Immigration and Firm Productivity: Evidence from the Canadian Employer-Employee Dynamics Database

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Abstract

Previous studies on the impact of immigration on productivity in developed countries remain inconclusive, and most analyses are abstracted from firms where production actually takes place. This study examines the empirical relationship between immigration and firm-level productivity in Canada. It uses the Canadian Employer-Employee Dynamics Database that tracks firms over time and matches firms with their employees. The main analyses are based on the relationship between the changes in the share of immigrants in a firm and firm productivity, whereas the change is measured alternatively over one-year, five-year, and ten-year intervals. The study includes only firms with at least 20 employees in a given year in order to derive relatively reliable firm-level measures. The results show that the positive association between changes in the share of immigrants and firm productivity was stronger over a longer period of changes. The overall positive association was small. Furthermore, firm productivity growth was more strongly associated with changes in the share of recent immigrants (relative to established immigrants), immigrants who intended to work in non-high skilled occupations (relative to immigrants who intended to work high-skilled occupations), and immigrants who intended to work in non-STEM occupations (relative to immigrants who intended to work in STEM occupations). These patterns held mostly in technology-intensive or knowledge-based industries. The implications of these results are discussed.

1. Introduction

The effect of immigration on the receiving country's economy is an issue of intense policy and academic discussions. Previous US and European studies find that the impacts of immigration on GDP per capita, the fiscal balance, and the wages of native-born workers, are generally small, either positive or negative (Borjas 2003; Card 2005; Ottaviano and Peri 2012). A few Canadian studies have also touched on this issue, and the results are mixed (Aydemir and Borjas 2007; Fung, Grekou and Liu 2017; Picot and Hou 2016; Tu 2010). Most previous studies in this area commonly treat immigrants as a shift in labour supply in labour markets, where the labour markets are often defined as local areas, the combination of local areas and industrial sectors, or the combination of worker's education and experience profiles in a national labour market (Kerr, Kerr, and Lincoln 2013). While each of these approaches faces specific methodological challenges (e.g., Dustmann and Preston 2012), a common limitation is that these analyses are abstracted from firms where production actually takes place and employment decisions are made.

An emerging, yet still scant, body of studies has examined the effect of immigration on firm productivity in the US and some European countries. These studies suggest that immigration can either negatively or positively affect the receiving country's productivity. On the one hand, if a large supply of immigrant labour reduces employment costs, the labour factor of production becomes more intensive in an economy and labour productivity may fall. This may be particularly evident if there is a large increase in the supply of lower-skilled immigrants; this reduces the costs of less skilled labour, and encourages firms to become more labour rather than capital intensive, thus reducing labour productivity. On the other hand, if immigrants bring skills that are complementary to domestic-born workers, or highly educated immigrants are more innovative than the domestic-born, perhaps because of the fields of study in which they are trained (as in the U.S.), the increase in immigration may increase specialization both within the firm and across firms in a local labour market, and stimulate innovation and the adoption of new technology in the firm, all of which are major drivers of labour productivity. Therefore, the increase in immigrant labour may affect firm productivity both directly through altering the factors of productions, investment, and innovation activities in the firm, or indirectly through changing the industrial structure in a local labour market.

This study examines the empirical connection between immigration and firm-level productivity in Canada. Using the Canadian Employer-Employee Dynamics Database (CEEDD), this study follows individual firms over time, and attempts to assess whether an increase in the share of immigrants by various characteristics leads to an increase in firm productivity.

2. Previous studies on immigration and productivity

Like the general literature on the effect of immigration on native-born workers and the receiving-country economy, empirical studies on the extent to which immigration may contribute or impede productivity growth in Western developed countries remain divided. The results of previous studies tended to vary with the receiving countries, the characteristics of immigrants, industrial sectors, and the length of observation period used to measure changes in immigrant labour supply and productivity growth.

The characteristics of immigrants in terms of education, fields of study and occupational skills are often considered to have differential effects on productivity. For instance, recent American research finds that highly educated immigrants are more likely to be involved with innovation than their American-born counterparts, as measured by the number of patents filed and commercialized (Hanson 2012). This immigrant advantage is largely due to the fact that they are more likely to be in the fields that promote such innovation (e.g. engineering, science and IT). Similarly, Ghosh, Mayda, and Ortega (2014) show that firms that conduct R&D and are heavy users of H-1B migrants would gain in average labour productivity, firm size, and profits from increases in H-1B visas. In comparison, Lewis (2011) found that manufacturing plants in metropolitan areas experiencing faster growth in low-skilled immigrant labours adopted automation technology more slowly in the US. The implication of the results is that firms may adapt to less-skilled immigration by make greater use of less-skilled intensive production methods. Quispe-Agnoli and Zavodny (2002) observed that productivity increases at a lower rate in states that experience higher levels of low-skilled immigration in the US.

The effect of immigrants could also vary by the type of industries (e.g., high- vs. low-tech industries, manufacturing vs other sectors). For instance, Paserman (2013) showed that, during the 1990s, the immigrant share in a firm was strongly negatively correlated with firm productivity in low-tech manufacturing industries in Israel. However, in high-technology manufacturing industries, the relationship was mostly positive, implying complementarities between technology and the skilled immigrant workforce. Kangasniemi et al. (2012) also observe large heterogeneity across industries sectors in the U.K. and Spain in the effect of immigrants on productivity over the 1996-2005 period. They found that finance, real estate and business services, and hotels and restaurants experienced the most negative overall effects. However, Quispe-Agnoli and Zavodny (2002) observed that immigration results in lower labour productivity in both low skilled and high skilled sectors in the US. Based on sectoral level analysis across 12 European countries, Huber et al. (2010) found that immigration on the whole had little effect on productivity, but high-skilled migrants seem to increase productivity in skill-intensive industries.

The time span of the observation period may also matter. Kangasniemi et al. (2012) found a positive relationship between immigration and total factor productivity in the long run, but not in the short run. They suggest that innovation and the complementarity between migrant workers and other inputs are likely to occur over time rather than as an instantaneous response to annual changes in the migrant labour supply. Quispe-Agnoli and Zavodny (2002) attribute the negative effect of immigration on productivity observed in their study to problems of immigrant assimilation; and they argue it could disappear as immigrants improve their language and social skills. Indeed, using a longer period and state-level data, Peri (2012) found that immigration was significantly and positively associated with total factor productivity growth in the US.

Major methodological difficulties in studying the impact of immigrants at the firm level include unobserved factors that may simultaneously drive productivity and the presence of immigrants in a firm, and endogeneity. Selective sorting of high-(or low-) productivity firms and immigrants across local labour markets may lead to a spurious correlation between the population size of immigrants and productivity levels of the firms in those markets. Similarly, within a local labour market, immigrants may be selectively sorted into different firms. Some studies took advantages of some large and sudden increases in immigrants to deal with endogeneity. For instance, Paserman (2013) explored the impact of the large and sudden influx of high-skilled immigrants from the former Soviet Union to Israel. In the absence of such "natural experiments", various estimation techniques have been used in the previous studies, including shift-share instruments based on initial spatial distribution of immigrants, fixed effects estimation, and internal instruments constructed from lagged variables (Mitaritonna, Orefice and Peri 2017; Paserman 2013).

The basic analytical approach of this study is to determine the relationship between the changes in the share of immigrant employment in a firm and the firm's labour productivity, after accounting for time-invariant omitted variables at the firm level, regional and sectoral shocks to productivity growth, and some key time-variant predicators of firm productivity. The changes are measured alternatively at one-year, five-year, and ten-year intervals to distinguish possible short-term vs long-term associations. Instrumental variable estimates will also be explored to deal with endogeneity.

This study also considers the effects of immigrants by length of stay in Canada, education, language, and immigration class. Economic class principle applicants, who are selected for economic reasons, may have a stronger effect on productivity growth than other immigrants. By focusing on economic class principle applicants, we also have information about the skill level of their intended occupations and can identify intended STEM workers.

This study further examines the effect of immigrants on firm productivity by industry sectors in terms of technological intensity and knowledge use.

3. Data and Methods

3.1 Data

This study uses three linkable data files at Statistics Canada. The first file is the T2-LEAP longitudinal database. The T2 file refers to the Corporate Tax Statistical Universal File. It includes all incorporated firms that file a T2 tax return with the Canada Revenue Agency. It provides data on, among other things, sales, gross profits, equity and assets for all incorporated firms in Canada. The LEAP – Longitudinal Employment Analysis Program – is an administrative databank that combines information from administrative tax records, the Business Register, and the Survey of Employment, Payrolls and Hours (SEPH) to derive the employment profile of businesses over time. The LEAP contains annual employment, annual payroll and industry for every employer in Canada at the national level. This study uses the T2-LEAP to derive firm-level productivity and other firm level characteristics originated from the T2 File.

