.

Determining whether immigrants generate positive economic benefits is becoming increasingly important. Since the economic turmoil brought about by the financial crisis of 2008, voters' support of immigration has waned. 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 its importance to long-term economic growth, on innovation. Although the precise theoretical mechanisms through which immigration increases innovation are less well developed, the economics literature linking skilled immigration with higher patenting rates provides remarkably compelling evidence of an empirical link.

Beginning with U.S. studies by Peri (2007), Chellaraj, Maskus, and Mattoo (2008), Hunt and Gauthier-Loiselle (2010), and Kerr and Lincoln (2010), but now also including a number of European studies (Bosetti, Cattaneo, and Verdolini (2012); 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 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. Kerr and Lincoln (2010) also find that U.S. immigration (in their case through the H-1B program) increases patenting, but this is largely driven by increases in patenting by immigrants, and not by spillover effects on natives. Regardless of whether it is through the direct channel of patenting themselves, or the indirect channel of increasing the patenting rates of natives, the U.S. evidence suggests that skilled immigration can raise innovation, thus potentially making a strong economic argument for immigration.

The primary challenge in examining the Canadian case is its relatively small population, which limits the number of cities with large numbers of immigrants and patents. Nonetheless, relating changes in university-educated immigrant shares within the 98 largest 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 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 (and in fact larger than that of skilled Canadian-born individuals). 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 evidence elsewhere that U.S. immigrants are relatively positively selected owing to a greater role of U.S. employers in immigrant selection and higher economic returns to skill in U.S. labour markets (Clarke, Ferrer, and Skuterud 2018).

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 data and methodological approach. In Section 4 we discuss our main results and in section 5 we more closely examine STEM education-job mismatch among immigrants as a plausible explanation for our findings. In the final section, we summarize our main results and discuss their policy relevance.

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 `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 2.1% in the early 1980s to 3.3% in the early 1990s and 6.4% by the mid-2000s. Canada's 'points system'

The success of the Canadian `points 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 immigrant's skills match current labour market needs. 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). [1]

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 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 less patenting spillovers on natives. However, the focus of our analysis is whether Canada's `points 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 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 the current literature, this increase should have served to raise patenting rates proportionally more in Canada than in the United States. Interestingly, the Canadian patenting rate

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[1] This has led the Canadian government to make significant 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 applications, 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.

did, in fact, increase more over this period than the U.S. rate.[2] Whereas patents per capita (x 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 increases 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 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.

3   Data and Methodology

To estimate the impact of skilled Canadian immigration on patenting rates, we combined patent data from the United States Patent and Trademark Office (USPTO) and Census data from Statistics Canada to construct a panel of 98 Canadian Census Metropolitan and Agglomeration Areas (CMA/CAs)[3] for the years 1981, 1986, 1991, 1996, 2001, and 2006.[4] Our cities range in population (aged 15-70) in 2006 from a low of 8,448 to a high of 3,684,821, with 66 cities above 25,000 individuals, 46 above 50,000, 26 above 100,000, and 7 above 500,000.

We construct patent counts at the level of the city and year using USPTO data on patents granted to inventors residing in Canada. Alternatively, we could have examined patents granted by the Canadian

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[2] 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 communications" fields (Carley, Hedge, and Marco 2003). 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.

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

[4] We begin in 1981, because the 1976 Census did not identify immigrant status. We do not include more recent data for two reasons. First, while our interest is in the year of patent applications, we only observe patents once they have been granted. Due to the time lag in granting, there is substantial truncation in the number of patents observed after 2006. Second, the Canadian Census was replaced with a voluntary survey in 2011. Due to the low overall response rate (65%), we have concerns about the quality of estimated city-level immigrant population shares from these data.

Intellectual Property Office (CIPO) to Canadian inventors. However, this would have underestimated the number of 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.[5]

Patents are assigned to cities by linking the address of inventors to Canadian CMA/CAs. Where patents contained multiple inventors, we assigned fractions of patents to cities, so that each patent received equal weight. For example, a patent with two inventors from Toronto and one from Kitchener-Waterloo (KW) is counted as two-thirds of a patent for Toronto and one-third for KW. 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 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, 86% within 5 years, 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 year 2006 fixed effect.

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.[6] In 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.

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[5] 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.

[6] 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 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.

