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

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Abstract

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

Keywords: innovation; ethnic patenting, patents, immigration, immigration policy, STEM

JEL Classifications: J24, J61, O38

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1. Introduction

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

While the root causes of Canada's productivity gap remain elusive, the solution is increasingly being framed in terms of labour market skills, and in particular the need to increase the proportion of the workforce with advanced skills in science, technology, engineering, and mathematics (STEM). For example, the government of Ontario recently announced a commitment to increase the annual number of STEM graduates from 40,000 to 50,000.[1] STEM workers are seen as having not only the cutting-edge knowledge necessary to augment and expand existing technologies, but are believed to also have the potential to create knowledge spillovers on neighbouring workers within cities, regions, and countries. Harnessing the economic growth potential of STEM workers is central to the current Liberal government's innovation agenda, which includes: plans to invest in the digital and coding skills of school-age children; skills training for the unemployed and underemployed; and policies to facilitate the recruitment of foreign workers within 10 designated occupations, all of which fall within the information and communications technology (ICT) sector.[2]

Notwithstanding the government's policy efforts, the reality is that we know little about who is driving innovation in Canada. If governments are to lever education, training, and

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[1] See Ed Clark, "Ontario can offer Amazon a deep growing pool of tech talent," *Globe and Mail*, October 18, 2017.
[2] The list includes computer and information systems managers (0213), computer engineers (2147), information systems analysts and consultants (2171), database analysts and data administrators (2172), software engineers and designers (2173), computer programmers and interactive media developers (2174), web designers and developers (2175), electrical and electronics engineering technologists and technicians (2241), information systems testing technicians (2283), and digital media designers (subset of 5241).

immigration policies to raise innovation, a first step is knowing what types of workers are contributing to Canadian innovation growth. While immigrants comprise less than one-quarter of the adult population, they represent 41% of individuals educated in STEM, 53% of individuals with a PhD degree, and 66% of STEM-employed PhDs, suggesting that they may play an important role.[3] To what extent are immigrants contributing disproportionately to innovation, and are there differences between the contributions of immigrants educated in Canada and immigrants educated abroad? Is innovation primarily being generated by Canadians educated in STEM fields and/or employed in STEM occupations? And what are the education levels of our most innovative workers?

In this article, we provide evidence on the human capital driving Canadian innovation by relating changes in the patenting rates of 11 ethnic populations over the 1986-2011 period to changes in the educational and employment characteristics of these populations. To estimate patenting rates for ethnic groups, we use the first and last names of inventors recorded in patent applications to infer inventors' ethnic backgrounds, and ancestry data from the Census and National Household Survey (NHS) to estimate ethnic populations. The resulting annual time-series data reveal higher patenting rates among ethnic minority groups, particularly Korean-, Japanese-, and Chinese-Canadians, and suggest that immigrants, while less than one-quarter of the population, account for roughly one-third of Canadian patents in recent years. The educational and employment characteristics of ethnic minorities, in particular the share with a PhD, with a STEM education, and employed in a STEM job, account in large part for these differences. Lastly, our results suggest larger contributions to patenting among the foreign-educated, relative to Canadian-educated, immigrants. This difference, which runs counter to recent immigrant selection policy reforms favouring former international students, is also evident in substantially lower STEM employment rates of Canadian-educated immigrants with a STEM education (particularly among Master's and PhD educated immigrants).

The remainder of the paper is organized as follows. In the following section, we briefly review the current literature and the Canadian evidence. In section 3, we describe our

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

methodological approach, including the data that we employ. In Section 4 we discuss our main findings and their policy relevance. Section 5 concludes.

2 Existing Literature

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

Patenting rates in Canada have historically been low, particularly in comparison to the United States. Figure 1 presents patents per capita for Canada and the U.S. between 1986 and 2011. There is a clear and persistent gap between the two countries. While some of the gap is undoubtedly explained by structural differences, such as Canada's relative industrial mix, degree of firm foreign ownership, and smaller firm sizes, identifying the human capital factors underlying the gap remains a first-order policy question.

Knowledge of the human capital characteristics of inventors (patent creators) can provide useful insights to inform both innovation and immigration policy. The most direct way to examine inventor characteristics is to analyse patent citations, which, among other things, provide information on the geographic residence of inventors (Jaffe et al., 1993), the firms they work for (Song et al., 2003), and their gender, since first names in most cultures are gender-specific (Frietsch et al., 2009; Kugele, 2010). Patents, however, provide no information on the educational or other human capital characteristics of inventors. To obtain richer information, researchers have relied on surveys of inventors using patent databases for sampling frames. The first such study by Schmookler (1957), surveyed 87 inventors who were granted U.S. patents in 1953. Since then, numerous inventor surveys have been conducted including Amasse et al. (1991) who surveyed 374 Canadian individual inventors, Giuri et al. (2007) who surveyed 9,017 European inventors, and

Walsh and Nagaoka (2009), who examined 3,658 inventors residing in Japan and 1,919 inventors residing in the United States. Typical findings in these studies are: a significant underrepresentation of women (they represent 1.1% of Canadian, 2.8% of European, 1.7% of Japanese, and 5.2% of U.S. inventors); a large fraction of inventors with tertiary education (58%, 76.9%, 87.9%, and 93.6%, respectively); and an important overrepresentation of individuals with doctoral degrees (26.0%, 12.9%, and 45.2% of Japanese, European, and U.S. inventors, respectively).

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

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

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

As noted above, there is a dearth of research on the human capital characteristics that are associated with patenting in Canada. The 1991 paper of Canadian inventors by Amasse et al., described above, is the most recent Canadian study prior to Blit, Skuterud, and Zhang (2017). Moreover, it only examines the characteristics of the minority of inventors that patent as individuals (and not as employees of a firm). The dearth of Canadian evidence presumably reflects the dearth of data. Most notably, Canada's survey of university graduates -- the National Graduates Survey (NGS) -- does not identify the patenting activity of respondents. We are, in fact, unaware of any large nationally representative Canadian survey that queries patenting activity. To further advance the Canadian evidence, in this article we examine aggregated patent rates, but rather than exploit spatial variation, as in our previous study, we use the names of Canadian inventors provided in patent applications to estimate patenting rates for different ethnic populations. We then investigate which educational and employment characteristics of these populations appear related to Canadian innovation growth, and what is the relative contribution of immigrants to Canadian patenting.

3 Methodology

We collected data on all patents granted by the USPTO between January 1986 and November 2014 and identified the subset of patents in which one or more inventors have a Canadian residential address. We use USPTO patents because they are a better measure of innovation by Canadians than Canadian Intellectual Property Office (CIPO) patents.[4] In total, we have 85,658 Canadian patents with an application year between 1986 and 2011.

While we do not directly observe the ethnicity of patent inventors, we can estimate probable ethnicities based on inventors' names reported in full in patent citations for all inventors involved in the innovation. Our data use two commercial ethnic name databases and an associated name-matching algorithm, developed and customized by Kerr (2007) for UPSTO data, to match inventors to one of nine groups: English, European (including French), Chinese, Indian, Japanese, Korean, Vietnamese, Russian, and Hispanic.[5] The matching procedure, uses the first, middle, and last names, and has been used in Kerr (2007) and Kerr and Lincoln (2010).[6] The algorithm places the largest emphasis on the surname. For example, the inventor "James Wong" is assigned to the Chinese ethnic group and "John Rodriguez" to the Hispanic group, despite both inventors having English first names. First and middle names are influential when the surname is either ambiguous or does not correspond to one of the nine groups. Kerr (2007) provides further details on the procedure, as well as summary statistics and robustness checks.[7] The match rate for our sample of Canadian inventors is 98.9%. The small fraction of unmatched names are assigned to the group "Others."