The second file is the Longitudinal Worker file (LWF) which is constructed from four administrative sources: the T1 and T4 tax files of Canada Revenue Agency, the Record of Employment (ROE) files of Employment and Social Development Canada, and the Longitudinal Employment Analysis Program (LEAP) (see Chan, Qiu and Morissett 2017). It contains the records of all workers in a firm, which allows the computation of firm-level compositions by workers' characteristics. It also contains a firm's longitudinal ID which can be used to link with the T2-LEAP file.

The third data source is the Immigrant Landing File (ILF), which includes sociodemographic characteristics at landing for immigrants who arrived in Canada since 1980. This study uses the ILF to identify immigrants and their characteristics including year of immigration, education, language, admission class, and intended occupation and the skill level of the intended occupation.

The ILF is first linked to LWF using individuals' ID as the linking key. With the linked ILF-LWF file, the share of immigrants by various characteristics can be aggregated to the firm level. The derived firm-level data file with immigrant composition information is further linked to T2-LEAP. The combined firm-level data file with productivity, immigrant composition and other covariates is the final data set used in this study.

Since ILF only includes immigrants who arrived in Canada since 1980, immigrants who arrived before 1980 cannot be identified in the data. To reduce the impact of this limitation, this study uses data points from 2000 on, and defines immigrants as those who have stayed in Canada for 20 years or less.[1] This definition is kept consistent from 2000 to 2015 which is the most recent year for which all the data components are available.

The analysis is further restricted to firms with at least 20 employees in a given year. The exclusion would affect a large number of firms and disproportionately immigrants. This is because about 90% of firms have a work force less than 20, and immigrants are more likely to work in small firms than non-immigrants (Fund, Grekou and Liu 2017; Kanagarajah 2006). However, about 80% of the total employment are distributed in firms with at least 20 employees. More importantly, the exclusion of smaller firms would increase the reliability of derived firm-level measures, particularly the share of immigrants by various characteristics. The study further excludes firms in the agriculture and mining sector as the data on capital and tangible assets are incomplete for those two sectors. It also excludes the public administration sector as there is no direct measure of productivity for the sector. The yearly data from merging T2-LEAP with LWF-IFL files yield 61,658 firms in 2000 to 84,061 firms in 2015. In regression analysis, the top 0.5% firms with the highest value-added productivity are excluded to reduce the influence of outliers.

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[1] Immigrants who had been in Canada over 20 years are treated as part of the non-immigrant population. Most immigrants who passed prime working ages (say, 45 or over) upon arrival would no longer be in the workforce 20 years after immigration. Thus, it should not matter whether these immigrants are treated as non-immigrants. Immigrants who arrived at prime working ages (say 20 to 44) would generally have similar economic outcomes as the native-born workers (Picot and Hou 2016), so treating them non-immigrants is not problematic. Immigrants who arrived as young children generally have higher educational levels and likely have a higher level of entrepreneurship when they grow up than their native-born counterparts (Bonikowska and Hou 2010; Kerr and Kerr 2016). Therefore, treating them as non-immigrants would likely underestimate the overall economic contribution of the immigrant population. However, from the perspective of immigrant selection, the economic outcomes and contributions of recent adult immigrants are of direct policy implications.

3.2 Measures

Firm level labour productivity is measured by value added output divided by labour input. Value added is computed as the sum of personnel cost (payroll from all T4 slips issued by enterprise) and profit (net non-farm income). Value added is adjusted for inflation for comparison over time. Labour input for each firm is estimated as its annual average employment derived from dividing total payroll by the average annual earnings (AAE) of a typical worker in the firm's particular 4-digit industry, province and enterprise size class, where AAE are derived using information from Statistics Canada's Survey of Employment, Payrolls and Hours (Lafrance and Leung 2010). An alternative productivity measure is total revenue (the sum of sales of goods and services and other revenues, such as interest income) divided by labour input. The results based on this alternative measure are generally in the same direction as, but tended to be somewhat weaker than the ones based on our chosen measure (results are available upon request).

Labour productivity can increase as a result of increases in capital-labour ratios. To control for the effect of capital-labour ratio on labour productivity, we use total tangible assets (building and machinery and equipment), deflated by industry capital stock deflator as a measure of capital for a firm.

In addition to the share of immigrants as the main independent variable, this study further splits immigrants into subgroups by seven characteristics: (1) Length of residence in Canada: recent immigrants (those who have been in Canada for 10 years or less) versus established immigrants (in Canada for 11 to 20 years), (2) Official language: immigrants who mother tongue is English or French versus other mother tongues; (3) immigrant class: skilled principal applicants versus immigrants in other admission classes; (4) skill level: immigrants who intended to work in managerial or professional occupations versus other immigrants; (5) intended STEM occupations: Immigrants who intended to work in Science, Technology, Engineering, and Math (STEM) occupations versus non-STEM immigrants; and finally, (6) education: university-educated immigrants versus immigrants without a university degree.

3.3 Methods

The analysis starts with simple correlations between yearly or multi-year changes in the share of immigrants and corresponding changes in firm labour productivity over the 2000-2015 period. Multivariate models are constructed to examine this correlation controlling for changes in firm capital-labour ratio, year, province and industry fixed effects. Further analysis will be conducted to address endogeneity issues.

The multivariate analysis takes the following general form:

$$Y_{f,t} = \beta^{*}IM_{f,t} + v^{*}X_{f,t} + \phi_{f} + \rho_{j,t} + \eta_{i,t} + \varepsilon_{f,t}$$

where $Y_{f,t}$ is labour productivity (value added per unit of labour) for firm f in year t. In multivariate models, the logarithm of value-added productivity is used, although models are also run with the actual value as the outcome to check the sensitivity of the results. $IM_{f,t}$ represents the share of immigrants or the shares of sub-groups of immigrants (e.g., by length of residence, language, education, etc.) employed in year t by firm f. $X_{f,t}$ is the capital-labour ratio in a firm. A vector of firm fixed effects ϕ_f is included to control for time-invariant differences across firms. The model also controls for province-year $\rho_{j,t}$ and industry-year fixed effects $\eta_{i,t.}$ for 89 industries according to 3-digit codes of the North American Industry Classification System (NAICS). The province of a firm is defined by the location of its headquarter. The industrial sector i for each firm is defined as the industry in which the firm employs the most workers in the initial period.

To eliminate the firm-fixed effects, the first-difference of the above equation is taken,

$\Delta Y_f = \beta^*\Delta IM_f + v^*\Delta X_f + \rho_j + \eta_{i,} + \xi_f$

In the first difference model, a variable representing changes in the firm employment size is also included as a control (i.e. part of ΔX_f in addition to change in firm capital-labour ratio). It is possible that a change in the share of immigrants is related to the changes in a firm's overall employment size. For instance, firms with growing productivity may hire more workers and immigrants are likely over-represented in the new hires because they have a higher rate of unemployment or underemployment and lower reservation wages. Conversely, firms with declining productivity may layoff disproportionately more immigrant workers because they tend to have shorter tenures or lower seniority in the firm.

With the first-difference models, this study first tests the sensitivity of the results to the choices of different length of periods for computing the changes: one year (e.g. between 2000 and 2001) to 10 years (e.g., between 2005 and 2015). The results show that the longer the period, the stronger the correlation between the changes in firm productivity and the share of immigrants. For this paper, only the results based on one-year, five-year, and ten-year changes are presented in this study. The results for other different lengths generally lie somewhere in between the represented results.

For the analysis with one-year lag, 15 panels (e.g., 2000-2001, 2001-2002, … 2014-2015) of first differences are pooled together. For the five-year lag, 11 panels (e.g., 2000-2005, 2001-2006, … 2010-2015) of first differences are pooled together. Similarly, for the ten-year lag, 6 panels (e.g. 2000-2010, 2001-2011, … 2005-2015) are pooled together. The corresponding panel (or period) fixed effects are added to the first-difference models. Since a same firm could appear multiple times in these pooled data, cluster standard errors at the firm level are estimated. All models estimates are weighted by the log of the firm's average employment size in the initial and end years. The weights in the first-difference estimations implicitly give more weight to larger firms and emphasize more reliably measured observations. The results are generally similar to those without using weights in the estimation.

We first run Ordinary-least Squares (OLS) models based on change scores for all industries (excluding the agriculture and mining sector, and public sector) as a whole. We then split the industries by industry technology and knowledge intensity. The definition of technology industries is based on a classification developed by Hecker (2005) of US Bureau of Labour Statistics. He considered an industry as high Tech if the share of employment in scientific, engineering, and technical occupations in that industry is at least twice the average for all industries in the US. Following this definition, 44 four-digit NAICS industries are classified as high tech industries. Knowledge-based industries are defined by an industry's research and development activity and the educational attainment of its workforce, and include 22 four-digit

NAICS industries covering engineering and science-based manufacturers, telecommunications, data processing, computer systems design, and consulting services (Government of Canada 2000). Most, but not all, of knowledge-based industries are also technology-intensive industries.

