Third-Country Effects of U.S. Immigration Policy*

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Abstract

We study the effects of U.S. restrictions on skilled immigration on the Canadian economy and American workers' welfare. In 2017, there was a policy that tightened the eligibility criteria for U.S. visas and was immediately followed by a trend break in the number of skilled immigrant admissions to Canada. We use quasi-experimental variation introduced by this policy over time and across immigrant groups, along with U.S. and Canadian visa application data, to show that Canadian applications in 2018 were 30% larger than without the restrictions. We then study how the restrictions affected Canadian firms using comprehensive Canadian administrative databases containing the universe of employer-employee-linked records, immigration records, and international trade data. We find that the restrictions increased firms' production, exports, and employment of Canadian workers. Finally, we study the policy's impact on American workers by incorporating immigration policy into a multi-sector international trade model. With international trade, the increase in immigration to other countries due to the restrictions affects American wages through U.S. exports and consumption prices. We calibrate the model using our novel data and reduced-form estimates. We find that the welfare gains for American workers targeted for protection by the 2017 policy are up to 25% larger in a closed economy than in an open economy with the observed trade levels.

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1 Introduction

Immigration restrictions are becoming increasingly common in developed countries. While the effects of these restrictions are likely to depend on where the affected immigrants migrate to, the policy debate has often overlooked it both empirically and theoretically. Fundamental theorems of international trade (Rybczynski, 1955; Samuelson, 1948) suggest that the inflow of the affected workers to receiving countries can increase production and exports in sectors that employ this factor of production relatively intensively, without necessarily reducing wages. Similarly, the outflow of the affected workers from the restricting economy can increase imports of goods from precisely these sectors. This import competition can drive down wages in the restricting economy, attenuating the intended effect of the restrictions. Thus, it is important to understand these cross-country general equilibrium effects of immigration restrictions not only to inform the policy debate in restricting economies but also for third countries that are more open to receiving these affected migrants.

This paper studies the effects of a 2017 US restriction on college-educated immigrants, given by a tightening in the eligibility criteria for H-1B visas.[1] One year later, Canada experienced a trend break in the number of skilled immigrant admissions. In the period between 2018 and 2019, there were about 76,000 additional admissions, representing a 3.5% increase in the number of college-educated immigrants, or about 1% of all college-educated workers in Canada.[2,3] In light of this, we ask three questions: To what extent did the US restrictions cause the increase in skilled immigration to Canada? How did this immigrant influx affect Canadian production, exports, and Canadian workers' welfare? Did the influx of workers to Canada and other economies ultimately impact American workers' welfare via international trade?

To address these questions, we exploit plausible exogenous variation introduced by the policy across time and immigrant groups. We combine this variation with a novel dataset to document the impact of these restrictions on Canadian immigration and firms. We assemble this dataset by including US visa application data obtained from a Freedom of Information Act (FOIA) request, a novel Canadian visa application dataset, and Canadian administrative databases containing the universe of employer-employee-linked records, immigration records, and international trade in goods and services data. Finally, we develop a new general equilibrium model of immigration and trade to study the impact of the observed restrictions on aggregate outcomes and welfare in the US and Canada. Additionally, this multi-country model allows us to study the effect on American workers of having fewer immigrant workers in the US and more immigrant workers elsewhere. We do so through analytical and counterfactual analysis.

[1] The H-1B program is the main pathway for college-educated workers seeking to migrate to the US.

[2] We refer to admissions granted under Permanent Residence programs commonly used by skilled workers, namely: Canadian Experience, Skilled Trade, Skilled Worker, and Provincial Nominee Program.

[3] This increase in admissions represented an average annual increase of approximately 30%.

The new policy was implemented through policy memorandums (PMs) issued by the US Citizenship and Immigration Services (USCIS) and entered into effect immediately. By the end of 2018, there was a decrease of 140,000 H-1B approvals (relative to trend) and an unprecedented spike in H-1B denial rates. Denial rates increased from about 6% 2016 to 16%. Guided by these PMs, we use data on H-1B visa applications to extract plausible exogenous variation introduced by the policy across applicants' occupations and nationalities (e.g. computer scientists (CS) from India). We combine this cross-section variation with the time variation introduced by the policy to provide reduced-form evidence of the effects of the restrictions on the Canadian economy and to estimate structural parameters.

We first document that increasing H-1B denial rates cause an increase in skilled immigration in Canada. To that end, we use our Canadian permanent residence (PR) visa applications and estimate the effect of the policy on the change in the number of Canadian applications after the policy introduction for immigrant groups that were differently affected. Our event-study estimates imply that a 10pp increase in H-1B denial rates increases Canadian applications by 30%. Based on the estimated response of Canadian applications and H-1B visa approvals, a back-of-the-envelope calculation suggests that for every 4 forgone H-1B visas, there is an associated increase of about 1 Canadian PR application. These estimated (relative) effects are remarkably similar to the analogous values implied by the raw data.

We then document a large impact of the immigrant influx on Canadian firms' production decisions using our Canadian administrative databases. We use information on the nationality of the firm's workforce to measure differences across firms in the exposure to the US policy change. Specifically, we rely on variation across firms given by both the nationality composition of their workforce and the occupational composition of their industry.[4] We combine this cross-sectional variation with the time variation of the policy within an event study framework to estimate the effect of the policy. Our estimates imply that, on average, a firm hired approximately 0.5 native workers per new immigrant hired due to the H-1B restrictions. In terms of sales, an additional immigrant hired in 2017-2018 translated into an increase of 112,000 Canadian dollars in 2018 for the median firm in skilled service sectors, which represents 3.2% of the pre-shock sales.[5] The rise in total sales can be partly attributed to the growth in total exports, which exhibited a stronger response compared to overall sales. Our findings are consistent with a neoclassical framework where immigrants and natives are imperfect substitutes, which motivates our modeling assumptions.[6]

Based on the documented facts, we develop a general equilibrium model to study the effects of

[4]These differences at the firm level allow us to isolate the effects of actual immigrant hires from policy-induced changes in surrounding conditions influenced by the immigrant inflow.

[5]We interpret the results for these sectors because they are the most affected by the restrictions.

[6]Although skilled immigration may lead to economies of scale at the aggregate level (Bound et al., 2017), especially in the long term, our short-run estimates suggest that this is not the primary driver.

immigration policy in an economy with international trade. The international trade component of our model is based on a Ricardian model with multiple countries and sectors. Production features constant returns to scale and requires workers from different occupations and origin countries, who are imperfect substitutes. Motivated by our evidence, we incorporate immigration policy and migration decisions under uncertainty into an otherwise standard model of migration. Immigration policy is represented as an exogenous probability of obtaining a visa. Given this uncertainty of obtaining visas, immigrants decide between staying in their home country or applying for a specific visa.

When there is a reduction in the US visa approval rate, more workers choose to stay in their home countries or migrate to other foreign nations. This inflow of workers reduces production costs in those economies and increases production, particularly in sectors that are immigrant-intensive (e.g. Rybczynski effect). Additionally, this influx of immigrants can affect American workers's welfare indirectly through international trade (Samuelson, 1948; Rybczynski, 1955). To further understand the determinants of this indirect effect, we derive an analytical expression for the effect on American workers' welfare that takes into account the inflow of workers elsewhere. This expression is composed of a direct effect and the mentioned indirect effect. The direct effects arise from having fewer immigrants in the US. On one hand, it increases the wage of American workers who are close substitutes. On the other it decreases the production of sectors that are immigrant intensive, lowering American wages. Regarding the indirect effect, the reduction of production costs of foreign competitors diminishes the international price of American goods and, in turn, decreases American wages. Simultaneously, it benefits American workers by providing access to cheaper imported goods and services, increasing American wages' purchasing power. The overall indirect effect on American workers in a specific sector can be either positive or negative, depending on how the export price of US sectors and import prices for consumers adjust.

After establishing this analytical result, we use the model to quantify the impact of the observed policy change. To that end, we calibrate the model using our novel data and the exogenous variation introduced by the policy. Specifically, we estimate the elasticity of substitution between emigrating to the US and Canada directly from a regression coefficient using our cross-border visa application data. To estimate other key parameters, we follow an indirect inference approach. We estimate regression coefficients using model-generated data and match them with coefficient estimates obtained using real data, which are based on our earlier event study estimates.

We find that the observed drop in the H-1B visa approval rates led to a 3.4% increase in immigrant labor in Canada and an expansion in production in all sectors, especially in high-skilled service sectors (2.5%). The impact on the welfare of Canadian workers was large, ranging from -3.4% to 1%, depending on the occupation and the sector of employment. In the US, immigrant labor decreased by 1.6%. While production dropped in all sectors, the impact was most pronounced in the high-skilled service and high-tech manufacturing sectors (-0.5%). The policy benefited primarily American computer scientists, who directly compete with the affected immigrants. However, it harmed American workers in other occupations employed in sectors that contracted. For instance, in the IT sector, CS experienced a 0.8% welfare increase, while lower-skilled workers experienced a 0.3% welfare decrease. These effects on American workers include both the direct and indirect effects. To assess the importance of the indirect effects, we simulate the same policy in a global economy without international trade. We find that the welfare gains for American CS, the group presumably targeted for protection by the policy, are up to 25% larger in an economy without international trade, compared to one with the current trade levels. This result indicates that US immigration restrictions may reduce direct competition between immigrants and American workers in the US labor market, but the competition may still exist through the international trade of goods that embody the labor services of these immigrants.

Related literature: Our paper contributes to the literature studying the economic effects of immigration. Existing studies have predominantly studied the impact of immigration on the receiving country, with seminal papers including Card (1990, 2001), Borjas (2003, 2005), Ottaviano and Peri (2012), Bound et al. (2017), or the sending country (see Docquier and Rapoport (2012) for a review of the so-called "brain drain" literature). Our paper is more closely related to the empirical literature that studies the labor market effects of immigration policies (e.g. Peri et al. (2015), Clemens et al. (2018), Moser and San (2020), Beerli et al. (2021), Khanna and Morales (2021), Abarcar and Theoharides (2021) , Abramitzky et al. (2023)), which typically does not study the effects on third countries as well. The closest paper to ours is Glennon (2023), who shows that US multinational corporations (MNCs) experiencing H-1B visa constraints increased employment in their affiliates. Our paper contributes to this literature by offering quasi-experimental evidence of spillover effects of immigration policy on third countries. Relative to Glennon (2023), our results are robust to the exclusion of MNC firms, suggesting that spillover effects on other countries may not require MNC linkages with the imposing country.

Our paper also relates to the recent literature on the impact of immigration on firms (Kerr and Lincoln, 2010; Paserman, 2013; Kerr et al., 2015; Mitaritonna et al., 2017; Ottaviano et al., 2018; Beerli et al., 2021; Brinatti and Morales, 2021; Doran et al., 2022; Clemens and Lewis, 2022; Mahajan, 2022; Brinatti et al., 2023). To a large extent, this literature relies on shift-share designs that use the change in the stock of immigrants as the shift, or on quasi-experimental designs focusing on a relatively small subset of firms. We bridge the gap between these works by using quasi-natural variation in the aggregate supply of skilled workers to study the effects among all firms in the economy and the aggregate GE effects.

We contribute to the literature in international trade studying how changes in factor endowment affect factor prices (Samuelson, 1948; Rybczynski, 1955; Davis et al., 1997; Hanson and Slaughter, 2002; Romalis, 2004; Zimring, 2019). According to Rybczynski's theorem, in a multi-sector neoclassical economy with free trade, changes in factors endowment, and thus immigration policy, may not affect wages. The mechanisms in our model through which international trade and migration interact are rooted in this theorem. We contribute to this literature by quantifying the extent to which the predictions of those fundamental theorems apply in modern quantitative models with current levels of trade.

A related literature studies the effects of immigration using quantitative models of trade (Di Giovanni et al., 2015; Bound et al., 2017; Desmet et al., 2018; Allen et al., 2019; Monras, 2020; Burstein et al., 2020; Khanna and Morales, 2021; Brinatti and Morales, 2021; Caliendo et al., 2021). The closest papers to ours are Burstein et al. (2020) who study the impact of US immigration policy on American workers but in a closed economy, and Caliendo et al. (2021) who study the interaction between international trade and migration in the context of the European Union enlargement using a single-sector model. Our paper offers a new quantitative trade model that incorporates migration policy and migration choice under uncertainty in a tractable way. Additionally, it quantifies the role of international trade in the efficacy of immigration policy in a multi-sector model. In our model, unlike in a single-sector model, the impact of international trade on the welfare implications of the immigration policy can be either positive or negative.

The paper is organized as follows. Section 2 introduces the data and institutional background. Section 3 describes the H-1B policy change and provides reduced-form evidence of its effects on the Canadian economy. Section 4 develops the quantitative model and offers analytical results for the effects of US immigration restrictions on third countries and American workers' welfare. Section 5 calibrates and validates the model. Section 6 presents the quantitative results. Section 7 concludes.

2 Data and institutional background

2.1 Assembly of a novel dataset

Our data includes US and Canadian visa application data, and a Canadian administrative dataset containing the universe of employer-employee-linked records, immigration records, and international trade records. This section describes these datasets and how we use them. The appendix provides details on the datasets, measurements, samples, and the crosswalk we manually developed between the occupational classifications used in the H-1B application dataset and the PR application dataset.

2.1.1 US H-1B visa application data

Our data contains the universe of processed I-129 petitions for H-1B workers from fiscal year 2000 to 2018 (e.g., Oct-2000 to Sept-2018). It was obtained from the USCIS through a FOIA request. For each petition, the dataset provides the name and location of the sponsoring firm, the country of birth and education level of the worker, and the salary and occupation of the job. It also specifies the type of H-1B petition, which allows us to determine whether the application is a new or a continuing application (e.g. renewal, change of employment or employer, and amendment), whether the application has been approved or denied, and the date when the decision was made. We use this dataset to construct the exposure measure of different immigrant groups to the H-1B policy change.

The USCIS stops processing and recording petitions after the annual cap of new H-1B visas for-profit organizations has been reached. This lack of information regarding unprocessed new H-1B visas motivates us to use continuing visas to measure the US policy shock in section 3.2.

2.1.2 Canadian Permanent Resident visa application data

Our application data, obtained from the Canadian immigration agency (IRCC), covers the period from 2012 to 2018 and includes the total number of individuals who submitted complete applications for permanent residency. The data is organized by year, occupation (4-digit National Occupational Classification, NOC), country of citizenship, visa program of the permanent residency application, and education. We retain applications from individuals holding a bachelor's degree or higher and aggregate them based on occupation, country of origin, and year.

2.1.3 Canadian administrative data

The following Canadian administrative data sets except for the Labor Force Survey (LFS) are part of the Canadian Employer-Employee Dynamics Database (CEEDD). We use the CEEDD data to measure a comprehensive set of firm's outcomes. We use the firm-level employment composition by nationality from the CEEDD, and the industry-level employment composition by occupation from the LFS to compute the exposure of each firm to the H-1B policy change.

Employer-employee link records (T4-ROE): This dataset includes the universe of payroll records in Canada between 2012 and 2018.

Immigrant landing records (IMDB): This dataset collects information on all the foreign citizens who came to Canada but were not on a temporary visitor visa when they landed as permanent residents or applied for a non-temporary visiting visa. It includes information on the birth country of each immigrant, the year of landing for the immigrants who have become

Canadian permanent residents (PR), and the effective dates of all the non-PR visas applied by each immigrant.

Corporate tax filing (NALMF): National Accounts Longitudinal Microdata File (NALMF) is a longitudinal administrative database of the universe of Canadian firms that includes the firm's total revenue and cost.

Personal tax filing (T1-PMF): This data is a longitudinal database of the universe of individuals paying taxes. We use the granular location information of each individual to determine the labor market of a firm because the NALMF data does not include granular information about the firm's location.

Goods trade records (TIC and TEC) This data records each firm's goods trade activities reported to Canadian customs by product and country of the trading partner.

Activities of multinational enterprises in Canada (AMNE) It includes the total value of imports and exports of services of all firms in Canada with a valid business registration record, including non-multinational enterprises.

Labor force survey (LFS) This is a monthly survey data conducted by Statistics Canada. In this survey, the respondents report their country of birth, the sector and occupation of their main job, and the associated weekly earnings. We use this information to compute each industry's employment and wage-bill composition by country of origin and occupation.

2.2 Institutional background

H-1B program

The H-1B visa program enables U.S. employers to hire highly skilled foreign workers in specialized occupations that demand advanced knowledge and a minimum of a bachelor's degree.[7] To obtain an H-1B visa, an individual must have a qualifying job offer from a sponsoring firm. The firm is required to submit a Labor Condition Application (LCA) to the Department of Labor, which verifies that the employment offer meets the criteria of the H-1B visa program. For instance, it verifies that the wage level specified by the employer aligns with the education and the years of experience required for the position. Once the LCA is approved, the firm can file an I-129 petition with the USCIS, which makes the ultimate decision about the visa application. Initially valid for three years, the H-1B visa can be extended for an additional three years. An H-1B

[7] The H-1B authorized-to-work population is an important part of the high-skilled employment in the U.S.In 2016, approximately 564,663 immigrants were working with the H-1B visa, which represents 7% of immigrants holding a college degree of higher and 30% of immigrants in STEM occupations.

holder must submit a petition if she decides to renew her visa or if there are significant changes in her employment conditions such as a change of employer or occupation.

In the pre-shock period, there were approximately 350,000 annual applications, with 40% being new H-1B visas and 60% continuing visas. The distribution of applications across nationalities and occupations exhibits skewness. Most H-1B visas are issued to workers from India (69%), followed by workers from China (9%), Canada (2%), the Philippines (2%), and Korea (1%). In terms of occupations, computer-related occupations account for 64%, followed by occupations in engineering (9%), administrative specializations (6%), education (6%); and medicine and health (5%). Regarding the sector of the employer sponsoring the H-1B visa application, they are concentrated in the skilled-intensive service sector. Approximately 60% of the firms operate in the business service sector, 8% in the high-tech manufacturing sector, 7% in educational services, 6% in Finance and Insurance services and 5% in Informational and Cultural services.

Canadian visa program: Point-based system

The main channels for skilled immigration intake in Canada are the Permanent Residence (PR) visa programs.[8] Prospective PR visa applicants must fulfill core eligibility criteria to enter an application pool, where they are automatically ranked using a point system. This system assesses points based on factors such as education, work experience, language proficiency, age, and having a valid job offer in place (See Appendix table 7), and there are no limits on the number of visas granted. Approximately every two weeks, the ministry announces the number of individuals who will receive an Invitation to Apply (ITA) for permanent residence. Starting from the highest-ranked candidates in the pool, invitations are extended until the specified number of intended ITAs is reached. Recipients have up to 60 days to submit a complete application. The estimated target processing time from the submission of a completed visa application to the final decision by Immigration, Refugees, and Citizenship Canada (IRCC) is six months. However, it could be as fast as two weeks.

These features of the Canadian immigration system have two implications for the effects of H-1B restrictions on Canadian immigration. First, given the H-1B qualifications of the typical H-1B applicant, they are likely to have a competitive profile among the applicant pool. Second, they have the opportunity to relocate to Canada quickly due to favorable processing times and no numerical limits.

Regarding the composition of applicants by occupation and nationality, two features emerge. First, the distribution of countries is significantly less skewed compared to the U.S. case. The largest countries in terms of skilled applications include India (10%), the Philippines (12%), China (10%), France (5%), and Iran (5%). Secondly, immigrants in Canada and the U.S.

[8]Workers can use temporary migration programs, but the complicated process for temporary migration often leads them to opt for permanent migration instead (OECD., 2019).

appear to perform distinct tasks, a variation that our identification strategy will exploit. For example, while 83% of Indians applying for an H-1B are computer scientists and only 1% are managers, the respective fractions among Indians applying for a PR visa are 35% and 12% for computer scientists and managers. The divergence in the jobs performed by immigrants in the U.S. and Canada can be attributed, in part, to the contrasting systems employed to allocate H-1B and PR visas. The sponsorship system in the U.S. establishes strong links between application numbers and labor demand, resulting in a concentration of H-1B visas in computer-related occupations. Conversely, Canada's point-based system prioritizes individuals with higher overall human capital.

3 H-1B policy change: Reduced-form analysis

3.1 H-1B policy change

Advocates of more stringent H-1B requirements argue that loopholes in the law allow employers to use the program to replace American workers at lower pay (Matloff, 2002; Hira, 2010). President Donald Trump aimed to end program misuse, and during his mandate, immigration policy change to "create higher wages and employment rates for U.S. workers and to protect their economic interests by rigorously enforcing and administering our immigration laws".[9]

Beginning in March 2017, the USCIS issued a series of internal policy memorandums (PM) that tighten the eligibility criteria for H-1B visas and entered into effect immediately.[10] First, while a bachelor's degree used to be sufficient to meet the requirements of a specialty occupation, this was no longer the case unless the Occupational Outlook Handbook (OOH) from the Bureau of Labor Statistics (BLS) explicitly specifies that a bachelor's degree is required for that occupation. For example, computer programmers with a bachelor's degree now need to provide additional evidence to meet the requirement, as the OOH states that individuals may enter the field with an associate degree. Conversely, the OOH specifies that several positions in health-related occupations require a bachelor's degree or higher. These examples illustrate that the new PM effectively tightened the eligibility criteria for some occupations more than for others. Our empirical design will exploit variation across occupations introduced by the policy. Second, the USCIS required additional evidence when the complexity of the job duties was inconsistent with a low-wage position in the petition. Third, USCIS stopped giving deference to previously approved petitions (e.g. renewals), which were now subject to the same scrutiny as new H-1B visas. Fourth, the scrutiny of H-1B petitions for workers who work at third-party worksites increased to ensure their genuine employment by the petitioning employer. This new rule especially

[9]See this Presidential campaign's press release and the executive order "Buy American and Hire American".

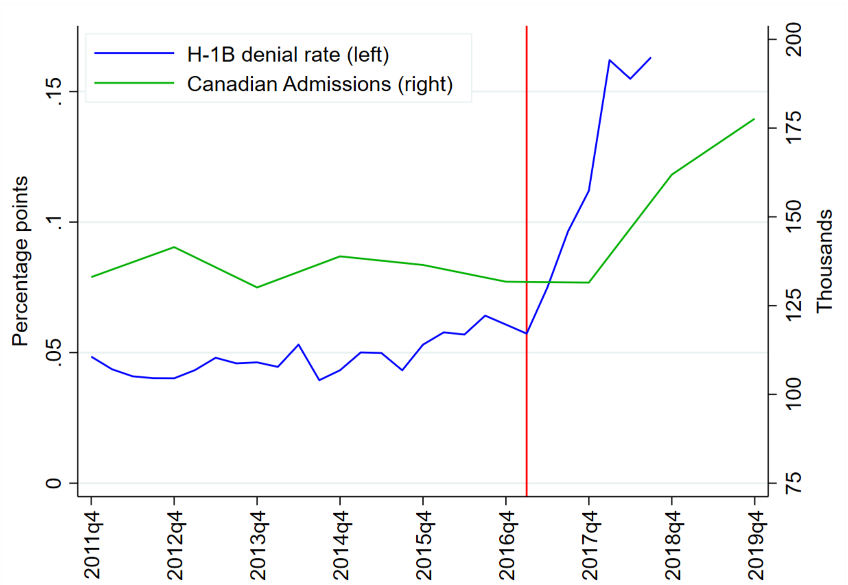
[10]These PMs were not public information. The PMs and additional documentation have been made publicly available by the American Immigration Lawyers Association and the American Immigration Council who filed a FOIA lawsuit to obtain records concerning USCIS's adjudication of H-1B petitions.

affected companies providing IT and other business services to American firms.[11]

Applications that failed to meet these new requirements were denied, leading to a sharp increase in denial rates and a decrease in H-1B approvals. Denials rates increased from 6% in 2016 to an unprecedented 16% in 2018 (see Figure **??**) and H-1B approvals drooped by approximately 140,000 visas (relative to trend) by the end of 2018 (see Appendix Figure 10 for the time series of this levels).[12]

One year later, Canada experienced a trend break in the number of skilled immigrant admissions with an average annual increase of approximately 30% relative to 2016 (Figure Figure **??**). In the period between 2018 and 2019, there were about 76,000 additional admissions, representing a 3.5% increase in the number of college-educated immigrants, or about 1% of all college-educated workers in Canada. It is plausible that U.S. immigration restrictions explain the increase in

Figure 1: Increasing H-1B Restrictions and Skilled Immigration to Canada



Note. The blue line, which corresponds to the left y-axis, plots the number of denied H-1B applications divided by the total number of H-1B applications. It includes new and continuing H-1B. Given that the period to apply for new H-1B visa applications is March-April, we remove seasonality by computing a four-quarters moving average for new H-1B applications. The green line, which corresponds to the right y-axis, plots the number of admissions granted under Permanent Residence programs commonly used by skilled workers. These programs are the Canadian Experience, Skilled Trade, Skilled Worker, and Provincial Nominee Program.

immigration to Canada. However, other factors may explain the increase in immigration to Canada, such as changes in U.S. trade policy, increased xenophobia, or demand shocks in Canada. In the next section, our empirical strategy aims to isolate the effect of US immigration policies on Canadian immigration from the effect of other factors.

[11]See this PM about the specialty occupation requirements, this PM about renewals, this PM on third-party worksites, and this official document about actions taken to ensure employer compliance with approved petitions.

[12]The spike in denials explains the spike in denial rates. The denial rate of renewals exhibits a similar pattern (see Appendix Figure 9).

3.2 Effects of US restrictions on skill immigration to Canada

Our strategy leverages plausibly exogenous variation across time and immigrant groups introduced by the new policy and controls for the effects of unobservable factors on Canadian immigration with a comprehensive set of fixed effects.

3.2.1 Event-study framework

We employ an event-study framework to document the effect of the new H-1B policy on Canadian applications. Intuitively, this framework compares the change in Canadian applications before and after the introduction of the new PMs for immigrant groups that were differently exposed. An immigrant group is given by the combination of the applicant's country of origin and occupation, denoted by c and o respectively.Our measure of exposure to the new eligibility criteria, denoted by $Intensity_{co}$, proxies for the fraction of the immigrant group co who got the H-1B visa application denied. Our event study model takes the following form:

$$log(App_{co,can,t}) = \sum_{\tau \neq 2016} \theta_\tau \times Intensity_{co} \times 1(t = \tau) + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot} \tag{1}$$

where $App_{co,can,t}$ is the number of Canadian visa applications of an immigrant group co in year t, δ_{co} are fixed effects at the immigrant group level, δ_{ot} are fixed effects at the occupation-year level, δ_{ct} are fixed effects at the country of birth-year level, and ϵ_{cot} is the error term, which we cluster at the immigrant group level. The coefficients θ_τ measure the difference in the outcome variable between year t and year 2016, our baseline year, for immigrant groups that are differently exposed to the new U.S. restrictions. Given that the effect of the new H-1B policy should affect outcomes only after the PMs were introduced, we expect θ_τ to be zero for $\tau < 2016$ and to be different from zero for $\tau = \{2017, 2018\}$.

We measure $Intensity_{co}$ as the fraction of the initial number of applications to North America, either the US or Canada, that were denied under the new policy:

$$Intensity_{co} = \frac{Denial\ Rate_o^{2018} \times Initial\ US\ Applications_{co}}{Initial\ US\ \&\ Canada\ Applicantions_{co}} \tag{2}$$

where "Initial" refers to the years before the introduction of the policy memos (i.e. FY2012-FY2015). The numerator can be interpreted as the number of immigrants denied in the US who can potentially consider migrating to Canada. $Intensity_{co}$ can be written as the interaction between the denial rate and the share of the US in the total number of applications. This share, which we denote by $\pi_{co,usa}$, aims to measure the propensity of an immigrant group to apply for a US visa.[13] The choice of occupation as the level of variation is motivated by the instructions

[13]To the extent that which $\pi_{co,usa}$ accurately predicts post-treatment value, $Intensity_{co}$ can be interpreted as an accurate measure of the actual fraction denied. The empirical evidence on immigrant networks suggests that this fraction is likely to be stable over time because immigrants tend to follow the occupational choices of their

specified in the PM.[14]

We compute the denial rate in the numerator of equation 2, denoted by dr_o, using only continuing H-1B visa applications and we exclude applications of new H-1B visas.[15] We worry that if we use all H-1B applications, the spike in denial rates may correlate with factors that affected immigration in Canada after 2016. Shocks in Canada or home countries affect the number of Canadian applications and, at the same time, it can impact the pool of H-1B applicants or the number of H-1B applications, eventually affecting H-1B denial rates. For example, changes in the number of H-1B applications would mechanically affect the approval rate of new H-1B visas that are subject to a cap. In such instances, our estimates would account for the effect of both H-1B policy change and these unobservable factors. To mitigate this concern, we compute the denial rates for continuing visas only because we expect that these applicants are less likely to respond to such factors. Applicants for continuing visas already live in the U.S., which reveals their preference for this country, and have secured a job, which increases the (opportunity) cost of leaving the U.S. Consequently, applicants for continuing visas may be less likely to suddenly respond to demand shocks in Canada or their home country.[16]

Figure 2 illustrates the *sources* of variation of the fraction affected by the policy: Figure 2a presents the denial rates of continuing H-1B visas by broad occupation in a typical year (red bar) and in the years following the introduction of the PMs (blue bar). The red bars have similar sizes suggesting that there are small differences across occupations in normal years. However, large differences arise upon the introduction of the PMs: on one extreme of the spectrum, computer-related occupations experienced a probability of denial of 18%, 14.6 percentage points larger than an average year. On the other extreme, health-related occupations experienced a denial rate of 4%, 1.1 percentage points larger than the average year. Figure 2b emphasizes the variation across countries introduced by $\pi_{co,usa}$. It plots the top and bottom five countries in terms of $\pi_{co,usa}$ for CS, showing that Indian CS are 60% more likely to apply to the U.S. than French CS (e.g., $\pi_{India,cs,usa}/\pi_{France,cs,usa} = 1.6$). Consequently, the fraction of Indian CS affected is 60% larger than that of French CS.

Threats to our identification strategy arise if other determinants of Canadian applications change when the H-1B policy changes and correlate with our measure of the fraction affected. In such cases, our estimates of θ_{2017} and θ_{2018} will be contaminated by the effect of the changes in these

compatriots (Bartel, 1989; Altonji and Card, 1991; Card, 2001; Patel and Velia, 2013).

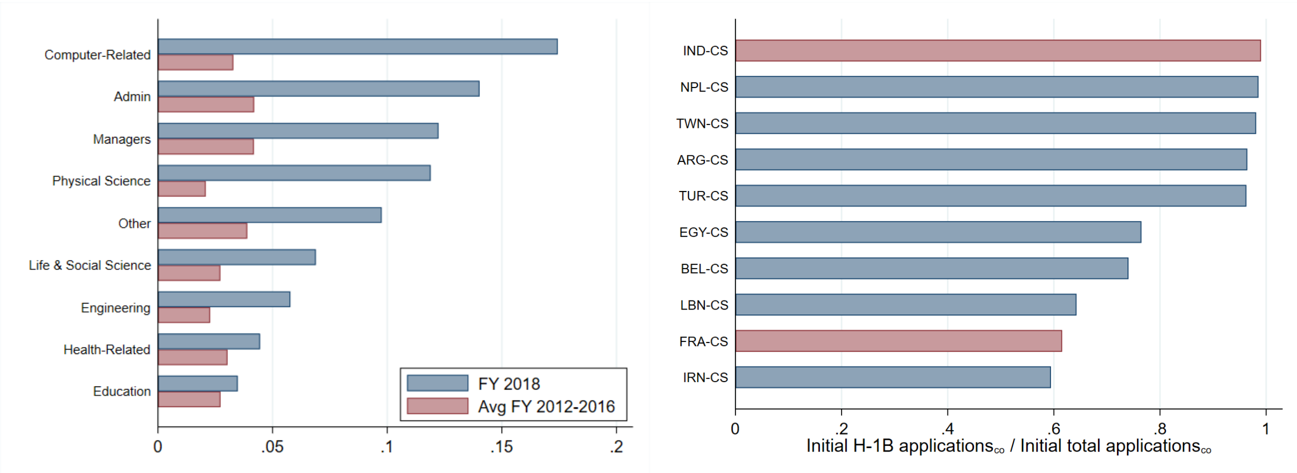
[14]We do not find evidence in the data, nor the PM, suggesting that the policy changed for immigrants from different nationalities working in the same occupations.

