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Immigrants and Patents: Evidence from Canadian Cities

Joel Blit, Mikal Skuterud, and Jue Zhang
Department of Economics
University of Waterloo

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Abstract

We examine the effect of changes in skilled-immigrant population shares in 98 Canadian cities between 1981 and 2006 on patents per capita granted to inventors residing in those cities. The Canadian case is of interest because its points system for selecting immigrants is viewed by many as a model of skilled immigration policy. Our naïve and instrumental variables estimates suggest much smaller beneficial impacts of increasing the university-educated immigrant population share than comparable U.S. estimates, whereas our estimates for university-educated natives are virtually identical. The relatively modest contribution of Canadian immigrants to innovation appears to be largely explained by the relatively low employment rates of Canadian immigrants in STEM jobs, including among those educated in STEM fields.

Keywords: Immigration; innovation; immigration policy
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1 Introduction

An important consequence 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 among economists 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 economics 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, 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 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 1 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 not only raise

[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, De Dreu, and Homan 2004), sociology (Herring 2009), management studies (Ely and Thomas 2001; Richard, McMillan, Chadwick, and Dwyer 2003), and economics.

innovation levels directly through their own patents, but also make natives more innovative, goes a long way in making the economic case for immigration.

In this paper, we begin by replicating the analysis of Hunt and Gauthier-Loiselle (2010) (hereafter HGL) as closely as possible using Canadian data. We follow the methodology of HGL for three reasons. First, HGL has attracted the most interest.[2] Second, 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 replication more feasible. Third, they find evidence of large direct and spillover effects of immigrants on U.S. patenting rates.[3] An important question for us is to what extent these large effects are evident in the Canadian data. On the one hand, the Canadian point system for screening prospective economic immigrants is often held up as a model of effective skilled immigration policy. Between the mid-1980s and mid-1990s, both the annual inflow of new permanent residents and the share of the inflow admitted under the point system more than doubled.[4] As a consequence, 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. The HGL estimates imply that this increase should have boosted Canada's patenting rate by 36-72 log points. On the other hand, comparative analyses of the labour market earnings of Canadian immigrants to their Australian and U.S. counterparts points to large and growing performance gaps, suggesting that the increase in the labour market skills of Canadian immigrants has not kept pace with the large increase in their education levels (Clarke and Skuterud 2013, 2016). An important question for us is to what extent the poor earnings performance of Canadian immigrants is evident in their relative contributions to innovation.

Relating changes in patenting rates within 98 Canadian cities between 1981 and 2006 to changes in skilled immigrant population shares, we find relatively modest effects of skilled immigration on Canadian innovation. In contrast to the HGL estimates, our estimates of the effect of increasing the university-educated immigrant share on patents per capita are positive, but relatively small and never statistically significant. 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 contribution of Canadian-born university-educated individuals to patenting rates is substantially larger than that of university-educated immigrants and virtually identical in magnitude to the HGL estimate for U.S. natives,

[2] 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.
[3] Kerr and Lincoln (2010) do not find strong evidence of spillover effects.
[4] Include precise numbers.

suggesting that the smaller magnitude of our immigrant estimates does not reflect greater measurement error in our data. Our estimates do, however, become substantially larger when we isolate the effect of university-educated immigrants who were educated in a STEM field *and* are currently employed in a STEM occupation. 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. Moreover, the relatively small Canadian estimates appear to primarily reflect the relatively low employment rates of Canadian immigrants in STEM jobs, including among those educated in STEM fields.

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 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 educational 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 underlying rational of the Canadian approach is that the human capital immigrants bring to the host country is better able to predict long-run economic success than is selecting immigrants on the basis of current local labour market needs, which are difficult to identify empirically, are often short-lived, and are 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). This has led the Canadian government to make significant policy shifts in recent years towards giving employers a greater role in immigrant selection.[5]

[5] In particular, a sufficient condition for obtaining an invitation for permanent residency in the new Express Entry system introduced in January 2015 for processing applications is having a job offer from a Canadian employer that has cleared a labour market test intended to insure that the employer was unable to fill the job domestically.