The above Ordinary-least Squares regression based on first-differences may still be affected by endogeneity. It is possible that firms with growing productivity may be likely to hire more workers and immigrants are over-represented among new employees because they are the main source of new labour supply. Particularly, new immigrants have lower employment and higher employment rates than Canadian born workers and thus have lower reservation wages. Firms with declining productivity may lay off disproportionately more immigrants because immigrants tend to have shorter tenures or lower seniority.

As a way to deal with endogeneity, this study uses an instrumental variable estimate. The instrumental variable is based on the shift-share instrument approach pioneered by Altonji and Card (1991) and used by Mitaritonna, Orefice and Peri (2017) in their study on immigrants and firm outcomes. This approach assumes that new immigrants are more likely to settle in communities where previous immigrants are concentrated, thus the subsequent change in the share of immigrants is determined by the distribution of previous immigrants and the national-level increase in new immigrants. These two factors should not be affected by changes in productivity in a specific firm.

To derive the instrument variable, we first derive the expected number of immigrants in year t1 by the combination of province (10 plus combined territories) and NAICS 2-digit sectors (24 units) as follows: $EIM_{jt} = (IMj_{t0}/IM_{t0})*IM_{t1}$. IMj_{t0} is the number of immigrant workers in cell j in the initial year (t0), where j is the combination of province and 2-digit NAICS codes. IM_{t0} is the total number of immigrant workers in Canada in the initial year, and IM_{t1} is the total number of immigrant workers in Canada in the end year (t1). The expected share of immigrants in cell j at t1 is $EPIM_{jt} = EIM_{jt} /(EIM_{jt} +CBj_{t0})$ where CBj_{t0} is the number of non-immigrant workers in cell j at t0. The expected change in the share of immigrants in cell j is the difference between $EPIM_{jt}$ and the initial share of immigrants in the same cell. Mitaritonna, Orefice and Peri (2017) used geographic regions to define local labour market cells, rather than the combination of broad regions and industrial sectors as in this study. In the data file used for this study, the information on the geographic location of a firm is not available below the provincial level, thus we have to rely on the combination of provinces and broad industrial sectors.

4. Results

4.1 Descriptive statistics

Table 1 presents the cross-sectional correlations (Pearson r) between the firm-level share of immigrants by various characteristics and value-added productivity in the selected years of 2000, 2005, and 2015. The results for other years generally fall between the presented data points.

The results in Table 1 show that the cross-sectional association between the share of immigrants and firm labour productivity changed from weak positive in 2000 to weak negative in 2015. Similar patterns are observed for value-added productivity and its logarithmic transformation. However, the association varied by immigrant characteristics. New immigrants, immigrants whose mother tongue is not English or French, immigrants who did not come as principal applicants in the economic class, immigrants who did not intend to work in high-skill or STEM occupations, and immigrants without a university degree were more concentrated in low-productivity firms. These negative associations became stronger from 2000 to 2015, suggesting the immigrants who were less likely to do well in the labour market were becoming increasingly concentrated in low-productivity firms. In contrast, skilled principal applicants, high-skill immigrants, STEM immigrants, and university-educated immigrants were more likely to be found in high productivity firms. These positive associations were relatively stable over the 15 year study period.

Table 1. Cross-sectional correlations between the share of immigrants and firm productivity, selected years

	Log value-added productivity						Value-added productivity					
	2000		2005		2015		2000		2005		2015	
	correlation coefficients											
Immigrants	0.017	***	0.000		-0.040	***	0.028	***	0.006		-0.017	***
Recent immigrants	-0.002		-0.019	***	-0.082	***	0.010	*	-0.010	*	-0.057	***
Established immigrants	0.058	***	0.029	***	0.041	***	0.064	***	0.028	***	0.054	***
Official language immigrants	0.057	***	0.033	***	-0.021	***	0.070	***	0.040	***	-0.002	
Non-Official language immigrants	-0.029	***	-0.037	***	-0.059	***	-0.021	***	-0.035	***	-0.036	***
Skilled principal applicants	0.115	***	0.120	***	0.090	***	0.131	***	0.122	***	0.100	***
Immigrants in other classes	-0.018	***	-0.043	***	-0.086	***	-0.009	*	-0.037	***	-0.062	***
High-skilled immigrants	0.136	***	0.135	***	0.116	***	0.149	***	0.134	***	0.122	***
Non-high-skilled immigrants	-0.032	***	-0.055	***	-0.096	***	-0.022	***	-0.047	***	-0.070	***
STEM immigrants	0.155	***	0.159	***	0.194	***	0.167	***	0.158	***	0.191	***
Non-STEM immigrants	-0.005		-0.028	***	-0.078	***	0.006		-0.022	***	-0.053	***
University-educated immigrants	0.120	***	0.105	***	0.062	***	0.139	***	0.111	***	0.074	***
Immigrants with lower education	-0.016	***	-0.042	***	-0.089	***	-0.008		-0.038	***	-0.065	***
Number of firms	61345		67643		83640		61345		67643		83640	
** significant at p<0.01; *** p < 0.001												
Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015												

The above observed correlations certainly do not have a clear causal interpretation. It is highly possible that high productivity firms are more likely to have a high-skilled, well-educated work force, while low productivity firms are more likely to hire low-skilled, less educated work force, regardless of immigrant status. What is more revealing is whether at a given initial productivity level, an increase in the share of immigrants is positively associated with increased firm productivity.

Table 2 presents the simple correlations (Pearson r) between changes in firm productivity and changes in the share of immigrants. These correlations are very different from the observed cross-sectional correlations as in Table 1, as a result of removing firm-fixed effects. Overall, the change in the share of immigrants was positively associated with the change in firm productivity.

Furthermore, the change in the firm productivity had generally lower correlations with the changes in the shares of immigrants with higher levels of some human capital factors (education, high-skill occupations, and STEM occupations) than with the changes in the shares of immigrants with lower levels of these factors. The change in firm productivity was positively associated with the change in the share of recent immigrants, but negatively or not significantly associated with the changes in the share of established immigrants. The change in firm productivity had similar associations with the changes in the share of immigrants whose mother tongue is English or French and whose mother tongue is not an official language.

Table 2. Simple correlations between changes in firm productivity and changes in the share of immigrants

	Log value-added productivity			Value-added productivity		
	One-year change	Five-year change	ten-year change	One-year change	Five-year change	ten-year change
	correlation coefficient					
Immigrants	0.005 ***	0.021 ***	0.056 ***	0.003 **	0.017 ***	0.042 ***
Recent immigrants	0.008 ***	0.026 ***	0.060 ***	0.005 ***	0.020 ***	0.043 ***
Established immigrants	-0.003 **	-0.004 **	0.000	-0.003	-0.002	0.003
Official language immigrants	0.003 **	0.017 ***	0.055 ***	0.002 ***	0.012 ***	0.037 ***
Non-Official language immigrants	0.004 ***	0.015 ***	0.030 ***	0.003 ***	0.014 ***	0.030 ***
Skilled principal applicants	-0.002	0.011 ***	0.049 ***	0.000 ***	0.010 ***	0.037 ***
Immigrants in other classes	0.007 ***	0.019 ***	0.045 ***	0.003 ***	0.015 ***	0.034 ***
High-skilled immigrants	-0.002 *	0.010 ***	0.041 ***	-0.001	0.009 ***	0.033 ***
Non-high-skilled immigrants	0.007 ***	0.020 ***	0.050 ***	0.004 ***	0.016 ***	0.037 ***
STEM immigrants	-0.001	0.008 ***	0.022 ***	0.000	0.011 ***	0.025 ***
Non-STEM immigrants	0.005 ***	0.020 ***	0.055 ***	0.003 **	0.015 ***	0.040 ***
University-educated immigrants	0.001	0.010 ***	0.040 ***	0.001	0.008 ***	0.028 ***
Immigrants with lower education	0.005 ***	0.020 ***	0.049 ***	0.003 **	0.016 ***	0.038 ***
Number of firm-periods	960432	561909	242825	960432	561909	242825

* significant at p<0.05; ** p<0.01; ***<0.001.

Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015

Table 2 also shows that the magnitude of the correlation tended to increase with the length of the period used to measure changes (except the correlations with the share of established immigrants). With the one-year period, all correlations were close to zero, and some were not statistically significant. With the five-year period, the correlations were mostly positive and stronger. With the ten-year period, the correlations became even stronger. Except the share of established immigrants, other immigrant characteristics all had a positive association with the change in firm productivity. In most cases, log value-added productivity had somewhat higher correlations with the selected immigrant characteristics than value-added productivity did. It is possible that logarithm transformation reduces the influence of extreme values and thus increases the overall correlation. This point is confirmed by the visual display of the changes in firm productivity and the percentage of immigrant workers in a firm, as shown below.