For the purpose of our analysis of Canadian inventors, we further subdivided the European group into French and non-French patents using historical records of baptismal certificates from

[4] Not only do Canadian inventors patent at much higher rates at the USPTO than they do at CIPO, there is also some evidence that CIPO patents are largely a subset of USPTO patents. As reported in Blit (2017), Canadian residents applied for 1,129 CIPO patents and 4,300 USPTO patents in 2000, and 2,937 CIPO patents and 8,903 USPTO patents in 2015. In addition, among 100 CIPO patents sampled, 93 had a corresponding USPTO patent.
[5] The Hispanic group includes Filipino, since the most common Filipino surnames are all of Spanish origin.
[6] We thank Bill Kerr for conducting this matching procedure on our data.
[7] For example, he shows that 85% of UK inventors are assigned to the English group, 74% of inventors in Hispanic countries to the Hispanic group, 88% of Indian inventors to the Indian group, 88% of Chinese and Singapore inventors to the Chinese group, 81% of Russians to the Russian group, 84% of South Korean inventors to the Korean group, and 100% of Japanese inventors to the Japanese group. The one surprise is that only 36% of Vietnamese inventors are assigned to the Vietnamese group.

Quebec Catholic parishes from the years 1621-1849[8] and a listing of the family names of individuals born in France between 1890 and 2015.[9] We classified any inventor whose last name either appeared in a Quebec historical baptismal certificate or was in the 25,000 most common surnames in France as French. To be sure, this aggressive classification results in some non-Franco European names, such as "Schmitt", being classified as French. However, we prefer, if anything, to overestimate French patenting rates, since we find French rates to be exceptionally low relative to other ethnic groups in the Canadian population.

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

In constructing our time-series of ethnic patenting rates, we assign patent years according to the year of the initial application, rather than the year in which the patent was granted, since applications will be closer in time to the creation of the intellectual property underlying the patent. However, since patent applications typically take multiple years to process and we only observe patents granted up to November 2014, our patent counts for the later application years will tend to be lower due to data truncation. Within our sample of patents granted in 2013, 58% of patents were granted within 3 years after application, 75% within 4 years, 86% within 5 years, 93% within 6 years, and 96% within 7 years. Our estimated patent counts should, therefore, be roughly 42%, 25%, 14%, 7%, and 4% lower for 2011, 2010, 2009, 2008, and 2007, respectively.

This truncation is evident in the decline in the national-level patenting rates plotted in Figure 1. To account for this truncation in the empirical estimation, we control for quadratic time

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[8] We thank Bertrand Desjardins and the Programme de Recherche en Demographie Historique for providing us with these data.

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

trends in all of our models. Our models also include a time trend for each ethnic group. These trend terms should absorb any differential growth in patenting due to ethnic groups that are concentrated in sectors with higher patenting growth, as well as the effects of institutional changes in the USPTO, which have resulted in the granting of more, and possibly lower value, patents (Jaffe and Lerner 2011).

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

The Census data files provide 20% random samples of the Canadian population. However, in 2011 the long-form Census was replaced with a voluntary survey, the NHS, which sampled one-in-three Canadian households and obtained a 68.6% response rate. We use the sampling weights provided in the NHS and Census data, which are designed to ensure the national representativeness of the samples. Table 1 shows the estimated population of individuals aged 18-70 by ethnic group for each of the Census years, in addition to the fraction of the group that are immigrants and the group's unconditional patenting rate. The growth rates in the estimated populations between 2006 and 2011 do not suggest any significant biases owing to selective non-response in the 2011 NHS. Finally, to obtain annual population estimates to combine with our annual patent counts, we linearly interpolate populations in the years between the quinquennial Census and NHS years.

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

$$\frac{patents_{et}}{pop_{et}} = \alpha + \bar{x}_{et}'\beta + \bar{z}_{et}'\delta + \phi_e + \lambda_e t + \lambda t^2 + \varepsilon_{et} \tag{1}$$

where the dependent variable is the number of granted patents with application year t filed by inventors from ethnic group e divided by the group's population in year t; $\bar{x}_{et}$ is a vector of explanatory population-share variables, which we expect to influence individuals' propensity to patent; $\bar{z}_{et}$ is a vector of control variables; ϕ_e are fixed effects for ethnic groups; t is a time trend equal to 1 in 1986; and ε_{et} is a random error. The vector of explanatory variables includes the shares of group e in year t who: hold a doctoral degree, a master's degree, a bachelor's degree, and a non-university post-secondary diploma or certificate; are educated in a STEM field; are employed in a STEM occupation; are born in Canada, are born abroad but educated in Canada, and are born and educated abroad; and are self-employed. Appendix B outlines in detail which fields of education are included in the STEM category. Our education source variables measure the share of foreign-born individuals who are educated in Canada and educated abroad (the omitted group is Canadian-born individuals), which we estimate using information on years of schooling and age at immigration. Finally, STEM employment is captured by the share that are STEM professionals and, separately, the share that are employed in technical STEM occupations. Appendix C gives a detailed discussion of the STEM occupation classification. The vector of control variables includes the male population share, average age, and the population share between 40 and 54 years of age.[10] Finally, note that we restrict the quadratic term of the time trends, intended to capture the truncation in the patent rates after 2006, to be the same across ethnic groups.

We estimate the parameters of equation (1) using a feasible generalized least squares (FGLS) estimator assuming an error-term structure with group-specific heteroskedasticity and AR(1) serial correlation with contemporaneous correlations between ethnic groups. We have also estimated equation (1) by OLS with standard errors clustered by ethnic groups. While the standard errors roughly double, the findings on which we draw our main conclusions do not change. This is also true when we assume a different error structure in the FGLS estimation. Given the considerable variation in the size of ethnic groups (see Table 1), the variance of the error term

[10] The latter "prime aged" variable was included because Amasse et al. (1991) found a disproportionate number of Canadian inventors in this age group. Adding this variable to the model yields a better fit than adding the square of the average age.

across ethnic group observations will vary considerably. We, therefore, weight our regressions by the unweighted group sample sizes in the Census/NHS data to improve the efficiency of the FGLS estimator.

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

A complication in the analysis is that the patenting rates and the ethnic minority population shares, as well as many of the explanatory variables in the model, such as the PhD population shares, are trending upwards over the sample period. To limit the possibility that our estimates are capturing spurious correlations over time, we control for group-specific time trends. Using a Levin-Lin-Chu (2002) unit root test with group-specific intercepts and linear time trends, we are able to reject the null hypothesis that the patent rates time-series contain a unit root over the years with no truncation (1986-2006).[11] Nonetheless, in the absence of valid instrumental variables for

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

the population shares in the vector $\bar{x}_{et}$, the estimated marginal effects cannot be given a causal interpretation. Some caution should therefore be exercised when inferring what the effect might be of, for example, a policy directed at raising the share of Canadians with a STEM education on Canadian patenting rates.

Finally, it turns out that the ethnic fixed effects alone account for 74% of the variation in our pooled sample of 286 ethnic patenting rates. When we also add ethnicity-specific time trends, the R-squared statistic rises to 0.88.[12] Consequently, the remaining variation used to identify the marginal effects of the education and employment characteristics is small. Moreover, the human capital variables tend to be highly collinear over time within ethnic groups. Therefore, although we would like to identify the effects of interactions of the elements in $\bar{x}_{et}$, such as the differential influence of STEM educational credentials obtained in Canada and abroad on patenting rates, we are unable to do so with any meaningful precision using our aggregated data, and therefore focus on estimating more parsimonious specifications.

4 Results

We begin our data analysis by examining the sample means of our dependent, explanatory, and control variables by Census/NHS year. The sample means, reported in Table 2, are weighted by the number of individuals in each group, so that they are representative of the Canadian population. Canada's patenting rate per capita nearly doubled between 1986 and 2011 (in spite of the undercounting of patents in 2011 due to data truncation). A number of factors, beyond changes to the institutional setting within which patents are granted and governed in the U.S., likely contributed to this large increase. First, the educational attainment of Canadians increased substantially over the period. The share of Canadians with a high school diploma or less decreased from 65% to 41%, while the share with a doctoral degree doubled. In addition, the share of the population with postsecondary credentials in STEM fields increased substantially, particularly among immigrants, as did the share of the population in professional STEM occupations (which increased from 1.7% to 3.2%).