[15]Continuing H-1B visas account for 55% of all denials and also experienced a spike in denial rates (see Appendix Figure 9).

[16]In line with this hypothesis, Appendix Figure 11 shows that immigrants living in the U.S. do not generally apply for Canadian visas. However, in 2017, there was a significant and sudden surge in applications. This pattern is consistent with a more restrictive US policy that left this group of immigrants with denied visas no alternative but to leave the country.

Figure 2: Source of cross-sectional variation in $Intensity_{co}$

(a) Denial rates by broad occupation (b) Variation across nationalities: Examples



Note. Figure 2a plots the denial rate for continuing H-1B visas by broad occupations. The red bars represent the denial rates in an average year before the introduction of the policy memos, and the blue bars present the denial rates of FY 2018, after the introduction of the PMs. Figure 2b plots $\pi_{co,usa}$ for the top and bottom five countries in terms of $\pi_{co,usa}$ for CS.

other factors. To address these concerns, we control for a rich set of fixed effects. We include immigrant groups-fixed effects δ_{co} that control for preexisting differences between groups. Therefore, the change *over time* in Canadian applications for immigrant groups differently exposed will identify θ_τ. We also include in occupation year fixed effects, δ_{ot} to prevent attributing the effect of occupational trends to the effect of H-1B restrictions. This is important because some of the occupations that were more affected by the new eligibility criteria were growing relatively more quickly. Additionally, some countries were experiencing worsening political and economic conditions that may have pushed their citizens to emigrate. For example, immigration from India has been on an upward trend to several developed countries, including the US and Canada. If countries that experienced worsening conditions are those that tend to emigrate to the U.S., our estimate will be upward biased. To control for factors of this nature, we include country of origin-year fixed effects, δ_{ct}.

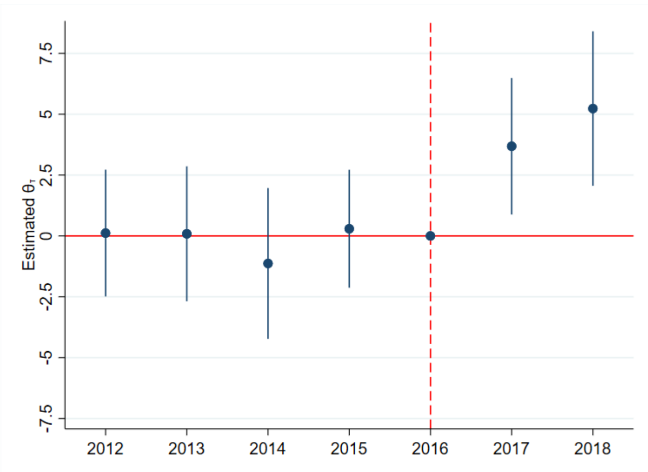
The identifying assumption is that the change in the outcome variable in the years 2017 and 2018 would have been the same for immigrant groups that were differently exposed to US immigration restrictions, conditional on controls. We assess the plausibility of this assumption by formally testing whether θ_τ is zero for τ between 2012 and 2015. Failing to reject that θ_τ is zero suggests that the outcome variable of immigrant groups that will later be differently exposed to the U.S. restrictions were in parallel trends. It would then be plausible that these units would have grown at the same rate in the absence of the H-1B restrictions.

3.2.2 Results

Figure 3 plots the estimates of θ_τ for the years 2012-2018. It was only after the US restrictions were imposed that Canadian visa applications of immigrants more exposed to the US restrictions grew faster than less exposed immigrant groups. The estimates for the years after the US shock, $\hat{\theta}_{2017}$ and $\hat{\theta}_{2018}$, are 3.7 (s.e.=1.4) and 5.2 (s.e.=1.6) respectively. They are statistically significant at conventional levels (1%) and economically large. Our estimates predict that Canadian applications in 2018 were 31% larger than what they would have been in the absence of the H-1B restrictions.[17]

Our event-study estimates offer two statistics that are useful for policy-relevant analysis. First, a 10-percentage point increase in the fraction of immigrants who are affected results in a 5.2% rise in Canadian applications in 2018. Alternatively, with an average exposure $\pi_{co,usa}$ of 0.57, a 10-percentage point increase in H-1B denial rates leads to a 30% growth in Canadian applications compared to the scenario without these restrictions. Second, when we consider the response of Canadian applications and H-1B visa approvals, a back-of-the-envelope calculation suggests that roughly every 4 H-1B visa approvals forgone result in an increase of about 1 Canadian Permanent Resident (PR) application.[18]

Figure 3: Effect of H-1B restrictions on PR Canadian Applications



Note. The y-axis plots the estimated event study coefficients, θ_τ, of equation 1. The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The coefficients plotted correspond to column 1 in Appendix Table 8.

Several reasons can explain this large response in the number of Canadian applications. First, immigrants may choose Canada due to its economic opportunities, labor market integration, language, and cultural similarities. Second, the Canadian government is open to receiving skilled

[17] This prediction follows from $\hat{\theta}_t \times \sum_{co} \omega_{co}\ Intensity_{co}$ where ω_{co} is the share of applications of immigrant group co in total Canadian applications in the baseline year 2016.

[18] We estimated the difference-in-difference version of regression (1) for Canadian applications and H-1B visa approvals. Let $\hat{\theta}^{relative}$ be the ratio of the response of Canadian applications and the response of H-1B approvals. Our back-of-the-envelope computation is given by $\hat{\theta}^{relative} \times \frac{Applications^{can}_{2012-2016}}{Aprovals^{H-1B}_{2012-2016}}$.

immigrants and actively positions itself as an attractive alternative to the U.S. Third, American firms, which have long faced immigration challenges, are prepared to quickly relocate their employees to Canada.[19]

3.2.3 Discussion of threats to identification

Several factors may threaten the identification of the impact of US immigration restrictions. These concerns include potential correlations over time of confounding factors, which would imply that ϵ_{cot} correlates with past applications and thus hence $\pi_{co,usa}$; the possibility of the policy change being a response to increasing immigration of specific groups, which would bias our estimates upward; and the influence of contemporaneous changes in Canadian immigration policy on affected immigrant groups. We address these concerns through robustness exercises, detailed in Appendix section C, which yield consistent results with our baseline specification. We also test for linear trends that would violate our identification assumption (Roth, 2022). Finally, we show that results are unlikely to be driven by outliers.

3.3 Effects of skilled immigration on Canadian firms

After establishing that the H-1B restrictions resulted in increased skilled immigration to Canada, this section documents the extent to which H-1B restrictions affected production in Canada and native employment.

3.3.1 Event-study framework

To quantify the effect of the H-1B restrictions on firms' outcomes, we compare the difference in the outcome before and after the introduction of the PMs of firms that were more exposed to the H-1B restrictions relative to firms that were less exposed. We implement this idea through an event-study design. This design allows us to exploit plausible exogenous variation given by the immigrant groups that were affected by the restrictions and to control for the effect of other factors that may have affected the firms' outcomes after 2016. Our empirical model for outcome y of firm i in year t is as follows:

$$y_{it} = \sum_{\tau \neq 2016} \beta_\tau \times Intensity_i \times 1(t = \tau) + \delta_i + \delta_{mt} + \gamma' X_{ikt} + \epsilon_{it} \tag{3}$$

where we consider several outcome variables y_{it} that are scale-independent such as the logarithm of sales or, as commonly done in the literature of immigration, the number of native workers hired relative to the employment level in the baseline year. $Intensity_i$ is an exposure intensity measure to the H-1B policy change, which we describe shortly. The index k refers to the industry where the firm operates according to the 4-digit NAICS classification, and m refers to the location of

[19] See Envoy Global's 2019 Report, based on a survey of more than 500 HR professionals in U.S. companies.

the firm. δ_i are firm-fixed effects, δ_{mt} are labor markets-year fixed effects, X_{ikt} is a set of control variables that vary over time and across firms and industries, and ϵ_{it} is the error term, which we cluster at the firm level. The coefficients β_τ measure the difference in the outcome variable y between year τ and year 2016, our baseline year, for firms that are differently exposed to the introduction of the PMs. Given that the effect of the new H-1B policy should affect outcomes only after the PMs were introduced, we expect β_τ to be zero for $\tau < 2016$ and to be different from zero for $\tau = \{2017, 2018\}$.

Firm exposure to the H-1B restrictions $Intensity_i$ aims to predict which firms hire the immigrants that migrate to Canada due to the H-1B restrictions. Because these restrictions increased the inflow of immigrants from specific countries working in certain occupations, we expect that the impact will be greater on the firms that typically absorb these immigrant groups. For instance, given that the fraction affected of CS from India was relatively high, we expect a firm that tends to hire many CS from India to be more affected compared to a firm that hires Canadian workers. Our expectation builds on the idea that immigrants may sort into firms based on their networks. Firms, like labor markets, serve as important channels for immigrant networks due to the vital role that co-nationals play in sharing information and providing referrals for immigrants (Egger et al., 2021).

We construct a measure of exposure that builds on this idea. Let $Flow_{co}^{post}$ be the number of workers migrating to Canada due to the H-1B policy, and $\frac{L_{coi}}{L_{co}}$ be the initial share of firm i in the aggregate employment of workers *co*. Suppose that this inflow of workers is assigned to firms according to this share (e.g., a firm that tends to hire 1% of CS from India in the Canadian labor market, gets assigned 1% of $Flow_{co}^{post}$). Then the number of *co* workers assigned to firm i is $\frac{L_{coi}}{L_{co}} \times Flow_{co}^{post}$ and the total number of workers assigned to firm i relative to its initial number of workers, L_i, is:

$$\frac{Hires_i^{post}}{L_i} \approx \sum_{co} \frac{L_{coi}}{L_{co}} \frac{Flow_{co}^{post}}{L_i} \tag{4}$$

In this equation, the growth in employment of firm i depends on the aggregate growth in the number of workers due to the H-1B restrictions ($Flow_{co}^{post}$) scaled by the aggregate employment level (L_{co}) and weighted by the share of this immigrant group in the employment of the firm ($\frac{L_{coi}}{Li}$). This exposure measure can be thought of as a Bartik exposure with the shift given by $\frac{Flow_{co}^{post}}{L_{co}}$ and the share by $\frac{L_{coi}}{Li}$. According to this measure, firms with a workforce composition tilted to the immigrant groups that were relatively affected by the policy are more exposed to the US policy change.

We can not measure (4) directly from the data because we do not have occupation information at the firm level, and do not observe the change in the number of immigrants *co* coming to Canada after 2016. However, we can proxy for both the shift and the share as follows. Regarding the proxy of the share, we first note that this share can be expressed as the multiplication of the share of nationality c within occupation o ($\frac{L_{coi}}{L_{oi}}$) and the occupation share in the firm's total workforce ($\frac{L_{oi}}{L_i}$). We proxy $\frac{L_{coi}}{L_{oi}}$ with the overall nationality share ($\frac{L_{ci}}{L_i}$), and the occupational structure of the firm $\frac{L_{oi}}{L_i}$ with that of the industry where it operates ($\frac{L_{ok(i)}}{L_{k(i)}}$). Regarding the shift component, we multiply and divide it by the flow of immigrants in the baseline year $Flow_{co}$ to obtain $\frac{Flow_{co}^{post}}{L_{co}} = \frac{Flow_{co}^{post}}{Flow_{co}} \times \frac{Flow_{co}}{L_{co}}$. We assume that the growth in the inflow of immigrants is proportional to the growth of their applications (e.g. $\frac{Flow_{co}^{post}}{Flow_{co}} \propto \Delta log(App_{co})$) and measure the cross-sectional variation in the growth of applications with plausible exogenous variation introduced by the policy change (e.g. $\Delta log(App_{co}) \approx \theta \ Intensity_{co}$). As a result, $Intensity_i$ is proportional to (4) and given by:

$$Intensity_i = \sum_{co} \frac{L_{ci}}{L_i} \frac{L_{ok(i)}}{L_{k(i)}} \ Intensity_{co} \ \frac{Flow_{co}}{L_{co}} \tag{5}$$

This firm's exposure predicts that firms are relatively exposed if they tend to hire immigrants from the affected nationalities *and* are in industries intensive in occupations that experienced a large increase in H-1B denial rates.

Appendix Table 9 provides summary statistics for $Intensity_i$ by sector, highlighting significant variations in average firm exposure. The top quartile of sectors includes high-skilled service industries such as Information and cultural industries (IC), IT, management of enterprises, financial services, and educational services (NAICS 51, 54, 55, 52, and 61, respectively). Each of these sectors also exhibits substantial dispersion across firms.

Control variables We include firm-fixed effects δ_i that control for time-invariant differences between firms. Therefore, β_τ is identified by the change *over time* in the outcome variable for firms with different initial exposure to the policy.

Additionally, we control for potential industry-level confounders. One approach would be to include industry-year fixed effects. Given that the policy shock affected specific occupations, the immigrant inflow was concentrated in certain industries. Consequently, some industries have limited variation in $Intensity_i$ across firms. By including industry-year fixed effects, our estimate would capture the average impact of the policy within truly affected industries and unaffected industries. Instead of industry-year fixed effects, our baseline specification uses the rich cross-industry variation resulting from the policy change and incorporates the industry-year control variables. We discuss the within-industry estimates in Appendix Section D. First, we include sector-specific trends in X_{ikt} because some industries that were growing faster happened to be intensive in the occupations affected by the rise in H-1B denials, such as the IT sector. Second, we control for global industry-specific shocks by including the number of jobs created in the UK, denoted as $JobsUK_{kt}$. Appendix Figure 15 illustrates a pre-shock correlation of approximately 0.95 between the UK and Canada. Finally, we include the employment growth of the industry in 2011 interacted with a year-fixed effect to account for the effect of domestic factors.

Another concern arises from reverse causality, which occurs when immigrants choose where to locate. The expansion of firms operating within a market might be the cause of increased immigration, rather than the reverse. To insulate our estimates from local shocks and reverse causality concerns, we aim to compare firms that were differently exposed to the H-1B restrictions and were located in the same labor market (e.g. a firm in the IT sector and a firm in hospitality in Toronto). To that end, we include labor market-year fixed effects. Notice that these fixed effects also absorb the consumption effect of immigration, which arises because immigrants are consumers of goods produced by firms located in the market where they settle. We thus interpret β_τ as the effect of increasing immigrant labor supply on firm outcomes.

Additionally, firms that typically hire immigrants might experience relatively faster growth even in the absence of H-1B restrictions, due to the ongoing immigration inflow. To disentangle these two effects, we would like to compare firms with similar reliance on immigrant labor but with different exposure to the H-1B policy change. This motivates us to include two controls that we interact with year dummies: the log of one plus the number of likely-skilled immigrants in 2016 and the immigrant share of the wage bill. Given that we do not have the education of information on all immigrants, we proxy skills with information about the nationality and the visa program (see Appendix B.2).

Another threat to identification is the confounding effects of changes in U.S. trade policy. For example, if the trade war between the US and China during Trump's administration diverted trade towards (or away from) Canadian sectors affected by the H-1B restrictions, $\hat{\beta}$ will be upward (downward) biased. To control for this potential concern in a flexible way, we include two control variables evaluated in the pre-shock period interacted with year dummies: the share of exports in total sales, and the share of service exports in total exports.

3.3.2 Results

Effect on Canadian workers We begin the analysis by showing that the new H-1B restriction increased the hiring of immigrant workers, as motivated in the construction of $Intensity_i$. Figure 4a presents the event-study estimates for the net hiring of immigrants relative to the firm's employment level in 2016. Prior to the US policy change, there were no significant differences in the hiring behavior of immigrants and natives between firms with different exposure to the restrictions. However, following the implementation of the policy change, firms with higher exposure exhibited increased hiring of both immigrants compared to firms with lower exposure. This evidence is consistent with the idea that our measure $Intensity_i$ serves as a proxy for $\frac{Hires_i^{post}}{L_i}$ in equation 4.

Figure 4a also plots the hiring of native workers and shows that relatively exposed firm also increased their hiring. This increase in total hiring is substantial. For reference, the average ratio of total hiring to employment in 2016 among exposed firms in the skilled service sector was 0.5%. Our estimates indicate that, for the average exposed firm in this sector, this ratio increased to 1.2% in 2017 and to 1.5% in 2018. The hiring of natives accounted for approximately 35% of the total hiring increase in 2017 and for 30% in 2018.[20] In other words, our estimates suggest that immigrants *crowd in* natives at the firm: on average, a firm hires approx. 0.5 additional native workers per immigrant hired due to the H-1B restrictions. We also find a substantial increase in terms of the stock of native workers. The event study estimates of log(native employment) shown in Figure 4b, suggest that the effects are statistically and economically significant. For instance, the average exposed firm in the skilled service sector would be expected to have a 1.3% larger number of native employees in 2018 than what it would have had in the absence of the H-1B restrictions. Regarding the earnings of native workers, Figure 4c shows the effect on earnings per worker and median earnings. Our estimates imply a modest drop in 2017 and an approximate drop of 0.5% in 2018 at the average exposed firm in the high-skilled service sector.

As the model will make clear, our findings align with a classic supply and demand model in a competitive labor market where immigrants and natives are imperfect substitutes, and there are several "types" of native workers. When the supply of foreign labor increases, it impacts firms in two ways. First, it can make hiring foreign labor cheaper compared to native workers, inducing firms to substitute natives for immigrants. Second, it can drive down the wages of other workers and overall labor costs, inducing firms to expand their production scale. If the scale effect outweighs the substitution effect, we would expect firms to increase both native and immigrant hiring. Therefore, our findings would be supported if firms indeed expand their production. We present evidence for this production response next.[21]

Effect on production Firms with higher exposure to the immigration restrictions exhibited a larger change in (log) sales compared to less exposed firms, but only after the implementation of the restrictions (Figure 4d). The average exposed firm in the skilled service sector would be expected to register 1% larger sales than what it would have had in the absence of the H-1B restrictions. This estimate implies that an additional immigrant hired in 2017-2018 translated into an increase of 112,000 Canadian dollars in 2018 for the median firm in the skilled service

[20]For each year, we compute this number as follows: $\frac{\hat{\beta}_{\tau}^{HireImm}}{\hat{\beta}_{\tau}^{HireImm}+\hat{\beta}_{\tau}^{HireNat}}$.

[21]Through the lens of the model that we will introduce in the next section, workers tend toward sectors with higher exposure as these sectors expand relative to other sectors. Regarding the response of earnings per worker, the model predicts that native workers who are close substitutes to the incoming immigrants experienced a drop in wages, while other native workers experienced an increase. Because exposed sectors heavily employ occupations that experienced wage reductions, the earnings per worker in these sectors decrease compared to less exposed sectors.

sector, which represents a 3.2% of pre-shock sales.[22] The rise in sales is likely indicative of an increase in production because we found no evidence of changes in mark-ups (see event studies in column 12 in Appendix Table 10).

The rise in total sales in 2018 is in part explained by the growth in exports, which exhibited a delayed yet more significant response compared to overall sales. Figure 4e shows that the restrictions led to an increase in the share of exports in total sales in 2018 of 0.34 percentage points or 8%. A back-of-the-envelope calculation suggests that exports explain 38% of the increase in sales. The increase in the share of exports in total sales is explained by an increase in the export of firms that were already exporting (e.g. intensive margin).[23] Figure 4f plots the estimates for the log of exports and, thus, excludes observations with zero exports. The figure shows that exports registered a substantial increase: exports were 7.4% larger for the average exposed exporter in the skilled service sector due to the H-1B restrictions.

Effect on domestic firms One way through which H-1B restrictions can affect the Canadian economy is through multinational corporations (MNCs) that have locations in both, the US and Canada. Glennon (2023) shows that U.S. multinational corporations (MNCs) experiencing H-1B visa constraints increased employment in their affiliates in other countries, including Canada. Given these findings from prior research, our interest lies in determining whether our findings are attributed to the presence of multinational corporations or if they are a salient feature of domestic firms' responses. Appendix Figure 20 and Table 12 show estimation details when we estimated equation (3) excluding MNC for the main outcome variables (e.g. hiring of immigrants and natives relative to their employment in 2016, log of sales, log of exports, and the share of export sales in total sales). As expected, given that domestic firms account for the majority of the baseline observations, the estimates are similar to the baseline estimates. These results imply that the effect of US immigration restrictions extends beyond their direct impact on affected (American) firms, as previously documented. This novel fact suggests that MNC linkages are not needed for the US restrictions to affect third countries.

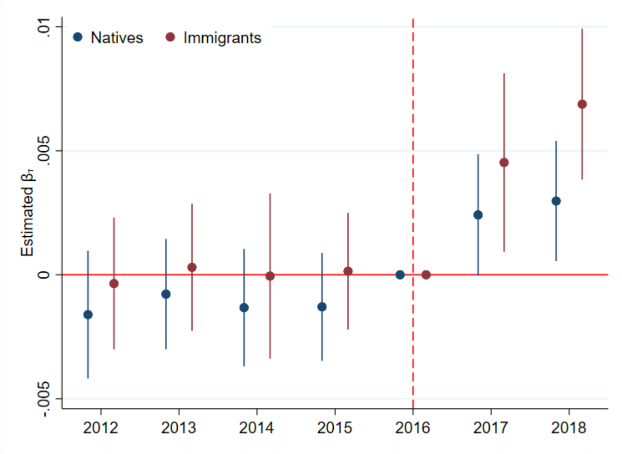
3.3.3 Robustness exercises

In Appendix section A, we address potential identification concerns and explain in detail the corresponding robustness exercises. First, we present estimates of the effect of the H-1B policy change that only uses within-industry variation (e.g., we include industry-year fixed effects in

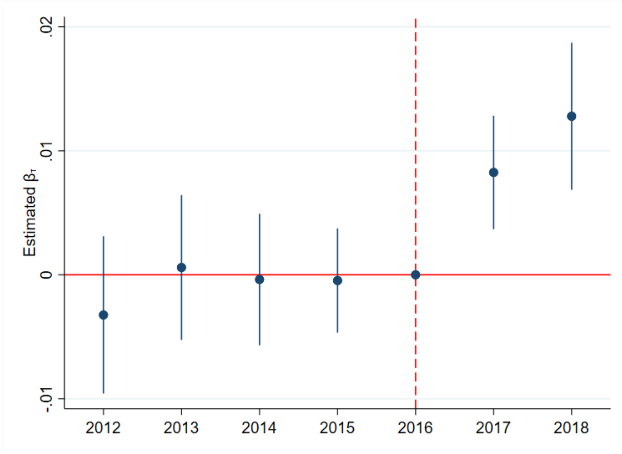
[22]Let $\hat{\beta}^y_\tau$ be the event-study estimate of the outcome variable y. We approximate the change in sales in 2017 and the hiring of immigrants in 2017-2018 as follows: $\Delta y_i \approx \hat{\beta}^y \; Intensity_i \; y_{i\,2016}$, for y being the log of sales and the net hiring of immigrants relative to the employment level in 2016. Then $\frac{\Delta sales}{\Delta hiring \; immigrants} = \frac{\beta^{log(sales)}_{2018}}{\beta^{HireImm}_{2017}+\beta^{HireImm}_{2018}} \times \frac{sales_{2016}}{employment_{2016}}$. Using the median value for the ratio of sales to employment in the skilled service sector yields the reported value.

[23]To obtain more precise estimates of the response of the log of exports, we restricted the observation to those with export values above \$8000, which is given by the 1st percentile of the sales distribution.

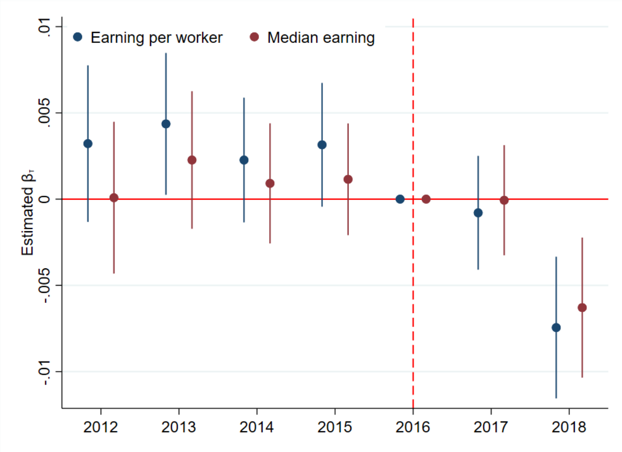
Figure 4: Effect of H-1B restrictions on Canadian firms



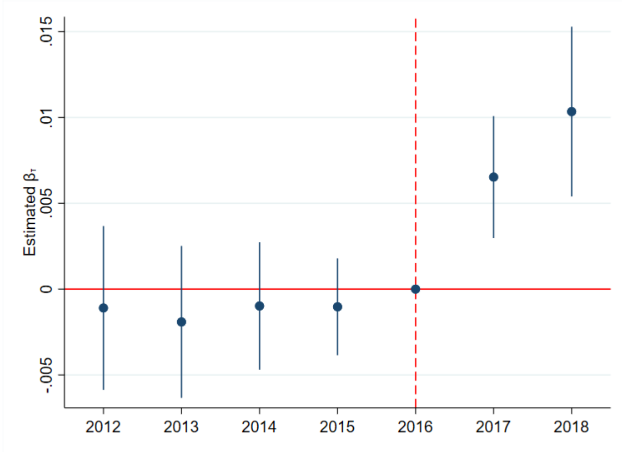
(a) Hiring relative to Employment in 2016



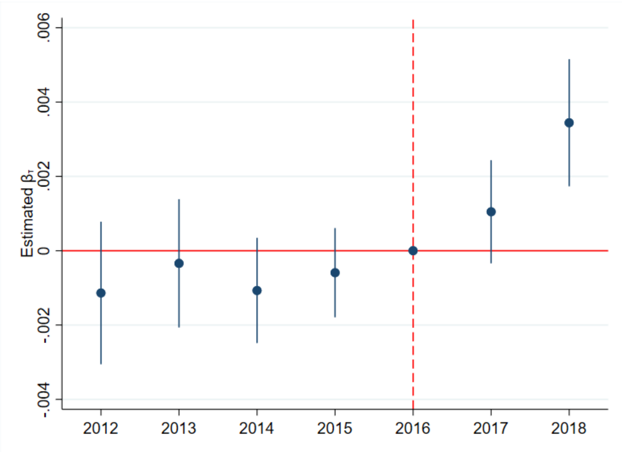
(b) Native employment (in log)



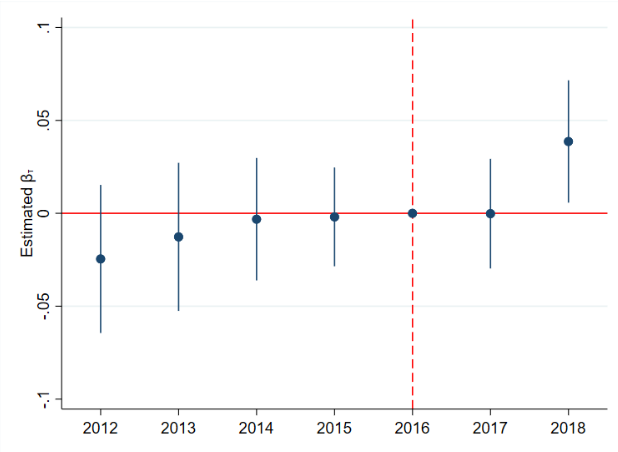
(c) Earning of native workers (in log)



(d) Sales (in log)



(e) Exports relative to total sales



(f) Exports (in log)

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation (3) multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The outcome variables considered are net hiring of immigrants and net hiring of natives with respect to the employment level in the baseline year 2016 (panel a), log number of native workers and total workers (panel b), log earning per worker (panel c), log sales (panel d), export sales relative to total sales (panel e), and log export sales (panel f). The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The coefficients plotted correspond to those reported in Appendix Table 10.

our baseline specification). Second, we test the potential impact of non-random assignment of $Intensity_i$ on our identification assumption. Third, we show the robustness of our estimates to foreign shocks by re-estimating equation 3 excluding importers and exporters. Finally, we show estimates are also robust to include additional control variables to account for changes in Canadian immigration policy leading up to the US policy change.

3.3.4 Takeaways to design the model

The evidence in this section and Appendix Table 10 provide a comprehensive description of why Canadian firms expanded, how they did so, and to which markets. We find that the inflow of immigrants reduced labor costs of Canadian firms, driving an expansion of production (see negative response of total earnings per worker in column ??). Although immigrants may lead to economies of scale (Bound et al., 2017), especially in the long term, our two-year analysis suggests it is not the primary driver. For instance, sales per worker did not show a significant response, and wages of domestic workers did not increase. Additionally, we find that firms expanded by increasing labor input in proportion to production. For instance, our estimate of β_{2018} for log sales closely aligns with our estimates for employment growth. This similarity can be seen in our estimate for the log of employment (as shown in column 6) or by adding our estimates for immigrant and native net hiring in relation to the employment level in 2016.[24] We also find that firms become more immigrant-intensive, as indicated by Figure 4a and the increase in the share of immigrants in the wage bill (Column 8). Finally, we find that firms expanded domestically and internationally. This evidence motivates the assumptions and mechanisms introduced in our quantitative model.

4 Theory: Immigration policy and international trade

Our next goal is to understand the aggregate and the distributional welfare effects of the H-1B policy change, and the extent to which its efficacy is affected by international trade. These goals ask for a quantitative general equilibrium model of international trade, international migration, and migration policy that can be quantified using our data and facts. In our model, we introduce a new modeling assumption to capture the effects of the observed policy change: workers decide to migrate with uncertainty about whether they will obtain a visa. In this section, we set up the model and use it to analytically study how US immigration restrictions spill over to other countries and affect the welfare of American workers.

[24] Although we do not observe the use of non-labor, our estimates for the response of total costs are consistent with other inputs responding in similar proportions (see column 12).

4.1 Setup

Environment The model is static. The world comprises multiple countries $c \in \mathcal{C}$ and sectors $k \in \mathcal{K}$. Countries can be divided into two groups: immigration-origin countries $\mathcal{C}^o$ and immigration-destination countries $\mathcal{C}^d$. There are multiple worker groups. As in the empirical analysis, each worker group is characterized by the combination of country of origin $c \in \mathcal{C}$ and occupation $o \in \mathcal{O}$. Goods and labor markets are perfectly competitive.

International migration Workers can only move from immigration-origin countries to immigration-destination countries. Workers who move from c to d lose a fraction $(1 - \zeta_{cod})$ of income at destination. Immigration policy is destination country d is given by an exogenous probability of approving a visa application $p_{cod} \in [0, 1]$.

Workers There is an exogenous mass of workers of group *co*, L_{co}. Within each immigration-origin country $c \in \mathcal{C}^o$, only an exogenous fraction ψ_{co}^{emm} of them can make the migration decision. Additionally, there is an exogenous mass of immigrants from country $c \in \mathcal{C}^o$ in destination country $d \in \mathcal{C}^d$, $\bar{L}_{cod}$.