Figure 1 to Figure 3 plot the average changes in firm productivity against average changes in the share of immigrants with selected characteristics by the percentile of the change in log value-added productivity and value-added productivity. Figure 1 is based on one-year changes, while Figure 2 and Figure 3 are based on five-year and ten-year changes, respectively. In each figure, the right panel uses log value-added productivity, and the left panel uses value-added productivity. Two main points can be summarized from these figures.

First, consistent with the results in Table 2, changes in log value-added productivity and value-added productivity had similar correlations with changes in the share of immigrants. But the former is closer to a linear relationship than the latter. Thus, from this point on, multivariate analyses will be performed only with log value-added productivity as the outcome.

Second, the variations in the changes in productivity and particularly in the shares of immigrants increased with the length of period used to measure the changes. For instance, across the percentiles of changes in log value-added productivity, the change in the average share of immigrants ranged from -0.1 to 0.2 percentage points with the one-year lag, from -0.2 to 1.0 percentage points with the five-year lag, and from -0.5 to 1.8 percentage points with the ten-year lag. Similarly, the change in the average share of university-educated immigrants ranged from 0.1 to 0.2 percentage points with one-year lag, from 0.2 to 0.7 percentage points with five-year lag, but from 0.5 to 1.5 percentage points with ten-year lag. When the variation of a variable is very small, it is often unlikely to detect a strong correlation with other variables.

Figure 1. changes in average productivity and the share of immigrants across percentiles of the change in productivity, one year change

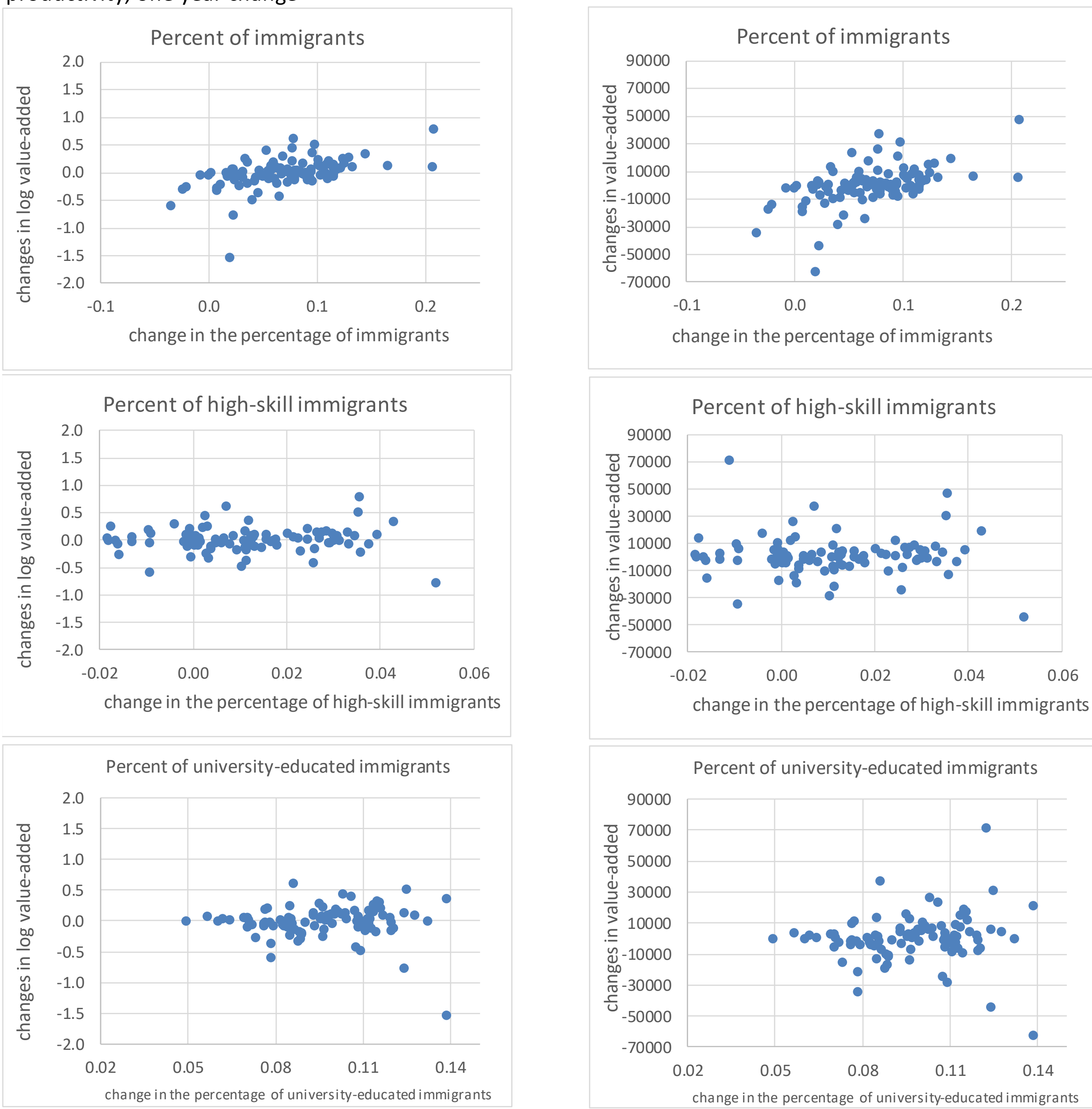


Figure 2. changes in average productivity and the share of immigrants across percentiles of the change in productivity, five-year change