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 R&D (2.0% in Canada vs. 2.5% in the U.S. in 2006) and generates fewer patents per capita (19.9 patents per 100,000 in Canada vs. 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 that they generate less patenting spillovers on natives. However, the key question of interest for us is to what extent the historical emphasis of the Canadian immigration system on the human capital of applicants, and in particular their educational attainment levels, has resulted in Canadian immigrants 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 began more than twice as high as the U.S. (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.[6] 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

[6] 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 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, data truncation likely explains only a small fraction of this decrease.

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. There are undoubtedly 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, not only do we need more cross-sectional observations, but we also 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 Methodology

With only 10 Canadian provinces, two of which account for roughly 60% of its population (Ontario and Quebec), we examine the relationship between immigrants and patents at the city level. 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 8,448 to a high of 3,684,821, with 66 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 cases where the population shares

[7] 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.

[8] Specifically, we assume schooling is strictly continuous, so that years of schooling plus 6 identifies the age of schooling completion. Comparing this age to the age at immigration identifies whether the terminal degree was obtained in Canada or abroad. The resulting variables contain 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.

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 immigrant patent applications tend to peak roughly four years after landing.[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 patents 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 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 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

[9] To identify immigrant patents in this analysis, we used the predicted ethnicity of inventors based on inventor names, as in Kerr and Lincoln (2010). We thank Bill Kerr for creating this file using his algorithm to predict ethnicities of our Canadian inventor names.

[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.

richer set of controls intended to address the possible endogeneity of within-city changes in skilled immigrant population shares. Specifically, we estimate the equation:

$$\Delta \log\left(\frac{\sum_{j=1}^{5} patents_c(t+j)}{pop_c(t)}\right) = \beta_m \Delta\left(\frac{sm_c(t)}{pop_c(t)}\right) + \beta_n \Delta\left(\frac{sn_c(t)}{pop_c(t)}\right) + \Delta X_c(t)\delta + Z_c(1981)\theta + y(t) + \varepsilon_c(t) \quad (1)$$

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 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; $\varepsilon_c(t)$ 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.

Following HGL, we begin by estimating equation (1) including log mean age in $X_c(t)$ and both log mean income and log population in $Z_c(1981)$. 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 flows. 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]

[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

It is, of course, possible to estimate equation (1) using a fixed-effects (FE) estimator instead. With more than 2 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 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-driven 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 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 $sm_c(t)$ in equation (1) using the constructed variable:

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estimated all our models excluding Toronto. Although the naïve FD-WLS estimates do suggest substantially larger beneficial impacts of immigration, our IV estimates are almost identical to those reported in Table 5.

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

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.[12] 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 Kitchener-Waterloo (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.

A potential flaw with the standard approach described above is that changes in immigrant stock populations at the national level between Census years (that is, changes in $sm_j(t)$ in equation (2)) are influenced by both immigration inflows between Census years and outflows. While the instrument arguably does a good job of addressing endogeneity in the location choice of new immigrants (inflows), it is less able to address endogeneity in the choice of immigrants from a given stagnating city to leave Canada (outflows). For example, if KW's economy is adversely affected, some portion of the immigrants from that city might choose to leave Canada and since these immigrants would disproportionately be of German origin, the predicted immigrant shares for KW would be lower. Further, these outflows are arguably much more likely to be endogenous to latent changes in city innovation activity than inflows, since existing immigrants will tend to have better information about these changes than immigrants living abroad and they could respond immediately by leaving the country. For this reason, restricting the identifying correlation between actual and predicted changes in skilled immigrant populations to inflows

[12] 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.

of skilled immigrants seems more valid. To address this issue, we examine the robustness of our IV estimates to instead instrumenting $\Delta(sm_c(t)/pop_c(t))$ in equation (1) using:

$$\widehat{\Delta \frac{sm_c(t)}{pop_c(t)}} = \frac{1}{pop(t-5)} \sum_j \lambda_{cj}(1976) \sum_{k=1}^{5} sf_j(t-k)$$

where $sf_j(t\text{-}k)$ is the number of new economic-class immigrants originating from country j who were admitted to Canada in calendar year $t\text{-}k$. The data, obtained from Immigration, Refugees, and Citizenship Canada (IRCC), provide annual inflows of new permanent residents by immigration category (economic class, family class, and humanitarian class) and country of birth. [13] We use inflows of economic class immigrants, since it is under this program that the large majority of skilled immigrants enter Canada.

