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

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Abstract

We study the effects of US restrictions on skilled immigrants on the Canadian economy and American workers' welfare. We focus on a 2017 policy change that raised the eligibility criteria for US visas, which offers quasi-experimental variation across time and immigrant groups. We assemble a novel dataset that includes US and Canadian visa application data and Canadian administrative databases containing the universe of employer-employee-linked records, immigration records, and international trade records. We find that US restrictions increased applications of skilled immigrants to Canada by 30% in 2018. Additionally, we document that they increased Canadian firms' production, exports, and employment of Canadian workers. We then turn to study the effect of the policy on American workers, taking into account the increase in immigration to other countries. To that end, we incorporate immigration policy into a model of trade. In our model, the increase in immigration to other countries affects US export and consumption prices and, thus, American wages. We calibrate the model using our novel data and our event-study 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 the open economy with current trade levels.

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1 Introduction

Immigration restrictions are becoming increasingly common in developed countries.[1] While the policy debate typically centers on the direct impact of restrictions on domestic workers, it often overlooks how it affects complex migration decisions. Discouraged immigrants may seek to migrate to other countries, leading to increased economic activity in the receiving economies. Moreover, if these receiving economies compete in international markets with the economy imposing the restrictions, this tougher competition may drive down wages for the native workers that the policy is meant to protect. Thus, where the affected workers seek to migrate can have direct policy implications not only for the imposing country but also for third countries seeking to benefit from those restrictions.

We study the effects of a recent US restriction on skilled immigration and we focus on Canada, a relevant host for affected immigrants.[2] This focus on skilled immigration is especially important because of its policy relevance. Highly educated individuals tend to be more mobile (Greenwood, 1975), and other developed countries actively compete to attract them (Kerr, 2018).[3] This paper asks three questions: (i) To what extent do US restrictions on skilled immigrants increase skilled immigration to Canada? (ii) How does this immigrant influx affect Canadian production and Canadian workers' welfare? (iii) How do general equilibrium effects on immigrant-receiving economies impact American workers' welfare via international trade?

To address these questions, we identify quasi-experimental variation introduced by this policy across time and immigrant groups. We then assemble a dataset that includes US and Canadian visa application data, and a comprehensive collection of Canadian administrative databases. We use the visa application data to document the effect of the US restriction on immigration to Canada, and the administrative data to document its effects on firms' outcomes. This data includes immigrant employment within firms, which allows us to isolate the effects of actual immigrant hires from policy-induced changes in surrounding conditions influenced by the immigrant inflow. Finally, we study the impact of US restrictions on aggregate outcomes and welfare in the US and Canada. To that end, we incorporate immigration policy into a model of model of international trade. We calibrate this model using our novel data and our reduced-form estimates from earlier empirical findings. Through counterfactual analysis, this model allows us to quantify

[1] Notable examples are the United Kingdom's implementation of Brexit and a 25% drop in the number of US immigrant visas issued between 2016 and 2019 during President Trump's administration.

[2] Opponents of restrictions argued that foreign nationals have been migrating to Canada due to difficulties obtaining H-1B visas or permanent residence in the US (see the 2021 US Congressional hearing named *"Oh, Canada! How Outdated US Immigration Policies Push Top Talent to Other Countries"*).

[3] For example, in June 2023, Canadian Minister Fraser announced a visa program for H-1B holders.

the role of international trade in the effect of US immigration restrictions on American workers' welfare.

Starting in March 2017, US Citizenship and Immigration Services (USCIS) raised the eligibility criteria for the H-1B visa program, which is the main pathway for college-educated workers seeking to migrate to the US As a result, H-1B approvals decreased and denial rates skyrocketed.[4] Denial rates increased from about 6% to an unprecedented 16% by the end of fiscal year 2018. One year later, there was a trend break in the admissions of skilled immigrants to Canada, with an average annual increase of approximately 30%. The overall influx of immigrants was substantial, resulting in approximately 76,000 additional admissions by 2019, or 3.5% of the total number of college-educated immigrants. Given that nearly 40% of the college-educated workforce are immigrants, this increase in immigrant labor can have a significant impact on the Canadian economy.

We first document that increasing H-1B denial rates had a causal impact on skilled immigration in Canada. To that end, we obtain novel data on Canadian permanent residence (PR) visa applications from Immigration, Refugees and Citizenship Canada and H-1B visa applications from a Freedom of Information Act (FOIA) request. Both datasets include information on the occupation and nationality of applicants (e.g., computer scientists from India). We use this data and plausible exogenous variation introduced by the policy across time, applicant's occupation, and nationality within an event-study framework. Specifically, we estimate the effect of the policy with the change in the number of Canadian applications after the policy introduction for immigrant groups that were differently affected. We find that a 10pp increase in H-1B denial rates, as observed between 2016 and 2018, increased 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 approximately 1 Canadian PR application.

We then document a large impact of the restrictions on Canadian firms' production decisions, especially among firms in high-skilled service industries. To that end, we use our Canadian administrative databases, which includes information on firms' industry, the nationality of their workforce, and exports in goods and services, among others. For identification, we rely on variation across firms given by both the nationality composition of their workforce and the occupational composition of their industry. Within an event-study framework, we compare the change in firms' outcomes after the H-1B policy was introduced across firms that were differently exposed to the policy. Our estimates imply that, on average, earnings per Canadian worker dropped by 0.5% in 2018. However, native

[4] In 2018, there were about 47,000 fewer visa approvals compared to 2016, and 140,000 fewer H-1B visa approvals than what was expected based on the linear trend (see Appendix Figure 10).

employment increased. A firm hired approx. 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 the skilled service sector, which represents 3.2% of the pre-shock sales. The rise in total sales can be partly attributed to the growth in total exports, which exhibited a stronger response compared to overall sales.

Finally, we develop a general equilibrium (GE) model to study both analytically and quantitatively the effects of 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 nativity, who are imperfect substitutes. Our model is novel because it incorporates immigration policy and migration decisions under uncertainty. Immigration policy is represented as an exogenous probability of obtaining a visa, which we directly observe in the data. Given this uncertainty of obtaining visas, immigrants decide between staying in their home country or applying for a specific visa.

The shock of interest is a reduction in the US visa approval rate. According to our model, this decrease directly affects migration decisions, leading to more immigrants choosing to stay in their home countries or migrate to other foreign nations. This increase in the number of workers in other countries reduces their production costs and increases production, particularly in sectors that are immigrant-intensive.
Additionally, the drop in the US visa approval rate reduces the number of immigrant workers in the US. This policy-induced reallocation of immigrants from the US to other countries has both direct and indirect effects on American workers. On the one hand, the decrease in immigrant labor in the US may increase wages of American workers who work in the same occupations as the affected immigrants because they are relatively close substitutes. However, it could lead to the contraction of certain sectors, negatively impacting American wages. On the other hand, the increase in immigrant labor elsewhere affects American workers indirectly. It reduces the production costs of foreign producers relative to US producers, which affects the price of US exports and imports (known as terms of trade). Depending on how the terms of trade change for US sectors, the indirect effect on American workers can be either positive or negative.

We use the model to quantify the impact of the observed policy change. To achieve this, we need several key statistics, including model parameters, which we calibrate using our novel data and the exogenous variation introduced by the US policy change. Specifically, we estimate the elasticity of substitution between the US and Canada directly from a regression coefficient using our cross-border visa application data. For the other elasticities, we estimate regression coefficients with model-generated data and real data and follow an indirect inference approach. These data-based coefficients 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. The response was especially strong in high-skilled service sectors, which increased production by approximately 2.5% and exports by 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 the production of all sectors was negatively affected, the impact was most pronounced in the high-skilled service and high-tech manufacturing sectors (-0.5% approx.). The policy benefited primarily American computer scientists (CS), 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 suggests that US immigration restrictions may mitigate direct competition between immigrants and American workers in the US labor market, but they may still lead to indirect competition through international goods markets. If policymakers do not consider the general equilibrium effects of international trade, they might overestimate the efficacy of the policy.

Related literature: Our paper contributes to three strands of literature. First, it contributes to the empirical literature that studies the labor market effects of immigration policies. Existing studies have predominantly studied the impact of immigration policies on the country imposing the restrictions (Peri et al., 2015; Clemens et al., 2018; Yoon and Doran, 2020; Moser and San, 2020; Beerli et al., 2021; Abramitzky et al., 2023) or the sending country (Abarcar and Theoharides, 2021; Khanna and Morales, 2021; Coluccia and Spadavecchia, 2021). However, they have not typically studied the effect on third countries. 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 by offering quasi-experimental and comprehensive evidence of spillover effects of immigration policy on third countries. Moreover, our firm-level evidence is robust to the exclusion of MNC firms, suggesting that spillover effects on other countries may not require MNC linkages with the imposing country.

Second, the paper contributes to the recent literature on the impact of immigration on firms (Beerli et al., 2021; Paserman, 2013; Kerr and Lincoln, 2010; Kerr et al., 2015; Mitaritonna et al., 2017; Ottaviano et al., 2018; 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.[5] 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.

Our paper contributes to the literature on the literature studying the effects of immigration using quantitative models of trade. Fundamental theorems in international trade, the Factor Price Equalization Theorem (Samuelson 1949) and Rybczinski theorem (1955), have suggested that immigration restrictions may be ineffective in increasing domestic wages in an open economy. While the mechanisms of these theorems are commonly operational in quantitative models of trade, particularly within neo-classical frameworks like ours, the quantitative importance of international trade for the efficacy of immigration policy is not often studied explicitly. The closest papers to ours are Burstein et al. (2020) who study the impact of US immigration policy on American workers in a closed economy, and Caliendo et al. (2021a) who study the impact of trade and labor market using a one-sector model. Our paper contributes to this literature in two ways. First, it offers a new quantitative trade model that incorporates migration policy and migration choice under uncertainty in a tractable way. Second, it quantifies the importance of international trade in the efficacy of immigration policy in a global economy with the current levels of trade. In our multi-sector model, the impact of international trade on the welfare effect of the policy depends on changes in the export prices of the worker's employment sector. As such, international trade can either increase or decrease the welfare gains.

The paper is organized as follows. Section 2 introduces the data. Section 3 outlines the institutional background. Section 4 describes the H-1B policy change. Sections 5 and 6 discuss the empirical strategy and present the results regarding the effects of the policy on Canadian immigration and Canadian firms, respectively. Section 7 develops the quantitative model. Section 8 calibrates it. Section 9 presents the aggregate and welfare effects of the policy, and quantifies the role of international trade in its efficacy. Section 10 concludes.

[5]Papers using quasi-experimental variation introduced by the random allocation of new H-1B visas often have a relatively small sample, e.g., the number of firms in Kerr and Lincoln (2010), Kerr et al. (2015), and Doran et al. (2022) is 77, 319, and 2750 respectively.

2 Data

We assemble three datasets. The first one is the H-1B visa application data, which allows us to compute the change in H-1B visa denial rate, serving as a measure of the increased stringency of U.S. immigration policy. The second data source is the Canadian visa application data, which enables us to quantify the intended immigration flow into Canada. The third data source comprises a combination of Canadian administrative databases that includes the universe of employer-employee-linked records, immigration records, and international trade records. 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 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.

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 5.

2.2 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.

2.3 Canadian administrative data

All of the Canadian administrative data sets except for the Labor Force Survey (LFS) are parts of the Canadian Employer-Employee Dynamics Database (CEEDD). When Statistics Canada creates this database, they construct a unified identifier for all the individual persons and firms, which allows us to link the various data sets. Because the intensity of our treatment varies across the country of origin and occupation but CEEDD does not have information on the occupation of the firm's employees, we use the LFS data to measure the sector-level employment composition by occupation and use it to approximate the firm-level counterpart.

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

Immigrant landing records (IMDB): This data 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.

3 Institutional aspects

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.[6] 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 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.

3.1 Canadian Visa program: Point-based system

The main channels for skilled immigration intake in Canada are the Permanent Residence (PR) visa programs.[7] Prospective PR visa applicants must fulfill core eligibility criteria

[6] 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.

[7] Workers can migrate through temporary programs but "the burdensome procedure for temporary labor migration, especially for those migrants who are paid above the provincial average, encourages labor migration that might otherwise be temporary to pass through permanent streams" (OECD., 2019)

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. 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.

4 H-1B Policy Change

The H-1B program was created to ameliorate the shortage of talent in the domestic labor market. However, critics argue that loopholes in the law allow employers to use the program to replace American workers at lower pay (Hira, 2010; Matloff, 2002). During his campaign, President Donald Trump expressed his intentions to end practices of misuse of the program, and during his mandate immigration policy shifted towards a more antiimmigrant rhetoric.[8] The new immigration policy aimed 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]

Under the new administration, the USCIS issued a series of internal policy memorandums (PM) beginning in March 2017. These internal PMs were not public information and took effect immediately as they did not require changes in law or regulation.[10] These PMs essentially required more evidence to prove that the H-1B eligibility criteria were met. First, a bachelor's degree was no longer accepted as sufficient evidence for some occupations. Specifically, the policy memo reads as follows:

"The OOH states "Most computer programmers have a bachelor's degree in computer science or a related subject; however, some employers hire workers with an associate's degree". The fact that the OOH states that an individual may enter the field with an associate degree suggests that entry-level computer programmer positions do not necessarily require a bachelor's degree and would not generally qualify as a position in a specialty occupation. Therefore, for all computer programmer petitions, the petitioner will not have met its burden of proof based on the OOH alone. (...) The Policy Memorandum is specific to the computer programmer occupation. However, this same analysis should be conducted for occupations where the OOH does not specify that the minimum requirement for a particular position is normally a bachelor's or higher degree in a specific specialty."

This new requirement implied that a bachelor's degree was no longer sufficient unless the Occupational Outlook Handbook (OOH) from the Bureau of Labor Statistics (BLS) explicitly specifies that a bachelor's degree is required for the occupation. As a result, this new requirement affected some occupations such as computer-related occupations but it did not affect other occupations such as health-related occupations. Second, additional evidence was required when the complexity of the job duties described in a petition did not correspond with a low-wage position. Third, renewals started to be subject to the same scrutiny as new H-1B visas. In particular, USCIS stopped giving deference to a previously approved petition, even if the key elements were unchanged and there was no inconsistency in the prior determination. Fourth, the scrutiny for petitions of H-

[8]During his campaign, on March 3rd, 2016, President Donald Trump stated in a press release *"The H-1B program is neither high-skilled nor immigration: these are temporary foreign workers, imported from abroad, for the explicit purpose of substituting for American workers at lower pay. I remain totally committed to eliminating rampant, widespread H-1B abuse and ending outrageous practices such as those that occurred at Disney in Florida when Americans were forced to train their foreign replacements. I will end forever the use of the H-1B as a cheap labor program, and institute an absolute requirement to hire American workers first for every visa and immigration program. No exceptions".*

[9]See the executive order "Buy American and Hire American" here.

[10]The PMs and additional documentation have been made publicly available through the efforts of the American Immigration Lawyers Association and the American Immigration Council. They filed a FOIA lawsuit to obtain records concerning USCIS's adjudication of H-1B petitions.

1B workers who will work at third-party worksites increased. USCIS wanted to know whether the employee would truly work for the petitioning employer, or whether the employer was trying to get around the rules by acting as a "job shop," placing employees on subcontracting assignments. This new rule especially affected firms providing IT and other business services to American firms. In addition to these policy memos, USCIS has taken numerous actions to ensure that employers are complying with the terms of approved petitions. For example, it increased inspections and targeted site visits of businesses employing H-1B workers.[11]

Applications that failed to meet these new requirements were denied, leading to a sharp increase in the denial rates of H-1B visa applications. Figure 1a shows that the denial rate was stable and low until 2017, and it jumped when the first was introduced. This surge in denial rates from 6% in FY 2016 to 16% in FY 2018 represented an unprecedented increase of 255%.[12]

The policy memos also induced a drop in the number of H-1B approvals because denial rates increased and the number of applications leveled off. Appendix figure 10 shows that by the end of 2018, there were approximately 47,000 fewer visas approved relative to 2016, and 140,000 fewer relative to its linear trend. Notably, this policy affected even continuing H-1B visas, which constituted 55% of denied applications. To extract plausible exogenous variation introduced by the policy, we measure the policy change based on continuing visas only (see Section 5).

