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

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Abstract

We study the effects of U.S. skilled immigration restrictions on the Canadian economy and on American workers' welfare. In 2017, a new policy tightened the eligibility criteria for U.S. visas and was followed by a sharp increase in the number of skilled immigrant admissions to Canada. We use time and cross-sectional quasi-experimental variation introduced by this policy, along with U.S. and Canadian visa application data, to show that the policy led to a 30% higher level of Canadian applications in 2018. We then use the universe of Canadian employer-employee-linked records, immigration records, and data on international trade in goods and services to show that Canadian firms that were relatively more exposed to the inflow of immigrants increased production, exports, and the wage bill paid to native workers. Finally, we study the policy's impact on the welfare of American and Canadian workers by incorporating immigration policy into a multi-sector model of international trade. Our analytical results show that U.S. restrictions affect immigration to other countries, in turn affecting American wages through changes in consumption and U.S. export prices. We calibrate the model using our data and reduced-form estimates. We find that the welfare gains for American workers targeted for protection are up to 25% larger in a closed economy compared to an economy with the observed trade levels.

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1 Introduction

Restrictions on high-skilled immigration are becoming increasingly common in some developed countries that aim to protect domestic wages.[1] Other developed countries, however, are competing to attract high-skilled migrants, expecting their skills to meet the demands of key sectors, making these sectors more competitive in the global marketplace (Kerr, 2018). These conflicting policies alter the appeal of destinations for skilled workers. In fact, detractors of U.S. skilled immigration restrictions recently argued that such restrictions push skilled migrants to other more receptive developed countries.[2] If this is indeed the case, U.S. restrictions could make receptive countries more competitive in the global marketplace, ultimately affecting the U.S. economy through international trade. Despite the potential welfare implications for both the U.S. and the receiving economies, we do not yet know how such restrictions affect third countries and whether these effects spill back into the U.S. economy.

One challenge to answering these questions is the absence of significant changes to laws regulating U.S. skilled worker visas since the early part of this century. This paper exploits a sudden change in the interpretation of the law at the beginning of 2017 that tightened the eligibility criteria for college-educated immigrants applying for U.S. H-1B visas.[3] Immediately following this policy change, Canada experienced a surge in the number of skilled immigrant admissions, equivalent to 76,000 additional admissions in the period between 2018 and 2019.[4] This inflow represents 3.5% of the stock of college-educated immigrants in Canada, or about 2% of all workers in the high-skilled service sector. To what extent did the U.S. restrictions cause this increase in skilled immigration to Canada? How did this immigrant influx affect Canadian production, exports, and Canadian workers' welfare? How does the influx of workers to Canada and other economies ultimately impact American workers' welfare via international trade?

We address these questions by exploiting plausible exogenous variation introduced by the policy across time and immigrant groups. We combine this variation with a novel dataset to document the impact of these restrictions on Canadian immigration and firms. Our novel dataset includes U.S. work visa application data obtained through a Freedom of Information Act (FOIA) request, a novel Canadian visa application dataset, and Canadian administrative databases containing the universe of employer-employee-linked records, immigration records, and data on international trade in goods and services. Finally, we develop a new general equilibrium model of immigration and international trade to study the welfare effects of the policy and the role of international trade in determining the policy's efficacy in increasing American wages.

[1]For example, the United Kingdom implemented Brexit, and during President Trump's administration, the number of U.S. immigrant visas dropped by 25% between 2016 and 2019.

[2]See the Congress hearing *"How Outdated U.S. Immigration Policies Push Top Talent to Other Countries"*.

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

[4]We refer to admissions granted under permanent residence programs commonly used by skilled workers.

The new policy was implemented through policy memorandums issued by U.S. Citizenship and Immigration Services and became effective immediately. By the end of 2018, there was a decrease of 140,000 H-1B approvals (relative to trend) and an unprecedented spike in H-1B denial rates. Denial rates increased from about 6% in 2016 to 16% in 2018. The policy memorandums had different effects on the eligibility criteria in different occupations, which disproportionately affected immigrants from certain nationalities based on their propensity to apply for U.S. visas. We use this variation across time and immigrant groups to provide reduced-form evidence of the restrictions' effects on the Canadian economy and calibrate the model.

We first document that the increasing H-1B denial rates led to an increase in skilled immigration to Canada, using Canadian permanent residence visa application data. We estimate the effect of the policy on the change in the number of Canadian applications for immigrant groups that were differently affected by the policy introduction. Our event-study estimates imply that a 10 percentage point increase in H-1B denial rates increases Canadian applications by 30%. A back-of-the-envelope calculation suggests that for every four forgone H-1B visas, there is an associated increase of one Canadian application. These estimated (relative) effects are remarkably similar to those observed in the time series, which suggests potentially large effects on production.

We then document a large impact of the immigrant influx on Canadian firms, using our Canadian administrative dataset. To that end, we derive a shift-share exposure, which is motivated by the role of firms as channels for immigrant networks (e.g. referrals, Egger et al. (2021)) and our model. This measure implies that firms with a workforce composition tilted to the affected nationalities and occupations are relatively exposed.[5] We use this variation across firms and time variation within an event-study framework to estimate the effect of the policy. We find that firms that were more exposed to the immigrant inflow increased sales. For instance, for the median-sized firm in the skilled service sector, an additional immigrant hired in 2017-2018 translated into 3.2% larger sales in 2018. Exports are an important margin of adjustment as they account for about 40% of the increase in sales. Consistent with a strong increase in production, we find that more-exposed firms not only hired more immigrants but also native-born workers. Our estimates imply that a firm hired, on average, 0.5 additional native workers per new immigrant. The increase in production is likely driven by a drop in labor costs, as we find reductions in earnings per worker and per native-born worker at relatively exposed firms.

Finally, we develop a general equilibrium model to study the welfare effects of the policy, and the extent to which the expansion of economies absorbing the immigrants affects American workers' welfare via international trade. The model's novel aspect is to incorporate immigration policy into a standard model of immigration and international trade. There are multiple sectors, countries, and worker types given by their nationality and occupation. The international trade

[5] In practice, due to lack of occupation data at the firm, our empirical measure exploits differences across firms due to the nationality composition of their workforce and the occupational composition of their industry.

component is based on a Ricardian model where production features constant returns to scale and requires immigrants and native workers from different occupations, who are imperfect substitutes. Workers decide whether and to which destination country to migrate based on exogenous probabilities of obtaining visas, which is motivated by our evidence. These probabilities are the immigration policy tool. Workers also choose sectors. Since worker types differ in their pattern of comparative advantage, the supply of labor to sectors is nationality-occupation-specific. Thus, an immigrant inflow induces a larger labor supply shock to sectors with a workforce composition tilted toward nationalities and occupations with a larger inflow.

We derive an expression for the impact of an increase in the U.S. visa denial rate on American workers' welfare that is composed of a direct and indirect effect. The direct effect depends on how substitutable immigrants and American workers are, and the extent to which U.S. sectors contract due to the lower immigrant labor. This effect tends to be present in standard models of immigration. The indirect effect depends on how the restrictions impact migration flows to other economies, which is affected by the substitutability between emigrating to the U.S. and emigrating to other economies. An inflow of workers reduces production costs and increases production in the receiving economies, particularly in sectors that intensively use worker groups of the incoming immigrants. This increase in the production of foreign competitors diminishes the international price of American goods and, in turn, decreases American wages. Simultaneously, the drop in production costs abroad benefits American workers by providing access to cheaper imported goods and services, increasing their wages' purchasing power. The overall indirect effects on American workers in a specific sector can be either positive or negative, depending on how the export prices of U.S. sectors and the import prices for consumers adjust.