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

The extent to which individuals educated in a STEM field are employed in STEM sectors, where R&D is concentrated, is potentially an important determinant of patenting rates. Table 3 presents conditional probabilities of being employed in a STEM occupation given a STEM education, by educational attainment, and for three groups: natives, immigrants whose highest degree was obtained in Canada, and immigrants whose highest degree is foreign. The estimates indicate that STEM-educated natives experienced the lowest rates of education-job mismatch in recent years, followed by immigrants who obtained their STEM degree abroad (first and third rows). While some of this mismatch is clearly voluntary, we would expect Canadian-born STEM-educated individuals to be most likely to opt for jobs outside STEM, since these jobs typically require stronger language and culturally-specific interpersonal skills. Thus, if anything, voluntary mismatch is likely to be masking even bigger differences in labour market mismatch between STEM-educated immigrants and natives.

The results in Table 3 also indicate that natives and immigrants educated abroad have experienced substantial improvements in matching over time, while the same is not true for Canadian-educated immigrants. The divergent experience of foreign- and Canadian-educated immigrants is most apparent at higher levels of educational attainment. Most striking is the fact that 32.9% of immigrants with foreign PhDs in a STEM field were employed in STEM jobs in 2011, compared to only 21.7% of immigrants with Canadian STEM PhDs and 23.4% of native STEM PhDs. This is as much explained by the improving education-job match rates of immigrants with foreign PhDs as by the increasing mismatch of immigrants with Canadian PhDs. In fact, in the mid-1980s, Canadian-educated immigrants with STEM PhDs had the highest job-education match rates of the three groups, but they seem to have been especially adversely affected by the dot-com crash of the early 2000s.[13] An important consideration in our analysis is to what extent the apparent labour market challenges of immigrants with Canadian STEM education are reflected in their relative contributions to patenting.

Table 1 presents our estimated patenting rates for each ethnic group and each Census year, and Figure 2 plots these for all the years in our sample (we exclude the European and Other group

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

from the figure as they are the most heterogeneous and, therefore, least interesting). The figure reveals markedly different patenting intensities across groups, with Canada's ethnic minorities making larger contributions to Canadian patenting. Almost all of the ethnic minority groups have higher patenting rates than French and English Canadians, with Koreans and Chinese having particularly high rates, especially in the most recent years.

These ethnic patenting rates, while interesting in and of themselves, also offer a glimpse into the relative contribution of immigrants to patenting in Canada. In 2011, immigrants outnumbered natives in 7 of our 11 ethnic groups, with the English-, French-, European-, and Russian-Canadians being the exceptions (see Table 1). Together, the seven majority-immigrant groups accounted for 29.1% of all Canadian patents, even though they represented only 19.6% of the population. We can obtain a better estimate of the fraction of patents that are generated by immigrants if we assume that immigrants and natives patent at the same rate within ethnic groups. This would be true if, for example, the differences in ethnic patenting rates are driven by cultural factors that are passed on across the generations, as opposed to the higher concentration of immigrants within some groups. As some suggestive evidence of the importance of cultural factors, South Korea consistently ranks as one of the most innovative countries in the world, just as Canadians with Koreans ancestry do within Canada.[14] Multiplying our ethnic patenting rates by the number of immigrants in the ethnic group, and summing the result across all groups, suggests that immigrants contributed 32.3% of Canadian patents in 2011, even though they represented only 24.8% of the population. The fact that the majority of our groups are either largely immigrants or natives implies that this estimate should be reasonably accurate even if immigrants and natives within the same group have somewhat different patenting rates. And to the extent that even within ethnic groups immigrants patent at somewhat higher rates than natives, our estimate of 32.3% will understate the actual fraction of patents that are generated by immigrants.[15]

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

[15] An alternative assumption, consistent with the view that cultural differences across groups are unimportant for driving innovation and what matters is whether individuals are immigrants (and the skills and attitudes that immigrants bring with them), is that within each group the relative patenting rate of immigrants and natives is the same as the relative patenting rate of immigrants and natives at the national level. We can then compute the immigrant share of national patenting by initially assigning equal patenting rates to all individuals within a group and computing the ensuing relative patenting rates of immigrants and natives at the national level. We then assign

Several factors could explain the higher patenting rates of Canada's ethnic minorities (and immigrants). First, as shown in Figure 3, ethnic minorities are more likely to have university degrees at all levels. The education levels of Canadians with Korean, Japanese, and Chinese ancestry are especially high in the most recent years, with nearly one-half of all Korean-Canadians and 40% of Japanese- and Chinese-Canadians being university educated. These levels reflect a substantial acceleration in educational attainment observed after 1996, which has been linked to the effects of a 1993 reform of Canada's `points system' used for screening skilled migrants, which put greater weight on university education and less on short-run occupational needs (Beach, Green, and Worswick 2007). In addition, Figure 4 reveals that the postsecondary credentials of ethnic minorities are more likely to be in STEM fields. While the fraction of individuals with a STEM education is increasing over time for most groups, the rise is particularly stark for the Chinese-, Indian-, and Korean-Canadians. By 2011, almost one-quarter of Chinese-Canadians were STEM educated and nearly 20% of Indian- and Korean-Canadians. This appears to be an unintended consequence of the 1993 policy reform, since the revised `points system' did not give preference to STEM-educated migrants. The share of Chinese individuals with a STEM occupation is also exceptionally large, reaching almost 10% by 2011. As it turns out, this steep rise in STEM degrees and occupations for Chinese-Canadians after 1996 (and a similar rise in educational attainment) closely matches the increase in Chinese-Canadian patenting rates after that year.

While the above descriptive statistics suggest a relationship between education, occupation, and patenting rates, we now turn to a formal regression analysis of our data. The first column of Table 4 shows the results when we estimate equation (1) with the ethnic fixed effects, time trends, and control variables, but without the explanatory variables. Rather than report the ethnic-specific intercepts and time trends separately, we report the difference in the (conditional) mean patenting rates of each ethnic group relative to the English group over the 1986-2011 sample period. For each ethnic group *e*, this is calculated as $\hat{\phi}_e + 13\hat{\lambda}_e$. Consistent with Figure 2, the results

this relative patenting rate between immigrants and natives to each group (instead of assuming equal patenting rates) and compute a new relative patenting rate at the national level. We continue iterating in this way until the national relative patenting rate reaches a steady state (a fixed point). This approach yields the estimate that immigrants account for 41.4% of all Canadian patents in the year 2011, though we should note that this procedure can overestimate the national patenting contributions of immigrants if the relative patenting rates of immigrants and natives within groups are on average lower than the national relative rate.

point to larger contributions of Canada's ethnic minorities on Canadian innovation. Six of the seven majority-immigrant groups (the only exception being the "Other" group) are estimated to have higher patenting rates than English-Canadians, though the difference is not significant for the Vietnamese group. The Korean estimate is the largest and indicates that, after accounting for our controls, over our sample period Korean-Canadians produced 22.14 more patents per 100,000 adults than the Anglo-Canadian reference group. This is a substantial difference given that the national-level Canadian patenting rate never exceeded 22 patents per 100,000 adults aged 18-70 in the 1986-2011 period. The estimates also point to a significant patenting advantage for Japanese- and Chinese-Canadians.

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

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

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

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

To what extent can human capital characteristics account for the higher patenting rates of ethnic minorities identified in column 1 of Table 4? For all of our ethnic groups, with the exception of Hispanics, we observe a decrease in the ethnic patenting rates differences when we include the explanatory variables in the model. The large patenting advantage of Korean- relative to Anglo-Canadians almost entirely disappears, suggesting that the human capital characteristics of Korean-Canadians fully account for their higher patenting rates. In the case of Chinese-Canadians, on the other hand, we now find appreciably *lower* conditional patenting rates compared to Anglo-Canadians, though the difference is not statistically significant. Only Japanese- and Hispanic-Canadians now exhibit substantially higher (but not statistically significant) conditional patenting rates than Anglo-Canadians.