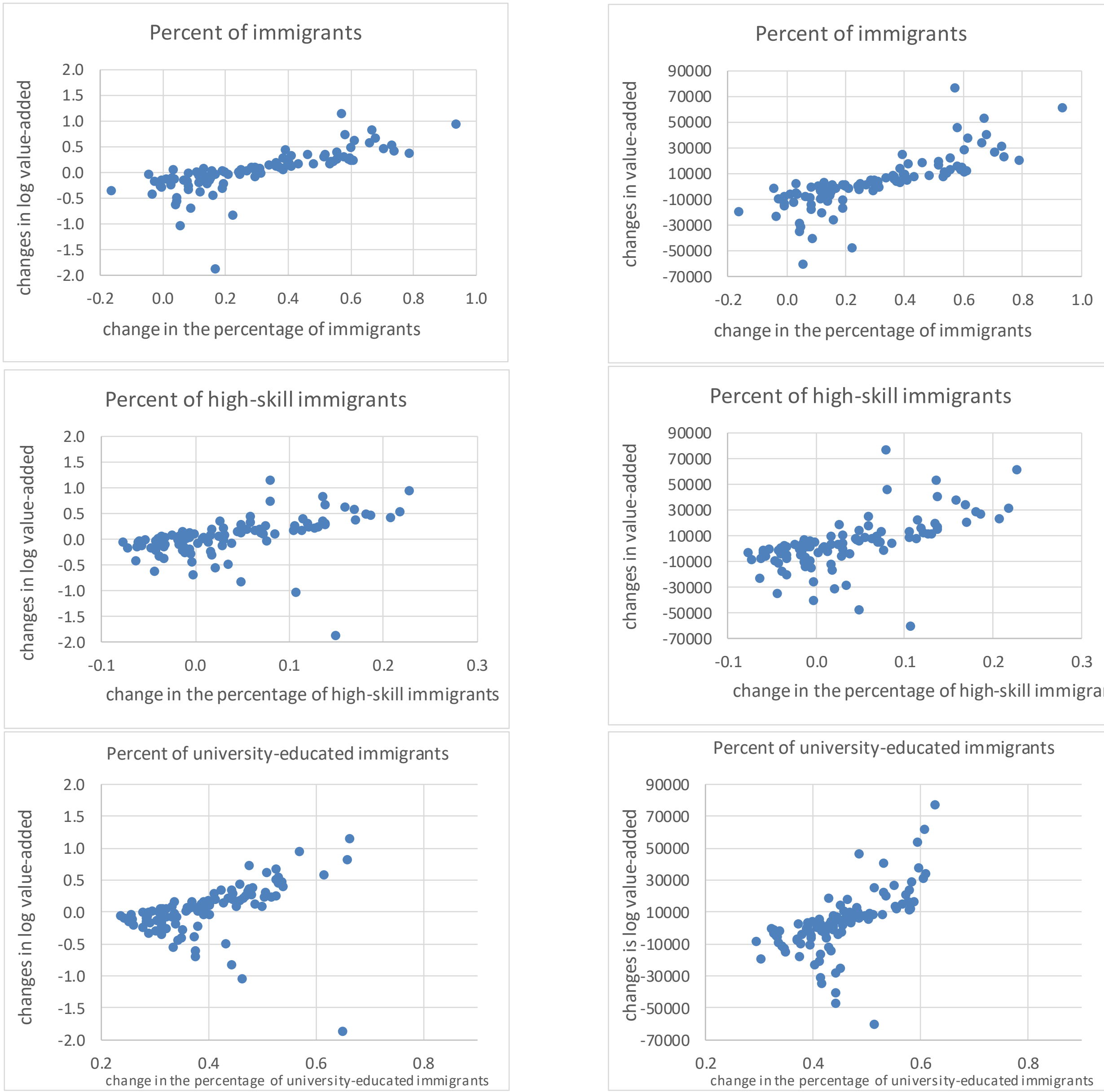
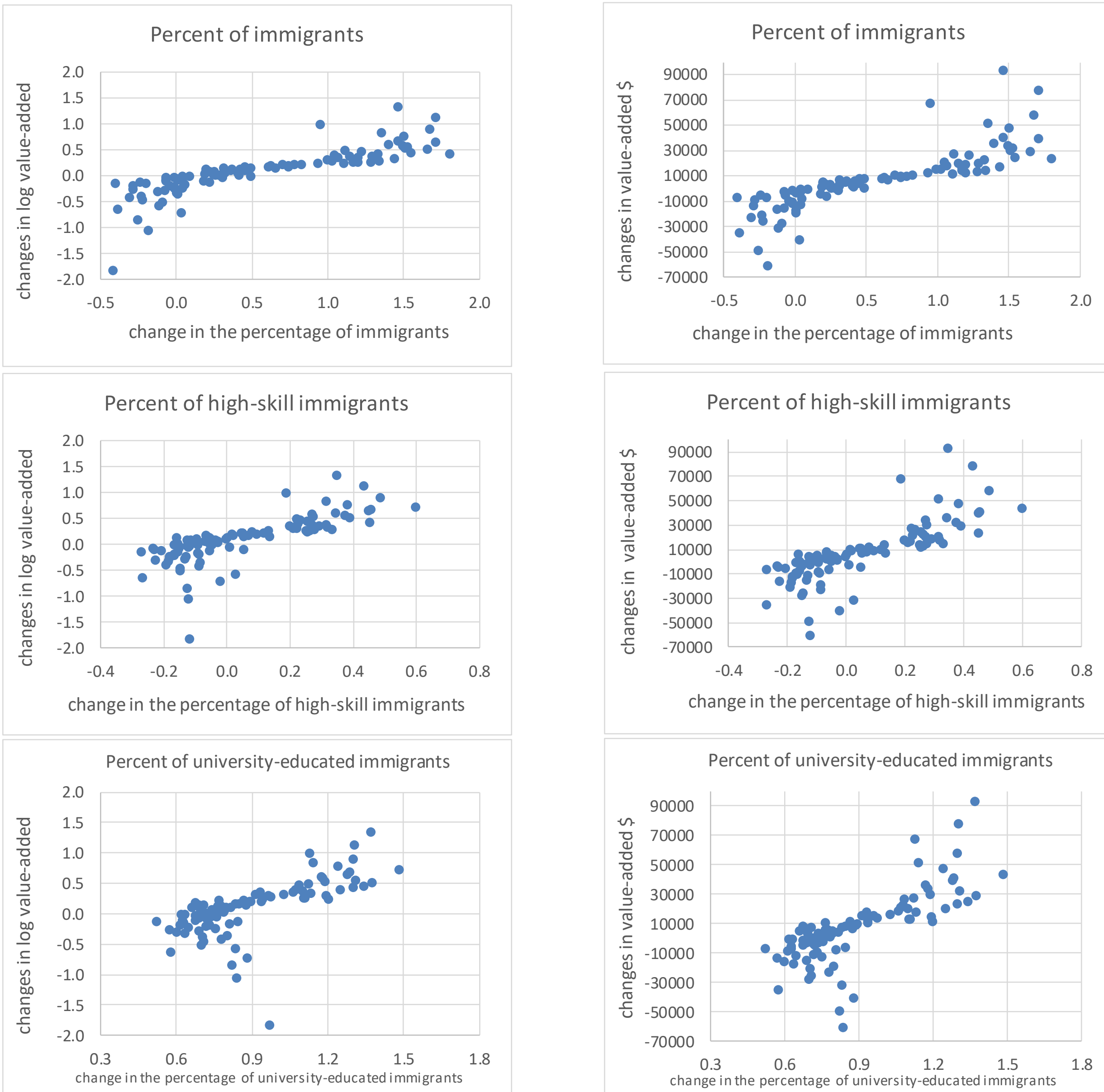


Figure 3. changes in average productivity and the share of immigrants across percentiles of the change in productivity, ten-year change



4.2 OLS estimates of changes

Table 3 presents the OLS estimates of the association between changes in the share of immigrants and log value-added productivity, controlling for period, province, 3-digit industry fixed effects, changes in firm capital-labour ratio, and changes in the size of employment in the firm. To simplify the presentation, the table only presents the coefficients associated with changes in the share of immigrants, while the coefficients of all control variables are not presented but available up on request. Separate analyses are conducted for three samples: the changes with a one-year lag, the changes with a five-year lag, and the changes with a ten-year lag.

Within each sample, there are seven separate models that differ in the focal independent variables – the share of immigrants by characteristics. Model 1 uses the share of all immigrants. The other models split the share of immigrants into two types by the following characteristics: recent immigrants and established immigrant; official language immigrants and immigrants whose mother tongue is not English or French; skilled principal applicants and immigrants in other classes; immigrants who intended to work in managerial or professional occupations and non-high skilled immigrants; STEM immigrants and non-STEM immigrants; and university-educated immigrants and immigrants without a university degree.

The changes in the shares of each pairs of these characteristics were moderately correlated, with Pearson correlation ranging from -0.22 to 0.04 in the one-year lag sample, from -0.24 to 0.12 in the five-year lag sample, and from -0.23 to 0.32 in the ten-year lag sample. However, the correlations across pairs tended to be high. For instance, in the ten-year lag sample, the change in the share of new immigrants was highly correlated with the change in the share of not being skilled principal applicants (Pearson correlation r =0.71), non-high skilled immigrants (r=0.69), non-STEM immigrants (r=0.76), and immigrants without a university degree (r=0.68). Thus it is not appropriate to include different pairs of immigrant characteristics in the same model.

All the models in Table 3 have relatively small R-squares, ranging from 0.048 to 0.074. These small values suggest that only a small portion of the variation in the changes of firm productivity was accounted for by the variables included in the model. However, the purpose here is not to predict the changes in firm productivity, thus the overall model R-square is not a concern as long as the omitted potential predictors are not correlated with the variable of our main interest – the change in the share of immigrant workers. The discussion of results below focuses on the coefficients of immigrant variables.

The OLS estimates in Table 3 show that, consistent with the simple correlations in Table 2, the association between the changes in the share of immigrants and firm productivity increased with the length of period used to measure the change. Second, the change in firm productivity had stronger associations with the change in the shares of immigrants who tended to have some relatively less favourable labour market outcomes at the individual level, including new immigrants (relative to established immigrants), immigrants who were not principal applicants in the economic class (relative to principal applicants in the economic class), non-high-skilled immigrants (relative to high-skilled immigrants), and non-STEM immigrants (relative to STEM immigrants).

With the one-year changes, a ten percentage-point increase in the share of immigrants was associated with 0.8% increase in firm productivity. Associations in the similar magnitude were observed with the change in the share of recent immigrants, immigrants who were not principal applicants in the economic class, non-high-skilled immigrants, non-STEM immigrants, and immigrants without a university degree. Whether immigrants with an official language as the mother tongue or not made little difference to the positive association. The associations between the change in the firm productivity and the changes in the share of established immigrants, skilled principal applicants, high-skilled immigrants, and STEM immigrants were not statistically significant.

With the five-year changes, the relationship between the share of immigrants and firm productivity became somewhat stronger. A 10 percentage-point increase in the share of immigrants was associated with 1.1% increase in firm productivity. Over the study period, the share of immigrants increased by 0.36 percentage points on average over a five year period in the firms included in this study.[2] This implies that overall the increase in the share of immigrants was associated with 0.04% increase in firm productivity over a five year period. The patterns of associations by immigrant characteristics remained similar to those observed for the one-year change.