4 Results

Before examining the results of our regression analysis, in Table 1 we report 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 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

[13] We would like to thank Umit Kiziltan and Ima Okonny for making these data available to us.

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 cliché in Canada (Xu 2012). Given that the vast majority of patenting happens through corporate research and development (R&D) 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 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 also employed in a STEM occupation increased by less than 1 percentage point.

In Table 2, we examine this education-job mismatch more closely by reporting conditional probabilities of employment in a STEM occupation separately for immigrants and natives. The results reveal that not only are Canadian immigrants 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).[14] 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 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, this employment gap has grown in importance over time 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 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 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 (1) using both the HGL specification (1) and a richer set of controls (2) are reported in Table 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

[14] 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.

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 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.[15]

The second column of Table 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 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 9.0 and 5.0 for immigrants and natives, respectively, but neither estimate is statistically significant. However, using the richer set of controls increases these estimates to 26.2 and 17.0, respectively, and now the immigrant coefficient, but not native coefficient, is statistically significant at the 10% level. Taken as a whole, the results in Table 3 appear to suggest that the impact of university-educated immigration on Canadian patenting has been modest and, moreover, that this in large part due to the low employment rates of STEM-educated Canadian immigrants in STEM jobs.

In Table 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 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

[15] These results are available from the authors on request.

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 4, 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 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 (1) and (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 naïve FD estimates are downward biased, perhaps as a consequence of measurement error in the Canadian population shares. In Table 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 both stock populations based on Census data and economic immigration inflows from administrative data. In both cases, our first stage estimates are significant at the 1% level.

Using our complete sample, we define skill either broadly, as university-educated, or narrowly, as university-educated and employed in a STEM job. Basing our instrument on immigrant stock population from Census data, as HGL do, the university-educated immigrant share estimates change little and continue to suggest small positive effects. Isolating 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 3. When we base our instrument on economic-class immigration inflows alone, all of our immigrant share coefficients are smaller and none are larger than 2.1, even when we restrict attention to immigrants employed in STEM jobs. The standard errors on the IV estimates are, however, large. Nonetheless, taken together, they appear to provide evidence that the naïve Canadian estimates are, if anything, upward biased, due to immigrants settling in more innovative cities. Furthermore, the significant drop in the coefficient on immigrant shares when using the flow-based IV, suggests that the stock-based IV could be upward biased due to immigrant outflows.[16]

5 Conclusions

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 patent rates in a significant way. However, with little more than one-third of STEM-educated immigrants finding employment in STEM jobs, the impact of Canadian skilled immigration on patent rates has been relatively modest in comparison to that of U.S. skilled immigration. The fact that the employment rates of Canadian STEM-educated immigrants in STEM jobs has, if anything, tended to decrease over time, while the comparable rate for Canadian natives has been increasing, should be cause for concern among Canadian policymakers. 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 modifying the Canadian point system so as to put more weight on STEM educational backgrounds would not have the desired effect of boosting innovation. 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 STEM-employment barriers immigrants appear to face reflect differences in the skills and abilities of Canadian immigrants or labour market inefficiencies arising from information frictions in job search, foreign credential assessment, or racial discrimination. In this regard, we find it telling that STEM-educated immigrants find STEM employment less frequently than natives even when they were educated in Canada universities and that the contribution of STEM-educated

[16] 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.

immigrants from Canadian universities appears to also fall far short of the comparable contribution to innovation of native-born Canadians.