Given this reduced probability of obtaining a visa in the United States, immigrants may turn to Canada for its similarities in economic opportunities, labor market integration, language, and cultural affinity. Additionally, two factors may facilitate the migration of workers to Canada. First, American firms, having long faced challenges due to immigration restrictions, are now prepared to relocate their employees abroad. Canada has emerged as an attractive option for these firms due to its more favorable immigration policies, geographical proximity, strong bilateral trade agreements, and similar copyright frameworks compared to the United States. Based on a survey of more than 500 HR professionals in U.S. companies, Envoy Global's 2019 report finds that 86% of companies hired employees outside the U.S. for roles originally intended to be based in the U.S. due to visa-related issues, with Canada being the top destination country. Second, as part of its objective to attract global talent, the Canadian government actively positions itself as an appealing alternative to Silicon Valley, the primary beneficiary of the H-1B program. An illustration of this marketing campaign was a billboard installed by Canadian author-

[11] See this PM about renewals, this PM on third-party worksites, and this official document for a description of actions taken.

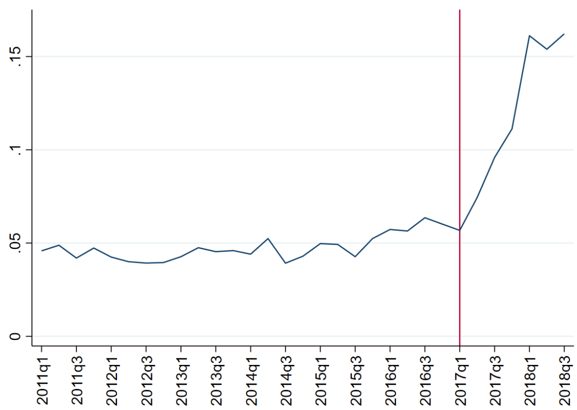
[12] This increase in the denial rate is driven by the spike in the number of denials. The denial rate of renewals exhibits a similar pattern (see Appendix Figure 9).

ities over U.S. 101, the highway that runs through the heart of Silicon Valley, that reads "H-1B problems? Pivot to Canada." More recently, in July 2023, Canada created an open work permit stream for H-1B visa holders in the U.S. to apply for a Canadian work permit, and study or work permit options for their accompanying family members.

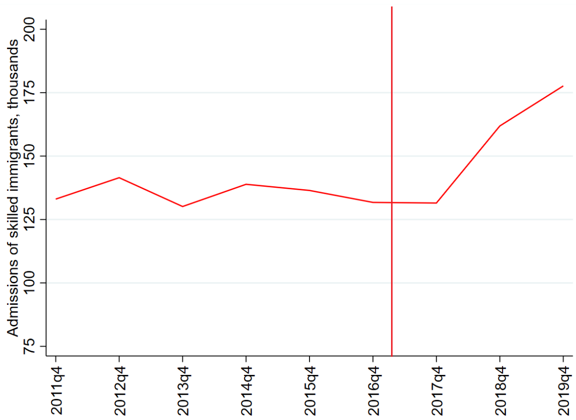
Due to these factors, it is plausible that Canada became a destination for numerous immigrants affected by the changing stringency of the H-1B program. Consistent with the hypothesis, Figure 1b shows that there was a breaking trend in admissions of skilled immigrants in Canada one year after the introduction of the PMs. Relative to 2016, admissions through visa programs commonly used by skilled workers increased by an unprecedented 24% in 2018 and 35% in 2019 - from 132,000 to 162,000 in 2018 and to 178,000 in 2019. This inflow of immigrants represents approximately 3.5% of the number of college-educated immigrants.

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

(a) Denial rate of H-1B visa applications



(b) Canadian admissions of skilled immigrants



Note. Figure 1a 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. Figure 1b 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.

5 Effect on Immigration to Canada

Our goal is to isolate the effect of US immigration policies on Canadian immigration from the effect of other factors. 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.

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. Our measure of exposure to the new eligibility criteria, denoted by $Intensity_{co}$, proxy the fraction of the immigrant group co who got the H-1B visa application denied. Our event study model takes the following form:[13]

$$log(App^{can}_{cot}) = \sum_{\tau \neq 2016} \theta_\tau \times Intensity_{co} \times 1(t = \tau) + \ \delta_{co} \ + \ \delta_{ot} \ + \ \delta_{ct} \ + \ \epsilon_{cot} \qquad (1)$$

where App^{can}_{cot} 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:[14]

$$Intensity_{co} = \frac{Denial \ Rate^{2018}_{o} \ \times \ Initial \ US \ Applications_{co}}{Initial \ US \ \& \ Canada \ Applicantions_{co}} \qquad (2)$$

where "Initial" refers to the years before the introduction of the policy memos (e.g. 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 π^{usa}_{co}, indicates the propensity of an immigrant group to apply for a US visa.[15] The choice of occupation as the level of

[13] See Callaway et al. (2021) and De Chaisemartin and d'Haultfoeuille (2022) for recent developments on the literature of difference-in-difference design with continuous treatment.

[14] Similar measures of the fraction of people affected by a policy change have been used in the minimum wage literature such as Card (1992) or Draca et al. (2011). In the literature of immigration policy, see Clemens et al. (2018).

[15] To the extent that which π^{usa}_{co} 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 compatriots. For example, there is extensive literature showing that immigrants follow their compatriots (Bartel, 1989; Altonji and Card, 1991; Card, 2001) and that they are likely to be hired in the same occupations (Patel and Velia, 2013). There is also a rich literature in

variation is motivated by the instructions specified in the PM.[16]

To compute dr_o, we only use continuing H-1B visa applications and we exclude applications of new H-1B visas. 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.[17] Appendix Figure 9 plots the version of Figure 1a corresponding to the denial rate of continuing visas only.

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 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

sociology discussing the importance of immigrant networks in developing occupation niches (e.g. Model, 1993; Waldinger, 1994).

[16] 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.

[17] 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.

country of origin-year fixed effects, δ_{ct}.

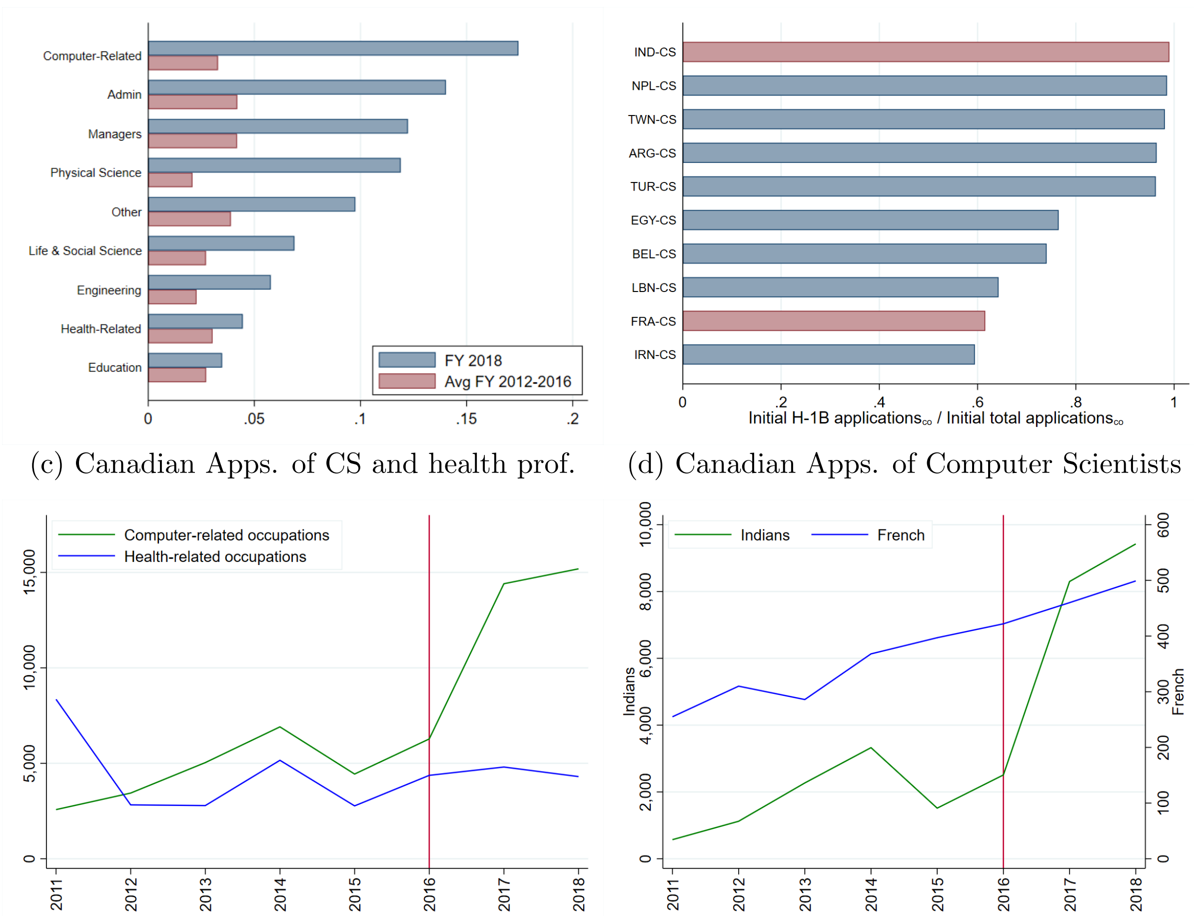
The identifying assumption is that the change in the outcome variable in the years 2017 and 2018 would have been the same for immigrant groups that were differently exposed to US immigration restrictions, conditional on controls. We assess the plausibility of this assumption by formally testing whether the outcomes of differently exposed immigrant groups evolved in parallel before the treatment. That is, we test 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.

Identification strategy: Illustrative examples

What variation does the policy change deliver? How do we use it to identify the effect on Canadian applications? The top panel of 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). Relative to the blue bars, the red bars are lined up, 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 or 5.3 times larger than an average year. On the other extreme, health-related occupations experienced a denial rate of 4%, 1.1 percentage points or 1.4 times larger than the average year. Figure 2b emphasize the variation across countries introduced by π^{usa}_{co}. It plots the top and bottom five countries in terms of π^{usa}_{co} for CS. Consider the exposure of CS from India and from France: CS from India are 60% more likely to apply to the U.S. than CS from France (e.g., $\pi^{usa}_{cs,India}/\pi^{usa}_{cs,France} = 1.6$). As a result, the fraction of Indian CS affected by the denial rates is 60% larger than the fraction of French CS affected. Our empirical model uses both sources of variation, across occupations and across countries, for identification.

To offer an intuition about how our strategy uses the variation illustrated in the top panels to identify the impact of the H-1B policy on Canadian applications, consider the bottom panels. Figure 2c shows that Canadian applications of computer scientists (high dr_o) and health professionals (low dr_o) co-moved until 2016, after which they diverged due to a significant spike in applications of computer scientists. This relative spike in applications for computer scientists may have been influenced by the H-1B policy change but also by a positive demand shock. To disentangle these effects, our event-study design includes occupation-year fixed effects and, thus, compares the growth of applications of

Figure 2: Canadian appls. for immigrants differently exposed to the H-1B restrictions



(a) Denial rates dr_o (b) Variation across nationalities: Examples

(c) Canadian Apps. of CS and health prof. (d) Canadian Apps. of Computer Scientists

Note. The upper panels plot the source of cross-sectional variation in $Intensity_{co}$. *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* π^{usa}_{co} *for the top and bottom five countries in terms of* π^{usa}_{co} *for CS.*

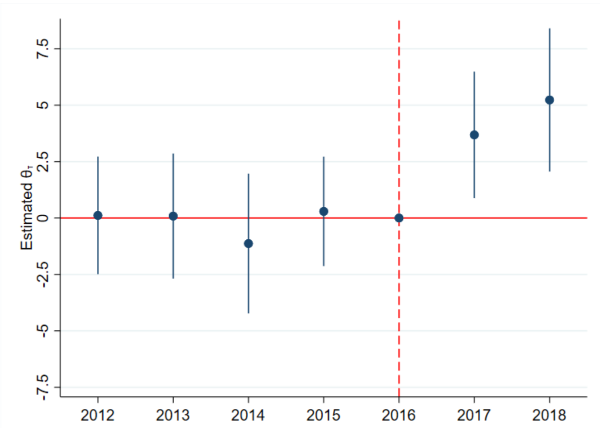
workers from different origins working in the same occupation. Figure 2d shows the surge in applications of Indian computer scientists (high π^{usa}_{co}), relative to their French counterparts (low π^{usa}_{co}). Intuitively, our identification strategy uses the correlation between this differential change in Canadian applications and the differential fraction of Indian CS and French CS who apply to the U.S. to isolate the effect of the H-1B policy restrictions.

Results

Figure 3 plots the estimates of θ_τ for the years 2012-2018. It is 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.[18]

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 π_{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.[19]

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.

Discussion of threats to identification

Correlation over time of confounding factors may threaten identification as it will imply that ϵ_{cot} correlates with past applications and, hence, π_{co}^{usa}. It is plausible that π_{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 π_{co}^{usa}, concerns regarding its correlation with ϵ_{oct} may be mitigated. We assess the plausibility of this correlation by controlling

[18]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.

[19]We estimated the difference-in-difference version of 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 $\hat{\theta}^{relative} \times \frac{Applications^{can}_{2012-2016}}{Aprovals^{H-1B}_{2012-2016}}$.

for the elements used to compute π^{usa}_{co} interacted with year dummies (e.g. $App^{usa}_{co} \times \delta_t$ and $App^{can}_{co} \times \delta_t$). 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 π^{usa}_{co} 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 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. It is worth mentioning that changes in Canadian policy in response to the new US policy would not threaten the identification of the effect of interest. Also, 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.

Fourth, we perform additional tests of the identifying assumption recommended by the recent research on difference-in-difference design. In particular, based on the immigration plan for the years 2016 and 2017, we test the hypothesis of linear trends (Roth, 2022) with a slope of 7%. We reject the hypothesis of an annual trend of 7% at a significance level of 1% (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 $log(App^{can}_{oct})$ and $Intensity_{co}$) using raw data. The distribution of observations in the scatter plot suggests that it is unlikely that outliers affect our estimates.

6 The effect 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.

6.1 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:

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

where we consider several outcome variables y_{it} that are scale-independent such as the logarithm of sales or 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 s refers to the industry where the firm operates according to the 4-digit NAICS classification, and m refers to the location of the firm. δ_i are firm-fixed effects, δ_{mt} are labor markets-year fixed effects, X_{ist} 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 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.[20] 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

[20]Our micro-level data on immigration records does not have information about the occupation of employment and our LFS data has information on occupations but does not properly account for the arrival of recent immigrants to the country (e.g. year 2017 and 2018 in our case).

industry where it operates ($\frac{L_{os(i)}}{L_{s(i)}}$). 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:

$$Intensity_i = \sum_{co} \frac{L_{ci}}{L_i} \frac{L_{os(i)}}{L_{s(i)}} \; Intensity_{co} \; \frac{Flow_{co}}{L_{co}} \tag{5}$$

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.