Given the strong correlation between the PhD population shares and patenting rates identified in Table 4, we examine the patent contributions of the PhD population further by estimating separate marginal effects of PhDs with STEM education and STEM jobs, as well as for foreign- and Canadian-educated doctorates. The results are presented in Table 5. Not surprisingly, the estimates in column (1) suggest that the exceptional contribution of PhDs is entirely due to PhDs educated in STEM fields. Specifically, a one-tenth of a percentage point increase in the STEM-PhD share (which was 0.4% in 2011) is associated with an additional 2.95 patents per 100,000 individuals (an increase of 14% from the peak rate of 21.39 in 2002), conditional on the remaining population shares in the regression. Interestingly, the magnitude of the coefficient on "STEM educated" drops drastically relative to that reported in Table 4, suggesting that the relationship between patents per capita and the STEM-educated share is largely driven by STEM-educated PhDs, and not by STEM-educated individuals with lower educational attainment.

The effect of PhDs also appears to be almost entirely driven by PhDs employed in a STEM occupation. The point estimate in column (2) suggests that a one-tenth of a percentage point increase in the share of PhDs employed in STEM jobs (which was 0.12% in 2011) is associated with an additional 3.76 patents per 100,000 (an 18% increase in the peak 2002 rate). The coefficient on "STEM professional" is substantially smaller than it was in Table 4, suggesting that an appreciable portion of the relationship between patents per capita and the share of STEM professionals is due to STEM professionals with a PhD.

Finally, the estimates in column (3) of Table 4 suggest that Canadian-born PhDs are contributing the most to Canadian patenting, with a one-tenth of a percentage point increase in the share being associated with an additional 5.18 patents per 100,000. Foreign-educated immigrants with doctorates also make large and significant contributions to Canadian patenting. Conversely, the effect of Canadian-educated immigrants with PhDs is statistically indiscernible from zero. We note, as well, that the coefficient on "Foreign educated" (pertaining to immigrants with all levels of educational attainment) is also positive and significant, suggesting that the superior performance of foreign-educated immigrants also holds for lower levels of educational attainment than doctorates. This result is observed consistently across all specification and is unexpected, given that Canadian-educated immigrants are less likely to experience credential recognition issues. Across all specifications, a larger share of the population comprised of Canadian-educated immigrants is associated with a decline in patents per capita (although the coefficient is never significant), while an equivalent trade-off between foreign-educated immigrants and native Canadians appears to have a positive impact on patents per capita (and is always significant).

This could be explained by the fact that, as shown in Table 3, the share of Canadian-educated immigrants with STEM degrees who are employed in STEM jobs declined significantly through the 2000s, while at the same time, the STEM-employment rates of foreign-educated immigrants were stable. The difference in education-job mismatch is particularly stark at the PhD level where in 2006 and 2011 the STEM employment rate of foreign-STEM-educated immigrants was more than 50% higher than that of Canadian-STEM-educated immigrants. This suggests that migrant selectivity, particularly at higher levels of education, may be more important than credential recognition issues. That is, migrants who are motivated to study in Canada by the pathway to permanent residency that a Canadian PhD education provides, may be very different from migrants who complete their doctorates abroad, are then recruited by a Canadian high-tech company or university, and arrive in Canada with pre-arranged employment.

Finally, we note that in our specifications which condition on separate STEM and non-STEM PhD population shares (column 1) and with separate STEM and non-STEM occupation PhD shares (column 2), there is little to no evidence of higher patenting rates among Canada's ethnic-minority populations. This is consistent with the view that cultural factors, emphasized elsewhere in the literature, and which could produce persistent differences across generations of Canadians with varying ethnic ancestries, are not nearly as important as human capital factors in explaining ethnic differences in the innovativeness.[16]

5 Conclusions

We estimate patenting rates for eleven ethnic groups in the Canadian population and find that Canada's ethnic minorities, including both immigrants and their Canadian-born descendants, make important contributions to Canadian innovation. Given the high concentration of immigrants in these ethnic-minority populations, we infer that immigrants generate at least one-third of Canada's

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

patents, despite comprising less than one-quarter of its population. Relating changes over time in ethnic patenting rates to the human capital characteristics of the underlying ethnic populations, we find a large role for increases in STEM education and employment, and in particular, increases in the share of the population with doctoral degrees. Although we are unable to identify the precise causal links between these variables, our findings do suggest that the higher patenting rates of Canadian ethnic minorities largely reflect their education and employment characteristics, suggesting that ethnic and cultural traits, emphasized elsewhere in the literature, are relatively unimportant.

An important finding of our analysis is that Canadian-educated immigrants appear to be contributing less to Canadian patenting than their foreign-educated counterparts. This is consistent with our finding of lower STEM employment rates among STEM-educated immigrants with Canadian, as opposed to foreign, educational credentials. This difference appears especially large for individuals with a PhD and in the years following the dot-com crash of the early 2000s. These findings suggest that credential recognition issues may be less important than differences in the types of immigrants selected under various immigration programs. For example, programs that emphasize employer job offers, as opposed to Canadian educational credentials, may be more successful in identifying the types of highly educated immigrants in STEM fields that contribute most to innovation. Moreover, these findings suggest that the preference given to Canadian-educated immigrants in the Federal government's Express Entry system, and the Provincial Nominee Programs of all ten provinces, may be unwarranted.