An obvious and important remaining question that arises from our findings is to what extent the smaller effects we identify for Canada reflect the relative exogeneity of Canadian immigration flows, due to relatively small role of employers in Canadian immigrant selection. An alternative interpretation of our findings is that Canadian skilled immigration is, in fact, no less effective in raising patenting than U.S. immigration, but rather that the U.S. estimates are upward biased. Ultimately, we are unable to provide any direct evidence on this question. However, our inclination is to believe that the weaker Canadian estimates are real. There are important differences in Canadian and U.S. skilled immigration policy that result in clear differences in the role of employers in the recruitment of STEM workers in the U.S. and the engagement of U.S. immigrants in corporate research and development activities in the first years after migrating. In addition, there is reason to expect the U.S. to have an advantage in competing for talent in STEM labour markets given their higher labour market returns to skill (Clarke and Skuterud 2016) and lower marginal income tax rates. In light of these differences, our modest Canadian estimates do not seem implausible. Nonetheless, it is possible that the larger U.S. estimates, at least partially, reflect relatively endogenous U.S. immigration flows. The fact that the HGL point estimates for immigrants employed as scientists and engineers are also substantially larger than our estimates for immigrants employed in STEM jobs suggests to us that the larger U.S. estimates at least partially reflect the challenges inherent in identifying causal effects using non-experimental data.

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Figure 1: University-educated immigrant population shares and patents per capita, Canada and the USA, 1980-2006