Control variables We include various fixed effects and controls to account for factors whose effect may confound the effect of the H-1B restrictions. First, 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. Second, we control for potential industry-level confounders. One might worry that the 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. To prevent mistakenly attributing secular growth trends to the effect of H-1B restrictions, we include sector-specific trends in X_{ist}. As a result, β_τ only picks up the impact of H-1B restrictions on firm growth that are departures from industry trends. A number of industries experienced deviations from the trend around the years of the shock due to changing demand and cost conditions. If these deviations are a characteristic of only industries that are intensive in the occupations that experience larger increases in denial rates, these demand and cost factors may contaminate the estimates of β_τ. Controlling for these factors begins with the observation that many industry-specific shocks that affected Canada also affected other economies. Because the correlation between employment in the UK and Canada is high (see Appendix Figure 15), we include as a control the number of jobs created in the UK, $JobsUK_{st}$. To account for factors that may affect Canada but not the UK, we include a flexible time-varying control that is tied to the growth of the sector at the beginning of our sample. Specifically, we include the employment growth of the industry in 2011 interacted with a year-fixed effect.

Another concern arises from reverse causality, which occurs when immigrants choose where to locate. It has been extensively documented that labor markets experiencing growth tend to attract more immigrants. Consequently, the expansion of firms operating within these markets 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.

A key issue for studying the effect of US immigration restrictions is to separate the inflow of immigrants induced by the restrictions from the inflow of immigrants who would migrate at any rate. If immigrants affected by the H-1B policy were in a different trend than other immigrants, firms that typically hire them would probably grow relatively faster, even in the absence of the H-1B restrictions. 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.

6.2 Results

Distribution of $Intensity_i$ Appendix Table 9 displays the distribution of $Intensity_i$ revealing two facts. First, skilled-intensive service sectors exhibit the highest exposure to the H-1B policy change. The top five broad sectors in terms of firm average exposure $Intensity_i$ are the Information and cultural industries (IC), IT, management of enterprises, Financial services, and educational services sectors (NAICS 51, 54, 55, 52, and 61, respectively). Second, there is substantial variation both across sectors and within sectors.

Since the distribution of $Intensity_i$ is skewed, it is of interest to know the effect of H-1B restrictions on the most impacted group of firms. We will often interpret the economic implication of our estimates in terms of the group of firms in the skilled-intensive sector.[21] For expositional purposes, we normalize $Intensity_i$ by the average value among firms in the skilled-intensive sector. Therefore, the interpretation of our estimates (and the values in the y-axis of the plots) can be interpreted as the effect of H-1B restrictions on the average exposed firm in high-skilled service sectors.

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.[22] 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.

[21] Importantly, this group of firms is large; it accounts for 26% of employment and 30% of sales.

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

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.

Effect on production In relation to sales, 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 sector, which represents a 3.2% of pre-shock sales.[23] The rise in sales is likely indicative of an increase in production because we found no evidence of changes in mark-ups (see even 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 4f 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).[24] Figure 4e 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

[23] 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.

[24] 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.

other countries, including Canada. Given these findings from prior research, our interest lies in determining whether our own 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 directly affected (American) firms, as previously documented. This novel fact suggests that MNC linkages are not needed for the US restrictions to have an effect on third countries.

6.3 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 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.

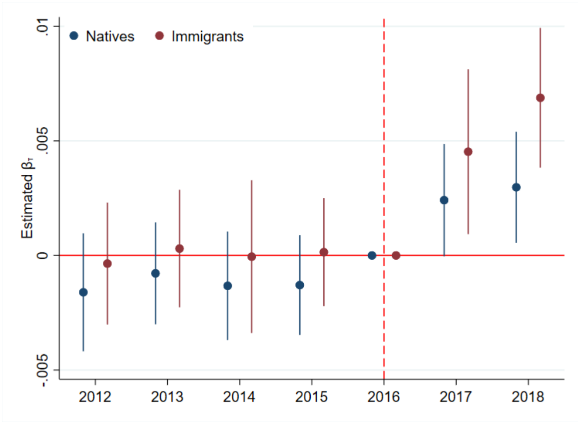
6.4 Taking stock

The evidence in this section and Appendix Table 10 provide a comprehensive description of what explains why Canadian firms expanded, how they did so, and to which markets.

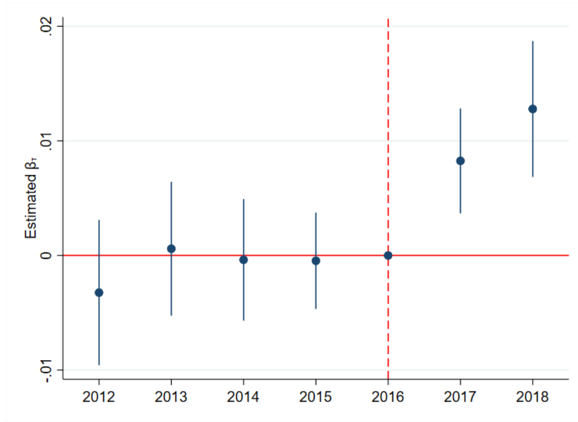
The inflow of immigrants reduced labor costs of Canadian firms, driving an expansion of production (see negative response of total earnings per worker in column ??). Although immigrants may lead to economies of scale (Bound et al., 2017), especially in the long term, our two-year analysis suggests it's not the primary driver. For instance, sales per worker did not show a significant response, and wages of domestic workers did not increase.

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

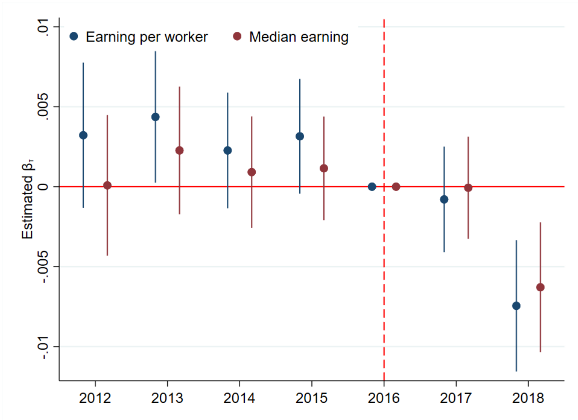
Figure 4: Effect of H-1B restrictions on Canadian firms



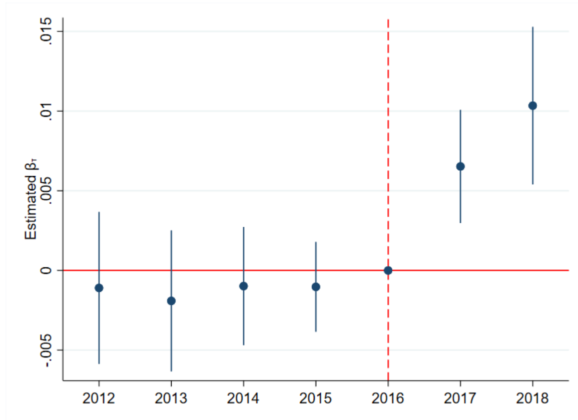
(a) Hiring relative to Employment in 2016



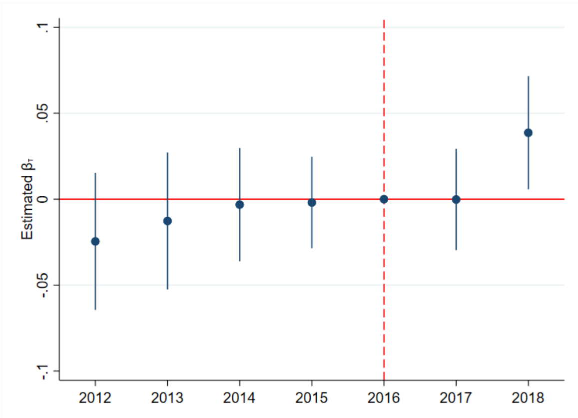
(b) Native employment (in log)



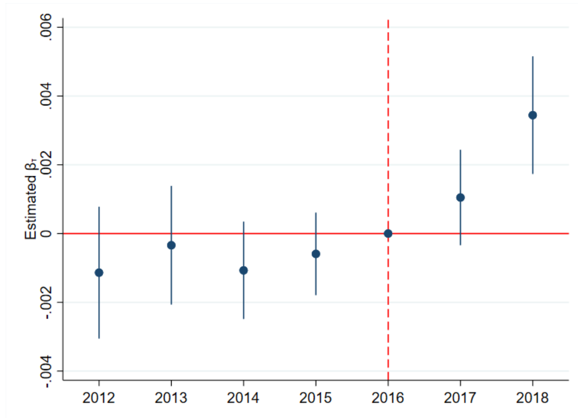
(c) Earning of native workers (in log)



(d) Sales (in log)



(e) Exports (in log)



(f) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 corresponding to different outcome variables: 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), log export sales (panel e), and export sales relative to total 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.

(as shown in column 6) or by adding our estimates for immigrant and native net hiring in relation to the employment level in 2016.[25] 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).

Firms expanded domestically and internationally. While we lack data on the destination of total exports, it is plausible that the US is a relevant destination market. First, the US accounts for a large share of Canadian exports in the most affected sectors such as IT (around 60%). Second, we provide indirect evidence consistent with the idea that Canadian firms with US linkages play a crucial role in the increase of exports. Specifically, firms that in the pre-shock period hired immigrants who lived in the US, explain the positive response in 4e and 4f.

This evidence motivates the assumptions and mechanisms introduced in our quantitative model.

7 Theory: Incorporating immigration policy

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 that features endogenous migration and that can be quantified using our empirical evidence. In this section, we first present the model setup, where we emphasize the key elements that are tightly connected to our empirical evidence. The migration choice under uncertainty is the novel part of our quantitative model. We then illustrate analytically the mechanism through which US immigration restrictions spill over to other countries and affect the welfare of American workers.

7.1 Setup

Environment The model is static. The world comprises multiple countries $c \in \mathcal{C}$, worker groups $g \in \mathcal{G}$, and sectors $k \in \mathcal{K}$. The countries are connected through trade and migration, and they can be divided into two groups: immigration-origin countries $\mathcal{C}^o$ and immigration-destination countries $\mathcal{C}^d$. Countries trade because they have comparative advantages in producing different goods, trade costs are of the "iceberg" type, and goods markets are perfectly competitive. The immigration flow in this world only goes from the immigration-origin countries to the immigration-destination countries. As in the empirical analysis, each worker group is characterized by the combination of country of

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

origin $c \in \mathcal{C}$ and occupation $o \in \mathcal{O}$. Each worker from immigration-origin countries has to choose which country to live in and work in. Immigration policy is given by an exogenous probability of approving a visa application $p_{cod} \in [0, 1]$ for $c \in \mathcal{C}^o$, $o \in \mathcal{O}$, and $d \in \mathcal{C}^d$. Migration costs are proportional to income (Borjas, 1999). Conditional on residing in a specific country, each worker also needs to choose which sector to work. The labor market is segmented for native and foreign workers within each sector and occupation. Each segmented labor market is perfectly competitive.

Migration decision Within each immigration-origin country $c \in \mathcal{C}^o$, we denote the total population of the workers in occupation $o \in \mathcal{O}$ as L_{co} and assume only a fraction ψ_{co}^{emm} of them can make the migration decision. They can choose to stay in their home country or migrate to an immigration-destination country $d \in \mathcal{C}^d$. If they choose to migrate to country d, they have to face the risk that their visa application can be rejected with probability $1-p_{cod}$. If they are rejected, they have to stay in their home countries. To make the choice decision under uncertainty tractable in a general equilibrium, we bring the expected utility theory into an otherwise standard migration model. We assume that the utility of a worker ι from choosing country d is given by the expected value of the payoff over each contingent state. As commonly done in this literature, we model individuals as risk-averse agents by assuming that this payoff is given by the log of the utility in a given state. Specifically, the utility of worker ι of choosing country d, denoted by $U_{cod}(\iota)$, is:

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

Here, p_{cod} is the probability of a visa being approved, which captures the US immigration policy changes and can be directly measured in our H-1B application data. $u_{cod}(\iota)$ and $u_{coc}(\iota)$ are the utilities that the worker expects to enjoy in country d and at home respectively, which incorporates the optimal sector choice of the worker and will be specified soon later in this section. $v_{cod}(\iota)$ is an individual-specific preference shock for applying to country d, which is assumed to be Type-I generalized extreme value distributed.

What is worth to mention here is the structure we impose on $v_{cod}(\iota)$. If we assume that $v_{cod}(\iota)$ is independent and identically distributed (i.i.d), we would severely restrict the substitution patterns across countries: any pair of countries would be equally substitutable. This is a strong assumption, especially because individuals may find it harder to find a close substitute for home. To capture the idea that a foreign country and home may not be as close substitutes as two foreign countries, we relax the i.i.d assumption. Instead, we assume that $v_{cod}(\iota)$ the preference shocks are correlated (in a restricted fashion) across destination choices d as in Allen et al. (2019). This leads us to a nested logit or tree extreme value model, as commonly referred to in the Industrial Organization literature (McFadden, 1978; Cardell, 1991; Berry, 1994). The "tree" has an upper nest between home and foreign countries and an inner nest within foreign countries. This structure implies that the elasticity of substitution between home and any foreign country, ν_h, is different from the elasticity of substitution between two pairs of foreign countries, ν_d.

Sector choice The utility u_{cod} and u_{coc} are expected real income net of migration costs earned by worker ι in country d and at home respectively. Given that the worker chooses the sector based on random productivity draws $a_{codk}(\iota)$, $u_{cod} = \mathbb{E}\Big(max_k\ u_{codk}(\iota)\Big)$ where $u_{codk}(\iota)$ is the real earning in sector k in country d 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, $\zeta_{cod} \in (0,1)$, are migration costs which are assumed to be proportional to income, w^f_{odk} and w^n_{odk} is the wage per efficient unit of **f**oreign labor and **n**ative labor in country d working in occupation o in sector k, and $a_{codk}(\iota)$ is the number of efficient units of the worker ι in sector k in country d.[26] We assume that $a_{codk}(\iota)$ is distributed Frechet with dispersion parameter κ and with group-specific scale parameter a_{codk}.

Consumption Consumers have two-tier CES preferences over goods and services. 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 We assume that a firm produces variety ω in sector k in country d using only labor input. We assume that workers from different occupations and nativity are imperfect substitutes. We model this imperfect substitution as a two-tier CES technology similar to Burstein et al. (2020). This technology combines services from different occupations o with an elasticity of substitution η. 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).

[26]Allowing productivities 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.

Specifically, the production function takes the following form:

$$
\begin{aligned}
l_{dk}(\omega) &= z_{dk}(\omega)\left(\sum_{o} \psi_{dko}\, l_{dko}(\omega)^{\frac{\eta-1}{\eta}}\right)^{\frac{\eta}{\eta-1}} \\
l_{dko}(\omega) &= \left(\beta_{dko}\, l^{n}_{dko}(\omega)^{\frac{\epsilon-1}{\epsilon}} + (1-\beta_{dko})\, l^{f}_{dko}(\omega)^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}
\end{aligned}
\tag{7}
$$

where ψ_{dko} are productivity shifters, and β_{dko} are productivity shifters that are biased towards native workers, and $z_{dk}(\omega)$ is a hicks-neutral productivity level. We follow Eaton and (2002) and assume that $z_{dk}(\omega)$ is a random variable distributed Frechet with shape parameter $\theta > \sigma - 1$ and scale parameter T_{dk}.