Our analysis relates skilled immigrant population shares in Census years 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.[7]

Our baseline empirical model is a first-difference (FD) weighted least squares (WLS) specification similar to that of HGL.[8] Our estimating equation is:

$$\Delta \log \left(\frac{\sum_{j=1}^{5} patents_c(t+j)}{pop_c(t)} \right) = \beta_m \Delta \left(\frac{sm_c(t)}{pop_c(t)} \right) + \beta_n \Delta \left(\frac{sn_c(t)}{pop_c(t)} \right) + \tag{1}$$

$$\Delta X_c(t)\delta + Z_c(1981)\theta + y(t) + \varepsilon_c(t)$$

where $patents_c(t+j)$ 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 university-educated 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; $\varepsilon_c(t)$ 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.

We begin by estimating equation (1) including log mean age in $X_c(t)$ and both log mean income and log population in $Z_c(1981)$. This specification most closely resembles that of HGL. 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-

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[7] 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).

[8] Since HGL also focuses on the impact of college-educated immigrant shares, as opposed to international students or H-1B visa holders, one side-benefit of our choice of specification is that it more directly allows a comparison with the U.S.. We note, however, that rather than examine state-level (or province-level) immigration shares, as HGL do, we relate immigrant shares to patent rates at the city level. With only 10 Canadian provinces, two of which account for roughly 60% of the national population, an analysis at the province level is not viable.

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 flows. In this 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.[9]

It is, of course, possible to estimate equation (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 (1) are uncorrelated with $\varepsilon_c(t)$ 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 `points 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-driven changes in immigration flows to Canadian cities are correlated with

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[9] 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 naïve FD-WLS estimates do suggest somewhat larger beneficial impacts of university educated immigration, these are still unambiguously smaller than those in HGL (see Table A1 in the appendix), and our IV estimates are almost identical to those reported in Table 5. Alternatively, we have also estimated unweighted regressions for the largest 53 cities (those with a population of at least 40,000 in 1981). The estimates are also larger (see table A2 in the appendix) but still significantly smaller than those in HGL.

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 naïve estimates of equation (1) are upward biased.

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 patterns of immigrants from particular origin countries and national-level populations of immigrants from those countries. That is, we instrument the skilled immigrant share $sm_c(t)$ in equation (1) using the constructed variable:

$$sm_c(t) = \sum_j \lambda_{cj}(1976) \ sm_j(t) \tag{2}$$

where $\lambda_{cj}(1976)$ 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.[10] Using first-differences 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 KW to receive a disproportionately large share of this increase, not because these immigrants were attracted by the expectation of heightened innovative activity in KW, but because the historical population of German migrants residing in KW and the associated cultural amenities they offer attracts them.

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[10] To obtain 1976 immigrant city populations 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 $\lambda_{cj}(1976)$. 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.

4   Results

4. 1 Descriptive Statistics

Before examining the results of our regression analysis, we report in Table 1 sample means of the variables used in the regressions separately by Census year. The means are 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 1 are roughly five times larger than those in Figure 1 because they are cumulative sums of patents in the 5 years following the Census year (the dependent variable in equation 1). Consistent with the national-level Canadian patenting rate in Figure 1, the first row of Table 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 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 the 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 `points 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 `points 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.

4.2 Regression Results

The results from estimating the HGL specification (1) and a richer set of controls (2) are reported in Table 2. 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 estimates does not reflect greater measurement error in our population shares, structural economic differences between the two countries, or other 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.[11]

The second column of Table 2 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 we instead define the skilled population as university-educated individuals who are employed in a STEM occupation. As expected, the point estimates increase substantially, and the coefficients on immigrants and natives are now similar and much larger. 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 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.

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

In Table 3, 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 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 (1) and (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 3, we distinguish between Canadian- and foreign-educated immigrants. 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 3 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 (1) and (2), respectively. The latter coefficient is statistically significant at the 10% level, larger than the coefficient for natives (although not significantly so), 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 difficulties finding employment in STEM jobs are the primary source of their modest contribution to innovation, an issue that we delve further into in Section 5.

It is, of course, possible that our naïve FD estimates are downward biased, perhaps as a consequence of measurement error in the Canadian population shares. In Table 4, 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.