Workers' heterogeneity We assume that workers are heterogeneous due to differences in productivity across sectors. Each worker ι from group *co* draws a random number of efficient units in sector k in country d, $a_{codk}(\iota)$, from a distribution F_{codk}^a. Given that this distribution is worker group-destination country-sector-specific, workers within each group *co* in country d are *ex-ante* identical but they are heterogeneous after $a_{codk}(\iota)$ is realized, while workers across groups also differ in that they draw their productivity from different distributions.

Workers are also heterogeneous due to preferences for applying for visas from different countries and home. We assume that worker ι draws taste shocks $\nu_{cod}(\iota)$ from a distribution F_{cod}^{ν}.

Timing assumptions All workers choose the sector of employment and only the fraction ψ_{co}^{emm} of L_{co} with $c \in \mathcal{C}^o$ make the migration decision. We impose the following timing assumptions for tractability. Worker ι draws $\nu_{cod}(\iota)$, and then makes the migration decision. After this decision is made, she draws $a_{codk}(\iota)$ and then chooses the sector of employment. This assumption allows us to solve the worker problem through backward induction.

Sector choice Each worker in country d draws $a_{codk}(\iota)$ from a Frechet distribution with dispersion parameter κ and with scale parameter a_{codk}, which can be interpreted as the comparative advantage of workers *co* in sector k in d.[25] Workers choose the sector that yields the highest

[25] Allowing productivity units to vary across sectors and destination countries implies that workers may choose different sectors depending on the country in which they live. This is consistent with the evidence provided by Khanna and Morales (2021) about skilled immigrants from India.

utility $u_{codk}(\iota)$, which is given by the real income net of migration costs:

$$u_{codk}(\iota) = \frac{\zeta_{cod}\ a_{codk}(\iota)\ w^f_{odk}}{P_d} \qquad u_{cock} = \frac{a_{cock}(\iota)\ w^n_{ock}}{P_c} \tag{6}$$

where P_c is the price index in country c, w^f_{odk} and w^n_{odk} is the effective wage per efficient unit of **f**oreign labor and **n**ative labor in country d working in occupation o in sector k.

Migration decision To migrate to country d, workers must apply for a visa. We assume that workers can only apply for one visa.[26] If their visa application is denied, they have to stay in their home countries. We bring the expected utility theory into an otherwise standard migration model to make the choice decision under uncertainty tractable in general equilibrium. We model individuals as risk-averse agents by assuming that the payoff in each contingent state is given by the log of the utility in that state, denoted by u_{cod}.

Workers choose the country to apply for a visa with the highest utility $U_{cod}(\iota)$:

$$U_{cod}(\iota) = p_{cod}\ \log(u_{cod})\ + (1 - p_{cod})\ \log(u_{coc})\ +\ v_{cod}(\iota)$$

where u_{cod} is real wage ι expects to earn in country d taking into account her optimal choice of k, e.g. $u_{cod} \equiv \mathbb{E}\Big(max_k\ u_{codk}(\iota)\Big)$. For tractability, we assume that $v_{cod}(\iota)$ is identically and Type-I generalized extreme value distributed. We allow for correlation (in a restricted fashion) across destination choices d as in Allen et al. (2019) to capture the idea that a foreign country and home may not be as close substitutes as two foreign countries. These distributional assumptions lead us to a tree extreme value model (McFadden, 1978; Cardell, 1991; Berry, 1994), where the "tree" has an upper nest between home and foreign countries, with elasticity of substitution ν_d, and an inner nest within foreign countries, with elasticity of substitution ν_h.

Consumption Consumers have two-tier CES preferences over goods. The upper nest is a composite bundle of goods from different sectors k, with elasticity of substitution α. Each good is in turn a composite of a continuum of varieties ω with an elasticity of substitution σ.

Production The technology to produce goods follows Burstein et al. (2020). Each variety in sector k and country d is produced by combining labor services from different occupations,

$$l_{dk}(\omega) = z_{dk}(\omega) \left(\sum_o\ \psi_{dko}\ l_{dko}(\omega)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{7}$$

[26] This assumption allows us to derive an equation to estimate ν_d that we can take directly to the data (see Section 5.1). If the correctly specified model is one in which multiple applications are possible, our estimate would be biased towards zero.

where $l_{dk}(\omega)$ is the production of variety ω, $z_{dk}(\omega)$ is the productivity level to produce variety ω, ψ_{dko} is the efficiency units of occupation o, $l_{dko}(\omega)$ are the units of labor services of occupation o used to produced ω, and $\eta > 0$ is the elasticity of substitution between occupations in production. We assume that $z_{dk}(\omega)$ is a random variable distributed Frechet with shape parameter $\theta > \sigma - 1$ and scale parameter T_{dk} as in Eaton and Kortum (2002).

The services of an occupation are produced by combining effective units of native labor (l^n_{dko}) and foreign labor (l^f_{dko}) with an elasticity of substitution ϵ. This modeling assumption follows a long tradition in the immigration literature, which understands immigrants and natives as having comparative advantages in different tasks (Ottaviano et al., 2013; Peri and Sparber, 2011, 2009). Specifically, the production function takes the following form:

$$l_{dko}(\omega) = \left(\beta_{dko}\, l^n_{dko}(\omega)^{\frac{\epsilon-1}{\epsilon}} + (1-\beta_{dko})\, l^f_{dko}(\omega)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}} \tag{8}$$

where β_{dko} is a sector-occupation-specific parameter that captures the productivity of native labor relative to immigrant labor.

Trade costs Varieties ω can be traded internationally. Delivering a unit of variety ω in sector k from country d to country c requires producing $\tau_{cdk} \geq 1$ of the good. We assume that trading domestically is costless $\tau_{ddk} = 1$.

4.2 Labor supply based on workers' migration and sector choices

Sector choice Given the assumed Frechet distribution of $a_{codk}(\iota)$, the fraction of workers co in country d choosing sector k is π_{cock} for natives and π_{codk} with $d \neq c$ for immigrants:

$$\pi_{codk} = \begin{cases} \left(\frac{a_{codk}\, w^f_{odk}}{\Phi_{cod}}\right)^{\kappa} & \text{with} \quad (\Phi_{cod})^{\kappa} \equiv \sum_k a^{\kappa}_{codk}\, (w^f_{dko})^{\kappa} \quad \text{if} \quad d \neq c \\ \left(\frac{a_{cock}\, w^n_{ock}}{\Phi_{coc}}\right)^{\kappa} & \text{with} \quad (\Phi_{coc})^{\kappa} \equiv \sum_k a^{\kappa}_{cock}\, (w^n_{cko})^{\kappa} \quad \text{if} \quad d = c \end{cases} \tag{9}$$

and $u_{cod} = \Gamma_{\kappa} \frac{\zeta_{cod}\, \Phi_{cod}}{P_d}$, where Γ_{κ} is the gamma function evaluated at $\frac{\kappa-1}{\kappa}$.

Migration choice Given the assumed extreme value distribution of $\nu_{cod}(\iota)$, the probability that worker ι chooses to stay in her home country is π_{coc} and, conditioning on choosing to emigrate, the probability that she chooses destination country d is π_{cod}:

$$\pi_{cod} = \frac{(u^{p_{cod}}_{cod}\, u^{1-p_{cod}}_{coc})^{\nu_d}}{\sum_{d' \in \mathcal{C}^d} (u^{p_{cod'}}_{cod'}\, u^{1-p_{cod'}}_{coc})^{\nu_d}} \qquad \pi_{coc} = \frac{u^{\nu_h}_{coc}}{u^{\nu_h}_{coe} + u^{\nu_h}_{coc}} \tag{10}$$

where $u_{coe} \equiv \Gamma_{\nu_d} \left(\sum_{d \neq c} (u^{p_{cod}}_{cod}\, u^{1-p_{cod}}_{coc})^{\nu_d}\right)^{\frac{1}{\nu_h}}$ is the expected utility of emigrating. Due to the law of large numbers, π_{cod} and π_{coc} are also the fraction of workers co choosing destination country d and home respectively.

Immigrant labor supply The stock of workers of type co that supply labor in the destination country d, L_{cod}, is the sum of the number of workers who were already in the country $\bar{L}_{cod}$ and those from the immigration-origin countries that emigrate to d. The actual number of workers who emigrated to d is the fraction of workers who got their visa approved among those who applied:

$$L_{cod} = \underbrace{p_{cod} \ \times \ \pi_{cod} \ \times \ (1-\pi_{coc}) \ \times \ \psi_{co}^{emig} \ \times \ L_{co}}_{\text{Flow of new immigrants}} + \underbrace{\bar{L}_{cod}}_{\text{Immigrants already in d}} \tag{11}$$

Given the assumed Frechet distribution of $a_{codk}(\iota)$, the average productivity of workers co in d choosing k is Galle et al. (2023):

$$\int_{\Omega_{codk}} a_{codk}(\iota) \ F_{codk}(a) = \Gamma_{\kappa} \ \frac{\Phi_{cod}}{w_{odk}^{f}} \ \pi_{codk} \tag{12}$$

where Ω_{codk} is the set of workers co in d choosing k. Therefore, the supply of efficient units of immigrant labor in occupation o in country d to sector k is:

$$LS_{dko}^{f} = \sum_{c \in \mathcal{C}^{o}} \ \Gamma_{\kappa} \ \frac{\Phi_{cod}}{w_{odk}^{f}} \ \pi_{codk} \ L_{cod} \tag{13}$$

Native labor supply The stock of workers who supply labor at home for immigration-origin countries is given by the number of workers who can not make migration decisions, plus those who choose to stay at home, plus those who choose to emigrate but their visa was denied:

$$L_{coc} = \Big(\pi_{coc} + \sum_{d \in \mathcal{C}^{d}} (1-p_{cod}) \times \pi_{cod} \times (1-\pi_{coc})\Big) \ \times \ \psi_{co}^{emig} \ \times \ L_{co} + (1-\psi_{co}^{emig}) \ \times \ L_{co}. \tag{14}$$

For immigration-destination countries $L_{coc} = L_{co}$. The supply of efficient units of labor is:

$$LS_{cko}^{n} = \Gamma_{\kappa} \ \frac{\Phi_{coc}}{w_{ock}^{n}} \ \pi_{cock} \ L_{coc} \tag{15}$$

4.3 Labor demand based on firms' hiring decisions

The demand for efficiency units of native and foreign labor is the wage bill that the sector spends on each type of labor deflated by their wages. Given that firms earn zero profits in equilibrium, wage bill and sales (Y_{dk}) are equal, and the demand for labor becomes:

$$LD_{dko}^{x} = \frac{s_{dko}^{x} \ \ s_{dko} \ \ Y_{dk}}{w_{dko}^{x}} \quad x = \{n, f\} \tag{16}$$

where s_{dko} is the share of occupation o in the wage bill of sector k in country d and s^f_{dko} is the share of foreign labor in that occupation. Given that the nested-CES production function, these shares are given by 17:

$$\begin{aligned} s^n_{dko} &= \frac{\beta^{\epsilon}_{dko} w^{n\ 1-\epsilon}_{dko}}{w^{1-\epsilon}_{dko}} \qquad & w^{1-\epsilon}_{dko} &= \beta^{\epsilon}_{dko} w^{n\ 1-\epsilon}_{dko} + (1-\beta_{dko})^{\epsilon} w^{f\ 1-\epsilon}_{dko} \\ s_{dko} &= \frac{\psi^{\eta}_{dko} w^{1-\eta}_{dko}}{c^{1-\eta}_{dk}} \qquad & c^{1-\eta}_{dk} &= \sum_o \psi^{\eta}_{dko} w^{1-\eta}_{dko} \end{aligned} \tag{17}$$

where w_{dko} are the CES wage index of occupation o and c_{dk} are the unit cost of production.

Total sales of sector k in country d, Y_{dk}, is given by the sum of sales to each country c. The expenditure of each country in goods produced by sector s in country c is given by three terms: the total expenditure of the country X_c, the share of it that is allocated to goods from different sectors α_{ck}, and the share of expenditure in k that is bought from producers in different countries λ_{dcs}:

$$Y_{dk} = \sum_c \underbrace{\frac{T_{dk}\ (\tau_{dck}\ c_{dk})^{-\theta}}{\sum_{d'} T_{d'k}\ (\tau_{d'ck}\ c_{d'k})^{-\theta}}}_{\lambda_{dck}} \underbrace{\frac{P^{1-\alpha}_{ck}}{\sum_{k'} P^{1-\alpha}_{ck'}}}_{\alpha_{ck}} X_c \tag{18}$$

where $P_{ck} \equiv \Gamma\left(1 - \frac{\sigma-1}{\theta}\right)^{-1} \left(\sum_d T_{dk} (\tau_{dck}\ w_{dk})^{-\theta}\right)^{-\frac{1}{\theta}}$ is the price index in sector k in country c. We assume that trade is balanced, implying that total spending equals total labor income, $Y_c \equiv \sum_k Y_{kc}$:[27]

$$X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \tag{19}$$

4.4 Equilibrium

Let $\Omega \equiv \{\zeta_{cod}, a_{codk}, \psi_{dko}, \beta_{dko}, \bar{L}_{coc}, \bar{L}_{cod}, D_c, T_{dk}, \tau_{dck}\}$ be the set of fundamentals, $\Upsilon \equiv \{\nu_d, \nu_h, \alpha, \sigma, \epsilon, \eta, \theta, \kappa\}$ the set of parameters, and $\mathrm{P} = \{p_{cod}\}$ is the visa approval rates. Given $(\Omega, \Upsilon, \mathrm{P})$, an equilibrium is a collection of:

1. workers' decisions of migration and sector allocation $\{\pi_{cod}, \pi_{codk}\}$;

2. firms' hiring decisions $\{s^f_{dko}, s^n_{dko}\}$;

3. aggregate quantities and price $\{Y_c, Y_{dk}, LS^n_{dko}, LS^f_{dko}, LD^n_{dko}, LD^f_{dko}, P_c, w^f_{dko}, w^n_{dko}\}$;

such that:

1. workers' decisions of migration and sector allocation satisfy equation (9) and (10);

2. firms' hiring decisions satisfy equation (17); and

[27] The quantitative results of our model are similar when we allow for trade imbalances as in Dekle et al. (2007).

3. the markets for labor and goods all clear:

$$LD^i_{dko} = LS^i_{dko} \quad \forall i \in \{n,\ f\} \tag{20}$$

$$X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \tag{21}$$

4.5 Effects of US immigration restrictions: Analytical results

In this section, we analytically study the effect of an exogenous change in the US approval rate p_{cod} on third countries and the welfare of American workers. We first show how the policy affects economies that absorb immigrants affected by the restrictions, emphasizing the role of the relevant parameters. Then, we offer an expression for the effect of U.S. immigration restrictions on the welfare of American workers, where our discussion focuses on how the adjustment of other economies can ultimately influence American workers' welfare. For notational convenience, let $\hat{x} \equiv \frac{x'}{x}$ and $d\tilde{x} \equiv \log(\hat{x})$ in the rest part of paper, where x and x' denote the equilibrium level of endogenous variable x before and after the immigration policy change.

4.5.1 Effects of US immigration restrictions on third countries

We begin the analysis by studying how immigration to Canada responds to changes in US immigration policy. Equation (22) shows, to a first-order approximation, the factors affecting the change in the number of Canadian applications:

$$d\widetilde{App}_{cod} = (\nu_h\ \pi_{coc} - \nu_d)\ \pi_{co,usa}\ \Delta p_{co,usa}(\tilde{u}_{co,usa} - \tilde{u}_{coc}) + \eta_{cod} \tag{22}$$

where η_{cod} is a structural error that includes general equilibrium variables $d\tilde{u}_{cod}$, $d\tilde{u}_{co,usa}$ and $d\tilde{u}_{coc}$ (see Appendix F.1). On the one hand, the expected benefits of emigrating relative to staying at home decline, resulting in a reduced proportion of immigrants seeking to emigrate. The strength of this effect depends on the elasticity of substitution between home and abroad, ν_h: a higher ν_h implies a larger fraction of people decide to stay at home. On the other hand, the relative attractiveness of emigrating to Canada compared to the US increases, leading to a larger proportion of immigrants who desire to emigrate choosing to apply to Canada. The strength of this effect depends on the elasticity of substitution between Canada and the US, ν_d: a higher ν_d implies a larger fraction of people decide to emigrate to Canada. Depending on the strength of these forces, U.S. immigration restrictions can either increase or decrease immigration to Canada.

If immigration to Canada increases, immigrant workers will sort themselves across various sectors, leading to a sector-specific expansion in the foreign labor supply and a drop in production costs.The inflow of immigrants reduces their wages which, in turn, leads to a decline in wages for their native counterparts. As shown in equation (23), the reduction in native wages is more pronounced when immigrants and natives are closer substitutes (higher ϵ). In the limiting case of $\epsilon \to \infty$, the drop in native wages is as strong as that of immigrant wages.

$$d\tilde{w}^n_{dko} = d\tilde{w}^f_{dko} + \frac{1}{\epsilon}(d\tilde{l}^f_{dko} - d\tilde{l}^n_{dko}) \tag{23}$$

This decline in immigrant and native wages reduces the cost of the bundle w_{dko} which drives down the wages of workers in other occupations o'. The decline in $w_{dko'}$ is stronger when occupations are closer substitutes (higher η). The drop in the wages of the various types of workers affects production costs depending on how important each labor input is in the cost structure of the sector. Equation (24) shows that the change in the cost of production of sector k is approximately a weighted average of the wage changes for each labor input. These weights are determined by their respective shares in the total wage bill. Therefore, sectors with a cost structure skewed towards workers with bigger wage reductions will experience greater cost reductions:

$$d\tilde{c}_{dk} = \sum_o s_{dko} \left((1 - s^f_{dko})\, d\tilde{w}^n_{dko} + s^f_{dko}\, d\tilde{w}^f_{dko} \right) \tag{24}$$

The reduction in production costs leads to a proportional decrease in the price of the final good because the good market is perfectly competitive. In response to these price changes, consumers adjust their spending patterns by favoring relatively cheaper varieties. This reallocation of expenditure across sectors and varieties affects sales as illustrated by the following equation:

$$d\tilde{Y}_{dk} = \sum_c \omega^Y_{dck} \left(\underbrace{-\theta(d\tilde{c}_{dk} - \sum_d \lambda_{dck}\, d\tilde{c}_{dk})}_{d\tilde{\lambda}_{dck}} + \underbrace{(1-\alpha)(d\tilde{P}_{ck} - d\tilde{P}_c)}_{d\tilde{\alpha}_{ck}} + d\tilde{X}_c \right) \tag{25}$$

where ω^Y_{dck} is the share of country c in total sales of producers in sector k in country d, and $d\tilde{\lambda}_{dck}, d\tilde{\alpha}_{ck}$ and $d\tilde{X}_c$ is the change in sales due to the reallocation across varieties within the same sector, reallocation across sectors, and market size, respectively. The response in sales is more pronounced when there is a higher degree of substitutability among goods from different sectors (higher α) and when the varieties produced by sellers from different countries within a sector are more similar (higher θ).

In summary, our model predicts that country d might experience an increase in the influx of immigrants if immigrants consider it as a close substitute to the US. This aggregate inflow of immigrants leads to a sector-specific drop in the unit cost of production and an increase in production. This increase in production is placed in both the domestic and international markets, depending on the tradeability of the sector and the change in the unit cost of production of other economies in the world. This is consistent with the evidence presented in Sections 3.2 and 3.3.

4.5.2 Effects of US immigration restrictions on American workers' welfare

The adjustment on third countries just described as well as on home economies open the door to an indirect effect of US immigration restrictions on American workers. In this section, we use the model as a framework to understand the various channels through which US immigration restrictions affect the welfare effect on American workers.

To build intuition, we derive our analytic results in a simplified version of our model. We now assume that native supply l^n_{dko} is fixed, preferences are Cobb Douglas with shares α_{dk}, and the occupation nest in equation (7) is Cobb Douglas ($\eta = 1$) with shares s_{dko}. Given that trade is balanced, the change in the welfare of a native worker in the US working in occupation o in sector k, denoted by $W^n_{usa,ko}$, coincides with the change in the real wage. The wage earned by a worker is the marginal revenue product of her labor because labor markets are perfectly competitive. Therefore, given the production function 7, the wage of a worker $x = \{f, n\}$ in occupation o in sector k in country d, w^x_{dko}, is given by (26):

$$w^x_{dko} = p(\omega)_{dk}\ z(\omega)\ \left(\frac{l_{dko}}{l_{dk}}\right)^{-1} \left(\frac{l^x_{dko}}{l_{dko}}\right)^{-\frac{1}{\epsilon}} \tag{26}$$

Given that the goods market is perfectly competitive $p(\omega)_{dk} = \frac{c_{dk}}{z(\omega)}$. Therefore we can replace $p(\omega)_{dk}\ z(\omega)$ by c_{dk}. Moreover, given that the total cost of production of a sector, $c_{dk}\ l_{dk}$, equals total sales, Y_{dk}, the unit cost of production equals total sales per unit of output (or composite labor input): $c_{dk} = \frac{Y_{dk}}{l_{dk}}$. After substituting these equilibrium conditions into (26), we obtain the following expression for the welfare of American workers:

$$W^n_{usa,ko} = \frac{w^n_{usa,ko}}{P_{usa}} = \frac{Y_{usa,k}\quad l^{\frac{1}{\epsilon}-1}_{usa,ko}\quad l^{n\ -\frac{1}{\epsilon}}_{usa,ko}}{P_{usa}} \tag{27}$$

where $Y_{dk} = \sum_j \lambda_{djk}\ \alpha_{jk}\ X_j$. Based on expression (27), the following proposition specifies the impact of U.S. immigration policy changes on the welfare of American workers.

Proposition:

Suppose that the U.S. imposes restrictions on skilled immigration that lead to infinitesimal (negative) changes in immigrant labor supplies $\tilde{l}^f_{usa,ko}$*. Let* $d\tilde{x}$ *denote an infinitesimal change from to the initial equilibrium value of the log of variable* x*. The log change in the welfare of an*

American worker in occupation o in sector k is:

$$
\begin{aligned}
d\tilde{w}^{n}_{usa,ko} - d\tilde{P}_{usa} = & \overbrace{\left(\frac{1}{\epsilon}-1\right) s^{f}_{usa,ko}\, d\tilde{l}^{f}_{usa,ko}}^{\text{Substitution Effect}_{usa,ko}} \\
& \overbrace{\overbrace{-\sum_k \alpha_{usa,k}\, \lambda_{usa,usa,k}\, d\tilde{c}_{usa,k}}^{\text{Price effect}_{usa}} \overbrace{-\theta \sum_j \omega^{Y}_{usa,jk}\, (1-\lambda_{usa,jk})\, d\tilde{c}_{usa,k}}^{\text{Competition effect}_{usa,k}}}^{\text{Domestic General Equilibrium Effects - Increasing costs in the US}} \\
& \underbrace{\underbrace{-\sum_k \alpha_{usa,k}\, \lambda_{c,usa,k}\, \tilde{c}_{ck}}_{\text{Price effect}_{usa}} + \underbrace{\theta \sum_j \omega^{Y}_{usa,jk}\, \lambda_{cjk}\, \tilde{c}_{ck}}_{\text{Competition effect}_{usa,k}}}_{\text{International General Equilibrium Effects - Decreasing costs elsewhere}} + \epsilon_{usa,k}
\end{aligned} \tag{28}
$$

where $\epsilon_{usa,k} = \sum_j \omega^{Y}_{usa,jk}\ d\tilde{X}_j$, $d\tilde{l}_{usa,k} = \sum_o s_{usa,ko}\ s^{f}_{usa,ko}\ d\tilde{l}^{f}_{usa,ko}$ and $d\tilde{c}_{dk}$ is the change in production costs of sector k in country d induced by the US immigration policy change. This is given by $d\tilde{c}_{dk} = \sum_o s_{dko}\, \varepsilon_{dko}\, d\tilde{l}^{f}_{dko}$ and ε_{dko} is the elasticity of the cost of bundle o in sector k in country d, w_{dko}, with respect to the supply of immigrants l^{f}_{dko}, $\epsilon_{dko} \equiv \frac{d\tilde{w}_{dko}}{d\tilde{l}_{dko}}$.

Proof: See Appendix F.2.

The "Substitution Effect" arises when workers are imperfect substitutes in the production of good k.[28] Consider two occupations, skilled and unskilled occupations. If immigrants and natives within an occupation are closer substitutes than workers in different occupations ($\epsilon > \eta = 1$), restrictions to skilled immigrants increase the relative scarcity of skilled workers. Therefore, if $\epsilon > 1$, the effect of the policy has a more positive effect (or less detrimental) on skilled American workers relative to unskilled American workers. The opposite occurs if $\epsilon < 1$. The size of the substitution effect is also determined by the initial share of immigrants in the occupation and sector of employment $s^{f}_{usa,ko}$. The policy will be more beneficial the more immigrant-intensive the job is.

The "Domestic General Equilibrium Effect" arises when restricting the supply of immigrant labor in the U.S. increases the production costs of US sectors ($d\tilde{c}_{usa,k} > 0$). There are two implications of higher production costs. First, it translates into higher consumption prices which reduce the purchasing power of all American consumers ($\sum_{k'} \alpha_{usa,k'} \lambda_{usa,usa,k'}\ d\tilde{c}_{usa,k'} > 0$). Second, demand for US goods drops and so does production in sector k in the U.S. As a result, there is a corresponding decrease in the demand for all labor inputs in sector k and a downward pressure on equilibrium wages ($\sum_j\ \omega^{Y}_{usa,jk}(1-\lambda_{usa,jk}) d\tilde{c}_{usa,k} > 0$). Therefore, this standard GE effect unambiguously reduces the welfare of American workers.

[28] If they are perfect substitutes, $d\tilde{W}^{n}_{usa,ko}$ boils down to the ACR formula (Arkolakis et al., 2012).

The "International General equilibrium effect" arises when changes in migration flows lead to changes in production costs in country c. If migration inflows to country c increase and production costs drop, the welfare of American workers will be affected in two ways. On one hand, when country c reduces its production costs, it reduces the international demand for American goods. This lower demand reduces the price of American goods and the value of the marginal product of American workers, leading to a decline in American wages. The strength of this competition effect becomes more pronounced when there is a larger overlap between the markets served by country c and the US. To illustrate, if immigrants choose to migrate to Canada, which competes in international (and domestic) markets with the US, it can have a more adverse impact on American workers compared to their migration to a country like the Philippines, which does not tend to compete with the US in international markets. The extent of this market overlap is captured by $\sum_j \omega^Y_{usa,jk}\lambda_{cjk}$ in (28), where $\omega^Y_{usa,jk}$ is the share of country j in total US sales and λ_{cjk} gauges the size of the expansion of producers from country c in market j due to the drop in costs $d\tilde{c}_{ck} < 0$. On the other hand, American workers can benefit from importing cheaper goods and services from country c, which increases their wages' purchasing power. This effect is stronger when the share of country c in the expenditure that American consumers is larger ($\alpha_{ck'}\ \lambda_{c,usa,k'}\ \forall k'$). Given that the stronger competition effect and the access to cheaper importer goods operate in opposite directions, the new GE effect can be either positive or negative. This new GE effect operates via international trade. If countries do not engage in international trade, the reallocation of immigrant workers across countries due to the US policy does not affect the outcome of American workers. In the absence of international trade, each country serves its domestic market and there is no overlap between the markets served by the US and by other countries. Thus $\sum_j\ \omega^Y_{usa,jk}\ \lambda_{cjk}\ = \sum_j\ \omega^Y_{usa,jk}\ (1-\lambda_{usa,jk})\ = 0$ for all k. Additionally, if American workers are isolated from international trade, they allocate all their spending exclusively to US goods and $\lambda_{usa,ck} = 0$ for all k.[29] Therefore, according to the model, US immigration restrictions may lead to unintended consequences for American workers if two conditions are met: (i) the restrictions increase immigration and impact production costs in other countries, and (ii) these countries are integrated into the international good market with the US.

5 Quantification: Taking the model to our data

To study the effect of US immigration restrictions in the next section, we solve the model in proportional changes following the "hat algebra" approach pioneered by Dekle et al. (2008). This procedure requires data on initial visa approval probabilities, the earning per worker in the US relative to home, migration-related shares, non-migration shares and structural parameters, denoted by $\mathrm{P}, \mathbf{U}_u, \mathbf{S}^M, \mathbf{S}^{NM}$ and Υ respectively. This section discusses the calibration of the elasticities Υ, summarized in Table 1. Appendix section describes the calibration of $\mathrm{P}, \mathbf{U}_u, \mathbf{S}^M$,

[29] It worth noticing that the competition effect associated with changes in US production costs $d\tilde{c}_{usa,k}$ also vanishes because $\lambda_{usa,usa,k} = 1$ and $\lambda_{usa,jk} \neq 0$ for $j \neq usa$.

and $\mathbf{S}^{NM}$ and the "hat algebra" approach.

Given the data requirements, we group countries into four categories: the U.S., Canada, India, and a constructed rest of the world (RoW); occupations in six groups: business professionals, computer scientists, engineers, managers, other H-1B occupations, and non-H-1B occupations; and sectors in eight groups: Agriculture and Mining (Ag & Min), Finance (FIN), Information and Cultural sector (IC), business professional services (BPS), high-tech manufacturing sectors, low-tech manufacturing sectors, a wholesale and retail trade sector (WRT) and a constructed sector which includes the remaining sectors. We exclude from the analysis the non-profit and the public administration sector.

We inform the value of the structural parameters by extracting as much information as possible from our reduced-form regressions. As a result, we calibrate θ, κ, and η to estimates from the literature; we estimate ν_d directly from a coefficient of a reduced-form regression derived from the model; and we calibrate ν_h, α, and ϵ indirectly based on our event study estimates. We proceed in two steps. We first calibrate $\Upsilon^E \equiv (\theta, \kappa, \eta, \nu_d)$ outside the model and, given $(\mathrm{P}, \Upsilon^E, \mathbf{S}^M, \mathbf{S}^{NM}, \mathbf{U}_u)$, we calibrate $\Upsilon^I \equiv (\nu_h, \alpha, \epsilon)$ inside the model to match the impact of the spike in H-1B denial rates on Canada.

$$\Upsilon \equiv \{ \underbrace{\underbrace{\theta, \kappa, \eta}_{\text{Calibrated from literature}} \quad , \quad \underbrace{\nu_d}_{\text{IV approach}}}_{\text{Calibrated Externally, } \Upsilon^E} \quad , \quad \underbrace{\nu_h, \alpha, \epsilon}_{\text{Calibrated Internally, } \Upsilon^I} \}$$

Table 1: Calibration

Structural Parameters Υ			Value
θ	Trade elasticity	Romalis (2007)	6.7
η	Elast. of subst. occupations	Goos et al. (2014)	0.9
κ	Elast. of supply to sectors	Galle et al. (2023)	2.8
ν_d	Elast. of subst. US vs Canada	IV estimation of regression 67	3.6
ν_h	Elast. of subst. home vs abroad	Indirect inference: target $\hat{\gamma}$ in 31	2.3
ϵ	Elast. of subst. Imm. vs natives	Indirect inference: target $\hat{\gamma}$ in 32 for outcome log(*Earning per native*$_k$)	4.3
α	Elast. of subst. across sectors	Indirect inference: target $\hat{\gamma}$ in 32	1.2

Note. The table summarizes the calibrated values used for the quantitative analysis. All parameters in Υ^I are calibrated jointly.