7.2 Optimal choices and aggregation

7.2.1 Labor supply based on workers' migration and sector choices

The total labor supply for each sector within each country depends on how many workers choose to reside in this specific country and how many workers choose to work in this specific sector. Given the wages for foreign workers w^{f}_{odk} and native workers w^{n}_{odk}, the fraction of workers from group co in country d choosing sector k is analogous to Galle et al. (2023):

$$
\pi_{codk} = \begin{cases} \left(\frac{a_{codk}\, w^{f}_{odk}}{\Phi_{cod}}\right)^{\kappa} & \text{with} \quad \Phi^{\kappa}_{cod} \equiv \sum_k a^{\kappa}_{codk}\, (w^{f}_{dko})^{\kappa} \quad \text{if} \quad d \neq c \\ \left(\frac{a_{cock}\, w^{n}_{ock}}{\Phi_{coc}}\right)^{\kappa} & \text{with} \quad \Phi^{\kappa}_{coc} \equiv \sum_k a^{\kappa}_{cock}\, (w^{n}_{dko})^{\kappa} \quad \text{if} \quad d = c \end{cases}
\tag{8}
$$

and $u_{cod} = \Gamma_{\kappa} \frac{\zeta_{cod}\, \Phi_{cod}}{P_d}$ denotes the expected utility of working in country d for workers with occupation o from country c, and Γ_{κ} is the gamma function evaluated at $\frac{\kappa-1}{\kappa}$. Given the expected utility of working in different countries, the probabilities for the workers with occupation o from country c to choose to migrate to immigration-destination country d and stay in home country c are

$$
\pi_{cod} = \frac{(u^{p_{cod}}_{cod}\, u^{1-p_{cod}}_{coc})^{\nu_d}}{\sum_{d' \in \mathcal{C}^d} (u^{p_{cod'}}_{cod'}\, u^{1-p_{cod'}}_{coc})^{\nu_d}} \qquad \pi_{coc} = \frac{u^{\nu_h}_{coc}}{u^{\nu_h}_{coe} + u^{\nu_h}_{coc}}
\tag{9}
$$

where $u_{coe} \equiv \Gamma_{\nu_d}\left(\sum_{d \neq h} (u^{p_{cod}}_{cod}\, u^{1-p_{cod}}_{coc})^{\nu_d}\right)^{\frac{1}{\nu_h}}$ is the expected utility of emigrating.

Immigrant labor supply The stock of workers of type co that supply labor in the immigration-destination country d, L_{cod}, is the sum of the number of workers who were already in the country $\bar{L}_{cod}$, which is exogenously given, 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:

$$L_{cod} = \underbrace{p_{cod} \ \times \ \pi_{cod} \ \times \ (1-\pi_{coc}) \ \times \ (1-\psi_{co}^{emig}) \ \times \ L_{co}}_{\text{Flow of new immigrants}} + \underbrace{\bar{L}_{cod}}_{\text{Immigrants already in d}} \tag{10}$$

Following Galle et al. (2023), the supply of efficient units of immigrant labor in occupation o in country d to sector k is:

$$LS_{dko}^{f} = \sum_{c \in \mathcal{C}^o} \Gamma_\kappa \frac{\Phi_{cod}}{w_{odk}^{f}} \pi_{codk} L_{cod} \tag{11}$$

Native labor supply The stock of workers of type co that supply labor at home for immigration-origin countries, L_{coc}, is given by the exogenous number of workers who can not make migration decisions, $\bar{L}_{coc}$, plus those who choose to stay at home, plus those who choose the emigrate but did not obtain their visa approved:

$$L_{coc} = \pi_{coc} \times L_{co} + \sum_{d \in \mathcal{C}^d} (1-p_{cod}) \times \pi_{cod} \times (1-\pi_{coc}) \times L_{co} + \bar{L}_{coc}. \tag{12}$$

For the native labor supply in immigration-destination countries, it is simply given as $L_{coc} = \bar{L}_{coc}$. The fraction of native workers choosing sector k, π_{cock}, and the supply of efficient units of labor LS_{dko}^{n} is analogous to 9 and 11.

7.2.2 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:

$$LD_{dko}^{x} = \frac{s_{dko}^{x} \ s_{dko} \ Y_{dk}}{w_{dko}^{x}} \qquad x = \{n, f\} \tag{13}$$

where s_{dko} is the share of occupation o in the wage bill of sector k in country d and s_{dko}^{f} is the share of foreign labor in that occupation. Given that the nested-CES production function, these shares are given by 14:

$$\begin{aligned} s_{dko}^{n} &= \frac{\beta_{dko}^{\epsilon} w_{dko}^{n\ 1-\epsilon}}{w_{dko}^{1-\epsilon}} \qquad & w_{dko}^{1-\epsilon} &= \beta_{dko}^{\epsilon} w_{dko}^{n\ 1-\epsilon} + (1-\beta_{dko})^{\epsilon} w_{dko}^{f\ 1-\epsilon} \\ s_{dko} &= \frac{\psi_{dko}^{\eta} w_{dko}^{1-\eta}}{c_{dk}^{1-\eta}} \qquad & c_{dk}^{1-\eta} &= \sum_{o} \psi_{dko}^{\eta} w_{dko}^{1-\eta} \end{aligned} \tag{14}$$

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

7.2.3 Goods demand

Total sales of sector k in country d 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}:

$$Y_{dk} = \sum_c \underbrace{\frac{T_{dk}\left(\tau_{dck}\, c_{dk}\right)^{-\theta}}{\sum_{d'} T_{d'k}\left(\tau_{d'ck}\, c_{d'k}\right)^{-\theta}}}_{\lambda_{dck}} \underbrace{\frac{P_{ck}^{1-\alpha}}{\sum_{k'} P_{ck'}^{1-\alpha}}}_{\alpha_{ck}} X_c \tag{15}$$

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, $Y_c \equiv \sum_s Y_{sc}$:[27]

$$X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \tag{16}$$

7.3 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 rate, which is the immigration policy tool of country d. Given $(\Omega, \Upsilon, \mathrm{P})$, an equilibrium of this model 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 (8) and (9);
2. firms' hiring decisions satisfy equation (14); 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:

$$LD^i_{dko} = LS^i_{dko} \quad \forall i \in \{n,\ f\} \tag{17}$$

$$X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \tag{18}$$

7.4 Effects of US immigration restrictions

In this section, we analytically study the effect of an exogenous change in the US approval rate p_{cod} on third countries and on the welfare of American workers. We first show how the policy affects economies that absorb immigrants affected by the restrictions, emphasizing the role of 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, $\hat{x} \equiv \frac{x'}{x}$ 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.

7.4.1 Effect of US immigration restrictions on third countries

U.S. immigration restrictions can either increase or decrease immigration to Canada. Equation 19 shows, to a first-order approximation, the factors affecting the change in the number of Canadian applications:

$$d\widetilde{App}_{cod} = (\nu_h\ \pi_{coc} - \nu_d)\ \pi_{cou}\ \Delta p_{cou}(d\tilde{u}_{cou} - d\tilde{u}_{coc}) + \eta_{cod} \tag{19}$$

where η_{cod} is a structural error that includes the effects of changes in own immigration policy Δp_{cod} and general equilibrium variables $d\tilde{u}_{cod}$, $d\tilde{u}_{cou}$ and $d\tilde{u}_{coc}$ (see Appendix E.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 ($\hat{\pi}_{coe} < 1$). 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 ($\hat{\pi}_{cod} > 1$ for $d \neq u$). 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. Therefore, it is more likely that US restrictions will result in a higher number of Canadian applications when immigrants perceive the US and Canada as close substitutes or when they don't view foreign countries as close substitutes to their home country.

Once in Canada, immigrant workers sort themselves across various sectors, leading to a sector-specific expansion in the foreign labor supply and a drop in production costs.[28] The inflow of immigrants reduces their wages which, in turn, leads to a decline in wages for their native counterparts. As shown in equation 20, 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.

$$d\tilde{w}^{n}_{dko} = d\tilde{w}^{f}_{dko} + \frac{1}{\epsilon}(d\tilde{l}^{f}_{dko} - d\tilde{l}^{n}_{dko}) \tag{20}$$

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 21 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:

$$d\tilde{c}_{dk} = \sum_{o} s_{dko} \left((1 - s^{f}_{dko})\, d\tilde{w}^{n}_{dko} + s^{f}_{dko}\, d\tilde{w}^{f}_{dko} \right) \tag{21}$$

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:

$$d\tilde{Y}_{dk} = \sum_{c} \omega^{Y}_{dcs} \left(\underbrace{-\theta(d\tilde{c}_{dk} - \sum_{d} \lambda_{dck}\, d\tilde{c}_{dk})}_{d\tilde{\lambda}_{dck}} + \underbrace{(1-\alpha)(d\tilde{P}_{ck} - d\tilde{P}_{c})}_{d\tilde{\alpha}_{ck}} + d\tilde{X}_{c} \right) \tag{22}$$

where ω^{Y}_{dcs} 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).

[28] The change in the supply of workers from country c in occupation o to sector k in country d is $d\widetilde{L}_{codk} = \pi_{codk}\, d\widetilde{L}_{cod}$ where $d\widetilde{L}_{cod} = (1 - \psi^{imm}_{cod})\, d\widetilde{App}_{cod}$. That is, immigrants sort into sectors based on the initial share π_{codk}.

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 5 and 6.

7.4.2 Effect of US immigration restrictions on American workers's 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}.[29] 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_{uko}, 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 23:

$$w^x_{dko} = p(\omega)_{dk}\ z(\omega) \left(\frac{l_{dko}}{l_{dk}}\right)^{-1} \left(\frac{l^x_{dko}}{l_{dko}}\right)^{-\frac{1}{\epsilon}} \tag{23}$$

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, 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 23, we obtain the following expression for the welfare of American workers:

$$W^n_{uko} = \frac{w^n_{uko}}{P_u} = \frac{Y_{uk}\ \ l_{uko}^{\frac{1}{\epsilon}-1}\ \ l_{uko}^{n\ -\frac{1}{\epsilon}}}{P_u} \tag{24}$$

where $Y_{dk} = \sum_j\ \lambda_{djk}\ \alpha_{jk}\ X_j$. Based on expression 24, the following proposition specifies the impact of U.S. immigration policy changes on the welfare of American workers.

<u>Proposition:</u>

[29] In Appendix E.2 we do not restrict the value of η.

Suppose that the U.S. imposes restrictions on skilled immigration that lead to infinitesimal (negative) changes in immigrant labor supplies $\tilde{l}^f_{uko}$. 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:

$$\begin{aligned} d\tilde{w}^n_{uko} - d\tilde{P}_u = {} & \overbrace{\left(\frac{1}{\epsilon}-1\right) s^f_{uko}\, d\tilde{l}^f_{uko}}^{\text{Substitution Effect}_{uko}} \overbrace{\overbrace{-\sum_k \alpha_{uk}\,\lambda_{uuk}\, d\tilde{c}_{uk}}^{\text{Price effect}_u} \overbrace{-\theta \sum_j \omega^Y_{ujk}\,(1-\lambda_{ujk})\, d\tilde{c}_{uk}}^{\text{Competition effect}_{uk}}}^{\text{Standard General Equilibrium Effects - Increasing costs in the US}} \\ & \underbrace{\underbrace{-\sum_k \alpha_{uk}\,\lambda_{cuk}\,\tilde{c}_{ck}}_{\text{Price effect}_u} + \underbrace{\theta \sum_j \omega^Y_{ujk}\,\lambda_{cjk}\,\tilde{c}_{ck}}_{\text{Competition effect}_{uk}}}_{\text{New General Equilibrium Effects - Decreasing costs elsewhere}} + \epsilon_{uk} \end{aligned} \tag{25}$$

where $\epsilon_{uk} = \sum_j \omega^Y_{ujk}\ d\tilde{X}_j$, $d\tilde{l}_{uk} = \sum_o s_{uko}\, s^f_{uko}\, d\tilde{l}^f_{uko}$ 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}, $\epsilon_{dko} \equiv \frac{d\tilde{w}_{dko}}{d\tilde{l}_{dko}}$.

<u>Proof:</u> See Appendix E.2.

The "Substitution Effect" arises when workers are imperfect substitutes in the production of good k.[30] 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_{uko}. The policy will be more beneficial the more immigrant-intensive the job is.

The "Standard General Equilibrium Effect" arises when restricting the supply of immigrant labor in the U.S. increases the production costs of US sectors ($d\tilde{c}_{uk} > 0$). There are two implications of higher production costs. First, it translates into higher consumption prices which reduce the purchasing power of all American consumers ($\sum_{k'} \alpha_{uk'}\lambda_{uuk'}\ d\tilde{c}_{uk'} > 0$). 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 ($\sum_j \omega^Y_{ujk}(1-\lambda_{ujk})d\tilde{c}_{uk} > 0$). Therefore, this standard GE effect unambiguously reduces the welfare of American workers.

[30] If they are perfect substitutes, $d\tilde{W}^n_{uko}$ boils down to the ACR formula (Arkolakis et al., 2012).

The "New 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 $\sum_j \omega^Y_{ujk}\lambda_{cjk}$ in 25, where ω^Y_{ujk} 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 ($\alpha_{ck'}\ \lambda_{cuk'}\ \forall k'$). 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 $\sum_j\ \omega^Y_{ujk}\ \lambda_{cjk}\ = \sum_j\ \omega^Y_{ujk}\ (1-\lambda_{ujk})\ = 0$ for all k. Additionally, if American workers are isolated from international trade, they allocate all their spending exclusively to US goods and $\lambda_{uck} = 0$ for all k.[31] 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.

8 Calibration: Observed denial rate change and elasticities based on reduced-form coefficients

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.

[31] It worth noticing that the competition effect associated with changes in US production costs $d\tilde{c}_{uk}$ also vanishes because $\lambda_{uuk} = 1$ and $\lambda_{ujk} \neq 0$ for $j \neq u$.

(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 $\mathrm{P}, \mathbf{U}_u, \mathbf{S}^M, \mathbf{S}^{NM}$ 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 the Canadian economy.

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

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 28	3.6
ν_h	Elast. of subst. home vs abroad	Indirect inference: target $\hat{\gamma}$ in 29	2.3
ϵ	Elast. of subst. Imm. vs natives	Indirect inference: target $\hat{\gamma}$ in 30 for outcome $\log(\textit{Earning per native}_k)$	4.3
α	Elast. of subst. across sectors	Indirect inference: target $\hat{\gamma}$ in 30	1.2

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

8.1 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 model, our model delivers a new prediction, given by equation 26, that becomes the starting point of our approach to estimate ν_d. This is a crucial parameter to quantify the number of immigrants moving to Canada due to tightening immigration policies in the US. For clarity, in this section we modify the notation for subindexes and upperindexes. Here, subindexes represent the unit of observation in the data with t denoting year and the upperindex denoting the destination country $d = usa, can, home$.

According to the country choice decision 7.1, the log of the number of workers in occupation o from country c choosing Canada relative to the US is given by:

$$\tilde{App}_{cot}^{can} - \tilde{App}_{cot}^{usa} = \nu_d \left(p_{cot}^{can} \left(\tilde{u}_{cot}^{can} - \tilde{u}_{cot}^{home} \right) - p_{cot}^{usa} \left(\tilde{u}_{cot}^{usa} - \tilde{u}_{cot}^{home} \right) \right) \tag{26}$$

The elasticity of substitution between the US and Canada can be inferred by changes in relative number of applications due to changes in the relative pay-off of applying for the visas. This implies that changes in the approval rate of the US p_{cot}^{usa}, even if they change equally for all immigrant groups, can affect the outcome variable differently depending on the payoff of securing a US visa ($\tilde{u}_{cot}^{usa} - \tilde{u}_{cot}^{home}$).