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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) 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.[12]

5. STEM Education-Employment Mismatch

While the `points system' has been successful in dramatically increasing both the share of the Canadian population comprised of university-educated immigrants (from 0.027 in 1981 to 0.076 in 2006) and the share of these university educated immigrants holding a STEM degree (from one third in 1986 to almost two-fifths by 2006), our analysis suggests that this may not have had the desired impact on innovation. The reason may be challenges faced by Canadian STEM immigrants in finding STEM employment. Because the vast majority of patenting happens through corporate research and development activities, mismatched STEM immigrants likely a limited impact on patenting. There is, in fact, some evidence that this rate of mismatch is growing among immigrants in Table 1: the population share comprised of university-educated immigrants from STEM fields increased by 2 percentage points between 1986 and 2006, but the share also employed in a STEM occupation increased by less than 1 percentage point.

In Table 5, we examine this STEM education-employment mismatch more directly. Canadian immigrants are not only 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,

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[12] A further concern is that the inclusion of endogenous control variables could bias our results. We ran the IV specifications in Table 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.

whereas it has increased for natives. Consequently, by 2006 there was a nearly 5 percentage point gap in the STEM-employment rate of Canadian STEM-educated immigrants relative to natives (0.32 for immigrants, relative to 0.37 for natives). 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. The large gap between immigrants to Canada and the U.S. is in stark contrast to the similar rate for Canadian and U.S. natives (around 0.4 for both).[13]

A possible explanation for the low STEM-employment rates of foreign-STEM-educated Canadian immigrants, which the Canadian `points system' values highly, is that they face employment barriers due to lower average quality of schooling or because employers have 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 5 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 immigrants with foreign degrees (the only exception being the end of the dot-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 `points system' in immigrant selection. Once again, we would expect this trend to have limited the potential for Canadian skilled immigration to raise patent rates.

As an aside, the STEM immigrant education-job mismatch appears to be most prevalent among engineering graduates. This is particularly concerning because this group likely contributes disproportionately to patenting activity. For our most recent year of analysis (2006), we find that only 20.1% of immigrant university-educated engineering graduates were employed in an engineering occupation, compared to almost double that rate (39.0%) for Canadian-born university-educated engineering graduates. The share of engineering employment was even lower among the subset of immigrant engineers who obtained their degree outside of Canada (17.6%). Even for the subset of immigrants that were educated in Canada the share (24.2%) was much lower than for the Canadian-born.

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[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 driven in how STEM fields and occupations are being classified in the two data sources or by a different industrial mix across the two countries.

To better understand why immigrants appear to experience greater difficulties obtaining jobs in STEM occupations, we examine the determinants of mismatch in a regression framework for the cross-section of male individuals in the 2006 Census who are aged 18-70, reside in one of our 98 cities, and hold a university degree in a STEM field. It could be, for example, that immigrants are older on average and all workers tend to transition out of STEM jobs into management positions as they age. Or perhaps the higher mismatch rates of immigrants is due to them having different levels of educational attainment, being educated in different STEM subfields, or perhaps immigrants are more likely to voluntarily opt for jobs in non-STEM occupations.

Table 6 presents our results. Column 1 shows that controlling for age, educational attainment, and city of residence, STEM-educated immigrants are roughly five percentage points less likely to be employed in STEM than their Canadian-born counterparts (4.74% less for immigrants educated in Canada and 5.31% less for those educated abroad). This difference becomes much larger when we also account for the fact that immigrants disproportionately hold degrees in STEM educational fields such as electrical and computer engineering (fields that tend to have a high share of graduates working in STEM). In column 2, we show that controlling for subfield of study by adding Canadian Classification of Instructional Programs (CIP) fixed effects,[14] Canadian-educated immigrants are 8.28 percentage points less likely to be employed in STEM than Canadian-born individuals educated in the same subfield, while foreign-educated immigrants are 9.23 percentage points less likely. These are large differences, considering that only 38% of the STEM-educated individuals in our entire sample are employed in STEM. Lastly, our findings show that individuals with graduate degrees (who have invested more in their education) are more likely to be working in STEM and that the likelihood of being employed in STEM initially increases with age (peaking around 37.9 years old) before declining. This is consistent both with individuals needing time to find employment in their field, and with them eventually moving into managerial roles as their careers progress.