Our analytical results also show the role of certain shares and structural parameters in the welfare effects of the policy. We estimate the elasticity of substitution between emigrating to the U.S. and Canada directly from a coefficient of an equation that we derive from the model. For this estimation, we use our cross-border visa application data and the variation introduced by the policy change. We calibrate other key parameters following an indirect inference approach. We estimate regression coefficients using model-generated data and match them with coefficient estimates obtained using real data, which are based on our earlier event-study estimates. We use our data to calibrate the relevant shares, including the migration shares of each group, the share of each worker group in the costs of a sector, and the bilateral trade shares.

We find that the spike in U.S. visa denial rates observed in 2017 increases immigration to Canada, especially among computer scientists, and leads to a 3.4% overall increase in immigrant labor. This inflow decreases the welfare of Canadian computer scientists because the incoming immigrants are relatively close substitutes. However, the inflow increases the welfare of workers in other occupations because Canadian sectors expand, especially high-skilled service sectors. For instance, in these sectors, the welfare of computer scientists decreases by 2.9% and that of lower-skilled workers increases by 0.9% approximately. The overall welfare increase for all Canadian workers is 0.2%.

In the U.S., immigrant labor decreases by 1.6% and is particularly pronounced among computer scientists. As a result, we find that the rise in U.S. denial rates benefits primarily American computer scientists but tends to harm American workers employed in other occupations, especially if their sector contracts. For instance, the welfare of computer scientists in high-skilled service sectors increases by 0.7% and that of lower-skilled workers decreases by 0.3%. The overall welfare effect for American workers is close to zero. These effects on American workers include both direct and indirect effects. We assess the importance of the indirect effects by simulating the same policy in a global economy without international trade. We find that the welfare gains for American computer scientists, the group presumably targeted for protection by the policy, are up to 25% higher in an economy without international trade, compared to one with the current trade levels. This result indicates that the restrictions may reduce competition between immigrants and American workers in the U.S. labor market, but competition may still exist through the international trade of goods that embody the labor services of these immigrants.

Related literature: Our paper contributes to the extensive empirical literature studying the economic effects of immigration (seminal papers include Card (1990, 2001), Borjas (2003, 2005), and Ottaviano and Peri (2012)).[6] A stream of this literature studies the effects of skilled immigration on native-born workers' labor market outcomes.[7] Finding a clean source of exogenous supply of skilled immigrant labor is challenging because the inflow of economic migrants tends to be gradual, predictable, and driven by local economic conditions. To overcome this econometric challenge, some papers studied the impact of sudden refugee inflows, often to Europe (e.g., Hunt (1992), Friedberg (2001), Borjas and Monras (2016)). However, the occurrences of such episodes are limited, and the economic effects of refugee and economic migrant inflows may differ (Cortes, 2004). This paper focuses on an inflow of skilled economic migrants, which is sudden, unexpected, and driven by external conditions to tackle the identification challenge. We obtain the policy memorandums and use them, along with our own interpretation and institutional knowledge, to construct a novel measure of the shock suitable for empirical analysis.

Constructing this measure also allows us to contribute to the stream of the empirical literature studying the impact of skilled immigration on firms (Kerr and Lincoln, 2010; Kerr et al., 2015; Dustmann and Glitz, 2015; Mitaritonna et al., 2017; Ottaviano et al., 2018; Beerli et al., 2021; Egger et al., 2021; Mahajan, 2022; Dimmock et al., 2022; Doran et al., 2022; Arellano-Bover and San, 2023; Brinatti et al., 2023). We contribute to this literature by quantifying the aggregate effects of skilled immigration with a general equilibrium model that is disciplined with our

[6] See Hanson (2009), Lewis and Peri (2015) and Abramitzky and Boustan (2017) for reviews of the literature.

[7] For the effects of skilled immigration on innovation see for instance Hunt and Gauthier-Loiselle (2010), Akcigit et al. (2017), Burchardi et al. (2020), and Arkolakis et al. (2020), among others.

empirical evidence from the universe of Canadian firms.[8]

We also contribute to the empirical literature studying the labor market effects of immigration policies. Existing papers have mainly studied the impact of immigration policies on the country imposing the restrictions (e.g., Peri et al. (2015), Clemens et al. (2018), Yoon and Doran (2020), Kerr (2020), Moser and San (2020), Abramitzky et al. (2023)), or the sending country (e.g., Abarcar and Theoharides (2021), Khanna and Morales (2021), Coluccia and Spadavecchia (2021)). However, they have not often studied the effects of policies on third countries. The closest paper to ours is Glennon (2023), who shows that U.S. multinational corporations (MNCs) experiencing H-1B visa constraints increased employment in their affiliates. We contribute to this literature by offering quasi-experimental evidence of the effects of immigration policy on a third country. We also show that our results are robust to excluding MNCs, suggesting that the effects on third countries may not require MNC linkages with the imposing country.

We also contribute to the international trade literature studying the wage effects of changes in factor endowments dating back to Samuelson (1948) and Rybczynski (1955). Rybczynski's theorem predicts that, under free trade, changes in factor endowments affect countries' output mix and trade flows but should not affect wages. Intuitively, adjustments in trade flows mitigate wage adjustments. Several papers tested the theorem's empirical relevance, such as Davis et al. (1997), Hanson and Slaughter (2002), Gandal et al. (2004), Zimring (2019), and Muñoz (2023). Our paper quantifies the extent to which international trade mitigates the wage effects of changes in immigrant labor endowments in quantitative models calibrated to current levels of trade.

A related literature studies the effects of immigration using quantitative models of trade (Di Giovanni et al., 2015; Bound et al., 2017; Desmet et al., 2018; Allen et al., 2019; Monras, 2020; Khanna and Morales, 2021; Brinatti and Morales, 2021). The closest papers to ours are Burstein et al. (2020), who study the impact of U.S. immigration policy on American workers but in a closed economy, and Caliendo et al. (2021), who study the interaction between international trade and migration in the context of the European Union's enlargement using a single-sector model. Our paper develops a quantitative trade model that tractably incorporates migration policy and migration choice under uncertainty. Commonly used models of immigration would require us to observe the actual changes in migration flow levels resulting from the policy change, which is unobservable. In contrast, our model relies on observing actual changes in the denial rates, which are observable, allowing us to accurately assess welfare level changes due to the policy shock. Also, by incorporating multiple sectors, our model allows for the impact of international trade on the welfare effects of immigration to be positive or negative.

The paper is organized as follows. Section 2 introduces the data and institutional background.

[8] Brinatti and Morales (2021) do not focus on skilled immigration but is one of the few papers combining firm-level evidence with a general equilibrium model to study aggregate effects of immigration.

Section 3 describes the policy change and provides reduced-form evidence of its effects on Canada. Section 4 develops the quantitative model and analytically studies the effects of U.S. immigration restrictions on third countries and American workers' welfare. Section 5 calibrates and validates the model. Section 6 presents the quantitative results. Section 7 concludes.

2 Data and institutional background

2.1 Assembly of a novel dataset

Our data includes U.S. and Canadian visa application data and a Canadian administrative dataset containing the universe of employer-employee-linked records, immigration records, and records on international trade in goods and services. This section describes the content of these datasets. The appendix provides details on the datasets, the measurements, the samples, and the crosswalk we manually developed between the occupational classifications used in the U.S. and the Canadian visa application datasets.