To go from equation 26 to an estimating equation that we can take to the data, we introduce four changes. First, we rewrite 26 as follows:

$$\tilde{App}_{cot}^{can} - \tilde{App}_{cot}^{usa} = \nu_d \, p_{cot}^{usa} \, \tilde{w}_{cot}^{usa} + \eta_{cot} \tag{27}$$

where η_{cot} is a structural error that includes the effect of immigration policy in Canada (p_{cot}^{can}), wages and prices in Canada and the cost to migrate to Canada (through $\tilde{u}_{cot}^{can}$), wages and prices at home (through the average wage $\tilde{u}_{cot}^{home}$), prices in the U.S. (P_t^{usa}), 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} occupation-specific, as opposed to occupation-nationality-specific. Third, we set $\tilde{w}_{cot}^{usa}$ at its pre-shock average value because it jumps around over time for immigrant groups that are relatively small. By making $\tilde{u}_{co}^{usa}$ 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:

$$\tilde{App}_{cot}^{can} - \tilde{App}_{cot}^{usa} = -\nu_d \, p_{ot}^{usa} \, \tilde{w}_{co}^{usa} + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot} \tag{28}$$

where we measure App_{cot}^{can} and App_{cot}^{usa} as the number of PR applications and H-1B applications of immigrant group co in year t for $2012 \leq t \leq 2017$, p_{ot}^{usa} as the share of H-1B applications in occupation o that were approved, and $\tilde{w}_{co}^{usa}$ as the log of the average H-1B wage by immigrant group co for the pre-shock years 2012-2016.[32]

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 $p_{ot}^{usa} \, \tilde{w}_{co}^{usa}$ with $Intensity_{co} \times 1(t > 2016)$. In Section 5, 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 π_{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 5 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.

[32]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.

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

Equation 22 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.

8.3 Indirect inference approach: ν_h, α, and ϵ

To complete the calibration of the model, we must calibrate ν_d, 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 5 and 6.[33]

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 19 shows that the relationship between the response of the log of Canadian applications and $\pi_{cou}\Delta p_{ou}$ across immigrant groups, contains information about the underlying value of ν_h.[34] 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 Δp_{ou} 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

[33] We target cross-sectional responses because reduced-form estimates do not identify the aggregate effect (see Wolf (2023) and Nakamura and Steinsson (2018).)

[34] $\pi_{cou}\Delta p_{ou}$ is the portion of the expression 19 that we can measure directly in the data.

the following regression using both real data and model generated data:

$$\Delta log(App_{co}^{can}) = \gamma\ \pi_{cou}\Delta p_{ou}\ +\ \epsilon_{co} \tag{29}$$

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 G 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 7.4.1, 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 30

$$\Delta log(Sales_k) = \gamma\ \underbrace{\sum_{co} \omega_{cok}^{wb}\ (1 - \psi_{co}^{imm})\ \pi_{cou}\Delta p_{ou}}_{Intensity_k}\ + \epsilon_k \tag{30}$$

where ω_{cok}^{wb} 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.[35] 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 30 with the earning per native worker, and use the corresponding causal

[35]That is $\Delta log(LS)_k = \sum_{co} \omega_{cok}^{wb}\ (1 - \psi_{co}^{imm})\ \Delta log(App_{co}^{can})$ and we use $\pi_{cou}\Delta p_{ou}$ 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.

estimates from section 3.

Our calibrated values are: $\nu_h = 2.28, \epsilon = 4.30, \alpha = 1.16$. Although these values are from our specific settings, they fall within the range reported in the literature, showing consistency. 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.[36] 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).

8.4 Calibration results

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 29 and 30 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.

Table 2: Parameter values

	Immigration	Expansion		Crowd-in	
	log(Can App$_{co}$)	log(Sales$_k$)	Export share$_k$	log(Earning per native$_k$)	log(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

[36] 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.

9 Quantitative effects US immigration 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, $\bar{L}_{cou}$.

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, Δp_{ou}.

9.1 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, 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: $d\tilde{y}_{dk} = s^f_{dk}\, d\tilde{l}^f_{ds}$.[37] Notably, high-skilled service sectors

[37] Under the assumption that native supply to k is fixed, the change in production is approximately $d\tilde{y}_{dk} = \sum_o \frac{Y^f_{dko}}{Y_{dk}} d\tilde{l}^f_{dko} = \frac{Y^f_{dk}}{Y_{dk}} \sum_o \frac{Y^f_{dko}}{Y^f_{dko}} d\tilde{l}^f_{dko} = s^f_{dk} d\tilde{l}^f_{dk}$ where $s^f_{dk} \equiv \frac{Y^f_{dk}}{Y_{dk}}$

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.[38] 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, Δp_{ou}. 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 magnitude of the value. Sectors

[38] 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.

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.[39]

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 $s^f_{uko}\ d\tilde{l}^f_{uko}$ (see equation 25 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_{uko}. The scatter plot suggests that the immigrant share in that occupation-sector partially explains welfare differences of CS across sectors.[40] 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.[41] 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.[42]

In summary, Canadian workers in occupations experiencing a significant influx of immigrants often experienced losses due to direct labor market competition. However, workers

[39]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. This expected change in the immigrant labor force is a first-order approximation of the employment growth, $d\tilde{L}_{od}$. This measure uses information on initial shares and Δp_{ou} and, thus, does not account for general equilibrium effects. We found a high correlation (0.96). We interpret it as suggestive that the size of the influx of immigrants in their occupations explains, to a large extent, the large welfare differences across occupations.

[40]Their welfare differences in welfare across sectors are not closely related to Y_{uk} because the sector's expansion plays a secondary role in occupations that are more exposed to the influx of immigrants.

[41]We computed the expected employment growth as the first-order approximation to the log-change in L_{dk} due to Δp_{ou}. Specifically $d\tilde{L}_{dk} \approx \sum_{co} \omega_{codk}\ \pi_{codk}\ d\tilde{L}_{cod}$ where $\omega_{codk} \equiv \frac{Y_{codk}}{Y_{dk}}$ is the share of immigrant group co in the wage bill of sector k in country d, and $d\tilde{L}_{cod} \approx \sum_c \frac{Y_{cod}}{\sum_c Y_{cod}}\ (1-\psi^{imm}_{cod})\ d\widetilde{App}_{cod}$ where $d\widetilde{App}_{cod}$ is given by 19 without η_{cod}.

[42]The graph exhibits a similar qualitative pattern when we substitute the x-axis with the equilibrium change in the production of the sector. We opt for the expected employment growth to illustrate the underlying key mechanisms without including all general equilibrium forces.

from other occupations and from expanding sectors benefited from higher marginal revenue product from their labor.

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, Δp_{ou}. 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.

9.2 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 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, Δp_{ou}. 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.[43] 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.[44]

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

[44]Differences across sectors are less pronounced for American workers than for Canadian workers

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.

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, Δp_{ou}. 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.

9.3 Efficacy of the H-1B restrictions

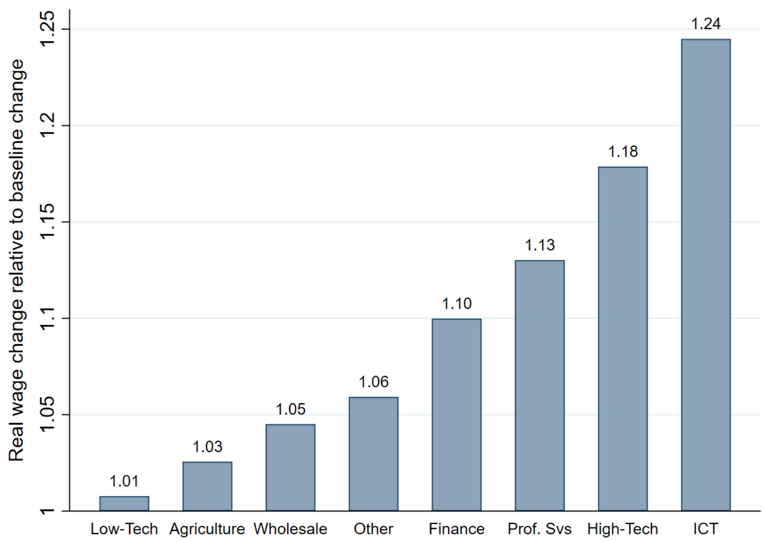
The welfare outcomes of American workers in Figure 7 are the result of a substitution effect and general equilibrium effects, with some of the latter operating via international trade. We are interested in quantifying the role of international trade in these welfare effects. To that end, we quantify the effects of the same policy change Δp_{ou} 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 Δp_{ou} 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.

because production changes were more uniform across US sectors, and the values of s^{f}_{dso} are smaller and more similar across sectors (see equation 25).

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, Δp_{ou}, 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 $\hat{w}^{BL}$.

10 Conclusion

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. These findings suggest that other countries can potentially benefit from US immigration restrictions by attracting the affected immigrants.

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. However, our model and its insights are not limited to the US-Canada context or high-skilled immigration. 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 like IT, where the US currently holds a comparative advantage.

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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

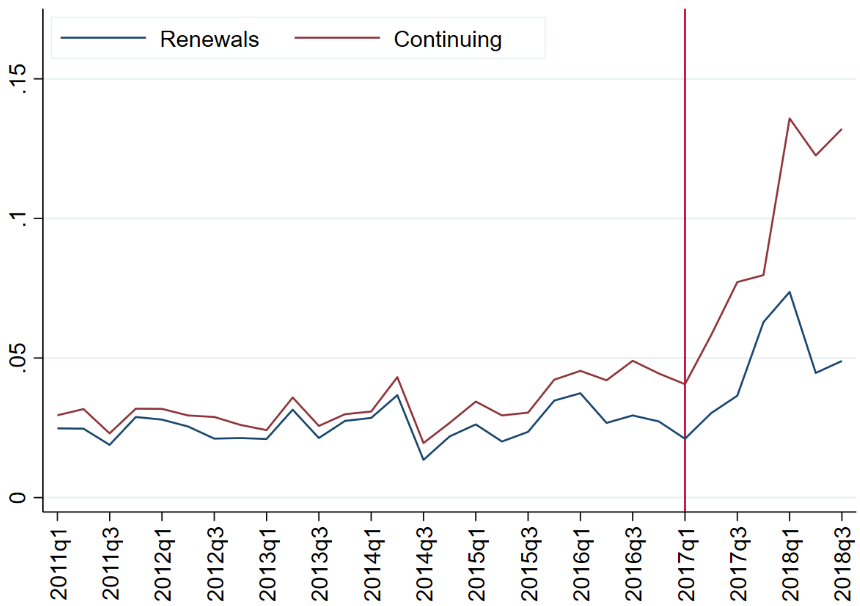
New		NOC (Classification in PR)		DOT (Classification in H-1B dataset)
group	Code	Description	Code	Description
30	2212	Geological and mineral technologists and technicians	024	Occupations In Geology
31	224	Technical occupations in electronics and electrical engineering	003	Electrical/Electronics Engineering 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

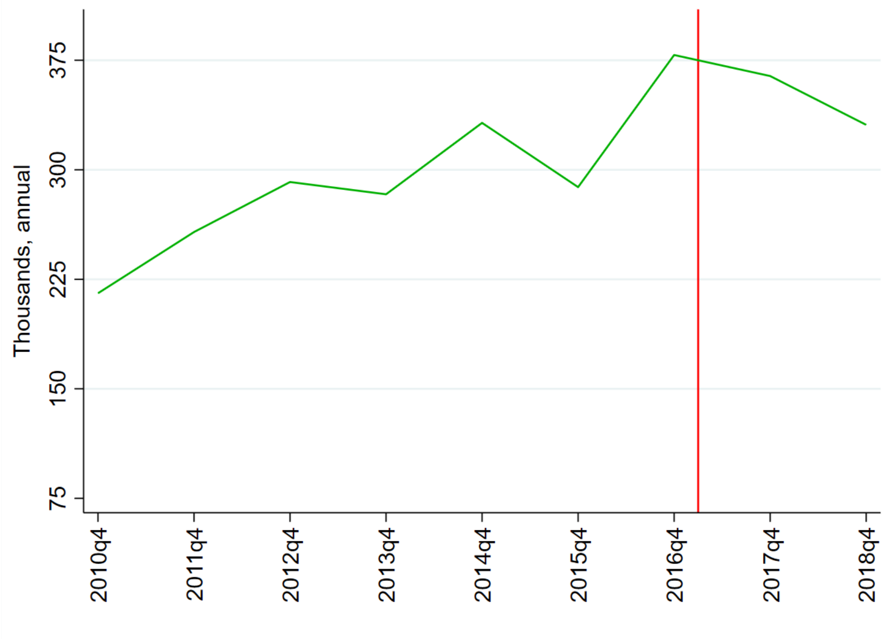
Source: IRCC's website Website (link), accessed June 2023.

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



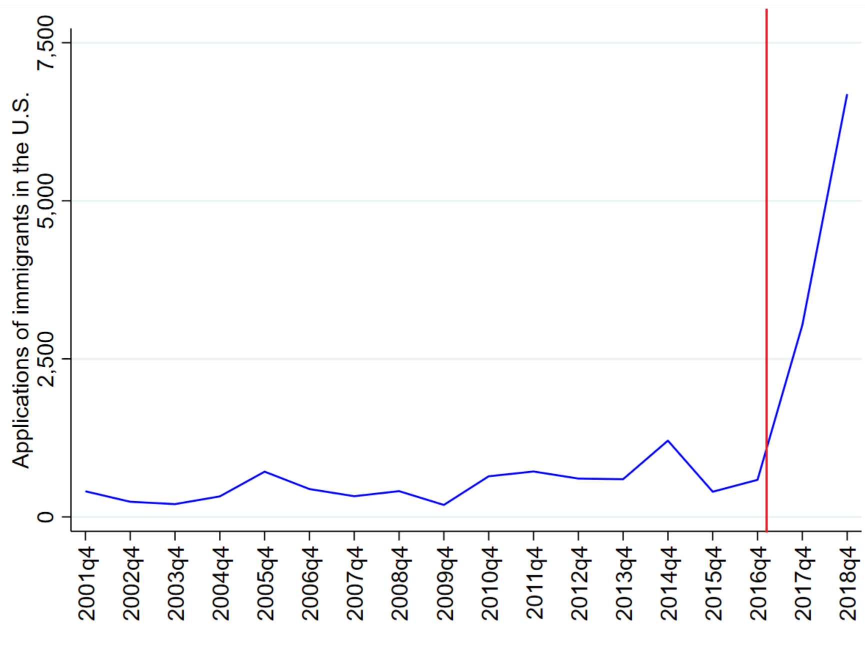
Note. Figure 1a plots the number of denied H-1B applications divided by the total number of H-1B applications. The red line includes continuing H-1B, and the blue lines only renewals.

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.