With the ten-year changes, the overall association between changes in the share of immigrants and firm productivity became even stronger: a 10 percentage-point increase in the share of immigrants was associated with 1.9% increase in firm productivity. This overall effect remains small given that the share of immigrant workers rose by about 0.7 percentage points on average over a ten-year period in the firms that were included in the study.[3] However, for some firms the effect could be more substantial as the changes in the share of immigrants range from -87 to 92 percentage points across individual firms. Furthermore, all the selected immigrant characteristics were positively associated with the change in firm productivity, except that the change in the share of STEM immigrants was still not significant. The changes in the share of university-educated immigrants and immigrants without a university degree were similarly associated with the changes in firm productivity.

[2] This average increase was smaller than the increase in the share of the immigrant population in Canada over the study period. For instance, immigrants accounted for 18.4% of the Canadian population in 2001, 19.8 in 2006, 20.6% in 2011, and 21.9% in 2016. In this study, immigrants are defined as those who had been in Canada for 20 years or less. Furthermore, in computing the average change in the share of immigrants in firms over a five year period, this study only included immigrants who worked in firms with at least 20 employees and those firms could be longitudinally followed over a five year period.

[3] See footnote 2. In computing the average change in the share of immigrants in firms over a ten year period, this study only included immigrants who worked in firms with at least 20 employees and those firms could be longitudinally followed over a ten year period.

Table 3. the coefficient of the immigrant variable in the first-difference model with log value-added productivity as the dependent variable and controlling for year, province, industry fixed effects, and the change in total tangible assets and change in the firm size							
		coefficient		Robust standard error	R Squared	sample size	unique firms
One-year changes							
	1: Immigrants	0.0008	***	0.0001	0.0509	960432	126427
	2a: Recent immigrants	0.0014	***	0.0001	0.0510	960432	126427
	2b: Established immigrants	-0.0002		0.0002			
	3a: Official language immigrants	0.0007	***	0.0001	0.0509	960432	126427
	3b: Non-Official language immigrants	0.0010	***	0.0002			
	4a: Skilled principal applicants	-0.0004		0.0002	0.0509	960432	126427
	4b: Immigrants in other classes	0.0012	***	0.0001			
	5a: High-skilled immigrants	-0.0006		0.0002	0.0509	960432	126427
	5b: Non-high-skilled immigrants	0.0013	***	0.0001			
	6a: STEM immigrants	0.0000		0.0005	0.0509	960432	126427
	6b: Non-STEM immigrants	0.0009	***	0.0001			
	7a: University-educated immigrants	0.0005	*	0.0003	0.0509	960432	126427
	7b: Immigrants with lower education	0.0009	***	0.0001			
Five-year changes							
	1: Immigrants	0.0011	***	0.0001	0.0476	561909	85462
	2a: Recent immigrants	0.0019	***	0.0002	0.0479	561909	85462
	2b: Established immigrants	-0.0003		0.0002			
	3a: Official language immigrants	0.0010	***	0.0002	0.0476	561909	85462
	3b: Non-Official language immigrants	0.0012	***	0.0002			
	4a: Skilled principal applicants	0.0002		0.0003	0.0476	561909	85462
	4b: Immigrants in other classes	0.0014	***	0.0002			
	5a: High-skilled immigrants	0.0000		0.0005	0.0476	561909	85462
	5b: Non-high-skilled immigrants	0.0015	***	0.0003			
	6a: STEM immigrants	0.0010		0.0006	0.0476	561909	85462
	6b: Non-STEM immigrants	0.0011	***	0.0001			
	7a: University-educated immigrants	0.0007	*	0.0003	0.0476	561909	85462
	7b: Immigrants with lower education	0.0013	***	0.0002			
Ten-year changes							
	1: Immigrants	0.0019	***	0.0002	0.0736	242825	55564
	2a: Recent immigrants	0.0022	***	0.0002	0.0737	242825	55564
	2b: Established immigrants	0.0010	***	0.0003			
	3a: Official language immigrants	0.0022	***	0.0003	0.0736	242825	55564
	3b: Non-Official language immigrants	0.0013	***	0.0003			
	4a: Skilled principal applicants	0.0017	***	0.0005	0.0736	242825	55564
	4b: Immigrants in other classes	0.0019	***	0.0002			
	5a: High-skilled immigrants	0.0012	*	0.0009	0.0736	242825	55564
	5b: Non-high-skilled immigrants	0.0021	***	0.0002			
	6a: STEM immigrants	0.0013		0.0011	0.0736	242825	55564
	6b: Non-STEM immigrants	0.0019	***	0.0002			
	7a: University-educated immigrants	0.0022	***	0.0006	0.0736	242825	55564
	7b: Immigrants with lower education	0.0017	***	0.0003			
* significant at p<0.05; ** p<0.01; ***<0.001.							
Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015							

4.3 OLS estimates by industry technology and knowledge intensity

In Table 4, the OLS models are estimated for technology-intensive industries and other industries. In general, the association between the changes in the share of immigrants and firm productivity was twice to three times as strong in technology-intensive industries as in other industries. However, as observed for all industries as a whole, even among technology-intensive industries, the changes in the shares of skilled principal applicants, high-skilled immigrants, and STEM immigrants were generally not or weakly associated with firm productivity growth. In technology-intensive industries, the changes in firm productivity had stronger associations with the change in the shares of immigrants who tended to have less favourable labour market outcomes at the individual level, including new immigrants (relative to established immigrants), immigrants who were not principal applicants in the economic class (relative to principal applicants in the economic class), non-high-skilled immigrants (relative to high-skilled immigrants), non-STEM immigrants (relative to STEM immigrants), and immigrants without a university degree (relative to university-educated immigrants). In contrast, these differences were much smaller or non-existent in non-technology industries.

Similar results are observed with the OLS estimates separately for knowledge-based industries and non-knowledge-based industries, as in Table 5.

Table 4. coefficientz of the immigrant variablez in the first-difference model with log value-added productivity as the dependent variable and controlling for year, province, industry fixed effects, and the changes in capital-labour ratio and firm size, by industrial technological intensity

		Technology industries				Non-technology industries		
		coefficient		Robust standard error		coefficient		Robust standard error
One-year changes								
	1: Immigrants	0.0021	***	0.0005		0.0007	***	0.0001
	2a: Recent immigrants	0.0033	***	0.0005		0.0012	***	0.0001
	2b: Established immigrants	-0.0003		0.0007		-0.0002		0.0002
	3a: Official language immigrants	0.0016	***	0.0006		0.0006	***	0.0001
	3b: Non-Official language immigrants	0.0033	***	0.0008		0.0008	***	0.0002
	4a: Skilled principal applicants	0.0004		0.0008		-0.0005	*	0.0002
	4b: Immigrants in other classes	0.0034	***	0.0006		0.0010	***	0.0001
	5a: High-skilled immigrants	0.0005		0.0008		-0.0008	**	0.0002
	5b: Non-high-skilled immigrants	0.0035	***	0.0006		0.0011	***	0.0001
	6a: STEM immigrants	0.0015		0.0010		-0.0007		0.0005
	6b: Non-STEM immigrants	0.0023	***	0.0006		0.0008	***	0.0001
	7a: University-educated immigrants	0.0011		0.0007		0.0004		0.0002
	7b: Immigrants with lower education	0.0031	***	0.0006		0.0008	***	0.0001
Five-year changes								
	1: Immigrants	0.0031	***	0.0005		0.0009	***	0.0001
	2a: Recent immigrants	0.0038	***	0.0006		0.0016	***	0.0002
	2b: Established immigrants	0.0015	*	0.0008		-0.0006	**	0.0002
	3a: Official language immigrants	0.0026	***	0.0007		0.0008	***	0.0002
	3b: Non-Official language immigrants	0.0044	***	0.0010		0.0010	***	0.0002
	4a: Skilled principal applicants	0.0010		0.0008		-0.0001		0.0003
	4b: Immigrants in other classes	0.0049	***	0.0007		0.0012	***	0.0002
	5a: High-skilled immigrants	0.0009		0.0008		-0.0003		0.0003
	5b: Non-high-skilled immigrants	0.0052	***	0.0008		0.0012	***	0.0002
	6a: STEM immigrants	0.0025	*	0.0010		-0.0002		0.0007
	6b: Non-STEM immigrants	0.0034	***	0.0007		0.0010	***	0.0001
	7a: University-educated immigrants	0.0016	*	0.0008		0.0005		0.0003
	7b: Immigrants with lower education	0.0049	***	0.0007		0.0010	***	0.0002
Ten-year lag changes								
	1: Immigrants	0.0035	***	0.0008		0.0016	***	0.0002
	2a: Recent immigrants	0.0046	***	0.0008		0.0020	***	0.0003
	2b: Established immigrants	0.0006		0.0011		0.0009	**	0.0003
	3a: Official language immigrants	0.0029	**	0.0010		0.0021	***	0.0003
	3b: Non-Official language immigrants	0.0048	**	0.0016		0.0009	**	0.0004
	4a: Skilled principal applicants	0.0020		0.0012		0.0016	**	0.0007
	4b: Immigrants in other classes	0.0047	***	0.0011		0.0016	***	0.0003
	5a: High-skilled immigrants	0.0017		0.0012		0.0010	*	0.0010
	5b: Non-high-skilled immigrants	0.0051	***	0.0012		0.0018	***	0.0002
	6a: STEM immigrants	0.0024		0.0015		0.0003		0.0011
	6b: Non-STEM immigrants	0.0038	***	0.0010		0.0017	***	0.0002
	7a: University-educated immigrants	0.0027	*	0.0014		0.0021	***	0.0006
	7b: Immigrants with lower education	0.0043	***	0.0014		0.0015	***	0.0003

* significant at p<0.05; ** p<0.01; ***<0.001.

Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015

Table 5. coefficients of the immigrant variables in the first-difference model with log value-added productivity as the dependent variable and controlling for year, province, industry fixed effects, and the changes in capital-labour ratio and firm size, knowledge based industries and other industries						
	Knowledge-based industries			Non-knowledge based industries		
	coefficient		Robust standard error	coefficient		Robust standard error
One-year changes						
1: Immigrants	0.0022	***	0.0005	0.0007	***	0.0001
2a: Recent immigrants	0.0031	***	0.0006	0.0012	***	0.0001
2b: Established immigrants	0.0004		0.0007	-0.0003		0.0002
3a: Official language immigrants	0.0016	**	0.0006	0.0006	***	0.0001
3b: Non-Official language immigrants	0.0039	***	0.0009	0.0008	***	0.0002
4a: Skilled principal applicants	0.0001		0.0008	-0.0005		0.0002
4b: Immigrants in other classes	0.0039	***	0.0007	0.0010	***	0.0001
5a: High-skilled immigrants	0.0002		0.0008	-0.0007		0.0002
5b: Non-high-skilled immigrants	0.0040	***	0.0007	0.0011	***	0.0001
6a: STEM immigrants	0.0008		0.0009	-0.0004		0.0005
6b: Non-STEM immigrants	0.0027	***	0.0006	0.0008	***	0.0001
7a: University-educated immigrants	0.0007		0.0007	0.0005	*	0.0002
7b: Immigrants with lower education	0.0039	***	0.0007	0.0008	***	0.0001
Five-year changes						
1: Immigrants	0.0035	***	0.0006	0.0009	***	0.0001
2a: Recent immigrants	0.0041	***	0.0007	0.0016	***	0.0002
2b: Established immigrants	0.0020	*	0.0009	-0.0005	**	0.0002
3a: Official language immigrants	0.0030	***	0.0007	0.0008	***	0.0002
3b: Non-Official language immigrants	0.0048	***	0.0011	0.0010	***	0.0002
4a: Skilled principal applicants	0.0015		0.0009	-0.0003		0.0003
4b: Immigrants in other classes	0.0052	***	0.0008	0.0012	***	0.0002
5a: High-skilled immigrants	0.0015		0.0008	-0.0004		0.0003
5b: Non-high-skilled immigrants	0.0055	***	0.0008	0.0013	***	0.0002
6a: STEM immigrants	0.0026	*	0.0011	-0.0003		0.0007
6b: Non-STEM immigrants	0.0038	***	0.0007	0.0010	***	0.0001
7a: University-educated immigrants	0.0023	**	0.0008	0.0002		0.0003
7b: Immigrants with lower education	0.0049	***	0.0008	0.0011	***	0.0002
Ten-year changes						
1: Immigrants	0.0045	***	0.0009	0.0016	***	0.0002
2a: Recent immigrants	0.0053	***	0.0011	0.0019	***	0.0002
2b: Established immigrants	0.0021		0.0015	0.0008	**	0.0003
3a: Official language immigrants	0.0041	***	0.0013	0.0020	***	0.0003
3b: Non-Official language immigrants	0.0053	***	0.0021	0.0011	***	0.0003
4a: Skilled principal applicants	0.0028	*	0.0012	0.0013	**	0.0005
4b: Immigrants in other classes	0.0058	***	0.0013	0.0017	***	0.0002
5a: High-skilled immigrants	0.0029	*	0.0012	0.0007		0.0010
5b: Non-high-skilled immigrants	0.0060	***	0.0013	0.0019	***	0.0002
6a: STEM immigrants	0.0028		0.0015	-0.0002		0.0011
6b: Non-STEM immigrants	0.0051	***	0.0011	0.0017	***	0.0002
7a: University-educated immigrants	0.0037	**	0.0015	0.0017	***	0.0005
7b: Immigrants with lower education	0.0053	***	0.0016	0.0016	***	0.0002
* significant at p<0.05; ** p<0.01; ***<0.001.						
Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015						

4.3 Other model specifications

To test the sensitivity of the study's analyses to model specifications, we run some additional models by altering the control variables or the study sample. One mode included the initial firm productivity measure as an additional control. The coefficients associated with immigrant variables became slightly smaller, but their statistical significance and direction remained the same. Another model excluded 3-digit industry fixed effects, and the coefficients of immigrant variables became slightly larger. In models that added the initial share of immigrants, the effects of immigrant variables became slightly smaller. In models that excluded firms without any immigrants in both the beginning and ending years, the coefficients associated with immigration variables increased slightly. In sum, the OLS estimates of change scores are quite robust.

In Table 6, we split the value-added productivity into its two components and repeat the analysis in Table 3 based on changes in a ten-year period. The first component is profits per worker, while the second average payroll (i.e., total payroll per worker). There are several interesting observations from this table. First, the same model had little predictive power for profits as indicated by the model R-squared less than 2%, but a rather high predictive power for average payroll with a model R-squared around 15%. Second, the change in the share of immigrants was about 4 times more strongly associated with the change in firm profits than with average payroll. A 10 percentage-point increase in the share of immigrants was associated with 6.8% increase in firm profits per worker, but only 1.5% increase in firm average payroll. Third, while the changes in the shares of immigrants with different characteristics were similarly associated with firm average payroll, this was not the case for firm profits per workers. Firm profits per worker were strongly associated with university-educated immigrants, new immigrants, STEM immigrants, immigrants who speak an official language; but not or weakly associated with the share of immigrants without a university degree, immigrants who were not intended to work in STEM occupations, and immigrants who could not speak an official language. However, the change in the share of immigrants who intended to work in high-skilled occupations was not significantly associated with firm profits per work, but the share of immigrants who intended to work in non-high skilled occupations was.

Table 6. the coefficient of the immigrant variable in the first-difference model with log profit and log payroll as the dependent variables and controlling for year, province, industry fixed effects, and the change in total tangible assets and change in the firm size, ten-year changes						
	coefficient		Robust standard error	R Squared	sample size	unique firms
Log profits per worker						
1: Immigrants	0.0068	***	0.0016	0.0157	242825	55564
2a: Recent immigrants	0.0100	***	0.0021	0.0158	242825	55564
2b: Established immigrants	-0.0009		0.0029			
3a: Official language immigrants	0.0078	***	0.0027	0.0157	242825	55564
3b: Non-Official language immigrants	0.0052		0.0033			
4a: Skilled principal applicants	0.0083	*	0.0037	0.0157	242825	55564
4b: Immigrants in other classes	0.0063	***	0.0020			
5a: High-skilled immigrants	0.0039		0.0038	0.0157	242825	55564
5b: Non-high-skilled immigrants	0.0078	***	0.0020			
6a: STEM immigrants	0.0156	*	0.0071	0.0157	242825	55564
6b: Non-STEM immigrants	0.0060	***	0.0017			
7a: University-educated immigrants	0.0170	***	0.0036	0.0158	242825	55564
7b: Immigrants with lower education	0.0030		0.0020			
Log average payroll						
1: Immigrants	0.0015	***	0.0001	0.1452	242825	55564
2a: Recent immigrants	0.0016	***	0.0001	0.1450	242825	55564
2b: Established immigrants	0.0012	***	0.0002			
3a: Official language immigrants	0.0017	***	0.0002	0.1452	242825	55564
3b: Non-Official language immigrants	0.0013	***	0.0002			
4a: Skilled principal applicants	0.0018	***	0.0003	0.1452	242825	55564
4b: Immigrants in other classes	0.0014	***	0.0002			
5a: High-skilled immigrants	0.0017	***	0.0003	0.1452	242825	55564
5b: Non-high-skilled immigrants	0.0015	***	0.0002			
6a: STEM immigrants	0.0016	**	0.0006	0.1452	242825	55564
6b: Non-STEM immigrants	0.0015	***	0.0001			
7a: University-educated immigrants	0.0015	***	0.0004	0.1452	242825	55564
7b: Immigrants with lower education	0.0015	***	0.0002			
* significant at p<0.05; ** p<0.01; ***<0.001.						
Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015						

4.4 Instrumental variable estimates

Table 7 presents the instrumental variable (IV) estimates. The instrument is the expected changes in the share of immigrants at the joint provincial and 2-digit NAICS sector level. The IV estimates show that the effect of the change in the share of immigrants was not statistically significant in the models with one-year, five-year, and ten-year changes. In the first-stage regression, the instrument was positively and significantly associated with the firm-level changes in the share of immigrants only in the models for one-year and five-year changes. For the 10-year changes, the instrument was negatively associated with the firm-level change in the share of immigrants. Thus, the relationship between the instrument and the focal predictor was in an unexpected direction. This is likely a result of large shifts in the geographic distribution of recent immigrants since the early 2000s and thus early geographic distribution patter was not positively associated with subsequent distribution of new immigrants (Bonikowska, Hou and Picot 2016).