In columns 3 and 4 we examine the wage differentials of STEM-educated individuals employed in STEM and non-STEM jobs. Our results suggest large wage gaps between immigrant and Canadian-born individuals, though much of the gap disappears for immigrants that successfully find STEM employment. Focusing on column 4, which includes both city and CIP fixed effects, we see that Canadian-educated (foreign-educated) immigrants not working in STEM earn 40.2 log points (55.8 log points) less than natives not working in STEM. These large gaps, are substantially smaller in the case of immigrants in STEM

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[14] In our sample of STEM-educated individuals we observe a total of 233 different CIP codes.

employment. Canadian-educated (foreign-educated) immigrants employed in STEM earn 9.8 log points (23.7 log points) less than natives not working in STEM and 20.6 log points (34.42 log points) less than natives working in STEM. Put differently, the STEM-employment wage premium is much larger for immigrants (30.4 log points for Canadian-educated and 32.1 log points for foreign-educated) than it is for natives (10.8 log points), suggesting, among other things, that the education-job mismatch of immigrant STEM workers is not the result of immigrants voluntarily choosing to work outside of STEM occupations. It would seem that the relatively high rates of education-job mismatch among immigrants, not only adversely impacts their potential contribution to Canadian innovation, but it also severely affects their earnings potential.

6. Conclusions

Canada is an important case study for understanding the potential for a selective immigration policy to raise innovation, as its `points system' for screening prospective immigrants is seen by many as a model of how to raise the average skill levels of immigration inflows. Our analysis suggests that while the Canadian `points system' has been successful in raising the education levels of immigrants, it has been less successful in leveraging immigration to boost innovation. In this regard, our findings suggest that an increase in the share of university-educated immigrants has a smaller impact on innovation than an increase in the share of university-educated Canadian-born individuals, in spite of immigrants disproportionately holding STEM degrees. Moreover, our estimates suggest an unambiguously smaller impact of university-educated immigrants in Canada, relative to that of university-educated immigrants in the U.S., a difference which is not observed between the native-born in the two countries.

How can these empirical findings be reconciled? Our analysis suggests that these differences can be explained, in large part, by the difficulties that Canadian STEM-educated immigrants face in finding STEM employment. Whereas in the U.S., one-half of STEM-educated immigrants are employed in STEM, in Canada the share is roughly one-third (compared to a share of approximately 0.4 for natives in both countries). Consistent with this, we find that Canadian university-educated immigrants, and even Canadian STEM-university-educated immigrants have little impact on patenting rates, until we condition on STEM employment. Specifically, we find that an increase in the share of Canadian STEM-educated immigrants employed in STEM has a large and significant effect on patenting rates. Moreover, this effect is comparable (and in fact slightly larger) to that of Canadian-born individuals educated and employed in STEM, and also similar to the effect of scientist and engineer immigrants in the United States.

With the large majority of STEM-educated immigrants not finding employment in STEM, the impact of Canadian skilled immigration on patenting rates has been relatively modest. In fact, the rate of STEM education-job mismatch among immigrants is, if anything, increasing over time, particularly relative to that of natives. This should be cause for concern for Canadian policymakers and all policymakers who are contemplating adopting a `points system'. Selecting immigrants with STEM skills is unlikely to be sufficient to boost innovation. The critical question for policy is whether the employment barriers that STEM-educated immigrants appear to face primarily 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 and earn lower wages 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 information frictions around the value of immigrants' educational credentials, are not solely responsible.

A key difference between the Canadian and U.S. skilled immigration policy, is that skilled-stream immigrants arriving in Canada do not typically have pre-arranged employment, whereas the vast majority of U.S. skilled immigrants are admitted via temporary work permits from sponsoring employers (H-1B visas in particular).[15] The Canadian `points system' has historically granted permanent residency to foreign applicants solely on the basis of their foreign educational credentials and years of work experience. To the extent that U.S. employers have richer information regarding the productivity of foreign workers, STEM-educated immigrants in the U.S. are not only more likely to "hit the ground running" with a job, but may also be of higher labour market "quality" on dimensions unobservable to the `points system.' This suggests that a greater emphasis on pre-arranged employment in immigrant selection could be beneficial. Indeed, the past decade has seen the introduction of a number of new skilled immigration programs easing the transition to permanent residency for individuals with Canadian work experience and job offers from Canadian employers.[16] Time will tell whether these programs have been successful in raising the

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[15] 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, 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, Refugees, and Citizenship Canada, various years).

[16] These programs include the Canadian Experience Class program introduced in 2008, Provincial Nominee Programs (Ontario was the last province to introduce a program in 2007), and the Express Entry System for processing applications for permanent residency, which was introduced in 2015.