5.1 Instrumental variable approach: ν_d

The novel part of our model is the migration decision. Standard quantitative models of immigration often assume that migrants face migration costs that are proportional to the real wage at destination. Relative to these models, our model delivers a new prediction, given by equation 29, that becomes the starting point of our approach to estimating ν_d. According to the country choice decision 4.1, the log of the number of workers in occupation o from country c choosing

Canada relative to the US is given by:

$$\tilde{App}_{co,can,t} \;-\; \tilde{App}_{co,usa,t} = \nu_d \Bigg(\; p_{co,can,t} \Big(\tilde{u}_{co,can,t} - \tilde{u}_{coct} \Big) - \; p_{co,usa,t} \Big(\tilde{u}_{co,usa,t} - \tilde{u}_{coct} \Big) \Bigg) \tag{29}$$

where the relative difference in the number of applications to Canada and US is determined by the relative payoff difference of residing in these two destination countries. Since $\tilde{u}_{codt} = \tilde{w}_{codt} - \tilde{P}_{dt}$, we can estimate the parameter ν_d through the equation:

$$\tilde{App}_{co,can,t} \;-\; \tilde{App}_{co,usa,t} = \nu_d \; p_{co,usa,t} \; \tilde{w}_{co,usa,t} + \eta_{cot} \tag{30}$$

where η_{cot} is a structural error that includes the effect of immigration policy in Canada ($p_{co,can,t}$), wages and prices in Canada and the cost to migrate to Canada (through $\tilde{u}_{co,can,t}$), wages and prices at home (through the average wage $\tilde{u}coct$), prices in the U.S. ($P_{usa,t}$), and costs to migrate to the US $\tilde{\zeta}_{co,usa}$. Because $p_{co,usa,t}$ $\tilde{w}_{co,usa,t}$ correlates with this structural term, we include immigrant group fixed effects δ_{co}, occupation-year fixed effects δ_{co}, and nationality-year fixed effects δ_{co} and follow an IV approach. This approach uses $Intensity_{co}$ as the instrument and delivers an IV estimate of 3.6 (s.e: 1.3). Appendix Table 13 includes the estimation details and robustness exercises. In the Appendix section H we explain in detail the endogeneity concerns of the OLS estimate, and the IV approach.

5.2 Estimates calibrated from the literature: θ, κ and η

Equation 25 shows that θ regulates the extent to which relative sales of American and Canadian producers within a sector respond to changes in the relative cost of production. Given that we do not have the required data to properly estimate this elasticity, we set the trade elasticity at 6.70, based on Romalis (2007), which is a good fit for our specific context. This elasticity of substitution is estimated based on U.S. and EU imports from Canada, and it exploits plausible exogenous variation in the change in tariff preference that the US gives to goods of Canadian origin. Our calibrated value lies between estimates from Lai and Trefler (2002) and Clausing (2001). The elasticity of substitution across occupations η regulates the response of occupational wages. Since we do not observe occupation information, we calibrate it from Goos et al. (2014). Similar to our setting, Goos et al. (2014) estimate the elasticity of substitution across broad occupations within sectors to be 0.9. Finally, we model the supply of labor to sectors within a country as in Galle et al. (2023), which offers estimates of the dispersion parameter of the Frechet distribution κ for workers in the U.S. Our model assumes that κ is the same for all worker groups, including those workers in the US, and the granularity of the sectorial classification is similar to theirs. Therefore, we set $\kappa = 2.79$ based on their estimates.

5.3 Indirect inference approach: ν_h, α, and ϵ

To complete the calibration of the model, we must calibrate ν_h, α, and ϵ. We jointly choose these values to match cross-sectional responses to the H-1B policy change implied by our estimates from Sections 3.2 and 3.3.

The parameter ν_h regulates the change in the relative number of immigrants choosing to stay at home relative to emigrating. Given that we do not observe π_{coc} directly from the data, we can not use this relationship to estimate a reduced-form coefficient and directly recover the value of ν_h. However, equation (22) shows that the relationship between the response of the log of Canadian applications and $\pi_{co,usa}\Delta p_{o,usa}$ across immigrant groups, contains information about the underlying value of ν_h.[30] Therefore, we estimate this empirical regression and use an indirect inference approach to infer the value of ν_h. We proceed as follows. We first fix $(\mathrm{P}, \Upsilon^E, \mathbf{S}, \mathbf{U}_u)$ and input the observed $\Delta p_{o,usa}$ from the data into our model for a given set of parameters Υ^I. We then solve the model and extract the value of the change in Canadian applications by immigrant group. Finally we estimate the following regression using both real data and model generated data:

$$\Delta log(App_{co,can}) = \gamma \; \pi_{co,usa}\Delta p_{o,usa} \; + \; \epsilon_{co} \tag{31}$$

To obtain the outcome variable from real data that is comparable with that from the model, we must isolate the effect of the US policy change from other factors absent in our model. We do so by using our estimates of the causal impact of the H-1B restrictions on Canadian applications from equation 1. Given this estimated coefficients, we predict the impact of the H-1B restrictions on the applications of each immigrant group. Given that the categories of immigrant groups in this empirical regression are more granular than those in the model, we aggregate the predicted effect to the level of granularity consistent with the model (see Appendix section I for a detailed explanation).

The parameter α regulates the change in sales across sectors due to changes in their relative prices or unit cost. The challenge is that while we have data on sales, we do not observe prices or units costs. However, as explained in subsection 4.5.1, the drop in relative unit costs is the result of the sector-specific immigrant labor supply shock. We thus expect the strength of the empirical relationship between the change in sales across sectors facing different immigrant labor supply inflows to contain information about α. We use this empirical relationship to α. We follow an approach similar to that for ν_h with the difference that the regression is at the sector level and given by equation (32)

$$\Delta log(Sales_k) = \gamma \underbrace{\sum_{co} \omega^{wb}_{cok} \; (1 - \psi^{imm}_{co}) \; \pi_{co,usa}\Delta p_{o,usa}}_{Intensity_k} + \epsilon_k \tag{32}$$

[30] $\pi_{co,usa}\Delta p_{o,usa}$ is the portion of the expression (22) that we can measure directly in the data.

where ω^{wb}_{cok} is the share of immigrant group co in the wage bill of sector k, and $Intensity_k$ proxy the predicted change in efficient unit of labor to sector k.[31] Given that our causal estimates for the response of sales are at the firm-level, we aggregate the firm level responses to the sector-level.

Finally, ϵ determines the extent to which an inflow of immigrants in a specific labor market (e.g. occupation-sector) reduces the earnings of native workers in the labor market. While we do not have information on occupation, we observe the overall earning of native workers by sector. Therefore we establish an empirical relationship between the earning per native worker and the immigrants supply shock faced by each sector. We then use this empirical relationship to calibrate ϵ using similar approach as for sales. We simply replace sales in regression (32) with the earning per native worker, and use the corresponding causal estimates from section 3.

Our calibrated values are $\nu_h = 2.28, \epsilon = 4.30, \alpha = 1.16$, which fall within the range reported in the literature. Regarding ν_h, our nested structure for immigrants' country choice follows Allen et al. (2019), who explore how Mexican workers make migration decisions when selecting locations within the US. Their estimated values, $\hat{\nu_d} = 4.3$ (s.e.$=$ 0.8) and $\widehat{(\frac{\nu_h}{\nu_d})} = 0.4$ (s.e $=$ 0.17), closely align with our estimates. Regarding ϵ, our modeling assumption follows Burstein et al. (2020), who estimate an elasticity of substitution between immigrants and natives within occupations to be 4.6.[32] Finally, our calibrated value for the elasticity of substitution across our eight sectors (α) falls within the range of previous estimates in the literature, which vary depending on whether the categories are narrower or more general. For instance, in narrower categories like the 3-digit SITC sectors, Broda and Weinstein (2006) found a median estimate of 2.2. In contrast, for broader categories such as agriculture, manufacturing, and services, estimates tend to be around 0.5 (Cravino and Sotelo, 2019; Herrendorf et al., 2013; Comin et al., 2021).

5.4 Validation of the calibrated model

We validate the model by examining the matching of moments that were not targeted in the internal calibration procedure. The untargeted moments include the relative response across sectors of the share of exports in total sales and the logarithm of native employment. In Table 2, we present the coefficients of the regressions (31) and (32) using real data and model-generated data. A comparison between these coefficients suggests that the model matches well the cross-sectional response of the Canadian economy along targeted and untargeted dimensions.

[31] That is $\Delta log(LS)_k = \sum_{co} \omega^{wb}_{cok}\ (1 - \psi^{imm}_{co})\ \Delta log(App_{co,can})$ and we use $\pi_{co,usa}\Delta p_{o,usa}$ to measure the variation in $\Delta log(App_{co,can})$ in the data and in the model. Therefore, $Intensity_k$ in the regression with empirical data and model generated data are identical.

[32] The elasticity of substitution among workers within a CES aggregator has been estimated in various studies, but differences in nesting order and categories make comparisons challenging. That being said, Ottaviano and Peri (2012) reports an elasticity of 3.

Table 2: Parameter values

	Immigration	Expansion		Crowd-in	
	$log(\text{App}_{co,can})$	$log(\text{Sales}_k)$	Export share$_k$	$log(\text{Earning per native}_k)$	$log(\text{Native empl.}_k)$
Targeted?	Yes	Yes	No	Yes	No
Coefficient $\hat{\gamma}$ from data	3.1	2.0	0.7	-1.1	1.9
Coefficient $\hat{\gamma}$ from model	2.9	2.0	0.7	-1.1	1.6

6 Quantitative effects of the 2017 US restrictions

We feed the observed increase in H-1B denial rates directly into our calibrated model for our quantitative analysis. Consistent with our empirical setup, the input change in H-1B denial rates only varies by occupation. We keep the denial rate of non-H-1B occupations unchanged and the stock of immigrant workers that are already in the US, $\bar{L}_{co,usa}$.

This change in the US immigration policy essentially reduced the number of immigrants in the US and increased it in Canada (see Table 3). In the remaining parts of this section, we will first discuss how the changes in the immigrant flow affect Canadian and American business across different sectors and the welfare of native workers in each country. Then, we will shift the focus to the US economy and discuss to what extent international trade affects the effects of this policy change on American workers' benefit.

Table 3: Variations across occupations

Change in	CS	Engineers	Bss Prof.	Managers	Other H1B	Non H1B
US denial rate, p_o^{usa}	18.76	6.22	13.80	11.40	6.37	0.00
Immigrant empl. Canada (%)	11.40	4.25	6.50	2.62	2.23	0.44
Immigrant empl. US (%)	-4.55	-2.23	-4.55	-2.42	-0.73	-0.02

Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$.

6.1 Effects on Canada

Production and exports We find that the US policy shift resulted in a 3.4% increase in immigrant labor in Canada, with the largest increase among computer scientists (see Table 3). Once in Canada, these immigrants sorted into sectors, leading to a sector-specific expansion in the foreign labor supply. As a result, sectors with an immigrant workforce composition skewed toward the occupation with larger inflow growth experienced relatively stronger growth in their immigrant labor force. The first row of Table 4 shows that the immigrant labor force increased in all sectors, but the increase was especially strong in high-skilled service sectors.

This increase in the immigrant labor force reduced labor costs and induced an aggregate expansion of production of 0.8%. Even though all sectors expanded, sectors did not expand at the same rate. Intuitively, for a given native labor supply, the expansion of a sector is approximately the increase in immigrant labor supply to the sector, weighted by the immigrant share in the total cost s^f_{dk}, expressed as: $d\tilde{y}_{dk} = s^f_{dk}\, d\tilde{l}^f_{ds}$. Notably, high-skilled service sectors responded the most. This is due to the larger increase in the supply of immigrant labor and also due to their higher reliance on immigrants.

Although all sectors in Canada expanded, their global market performance did not always improve, with some sectors expanding their export sales and others contracting. The reason is the following. The US immigration restrictions decreased the number of immigrants in the US and increased immigration elsewhere. As a result, production costs of US sectors increased relative to those of other economies, leading to a reallocation of production across sectors and countries. The US reallocated production away from sectors that are relatively skilled immigrant-intensive, such as skilled-service sectors and high-tech manufacturing, towards sectors with lower dependence on skilled immigrant labor, such as agriculture, wholesale and retail, and low-tech manufacturing industries. Conversely, economies like Canada, which experienced an inflow of skilled immigrants, shifted their production composition in the opposite direction. As part of this reallocation of production across countries and sectors, Canadian exports increased in skilled-service sectors and high-tech manufacturing but contracted in other sectors (e.g., Rybczynski's effect).[33] The increase in Canadian exports to the US contributed significantly to the export growth: it explained 45% of the growth in exports of high-skilled service sectors and 75% of the increase in high-tech manufacturing exports.

Table 4: Aggregate and sector-level adjustment in Canada (%)

	Aggregate	By sectors							
		IC	BPS	FIN	High-Tech	Ag & Min	WRT	Low-Tech	Other
Immigrant labor force, l^f_{dk}	3.41	6.66	7.16	6.27	3.29	2.88	2.95	1.88	2.15
Production, y_{dk}	0.79	2.24	2.68	2.07	1.09	0.19	0.66	0.25	0.44
Sales, Y_{dk}	0.62	1.46	1.74	1.24	0.84	0.14	0.57	0.21	0.45
Export	0.23	3.94	5.99	5.39	0.6	-0.39	0.13	-0.35	-0.81

Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$. World sales is the numeraire.

Welfare of native workers The welfare effects on Canadian workers were large and varied significantly across occupations and sectors of employment. Two factors drive this variation: the direct substitution effect, which is specific to each occupation and sector, and general equilibrium effects that determine the expansion of her corresponding sector of employment. The substitution effect can potentially counteract the expansion effect for workers who directly compete with incoming immigrants in the labor market, resulting in negative welfare effects. Figure 5 shows a breakdown of the welfare effects by occupation and sector. Positive values are depicted in red, while negative values are represented in blue, with the intensity of the color reflecting the

[33] For some sectors like Finance, its exports grew at a large growth rate mostly due to its small initial size. Its initial size of export is only 8 billion (USD), which only accounts for 1.7% of the total export of Canada.

magnitude of the value. Sectors are arranged in descending order of production change, from largest to smallest, and occupations are organized from left to right based on the average welfare change.

The differences in welfare effects were particularly pronounced across occupations. These differences are largely explained by the concentration of US policy change within specific occupations. Therefore, a large component of the inflow of immigrants and the associated substitution effect is occupation-specific.[34]

The differences across sectors can be attributed to two main factors: the strength of the substitution effect in that specific sector and the extent to which the sector expanded due to the overall inflow of immigrants. The strength of the substitution effect is affected by $s^f_{usa,ko}\, d\tilde{l}^f_{usa,ko}$ (see equation (28) for a first order approximation). In occupations that are more exposed to the influx of immigrants, the differences in welfare among native workers are primarily explained by differences in this effect. We illustrate this point in Figure 6a, which plots the welfare effects for CS along with the share $s^f_{usa,ko}$. The scatter plot suggests that the immigrant share in that occupation-sector partially explains welfare differences of CS across sectors. On the other hand, the strength of the sectorial expansion depends on the size of the immigrant labor supply shift to the sector and the subsequent cost reduction. In less exposed occupations, cross-sector differences in the welfare of native workers are largely affected by differences in sectorial expansion. To illustrate this point, Figure 6b plots the change in the welfare of workers in three occupations and the expected employment growth in their respective sectors.[35] The plot focuses on the three occupations with the smallest influx of immigrants. The figure highlights that the inflow of immigrants was more beneficial for workers employed in sectors that absorbed a relatively larger number of immigrants. As the sector expanded, the marginal revenue product of workers increased, increasing wages in the sector.

In summary, Canadian workers in occupations experiencing a significant influx of immigrants often experienced losses due to direct labor market competition. However, workers from other occupations and from expanding sectors benefited from higher marginal revenue product from their labor.

6.2 Effects on the US

Production and exports The drop in visa approvals caused a 1.6% decline in total immigrant labor, with the largest drop among CS and business professionals. The drop in the immigrant labor force induced an aggregate contraction of -0.25%. Compared to the effects on the Canadian economy, the magnitude of the effects on the US economy are smaller. There are two reasons

[34]To arrive at this conclusion, we correlate the average change in the welfare by occupation with a measure of the expected change in the immigrant labor force, which does not account for GE effects.

[35]We computed the expected employment growth as the first-order approximation to L_{dk}.

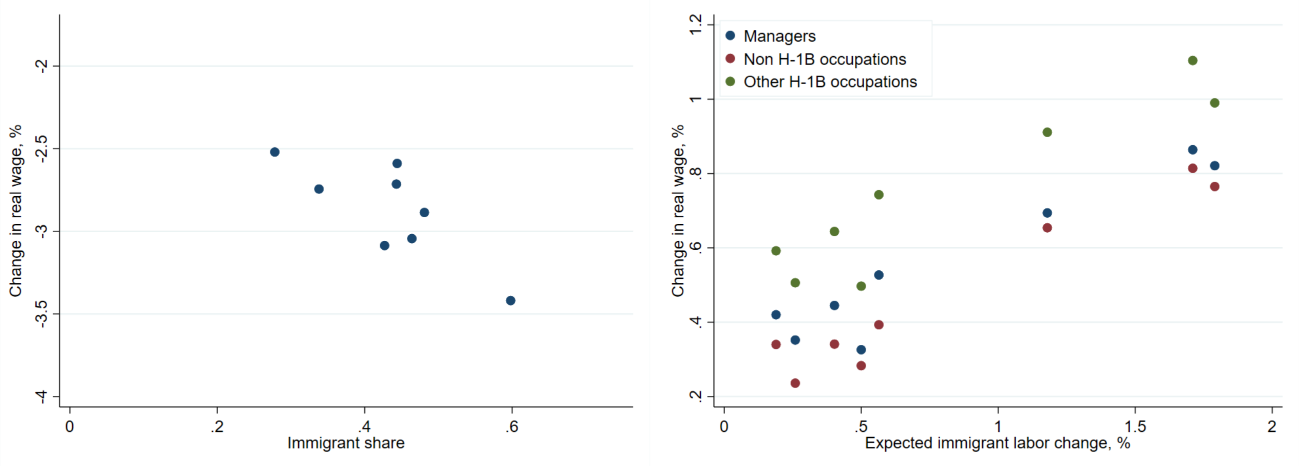
Figure 5: Change in real wage of Canadian workers (%)

	CS	Bss Prof.	Engineers	Managers	Other H-1B	Non-H-1B
BPS	-2.59	0.09	0.27	0.86	0.81	1.10
IC	-2.71	0.06	-0.05	0.82	0.77	0.99
FIN	-3.42	-0.15	0.27	0.69	0.65	0.91
High-Tech	-2.89	-0.27	-0.17	0.53	0.39	0.74
WRT	-3.09	-0.28	-0.29	0.45	0.34	0.64
Other	-2.74	-0.34	-0.15	0.42	0.34	0.59
Low-Tech	-2.52	-0.34	-0.21	0.35	0.24	0.51
Ag & Min	-3.04	-0.35	-0.18	0.33	0.28	0.50

Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$. Positive values are depicted in red, while negative values are represented in blue, with the intensity of the color reflecting the magnitude of the value. Sectors are arranged in descending order of production change, from largest to smallest, and occupations are organized from left to right based on the average welfare change.

Figure 6: Differences in welfare effects of Canadian workers across sectors

(a) Computer Scientists (b) Least exposed occupations



Note. The left panel plots the real wage change of Canadian CS and the immigrant share within CS across sectors s^f_{odk}. The right panel plots the real wage change of Canadian workers in the less exposed occupations and a measure of the expected employment growth, as described in the text.

for this difference. First, the change in the immigrant labor force is relatively smaller in the US, given its larger size compared to Canada.Second, Canadian sectors are significantly more immigrant-intensive than US sectors. For instance, the immigrant share in the wage bill in US high-skilled service sectors is 15% approximately, about half of that in Canada.

While all sectors were affected, the impact on production was most pronounced in the high-skilled service and high-tech manufacturing sectors. Production in these sectors decreased by approximately 0.5%. The contraction of these sectors is, in part, because these sectors are losing markets against international competitors. For instance, exports of the IC and business professional service sectors dropped by 1.4% approximately, and exports of high-tech manufacturing by 0.5%.

Table 5: Aggregate and sector-level adjustment in the US (%)

	Aggregate	By sectors							
		IC	BPS	FIN	High-Tech	Ag & Min	WRT	Low-Tech	Other
Immigrant labor force, l^f_{dk}	-1.56	-2.90	-2.50	-2.88	-2.15	-1.00	-1.59	-0.90	-0.78
Production, y_{dk}	-0.25	-0.62	-0.51	-0.44	-0.47	-0.10	-0.19	-0.06	-0.10
Sales, Y_{dk}	-0.34	-0.66	-0.47	-0.40	-0.54	-0.20	-0.25	-0.16	-0.25
Export	-0.07	-1.56	-1.25	-0.65	-0.50	0.42	0.39	0.60	1.15

Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$. World sales is the numeraire.

Welfare effect of native workers The welfare effects on American workers also vary significantly across occupations and sectors. The differences in welfare effects are particularly pronounced across occupations. The immigration restrictions increased the welfare of CS and, to a lesser extent, business professionals, because the policy reduced relatively more the supply of immigrant services in these occupations. Even though the drop in immigrant labor force is similar for CS than for business professionals, American CS are relatively more protected by the policy because this occupation is particularly immigrant intensive.[36] The policy change had a modest effect on the real wages of engineers and managers and a negative effect on the real wages of other H-1B occupations and lower-skilled American workers.

The impact on American workers' welfare is also affected by the extent of contraction in their employment sector. For those occupations with the smallest drop in immigrant labor force like non-H-1B, other H-1B occupations or managers, the colors in Figure 7 turn to blue or darker blue as we move from sectors on the bottom to the sectors on the top. This implies that the policy had a less beneficial or more detrimental effect on those working in sectors with greater contractions. For instance, the drop in welfare of lower-skilled workers in the IC sector was twice as strong as their counterparts in the low-tech manufacturing sector.

Overall, the results for American workers suggest that the policy improved the welfare of certain worker groups, presumably those it aimed to protect, but it did not benefit American workers in general. Moreover, given that lower-skilled workers and Other H-1B workers account for approximately two-thirds of the native workforce, the restrictions improved the welfare of a relatively small number of American workers at the expense of a larger number of American workers.

6.3 Efficacy of the restrictions: the role of international trade

The welfare outcomes of American workers in Figure 7 are the result of a substitution effect and general equilibrium effects, with some of the latter operating via international trade. We

[36]Immigrants account for 28% of the wage bill for CS and 12% for business professionals.

Figure 7: Change in real wage of American workers (%)

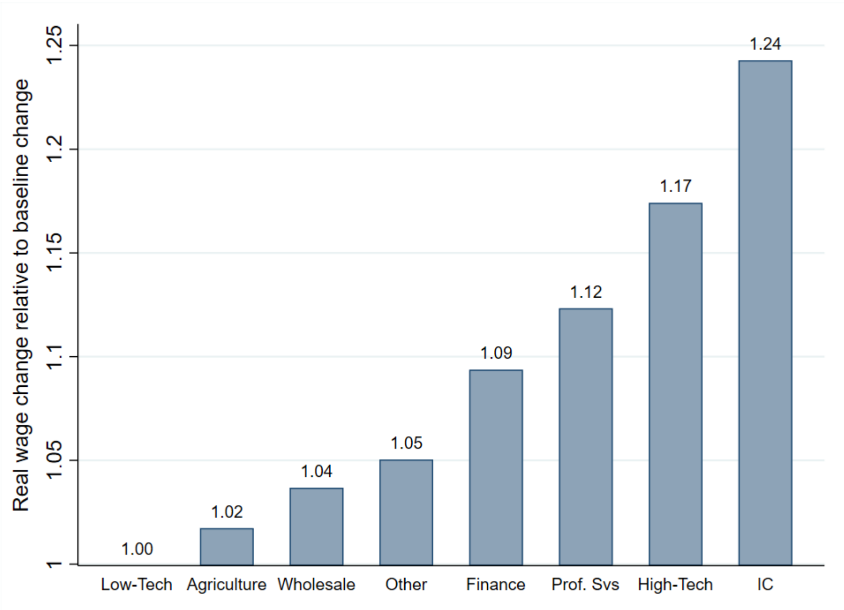
	CS	Bss Prof.	Engineers	Managers	Other H-1B	Non-H-1B
IC	0.68	0.04	-0.03	-0.11	-0.29	-0.36
BPS	0.76	0.14	-0.02	-0.03	-0.22	-0.29
High-Tech	0.73	0.12	-0.01	-0.05	-0.24	-0.32
FIN	0.76	0.13	0.06	-0.03	-0.19	-0.27
WRT	0.76	0.20	0.10	0.03	-0.13	-0.21
Ag & Min	0.83	0.23	0.13	0.06	-0.09	-0.19
Other	0.72	0.21	0.07	0.02	-0.13	-0.21
Low-Tech	0.70	0.21	0.07	0.05	-0.09	-0.17

Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$. Positive values are depicted in red, while negative values are represented in blue, with the intensity of the color reflecting the magnitude of the value. Sectors are arranged in descending order of production change, from largest to smallest, and occupations are organized from left to right based on the average welfare change.

are interested in quantifying the role of international trade in these welfare effects. To that end, we quantify the effects of the same policy change $\Delta p_{o,usa}$ assuming that the US is a closed economy. We compare the change in the real wage of American workers in this counterfactual exercise, denoted by $\hat{w}^{CE}$, with our baseline results, denote it by $\hat{w}^{BL}$. We interpret the difference in the wage changes as the impact of immigration policy on American workers due to international trade. To compute $\hat{w}^{CE}$, we proceed in two steps. First, we eliminate international trade by raising trade costs and solve for the equilibrium. This equilibrium, characterized by the absence of international trade, serves as the starting point for our implementation of the change in US immigration policy. We then introduce the observed $\Delta p_{o,usa}$ and calculate the new equilibrium.

Figure 8 plots the ratio $\hat{w}^{CE}/\hat{w}^{BL}$ for American CS working in different sectors. The plot focuses on CS because, presumably, the restrictions are intended to protect their wages. These results show that international trade dampens the welfare gains of American computer scientists, particularly in high-skilled service sectors and in high-tech manufacturing. For example, in a closed economy, the welfare gains of CS in the business professional service sector are approximately 25% higher than in a world economy with current levels of international trade. There are two factors at play in a global economy that are absent in a closed economy. First, the US restrictions reduce the number of immigrants in the US and increase it elsewhere, leading to a relative increase in US production costs. As a result, the economies that absorb these immigrants expand in sectors that compete with US sectors in international markets. This competition in the good markets drives American wages down and diminishes the benefits of immigration restrictions compared to autarky. On the positive side, American workers in a globalized economy can get access to relatively cheaper imported goods, which increases their purchasing power. If the negative competition effect is stronger than the positive price effect, the welfare gains in a closed economy would be larger than in a globalized economy, as found in Figure 8. Therefore, these results imply that US immigration restrictions may avoid direct competition between immigrants and American workers in the US labor market, but they could still indirectly compete through international goods markets. If policymakers overlook the general equilibrium effects of of international trade, they might overestimate the efficacy of the policy.

Figure 8: Change in real wage of American CS: $\hat{w}^{CE}/\hat{w}^{BL}$



Note. We compute the changes in equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $\Delta p_{o,usa}$, assuming that the US is a closed economy. The y-axis is the ratio between the change in the real wage of American CS in a closed economy, denoted by $\hat{w}^{CE}$, and in the baseline economy (see Figure 7), denoted by $\hat{w}^{BL}$.

7 Conclusion

Immigration restrictions are becoming increasingly common in developed countries. While the policy debate often focuses on the impact of restrictions on domestic workers' wages, it typically overlooks where the immigrants affected by the restrictions migrate to. This paper shows that this is an essential determinant of the effects of immigration restrictions on other economies and their efficacy.

We study empirically and theoretically the effects of immigration restrictions on both the country imposing the restrictions and other economies. We focus on the effects of restrictions on high-skilled immigration implemented in the US in 2017 on Canada and the US. First, we offer quasi-experimental evidence indicating that the US restrictions led to an increase in skilled immigration to Canada and had significant effects on production, especially in the high-skilled service sector.

Second, we offer a new quantitative model of international trade that incorporates migration policy. This model allows us to analytically and quantitatively study the impact of the policy on both the US and Canada. We find that the 2017 policy increased production in all Canadian sectors and had substantial welfare effects on Canadian workers. In the US, the policy positively affected a small group of American workers who compete directly with the immigrants in the labor market. However, it negatively affected American workers in other occupations employed in sectors that contracted. We also find that the role of international trade in the policy's effect on the welfare of American workers can be significant. When the US imposes restrictions, immigrants seek to migrate to other economies. Because these receiving economies compete in international markets with the US, this tougher competition drives down wages for American workers, undermining the initial goal of job protection. If policymakers overlook the general equilibrium effects of international trade, they may overestimate the efficacy of the policy. This consideration is especially relevant now that several developed countries like Canada are actively competing to attract highly educated individuals to develop innovative sectors. Our model and its insights are not limited to the US-Canada context or high-skilled immigration and can be adapted to different settings.

References

Abarcar, P. and C. Theoharides (2021). Medical worker migration and origin-country human capital: Evidence from us visa policy. *Review of Economics and Statistics*, 1–46.

Abramitzky, R., P. Ager, L. Boustan, E. Cohen, and C. W. Hansen (2023). The effect of immigration restrictions on local labor markets: Lessons from the 1920s border closure. *American Economic Journal: Applied Economics 15*(1), 164–91.

Agha, L. and D. Zeltzer (2022). Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy 14*(2), 1–33.

Allen, T., M. Morten, and C. Dobbin (2019). Border walls. *Working Paper*.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012). New trade models, same old gains? *American Economic Review 102*(1), 94–130.

Beerli, A., J. Ruffner, M. Siegenthaler, and G. Peri (2021). The abolition of immigration restrictions and the performance of firms and workers: Evidence from switzerland. *American Economic Review 111*(3), 976–1012.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The quarterly journal of economics 118*(4), 1335–1374.

Borjas, G. J. (2005). The labor-market impact of high-skill immigration. *American Economic Review 95*(2), 56–60.

Bound, J., G. Khanna, and N. Morales (2017). Understanding the economic impact of the h-1b program on the us. Technical report, National Bureau of Economic Research.

Brinatti, A., M. Chen, P. Mahajan, N. Morales, and K. Y. Shih (2023). The impact of immigration on firms and workers: Insights from the h-1b lottery. *Available at SSRN 4431106*.

Brinatti, A. and N. Morales (2021). Firm heterogeneity and the impact of immigration: Evidence from german establishments.

Broda, C. and D. Weinstein (2006, May). Globalization and the Gains From Variety. *The Quarterly Journal of Economics 121*(2), 541–585.

Burstein, A., G. Hanson, L. Tian, and J. Vogel (2020). Tradability and the labor-market impact of immigration: Theory and evidence from the united states. *Econometrica 88*(3), 1071–1112.

Caliendo, L., L. D. Opromolla, F. Parro, and A. Sforza (2021). Goods and factor market integration: a quantitative assessment of the eu enlargement. *Journal of Political Economy 129*(12), 3491–3545.

Caliendo, L., F. Parro, L. D. Opromolla, and A. Sforza (2021). Goods and factor market integration: a quantitative assessment of the eu enlargement. *Journal of Political Economy 129*(12), 3491–3545.

Card, D. (1990). The impact of the mariel boatlift on the miami labor market. *Ilr Review 43*(2), 245–257.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics 19*(1), 22–64.