Since the data used in this study do not have below-provincial local labour market identifiers for individual firms, we could not follow the exact shift-share approach used in previous studies (e.g. Mitaritonna, Orefice and Peri 2017) which were based on local geographic regions rather than the combination of broad regions and industrial sectors as in this study. Consequently, it is uncertain whether the chosen instrument is valid in this study. We also experimented with some alternative instrumental variables. One is using the combination of provinces and 3 digit NAICS codes to define cells. The second just uses 3-digit NAICS codes to define cells. Third uses the actual changes in the share of immigrants by the combination of province and 2 digit NAICS codes excluding own firm. The fourth uses the actual changes in the share of immigrants by the combination of province and 3 digit NAICS codes excluding own firm. These alternative IVs produced rather erratic results – either the first stage coefficients had the wrong sign or the IVs estimates were unreasonably large (over 10 times larger than the OLS estimates), negative or positive. More generally, IV estimates are more likely to be falsely significant and more sensitive to outliers than OLS (Young 2017). Caution has to be exercised in interpreting these IV estimate results.

Table 7. Instrumental variable estimates

	second stage estimates			first stage estimates		
	coefficient		Standand error	coefficient		F values
One-year changes	-0.013		0.031	0.018	***	12.1
Five-year changes	-0.0003		0.006	0.208	***	44.2
Ten-year changes	0.001		0.006	-0.346	***	42.9

* significant at p<0.05; ** p<0.01; ***<0.001.

Sources: T2-LEAP, the Longitudinal Worker file, and Immigrant Landing File, 2000-2015

5. Conclusion and Discussion

This study examines the empirical relationship between immigration and firm-level labour productivity in Canada. It uses the Canadian Employer-Employee Dynamics Database (CEEDD) that tracks individual firms over time and matches firms with their employees. The main analyses are based on the relationship between the changes in the share of immigrants in a firm and firm productivity, whereas the change is measured alternatively over one-year, five-year, and ten-year intervals. The study includes only firms with at least 20 employees in a given year in order to derive relatively reliable firm-level measures.

The results show that the associations between firm productivity growth and the change in the share of immigrant workers in the firm varied by the length of period used to measure changes. Over a one-year period, the association between changes in immigrant shares and firm productivity was weak. Over a longer period (five or ten year period), the positive association became stronger. There may be a few reasons for this outcome. First, the variation in both the changes in the immigrant shares and firm productivity tends to increase with a longer interval of the change, which may allow a stronger association to be "seen". The less variation over the shorter periods may be masking the size of the effect. Second, since the changes are measured by following the same firm longitudinally, a longer interval of observation involves firms that have survived longer. It may be among such firms that the positive effect is found. Third, the changes in both firm worker composition and productivity are less likely to subject to random measurement errors among more stable firms.

Even when measured over a ten-year interval, the positive association between changes in the share of immigrant workers and firm productivity was small. A 10 percentage-point increase in the share of immigrants was associated with a 1.9% increase in firm productivity. Among the firms included in the study, the share of immigrant workers rose by about 0.7 percentage points on average over a ten-year period. Thus the actual change in the share of immigrant workers was associated with 0.13% (0.7 times 0.19%) increase in productivity among all firms in this study. In comparison, firm productivity rose by about 11% for a 10 year interval on average over the study period. Put differently, the changes in the share of immigrant workers accounted for about 1% of the overall productivity growth among firms included in this study. However, for individual firms that experienced a large increase in the share of immigrant workers, the association could be substantial. For instance, the estimated association would suggest that a firm with 20 percentage-point increase in the share of immigrant workers could see an increase in productivity by 3.8%.

The association between immigrants and firm productivity also varied considerably by immigrant characteristics and industry sectors. Growth in firm productivity was more strongly associated with changes in the share of recent immigrants (relative to established immigrants), immigrants who intended to work in non-high skilled occupations (relative to immigrants who intended to work high-skilled occupations), and immigrants who intended to work in non-STEM occupations (relative to immigrants who intended to work in STEM occupations). These patterns held mostly in technology-intensive or knowledge-based industries. Furthermore, in these industries, where human capital and productivity-enhancing attributes supposedly matter the most, firm productivity was more strongly associated with changes in the share of immigrants without a university degree than with the change in the share of university-educated immigrants.

These results seem counter-intuitive, but they are not inconsistent with the proposition that immigrants can help firms increase productivity when they are complementary to native-born workers in skills and specialization of production (Peri and Sparber 2009; Mitaritonna, Orefice and Peri 2017). It is possible that technology-intensive or knowledge-based industries require a high degree of division of labour and specialization of functions. In these industries immigrants who are less-well educated or without high level skills may work on jobs different from, but complementary to the jobs of the native-born high-tech or knowledge workers. This possibility is consistent with the findings of some previous empirical studies in Canada. For instance, Bonikowska, Hou and Picot (2011) showed that recent immigrants with a university degree earned similar wages as Canadian-born workers with only a high school diploma, although university-educated immigrants still do better than less-educated immigrants in the long run. They suggested that university-educated recent immigrants were not engaging in the same segment of the labour market as the Canadian-born university graduates. Similarly, Lu and Hou (2018) found that university-educated recent immigrants were more than twice as likely as university-educated Canadian born workers to work in jobs that require only high-school education. This implies that many university-educated recent immigrants did not fully use their advanced education. Furthermore, Picot and Hou (2018) showed that over one-half of recent immigrants who were trained at the university level in the STEM fields did not work in STEM occupations. When not working in STEM occupations, about 80% of immigrant STEM graduates work in low-quality jobs and may not have the opportunities to apply their STEM training.

In industries that are not technology-intensive or knowledge-based, the association between the changes in the share of immigrants and firm productivity was generally positive and significant, but much weaker than those in the technology-intensive or knowledge-based industries. Furthermore, in these industries, the associations were not conditioned by immigrant characteristics in terms of human capital and occupational skills. It is possible that in these industries complementarity in skills and education levels among workers may matter less, and the contribution of immigrants to firm productivity is not through specialization of functions and division of labour. Rather, their contribution is likely through working harder or more efficiently than non-immigrant workers as immigration is a selective process (Kangasniemi et al. 2012).

If complementarity within the context of labour specialization is the key to understanding the results, that means that simply, say, increasing the share of immigrant workers in a firm would not necessarily, by itself, lead to productivity gains. The complementarity explanation demands that there be a sufficient highly skilled workforce for the less skilled immigrants to complement. Thus, to seek the productivity gains, it would be necessary to ensure a sufficient supply of highly skilled workers, along with a simultaneous increase in the share of immigrants.

The above associations between changes in the share of immigrants and firm productivity were estimated after taking into account time-invariant omitted factors at the firm level, any provincial level and 3-digit industrial sector level productivity shocks, and some time-varying predictors of firm level productivity including changes in firm capital-labour ratio and overall employment size. Furthermore, these estimates are robust to alternative model specifications that also control for initial firm productivity and initial share of immigrants. Therefore this study has dealt with the common sources of bias in estimating the effect of immigration on the receiving-country labour market using grouped data. Nevertheless, endogeneity remains a concern. Some of the instrumental-variable estimates showed that the effect of the change in the share of immigrants on firm productivity was not significant. However, the validity of the available instruments was not certain as some minor alternation of the instruments led to erratic results. Another limitation is that the study did not include small firms, thus the results should not be generalized for all firms. Furthermore, this study does not consider other channels through which immigrants can boost productivity. One such channel is immigrant entrepreneurship and dynamic, high-growth businesses that immigrants establish. Another chance is to alleviate skill shortages that represent production bottlenecks.

Overall, we believe that the estimated effects of immigration on productivity represent what a careful analysis of quite rich worker-firm micro-data can, and in this case did, produce. As always, theories, methodologies and data can be improved over time. Of course, replication is important. We look forward to subsequent studies to determine if these results are replicated.

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