2.1.1 U.S. 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., October 2000 to September 2018). The data was obtained from the United States Citizenship and Immigration Services (USCIS) through a Freedom of Information Act (FOIA) request. For each petition, the dataset provides the name and location of the sponsoring firm and the worker's country of birth, education level, salary, and occupation. It also specifies the type of H-1B petition, which allows us to determine whether the application was a new or continuing one (e.g., a renewal, a change of employment or employer, or an amendment), whether the application has been approved or denied, and the date when the decision was made. We use this dataset to construct the exposure measure of different immigrant groups to the H-1B policy change.

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

2.1.2 Canadian Permanent Resident visa application data

Our application data, obtained from Immigration, Refugees and Citizenship Canada (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 under which the permanent residency application was made, and the applicant's level of education. We retain applications from individuals holding a bachelor's degree or higher and aggregate them based on their occupation, country of origin, and year of application.

2.1.3 Canadian administrative data

The following Canadian administrative data sets, except for the Labor Force Survey (LFS), are part of the Canadian Employer-Employee Dynamics Database (CEEDD), which we use to measure a comprehensive set of firms' outcomes.

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

Immigrant landing records (IMDB): The IMDB is Canada's longitudinal immigration database. It collects information on all foreign citizens who came to Canada but were not on a temporary visitor visa when they landed as a permanent resident or had not applied for a non-temporary visiting visa. This database includes information on the birth country of each immigrant, the year of landing for the immigrants who became Canadian permanent residents, and the effective dates of all non-permanent resident visas held by each immigrant.

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

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

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

Activities of multinational enterprises in Canada (AMNE) This dataset 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 dataset provides information from a monthly survey conducted by Statistics Canada. In this survey, respondents report their country of birth, the sector and occupation of their main job, and the associated weekly earnings.

2.2 Institutional background

2.2.1 U.S. H-1B visa program

The H-1B visa program enables U.S. employers to hire highly skilled foreign workers in specialized occupations that demand advanced knowledge and a minimum of a bachelor's degree.[9] 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. 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 they decide to renew their visa or if there are significant changes in their 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 for new H-1B visas and 60% for 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 China (9%), Canada (2%), the Philippines (2%), and Korea (1%). In terms of occupations, computer-related occupations account for 64%, followed by engineering (9%), administrative specializations (6%), education (6%); and medicine and health (5%). Employers sponsoring H-1B visa applications are concentrated in the skilled-intensive service sector. Approximately 60% of these firms operate in the business service sector, 8% in high-tech manufacturing, 7% in educational services, 6% in finance and insurance services, and 5% in informational and cultural services.

2.2.2 Canadian visa program: points-based system

The main channels for skilled immigration intake in Canada are through permanent residence visa programs.[10] Prospective permanent resident visa applicants must fulfill core eligibility criteria to enter an application pool, where they are automatically ranked using a points system based on factors such as education, work experience, language proficiency, age, and having a valid job offer in place (See Appendix table E.3). 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 status. Starting from the highest-ranked candidates in the pool, invitations are extended until the specified number of intended ITAs is reached. The estimated target processing time is six months. However, it

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

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

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 typical H-1B applicant's qualifications, they are likely to have a competitive profile among the applicant pool. Second, these applicants can 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 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%). Second, 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 Canadian visa are 35% and 12% respectively. 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 U.S. H-1B and Canadian 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 points-based system prioritizes individuals with higher overall human capital.

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

3.1 A sudden H-1B policy change through policy memorandums

Advocates of more-stringent H-1B laws argue that employers use the program to replace American workers with lower-paid immigrant workers due to loopholes in the law (Matloff, 2002; Hira, 2010). President Donald Trump aimed to end program misuse and, during his mandate, immigration policy changed 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."[11]

Beginning in March 2017, the USCIS issued internal policy memorandums that tightened the eligibility criteria for H-1B visas and entered them into effect immediately.[12] First, while a bachelor's degree used to be sufficient to meet the requirements of a specialty occupation, this was no longer the case unless the Occupational Outlook Handbook (OOH) from the Bureau of Labor Statistics explicitly specifies that a bachelor's degree is required for that occupation. For example, given that the OOH states that computer programmers may enter the field with an associate degree, foreign computer programmers with a bachelor's degree now need to provide

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

[12] These policy memorandums have been made publicly available by the American Immigration Lawyers Association and the American Immigration Council via a FOIA lawsuit.

additional evidence to meet the new H-1B requirement. Conversely, given that the OOH specifies that several positions in health-related occupations require a bachelor's degree or higher, health professionals were largely unaffected by this policy memorandum. These examples illustrate that this new policy memo effectively tightened the eligibility criteria for some occupations more than for others. Our empirical design will exploit the variation across occupations. Second, the USCIS required additional evidence when the complexity of the job duties was inconsistent with a petition for a low-wage position. Third, USCIS stopped giving deference to previously approved petitions (e.g., renewals), which were now subject to the same scrutiny as new H-1B visas. Fourth, the scrutiny of H-1B petitions increased for applicants working at third-party worksites to ensure the applicant would truly work for the petitioning employer. This new rule especially affected companies providing business services to American firms.[13]

Applications that failed to meet these new requirements were denied, leading to a sharp increase in denial rates and a decrease in H-1B approvals. Denial rates increased from 6% in 2016 to an unprecedented 16% in 2018 (see Figure 1) and H-1B approvals dropped by approximately 140,000 visas (relative to the trend) by the end of 2018.[14] Immediately following the policy change, Canada experienced a spike in the number of skilled immigrant admissions, with an average annual increase of approximately 30% relative to 2016. Between 2018 and 2019 there were about 76,000 additional admissions, representing a 3.5% increase in the number of college-educated immigrants, or about 2% of all workers in the high-skilled service sector in Canada.

We aim to understand to what extent the U.S. restrictions cause the increase in skilled immigration to Canada. The next section proposes an empirical strategy to isolate the effects of U.S. immigration policies on Canadian immigration from the effects of other contemporaneous factors that may correlate with the H-1B policy change, such as changes in U.S. trade policy, increased xenophobia in the U.S., or positive demand shocks in Canada.

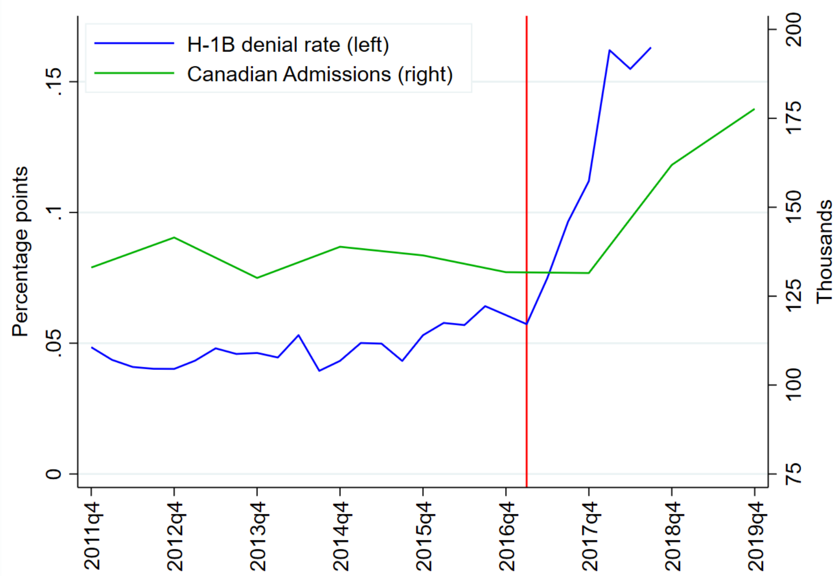
3.2 Effects of U.S. restrictions on skilled immigration to Canada

We aim to identify the effects of U.S. restrictions by using the plausibly exogenous variation across time and immigrant groups introduced by the new policy and by controlling for the effects of unobservable factors on Canadian immigration, with a comprehensive set of fixed effects.