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

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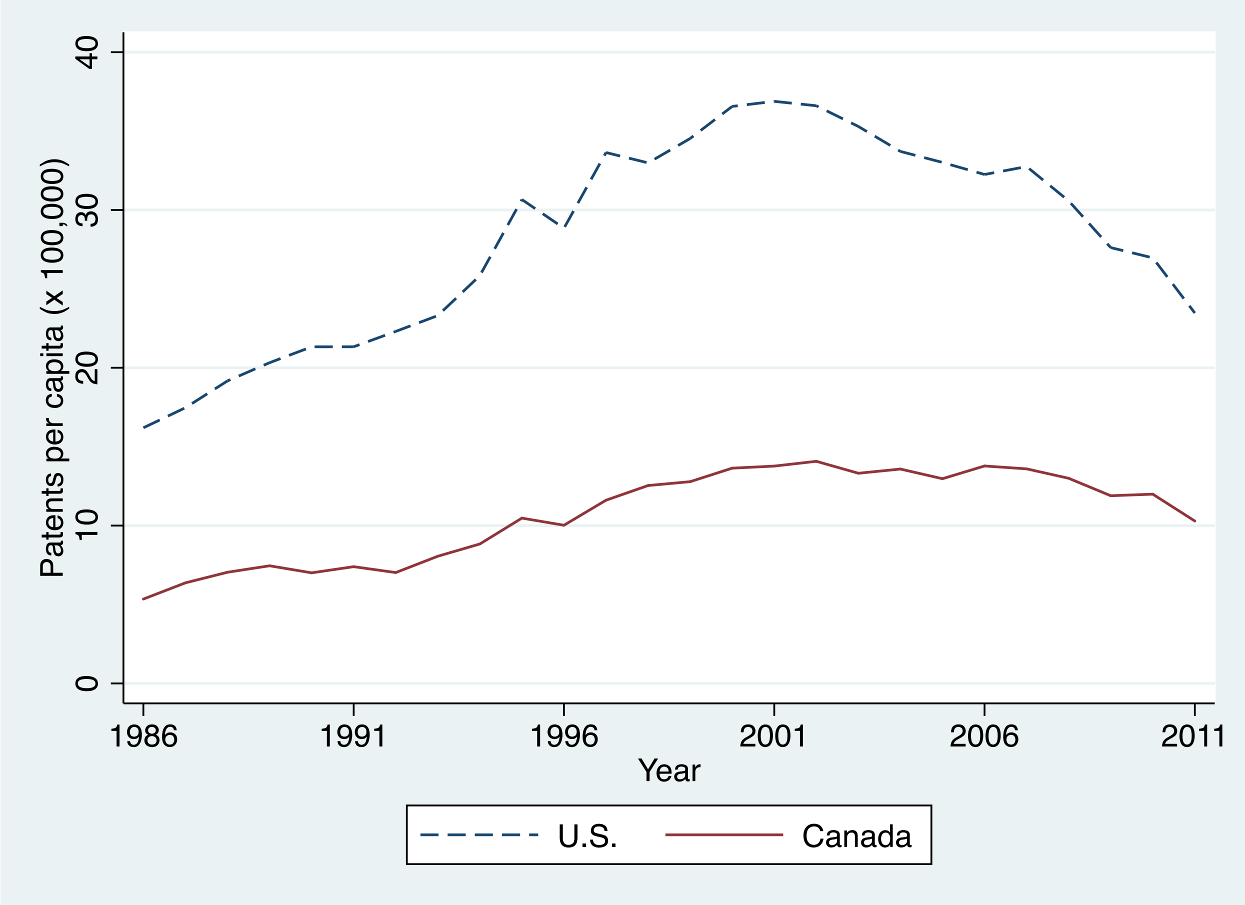
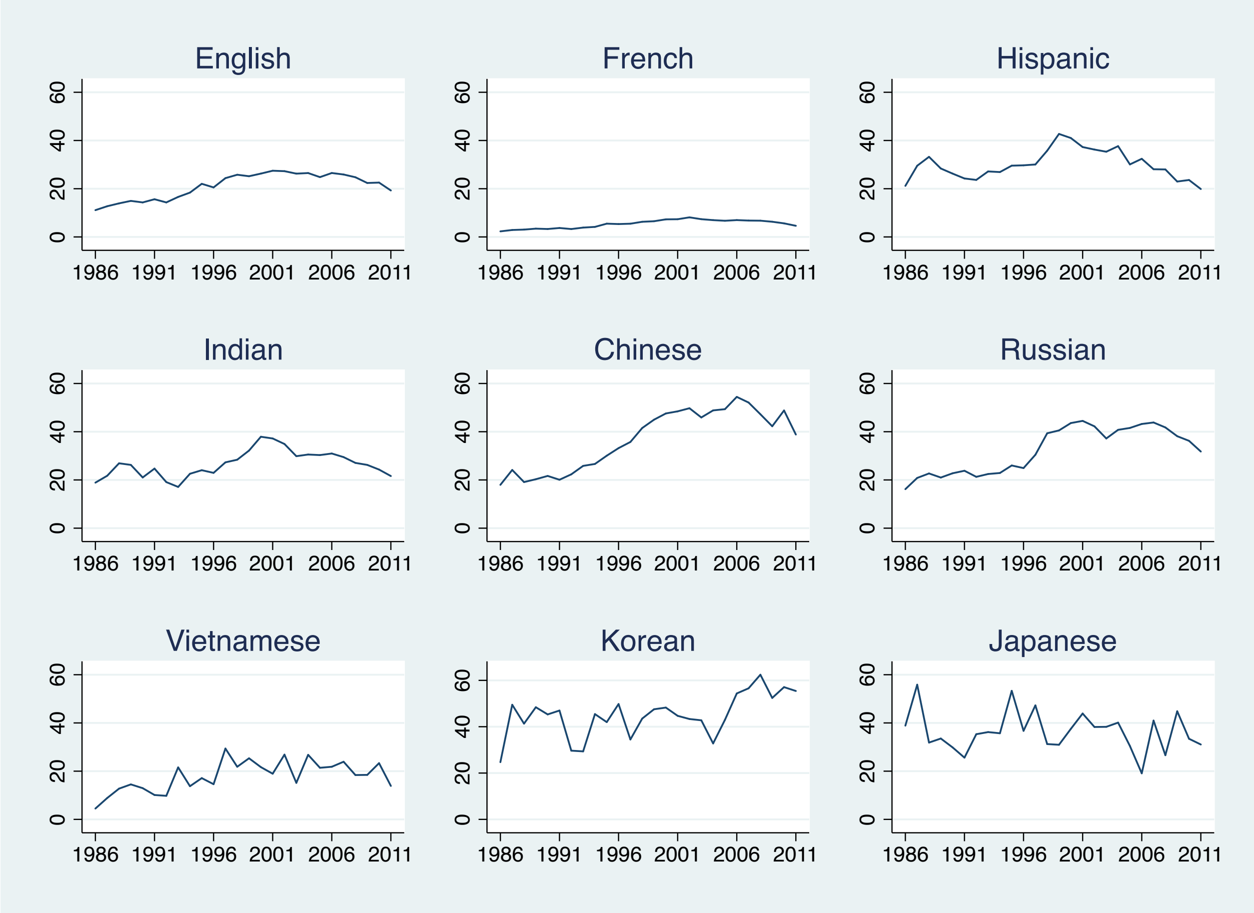
Figure 1: Patents per 100,000 population, Canada and the U.S., 1986-2011



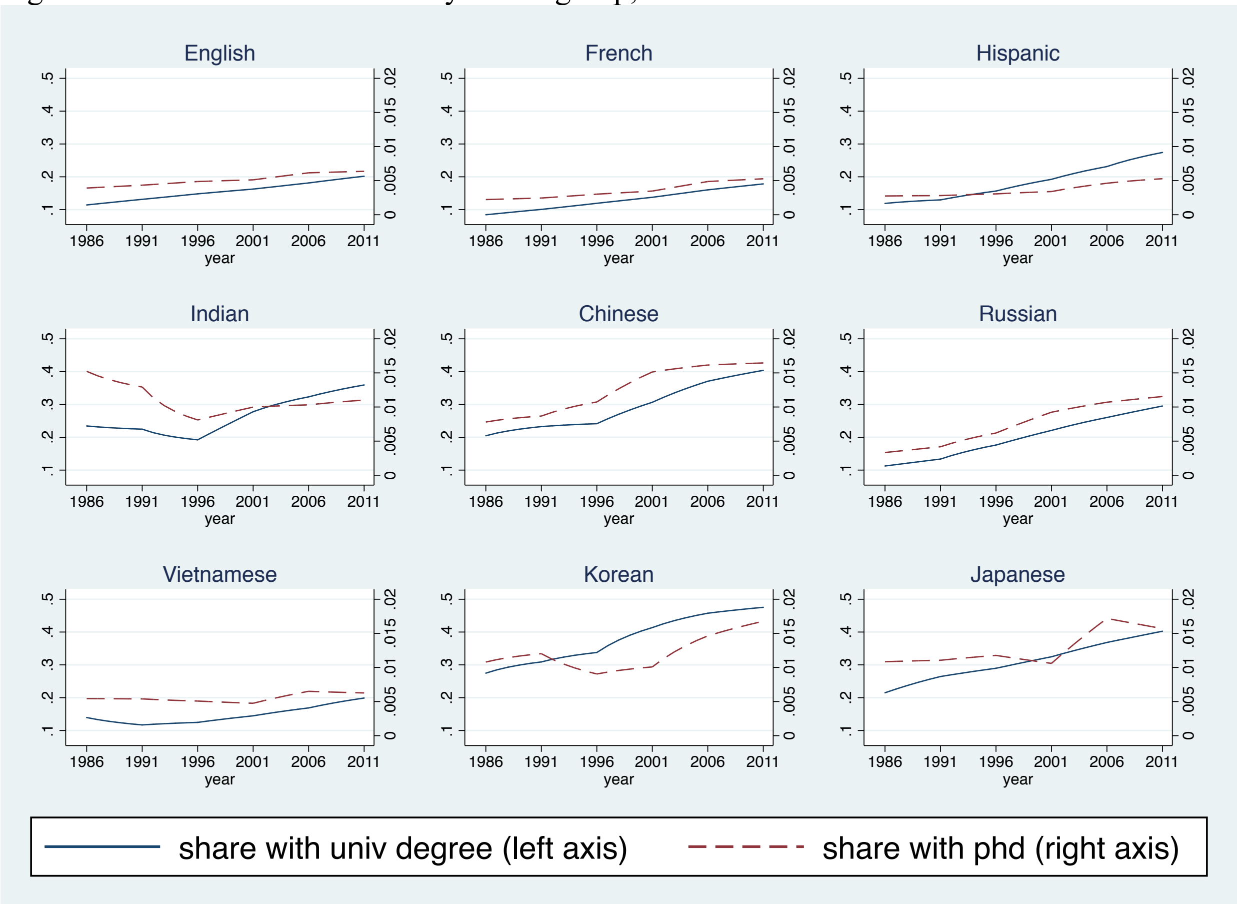
Notes: Number of USPTO patents granted to inventors residing in Canada and the U.S. per 100,000 population, by patent application year. Fractional patents were awarded to each country when the patent had multiple inventors from different countries. Population data was obtained from the World Bank World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