STEM-employment rates of Canada's STEM-educated immigrants and, in turn, the contribution of Canada's skilled immigration policy to innovation.

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Figure 1: University-educated immigrant population shares and patents per capita, Canada and the USA, 1980-2006
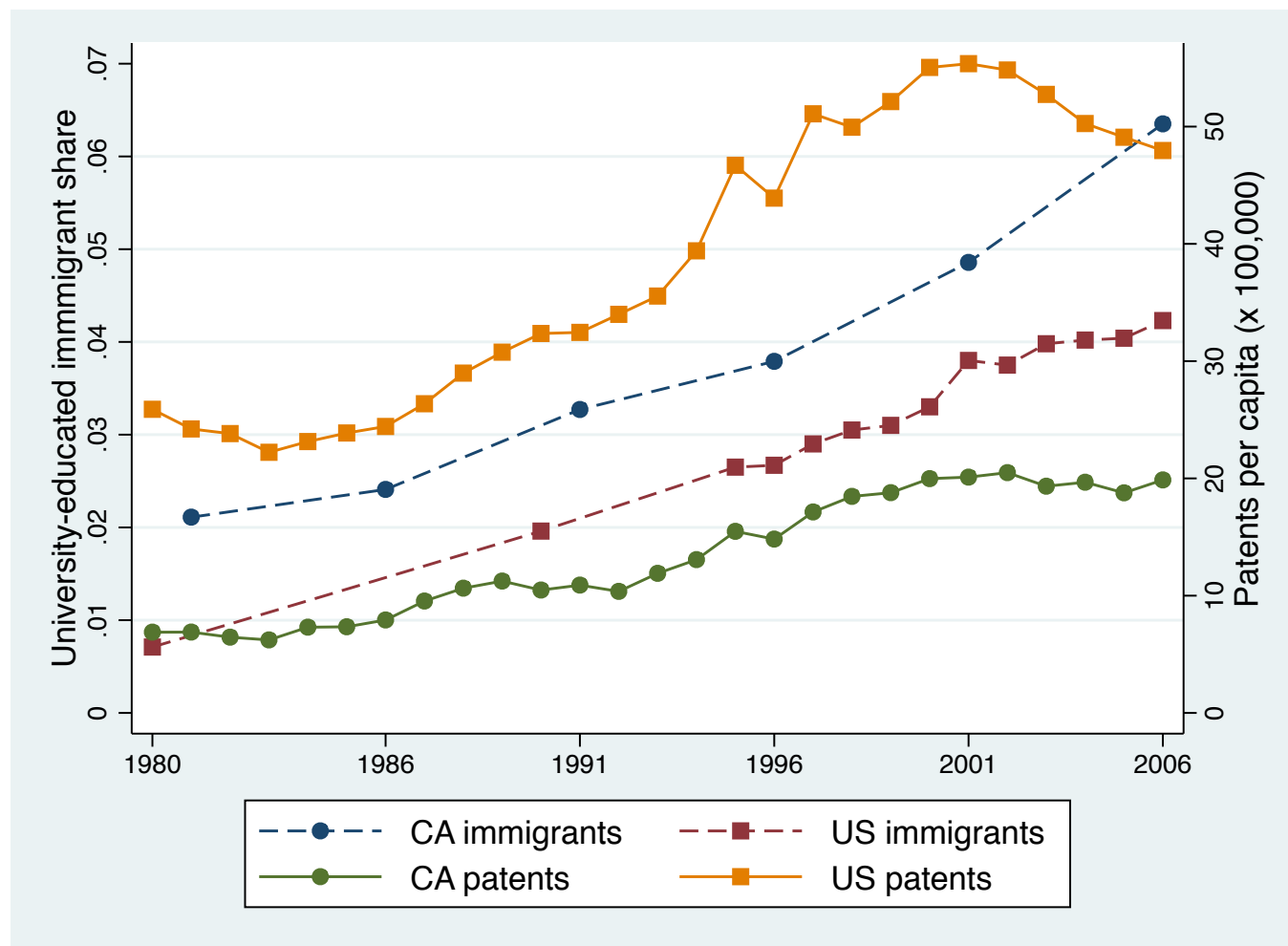
Notes: For each of Canada and the U.S. the figure presents the share of the population aged 25 and over that is comprised of university-educated immigrants (left hand side axis) and the number of USPTO patents granted to Canadian and U.S. inventors per 100,000 population (right hand side axis). For the latter series, the year is the application year of the patent. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Only patents granted up to November 2014 were tabulated. For both countries, both the share of University-educated immigrants and patents per capita show an overall increase.