[13] See this policy memo about the specialty occupation requirements, this memo about renewals, this memo on third-party worksites, and this official document about additional actions taken.

[14] The spike in denials explains the spike in the denial rates. The denial rate of renewals exhibits a similar pattern (see Appendix Figure E.1). See Appendix Figure E.2 for the time series of the levels of H-1B approvals.

Figure 1: Increasing H-1B restrictions and skilled immigration to Canada



Note. The blue line, which corresponds to the y-axis on the left-hand side of the figure, plots the number of denied H-1B applications divided by the total number of H-1B applications. It includes new and continuing H-1Bs. Given that the period to apply for new H-1B visa applications is during March and April, we remove seasonality by computing a four-quarters moving average for new H-1B applications. The green line, which corresponds to the y-axis on the right-hand side, plots the number of admissions granted under permanent residence programs commonly used by skilled workers. These programs are the Federal Skills Trades Program, Federal Skilled Worker (Express Entry), and Provincial Nominee Program (PNP).

3.2.1 Event-study framework

Motivated by our model, we estimate the effect of the policy on the change in Canadian applications before and after the introduction of the new policy for immigrant groups that were differently exposed. An immigrant group is defined by the combination of the applicant's country of origin and their occupation, denoted by c and o, respectively. Our measure of exposure to the new eligibility criteria, denoted by $Intensity_{co}$, proxies for the fraction of the immigrant group co whose H-1B visa applications were denied. Our event-study model takes the following form:

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

where $Can\ App_{co,t}$ is the number of Canadian visa applications of immigrant group co in year t, δ_{co} are the fixed effects at the immigrant group level, δ_{ot} are the fixed effects at the occupation-year level, δ_{ct} are the 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 differences in the outcome variables 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 new H-1B policy should affect outcomes only after the policy memorandums were introduced, we expect θ_τ to be zero.

We measure $Intensity_{co}$ as the fraction of the potential number of migrants to North America, either to the U.S. or Canada, affected by the new policy:

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

where "Initial" refers to the years before the introduction of the policy memos (i.e., FY2012-FY2015). The numerator can be interpreted as the number of immigrants with denied U.S. visas who could potentially consider migrating to Canada. The denominator proxies for the number of potential migrants to North America. $Intensity_{co}$ can be written as the interaction between the denial rate, denoted by dr_o, and the share of the total number of applications to North America that were submitted to the U.S., denoted by $\pi_{co,usa}$. The share $\pi_{co,usa}$ measures the propensity of an immigrant group to apply for a U.S. visa.[15] Our exposure measure predicts that the relatively affected groups work in occupations with high denial rates and high propensities to apply for U.S. visas. This measure is based on our model as shown in section 4.6.

The choice of occupation as the level of variation of dr_o is motivated by the instructions specified in the policy memorandum.[16] We compute these denial rates using only the applications for continuing H-1B visas and exclude applications for new H-1B visas.[17] We worry that if we include new H-1B applications, the correlated shocks to the U.S. and Canada could affect both the H-1B denial rates and the number of applications to Canada. For example, positive U.S. demand shocks that increase the number of H-1B applications would mechanically increase the denial rate for new H-1B visas, as new visas are subject to a cap, which would bias our estimates. We expect applicants for continuing visas to be less likely to respond to the shocks in Canada or at home because these applicants live in the U.S., which reveals their preference for this country and that they have secured a job, which would increase 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.[18]

Figure 2 illustrates the *sources* of the variation of the fraction affected by the policy: Figure 2a presents the denial rates for those applying for continuing H-1B visas by broad occupation in a typical year (red bar) and in the years following the introduction of the policy memorandums (blue bar). The red bars indicate small differences across occupations in normal years. However,

[15] To the extent to which $\pi_{co,usa}$ accurately predicts the post-treatment value, $Intensity_{co}$ can be interpreted as an accurate measure of the actual fraction of applicants 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 (Bartel, 1989; Altonji and Card, 1991; Card, 2001; Patel and Velia, 2013).

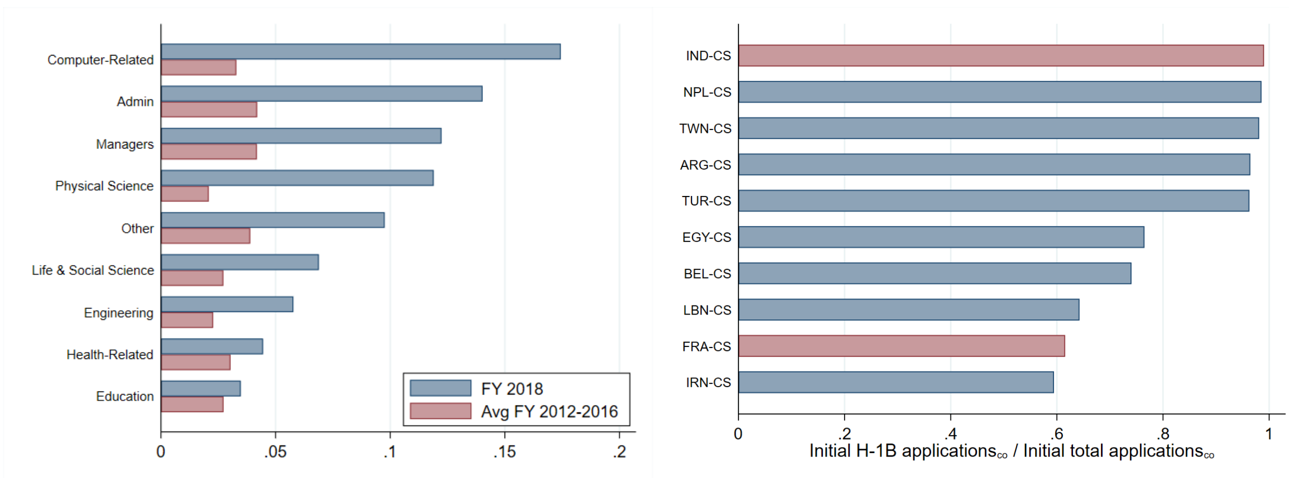
[16] We do not find evidence in the data, nor the policy memorandum, suggesting that the policy changed for immigrants from different nationalities conditional on working in the same occupations.

[17] Continuing visas account for 55% of all denials. See the spike in this denial rate in Appendix Figure E.1.

[18] In line with this hypothesis, Appendix Figure E.3 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 U.S. immigration policy that left this group of immigrants with denied visas and no alternative but to leave the country.

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

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



Note. Figure 2a plots the denial rate for applications 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 for FY 2018, after the introduction of the policy memos. Figure 2b plots $\pi_{co,usa}$ for the top and bottom five countries in terms of $\pi_{co,usa}$ for CSs.

large differences arise upon the introduction of the policy memorandums: Computer-related occupations experienced an 18% denial rate (14.6 percentage points above an average year), while health-related occupations have a 4% denial rate (1.1 percentage points higher than average). Figure 2b emphasizes the variation across countries, introduced by $\pi_{co,usa}$. The figure plots the top and bottom five countries in terms of $\pi_{co,usa}$ for computer scientists, showing that an Indian computer scientist is 60% more likely to apply to the U.S. than a French computer scientist (e.g., $\pi_{India,cs,usa}/\pi_{France,cs,usa} = 1.6$). Consequently, the fraction of Indian computer scientists affected is 60% larger than that of French computer scientists.