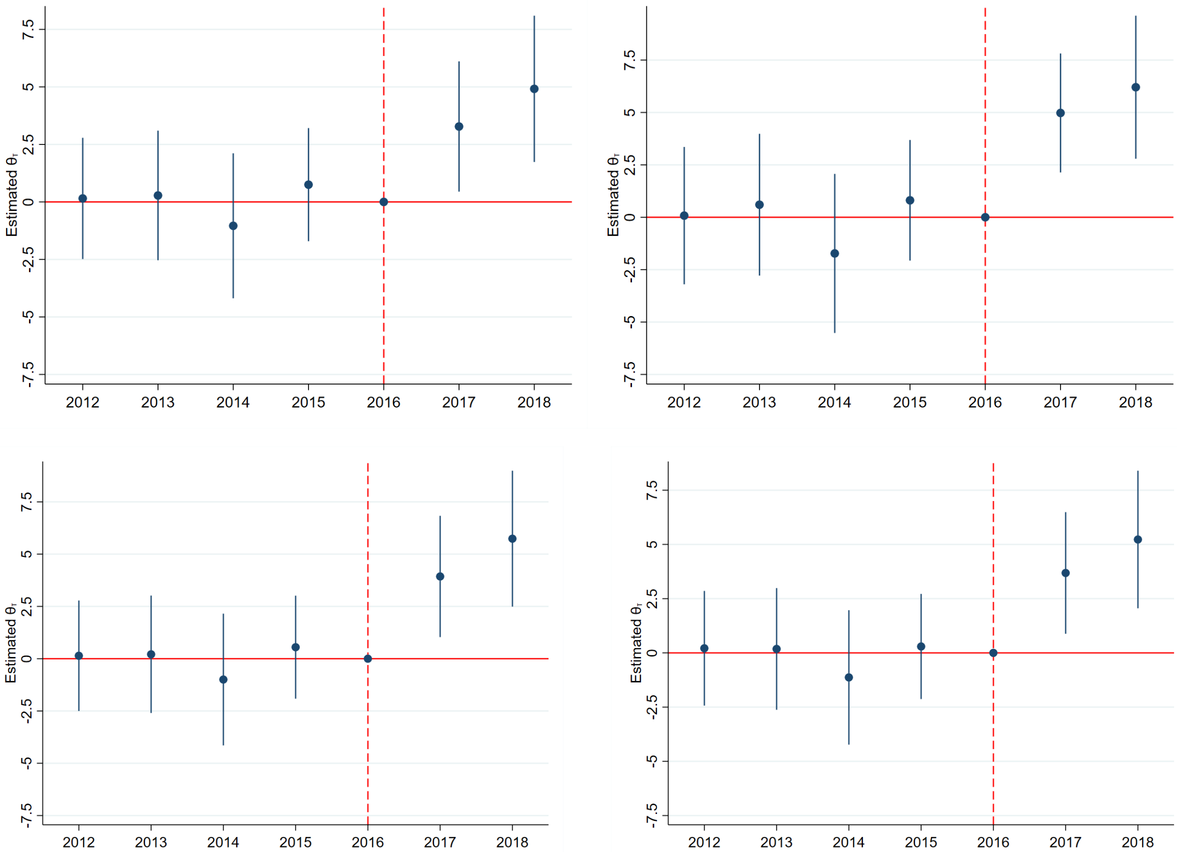
Table 8: Effect of increasing H-1B denial rates on Canadian Immigration

	(1)	(2)	(3)	(4)	(5)
	$log(app)^{can}_{cot}$	$log(app)^{can}_{cot}$	$log(app)^{can}_{cot}$	$log(app)^{can}_{cot}$	$log(app)^{can}_{cot}$
$Intensity_{co}\ 1(t = 2012)$	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 π^{usa}_{co} interacted with year dummies (e.g. $App^{can}_{co} \times \delta_t$ and $App^{usa}_{co} \times \delta_t$). 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

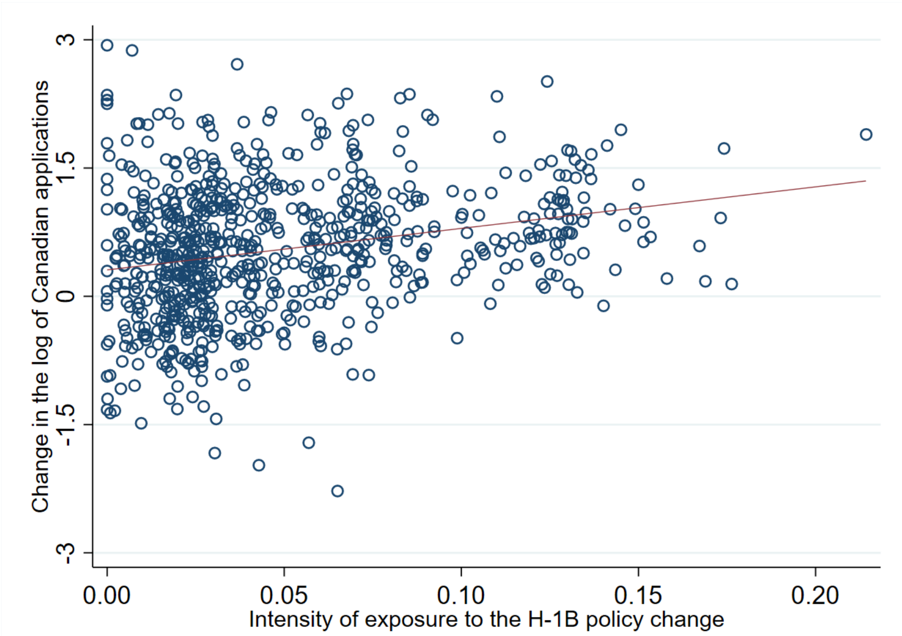
(a) Controlling for the elements in π_{co}^{usa} (b) Excluding apps. from India and China



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

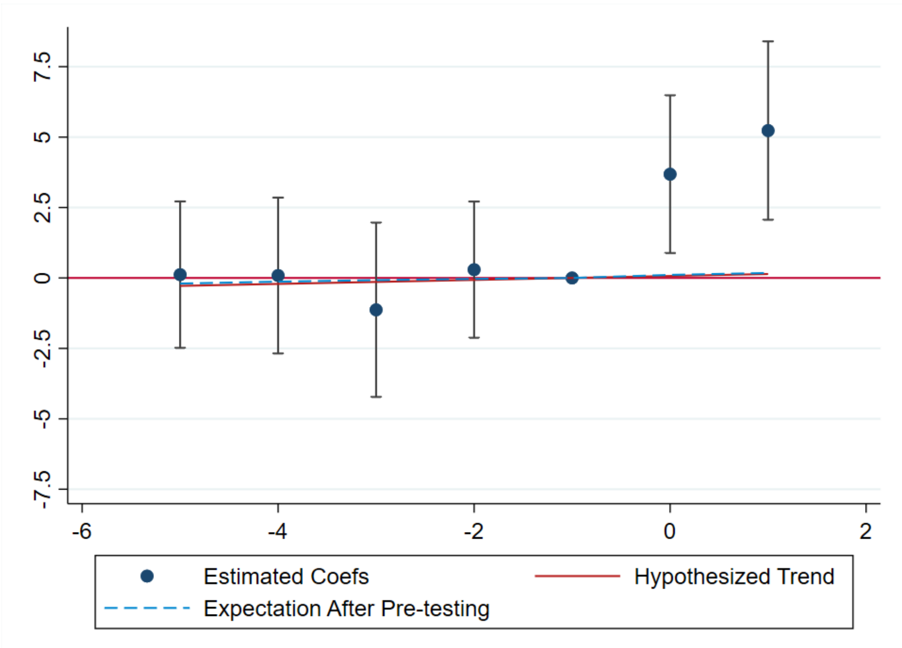
Note. The y-axis plots the estimated event-study coefficients corresponding to columns 2-4 from Appendix Table 8.

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



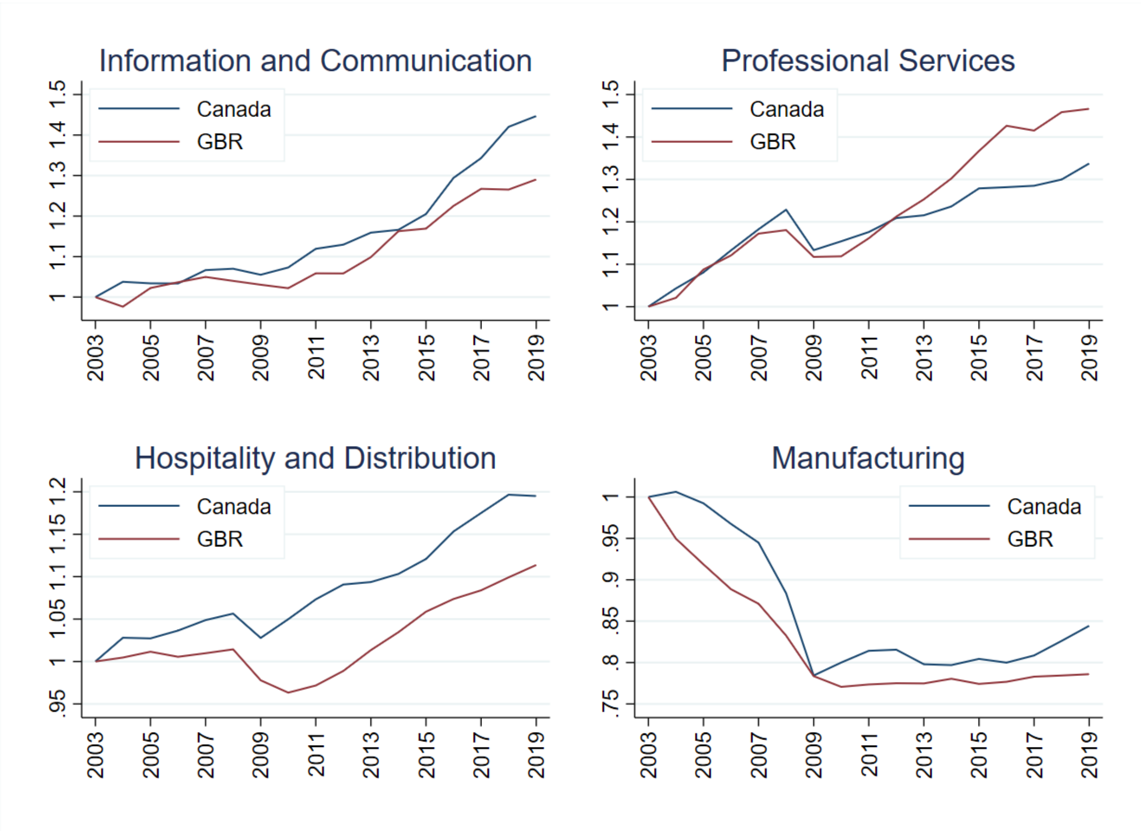
Note. The y-axis is computed as $\frac{\sum_{t=2017}^{2018} log(App_{co}^{can})}{2} - \frac{\sum_{t=2012}^{2016} log(App_{co}^{can})}{5}$ and the x-axis is $Fraction\ Affected_{co}$ in equation 2. An observation is an immigrant group co where c and o stands for the country of birth and occupations respectively.

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

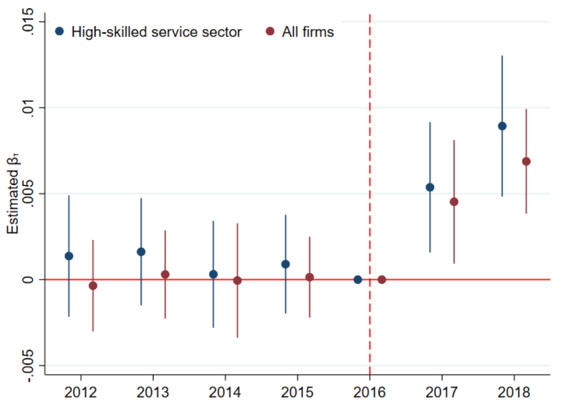
Note. This table reports the summary statistics of $Intensity_i$, normalized by the overall standard deviation. The statistics reported in the columns from left to right are the mean, standard deviation, median, 10th percentile, 90th percentile, and the number of firms, for firms with positive exposure. 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

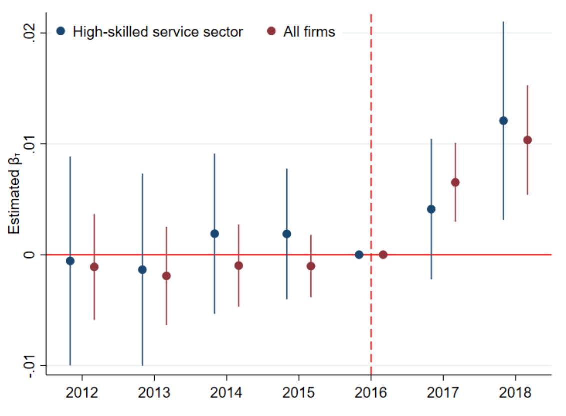
	Log of Revenues	Export-Rev ratio	Net hiring of imm.	Net hiring of natives	Log of Native empl.	Log of Total empl.	Log of earning per worker	Immigrant Share	Immigrant Share unskilled	Immigrant Share skilled	Log of markup	Log of cost	Log of Exports
$Intensity_i \times 1(\tau = 2012)$	-.0010915	-.001137	-.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 corresponding to different outcome variables. The event is defined as the spike in H-1B denial rate in 2017. Standard errors are clustered at the firm-level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$

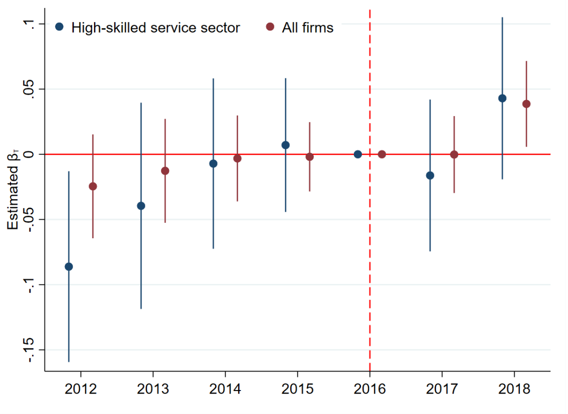
Figure 16: Effect of increasing H-1B denial rates on Canadian firms



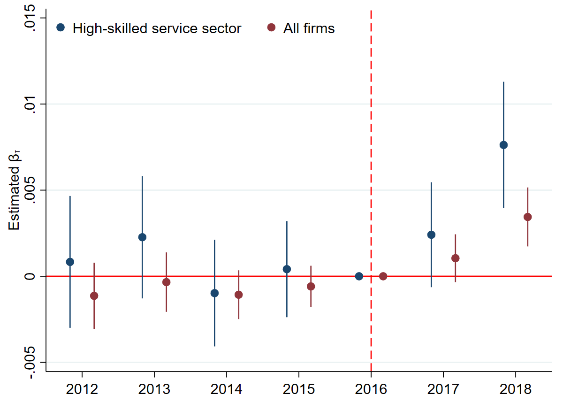
(a) Hiring of imm. relative to emp



(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 31. 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$_i$ × $1(SS = 0) \times 1(\tau = 2012)$	-.0010006	-.002744**	-.0016828	-.0009551	-.0036536
	.0026682	.0011522	.001895	.0015615	.0240137
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2012)$	-.0005609	.0008338	.0013644	.0026227	-.0861704**
	.0048058	.0019557	.0018041	.0022589	.0373395
Intensity$_i$ × $1(SS = 0) \times 1(\tau = 2013)$	-.0010915	-.0028501***	-.0000606	.0005609	-.0299413
	.0025166	.0010461	.0019405	.0014857	.0217397
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2013)$	-.0013493	.002274	.0016221	.0022437	-.0395377
	.0044268	.0018192	.0015918	.0019708	.0403564
Intensity$_i$ × $1(SS = 0) \times 1(\tau = 2014)$	-.0011067	-.0010006	.0006216	-.0001516	.0066705
	.0022134	.0008338	.0027137	.0015463	.0190563
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2014)$	.001895	-.0009854	.0003032	.0012735	-.0071253
	.0036839	.0015767	.0015918	.001895	.0333372
Intensity$_i$ × $1(SS = 0) \times 1(\tau = 2015)$	-.0018495	-.0015312**	-.0002729	-.0007732	-.0074285
	.0016979	.0006974	.0017434	.0014251	.0164336
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2015)$	.0018799	.0004093	.0008945	.0019102	.0070646
	.0030017	.0014251	.0014705	.0017131	.0261816
Intensity$_i$ × $1(SS = 0) \times 1(\tau = 2017)$	-.0024559	-.0009096	.0021679	-.0001364	-.0021376
	.0025166	.000758	.0029259	.0015767	.0176768
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2017)$	.0041084	.0024105	.0053667***	.0030017	-.0162365
	.0032291	.0015615	.0019405	.0019253	.0297139
Intensity$_i$ × $1(SS = 0) \times 1(\tau = 2018)$	-.0090809***	-.0009703	.0024408	-.0005912	.0013644
	.0032898	.0009096	.0022134	.0015312	.0204814
Intensity$_i$ × $1(SS = 1) \times 1(\tau = 2018)$	.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 31 corresponding to different outcome variables. $SS = 1$ 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