Figure 2: Patents per 100,000 individuals by ethnic group, 1986-2011



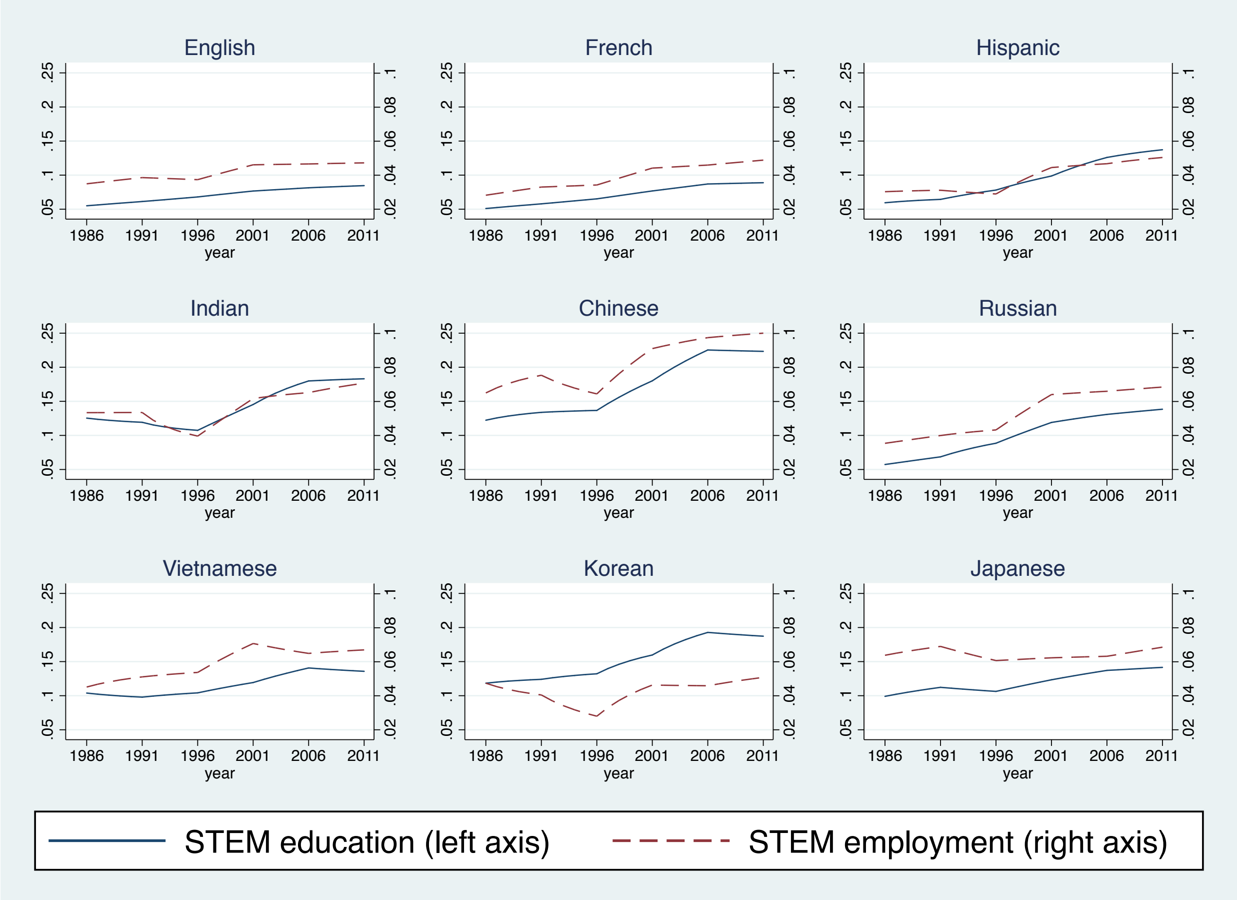
Notes: Number of USPTO patents granted to inventors residing in Canada per 100,000 individuals in each of the ethnic groups, by patent application year. Fractional patents were awarded to each ethnic group when the patent had multiple inventors from different groups and/or an inventor probabilistically matched to more than one group. Only patents granted up to November 2014 were tabulated. This truncation of the data explains the observed drop in patents per capita in the later years. European and Other ethnic groups are omitted in figure.

Figure 3: Educational attainment by ethnic group, 1986-2011



Notes: Share of each ethnic group aged 18-70 with a university degree (left-hand axis) and a doctoral degree (right-hand axis). Overall educational attainment has increased over time. For ethnic minorities, the increase accelerated after 1996, coinciding with a 1993 reform of Canada's `points system' which put greater weight on university education. The Chinese, Korean, and Japanese exhibit the highest overall levels of educational attainment. European and Other ethnic groups are omitted from the figure.

Figure 4: Share of individuals with STEM education and STEM employment by ethnic group, 1986-2011



Notes: Share of each ethnic group aged 18-70 with a STEM education (left-hand axis) and that is employed in STEM (right-hand axis). The share of individuals with a STEM education has increased over time and is particularly high among Chinese, Indians and Koreans. The fraction of individuals employed in STEM is also trending upwards with almost 10% of the Chinese group being employed in STEM by 2011. European and Other ethnic groups are omitted from the figure.

Table 1: Ethnic group population, immigrant share, and patenting rate per 100,000 individuals