We saturate the empirical model with a rich set of fixed effects to account for the effects of potential confounding factors. δ_{co} controls for pre-existing differences between groups, such as preferences for the U.S. relative to Canada. δ_{ot} prevents attributing the effect of occupational shocks to the effect of the H-1B restrictions. This is important because some of the occupations that were more affected by the new eligibility criteria had been growing relatively more quickly. Finally, immigration from certain countries, such as India, to several developed countries has been on an upward trend, including to the U.S. and Canada. If these nationals tend to have a high propensity to apply for U.S. visas, $\pi_{co,usa}$, our estimate may be upward biased. To control for factors of this nature, we include country of origin-year fixed effects, δ_{ct}.

Additionally, some countries were experiencing changing political and economic conditions that may have pushed their citizens to emigrate. For example, immigration from India to several developed countries has been on an upward trend, including to the U.S. and Canada. If countries that experienced worsening conditions are those that tend to experience emigration to the U.S., our estimate will be upward biased. To control for factors of this nature, we include country of origin-year fixed effects, δ_{ct}.

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

3.2.2 Results

Figure 3 plots the estimates of θ_τ for the years 2012 to 2018. It was only after the U.S. restrictions were imposed that Canadian visa applications of immigrants who were more exposed to the U.S. 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% higher than what they would have been in the absence of the H-1B restrictions.[19]

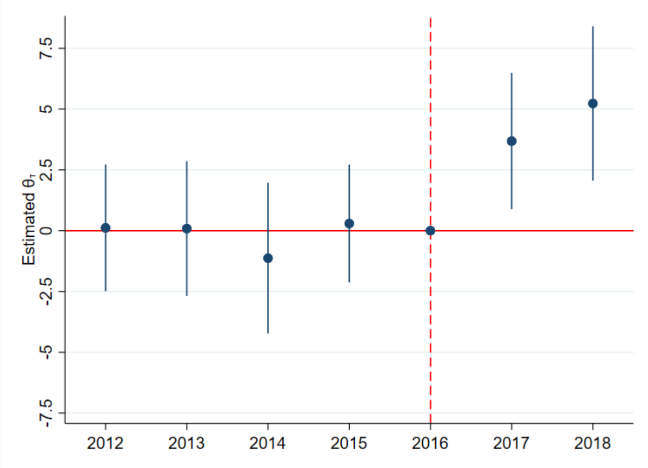
Our event-study estimates can also be interpreted in terms of two statistics useful for policy analysis. First, an increase in H-1B denial rates by 10 percentage points increases the number of applications to Canada by 30%, given that the average exposure $\pi_{co,usa}$ is 0.57. This is equivalent to saying that a 10 percentage point increase in the fraction of immigrants who are affected increases the number of applications to Canada in 2018 by 5.2%. Second, when we consider the relationship between Canadian applications and H-1B visa approvals, a back-of-the-envelope calculation suggests that roughly every 4 H-1B visa approvals forgone results in an increase of about one permanent resident application to Canada.[20]

There are several reasons for this large response in the number of applications to Canada. First, potential migrants to the U.S. may choose Canada due to its economic opportunities, labor market integration, language, and cultural similarities. Second, the qualifications of a typical H-1B visa applicant position these potential migrants favorably in terms of obtaining a Canadian visa within the framework of the points-based Canadian immigration system. Third, American firms, which have long faced immigration challenges, are prepared to quickly relocate

[19] 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.

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

Figure 3: Effect of H-1B restrictions on permanent resident applications to Canada



Note. The y-axis plots the estimated event-study coefficient, θ_τ, of equation 1. The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The plotted coefficients correspond to column 1 in Appendix Table E.4. The omitted year is 2016.

their employees to Canada.[21]

3.2.3 Discussion of threats to identification

Several factors may threaten the identification of the impact of U.S. immigration restrictions. These concerns include potential correlations of confounding factors over time, which would imply that ϵ_{cot} correlates with past applications and thus $\pi_{co,usa}$; the possibility of the policy change being a response to the increasing immigration of specific groups, which would bias our estimates upward; and the influence of contemporaneous changes in Canadian immigration policy on the affected immigrant groups. We address these concerns through robustness exercises, detailed in Appendix section B.1, which yield consistent results with our baseline specification. We also test for linear trends that would violate our identification assumption (Roth, 2022). Finally, we show that the results are unlikely to be driven by outliers.

3.3 Effects of increased skilled immigration on Canadian firms

After establishing that the H-1B restrictions increased skilled immigration to Canada, this section documents how the inflow of skilled immigrants affected production in Canada and the labor market outcomes of native-born Canadian workers. It then explains how these facts motivate the assumptions of our quantitative model.

3.3.1 Event-study framework

To estimate the effect of the inflow of immigrants induced by the H-1B restrictions on Canadian firms, we construct a measure that predicts which firms are likely to absorb these immigrants.

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

We expect that 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). Thus, our measure builds on the assumption that a Canadian firm that typically hires x% of a given immigrant group in the Canadian market will absorb x% of the number of that immigrant group that migrates to Canada due to the U.S. policy. We combine this variation across firms with the time variation of the policy within the following event-study framework to estimate the effect of the policy. Our empirical model for outcome y of firm i in year t is

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

where we consider several outcome variables y_{it} that are scale-independent such as the logarithm of sales or, as is commonly done in the immigration literature, the number of Canadian workers hired relative to the employment level in the baseline year. $Intensity_i$ is an exposure intensity measure of the H-1B policy change, which we describe shortly. The index k refers to the industry where the firm operates, according to the 4-digit NAICS classification, and m refers to the location of the firm. δ_i are the firm fixed effects, δ_{mt} are the labor markets' year fixed effects, X_{ikt} is a set of control variables that vary over time and across firms and industries, and ϵ_{it} is the error term, which we cluster at the firm level. The coefficient β_τ measures 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 policy memorandums. Given that the new H-1B policy should have affected firms' outcomes only after the policy memorandums were introduced, we expect β_τ to be zero for $\tau < 2016$ and to be different from zero for $\tau \in \{2017, 2018\}$.

Firm exposure to the H-1B restrictions $Intensity_i$ 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 Canadian domestic firm that tends to hire 1% of its CSs from India 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

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

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, relatively exposed firms have a workforce composition tilted to the immigrant groups that were relatively affected by the H-1B policy.

Given that we do not have occupation information at the firm level, we must approximate the firm-level share in (4). 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 then proxy $\frac{L_{coi}}{L_{oi}}$ with the overall nationality share ($\frac{L_{ci}}{L_i}$) and the occupational structure of the firm $\frac{L_{oi}}{L_i}$ with that of the industry where it operates ($\frac{L_{ok(i)}}{L_{k(i)}}$).