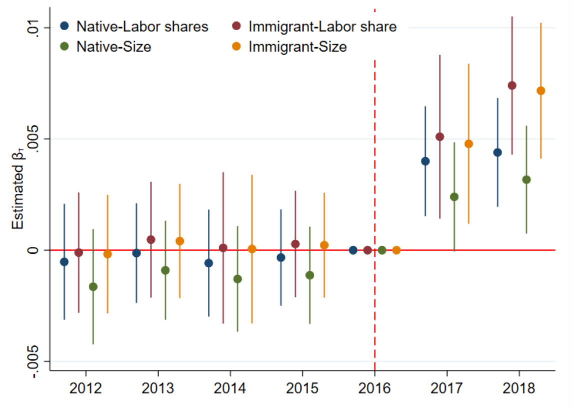
Note. The table displays the estimated event study coefficients, β_τ, of equation 3 where we include only domestic firms and exclude MNC. We plot these coefficients in Appendix Figure 20. The event is defined as the spike in H-1B denial rate in 2017. Standard errors are clustered at the firm-level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$

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

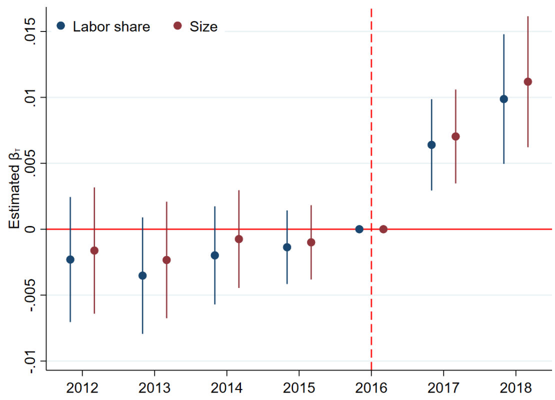
	(1) $log(\frac{app^{can}}{app^{usa}})_{cot}$	(2) $log(\frac{app^{can}}{app^{usa}})_{cot}$	(3) $log(\frac{app^{can}}{app^{usa}})_{cot}$	(4) $log(\frac{app^{can}}{app^{usa}})_{cot}$	(5) $log(\frac{app^{can}}{app^{usa}})_{cot}$	(6) $log(\frac{app^{can}}{app^{usa}})_{cot}$
$p^{usa}_{ot}\ \tilde{w}^{usa}_{co}$	-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 28. Columns (2)-(6) show 2SLS estimates. Column (2) estimates the baseline specification. Column (3) controls for the elements used to compute π^{usa}_{co} interacted with year dummies (e.g. $\pi^{can}_{co} \times \delta_t$ and $\pi^{usa}_{co} \times delta_t$). 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.

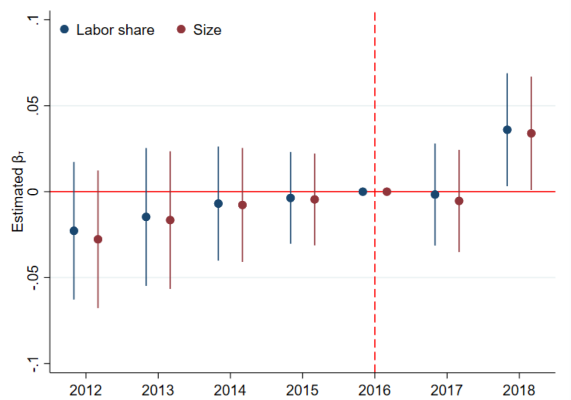
Figure 17: Robustness exercise to control for the effect of firm-characteristics



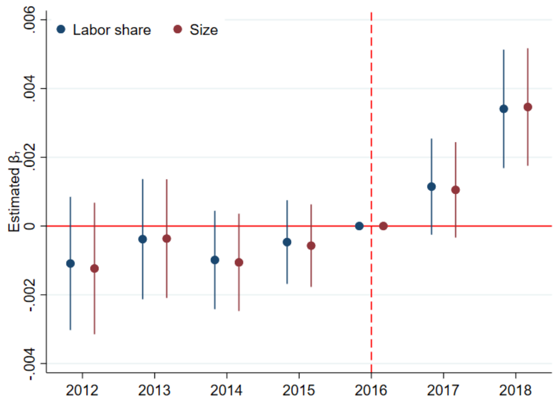
(a) Hiring relative to Employment in 2016



(b) Sales (in log)



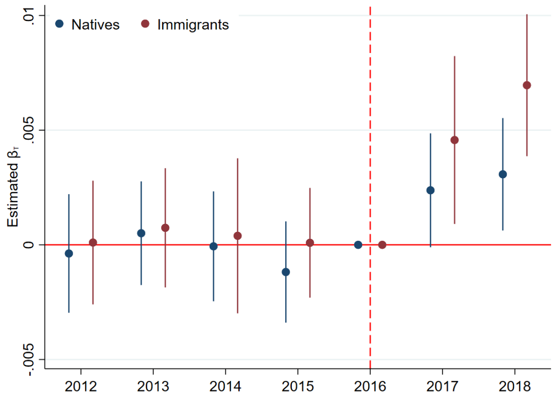
(c) Exports (in log)



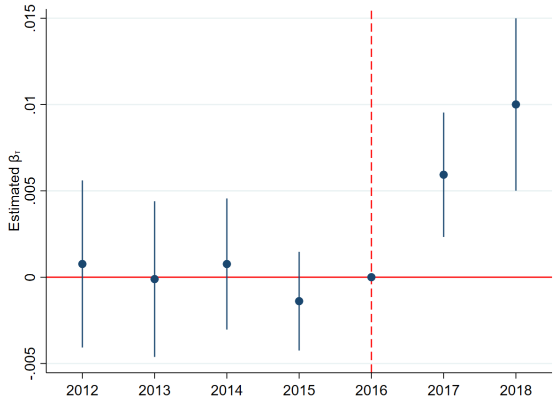
(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 with an additional control variables. 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.

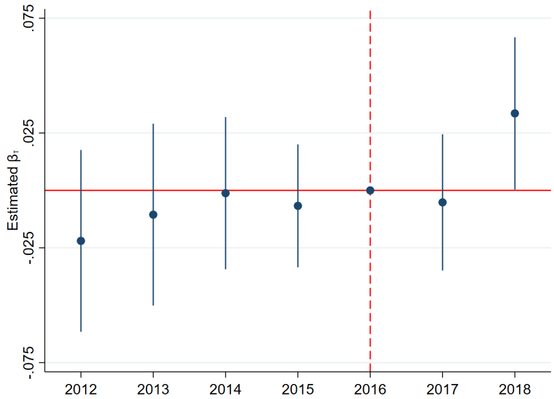
Figure 18: Robustness exercise to control for the effect of the Express Entry Program



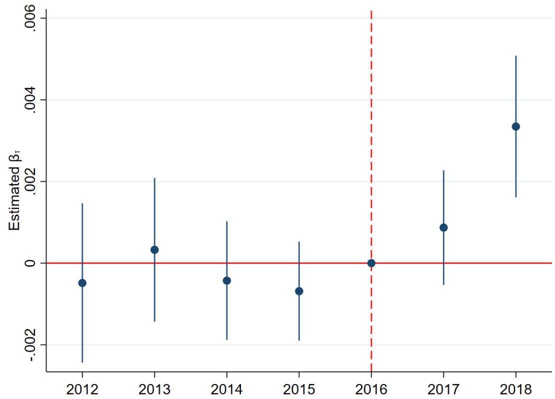
(a) Hiring relative to Employment in 2016



(b) Sales (in log)



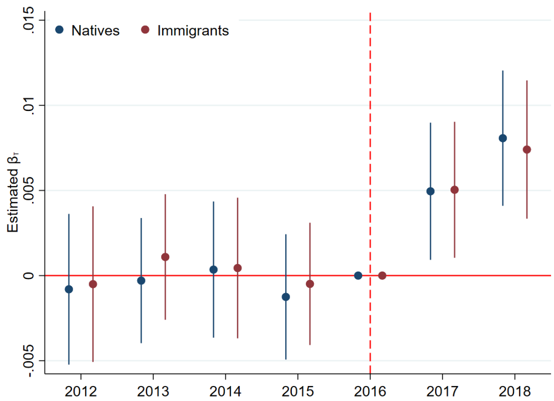
(c) Exports (in log)



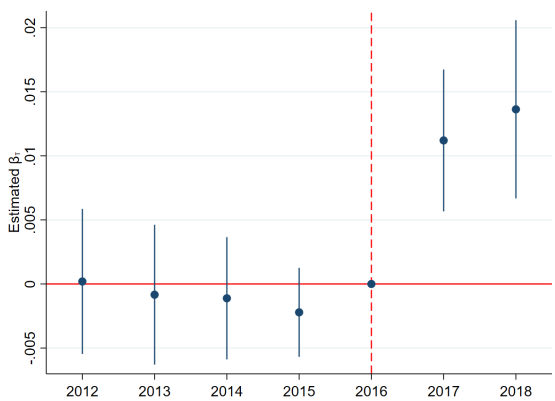
(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 with an additional control variable. 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



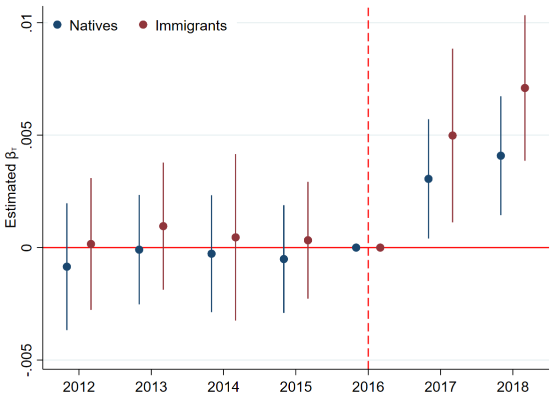
(a) Hiring relative to Employment in 2016



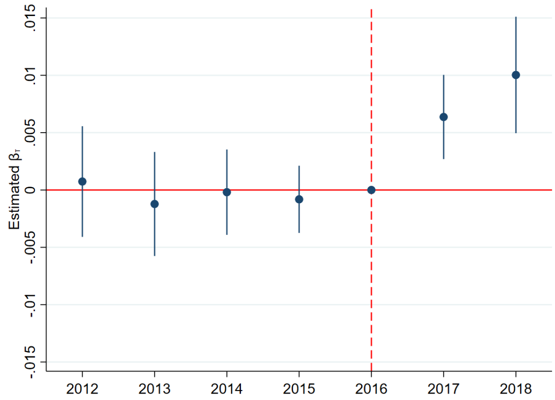
(b) Sales (in log)

Note. The y-axis plots the estimated event study coefficients, β_τ, of equation 3 excluding 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.

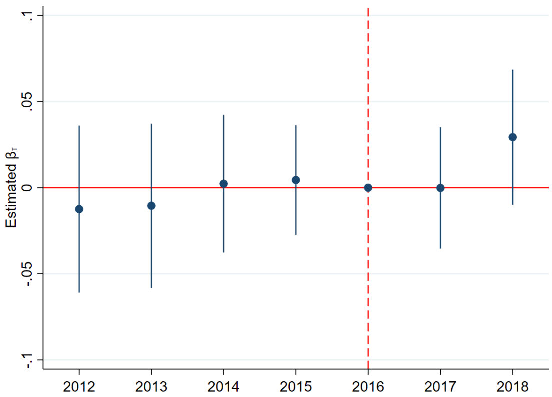
Figure 20: Effects on domestic firms



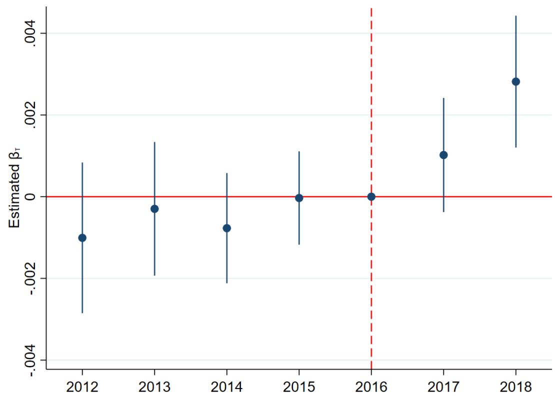
(a) Hiring relative to employment in 2016



(b) Sales (in log)



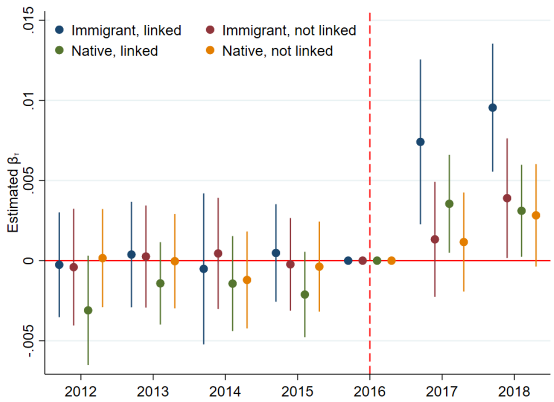
(c) Exports (in log)



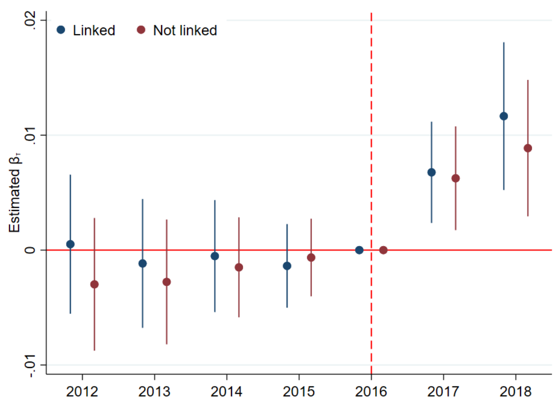
(d) Exports relative to total sales

Note. The y-axis plots the estimated event study coefficients of a modified version of equation 3 where we only 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

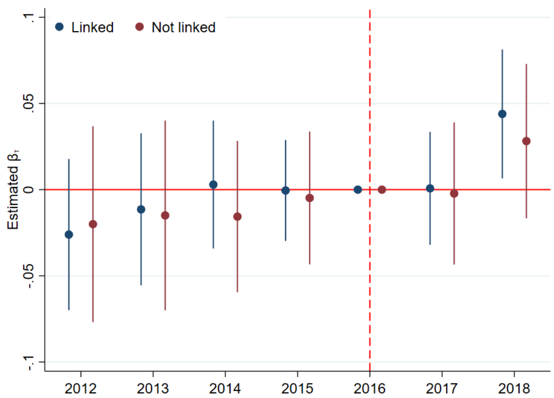
Figure 21: Effects on firms based on the share of workers who lived in the US



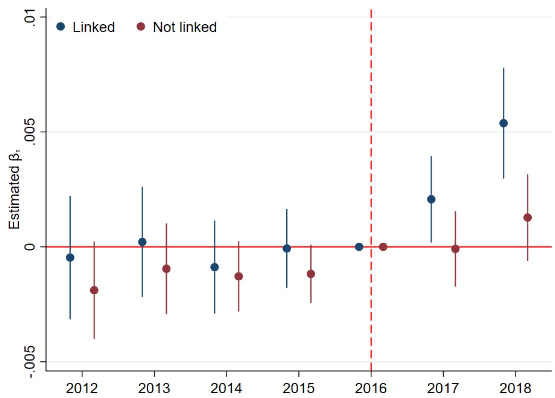
(a) Hiring relative to employment in 2016



(b) Sales (in log)



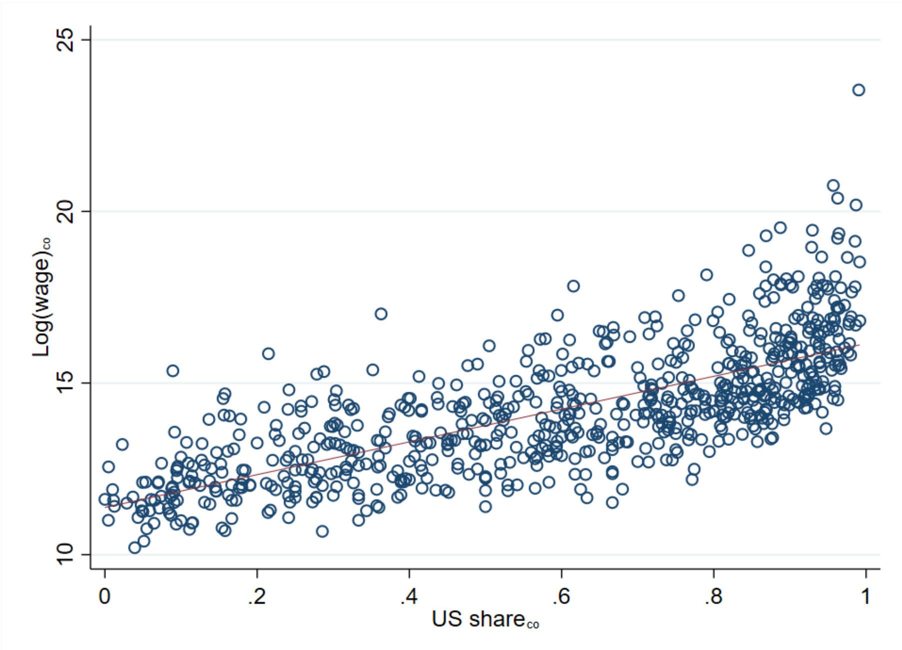
(c) Exports (in log)



(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.[45] 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).[46] 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

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

[46] 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).

share by dividing the number of immigrants from country c who have been permanent residents for not more 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.[47] 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.