Table 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	74.0	105.8	113.2	103.0	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**
- University educated	0.027	0.030	0.037	0.047	0.060	0.076	0.050***
- University STEM educated	--	0.010	0.012	0.016	0.022	0.030	0.020***
- Canadian-university STEM educated	--	0.005	0.006	0.008	0.10	0.013	0.008***
- Foreign-university STEM educated	--	0.005	0.006	0.008	0.012	0.017	0.012***
- University educated & STEM employed	0.004	0.004	0.005	0.006	0.009	0.011	0.007***
- University STEM educated & STEM employed		0.003	0.004	0.005	0.008	0.010	0.006***
Native-born population share	0.777	0.781	0.769	0.753	0.745	0.732	-0.046**
- University educated	0.073	0.087	0.102	0.115	0.128	0.142	0.069***
- University STEM educated	--	0.019	0.021	0.022	0.025	0.027	0.008***
- University educated & STEM employed	0.007	0.008	0.009	0.010	0.013	0.014	0.007***
- University STEM educated & STEM employed		0.006	0.007	0.008	0.009	0.010	0.004***
Mean age	32.6	33.7	34.6	35.4	36.7	38.0	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	0.700	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

Notes: Sample means of variables used in the regressions by Census year. The means are weighted by city populations so that they are representative of the Canadian population residing within one of Canada's largest 98 cities. Patents are the cumulative sum of annual patents in the five years following each Census year. Population shares are calculated as the fraction of individuals aged 15-70 that fall in each category. The 1981 Canadian Census does not report field of study. Incomes are not deflated. Expected patents per capita controls for the number of patents that each city would have based on its distribution of 1972-1980 patents across different patent classes and the subsequent national-level growth in the number of patents for each of those patent classes across Census years. *p < .10, **p < .05, ***p < .01.

Table 2: WLS-FD estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	University-educated		University-educated & STEM-employed	
	(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

Notes: Weighted least squares (observations are weighted by city population) regressions with five year first differences. The dependent variable is the log of patents per capita. Standard errors are clustered by city. The sample consists of Canada's 98 largest cities and 1986-1981, 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first differences. Specification (1) attempts to recreate the specification in HGL while specification (2) includes a richer set of controls. *p < .10, **p < .05, ***p < .01.

Table 3: 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

	University-educated		University-STEM-educated		University-STEM-educated		University-STEM-educated & STEM-employed	
	(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 university	--	--	--	--	4.295	3.406	--	--
					(29.814)	(42.164)		
Immigrant foreign university	--	--	--	--	-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**	0.009	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

Notes: Weighted least squares (observations are weighted by city population) regressions with five-year first differences. The dependent variable is the log of patents per capita. Standard errors are clustered by city. The sample consists of Canada's 98 largest cities and 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first-differences, since field of study information is not available in the 1981 Census. Specifications (1) attempt to recreate the specification in HGL while specifications (2) include a richer set of controls. *p < .10, **p < .05, ***p < .01

Table 4: IV (2SLS) estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	University-educated		University-educated & STEM-employed	
	(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

Notes: We instrument local skilled immigrant populations using predicted immigrant populations based on the historical city-level settlement patterns of immigrants from particular origin countries and national-level populations of immigrants from those countries. Estimates are from two-stage least square. Observations are weighted by city population. Standard errors are clustered by city. The sample consists of Canada's 98 largest cities and 1986-1981, 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first differences. Specifications (1) attempt to recreate the specification in HGL while specifications (2) include a richer set of controls. $*p < .10$, $**p < .05$, $***p < .01$.