We must also proxy the shift component of (4) because we do not observe the flow of immigrants, co, coming to Canada after 2016 due to the U.S policy, $Flow_{co}^{post}$. We rewrite $\frac{Flow_{co}^{post}}{L_{co}}$ as $\frac{Flow_{co}^{post}}{Flow_{co}} \times \frac{Flow_{co}}{L_{co}}$ and assume that the growth in the inflow of immigrants is proportional to the growth of their applications (e.g., $\frac{Flow_{co}^{post}}{Flow_{co}} \propto \Delta log(App_{co})$). This assumption allows us to use our previous empirical model to measure the growth of applications due to the H-1B policy (e.g., $\Delta log(App_{co}) \approx \theta \; Intensity_{co}$). As a result, $Intensity_i$ is proportional to (4) and given by

$$\frac{Hires_i^{post}}{L_i} \approx \sum_{co} \frac{L_{ci}}{L_i} \frac{L_{ok(i)}}{L_{k(i)}} \; Intensity_{co} \; \frac{Flow_{co}}{L_{co}} \equiv Intensity_i \tag{5}$$

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

This empirical measure exhibits rich variation across industries and across firms within relatively exposed industries, which we use to identify the effect of the U.S. policy on Canadian firms. We provide summary statistics for $Intensity_i$ by sector in Appendix Table E.5. The most exposed sectors, given by the top quartile of sectors in terms of the average $Intensity_i$, are information and cultural industries (IC), business professional services, management of enterprises, financial services, and educational services (NAICS 51, 54, 55, 52, and 61, respectively). We will refer to these five broad sectors as the high-skilled service sector.

Control variables We include firm fixed effects δ_i that control for time-invariant differences between firms that may correlate with their growth.

Additionally, we control for potential industry-level confounders by incorporating industry-year control variables in X_{ikt} rather than industry-year fixed effects. Because the policy change had impacts on specific occupations, the influx of immigrants was concentrated in particular industries, leading to limited variation in $Intensity_i$ across firms within some industries. If we include the industry-year fixed effects, our estimate would capture the average impact of the policy within truly affected industries and unaffected industries. Therefore we exploit the rich cross-industry variation resulting from the policy change in the baseline specification and include industry-year fixed effects in a robustness exercise.

We include sector-specific trends because some industries that were growing faster happened to be intensive in the occupations affected by the rise in H-1B denials, such as the IT sector. We also control for global industry-year specific shocks by including the number of jobs created in the U.K., as the correlation of employment between the U.K. and Canada is approximately 0.95 (see Appendix Figure E.7). Additionally, we include the industry's employment growth in 2011 interacted with the year fixed effect to account for the effects of domestic factors that correlate over time.

A related threat to identification is the confounding effects of changes in U.S. trade policy. For example, if the trade war between the U.S. and China during Trump's administration diverted trade towards (or away from) Canadian sectors affected by the H-1B restrictions, $\hat{\beta}$ would 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 and interacted with year dummies: the share of exports in total sales, and the share of service exports in total exports.

Another concern arises from reverse causality, which occurs when immigrants choose where to locate. The expansion of firms operating within a market might be the cause of increased immigration, rather than the reverse. To address reverse causality concerns and insulate our estimates from local shocks, we include labor market-year fixed effects, effectively comparing firms that were located in the same labor market but were differently exposed to the H-1B restrictions. 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.

Finally, firms that typically hire immigrants might experience relatively faster growth due to the ongoing immigration inflows, even in the absence of the H-1B restrictions. Therefore, we aim to compare firms with similar reliance on immigrant labor but with different exposure to the H-1B policy change. To do so, we control for the firms' immigrant share of the wage bill and the log of one plus the number of likely skilled immigrants in 2016, both interacting with year dummies.

3.3.2 Results

Effects on Canadian workers We begin the analysis by showing that the new H-1B restriction increased the net hiring of immigrant workers relative to the firms' employment level in 2016, as motivated in the construction of $Intensity_i$. The event-study coefficients plotted in Figure 4a show that it was only after the new U.S. policy was implemented that firms with higher exposure increased their hiring of immigrants compared to firms with lower exposure.

Firms that hired more immigrants also hired more native-born workers. The ratio of the estimates of the response of hiring Canadian and immigrant workers in Figure 4a suggest that, on average, a firm hires approximately 0.5 additional Canadian workers per immigrant hired, due to the H-1B restrictions. The impact is also detectable when we study the response of the stock of native-born workers. The estimates of the log(Canadian employment) shown in Figure 4b imply that the average-exposed firm in the skilled service sector would be expected to have a 1.3% higher number of Canadian employees in 2018 than it would have had without the H-1B restrictions.

The 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.

We also find that, in 2008, earnings per Canadian worker and the median earnings dropped in firms that were relatively more exposed. This drop, along with the fact that more-exposed firms were intensive in occupations that were more impacted by the U.S. restrictions, suggests that earnings per native worker in more affected occupations declined compared to less-affected ones.[22]

Effect on production and exports 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 a 1% increase in sales than it would have registered in the absence of the H-1B restrictions. This estimate implies that an additional immigrant hired in 2017-2018 translated into an increase of C$112,000 earned in 2018 for the median firm in the skilled service sector, which represents 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 event studies in column 12 in Appendix Table E.6).

Our results so far suggest that firms expanded by increasing their overall labor input in proportion to their production. For instance, our estimate of β_{2018} for the log sales closely aligns with our estimates for employment growth given by the sum of our estimates for immigrant and Canadian net hiring in relation to the employment level in 2016 (or by our estimate for the log of employment in column 6).[24] Additionally, we find that firms increased the share of immigrants in the wage bill (Column 8 in Appendix Table E.6), suggesting that production may have become more immigrant intensive.

The rise in total sales in 2018 is in part explained by the growth in exports, which exhibited

[22] Column 7 in Appendix Table E.6 shows the drop in earnings per worker, including all workers.

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

a delayed yet more-significant response compared to overall sales. Figure 4e shows that the restrictions led to an increase in the share of exports in total sales in 2018 of 0.34 percentage points or 8%. A back-of-the-envelope calculation suggests that exports explain 38% of the increase in sales. The increase in the share of exports in total sales is explained by an increase in the exports of firms that were already exporting (e.g., intensive margin).[25] Figure 4f plots the estimates for the log of exports and, thus, excludes observations with zero exports. These estimates imply that exports were 7.4% higher for the average exposed exporter in the skilled service sector, due to the H-1B restrictions.

Effect on domestic firms Prior research found that American multinational corporations that have locations in both the U.S. and Canada increased employment in Canadian affiliates due to H-1B restrictions (Glennon, 2023). To understand whether our findings are attributed to the presence of MNCs or are a feature of domestic firms' responses, we estimated equation (3) for the main outcome variables excluding MNCs and obtain estimates that are similar to our baseline estimates. These results imply that the effects of U.S. immigration restrictions extend beyond their direct impact on the affected (American) firms, as previously documented. This novel fact suggests that MNC linkages might not be needed for the U.S. restrictions to affect third countries.

3.3.3 Robustness exercises

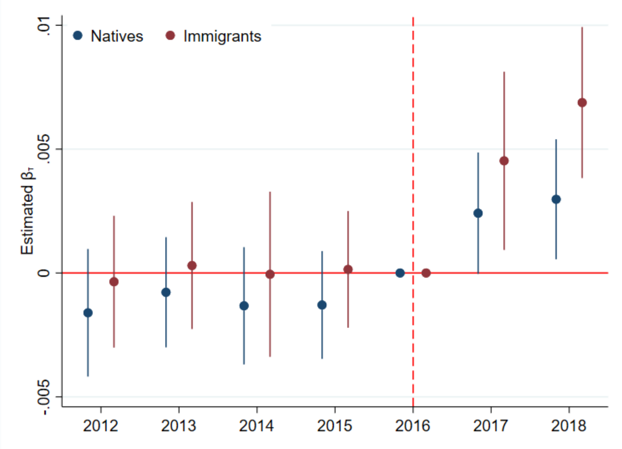
In Appendix section E, we address potential identification concerns and explain in detail the corresponding robustness exercises. First, we present estimates of the effects of the H-1B policy change that only use the within-industry variation (e.g., we include industry-year fixed effects in our baseline specification). Second, we test the potential impacts of the 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 that our estimates are also robust to including additional control variables to account for changes in Canadian immigration policy leading up to the U.S. policy change.