Clausing, K. A. (2001). Trade creation and trade diversion in the canada–united states free trade agreement. *Canadian Journal of Economics/Revue canadienne d'économique 34*(3), 677–696.

Clemens, M. A. (2013). Why do programmers earn more in houston than hyderabad? evidence from randomized processing of us visas. *American Economic Review 103*(3), 198–202.

Clemens, M. A. and E. G. Lewis (2022). The effect of low-skill immigration restrictions on us firms and workers: Evidence from a randomized lottery. Technical report, National Bureau of Economic Research.

Clemens, M. A., E. G. Lewis, and H. M. Postel (2018). Immigration restrictions as active labor market policy: Evidence from the mexican bracero exclusion. *American Economic Review 108*(6), 1468–87.

Comin, D., D. Lashkari, and M. Mestieri (2021). Structural change with long-run income and price effects. *Econometrica 89*(1), 311–374.

Cravino, J. and S. Sotelo (2019). Trade-induced structural change and the skill premium. *American Economic Journal: Macroeconomics 11*(3), 289–326.

Davis, D. R., D. E. Weinstein, S. C. Bradford, and K. Shimpo (1997). Using international and japanese regional data to determine when the factor abundance theory of trade works. *The American Economic Review*, 421–446.

Dekle, R., J. Eaton, and S. Kortum (2007). Unbalanced trade. *American Economic Review 97*(2), 351–355.

Dekle, R., J. Eaton, and S. Kortum (2008). Global Rebalancing with Gravity: Measuring the Burden of Adjustment. *IMF Staff Papers 55*, 511–540.

Desmet, K., D. K. Nagy, and E. Rossi-Hansberg (2018, June). The Geography of Development. *Journal of Political Economy 126*(3), 903–983.

Di Giovanni, J., A. A. Levchenko, and F. Ortega (2015). A global view of cross-border migration. *Journal of the European Economic Association 13*(1), 168–202.

Docquier, F. and H. Rapoport (2012). Globalization, brain drain, and development. *Journal of economic literature 50*(3), 681–730.

Doran, K., A. Gelber, and A. Isen (2022). The effects of high-skilled immigration policy on firms: Evidence from visa lotteries. *Journal of Political Economy 130*(10), 2501–2533.

Eaton, J. and S. Kortum (2002). Technology, geography, and trade. *Econometrica 70*(5), 1741–1779.

Galle, S., A. Rodríguez-Clare, and M. Yi (2023). Slicing the pie: Quantifying the aggregate and distributional effects of trade. *The Review of Economic Studies 90*(1), 331–375.

Glennon, B. (2023). How do restrictions on high-skilled immigration affect offshoring? evidence from the h-1b program. *Management Science*.

Goos, M., A. Manning, and A. Salomons (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American economic review 104*(8), 2509–2526.

Hanson, G. H. and M. J. Slaughter (2002). Labor-market adjustment in open economies: Evidence from us states. *Journal of international Economics 57*(1), 3–29.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2013). Two perspectives on preferences and structural transformation. *American Economic Review 103*(7), 2752–2789.

Hira, R. (2010). The h-1b and l-1 visa programs: Out of control.

Kerr, S. P., W. R. Kerr, and W. F. Lincoln (2015). Skilled immigration and the employment structures of us firms. *Journal of Labor Economics 33*(S1), S147–S186.

Kerr, W. R. and W. F. Lincoln (2010). The supply side of innovation: H-1b visa reforms and us ethnic invention. *Journal of Labor Economics 28*(3), 473–508.

Khanna, G. and N. Morales (2021). The it boom and other unintended consequences of chasing the american dream. *Working Paper*.

Lai, H. and D. Trefler (2002). The gains from trade with monopolistic competition: specification, estimation, and mis-specification.

Mahajan, P. (2022). Immigration and business dynamics: Evidence from us firms.

Matloff, N. (2002). On the need for reform of the h-1b non-immigrant work visa in computer-related occupations. *U. Mich. JL Reform 36*, 815.

Mitaritonna, C., G. Orefice, and G. Peri (2017). Immigration and Firms' Outcomes: Evidence from France. *European Economic Review 96*, 62–82.

Monras, J. (2020). Immigration and wage dynamics: Evidence from the mexican peso crisis. *Journal of Political Economy 128*(8), 3017–3089.

Moser, P. and S. San (2020). Immigration, science, and invention. lessons from the quota acts. *Lessons from the Quota Acts (March 21, 2020)*.

OECD. (2019). *Recruiting Immigrant Workers*. OECD Publishing.

Ottaviano, G. I. and G. Peri (2012). Rethinking the effect of immigration on wages. *Journal of the European economic association 10*(1), 152–197.

Ottaviano, G. I., G. Peri, and G. C. Wright (2018). Immigration, trade and productivity in services: Evidence from uk firms. *Journal of International Economics 112*, 88–108.

Ottaviano, G. I. P., G. Peri, and G. C. Wright (2013). Immigration, offshoring, and american jobs. *American Economic Review 103*(5), 1925–1959.

Paserman, M. D. (2013). Do high-skill immigrants raise productivity? evidence from israeli manufacturing firms, 1990-1999. *IZA Journal of Migration 2*(1), 1–31.

Peri, G., K. Shih, and C. Sparber (2015). Stem workers, h-1b visas, and productivity in us cities. *Journal of Labor Economics 33*(S1), S225–S255.

Peri, G. and C. Sparber (2009, July). Task Specialization, Immigration, and Wages. *American Economic Journal: Applied Economics 1*(3), 135–169.

Peri, G. and C. Sparber (2011). Highly-Educated Immigrants and Native Occupational Choice. *Industrial Relations 50:3*.

Romalis, J. (2004). Factor proportions and the structure of commodity trade. *American Economic Review 94*(1), 67–97.

Romalis, J. (2007). Nafta's and cusfta's impact on international trade. *The review of Economics and Statistics 89*(3), 416–435.

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights 4*(3), 305–322.

Roth, J., P. H. Sant'Anna, A. Bilinski, and J. Poe (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*.

Rybczynski, T. M. (1955). Factor endowment and relative commodity prices. *Economica 22*(88), 336–341.

Samuelson, P. A. (1948). International trade and the equalisation of factor prices. *The Economic Journal 58*(230), 163–184.

Zimring, A. (2019). Testing the heckscher–ohlin–vanek theory with a natural experiment. *Canadian Journal of Economics/Revue canadienne d'économique 52*(1), 58–92.

Appendix

A Additional tables and figures

Table 6: Crosswalk of classification of occupations

New	NOC (Classification in PR)		DOT (Classification in H-1B dataset)	
group	Code	Description	Code	Description
1	0111	Financial managers	161	Budget and Management Systems Analysis Occupations
2	0112	Human resources managers	166	Personnel Administration Occupations
3	0113	Purchasing managers	162	Purchasing Management Occupations
4	0121	Insurance, real estate and financial brokerage managers	186	Finance, Insurance, and Real Estate Managers and Officials
5	0124	Advertising, marketing and public relations managers	164	Advertising Management Occupations
5	0124	Advertising, marketing and public relations managers	165	Public Relations Management Occupations
6	041	Managers in public administration	188	Public Administration Managers and Officials
7	060	Corporate sales managers	163	Sales and Distribution Management Occupations
8	065	Managers in customer and personal services, n.e.c.	187	Service Industry Managers and Officials
9	073	Managers in transportation	184	Transportation, Communication, and Utilities Industry Managers and Officials
10	081	Managers in natural resources production and fishing	180	"Agriculture, Forestry, and Fishing Industry Managers and Officials "
10	081	Managers in natural resources production and fishing	181	Mining Industry Managers and Officials
11	111	Auditors, accountants and investment professionals	160	"Accountants, Auditors, and Related Occupations "
11	124	Office administrative assistants - general, legal and medical	169	Other Occupations In Administrative Specializations
12	2111	Physicists and astronomers	021	Occupations In Astronomy
12	2111	Physicists and astronomers	023	Occupations In Physics
13	2112	Chemists	022	Occupations In Chemistry
14	2114	Meteorologists and climatologists	025	Occupations In Meteorology
15	2121	Biologists and related scientists	049	Other Occupations in Life Sciences
15	2121	Biologists and related scientists	041	Occupations In Biological Sciences
16	2123	Agricultural representatives, consultants and specialists	040	"Occupations In Agricultural Sciences "
17	2131	Civil engineers	005	Civil Engineering Occupations
18	2132	Mechanical engineers	007	Mechanical Engineering Occupations
19	2134	Chemical engineers	008	Chemical Engineering Occupations
20	2141	Industrial and manufacturing engineers	012	Industrial Engineering Occupations
21	2142	Metallurgical and materials engineers	011	Metallurgy and Metallurgical Engineering Occupations
21	2142	Metallurgical and materials engineers	006	Ceramic Engineering Occupations
22	2143	Mining engineers	010	Mining and Petroleum Engineering Occupations
23	2144	Geological engineers	014	Marine Engineering Occupations
23	2253	Drafting technologists and technicians	017	Drafters
24	2146	Aerospace engineers	002	Aeronautical Engineering Occupations
25	2148	Other professional engineers, n.e.c.	015	Nuclear Engineering Occupations
25	2148	Other professional engineers, n.e.c.	013	Agricultural Engineering Occupations
25	2148	Other professional engineers, n.e.c.	019	Other Occupations in Architecture, Engineering, and Surveying
26	215	Architects, urban planners and land surveyors	001	Architectural Occupations
27	216	Mathematicians, statisticians and actuaries	020	Occupations In Mathematics
28	2171	Information systems analysts and consultants	030	"Occupations In Systems Analysis and Programming "
28	2175	Web designers and developers	039	Other Computer-Related Occupations
29	2172	Database analysts and data administrators	031	Occupations in Data Communications and Networks

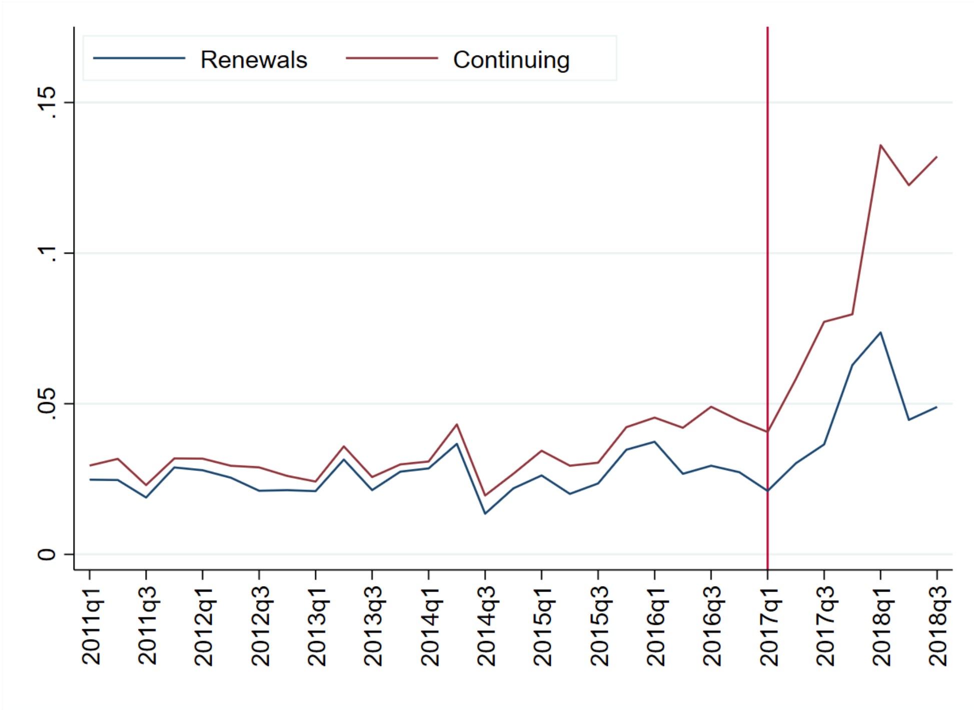
New	NOC (Classification in PR)		DOT (Classification in H-1B dataset)	
group	Code	Description	Code	Description
30	2212	Geological and mineral technologists and technicians	024	Occupations In Geology
31	224	Technical occupations in electronics and electrical engineering	003	Electrical/Electronics Engineering Occupations
32	2251	Architectural technologists and technicians	001	Architectural Occupations
33	2254	Land survey technologists and technicians	018	Surveying/Cartographic Occupations
34	2282	User support technicians	032	Occupations In Computer System User Support
35	301	Professional occupations in nursing	075	Registered Nurses
36	3111	Specialist physicians	070	Physicians and Surgeons
37	3112	General practitioners and family physicians	079	Other Occupations in Medicine and Health
38	3113	Dentists	072	Dentists
39	3114	Veterinarians	073	Veterinarians
40	3131	Pharmacists	074	Pharmacists
41	3132	Dietitians and nutritionists	077	Dietitians
42	314	Therapy and assessment professionals	076	Therapists
43	321	Medical technologists and technicians (except dental health)	079	Other Occupations in Medicine and Health
44	322	Technical occupations in dental health care	078	Occupations in Medical and Dental Technology
45	401	University professors and post-secondary assistants	090	Occupations in College and University Education
46	402	College and other vocational instructors	090	Occupations in College and University Education
47	403	Secondary and elementary school teachers and educational counsellors	091	Occupations in Secondary School Education
47	403	Secondary and elementary school teachers and educational counsellors	092	Occupations in Preschool, Primary School, and Kindergarten Education
48	4111	Judges	110	"Lawyers "
49	4112	Lawyers and Quebec notaries	111	Judges
50	415	Social and community service professionals	045	"Occupations In Psychology "
51	421	Paraprofessional occupations in legal, social, community and education services	119	Other Occupations in Law and Jurisprudence
52	5111	Librarians	100	"Librarians "
53	5112	Conservators and curators	102	"Museum Curators and Related Occupations "
54	5113	Archivists	101	Archivists
55	5121	Authors and writers	131	Writers
56	5122	Editors	132	Editors: Publication, Broadcast, and Script
57	5123	Journalists	137	Interpreters and Translators
58	5125	Translators, terminologists and interpreters	137	Interpreters and Translators
59	5132	Conductors, composers and arrangers	152	Occupations in Music
60	5133	Musicians and singers	152	Occupations in Music
61	5134	Dancers	151	Occupations in Dancing
62	5135	Actors and comedians	150	Occupations in Dramatics
63	5136	Painters, sculptors and other visual artists	144	Fine Arts
64	5211	Library and public archive technicians	100	"Librarians "
65	5212	Technical occupations related to museums and art galleries	102	"Museum Curators and Related Occupations "
66	5221	Photographers	143	Occupations in Photography
67	5222	Film and video camera operators	194	Sound and Film
68	5225	Audio and video recording technicians	194	Sound and Film
69	523	Announcers and other performers, n.e.c.	159	Other Occupations in Entertainment and Recreation
70	525	Athletes, coaches, referees and related occupations	153	Occupations in Athletics and Sports
71	621	Retail sales supervisors	185	"Wholesale and Retail Trade Managers and Officials "
72	652	Occupations in travel and accommodation	197	Ship Captains
73	720	Contractors and supervisors, industrial, electrical and construction trades and related workers	182	Construction Industry Managers and Officials
74	922	Supervisors, assembly and fabrication	183	Manufacturing Industry Managers and Officials

Table 7: Canadian point system

Selection Factor	Description	Maximum Points Awarded
Language skills (English or French)	Separate points for speaking, listening, reading and writing	28
Education	Maximum points for Ph.D., minimum points for high school diploma	25
Work Experience	Maximum points for 6 or more years of experience	15
Age	Maximum points for ages 18-35, zero points for under 18 and over 47	12
Employment offer	Maximum points for a job having a valid job offer	10
Adaptability	Includes spouse's language fluency, education and work experience, and relatives in Canada	10
Total possible points		100

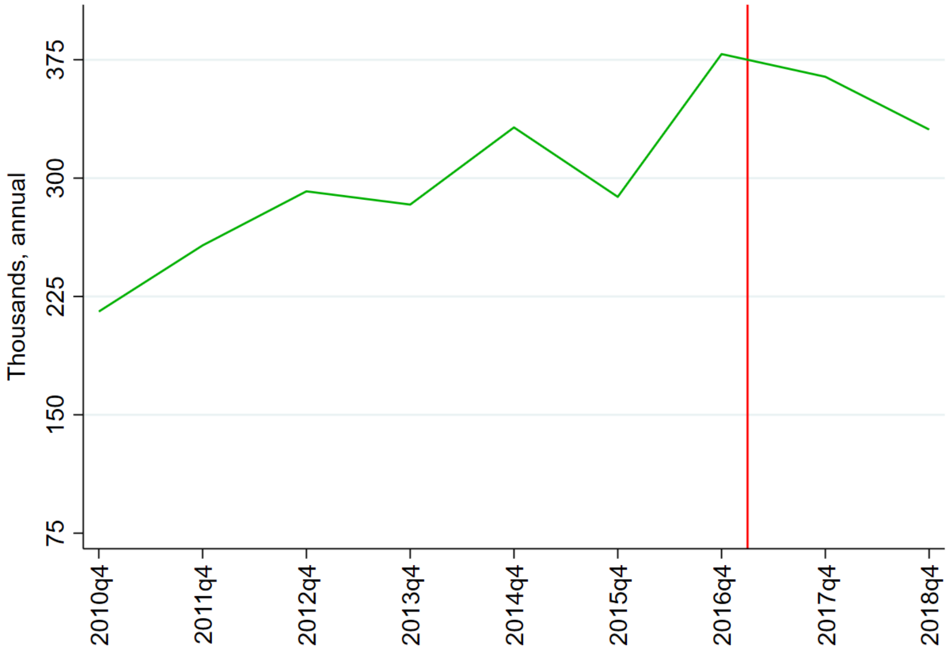
Source: IRCC's website Website (link), accessed June 2023.

Figure 9: Denial rates of continuing H-1B visas and renewals by quarter



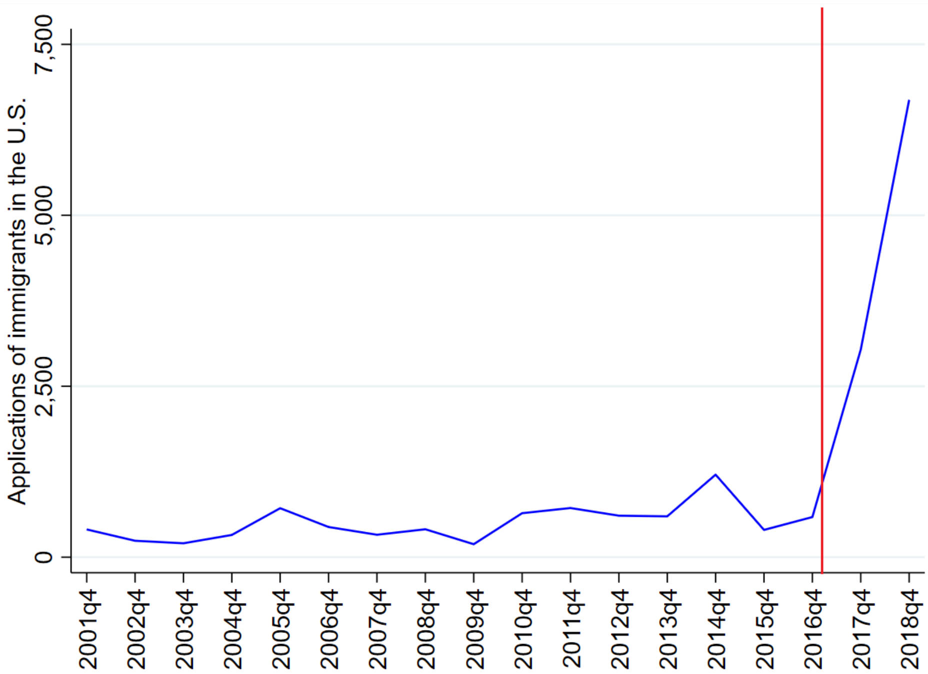
Note. Figure ?? plots the number of denied H-1B applications divided by the total number of H-1B applications. The red line includes continuing H-1B, and the blue lines only renewals.

Figure 10: Annual number of H-1B approvals



Note. We use our H-1B dataset to compute the number of H-1B approvals until 2018q3, and complement the data for 2018q4 from an additional FOIA request. The number of approvals in 2018 were approximately 47,000 fewer than in 2016 and 140,000 fewer that its linear trend.

Figure 11: Canadian visa applications of immigrants currently living in the U.S.



Note. The y-axis represents the number of applications for Canadian Permanent Residence visas from applicants residing in the U.S., excluding American applicants.

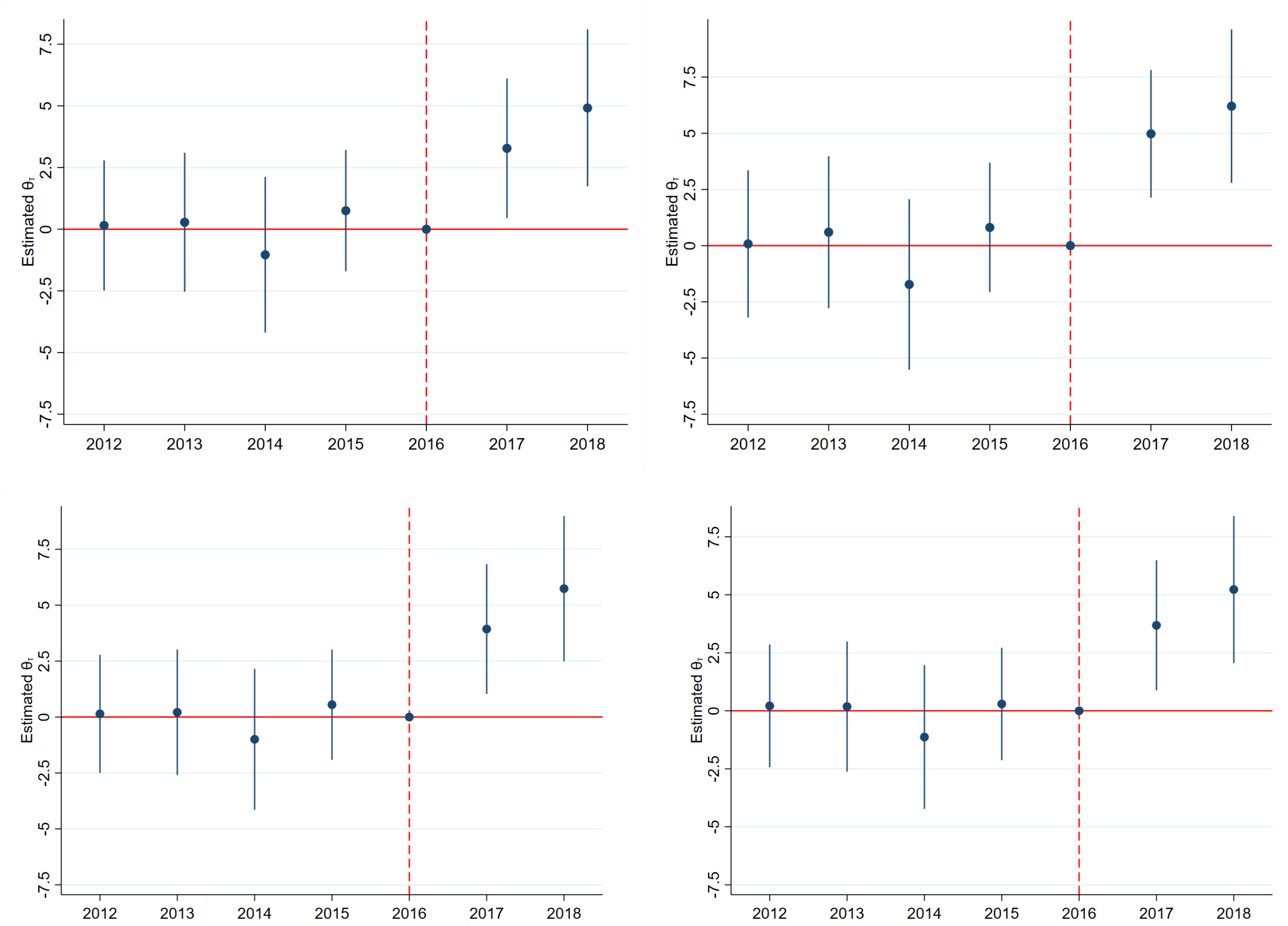
Table 8: Effect of increasing H-1B denial rates on Canadian Immigration

	(1)	(2)	(3)	(4)	(5)
	$log(App_{co,can,t})$	$log(App_{co,can,t})$	$log(App_{co,can,t})$	$log(App_{co,can,t})$	$log(app)^{can}_{cot}$
$Intensity_{co}\ 1(t=2012)$	0.117	0.153	0.078	0.142	0.213
	(1.326)	(1.342)	(1.669)	(1.345)	(1.347)
$Intensity_{co}\ 1(t=2013)$	0.086	0.282	0.600	0.212	0.182
	(1.411)	(1.435)	(1.723)	(1.430)	(1.429)
$Intensity_{co}\ 1(t=2014)$	-1.131	-1.038	-1.726	-0.996	-1.131
	(1.578)	(1.605)	(1.933)	(1.604)	(1.579)
$Intensity_{co}\ 1(t=2015)$	0.295	0.751	0.810	0.551	0.295
	(1.234)	(1.253)	(1.465)	(1.254)	(1.234)
$Intensity_{co}\ 1(t=2017)$	3.683**	3.279**	4.977***	3.933***	3.684**
	(1.428)	(1.442)	(1.445)	(1.477)	(1.428)
$Intensity_{co}\ 1(t=2018)$	5.232***	4.916***	6.205***	5.740***	5.227***
	(1.616)	(1.620)	(1.738)	(1.655)	(1.616)
Observations	5262	5262	4637	4909	5262

Note. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. All columns include occupation-nationality fixed-effects, occupation-year fixed effects, and nationality-year fixed effects. Standard errors are clustered at the occupation-level. Column (1) is the baseline specification given by 1. Column (2) controls for the elements used to compute $\pi_{co,usa}$ interacted with year dummies (e.g. $App_{co,can} \times \delta_t$ and $App_{co,usa} \times \delta_t$). Column (3) excludes applications of immigrants from India and China. Column (4) excludes applications of computer scientists. Column (5) includes $Share^{EE}_{oc2015} \times 1(t \geq 2015)$ and $Share^{EE}_{oc2016} \times 1(t \geq 2016)$ where $Share^{EE}_{oct}$ is the share of applications of an immigrant group oc in year t accounted by the Express Entry program.

Figure 12: Effect of increasing H-1B denial rates on Canadian Immigration

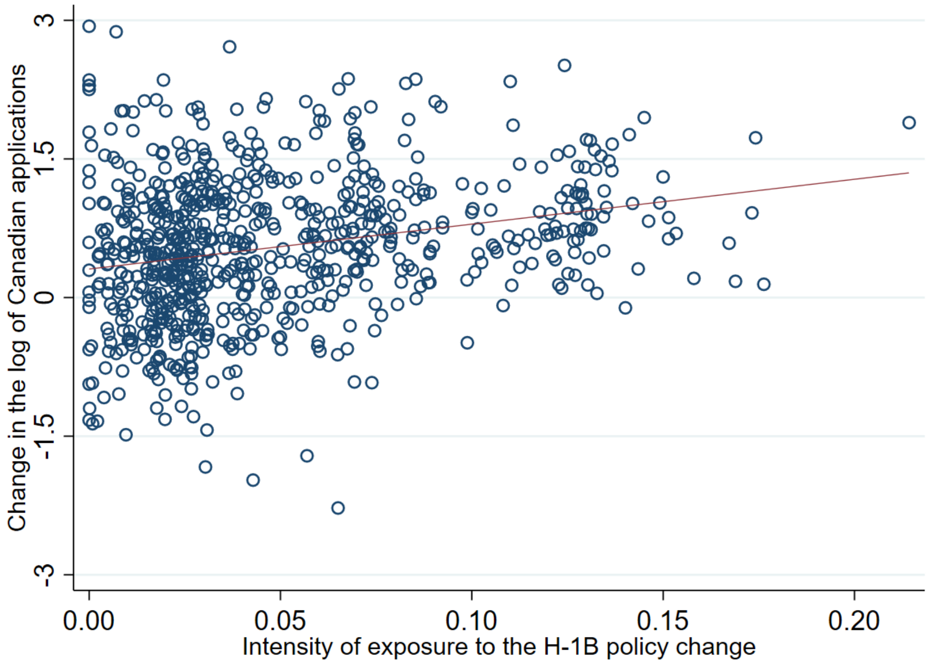
(a) Controlling for the elements in $\pi_{co,usa}$ (b) Excluding apps. from India and China



(c) Excluding apps. of computer scientists (d) Including Express Entry control variables

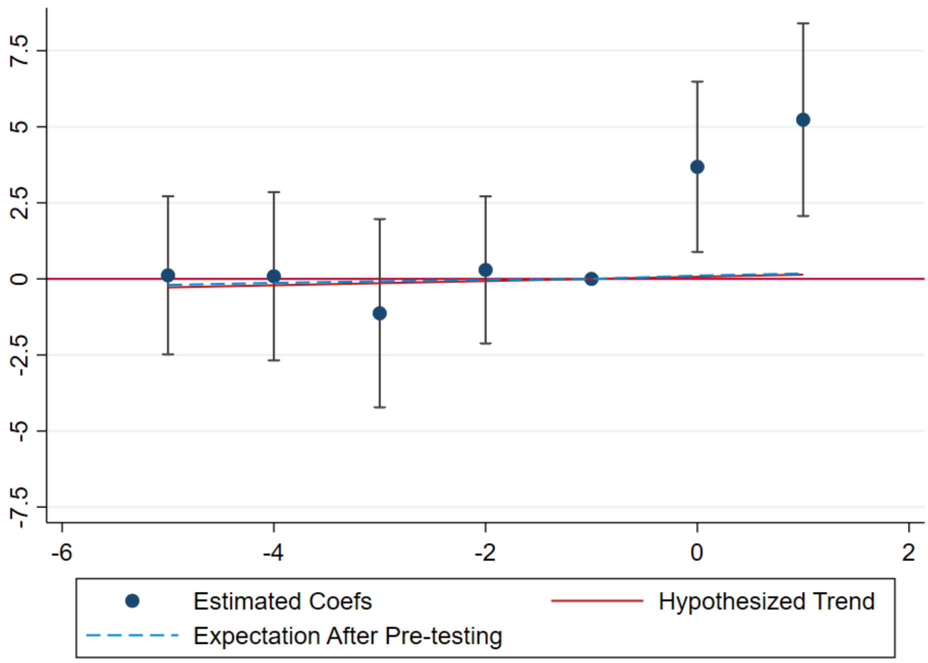
Note. The y-axis plots the estimated event-study coefficients corresponding to columns 2-4 from Appendix Table 8.