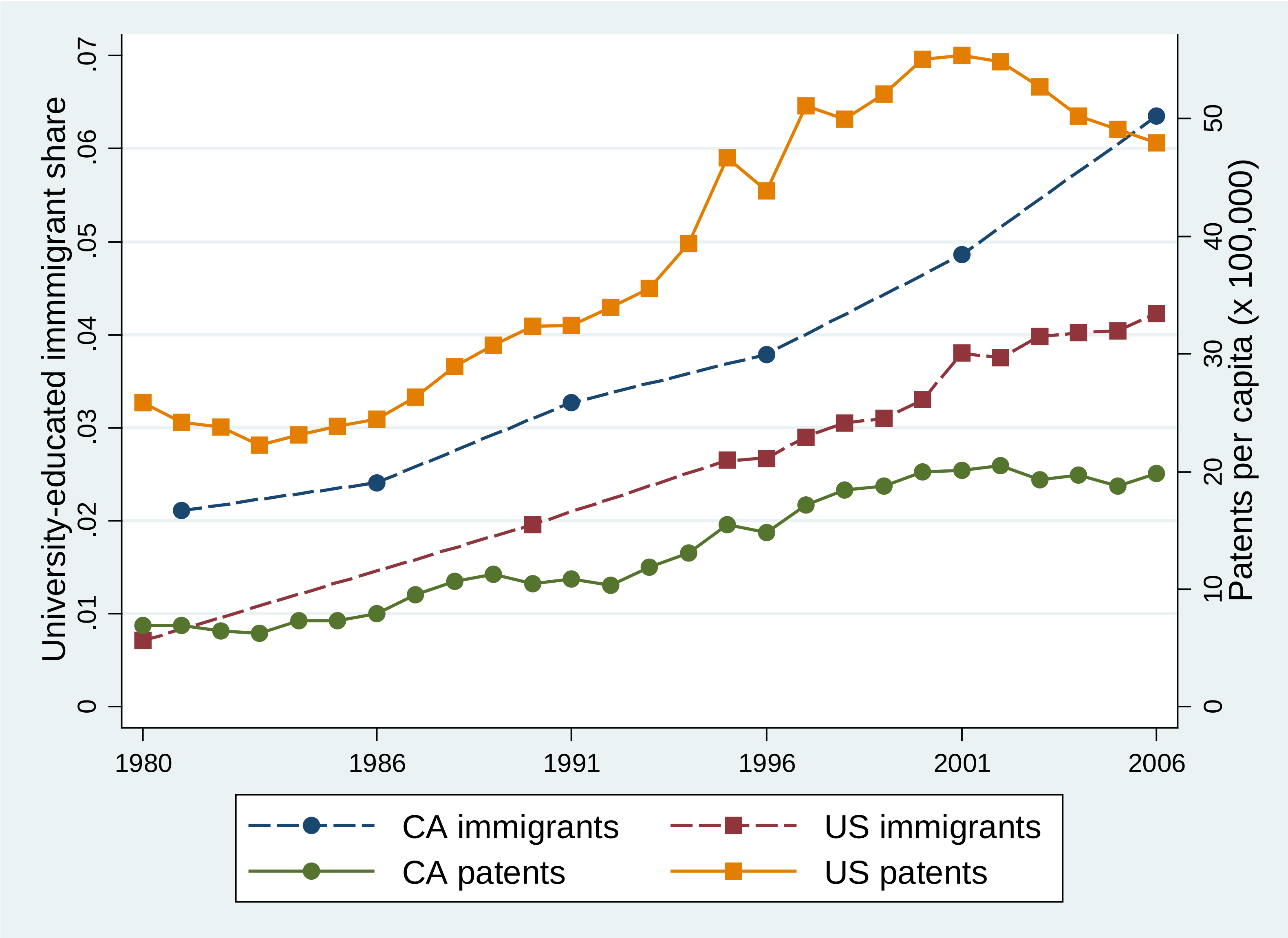

Table 1: Population-weighted sample means by Census year

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

Table 2: 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

Note: These probabilities are constructed using the mean population shares (weighted by population size) across Canada's largest 98 cities.

Table 3: 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	9.026	26.159*
	(1.677)	(2.992)	(9.795)	(14.881)
Native population share	4.457*	3.315	5.001	16.973
	(2.391)	(3.303)	(10.070)	(12.587)
Log mean age	0.494	-0.589	0.788	-0.438
	(1.257)	(1.507)	(1.233)	(1.452)
Log population (1981)	0.003	-0.006	0.006	-0.010
	(0.008)	(0.012)	(0.008)	(0.013)
Log mean income (1981)	0.053	--	-0.001	--
	(0.112)		(0.115)	
Log mean income	--	-0.028	--	-0.435
		(0.607)		(0.615)
Employment rate	--	-0.094	--	-0.137
		(1.266)		(1.261)
Log expected patents per capita	--	0.202*	--	0.230*
		(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: Observations are weighted using population sizes. Standard errors are clustered by city. *p < .10, **p < .05, ***p < .01

Table 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

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

Table 5: IV (2SLS) estimates of the effect of university-educated and university-educated-STEM-employed immigrant population shares on log patents per capita

	Census stocks IV				Economic-class inflows IV			
	University-educated		University-educated & STEM-employed		University-educated		University-educated & STEM-employed	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Immigrant population share	2.870	1.060	10.493	15.373	-0.969	-0.714	-28.152	-5.078
	(4.393)	(5.656)	(13.297)	(15.973)	(3.292)	(4.501)	(26.171)	(24.328)
Native population share	5.350	2.006	4.727	17.927	3.392	1.058	11.950	19.736
	(3.650)	(4.288)	(9.544)	(12.272)	(3.121)	(3.627)	(9.815)	(13.087)
Log mean age	0.733	-0.725	0.839	-0.545	0.209	-0.823	-0.487	-0.746
	(1.409)	(1.451)	(1.305)	(1.400)	(1.283)	(1.452)	(1.469)	(1.420)
Log population (1981)	-0.002	0.004	0.005	-0.004	0.009	0.011	0.015	0.009
	(0.015)	(0.022)	(0.009)	(0.011)	(0.011)	(0.018)	(0.011)	(0.016)
Log mean income (1981)	0.027	--	-0.006	--	0.085	--	0.130	--
	(0.107)		(0.116)		(0.112)		(0.150)	
Log mean income	--	0.121	--	-0.230	--	0.229	--	0.157
		(0.613)		(0.566)		(0.609)		(0.714)
Employment rate	--	-0.235	--	-0.268	--	-0.337	--	-0.516
		(1.251)		(1.247)		(1.263)		(1.351)
Log expected patents per capita	--	0.202*	--	0.222**	--	0.202*	--	0.209**
		(0.111)		(0.109)		(0.110)		(0.104)
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	0.285	0.331	0.284	0.339	0.284	0.329	0.259	0.330
Number of observations	490	490	490	490	490	490	490	490
First stage:								
Exp. Immigrant Share	0.622***	0.588***	0.893***	0.874***	0.515***	0.568***	0.034***	0.048***
	(0.157)	(0.144)	(0.294)	(0.186)	(0.087)	(0.091)	(0.009)	(0.010)

Notes: Estimates are from two-stage least squares. Observations are weighted using population sizes. Standard errors are clustered by city. *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'.