4 Theory: Immigration policy and international trade

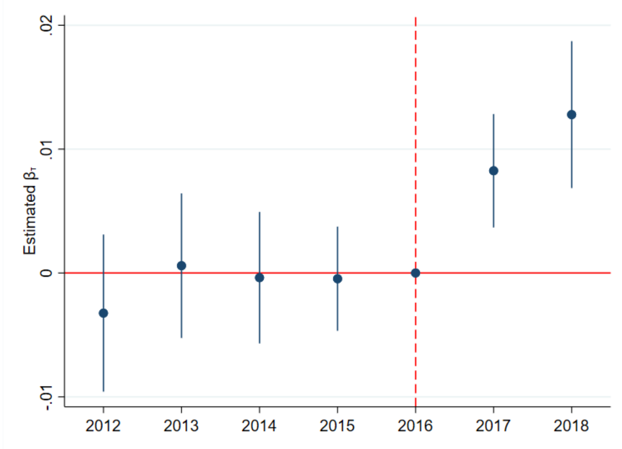
We documented that U.S. immigration restrictions affected immigration to Canada and production and domestic workers' labor market outcomes in Canada. Our next goal is to understand the welfare effects on Canadian workers associated with our empirical findings and the role of international trade in the welfare effects of U.S. immigration policy on American workers. These goals ask for a quantitative general equilibrium model of international trade, international migration, and migration policy that rationalizes our empirical facts and can be quantified using

[25] To obtain more-precise estimates of the response of the log of exports, we restricted the observation to those with export values above $8,000, which is given by the first percentile of the sales distribution.

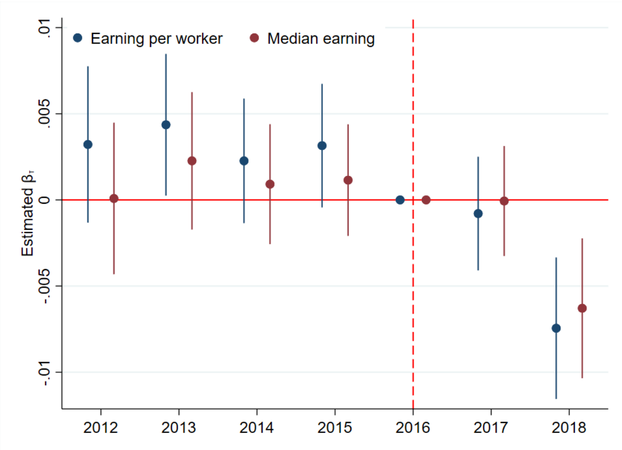
Figure 4: Effect of H-1B restrictions on Canadian firms



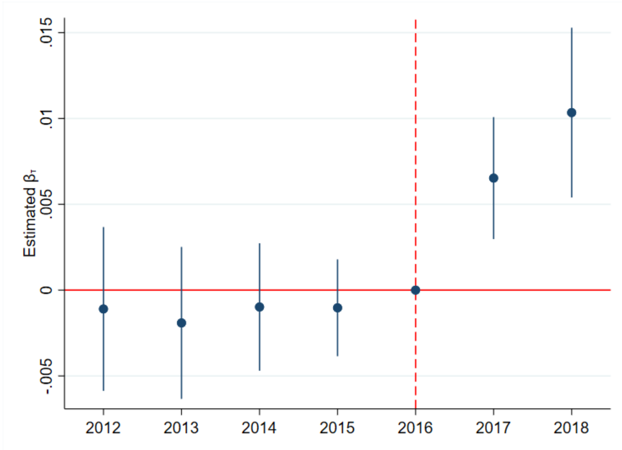
(a) Hiring relative to employment in 2016



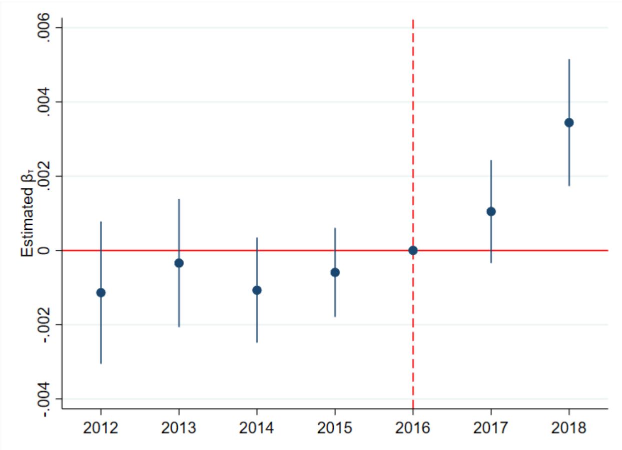
(b) Canadian employment (in log)



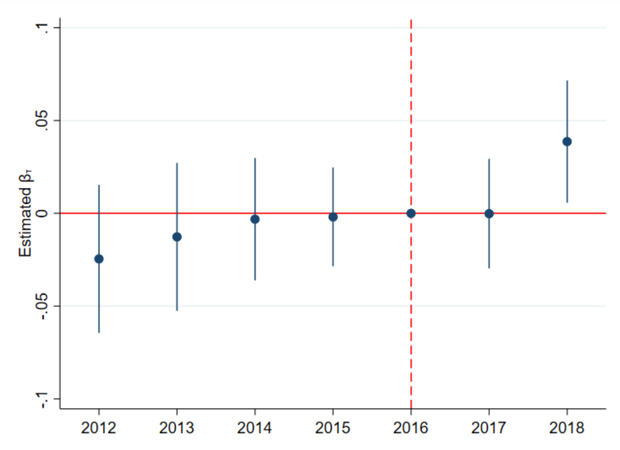
(c) Earning of native workers (in log)



(d) Sales (in log)



(e) Exports relative to total sales



(f) Exports (in log)

Note. The y-axis plots the estimated event-study coefficients, β_τ, of equation (3) multiplied by the average value of the $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The outcome variables considered are net hiring of immigrants and net hiring of Canadians with respect to the employment level in the baseline year, 2016 (panel a), the log number of Canadian workers (panel b), the log earnings per native worker and the log median earnings of native workers (panel c), the log sales (panel d), the log export sales relative to total sales (panel e), and the log export sales (panel f). The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals. The plotted coefficients correspond to those reported in Appendix Table E.6.

our data. This section sets up the model and analytically studies how changes in the probability of granting U.S. visas spill over to other countries and affect the welfare of American workers. To that end, we introduce new modeling assumptions so that immigration policy is given by an exogenous probability of granting visas and workers make their migration decisions with uncertainty about whether they will obtain a visa.

4.1 Building blocks of the model based on empirical facts

We aim to shed light on whether U.S. skilled immigration restrictions may affect the comparative advantages of the U.S., Canada, and other countries receiving the immigrants affected by the restrictions. To that end, we set up a standard multi-country, multi-sector model where international trade is driven by countries' comparative advantages in producing different goods.

We use the evidence of the effects of the inflow of immigrants on production and native-born workers' outcomes to guide the relevant modeling assumptions. The decrease in earnings per worker suggests that the increase in the scale of production of firms may be mainly driven by a drop in labor costs or wages. Additionally, the fact that sales per worker and earnings per native worker did not increase suggests that economies of scale may not be the primary driver of the increase in production. Therefore, we assume that production features constant returns to scale and requires both immigrants and native workers.