	1986	1991	1996	2001	2006	2011
English	7,802,939	8,117,804	7,956,656	8,341,782	8,405,577	8,887,691
	(0.125)	(0.118)	(0.093)	(0.100)	(0.093)	(0.085)
	[11.11]	[15.63]	[20.53]	[27.45]	[26.51]	[19.27]
French	4,998,735	5,180,095	5,045,584	5,113,238	5,135,302	5,250,895
	(0.027)	(0.026)	(0.028)	(0.028)	(0.030)	(0.034)
	[2.30]	[3.70]	[5.33]	[7.35]	[6.98]	[4.62]
European	2,520,096	2,754,033	3,441,931	3,474,174	3,812,260	3,818,533
	(0.448)	(0.422)	(0.344)	(0.320)	(0.285)	(0.252)
	[6.82]	[7.94]	[9.91]	[10.99]	[10.66]	[8.88]
Hispanic	291,655	447,178	541,978	651,089	812,818	1,074,072
	(0.911)	(0.892)	(0.851)	(0.823)	(0.797)	(0.799)
	[21.18]	[24.25]	[29.70]	[37.28]	[32.41]	[19.87]
Indian	188,680	305,513	599,785	617,698	844,928	1,032,611
	(0.965)	(0.949)	(0.884)	(0.886)	(0.874)	(0.863)
	[18.87]	[24.70]	[22.94]	[37.19]	[30.95]	[21.61]
Chinese	250,384	418,028	616,455	741,139	898,024	999,725
	(0.874)	(0.897)	(0.896)	(0.882)	(0.862)	(0.843)
	[17.96]	[20.08]	[33.18]	[48.45]	[54.45]	[38.83]
Russian	378,992	386,208	514,058	552,123	637,492	668,062
	(0.134)	(0.136)	(0.128)	(0.164)	(0.199)	(0.227)
	[16.17]	[23.81]	[24.92]	[44.50]	[43.21]	[31.77]
Vietnamese	38,066	59,083	81,559	92,647	107,566	132,832
	(0.989)	(0.991)	(0.983)	(0.954)	(0.898)	(0.838)
	[4.49]	[10.11]	[14.59]	[18.94]	[21.81]	[13.87]
Korean	17,789	29,949	46,546	71,391	102,067	119,807
	(0.988)	(0.955)	(0.918)	(0.911)	(0.915)	(0.918)
	[24.69]	[46.99]	[49.78]	[44.70]	[54.37]	[55.43]
Japanese	34,454	41,714	46,548	48,534	52,928	53,590
	(0.281)	(0.382)	(0.455)	(0.483)	(0.512)	(0.535)
	[38.88]	[25.60]	[36.73]	[43.91]	[19.10]	[31.06]
Other	517,012	754,744	562,846	665,436	901,996	1,128,498
	(0.348)	(0.446)	(0.683)	(0.701)	(0.717)	(0.755)
	[2.85]	[3.33]	[8.51]	[12.79]	[12.84]	[8.95]

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

Table 2: Population-weighted sample means and standard errors by Census year

	1986		1991		1996		2001		2006		2011	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
Patents	460.2	(118.7)	652.0	(173.1)	818.4	(215.5)	1134.7	(305.0)	1072.4	(291.5)	816.0	(224.5)
Patents per capita (x 100,000)	8.17	(1.56)	11.33	(2.08)	15.29	(2.60)	21.01	(3.81)	20.67	(3.93)	15.25	(2.90)
Educational Attainment												
- High school of less	0.646	(0.006)	0.600	(0.006)	0.555	(0.008)	0.512	(0.008)	0.441	(0.008)	0.406	(0.009)
- College	0.247	(0.004)	0.273	(0.006)	0.297	(0.008)	0.314	(0.011)	0.355	(0.013)	0.362	(0.015)
- Bachelor’s degree	0.072	(0.005)	0.083	(0.006)	0.099	(0.006)	0.114	0.008)	0.132	(0.011)	0.150	(0.011)
- Master’s degree	0.032	(0.002)	0.039	(0.003)	0.045	(0.003)	0.054	(0.005)	0.065	(0.007)	0.075	(0.008)
- Doctoral degree	0.004	(0.001)	0.004	(0.001)	0.005	(0.001)	0.006	(0.001)	0.007	(0.001)	0.008	(0.001)
STEM Education												
- Canadian-born	0.042	(0.003)	0.046	(0.004)	0.052	(0.005)	0.059	(0.006)	0.063	(0.007)	0.065	(0.007)
- Immigrant educated in Canada	0.007	(0.003)	0.011	(0.005)	0.013	(0.005)	0.015	(0.006)	0.019	(0.008)	0.020	(0.008)
- Immigrant educated abroad	0.008	(0.003)	0.009	(0.003)	0.011	(0.005)	0.015	(0.007)	0.022	(0.010)	0.024	
STEM Employed												
- Professional	0.017	(0.001)	0.021	(0.002)	0.021	(0.002)	0.029	(0.003)	0.030	(0.003)	0.032	(0.004)
- Technical	0.017	(0.001)	0.018	(0.000)	0.017	(0.000)	0.021	(0.000)	0.022	(0.001)	0.023	(0.001)
Canadian born	0.812	(0.067)	0.794	(0.075)	0.784	(0.083)	0.776	(0.084)	0.762	(0.087)	0.752	(0.092)
Foreign born educated in Canada	0.071	(0.021)	0.091	(0.030)	0.095	(0.033)	0.100	(0.033)	0.107	(0.034)	0.114	(0.037)
Foreign born educated abroad	0.116	(0.047)	0.115	(0.045)	0.121	(0.050)	0.124	(0.051)	0.131	(0.054)	0.134	(0.055)
Self-Employed	0.073	(0.006)	0.078	(0.006)	0.094	(0.006)	0.094	(0.006)	0.094	(0.005)	0.084	(0.005)
Age	39.4	(0.4)	40.2	(0.4)	40.9	(0.3)	41.8	(0.4)	42.6	(0.4)	43.3	(0.5)
Middle aged	0.243	(0.005)	0.273	(0.003)	0.309	(0.005)	0.342	(0.005)	0.348	(0.005)	0.328	(0.003)
Male	0.494	(0.003)	0.495	(0.003)	0.494	(0.003)	0.493	(0.003)	0.491	(0.003)	0.492	(0.004)
Observations	11		11		11		11		11		11	

Notes: Sample means and standard errors (in parenthesis) of variables used in the regressions by Census year. The means are weighted by ethnic group population so that they are representative of the Canadian population. The reported patents per capita are the number of patents divided by the number of individuals aged 18-70, and hence not directly comparable to those presented in figure 1 where the denominator is the total population. Population shares are calculated as the fraction of individuals aged 18-70 that fall in each category.

Table 3: Conditional probabilities of STEM employment given STEM education for native and immigrants by educational attainment

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

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

Table 4: FGLS estimates of patents-per-capita regression
Dependent variable: *Patents per capita x 100,000*

	(1)		(2)	
Ethnic Group Effects				
French	-14.89***	(1.29)	-13.38***	(2.83)
European	-11.01***	(1.04)	-23.64***	(5.42)
Hispanic	8.61**	(3.46)	15.99	(14.55)
Indian	8.27**	(3.26)	4.49	(12.96)
Chinese	15.35***	(2.49)	-14.09	(16.34)
Russian	8.63***	(2.23)	6.08	(4.20)
Vietnamese	2.75	(2.55)	-34.36**	(13.45)
Korean	22.14***	(3.10)	1.27	(27.38)
Japanese	15.65***	(2.78)	13.29	(16.35)
Other	-7.75***	(2.05)	-25.80***	(7.07)
Educational attainment				
Doctorate			2020.13***	(375.60)
Master's			-687.51***	(71.73)
Bachelor's			-81.18	(93.92)
College			-11.73	(22.81)
STEM educated			165.20**	(76.27)
STEM occupation				
Professional			486.04***	(160.58)
Technical			528.69*	(294.91)
Immigrant				
Canadian-educated			-34.53	(24.21)
Foreign-educated			34.58	(22.83)
Self-employed			277.03***	(65.96)
Controls				
Age	0.56	(0.57)	-1.41	(1.06)
Prime-aged	71.73***	(11.83)	-10.62	(17.82)
Male	-29.80	(47.68)	137.03	(95.98)
Constant	-12.83	(34.57)	-21.76	(56.59)
Ethnic group time trends	Yes		Yes	
Time trend squared	Yes		Yes	
Number of observations	286		286	

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

Table 5: FGLS estimates of patents-per-capita regression with doctoral degree interactions
Dependent variable: *Patents per capita x 100,000*