Figure 13: Change in Canadian applications and exposure measure: Raw data



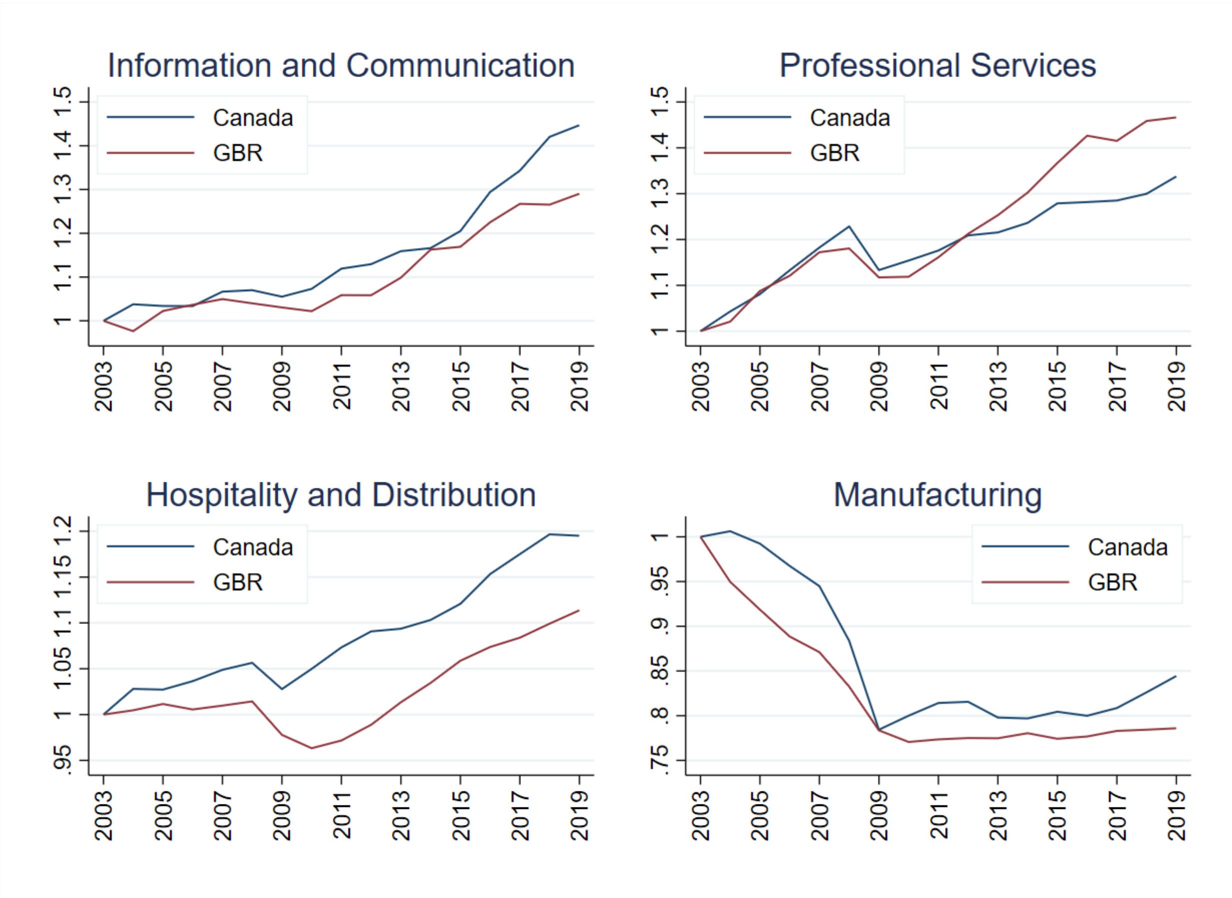
Note. The y-axis is computed as $\frac{\sum_{t=2017}^{2018} log(App_{co,can,t})}{2} - \frac{\sum_{t=2012}^{2016} log(App_{co,can,t})}{5}$ and the x-axis is $Fraction\ Affected_{co}$ in equation 2. An observation is an immigrant group co where c and o stands for the country of birth and occupations respectively.

Figure 14: Test for linear trends



Note. This plot shows our estimated coefficients along with the test of the hypothesis of linear trends with a slope of 7% according to Roth (2022).

Figure 15: Number of working hours relative to the year 2003



Note. The y-axis measures the number of working hours relative to the year 2003, from the OECD database (variable name "EEM"). The correlation of the time series for information and communication, professional services, hospitality and distribution, and manufacturing are 0.97, 0.95, 0.87, and 0.96 respectively.

Table 9: Distribution of the firm-level intensity of treatment

NAICS code	Firms with $Intensity_i > 0$ Mean	Std	Median	10th	90th	N firms	All firms N firms
31	0.963	1.355	0.418	0.026	2.891	1475	2085
32	0.711	1.122	0.292	0.016	1.943	2280	3410
33	0.861	1.288	0.369	0.028	2.296	4650	6215
41	0.821	1.196	0.386	0.034	2.071	5090	7790
44	0.397	0.733	0.162	0.009	0.931	7810	13975
45	0.350	0.599	0.156	0.015	0.870	1420	2505
48	0.374	0.823	0.071	0.003	1.060	1965	3680
49	0.577	0.984	0.240	0.014	1.378	245	340
51	1.825	2.198	0.853	0.089	5.230	790	1050
52	1.073	1.322	0.610	0.070	2.662	1190	1830
53	0.483	0.584	0.299	0.029	1.133	1210	1815
54	1.701	1.979	0.920	0.114	4.597	3520	4605
55	1.333	1.335	0.898	0.149	3.173	380	445
56	0.571	1.022	0.184	0.009	1.480	2855	4315
61	1.068	1.285	0.660	0.056	2.652	665	900
62	0.919	1.455	0.311	0.008	2.619	2655	5085
71	0.224	0.354	0.106	0.007	0.549	915	1670
72	0.427	0.665	0.155	0.008	1.256	12880	17715

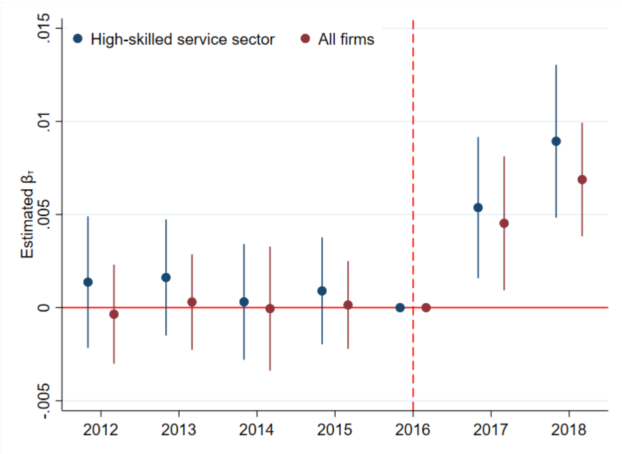
Note. This table reports the summary statistics of $Intensity_i$, normalized by the overall standard deviation. The statistics reported in the columns from left to right are the mean, standard deviation, median, 10th percentile, 90th percentile, and the number of firms, for firms with positive exposure. The last column reports the total number of firms in the sample, which include those firms with $Intensity_i = 0$. The total number of firms across all sectors is 79,430.

Table 10: Effect of increasing H-1B denial rates on Canadian firms

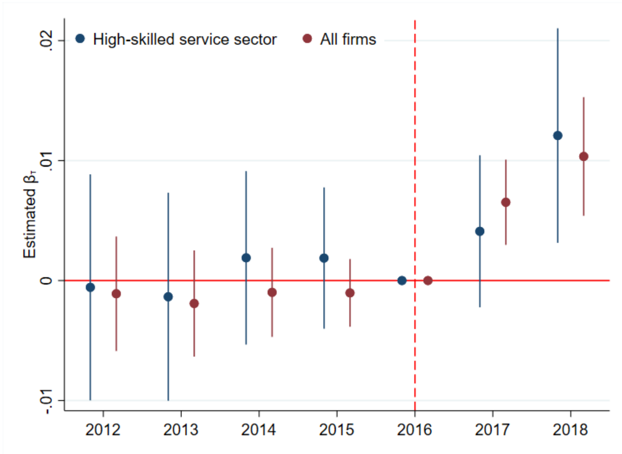
	Log of Revenues	Export-Rev ratio	Net hiring of imm.	Net hiring of natives	Log of Native empl.	Log of Total empl.	Log of earning per worker	Immigrant Share	Immigrant Share unskilled	Immigrant Share skilled	Log of markup	Log of cost	Log of Exports
$Intensity_i \times 1(\tau = 2012)$	-.0010915	-.001137	-.0003487	-.001607	-.0032443	.0028501	.0024256	.0003032	.0003487	-.0000455	-.0017131	-.0011219	-.0245746
	.0024408	.0009854	.0013644	.0013189	.0032291	.0019405	.0015463	.0007125	.0006064	.000667	.0017283	.0020011	.0203298
$Intensity_i \times 1(\tau = 2013)$	-.0019102	-.0003335	.0003032	-.0007732	.0005912	.0037446**	.001137	-.0002274	-.0004245	.0001971	-.0016221	-.0015767	-.0126891
	.0022589	.0008793	.0013038	.001137	.0029714	.0017737	.0014402	.0006367	.0005458	.0006064	.0013796	.0018647	.0203298
$Intensity_i \times 1(\tau = 2014)$	-.0009854	-.0010764	-.0000455	-.0013189	-.000379	.0019557	.000379	.0000758	-.0000152	.000091	-.0001819	-.0016221	-.0031685
	.001895	.0007277	.0016979	.0012128	.0026985	.0015918	.0012886	.0005458	.00047	.0005003	.0012583	.0016221	.0168126
$Intensity_i \times 1(\tau = 2015)$	-.0010309	-.0005912	.0001516	-.0012886	-.00047	.0007277	.001516	.0003032	.0000606	.0002274	.0000606	-.0012886	-.0019253
	.0014402	.0006064	.0011977	.0011067	.0021376	.0011977	.0011522	.0004093	.0003335	.0003638	.0010612	.0011825	.0135684
$Intensity_i \times 1(\tau = 2017)$	.0065189***	.0010461	.0045329**	.0024105	.0082471***	.0051545***	.0005609	.00047	-.0005458	.0010309***	.0005609	.0055638***	-.0001971
	.0018192	.0007125	.0018344	.0012431	.0023347	.0015312	.0010764	.0004093	.0003638	.000379	.0010461	.0014554	.0150541
$Intensity_i \times 1(\tau = 2018)$	.0103392***	.0034414***	.0068827***	.0029714**	.01278***	.0094145***	-.0033807**	.001895***	-.0002426	.0021527***	.0013189	.0091567***	.0386433**
	.0025166	.0008793	.0015615	.001228	.003032	.0020921	.0015009	.0006064	.0005761	.0005458	.0013038	.0021073	.0167975
Observations	537585	537585	537585	537585	537585	537585	537585	537585	537585	537585	532015	532115	79710
N firms	79430	79430	79430	79430	79430	79430	79430	79430	79430	79430	78955	78955	14345
R-squared	.9837	.9006	.1302	.1457	.9639	.9711	.9638	.9649	.9435	.929	.673	.9877	.9068

Note. The table displays the estimated event study coefficients, β_τ, of equation 3 multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The event is defined as the spike in H-1B denial rate in 2017. Standard errors are clustered at the firm-level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$

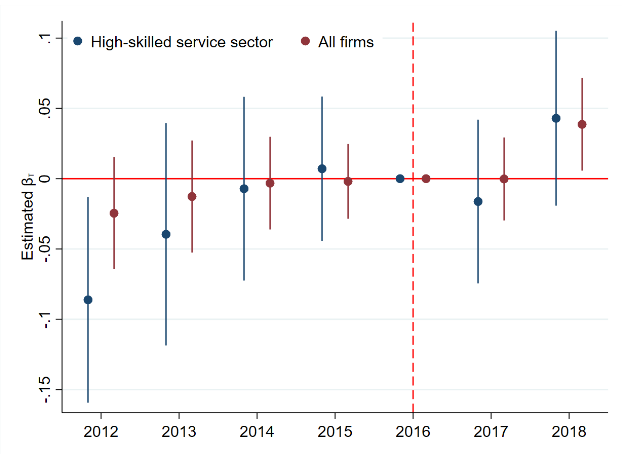
Figure 16: Effect of increasing H-1B denial rates on Canadian firms



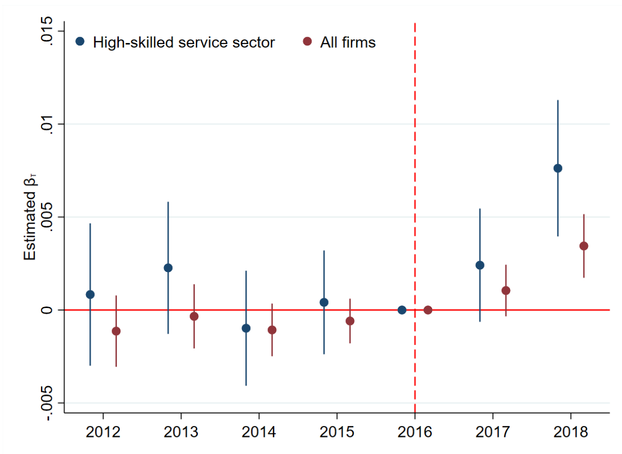
(a) Hiring of imm. relative to emp



(b) Sales (in log)



(c) Exports (in log)



(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ of equation 3 and β^E_τ of equation 33, multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The estimated coefficients β_τ plotted correspond to Appendix Table 8, and the estimated coefficients β^E_τ plotted correspond to $SkillSvs = 1$ in Appendix Table 11.

Table 11: Effect of increasing H-1B denial rates on Canadian firms: within sector estimates

	Log of Revenues	Export-Rev ratio	Net hiring of imm.	Net hiring of natives	Log of Exports
$Intensity_i \times 1(SS=0) \times 1(\tau=2012)$	-.0010006	-.002744**	-.0016828	-.0009551	-.0036536
	.0026682	.0011522	.001895	.0015615	.0240137
$Intensity_i \times 1(SS=1) \times 1(\tau=2012)$	-.0005609	.0008338	.0013644	.0026227	-.0861704**
	.0048058	.0019557	.0018041	.0022589	.0373395
$Intensity_i \times 1(SS=0) \times 1(\tau=2013)$	-.0010915	-.0028501***	-.0000606	.0005609	-.0299413
	.0025166	.0010461	.0019405	.0014857	.0217397
$Intensity_i \times 1(SS=1) \times 1(\tau=2013)$	-.0013493	.002274	.0016221	.0022437	-.0395377
	.0044268	.0018192	.0015918	.0019708	.0403564
$Intensity_i \times 1(SS=0) \times 1(\tau=2014)$	-.0011067	-.0010006	.0006216	-.0001516	.0066705
	.0022134	.0008338	.0027137	.0015463	.0190563
$Intensity_i \times 1(SS=1) \times 1(\tau=2014)$	.001895	-.0009854	.0003032	.0012735	-.0071253
	.0036839	.0015767	.0015918	.001895	.0333372
$Intensity_i \times 1(SS=0) \times 1(\tau=2015)$	-.0018495	-.0015312**	-.0002729	-.0007732	-.0074285
	.0016979	.0006974	.0017434	.0014251	.0164336
$Intensity_i \times 1(SS=1) \times 1(\tau=2015)$	.0018799	.0004093	.0008945	.0019102	.0070646
	.0030017	.0014251	.0014705	.0017131	.0261816
$Intensity_i \times 1(SS=0) \times 1(\tau=2017)$	-.0024559	-.0009096	.0021679	-.0001364	-.0021376
	.0025166	.000758	.0029259	.0015767	.0176768
$Intensity_i \times 1(SS=1) \times 1(\tau=2017)$	.0041084	.0024105	.0053667***	.0030017	-.0162365
	.0032291	.0015615	.0019405	.0019253	.0297139
$Intensity_i \times 1(SS=0) \times 1(\tau=2018)$	-.0090809***	-.0009703	.0024408	-.0005912	.0013644
	.0032898	.0009096	.0022134	.0015312	.0204814
$Intensity_i \times 1(SS=1) \times 1(\tau=2018)$	.0120827***	.0076256***	.0089293***	.0020921	.0429791
	.0045632	.0018647	.0020921	.0020769	.0317151
Observations	537585	537585	537585	537585	79695
N firms	79430	79430	79430	79430	14340
R-squared	.9839	.9021	.1317	.1474	.9076

Note. The table displays the estimated event study coefficients, β_τ, of equation 33 multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. $SS = 1$ refers to firms in the top 5 sectors in terms of the average value of $Intensity_i$, and $SS = 0$ refers to the remaining firms. The event is defined as the spike in H-1B denial rate in 2017. Standard errors are clustered at the firm-level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$.

Table 12: Effect of increasing H-1B denial rates on Domestic Firms

	Log of Revenues	Export-Rev ratio	Net hiring of imm.	Net hiring of natives	Log of Exports
$Intensity_i \times 1(\tau = 2012)$	.0007428	-.0010006	.0001668	-.000849	-.0124465
	.0024559	.0009399	.0015009	.0014402	.0247262
$Intensity_i \times 1(\tau = 2013)$	-.001228	-.0003032	.0009551	-.000091	-.0104908
	.0023195	.0008338	.0014402	.0012431	.0243169
$Intensity_i \times 1(\tau = 2014)$	-.0001971	-.0007732	.0004548	-.0002729	.0022892
	.001895	.0006822	.001895	.0013189	.0203753
$Intensity_i \times 1(\tau = 2015)$	-.0008186	-.0000303	.0003335	-.0005154	.0044419
	.0015009	.0005761	.0013189	.001228	.0162669
$Intensity_i \times 1(\tau = 2017)$	.0063673***	.0010157	.0049877**	.0030624**	-.0001516
	.0018799	.0007125	.0019708	.0013493	.01798
$Intensity_i \times 1(\tau = 2018)$	.010036***	.0028198***	.007095***	.0040781***	.0293349
	.0025924	.0008186	.0016525	.0013493	.0200114
Observations	510685	510685	510685	510685	61350
N firms	75470	75470	75470	75470	11290
R-squared	.9809	.8958	.1275	.1437	.8914

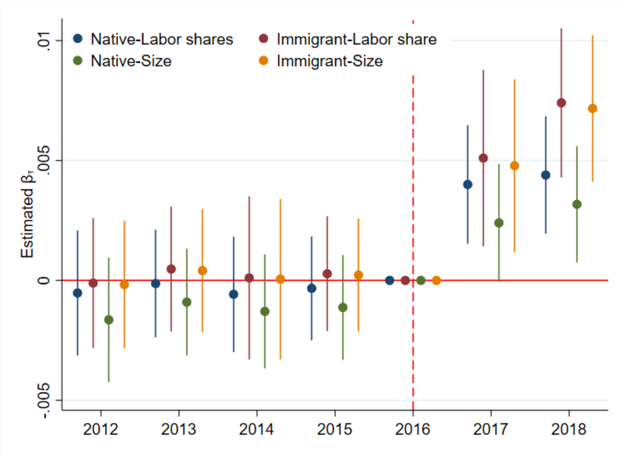
Note. The table displays the estimated event study coefficients, β_τ, of equation 3 multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The sample include only domestic firms and exclude MNC. We plot these coefficients in Appendix Figure 20. The event is defined as the spike in H-1B denial rate in 2017. Standard errors are clustered at the firm-level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$

Table 13: Estimate of the elasticity of substitution between the US and Canada

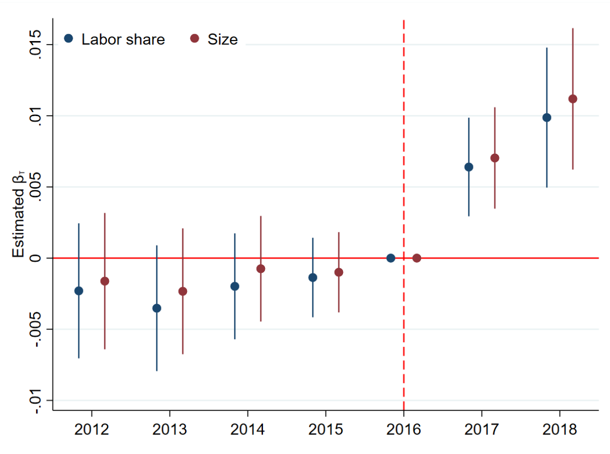
	(1) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	(2) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	(3) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	(4) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	(5) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	(6) $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$
$p_{o,usa,t}\ \tilde{w}_{co,usa}$	-0.116	-3.613***	-2.970***	-5.104***	-3.918***	-3.603***
	(0.255)	(1.293)	(1.080)	(1.397)	(1.386)	(1.302)
Observations	4060	4060	4060	3561	3752	4060
Specification	OLS	IV	IV	IV	IV	IV
F stat 1st stage		19.5	29.3	31.9	16.9	19.6

Note. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. All columns include occupation-nationality fixed-effects, occupation-year fixed effects, and nationality-year fixed effects. Standard errors are clustered at the occupation-level. Column (1) shows the OLS estimates of the baseline specifications given by 67. Columns (2)-(6) show 2SLS estimates. Column (2) estimates the baseline specification. Column (3) controls for the elements used to compute $\pi_{co,usa}$ interacted with year dummies (e.g. $\pi_{co,can} \times \delta_t$ and $\pi_{co,usa} \times delta_t$). Column (4) excludes applications of immigrants from India and China. Column (5) excludes applications of computer scientists. Column (6) includes $Share^{EE}_{oc2015} \times 1(t \geq 2015)$ and $Share^{EE}_{oc2016} \times 1(t \geq 2016)$ where $Share^{EE}_{oct}$ is the share of applications of an immigrant group oc in year t accounted by the Express Entry program.

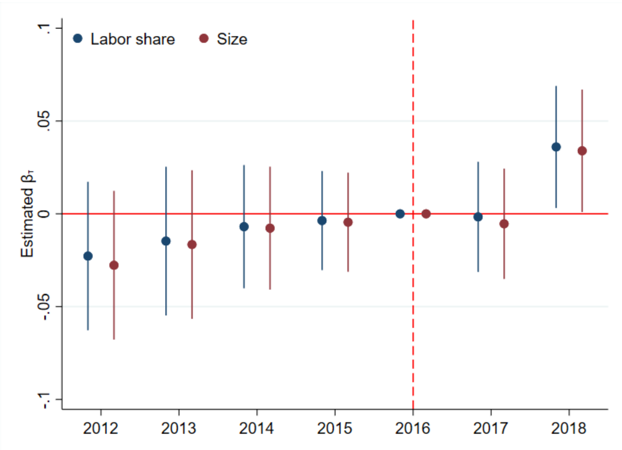
Figure 17: Robustness exercise to control for the effect of firm-characteristics



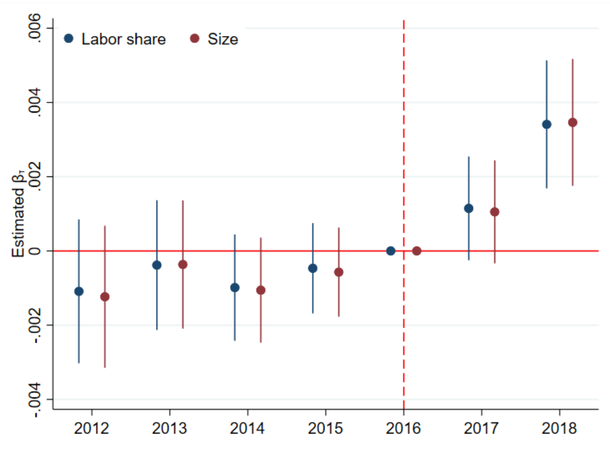
(a) Hiring relative to Employment in 2016



(b) Sales (in log)



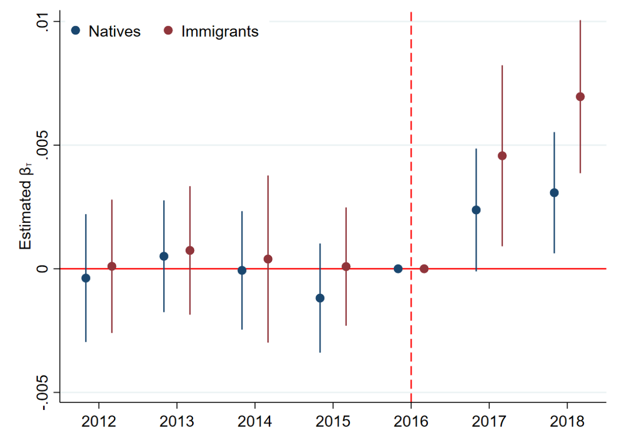
(c) Exports (in log)



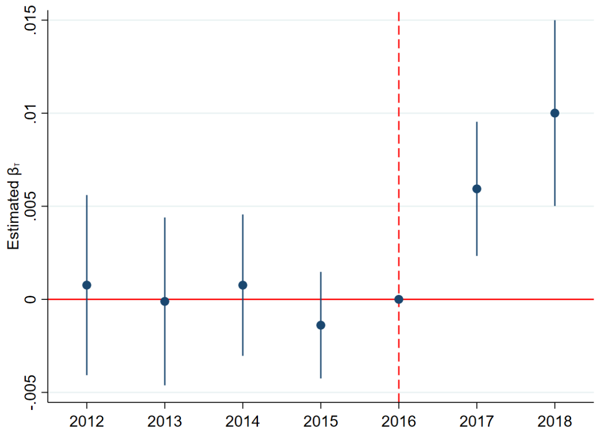
(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 with additional control variables, multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. These variables are pre-shock firm characteristics interacted with year dummies. The firm characteristics are the log of revenues and the share of the wagebill in total cost, referred to as "size" and "labor share" respectively. All these regressions include the pre-shock firm characteristics included in the baseline specification. The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals.

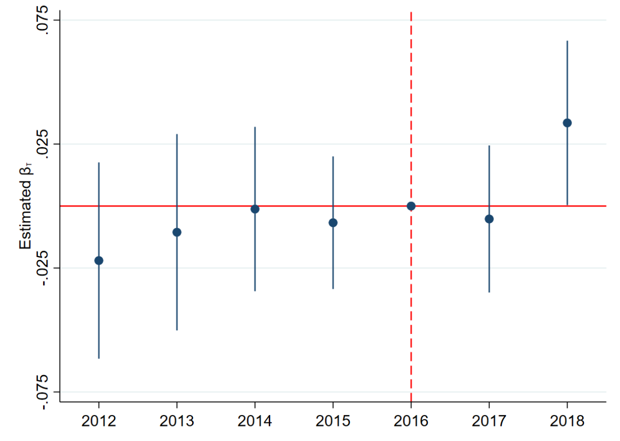
Figure 18: Robustness exercise to control for the effect of the Express Entry Program



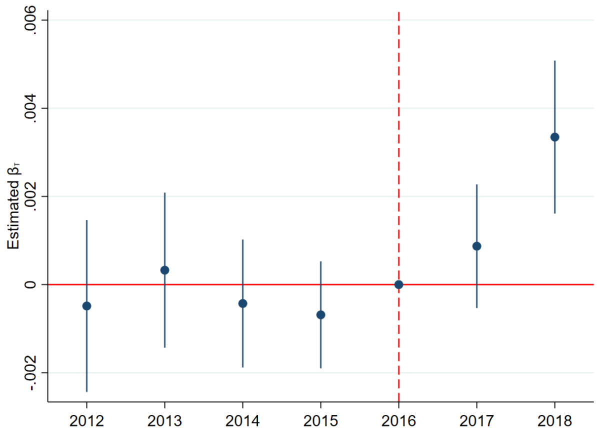
(a) Hiring relative to Employment in 2016



(b) Sales (in log)



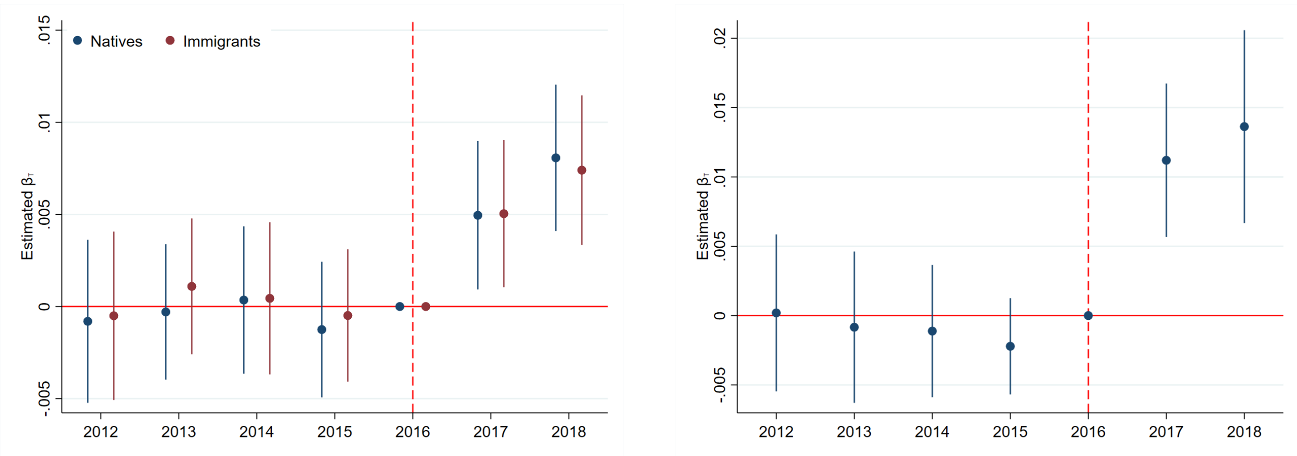
(c) Exports (in log)



(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 with an additional control variable, multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. This variable is the interaction between year dummies and the share of workers in 2016 who were admitted to Canada through this program. The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals.

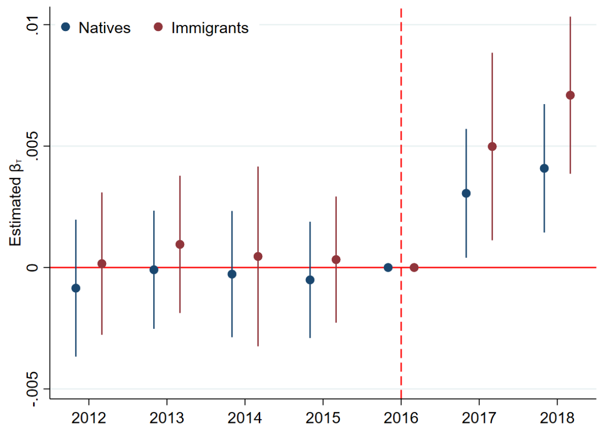
Figure 19: Robustness exercise to control for effect through international trade



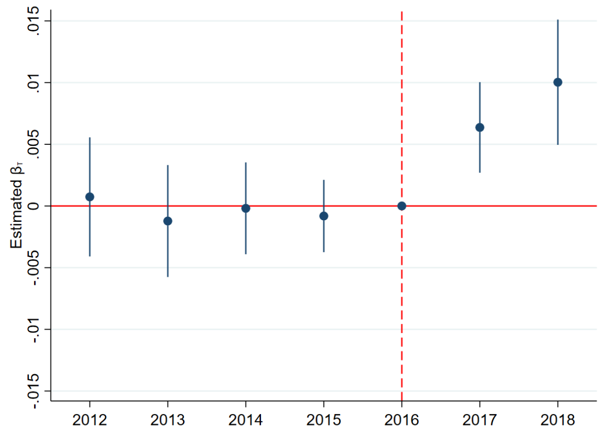
(a) Hiring relative to Employment in 2016 (b) Sales (in log)

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 , multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The sample exclude firms that exported or imported goods or services in the year 2016. The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals.