Table 5: Conditional probabilities of STEM education and STEM employment for immigrants and natives

	1986	1991	1996	2001	2006	2006 – 1981 difference
Immigrants						
Pr[University educated]	0.138	0.160	0.188	0.233	0.285	0.165
Pr[STEM educated | university educated]	0.324	0.328	0.337	0.374	0.387	0.062
Pr[Canadian education | STEM university educated]	0.505	0.519	0.500	0.447	0.429	-0.076
Pr[Foreign education | STEM university educated]	0.495	0.481	0.500	0.553	0.571	0.076
Pr[STEM employed | STEM university educated]	0.348	0.338	0.311	0.345	0.322	-0.026
Pr[STEM employed | Canadian STEM university educated]	0.363	0.355	0.322	0.343	0.343	-0.019
Pr[STEM employed | Foreign STEM university educated]	0.333	0.320	0.301	0.347	0.307	-0.027
Natives						
Pr[University educated]	0.112	0.132	0.153	0.172	0.194	0.101
Pr[STEM educated | university educated]	0.214	0.202	0.193	0.195	0.191	-0.023
Pr[STEM employed | STEM university educated]	0.342	0.355	0.355	0.370	0.370	0.028

Notes: Conditional probabilities constructed using the mean population shares (weighted by population size) for individuals aged 15-70 across Canada's largest 98 cities. Canadian immigrants are more likely to hold a university degree than their native-born counterparts and this difference has grown over time. University-educated immigrants are also more likely to be educated in a STEM field than their native-born counterparts and this difference has also become larger over time. 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. This suggests an education-job mismatch for immigrants.

Table 6: WLS regression coefficients of the effect of immigration status on probability of being STEM employed and the effect of mismatch on weekly earnings for STEM-educated male individuals in the 2006 Census

	STEM Employed		Weekly Earnings	
	(1)	(2)	(3)	(4)
Canadian-educated immigrant	-0.0474***	-0.0828***	-0.3808***	-0.4022***
	(0.0038)	(0.0037)	(0.0130)	(0.0131)
Foreign-educated immigrant	-0.0531***	-0.0923***	-0.5344***	-0.5579***
	(0.0036)	(0.0036)	(0.0116)	(0.0120)
STEM-employed Canadian-educated immigrant			0.3338***	0.3043***
			(0.0137)	(0.0139)
STEM-employed foreign-educated immigrant			0.3475***	0.3214***
			(0.0113)	(0.0114)
STEM-employed native			0.1510***	0.1077***
			(0.0086)	(0.0089)
Master's degree	0.0172***	0.0391***	-0.0100	0.0079
	(0.0037)	(0.0037)	(0.0085)	(0.0086)
Doctoral degree	-0.0704***	0.0315***	0.1649***	0.2301***
	(0.0051)	(0.0054)	(0.0134)	(0.0143)
Age	0.0280***	0.0258***	0.1305***	0.1301***
	(0.0008)	(0.0007)	(0.0026)	(0.0026)
Age^2	-0.0004***	-0.0003***	-0.0013***	-0.0013***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
City fixed effects	Yes	Yes	Yes	Yes
Field of study fixed effects	No	Yes	No	Yes
R-squared	0.0484	0.1246	0.1390	0.1513
Number of observations	135,530	135,530	99,670	99,670

Notes: Weighted least squares regressions (observations are weighted by Census sampling weights) at the level of the individual with robust standard errors. In columns 1 and 2 the dependent variable is an indicator for whether the individual is employed in a STEM field and in columns 3 and 4 the dependent variable is the log of weekly wages. The sample consists of all male individuals in the 2006 Census that are aged 15-70, have a university STEM education, and reside in one of Canada's 98 largest cities. For the wage regressions the sample is further restricted to individuals that are full-time employed and have strictly positive earnings. *p < .10, **p < .05, ***p < .01.

Appendix

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'.

Table A1: Sample without Toronto - FD estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	University-educated		University-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

Notes: Weighted least squares (observations are weighted by city population) regressions with five year first differences. The dependent variable is the log of patents per capita. Standard errors are clustered by city. The sample consists of Canada's 97 largest cities with the exception of Toronto and 1986-1981, 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first differences. Specifications (1) attempt to recreate the specification in HGL while specifications (2) include a richer set of controls.
*p < .10, **p < .05, ***p < .01

Table A2: 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

	University-educated		University-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

Notes: OLS first-difference regressions. The dependent variable is the log of patents per capita. Standard errors are clustered by city. The sample consists of the 53 cities with a population of at least 40,000 in 1981 and 1986-1981, 1991-1986, 1996-1991, 2001-1996, and 2006-2001 first differences. Specifications (1) attempt to recreate the specification in HGL while specifications (2) include a richer set of controls.

$*p < .10, **p < .05, ***p < .01$