	(1)		(2)		(3)	
Ethnic Group Effects						
French	-12.46***	(2.91)	-12.40***	(2.91)	-11.21***	(2.56)
European	-26.67***	(5.70)	-27.43***	(5.94)	-24.08***	(5.51)
Hispanic	5.41	(15.64)	1.85	(15.87)	16.99	(15.23)
Indian	-4.72	(14.06)	-5.73	(14.09)	1.07	(13.52)
Chinese	-26.70	(17.91)	-26.86	(17.92)	-9.51	(16.18)
Russian	6.07	(4.23)	2.95	(4.48)	4.30	(3.87)
Vietnamese	-43.59***	(14.50)	-37.97**	(14.03)	-39.30***	(13.48)
Korean	-13.19	(28.22)	-20.74	(29.13)	1.84	(26.96)
Japanese	5.30	(17.06)	4.96	(16.70)	22.71	(15.21)
Other	-28.21***	(7.34)	-24.99***	(7.19)	-24.66***	(7.68)
Doctorate						
STEM PhD	2948.17***	(677.37)				
Non-STEM PhD	-189.91	(1156.56)				
STEM occupation			3755.44***	(666.70)		
Non-STEM occupation			296.97	(787.62)		
Canadian-born					5183.04***	(1666.46)
Immigrant educated in Canada					-1505.82	(1043.18)
Immigrant educated abroad					3022.98***	(612.10)
Educational attainment						
Master's	-674.19***	(72.49)	-574.97***	(83.45)	-579.92***	(75.92)
Bachelor's	-22.00	(100.27)	5.96	(102.41)	-163.29*	(92.45)
College	7.04	(24.44)	7.71	(23.36)	-39.52	(24.89)
STEM educated	38.19	(104.18)	130.64*	(78.93)	154.15*	(81.85)
STEM occupation						
Professional	525.15***	(156.41)	291.71*	(164.46)	501.76***	(167.83)
Technical	663.73**	(322.16)	806.32***	(303.98)	478.62*	(289.10)
Foreign born						
Canadian educated	-24.60	(25.25)	-12.32	(25.08)	-17.74	(24.81)
Foreign educated	52.20**	(24.79)	46.42*	(25.41)	51.79**	(21.93)
Self-employed	313.72***	(66.45)	302.47***	(68.68)	324.63***	(60.28)
Controls						
Age	-1.85*	(1.10)	-1.02	(1.10)	-1.94*	(1.06)
Prime-aged	-4.46	(17.76)	3.77	(18.83)	-40.24**	(17.32)
Male	126.44	(93.39)	94.70	(98.22)	182.28**	(91.88)
Constant	-7.32	(56.65)	-32.78	(58.48)	-16.09	(57.66)
Ethnic group time trends	Yes		Yes		Yes	
Time trend squared	Yes		Yes		Yes	
Number of observations	286		286		286	

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

Appendix A: Ethnic Populations

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

Our ethnic population estimates for Census year is reported in Table 1. The estimates are based on Census and NHS questions on ethnicity and mother-tongue. The exact ethnicity question varies slightly by Census year. From 1986 to 2001 the question was "To which ethnic or cultural group(s) did this person's ancestors belong?"[17] For 2006 and the 2011 NHS, it was "What were the ethnic or cultural origins of this person's ancestors?" Table A1 shows which ancestral ethnicity reported in the Census are mapped to each of our 11 ethnic groups.

Table A1 Mapping of Census ancestral ethnicities to the 11 ethnic groups

Ethnic group	Ancestral ethnicities as reported in the Census and NHS
ENGLISH	English, Irish, Scottish, Welsh, British, American, Cornish, Manx, Australian, New Zealander, Bahamian, Bermudan, St. Lucian, Grenadian, Caribbean, Caribbean Black, West Indian, Trinidadian, Tobagonian, Vincentian, Belizean, Kittitian/Nevisian, Jamaican, Antiguan, Montserrantan, St.Lucian
CHINESE	Chinese, Taiwanese
HINDI	Bengali, Gujarati, Punjabi, Tamil, Sinhalese, Bangladeshi, Indian, Pakistani, Sri Lankan, Indo-Pakistani, East Indian, Sinhalese, Goan, Hindu, Kashmiri, Nepali, Khmer, Kashmiri, South Asian, Sikh
RUSSIAN	Ukrainian, Russian, Byelorussian
HISPANIC	Spanish, Hispanic, Portuguese, Filipino, Argentinean, Chilean, Cuban, Dominican, Ecuadorian, Peruvian, Brazilian, Mexican, Puerto Rican, Colombian, Salvadorean, Nicaraguan, Guatemalan, Uruguayan, Paraguayan, Uruguayan, Venezuelan, Honduran, Panamanian, Costa Rican, Bolivian, Other Latin/Central/South American, Central/South American Indian, Aboriginal Central/South American

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

FRENCH	French, Acadian, Franco-Ontarian, Franco-Manitoban, French Canadian, Haitian, Martinique, Martinican
EUROPEAN	European, Belgian, Dutch, Danish, Icelandic, Norwegian, Swedish, Scandinavian, Finnish, German, Austrian, Magyar(Hungarian), Swiss, Czech, Slovak, Slav, Kosovar, Czechoslovakian, Estonian, Lettish, Lithuanian, Polish, Romanian, Hungarian, Croatian, Serbian, Slovenian, Albanian , Macedonian, Bulgarian, Italian, Greek, Other European, Bulgar, Latvian, Maltese, Flemish, Yugoslav, Cypriot, Basque, Luxembourger, Frisian, Hutterite, Sicilian, Bosnian, Montenegrin, Afrikaner, Mennonite, Doukhobor, Gypsy
JAPANESE	Japanese
KOREAN	Korean
VIETNAMESE	Vietnamese
OTHER	Palestinian, Egyptian, North African Arab, Syrian,Cambodian, Laotian, Malaysian, Burmese, Thai, East/Southeast Asian, Singaporean, Mongolian, Turk, Armenian, Tibetan, Indonesian, Fijian, Polynesian, Other Pacific Islanders, Lebanese, Israeli, Guyanese, Ghanaian, Ethiopian, Somali, Maghrebi, Iraqi, Moroccan, Afghan, Kurdish, Berber, Algerian, Tunisian, Jordanian, Kurd, Ismaili Muslim, East African, South African, Tanzanian, Ugandan, Eritrean, Mauritian, Sudanese, African (Black), Nigerian, Kenyan, Rwandan, Zairian, Burundian, Assyrian, Kuwaiti, Libyan, Georgian, Tartar, Pashtun, Barbadian, Hmong, Maori, Hawaiian, Ugandan, Gambian, Angolan, Yoruba, Khmer, Samoan, Oromo, Seychellois, Sundanese, Cameroonian, Senegalese, Akan, Ashanti, Congolese, Guinean, Ivorian, Malagasy, Malian, Sierean Leonean, Togolese, Zimbabwean, Burundian, Afrikaner, Amhara, Bantu, Chadian, Dinka, Gabonese, Harari, Ibo, Ivorian, Peulh, Sierra Leonean, Tigran, Zambian, Zulu, Kuwaiti, Maghrebi, Azerbaijani, Pashtun, Tatar
AMBIGUOUS ETHNICITIES	Canadian, New Brunswicker, Newfoundlander, Nova Scotian, Ontarian, Quebecois, Other provincial or regional origins, Other North American origins, Black, Jewish, First Nations, Inuit, Metis

Some ancestral origins are too ambiguous to be classified to one of the 11 ethnic groups (see the last row of Table A1). For example, many individuals list their ethnic origins as being "Canadian." For these ambiguous cases, we use the reported mother tongue. Table A2 provides details on which mother tongues are mapped to each of the ethnic groups. For example, individuals of Canadian origin are grouped into the English group if their mother tongue is English, and are grouped into the French group if their mother tongue is French.

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

Table A2 Mapping of ambiguous ethnicities by mother tongue

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

Appendix B: STEM Field of Study

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

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

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

Appendix C: STEM Employment

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

The STEM occupation includes professional and technical occupations. According to Table C2, STEM professional occupations include those in the category `C0- Professional Occupations in Natural and Applied Sciences', `A12 Managers in Engineering, Architecture, Science and Information Systems'. STEM technical occupations include `C1 -Technical Occupations Related to Natural and Applied Sciences'.

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

Table C2 STEM occupation: National Occupational Classification for Statistics 2001 (NOC-S 2001)

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

C16	Other Technical Inspectors and Regulatory Officers
C17	Transportation Officers and Controllers
C18	Technical Occupations in Computer and Information Systems