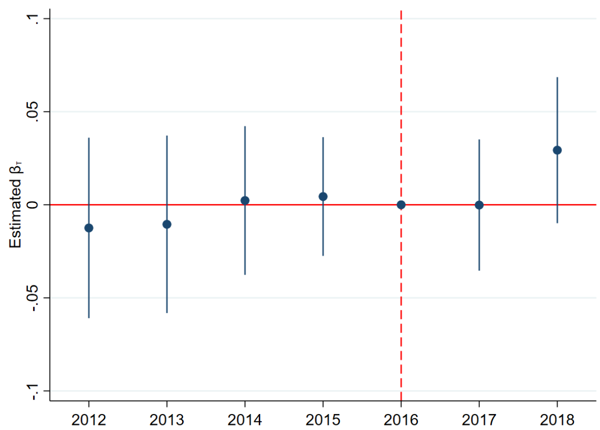
Figure 20: Effects on domestic firms



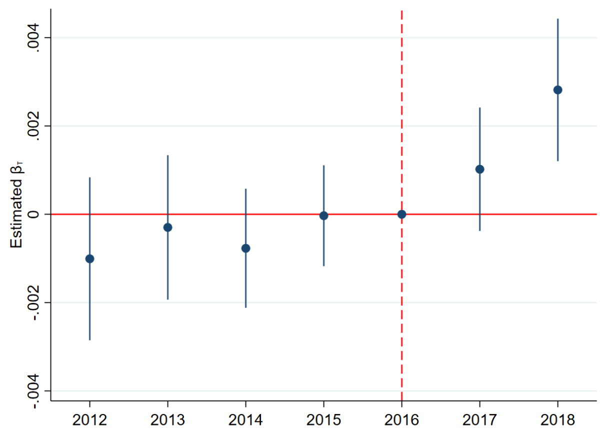
(a) Hiring relative to employment in 2016



(b) Sales (in log)



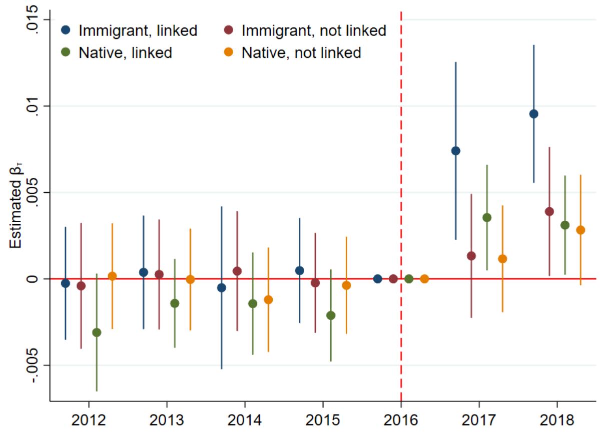
(c) Exports (in log)



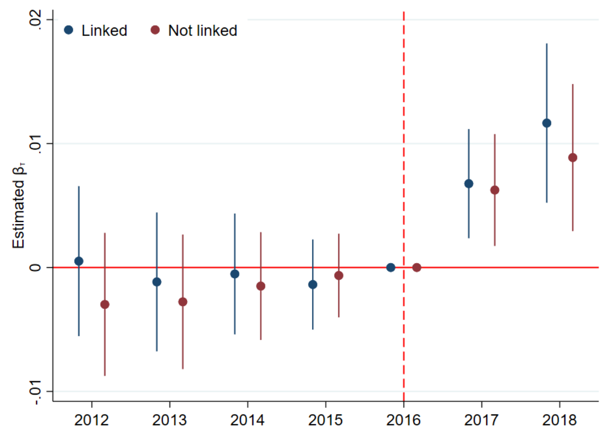
(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients , multiplied by the average value of $Intensity_i$ in the high-skilled service sector for ease of interpretation. The sample sample include domestic firms and exclude all MNC (we also exclude Canadian multinationals). The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. This figure correspond to the estimates in Table 12

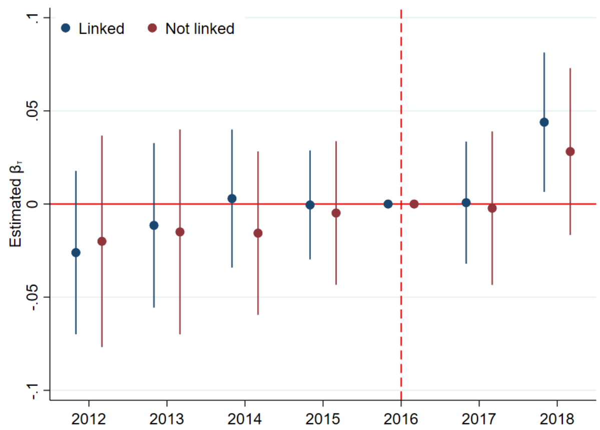
Figure 21: Effects on firms based on the share of workers who lived in the US



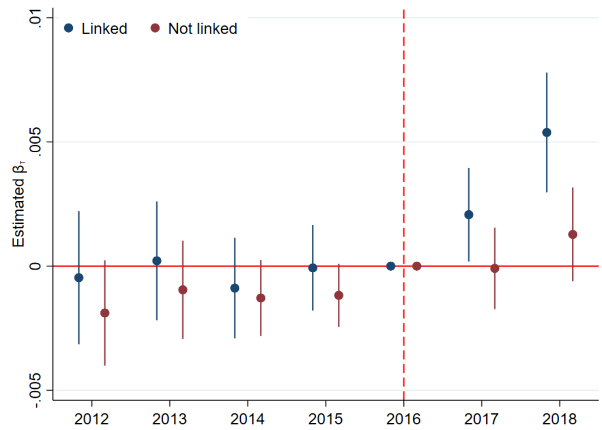
(a) Hiring relative to employment in 2016



(b) Sales (in log)



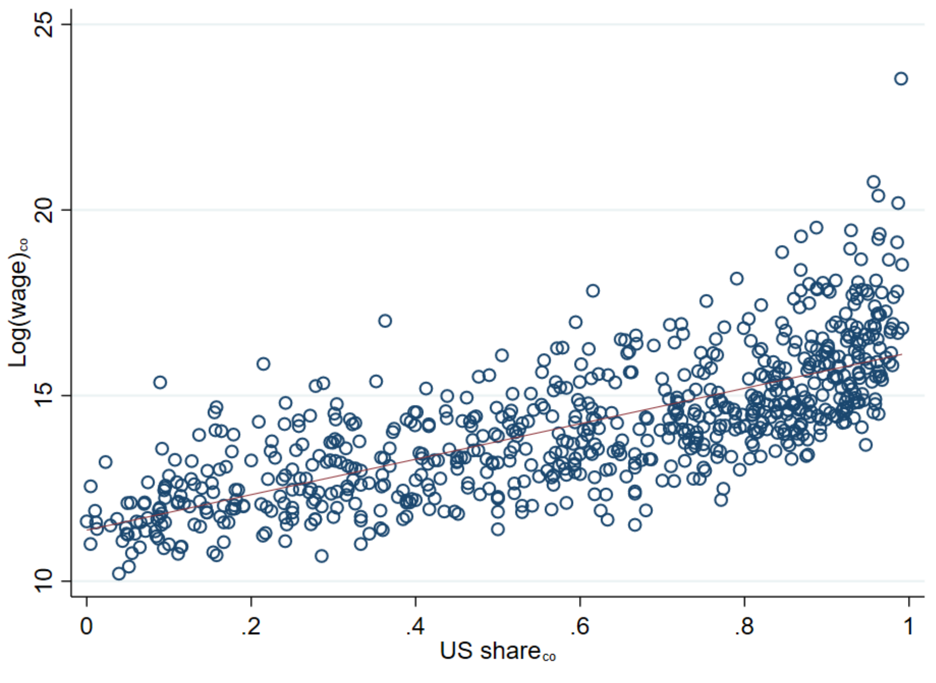
(c) Exports (in log)



(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients of a modified version of equation 3 where we allow for heterogeneous treatment effect. In particular, we allow for β_τ to be different for firms in two different groups. We split firms into two groups: those that had employed immigrants who had previously lived in the United States, and those that had not. We refer to these groups as "Linked" and "Not linked" respectively.The event is defined as the spike in H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals.

Figure 22: US wages and the share of immigrants choosing the US over Canada



Note. The y-axis is computed as the logarithm of the average annual earning reported in the H-1B visa application dataset. The x-axis is the US share in applications $pi_{co,usa}$. Both values are computed for the period before the introduction of the PM (2012-2015). An observation is an immigrant group co where c and o stands for the country of birth and occupations respectively.

Sectors in WIOD dataset	Sector in the quantitative model
Crop and animal production, hunting and related service activities	Agriculture and Mining
Forestry and logging	Agriculture and Mining
Fishing and aquaculture	Agriculture and Mining
Mining and quarrying	Agriculture and Mining
Manufacture of food products, beverages and tobacco products	Low-tech manufacturing
Manufacture of textiles, wearing apparel and leather products	Low-tech manufacturing
Manufacture of wood, cork and straw and plaiting materials	Low-tech manufacturing
Manufacture of paper and paper products	Low-tech manufacturing
Printing and reproduction of recorded media	Low-tech manufacturing
Manufacture of coke and refined petroleum products	Low-tech manufacturing
Manufacture of chemicals and chemical products	High-tech manufacturing
Manufacture of basic pharmaceutical products and preparations	High-tech manufacturing
Manufacture of rubber and plastic products	Low-tech manufacturing
Manufacture of other non-metallic mineral products	Low-tech manufacturing
Manufacture of basic metals	Low-tech manufacturing
Manufacture of fabricated metal products	Low-tech manufacturing
Manufacture of computer, electronic and optical products	High-tech manufacturing
Manufacture of electrical equipment	High-tech manufacturing
Manufacture of machinery and equipment n.e.c.	High-tech manufacturing
Manufacture of motor vehicles, trailers and semi-trailers	High-tech manufacturing
Manufacture of other transport equipment	High-tech manufacturing
Manufacture of furniture; other manufacturing	Low-tech manufacturing
Repair and installation of machinery and equipment	High-tech manufacturing
Electricity, gas, steam and air conditioning supply	Other
Water collection, treatment and supply	Other
Sewerage, waste collection and related activities	Other
Construction	Other
Wholesale and retail trade and repair of motor vehicles and motorcycles	Wholesale and retail trade
Wholesale trade, except of motor vehicles and motorcycles	Wholesale and retail trade
Retail trade, except of motor vehicles and motorcycles	Wholesale and retail trade
Land transport and transport via pipelines	Other
Water transport	Other
Air transport	Other
Warehousing and support activities for transportation	Other
Postal and courier activities	Other
Accommodation and food service activities	Other
Publishing activities	Information and communication (IC)
Motion picture, video, sound recording and related activities	Information and communication (IC)
Telecommunications	Information and communication (IC)
Computer programming, consultancy and related activities	Information and communication (IC)
Financial service activities	Finance
Insurance, reinsurance and pension funding	Finance
Activities auxiliary to financial services and insurance activities	Finance
Real estate activities	Other
Legal, accounting, and head offices activities	Professional, scientific and technical activities
Architectural and engineering activities; technical testing and analysis	Professional, scientific and technical activities
Scientific research and development	Professional, scientific and technical activities
Advertising and market research	Professional, scientific and technical activities
Other professional, scientific and technical activities	Professional, scientific and technical activities
Administrative and support service activities	Excluded
Public administration and defence; compulsory social security	Excluded
Education	Other
Human health and social work activities	Other
Other service activities	Other
Activities of households as employers	Excluded
Activities of extraterritorial organizations and bodies	Excluded

Source: The manufacturing sector has be sub-categorized by technological intensity according to the United Nations Industrial Development Organization (UNIDO).

B Data

B.1 Cross-walk of Occupation Codes

The H-1B dataset contains 106 occupation codes that follow the Dictionary of occupational titles (DOT) code and the PR dataset contains 177 3-digit NOC codes.[37] We construct a crosswalk between these occupations and, when necessary, we appealed to the information provided by the fourth digit of the NOC classification. For some NOC codes, there was not a DOT code in the H-1B dataset (e.g. cashiers or any low-skill occupation) and for some DOT codes, there was no NOC code (e.g. osteopaths). Among the matched cases, for some NOC occupations, there was more than one corresponding DOT code (e.g., NOC 0124 corresponds to DOT 164 and 165), for some DOT codes there was more than one corresponding NOC code (e.g., NOC 224 and 2133 corresponds to 003) and for a few cases, the match was from many to many (e.g., 2175 corresponds to 030 and 039; 2171, 2173, 2174 and 2283 corresponds to 030). We thus define a grouping given by the smallest possible mutually exclusive sets of matches which yield 74 distinct groups (see Table 6).[38] With this crosswalk at hand, we can aggregate the number of PR and H-1B applications at the new grouping level according to the corresponding NOC codes and DOT codes respectively.

B.2 Firm-level Regression: Measurement and Sample

B.2.1 Construction of Firm-Level Shocks

Firm-level Country Composition Combining the T4-ROE records and IMDB database, we compute the country share of each firm i by the pooled total employment between 2010 and 2013. In T4-ROE records, we compute the individual labor units (ILU) each employee provides to an associated firm.

Sector-level Occupation Composition We extract a sample of full-time employed individuals in 2015 from LFS to calculate this share by dividing the aggregate wage bill of individuals working in sector s and occupation o by the aggregate wage bill of the individuals working in sector s. Here, the wage bill is measured by the reported weekly earning, and the statistical weight provided in LFS is applied to the aggregation.

Share of Flow within the Population of Immigrants from Country c In LFS, we define the individuals not born in Canada as immigrants. Then we measure this flow share by dividing the number of immigrants from country c who have been permanent residents for not more

[37] See $https : //www.uscis.gov/sites/default/files/document/forms/m - 746.pdf$ and $https : //noc.esdc.gc.ca/$

[38] Most of these distinct groups have associated one DOT code (64 of the groups have one DOT code, 9 groups have two DOT codes, and 1 group has 3 DOT codes) and one NOC code (70 of the groups has one NOC code and 4 groups have two NOC codes).

than one year or have not become permanent residents in 2016 by the number of all immigrants from country c in 2016. When calculating these numbers of headcounts, the statistical weight provided in LFS is applied.

B.2.2 Construction of the Variables used as Controls

Firm-level Shares of Skilled Immigrant Employment In IMDB, we flag an immigrant as a skilled immigrant based on the available education, occupation, and visa program information. IMDB includes two separate data files: permanent-resident (PR) records and non-permanent-resident (Non-PR) records. In the PR records, an immigrant is flagged as a skilled immigrant if she satisfies one of the following three conditions:

1. with an education level above bachelor's degree;
2. admitted by Express Entry (EE) program;
3. qualified for the immigration category "Federal Skilled Workers", "Quebec Skilled Workers", "Skilled Trades", or "Provincial Nominees".

In the Non-PR records, an immigrant is flagged as a skilled immigrant if she is reported with an education level above a bachelor's degree or if she is reported with an occupation category of "Managerial", "Professionals", or "Skilled and Technical". We flag an immigrant as a skilled immigrant if she is flagged as a skilled immigrant in PR or Non-PR records. Based on this flag of skilled immigrants, we can directly measure the firm-level employment of skilled immigrants.

Local Labor Market Each local labor market corresponds to a census metropolitan area (CMA) or a census agglomeration (CA), equivalent to a metropolitan area in the US.[39] Statistics Canada provides a mapping between each postal code and a geographical location group. For most of the postal codes, they are directly a part of a CMA/CA. The postal codes in the remote areas do not directly belong to a specific CMA/CA, so we assign them to a CMA/CA that has the most influence on this postal code area based on the information provided by Statistics Canada. By combining the postal code information from T1-PMF and the employer-employee link records, we measure each firm's employment composition by local labor markets. Then we assign the local labor market for a firm by the one accounting for the largest share of its employment. This location measure is analogous to the commuting zone commonly used for the U.S.

[39]There are 151 CMA/CA in Canada, and a complete list of them can be found at https://en.wikipedia.org/wiki/List_of_census_metropolitan_areas_and_agglomerations_in_Canada.

B.2.3 Sample Selection

We first construct the regression sample by dropping the non-profit firms, firms with lifetime maximum employment smaller than 5, and the firms from the following sectors agriculture, forestry, fishing and hunting, mining, quarrying, oil and gas extraction, utilities, construction, public administration, and other services except for public administration (NAICS code 11, 21, 22, 23, 91 and 81 respectively). Then, we exclude the firms with a lifetime maximum annual employment growth rate above 2000% from the sample because these firms are very likely to experience significant organizational change. To minimize the impacts of extreme values on the precision of the estimates, we further drop the outlier firms in terms of $Intensity_i$, i.e., the firms with $Intensity_i$ above the 99% percentile of the positive $Intensity_i$. Finally, we restrict the sample to only include the firms with an observation in the baseline year 2016, at least two observations before 2016, and at least one observation in the year 2017 or 2018, so each firm in the sample has enough pre-shock and post-shock information for us to conduct the event study.

B.3 Data sources used in the quantitative model

Sources of data from Canada:

We use the income data by nativity, occupation, and sector in the Canadian Labor Force Survey Data (LFS) for the period 2012-2016 to compute the sectorial shares (s^n_{dso}, s^f_{dso}, and f_{dso}) and we use the number of immigrants by landing year to compute ψ^{imm}_{gh}.
We use publically available data from the IRCC's website on the approval rate by PR visa program for Canada in the year 2016. We assign a common approval rate to all occupations within skill because the data is not disaggregated by occupation. We compute the admission probability for skilled workers as the weighted average of the approval probability for PR applications under the following programs: Federal Skilled programs and Provincial Nominee program under Express Entry, Quebec skilled workers program, and Canadian Experience Class. For the lower-skilled group, we include the Provincial Nominee program under the non-express entry, and Caregiver Program.

Sources of data from the US:

We use the income data by nativity, occupation, and sector in the American Community Survey (ACS 1-year data corresponding) to the year 2015 to compute the sectorial shares for the US (s^n_{dso}, s^f_{dso}, and f_{dso}).
We also use this data to calibrate the occupational structure of sectors in RoW due to the lack of disaggregated data by occupation and sector of the largest countries included in RoW. In particular, we calibrate f_{dso} according to the distribution of income across occupations and sectors of immigrants from RoW in the US.

To compute ψ_{gd}^{imm}, we use the total number of immigrants by group and those who arrived in the US during the last year. We then use an extrapolation method to assign a value for a six-year period. Specifically, infer the six-year period for the U.S. as follows: $\psi_{gu}^{imm} = \frac{\psi_{gc}^{imm}}{\psi_{gc}^{imm}} \psi_{gu}^{imm}$, where we use Canadian data to compute the ratio or extrapolation factor.
We use the H-1B data described in section 2 to compute the admission probability of each skilled occupation, and official reports of I-129 petitions for H-2A and H-2B visas for the probability of lower-skilled occupation.[40] Specifically, we compute the admission probability for the lower-skilled occupation as the weighted average of the approval rate of the H-2A and H-2B visas for the fiscal year 2016.

C Immigration to Canada: Robustness exercises

Correlation over time of confounding factors may threaten identification as it will imply that ϵ_{cot} correlates with past applications and, hence, $\pi_{co,usa}$. It is plausible that $\pi_{co,usa}$ may be in part determined by pre-existing immigration conditions such as historical events (e.g. Canada was a French Colony), cultural factors (e.g. French is an official language of Canada), and institutional aspects of the immigration systems (e.g. the majority of sponsoring firms in the U.S. are Indian affiliates due to the IT boom in the 2000s). If these factors significantly contribute to determining $\pi_{co,usa}$, concerns regarding its correlation with ϵ_{oct} may be mitigated. We assess the plausibility of this correlation by controlling for the elements used to compute $\pi_{co,usa}$ interacted with year dummies (e.g. $App_{co,usa} \times \delta_t$ and $App_{co,can} \times \delta_t$). These estimates, reported in column 2 of Appendix Table 8, are not statistically different from our baseline estimates, reported in column 1. This suggests that unobserved factors affecting $\pi_{co,usa}$ and ϵ_{oct} are unlikely to drive our estimates. Note that correlation over time of unobserved factors at the occupation level only or at the country level only, do not threaten identification due to the inclusion of δ_{ot} and δ_{ct}.

The second potential concern is that the policy change was indeed the response to factors specific to certain immigrant groups (e.g. nationality and occupation). For example, critics of the program have argued that few outsourcing firms that provide IT and other business services are flooding the program with applications and are misusing the H-1B program. Many of the accused firms are intensive in computer-related occupations and tend to source most immigrants from India. Given that during his campaign, former President Donald Trump expressed his intentions to end the misuse of the H-1B program, the policy may have aimed to stop the increasing inflow of computer scientists from India. If the new restrictions targeted immigrant groups that were growing, our estimates would suffer from reverse causality issues and would be upward biased. To address this concern, we re-estimate the model by excluding India and China, the two largest nationalities, and computer-related occupations, the largest occupation. The estimates, reported in columns 3 and 4 of Appendix Table 8, are not lower than our baseline

[40]H-2A and H-2B visas are temporary visas for agricultural and non-agricultural jobs respectively.

estimates, suggesting that this concern may not affect our estimates.

A third concern is that immigrant groups affected by the U.S. policy change may have been affected by contemporaneous changes in Canadian immigration policy. Changes in Canadian immigration policy at the nationality level or at the occupation level are controlled by δ_{ct} and δ_{ot} respectively. The most important change in Canadian policy around the period of the H-1B policy change occurred in 2015 with the introduction so-called Express Entry program. We control for the potential effects of this program by including a regressor defined as the share of applications of an immigrant group co accounted by the Express Entry program in the years 2015 and 2016 interacted with a dummy that equals 1 for years 2015-2018 and zero otherwise. The estimates, reported in column 5, are similar to our baseline estimate, which suggests that the effect of the Express Entry program is unlikely to confound the effect of the US restrictions. It is worth mentioning that if the Canadian policy responded to the new US policy, our reduced-form estimates would incorporate these effects, and we should consider them when interpreting the coefficients.

Fourth, we perform additional tests of the identifying assumption recommended by the recent research on difference-in-difference design (Roth, 2022). We test the hypothesis of a 7% annual linear trend, as per the 2016-2017 immigration plan. At a 1% significance level, we reject this trend, indicating that our estimates may not capture pre-shock differential trends (see estimation details in Appendix Figure 14).We also test for steeper slopes up to 30%, yielding same qualitative results.

Finally, we verify that our estimates are not driven by outliers. In Appendix Figure 13, we plot the relationship between the change in the outcome variable and the main regressor (e.g. the change in $log(App_{co,can,t})$ and $Intensity_{co}$) using raw data. The distribution of observations in the scatter plot suggests that it is unlikely that outliers affect our estimates.

D Firm-level evidence

D.1 Robustness exercises

Within-sector effects Our empirical strategy for estimating β_τ leverages both inter-firm variation within the same industry and variation across different industries. One concern is that our industry-level controls do not fully account for potential demand or supply shocks that are specific to different industries. In such a case, the effect of these factors may confound the industry-level effect of the H-1B policy restrictions and bias our estimates. If such unobserved factors drive our estimates, we would expect to observe no effect on firm growth when using only within-industry variation to estimate β_τ. A related concern regards the interpretation of our coefficients. $Intensity_i$ may capture shifts in both the supply of immigrants and changes in the demand for goods due to H-1B restrictions. In particular, the adverse effects of restricting immigrant labor in the US mainly affected American firms operating in the skilled-intensive service sector. Consequently, Canadian firms that compete with these American counterparts, may have expanded compared to other Canadian firms, even if they have not hired immigrants. If our estimates of β_τ are driven by differences in demand for goods and services induced by the H-1B policy change, we would expect a less pronounced effect when estimating the differential hiring response of Canadian firms within the same industry. To assess the plausibility of these concerns, we estimate the effect of the H-1B policy within affected industries using only within-industry variation. To do so, we categorize sectors into "exposed" and "non-exposed". Specifically, we rank broad sectors according to the average firm exposure (see Appendix Table 9) and define the top quartile as the "exposed" group of sectors. The remaining sectors constitute the "non-exposed" sectors. Then we estimate the following event study:

$$\begin{aligned} y_{it} = &\sum_{\tau \neq 2016} \beta_\tau^E \times 1(s = \mathit{exposed}) \times \mathit{Intensity}_i \times 1(t = \tau) + \\ &\sum_{\tau \neq 2016} \beta_\tau^{NE} \times \mathit{Intensity}_i \times 1(t = \tau) + \ \delta_i \ + \delta_{st} + \delta_{mt} + \ \gamma' \ X_{ist} \ + \epsilon_{it} \end{aligned} \tag{33}$$

where $1(s = \mathit{exposed})$ is a dummy variable that equals one if the industry where the firm operates belongs to one of the "exposed" sectors, and zero otherwise. We compare the estimates of β_τ^E, which does not use variation across sectors for identification, with those from equation 3. Appendix Figure 16 shows this comparison for the hiring of immigrants and sales and export performance (Appendix Table 11 reports all the estimates and estimation details.) The pairwise comparison of estimates of these variables shows that the within-industry estimates are noisier but overall the point estimates are similar in magnitude to those documented previously. Moreover, we find that there are no statistically significant differences in the hiring of native workers for firms within the same industry with different exposure (see Appendix Table 11). Given this evidence, we consider that it is likely that our estimates are identifying the effect of H-1B restrictions due to the increase in the supply of immigrant labor to firms.

Firm characteristics Our empirical model allows the exposure of the firm $\mathit{Intensity}_i$ to be assigned non-randomly based on firm characteristics that affect the level of the outcome but requires the exposure to be mean-independent of factors that affect the trend in the outcome (Roth et al., 2023). If this requirement is violated if, for instance, firm size matters more in the economic context of the Canadian economy in the years prior to 2016 than in the year after. To assess whether it is plausible this requirement is violated, we re-estimate the model adding pre-shock firm characteristics interacted with year dummies. The firm characteristics that we add are firm size measured by revenues (in logs) and the labor intensity of the firm measured by the wage bill in total cost. All these regressions include the pre-shock firm characteristics included in the baseline specification (e.g., immigrant share in the wage bill, the share of exports in total sales, and the share of service exports in total exports). Appendix Figure 17 plots the event studies of net hiring of immigrants and natives relative to the employment level in 2016, the log of sales, the log of exports, and the share of export sales in total sales. Given the stability of the estimates across specifications, it seems plausible that our estimates are not contaminated by effects associated with firm characteristics affecting the performance of firms after 2016.

Foreign shocks A concern is the potential confounding effect of international demand shocks in 2017 and 2018, especially because the U.S. is a large trading partner of Canada. To assess whether foreign shock, including changes in U.S. trade policy, may be affecting our estimates of the effect of the H-1B restrictions, we re-estimate equation 3 restricting the sample to firms that do not export nor import in the year 2016. Appendix figure 19 shows the event study and suggests that the baseline results are robust to this subsample of firms.

Effect of Canadian immigration The Canadian firms who use this program to source immigrants from abroad may also be those who are more exposed to the H-1B policy change. For instance, computer scientists were the most prevalent professionals among immigrants who were admitted under the Express Entry program. Therefore, firms that tend to employ computer scientists may have benefitted from the introduction of the Express Entry program in 2015 and the following years. We assess whether our estimates may confound the effect of the express entry program by re-estimating the model with an additional control variable. This variable is the interaction between year dummies and the share of workers in 2016 who were admitted to Canada through this program. The estimates of immigrant and native hiring, and the expansion of firms in terms of sales and exports are robust to the inclusion of this control (see Appendix Figure 18). Given these results, it is plausible that the effect of the Express Entry program does not confound with the effect of the H-1B restrictions.

D.2 Additional results

Effect on firms depending on whether it hired immigrants who resided in the US Our firm-level exposure measure was motivated by the influence of immigrant networks based on the birth country. Immigrant networks can develop not only through shared birthplaces but also through shared locations of residence. To illustrate this, consider two immigrants, one from India and one from China, who previously resided in the United States. Suppose that one of them had relocated to Canada while the other had remained in the US. It is plausible that if the US imposes immigration restrictions, the immigrant still in the US might seek assistance from the one residing in Canada to facilitate their plan to move to Canada. Based on this idea, we divided firms into two distinct groups based on the residence of their immigrant employees. Specifically, our data on immigration records allows us to track the country of residence for each immigrant employee before they relocated to Canada. Based on this information, we categorize firms into two groups: those that had employed immigrants who had previously lived in the United States, and those that had not. We then modified our equation 3 to accommodate a heterogeneous treatment effect. In particular, we allow the β_τ coefficient to vary for firms belonging to each of these two groups (e.g. we incorporate a dummy interacting $Intensity_i$). Appendix Figure 21 plots these pair of coefficients β_τ for the main outcome variables. Our findings about the hiring of immigrants align with the idea of networks formed based on the previous locations of residence. We observe that, on average, firms that had hired immigrants who had previously resided in the United States exhibited a more pronounced response in terms of increased immigrant hiring. Interestingly, these firms seem to play a pivotal role in the response related to exports and the share of exports in total sales documented in Figure 4.

E Solving the equilibrium

Following Dekle et al. (2008), we rewrite all equilibrium equations with the proportional changes of different variables. Given $(\Omega, \Upsilon, \mathrm{P})$, the changes of the equilibrium induced by a change in the probability of granting a US visa $\Delta p_{ocu} \equiv p'_{co,usa} - p_{co,usa}$ can be summarized by the following equations 34-56. We divide these equations into three blocks: equations determining the labor supplies, those determining the labor demand, and those clearing the labor market.

Labor supply The equations in this block summarize the workers' optimal choice of migration destination and sector allocation.

$$\hat{\pi}_{cock} = \left(\frac{\hat{w}^n_{cok}}{\hat{\Phi}_{coc}}\right)^\kappa, \qquad \text{where } \hat{\Phi}^\kappa_{coc} = \sum_k \pi_{cock}(\hat{w}^n_{cok})^\kappa \tag{34}$$

$$\hat{\pi}_{codk} = \left(\frac{\hat{w}^f_{dok}}{\hat{\Phi}_{cod}}\right)^\kappa \quad \text{for } d \neq c, \qquad \text{where } \hat{\Phi}^\kappa_{cod} = \sum_k \pi_{codk}(\hat{w}^f_{dok})^\kappa \tag{35}$$

$$\hat{u}_{coc} = \frac{\hat{\Phi}_{coc}}{\hat{P}_c}, \quad \hat{u}_{cod} = \frac{\hat{\Phi}_{cod}}{\hat{P}_d} \quad \text{for } d \neq c \tag{36}$$

$$\hat{u}^{\nu_h}_{co} = \pi_{coe}\, \hat{u}^{\nu_h}_{coe} + \pi_{coc}\, \hat{u}^{\nu_h}_{coc} \tag{37}$$

$$\hat{u}^{\nu_d}_{coe} = \sum_{d \neq c} \pi_{cod}\, (\hat{u}^{p_{cod}}_{cod} \cdot \hat{u}^{1-p_{cod}}_{coc} \cdot u^{\Delta p_{cod}}_{cod} \cdot u^{-\Delta p_{cod}}_{coc})^{\nu_d} \tag{38}$$

where π_{coe} and π_{coc} denote the pre-shock level of the probability of workers with nationality c and occupation o choosing to emigrate and stay at home country respectively, and they satisfy $\pi_{coe} + \pi_{coc} = 1$. π_{cod} denotes the pre-shock level of the probability of workers with nationality c and occupation o choosing to emigrate to country d conditional on choosing to emigrate, and they satisfy $\sum_{d \in \mathcal{C}^d} \pi_{cod} = 1$.

$$\hat{\pi}_{coc} = \left(\frac{\hat{u}_{coc}}{\hat{u}_{co}}\right)^{\nu_h}, \ \hat{\pi}_{coe} = \left(\frac{\hat{u}_{coe}}{\hat{u}_{co}}\right)^{\nu_h}, \ \hat{\pi}_{cod} = \left(\frac{\hat{u}_{cod}^{p_{cod}} \cdot \hat{u}_{coc}^{1-p_{cod}} \cdot u_{cod}^{\Delta p_{cod}} \cdot u_{coc}^{-\Delta p_{cod}}}{\hat{u}_{coe}}\right)^{\nu_d} \tag{39}$$

$$\widehat{LS}_{coc} = \Big(\big(\psi_{coc}\hat{\pi}_{coc} + \sum_{d \neq c} \psi_{cod}\ \widehat{(1-p_{cod})}\hat{\pi}_{cod}\ \hat{\pi}_{coe}\big)(1-\psi_{co}^{emig}) + \psi_{co}^{emig}\Big)\hat{\Phi}_{coc} \tag{40}$$

$$\widehat{LS}_{cod} = \left(\hat{p}_{cod} \cdot \hat{\pi}_{co,d} \cdot (1-\psi_{cod}^{imm}) + \psi_{cod}^{imm}\right) \cdot \hat{\Phi}_{cod}, \text{ for } d \neq c \tag{41}$$

where $1-\psi_{cod}^{imm}$ is the fraction of workers of nationality c in occupation o working in destination country d accounted by the flow of new immigrants; $1-\psi_{coc}^{emig}$ is the fraction of workers from c in occupation o that are able to make the migration decision, and ψ_{cod} is the fraction of workers choosing country d among those who can make the migration decision.

$$\widehat{LS}_{codk} = \hat{\pi}_{codk} \cdot \widehat{LS}_{cod} \tag{42}$$

where LS_{codk} denotes the total wage bill of workers with nationality c and occupation o working in the sector k of country d.