[47]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: $\psi_{gu}^{imm} = \frac{\psi^{imm}{}_{gc}}{\psi^{imm1}_{gc}} \psi^{imm1}{}_{gu}$, where we use Canadian data to compute the ratio or extrapolation factor.

We use the H-1B data described in section 1 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.[48] 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 Firm-level evidence

C.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

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

the following event study:

$$
\begin{aligned}
y_{it} = &\sum_{\tau \neq 2016} \beta^{E}_{\tau} \times 1(s = exposed) \times Intensity_i \times 1(t = \tau) + \\
&\sum_{\tau \neq 2016} \beta^{NE}_{\tau} \times Intensity_i \times 1(t = \tau) + \ \delta_i \ + \delta_{st} + \delta_{mt} + \ \gamma' \ X_{ist} \ + \epsilon_{it}
\end{aligned} \tag{31}
$$

where $1(s = exposed)$ 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^{E}_{τ}, 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 $Intensity_i$ 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.

C.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.

D 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 $\Delta p_{ocu} \equiv p'_{cou} - p_{cou}$ can be summarized by the following equations 32-54. 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.

$$\hat{\pi}_{cock} = \left(\frac{\hat{w}^n_{cok}}{\hat{\Phi}_{coc}}\right)^{\kappa}, \qquad \text{where } \hat{\Phi}^{\kappa}_{coc} = \sum_k \pi_{cock}(\hat{w}^n_{cok})^{\kappa} \tag{32}$$

$$\hat{\pi}_{codk} = \left(\frac{\hat{w}^f_{dok}}{\hat{\Phi}_{cod}}\right)^{\kappa} \quad \text{for } \ d \neq c, \qquad \text{where } \hat{\Phi}^{\kappa}_{cod} = \sum_k \pi_{codk}(\hat{w}^f_{dok})^{\kappa} \tag{33}$$

$$\hat{u}_{coc} = \frac{\hat{\Phi}_{coc}}{\hat{P}_c}, \quad \hat{u}_{cod} = \frac{\hat{\Phi}_{cod}}{\hat{P}_d} \quad \text{for } d \neq c \tag{34}$$

$$\hat{u}^{\nu_h}_{co} = \pi_{coe}\, \hat{u}^{\nu_h}_{coe} + \pi_{coc}\, \hat{u}^{\nu_h}_{coc} \tag{35}$$

$$\hat{u}^{\nu_d}_{coe} = \sum_{d \neq c} \pi_{cod}\, (\hat{u}^{p_{cod}}_{cod} \cdot \hat{u}^{1-p_{cod}}_{coc} \cdot u^{\Delta p_{cod}}_{cod} \cdot u^{-\Delta p_{cod}}_{coc})^{\nu_d} \tag{36}$$

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 $\sum_{d \in \mathcal{C}^d} \pi_{cod} = 1$.

$$\hat{\pi}_{coc} =\Big(\frac{\hat{u}_{coc}}{\hat{u}_{co}}\Big)^{\nu_h}\ ,\ \hat{\pi}_{coe} = \Big(\frac{\hat{u}_{coe}}{\hat{u}_{co}}\Big)^{\nu_h}\ ,\ \hat{\pi}_{cod} = \Big(\frac{\hat{u}_{cod}^{p_{cod}}\cdot \hat{u}_{coc}^{1-p_{cod}}\cdot u_{cod}^{\Delta p_{cod}}\cdot u_{coc}^{-\Delta p_{cod}}}{\hat{u}_{coe}}\Big)^{\nu_d} \tag{37}$$

$$\widehat{LS}_{coc} =\Big(\big(\psi_{coc}\hat{\pi}_{coc} + \sum_{d\neq c}\psi_{cod}\ \widehat{(1-p_{cod})}\hat{\pi}_{cod}\ \hat{\pi}_{coe}\big)(1-\psi_{co}^{emig}) + \psi_{co}^{emig}\Big)\hat{\Phi}_{coc} \tag{38}$$

$$\widehat{LS}_{cod} = \big(\hat{p}_{cod}\cdot\hat{\pi}_{co,d}\cdot(1-\psi_{cod}^{imm}) + \psi_{cod}^{imm}\big)\cdot\hat{\Phi}_{cod},\ \text{for } d\neq c \tag{39}$$

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.

$$\widehat{LS}_{codk} =\hat{\pi}_{codk}\cdot\widehat{LS}_{cod} \tag{40}$$

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

$$\hat{s}_{dko}^{n} = \left(\frac{\hat{w}_{dko}^{n}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{41}$$

$$\hat{s}_{dko}^{f} = \left(\frac{\hat{w}_{dko}^{f}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{42}$$

$$\hat{f}_{dko} = \left(\frac{\hat{w}_{dko}}{\hat{w}_{dk}}\right)^{1-\eta} \tag{43}$$

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

$$\hat{w}_{dko}^{1-\epsilon} =s_{dko}^{n}\cdot(\hat{w}_{dko}^{n})^{1-\epsilon} + s_{dko}^{f}\cdot\left(\hat{w}_{dko}^{f}\right)^{1-\epsilon} \tag{44}$$

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

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

$$\hat{Y}_{dk} = \sum_{c} \omega^{Y}_{cdk}\ \hat{\lambda}_{dck} \cdot \hat{\alpha}_{ck} \cdot \hat{X}_{c} \tag{46}$$

$$\hat{\alpha}_{dk} = \left(\frac{\hat{P}_{dk}}{\hat{P}_{d}} \right)^{1-\alpha} \tag{47}$$

$$\hat{\lambda}_{dck} = \frac{\hat{w}_{dk}^{-\theta}}{\sum_{d} \lambda_{dck}\ \hat{w}_{dk}^{-\theta}} \tag{48}$$

$$\hat{X}_{c} = \sum_{k} \omega^{X}_{ck}\ \hat{Y}_{ck} +\ \omega^{X}_{cD} \tag{49}$$

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

$$\hat{P}_{dk}^{-\theta} = \sum_{i \in \mathcal{C}} \lambda_{idk} \cdot \hat{T}_{is} \cdot \left(\hat{\tau}_{idk} \cdot \hat{w}_{is}\right)^{-\theta} \tag{50}$$

$$\hat{P}_{d}^{1-\alpha} = \sum_{k} \alpha_{dk}\ \hat{P}_{dk}^{1-\alpha} \tag{51}$$

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

$$\widehat{LD}^{x}_{dko} = \hat{s}^{x}_{dko} \cdot \hat{f}_{dko} \cdot \hat{Y}_{dk},\ \forall x \in \{n,\ f\} \tag{52}$$

Labor market clearing conditions

$$\widehat{LD}^{f}_{dko} = \sum_{c \neq d} \omega^{LS}_{codk} \widehat{LS}_{codk} \tag{53}$$

$$\widehat{LD}^{n}_{dko} = \widehat{LS}_{dodk} \tag{54}$$

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

E Analytical results

E.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 $d \neq u$ is:

$$\Delta \tilde{App}_{cod} = (\nu_h \, \pi_{coc} - \nu_d) \, \pi_{cou} \, \Delta p_{cou} (\tilde{u}_{cou} - \tilde{u}_{coc}) + \eta_{cod} \tag{55}$$

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

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

E.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 $\tilde{l}^f_{uko}$. The change in the welfare of an American worker in occupation o in sector k is ($d = u$):

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

where $\epsilon_{uk} = \left(\frac{1}{\eta} - 1\right)\tilde{l}_{uk} \;+ \sum_j \omega^Y_{ujk}\;\; \tilde{X}_j$, $\tilde{l}_{uk} = \sum_o s_{uko}\, s^f_{uko}\, \tilde{l}^f_{uko}$ 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 56:

$$w^x_{dko} = p(\omega)_{dk}\; z(\omega)\, \left(\frac{l_{dko}}{l_{dk}}\right)^{-\frac{1}{\eta}} \left(\frac{l^x_{dko}}{l_{dko}}\right)^{-\frac{1}{\epsilon}} \tag{56}$$

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: $Y_{uk} = \sum_{c \in \mathcal{C}} \lambda_{uck}\; \alpha_{ck}\; X_c$. 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, λ_{uck}.

After substituting these equilibrium conditions into 56, we obtain the following expression for the welfare of an American worker in occupation o working in sector k:

$$W^n_{uko} = \frac{w^n_{uko}}{P_u} = \frac{Y_{uk}}{l_{uk}} \quad \left(\frac{l_{uko}}{l_{uk}}\right)^{-\frac{1}{\eta}} \quad \left(\frac{l^n_{uko}}{l_{uko}}\right)^{-\frac{1}{\epsilon}} \quad \frac{1}{P_u}$$

where the labor bundle l_{uko} and the overall production l_{uk} are given by 7.
Consequently, the change in welfare is given by the following expression:

$$\tilde{W}^n_{uko} = \;\; \tilde{Y}_{uk} \;\;+\;\; \left(\frac{1}{\eta} - 1\right)\tilde{l}_{uk} \;+\; \left(\frac{1}{\epsilon} - \frac{1}{\eta}\right) \tilde{l}_{uko} \;-\; \frac{1}{\epsilon}\, \tilde{l}^n_{uko} \;\;-\; \tilde{P}_u \tag{57}$$

Step 2: Expression for the change in the price-level in 57.

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

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

Log-differentiation of these expressions yields the following conditions:[49]

$$\tilde{P}_u = \sum_k \alpha_{uk} \; \tilde{P}_{uk} \quad \text{where} \quad \tilde{P}_{uk} = \sum_{i \in \mathcal{C}} \lambda_{iuk} \; \tilde{c}_{ik}$$

Suppose that the US immigration restrictions increased production costs in the US ($\tilde{c}_{uk} > 0$), 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:

$$\tilde{P}_u = \sum_k \alpha_{uk} \left(\lambda_{uuk} \; \tilde{c}_{uk} + \lambda_{cuk} \; \tilde{c}_{ck} \right) \tag{58}$$

Step 3: Expression for the change in sales of sector k in the US, Y_{uk} in 57.
Log-differentiating Y_{uk} yields:

$$\tilde{Y}_{uk} = \sum_{j \in \mathcal{C}} \omega_{ujk}^{Y} \left(\tilde{\lambda}_{ujk} + \tilde{\alpha}_{jk} + \tilde{X}_j \right) \tag{59}$$

where ω_{ujk}^{Y} be the share of country j in US sales of sector k.[50]
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:

$$\tilde{\lambda}_{ujk} = -\theta \; (1 - \lambda_{ujk}) \; \tilde{c}_{uk} + \theta \; \lambda_{cjk} \; \tilde{c}_{ck}$$

We can then write the change in the US sales of sector k as a weighted average of the change in the market shares within the sector and the change in the countries' expenditures:

$$\tilde{Y}_{uk} = -\theta \sum_j \omega_{ujk}^{Y} \; (1 - \lambda_{ujk}) \; \tilde{c}_{uk} \;\; + \;\; \theta \sum_j \omega_{ujk}^{Y} \lambda_{cjk} \; \tilde{c}_{ck} \;\; + \;\; \sum_j \omega_{ujk}^{Y} \; \tilde{X}_j \tag{60}$$

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

[50] That is: $\omega_{ujk}^{Y} \equiv \frac{\lambda_{ujk} \; \alpha_{jk} \; X_j}{\sum_d \; \lambda_{udk} \; \alpha_{dk} \; X_d}$

Step 4: Expression for the change in the labor bundle l_{uko} and l_{uk} in 57.
Log-differentiating 7 and using additional optimal conditions yields the following conditions:

$$\tilde{l}_{uko} = s^n_{uko}\, \tilde{l}^n_{uko} + s^f_{uko}\, \tilde{l}^f_{uko}$$
$$\tilde{l}_{us} = \sum_o s_{uko}\, \tilde{l}_{uko}$$

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

$$\tilde{l}_{uko} = s^f_{uko}\, \tilde{l}^f_{uko} \tag{61}$$
$$\tilde{l}_{uk} = \sum_o s_{uko}\, s^f_{uko}\, \tilde{l}^f_{uko} \tag{62}$$

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

Step 5: Expression for $\tilde{c}_{ck}$ in 57 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:

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

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 $\varepsilon_{dko} < 0$.

F 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)[51]
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.[52] 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.

[52]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 5.

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:

$$\frac{L_{coc}}{L_{co}} = \left(\pi_{coc} + \sum_{d \neq c} (1 - p_{cod}) \cdot \pi_{cod} \, (1 - \pi_{coc})\right) \, (1 - \psi^{emm}_{coc}) + \psi^{emm}_{coc} \tag{63}$$

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 63 is 0.4.[53] 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

[53]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. (2021b) 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.

computer scientists from India $\pi_{ind,cs,u}$:

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

This equilibrium condition allows us to recover the remaining π_{coc} as a function of data and 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 63 for lower-skilled workers, where we used the data for the non-college population from IAB.

G 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.[54]

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

$$log(App^{can}_{cot}) = \beta_t \, Intensity_{co} + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot}$$

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

$$log(App^{can}_{cot}) = \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot}$$

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

[54]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.

compute the log-change of applications of group G as follows:

$$
\begin{aligned}
log(App^{can}_{Gt}) - log(App^{can}_{G2016}) &= log\Big(\frac{\sum_{g\in G} App^{can}_{gt}}{\sum_{g\in G} App^{can}_{g2016}}\Big) \\
&= log\Big(\sum \frac{App^{can}_{g2016} e^{\beta_t Intensity_g}}{\sum_{g\in G} App^{can}_{g2016}}\Big) \\
&= log\Big(\sum_{g\in G} \omega^{app}_g e^{\beta_t Intensity_g}\Big)
\end{aligned}
$$

where the second equality follows from $log(App^{can}_{cot}) - log(App^{can}_{co2016}) = \beta_t \; Intensity_{co}$ and $\omega^{app}_g \equiv \frac{App^{can}_{g2016}}{\sum_{g\in G} App^{can}_{g2016}}$.

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 29 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.