Labor demand The equations in this block summarize the firms' optimal choice of employment and how their demand responds to prices. Firms' optimal employment choices follow

$$\hat{s}_{dko}^{n} = \left(\frac{\hat{w}_{dko}^{n}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{43}$$

$$\hat{s}_{dko}^{f} = \left(\frac{\hat{w}_{dko}^{f}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{44}$$

$$\hat{f}_{dko} = \left(\frac{\hat{w}_{dko}}{\hat{w}_{dk}}\right)^{1-\eta} \tag{45}$$

where the effective wages at the sector-occupation level and those at the sector level are determined by:

$$\hat{w}_{dko}^{1-\epsilon} = s_{dko}^{n} \cdot (\hat{w}_{dko}^{n})^{1-\epsilon} + s_{dko}^{f} \cdot \left(\hat{w}_{dko}^{f}\right)^{1-\epsilon} \tag{46}$$

$$\hat{w}_{dk} = \left(\sum_{o} f_{dko}\ \hat{w}_{dko}^{1-\eta}\right)^{\frac{1}{1-\eta}} \tag{47}$$

The total demand for the goods produced from the sector k of country d is given by

$$\hat{Y}_{dk} = \sum_c \omega^Y_{cdk} \, \hat{\lambda}_{dck} \cdot \hat{\alpha}_{ck} \cdot \hat{X}_c \tag{48}$$

$$\hat{\alpha}_{dk} = \left(\frac{\hat{P}_{dk}}{\hat{P}_d} \right)^{1-\alpha} \tag{49}$$

$$\hat{\lambda}_{dck} = \frac{\hat{w}_{dk}^{-\theta}}{\sum_d \lambda_{dck} \, \hat{w}_{dk}^{-\theta}} \tag{50}$$

$$\hat{X}_c = \sum_k \omega^X_{ck} \, \hat{Y}_{ck} + \ \omega^X_{cD} \tag{51}$$

where ω^Y_{cdk} is the share of country c in total sales of sector k in country d, ω^X_{ck} is the share of sales from sector k in total expenditure of country c and ω^X_{cD} is the share of deficit in total expenditure of country c. Since we impose balanced trade $D_c = 0$ in this model, $\omega^X_{cD} = 0$ for any $c \in \mathcal{C}$. The aggregated prices are given by

$$\hat{P}_{dk}^{-\theta} = \sum_{i \in \mathcal{C}} \lambda_{idk} \cdot \hat{T}_{is} \cdot (\hat{\tau}_{idk} \cdot \hat{w}_{is})^{-\theta} \tag{52}$$

$$\hat{P}_d^{1-\alpha} = \sum_k \alpha_{dk} \, \hat{P}_{dk}^{1-\alpha} \tag{53}$$

With the goods demand $\hat{Y}_{dk}$ and firms' optimal employment choices $\hat{f}_{dko}$ and $\hat{s}^x_{dko}$ $\forall x \in \{n, \ f\}$, the total labor demand for foreign and native workers in the sector k of country d is

$$\widehat{LD}^x_{dko} = \hat{s}^x_{dko} \cdot \hat{f}_{dko} \cdot \hat{Y}_{dk}, \ \forall x \in \{n, \ f\} \tag{54}$$

Labor market clearing conditions

$$\widehat{LD}^f_{dko} = \sum_{c \neq d} \omega^{LS}_{codk} \widehat{LS}_{codk} \tag{55}$$

$$\widehat{LD}^n_{dko} = \widehat{LS}_{dodk} \tag{56}$$

where ω^{LS}_{codk} is the share of c in the wage bill of occupation o in sector k in country d

F Analytical results

F.1 Application for Canadian visa

The number of applications to country d of workers from c in occupation o is:

$$App_{cod} = \pi_{cod} \times \pi_{coe} \times L_{co}$$

The change in the log of applications is:

$$\Delta \tilde{App}_{cod} = \Delta \tilde{\pi}_{cod} + \Delta \tilde{\pi}_{coe}$$

where the change in the log of emigrating is:

$$\begin{aligned}
\Delta \tilde{\pi}_{cod} &= \nu_d \left[\; p_{cod} \Delta \tilde{u}_{cod} + (1 - p_{cod}) \Delta \tilde{u}_{coc} + \Delta p_{cod} (\tilde{u}_{cod} - \tilde{u}_{coc}) - \Delta \tilde{u}_{coe} \; \right] \\
\Delta \tilde{\pi}_{coe} &= \nu_h \, (1 - \pi_{coe}) \left(\Delta \tilde{u}_{coe} - \Delta \tilde{u}_{coc} \right)
\end{aligned}$$

and the change in the log of u_{coe} is:

$$\Delta \tilde{u}_{coe} = \sum_{d \neq c} \pi_{cod} \left[\; p_{cod} \Delta \tilde{u}_{cod} + (1 - p_{cod}) \Delta \tilde{u}_{coc} + \Delta p_{cod} (\tilde{u}_{cod} - \tilde{u}_{coc}) \; \right]$$

Suppose that there is a marginal change in the approval rates of the U.S. The change in applications to country $d \neq usa$ is:

$$\Delta \tilde{App}_{cod} = (\nu_h \, \pi_{coc} - \nu_d) \, \pi_{co,usa} \, \Delta p_{co,usa} (\tilde{u}_{co,usa} - \tilde{u}_{coc}) + \eta_{cod} \tag{57}$$

where η_{cod} is the structure error includes the effects of changes in own immigration policy Δp_{cod} and general equilibrium variables $\Delta \tilde{u}_{cod}$, $\Delta \tilde{u}_{co,usa}$ and $\Delta \tilde{u}_{coc}$. Specifically:

$$\begin{aligned}
\eta_{cod} = \; & \nu_d \left[\; p_{cod} \Delta \tilde{u}_{cod} + (1 - p_{cod}) \Delta \tilde{u}_{coc} + \Delta p_{cod} (\tilde{u}_{cod} - \tilde{u}_{coc}) \right] - \nu_h \pi_{coc} \, \Delta \tilde{u}_{coc} \\
& + (\nu_h \, \pi_{coc} - \nu_d) \left[\pi_{cod} \, \Delta p_{cod} (\tilde{u}_{cod} - \tilde{u}_{coc}) + \sum_{d \neq c} \pi_{cod} \left(p_{cod} \Delta \tilde{u}_{cod} + (1 - p_{cod}) \Delta \tilde{u}_{coc} \right) \right]
\end{aligned}$$

F.2 Welfare of American workers

We derive our analytic results in a simplified version of our model, where labor supply l^x_{dko} is assumed to be exogenous, preferences across sectors are Cobb Douglas with shares given by α_{dk}, and trade is balanced.

Claim: Suppose that the US imposes restrictions on skilled immigration that lead to infinitesimal (negative) changes in immigrant labor supplies $\tilde{l}^f_{usa,ko}$. The change in the welfare of an

American worker in occupation o in sector k is ($d = usa$):

$$\begin{aligned}\tilde{W}^n_{usa,ko} \;\; = \;\; & \left(\frac{1}{\epsilon} - \frac{1}{\eta}\right) s^f_{usa,ko} \; \tilde{l}^f_{usa,ko} \\ & - \sum_k \alpha_{usa,k} \; \lambda_{usa,usa,k} \;\; \tilde{c}_{usa,k} \; - \theta \; \sum_j \omega^Y_{usa,jk} \; (1 - \lambda_{usa,jk}) \; \tilde{c}_{usa,k} \\ & + \sum_k \alpha_{ck} \; \lambda_{c,usa,k} \;\; \tilde{c}_{usa,k} + \quad \theta \sum_j \omega^Y_{usa,jk} \; \lambda_{cjk} \; \tilde{c}_{ck} \;\; + \;\; \epsilon_{usa,k}\end{aligned}$$

where $\epsilon_{usa,k} = \left(\frac{1}{\eta} - 1\right) \tilde{l}_{usa,k} \; + \sum_j \; \omega^Y_{usa,jk} \;\; \tilde{X}_j$, $\tilde{l}_{usa,k} = \sum_o s_{usa,ko} \; s^f_{usa,ko} \; \tilde{l}^f_{usa,ko}$ and $\tilde{c}_{dk}$ is the change in production costs of sector k in country d induced by the US immigration policy change. This is given by $\tilde{c}_{dk} = \sum_o \; s_{dko} \;\; \varepsilon_{dko} \; \tilde{l}^f_{dko}$ and ε_{dko} is the elasticity of the cost of bundle o in sector k in country d w_{dko} with respect to the supply of immigrants $\tilde{l}^f_{dko}$.

Proof: The proof proceeds in following five steps.

Step 1: Expression for the welfare of American workers.
Given that trade is balanced, the change in the real wage of a worker coincides with the change in utility. The nominal wage earned by a worker is the marginal revenue product of her labor because labor markets are perfectly competitive. Therefore, the wage of a worker $x \in \{f, n\}$ in occupation o in sector k in country d, w^x_{dko}, is given by 58:

$$w^x_{dko} = p(\omega)_{dk} \; z(\omega) \; \left(\frac{l_{dko}}{l_{dk}}\right)^{-\frac{1}{\eta}} \; \left(\frac{l^x_{dko}}{l_{dko}}\right)^{-\frac{1}{\epsilon}} \tag{58}$$

Given that the good market is perfectly competitive $p(\omega)_{dk} = \frac{c_{dk}}{z(\omega)}$. Therefore we can replace $p(\omega)_{dk} \; z(\omega)$ by c_{dk}. Moreover, in equilibrium, the total cost of production of a sector, $c_{dk} \; l_{dk}$, equals total sales, Y_{dk}. Therefore, the unit cost of production equals total sales unit of composite labor input: $c_{dk} \;\; = \frac{Y_{dk}}{l_{dk}}$. In equilibrium, sales of sector k in the U.S. equals demand: $Y_{usa,k} = \sum_{c \in \mathcal{C}} \; \lambda_{usa,ck} \; \alpha_{ck} \; X_c$. Increases in the cost of production in the U.S. in sector k relative to its competitors reduce the US share in the expenditure of consumers in country c, $\lambda_{usa,ck}$.

After substituting these equilibrium conditions into 58, we obtain the following expression for the welfare of an American worker in occupation o working in sector k:

$$W^n_{usa,ko} = \frac{w^n_{usa,ko}}{P_{usa}} = \frac{Y_{usa,k}}{l_{usa,k}} \quad \left(\frac{l_{usa,ko}}{l_{usa,k}}\right)^{-\frac{1}{\eta}} \quad \left(\frac{l^n_{usa,ko}}{l_{usa,ko}}\right)^{-\frac{1}{\epsilon}} \quad \frac{1}{P_{usa}}$$

where the labor bundle $l_{usa,ko}$ and the overall production $l_{usa,k}$ are given by 7.

Consequently, the change in welfare is given by the following expression:

$$\tilde{W}^n_{usa,ko} = \tilde{Y}_{usa,k} + \left(\frac{1}{\eta} - 1\right)\tilde{l}_{usa,k} + \left(\frac{1}{\epsilon} - \frac{1}{\eta}\right)\tilde{l}_{usa,ko} - \frac{1}{\epsilon}\,\tilde{l}^n_{usa,ko} - \tilde{P_{usa}} \tag{59}$$

Step 2: Expression for the change in the price-level in 59.

Given that preferences are Cobb Douglas, the price index of the consumption basket of American workers is given by the following expression:

$$P_{usa} = \prod_k P_{usa,k}^{\alpha_{usa,k}} \quad \text{where} \quad P_{usa,k} = \Gamma_k^{-1}\left(\sum_{i\in\mathcal{C}} T_{ik}(\tau_{ik,usa}\; c_{ik})^{-\theta}\right)^{-\frac{1}{\theta}}$$

Log-differentiation of these expressions yields the following conditions:[41]

$$\tilde{P}_{usa} = \sum_k \alpha_{usa,k}\, \tilde{P}_{usa,k} \quad \text{where} \quad \tilde{P}_{usa,k} = \sum_{i\in\mathcal{C}} \lambda_{i,usa,k}\;\; \tilde{c}_{ik}$$

Suppose that the US immigration restrictions increased production costs in the US ($\tilde{c}_{usa,k} > 0$), reduced them in country c ($\tilde{c}_{ck} < 0$), and did not affect them in any other country $i \neq \{u, c\}$ ($\tilde{c}_{ik} = 0$). The previous expression for $\tilde{P}_u$ simplifies to:

$$\tilde{P}_{usa} = \sum_k \alpha_{usa,k}\,(\lambda_{usa,usa,k}\;\; \tilde{c}_{usa,k} + \lambda_{c,usa,k}\;\; \tilde{c}_{ck}) \tag{60}$$

Step 3: Expression for the change in sales of sector k in the US, $Y_{usa,k}$ in 59.
Log-differentiating $Y_{usa,k}$ yields:

$$\tilde{Y}_{usa,k} = \sum_{j\in\mathcal{C}} \omega^Y_{usa,jk}\,\left(\tilde{\lambda}_{usa,jk} + \tilde{\alpha}_{jk} + \tilde{X}_j\right) \tag{61}$$

where $\omega^Y_{usa,jk}$ be the share of country j in US sales of sector k.[42]
Under the assumption that preferences are Cobb-Douglas, the change in the share of each sector in total expenditure is zero ($\tilde{\alpha}_{jk} = 0$). The change in the US market share within a sector takes the following form:

$$\tilde{\lambda}_{usa,jk} = -\theta\,(1 - \lambda_{usa,jk})\,\tilde{c}_{usa,k} + \theta\,\lambda_{cjk}\,\tilde{c}_{ck}$$

We can then write the change in the US sales of sector k as a weighted average of the change in

[41] This expression for $\tilde{P}_{usa}$ would be the same if we were to continue assuming CES preferences (the elasticity of substitution across sectors would not appear in the approximation).

[42] That is: $\omega^Y_{usa,jk} \equiv \frac{\lambda_{usa,jk}\;\alpha_{jk}\;X_j}{\sum_d\;\lambda_{udk}\;\alpha_{dk}\;X_d}$

the market shares within the sector and the change in the countries' expenditures:

$$\tilde{Y}_{usa,k} = -\theta \sum_j \omega^Y_{usa,jk} \left(1 - \lambda_{usa,jk}\right) \tilde{c}_{usa,k} \ + \ \theta \sum_j \omega^Y_{usa,jk} \lambda_{cjk} \, \tilde{c}_{ck} \ + \ \sum_j \omega^Y_{usa,jk} \ \tilde{X}_j \tag{62}$$

<u>Step 4</u>: Expression for the change in the labor bundle $l_{usa,ko}$ and $l_{usa,k}$ in 59.
Log-differentiating 7 and using additional optimal conditions yields the following conditions:

$$\begin{aligned} \tilde{l}_{usa,ko} &= s^n_{usa,ko} \, \tilde{l}^n_{usa,ko} + s^f_{usa,ko} \, \tilde{l}^f_{usa,ko} \\ \tilde{l}_{us} &= \sum_o s_{usa,ko} \, \tilde{l}_{usa,ko} \end{aligned}$$

Under the assumption that native labor supply to sectors is exogenous and constant, $\tilde{l}^n_{usa,ko} = 0$. Therefore, the change in the labor bundle and production are weighted averages of the exogenous changes in the supply of immigrant labor $l^f_{usa,ko}$:

$$\tilde{l}_{usa,ko} = s^f_{usa,ko} \, \tilde{l}^f_{usa,ko} \tag{63}$$

$$\tilde{l}_{usa,k} = \sum_o s_{usa,ko} \, s^f_{usa,ko} \, \tilde{l}^f_{usa,ko} \tag{64}$$

Conditions (18), (19), (21), and (22) imply the claim.

<u>Step 5</u>: Expression for $\tilde{c}_{ck}$ in 59 as a function of l^f_{cko}.
The change in the unit cost of production is

$$\tilde{c}_{dk} = \sum_o s_{dko} \left(s^n_{dko} \, \tilde{w}^n_{dko} + s^f_{dko} \, \tilde{w}^f_{dko} \right)$$

Given that the optimal labor demand of immigrants relative to natives is:

$$\frac{w^n_{cko}}{w^f_{cko}} = \left(\frac{l^n_{cko}}{l^n_{cko}}\right)^{-\frac{1}{\epsilon}} \rightarrow \tilde{w}^n_{cko} = \underbrace{\tilde{w}^f_{cko}}_{<0} + \frac{1}{\epsilon} \underbrace{\tilde{l}^f_{cko}}_{>0} \quad \text{for} \quad \tilde{l}^n_{cko} = 0$$

where we imposed that the supply of native labor is fixed, e.g. $\tilde{l}^n_{cko} = 0$.

Let $\varepsilon^f_{dko} \equiv \frac{\tilde{w}^f_{dko}}{\tilde{l}^f_{dko}}$ be the elasticity of immigrant wage with respect to the supply of immigrants. We do not provide an explicit solution for ε^f_{cko}; rather, we assume that parameter values guarantee that the following law of demand is satisfied: all else equal, an increase in immigrant labor supply, reduces the wage of immigrants, $\varepsilon^f_{cko} < 0$.

This simplification allows us to express native wages as follows:

$$\begin{aligned}
\tilde{c}_{dk} &= \sum_o s_{dko} \left(s^n_{dko} \, (\tilde{w}^f_{dko} + \frac{1}{\epsilon} \, \tilde{l}^f_{dko}) + s^f_{dko} \, \tilde{w}^f_{dko} \right) \\
&= \sum_o s_{dko} \left(\tilde{w}^f_{dko} + \frac{s^n_{dko}}{\epsilon} \, \tilde{l}^f_{dko} \right) \\
&= \sum_o s_{dko} \left(\varepsilon^f_{dko} \, \tilde{l}^f_{dko} + \frac{s^n_{dko}}{\epsilon} \, \tilde{l}^f_{dko} \right) \\
&= \sum_o s_{dko} \; \varepsilon_{dko} \, \tilde{l}^f_{dko}
\end{aligned}$$

where $\varepsilon_{dko} \equiv \left(\varepsilon^f_{dko} + \frac{s^n_{dko}}{\epsilon} \right)$ is the elasticity of the cost of bundle o in k with respect to the supply of immigrants $\tilde{l}^f_{dko}$. Finally, we assume that the We assume that native shares s^n_{dko} and ϵ are such that $\varepsilon_{dko} < 0$.

G Calibration

Table 14: Calibration

	Description	Source
Immigration policy: P		
p_{od}	Approval rate	H-1B application data, USCIS, IRCC
Earning per worker in the US relative to home: $\mathbf{U_u}$		
w^n_{odk}, w^f_{odk}	Nominal wages	H-1B application data for the US, NSS for India and IPUMS int'l for RoW
P_d	Consumption price level	Hanson and Groegger and CEPII data
	Exchange rate	Penn World Table
ζ_{cod}	Migration costs	Hanson and Groegger and CEPII data
Migration-related shares: $\mathbf{S^M}$		
π_{cod}	Share applying to d	H-1B application data and PR application data
π_{coc}	Share staying at home	Inferred using H-1B application data and IAB dataset
$1 - \psi^{imm}_{cod}$	Immigrant flow share	ACS for the US, and LFS for Canada
$1 - \psi^{emm}_{co}$	Share making migration decision	NSS for India and IPUMS int'l for RoW
Non migration-related shares: $\mathbf{S^{NM}}$		
π_{codk}	Share choosing sector k	ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW
s_{dko}	Cost share of occupation o	ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW
s^f_{dko}	Cost share of immigrants	ACS for the US, and LFS for Canada
λ_{dck}	Expenditure shares within sector	Trade in Value Database from the OECD (TiVA)[43]
α_{dk}	Expenditure shares across sectors	Trade in Value Database from the OECD (TiVA)

Note. The table summarizes the calibrated values used for the quantitative analysis not included in Table 1.

p_{od}: For the US, we compute the approval rate of each skilled occupation using the H-1B data. For the lower-skilled occupation, we use official reports of I-129 petitions for H-2A and H-2B visas.[44] For Canada, we use publicly available data from the IRCC on the approval rate by PR visa program. We assign a common approval rate to all occupations within skill because the data is not disaggregated by occupation.

[44] H-2A and H-2B visas are temporary visas for agricultural and non-agricultural jobs respectively.

ψ^{imm}_{cod}: We compute ψ^{imm}_{cod} as the proportion of immigrants from origin c employed in occupation o in country $d \neq c$ who have arrived in the country within the previous six years. We chose a six-year window to align it with the H-1B visa's validity period. For the US, we utilize 2015 data from the American Community Survey (ACS 1-year). To extend the annual proportion to a six-year duration, we apply an extrapolation procedure outlined in Appendix B.3. In the case of Canada, we rely on data from the 2012-2016 waves of the Canadian Labor Force Survey Data (LFS) for Canada.

ψ^{emm}_{co}: Given that the shares ψ^{emig}_{coc} are not directly observable, we proxy them according to the demographics of H-1B applicants. Specifically, we use the share of workers who are 20-40 years old and have a college education to proxy the share of immigrant workers for skilled occupations. For lower-skilled occupations, we only impose age restrictions.

π_{cod}: The share π_{cod} is calculated in the same manner as for the empirical regressions discussed in section 3.2.

π_{coc}: Given that we do not observe the number of workers making the migration decision, we cannot compute π_{coc} directly. To address this data limitation, we leverage the model's structure and follow a three-step approach. First, we estimate the share of Indian computer scientists, who constitute the majority of H-1B applicants, by employing the labor market clearing condition at home:

$$\frac{L_{coc}}{L_{co}} = \left(\pi_{coc} + \sum_{d \neq c} (1 - p_{cod}) \cdot \pi_{cod} \left(1 - \pi_{coc}\right)\right) \left(1 - \psi^{emm}_{coc}\right) + \psi^{emm}_{coc} \tag{65}$$

Here, co represents Indian computer scientists, and the left-hand side denotes the proportion of Indian computer scientists remaining in their home country. Although data on the global distribution of Indians by occupation is unavailable, education group data from IAB is accessible. Therefore, we approximate the left-hand side share for Indian CS with the share of college-educated Indians. Given this data, the value of π_{coc} consistent with condition 65 is 0.4.[45] Second, we infer the shares of other high-skilled occupations based on the computed share for Indian computer scientists. To that end, we use the model's equation for the number of applications to the US of each immigrant group relative to computer scientists from India $\pi_{ind,cs,u}$:

$$\frac{App_{cod}}{App_{ind,cs,usa}} = \frac{\pi_{cod}}{\pi_{ind,cs,usa}} \frac{1 - \pi_{coc}}{1 - \pi_{ind,cs,usa}} \frac{L_{co}}{L_{ind,cs}}$$

This equilibrium condition allows us to recover the remaining π_{coc} as a function of data and

[45] We verified the plausibility of this value as it forms the basis for subsequent steps, drawing on prior research. In a simplified version of the model where immigrants can migrate only to the US, the share $\pi_{cs,ind,u}$ is given by $\left(\frac{w_{cs,usa}}{w_{cs,ind}}\right)^{p_{usa}\ \nu}$. Using the US-India wage differential for Indian computer scientists applying for H-1B visas from Clemens (2013) and two ν values from Caliendo et al. (2021) and Allen et al. (2019), we obtained shares of 0.2 or 0.4, depending on ν_d. These calculations suggest that our calibration of aligns with previous studies.

the inferred value for $\pi_{ind,cs,ind}$. Given that we do not observe L_{co} for RoW, we proxy the last fraction of the right-hand side with the relative number of total employees. Finally, we apply the condition 65 for lower-skilled workers, where we used the data for the non-college population from IAB.

H Instrumental variable approach: ν_d

To go from equation 29 to an estimating equation that we can take to the data, we introduce four changes. First, we rewrite 29 as follows:

$$\ln App_{co,can,t} \; - \; \ln App_{co,usa,t} = \nu_d \; p_{co,usa,t} \; \ln w_{co,usa,t} + \eta_{cot} \tag{66}$$

where η_{cot} is a structural error that includes the effect of immigration policy in Canada ($p_{co,can,t}$), wages and prices in Canada and the cost to migrate to Canada (through $u_{co,can,t}$), wages and prices at home (through the average wage u_{coct}), prices in the U.S. ($P_{usa,t}$), and costs to migrate to the US $\tilde{\zeta}_{co,usa}$. Second, motivated by the policy memorandum and our data, we make the probability $p_{co,usa,t}$ occupation-specific, as opposed to occupation-nationality-specific. Third, we set $w_{co,usa,t}$ at its pre-shock average value because it jumps around over time for immigrant groups that are relatively small. By making $u_{co,usa}$ time-invariant, we eliminate random noise and increase the precision of the estimate. Additionally, it ensures that the identification of ν_d uses variation in the probability of getting an H-1B visa, which is the interest of our paper, and does not use variation is wages. Fourth, we include a rich set of fixed effects to account for factors in the structural term, η_{cot}. We include a group-specific fixed effect, δ_{co}, to control for time-invariant factors such as preferences, migration costs or long-run wage differences between the US and Canada. We include occupation-year fixed effects, δ_{ot}, to control for time-varying factors such as Canadian immigration policy that targets specific occupations, or demand shocks in Canada that change the economic prospects of working in Canada relative to the US. We include country-specific fixed effects δ_{ct} to control for changes in economic conditions at home that may push immigrants to migrate disproportionally more towards Canada or the US. The estimating equation becomes:

$$\ln App_{co,can,t} \; - \; \ln App_{co,usa,t} = -\nu_d \; p_{o,usa,t} \; \ln w_{co,usa} + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot} \tag{67}$$

where we measure $App_{co,can,t}$ and $App_{co,usa,t}$ as the number of PR applications and H-1B applications of immigrant group co in year t for $2012 \leq t \leq 2017$, $p_{o,usa,t}$ as the share of H-1B applications in occupation o that were approved, and $\ln w_{co,usa}$ as the log of the average H-1B wage by immigrant group co for the pre-shock years 2012-2016.[46]

[46] The regression omits 2018 due to our H-1B data's coverage until the end of FY 2018, preventing the calculation of the outcome variable for that year.

The OLS estimate of ν_d may be subject to omitted variable problems. Increases in the number of applications for H-1B cap-subject visas may decrease the approval rate p_{ot}, regardless of the US policy stance. Thus, any factor that induced immigrants to apply to Canada and to apply for cap-subject H1B visas, would bias our estimate of ν_d towards zero. Another omitted variable problem could arise if increases in wages at home discourage nationals to emigrate and affect the pool of immigrants applying to the US. If the pool of applicants improves, approval rates would likely decrease, which would bias our estimate of ν_d towards zero.

To address endogeneity concerns of the OLS estimate, we pursue an instrumental variable approach where we instrument $p_{o,usa,t}\ \ln w_{co,usa}$ with $Intensity_{co} \times 1(t > 2016)$. In Section 3.2, we explain why $Intensity_{co} \times 1(t > 2016)$ provides plausible exogenous variation introduced by the H-1B policy change. It worth mentioning that the model suggest the relevance condition of this instrument. In the model, higher US wages increase the value of securing a job in the US, leading to a larger share of immigrants choosing to apply to the US (e.g. larger $\pi_{co,usa}$). Appendix Figure 22 shows empirically that this relationship is significantly strong.

Columns 1 and 2 of Appendix Table 13 show that the OLS is not distinguishable from zero and that is biased towards zero, as the 2SLS estimate is 3.6 (s.e=1.3). Columns 3-6 perform the same robustness exercises as discussed in section 3.2 and show that the 2SLS estimate is robust to these alternative specifications. Thus, we set $\nu_d = 3.6$ in the calibration of the model.

I Indirect inference approach

Our goal is to obtain the outcome variable from real data that is comparable with that from the model. To that end, we must isolate the effect of the policy change on the outcomes of interests and then follow an aggregation step.[47]

According to the empirical model we used for estimation, the log of the number of Canadian applications is:

$$log(App_{co,can,t}) \ = \ \beta_t \ Intensity_{co} \ + \delta_{co} \ + \ \delta_{ot} \ + \ \delta_{ct} + \ \epsilon_{cot}$$

with $\beta_{2016} = 0$ given that year 2016 is our reference year. We use the same model to construct the counterfactual number of log of Canadian applications we would have observed had the H-1B policy change not happened (e.g. $Intensity_{co} = 0$). We assume that all other factors affecting Canadian applications, e.g., δ_{co}, δ_{ot}, δ_{ct}, ϵ_{cot}, would have been the same in this counterfactual

[47] The first step is conceptually similar to the detrending procedure followed by Agha and Zeltzer (2022), who residualize the outcome variable by the estimated linear pre-trend.

scenario. Then the counterfactual value of the log of Canadian applications becomes:

$$log(App_{co,can,t}) \; = \delta_{co} \; + \; \delta_{ot} \; + \; \delta_{ct} + \; \epsilon_{cot}$$

and the log-change in the number of Canadian applications between year t and year 2016 due to the H-1B policy change is $\beta_t \; Intensity_{co}$.

Next, we aggregate the effect of the policy on applications from narrowly defined groups up to the coarser groups used in the model. For the sake of clarity, we relabel a narrower immigrant group by g and coarser group by G. Let $App^{can}_{Gt} = \sum_{g \in G} App^{can}_{gt}$, we can then compute the log-change of applications of group G as follows:

$$\begin{aligned}
log(App_{G,can,t}) - log(App_{G,can,2016}) &= log\Big(\frac{\sum_{g \in G} App_{g,can,t}}{\sum_{g \in G} App_{g,can,2016}}\Big) \\
&= log\Big(\sum \frac{App_{g,can,2016} e^{\beta_t Intensity_g}}{\sum_{g \in G} App^{can}_{g2016}}\Big) \\
&= log\Big(\sum_{g \in G} \omega^{app}_g e^{\beta_t Intensity_g}\Big)
\end{aligned}$$

where the second equality follows from $log(App_{co,can,t}) - log(App_{co,can,2016}) = \beta_t \; Intensity_{co}$ and $\omega^{app}_g \equiv \frac{App_{g,can,2016}}{\sum_{g \in G} App_{g,can,2016}}$.

Finally, we used the estimate of the year 2018 to construct the target moments for the model because 2018 is the last year in our sample. Thus, our measure of the outcome variable of the data-regression 31 is $log\Big(\sum_{g \in G} \omega^{app}_g e^{\hat{\beta}_{2018} Intensity_g}\Big)$.

We follow a similar two-step procedure to compute the change in the sales and earning per native worker by sector implied by our estimates from equation 3.