The fact that the hiring of native-born workers increased and earnings per native worker decreased is consistent with a classic model with competitive labor markets where immigrants and Canadians working in different occupations are imperfect substitutes. In this framework, an inflow of immigrants in a given occupation affects the labor market outcomes of Canadian workers in two ways. First, an inflow of immigrants can make hiring foreign labor cheaper compared to hiring Canadian workers, inducing firms to substitute Canadians with immigrants. Second, it can drive down overall labor costs, inducing firms to expand their production scales. For Canadian workers for which the scale effects surpass the substitution effects, we would expect firms to increase the demand for and hiring of these workers. Additionally, we would expect that the wage effects of an inflow of immigrants are less beneficial (or more detrimental) for Canadian workers who are closer substitutes for these immigrants.

4.2 Setup

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

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

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

Workers' heterogeneity We assume that workers are heterogeneous due to differences in productivity across sectors. Each worker ι from group co draws a random number of efficient units in sector k in country d, $a_{codk}(\iota)$, from distribution F_{codk}^a. Given that this distribution is worker group-destination country sector specific, workers within each group co in country d are *ex-ante* identical but they are heterogeneous after $a_{codk}(\iota)$ is realized. Workers are also heterogeneous due to their preferences for applying for visas from different countries and staying at their home countries. We assume that worker ι draws preference shocks $\nu_{cod}(\iota)$ from distribution F_{cod}^{ν}.

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

Workers' choice of sector Consider workers living in country d: What sector do they choose to work in? Each worker in country d draws $a_{codk}(\iota)$ from a Frechet distribution with dispersion parameter κ and scale parameter a_{codk}, which can be interpreted as the comparative advantage of workers co in sector k in country d.[26] Workers choose the sector that yields the highest utility $u_{codk}(\iota)$, which is given by the real income net of the migration costs:

$$u_{codk}(\iota) = \frac{\zeta_{cod}\ a_{codk}(\iota)\ w_{odk}^{f}}{P_d} \qquad u_{cock} = \frac{a_{cock}(\iota)\ w_{ock}^{n}}{P_c} \tag{6}$$

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

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

Workers' migration decision Workers must apply for a visa if they want to migrate to country d. We assume that workers can only apply for one visa.[27] If their visa applications is denied, the workers have to stay in their home countries. To make the choice decision under uncertainty tractable in general equilibrium, we bring the expected utility theory into an otherwise standard migration model. We model individuals as risk-averse agents by assuming that the payoff in each contingent state is given by the log of the utility in that state, u_{cod}.

When applying for a visa, workers choose the country with the highest utility $U_{cod}(\iota)$:

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

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

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

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

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

where $l_{dk}(\omega)$ is the production of variety ω, $z_{dk}(\omega)$ is the productivity level of the technology used to produce variety ω, ψ_{dko} represents the efficiency units of occupation o, $l_{dko}(\omega)$ are the units of labor services of occupation o used to produce ω, and $\eta > 0$ is the elasticity of substitution between the occupations. We assume that $z_{dk}(\omega)$ is a random variable distributed Frechet with shape parameter $\theta > \sigma - 1$ and scale parameter T_{dk} as in Eaton and Kortum (2002).[28]

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

[28] The model is flexible to accommodating agglomeration effects. For example, the total factor productivity could be given by the interaction of an exogenous component specific to the variety $z_{dk}(\omega)$ and an endogenous

The occupation's services are produced by combining the effective units of native-born 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 native-born workers as having comparative advantages in different tasks (Ottaviano et al., 2013; Peri and Sparber, 2011, 2009). Specifically, the production function takes the following form:

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

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

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

4.3 Labor supply based on workers' migration and sector choices

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

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

and the expected real wage net of the migration costs in destination d and at home are $u_{cod} = \Gamma_{\kappa} \frac{\zeta_{cod}\, \Phi_{cod}}{P_d}$ and $u_{coc} = \Gamma_{\kappa} \frac{\Phi_{coc}}{P_c}$, where Γ_{κ} is the gamma function evaluated at $\frac{\kappa-1}{\kappa}$.

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

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

where $u_{coe} \equiv \Gamma_{\nu_d} \left(\sum_{d \in \mathcal{C}^d} (u^{p_{cod}}_{cod}\; u^{1-p_{cod}}_{coc})^{\nu_d}\right)^{\frac{1}{\nu_d}}$ is the expected utility of emigrating. Due to the law of large numbers, π_{cod} and π_{coc} are also the fractions of workers co choosing either destination country d or the home country, respectively. Equation (10) shows how changes in the approval

sector-level component given by the number of efficient units of skilled labor (Bound et al., 2017).

rate in destination country d' affect migration patterns to other countries, π_{cod} and π_{coc}, by directly affecting the expected value of emigrating u_{coe}.

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

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

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

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

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

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

Native-born labor supply The stock of workers who supply labor at home (immigration-origin countries) is given by the number of workers who cannot make migration decisions, plus those who choose to stay at home, plus those who choose to emigrate but are denied a visa:

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

For immigration-destination countries $c \in \mathcal{C}^d$, $L_{coc} = L_{co}$. The supply of efficient units of labor in occupation o in sector k is

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

4.4 Labor demand based on firms' hiring decisions

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

$$LD^x_{dko} = \frac{s^x_{dko} \;\; s_{dko} \;\; Y_{dk}}{w^x_{dko}} \qquad x = \{n, f\} \tag{16}$$

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

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

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

The total sales of sector k in country d, Y_{dk}, are given by the sum of the sales to each country c. Each country's expenditures on goods produced by sector k in country c are defined by three terms: the country's total expenditures X_c, the share of the expenditures that are allocated to goods from different sectors α_{ck}, and the share of the expenditures in k for goods bought from producers in different countries λ_{dck}:

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

where $P_{ck} \equiv \Gamma\left(1 - \frac{\sigma-1}{\theta}\right)^{-1} \left(\sum_d T_{dk}(\tau_{dck}\; w_{dk})^{-\theta}\right)^{-\frac{1}{\theta}}$ is the price index in sector k in country c. We assume that trade is balanced, implying that total spending equals total labor income, $Y_c \equiv \sum_k Y_{kc}$:[29]

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

4.5 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, $\Upsilon \equiv \{\nu_d, \nu_h, \alpha, \sigma, \epsilon, \eta, \theta, \kappa\}$ be the set of parameters, and $\mathrm{P} = \{p_{cod}\}$ be the visa approval rates. Given $(\Omega, \Upsilon, \mathrm{P})$, an equilibrium is a collection of the following:

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

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

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

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

such that

1. workers' migration decisions and sector allocations satisfy equations (9) and (10);

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

3. the markets for labor and goods all clear:

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

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

4.6 Effects of U.S. immigration restrictions: comparative statics

In this section, we study analytically the effects of a drop in U.S. visa approval rates on other economies and the welfare of American workers. For notational convenience, we let $dx \equiv x' - x$ and $\tilde{x} \equiv \log(x)$, where x and x' denote the equilibrium level of endogenous variable x before and after the change in the immigration policy.

4.6.1 Effects on third countries

We derive the analytic results for the effects of infinitesimal changes in the U.S. visa approval rate $p_{co,usa}$ on other economies absorbing the immigrants affected by the restrictions. We focus on tracing out the direct effects of $p_{co,usa}$ on the outcomes of the receiving economy to explain the underlying mechanisms and roles of the parameters.

Change in applications A reduction in the probability of obtaining a U.S. visa $p_{co,usa}$ reduces the average value of emigrating $\widetilde{u}_{coe}$, depending on the conditional probability of choosing to emigrate to the U.S., $\pi_{co,usa}$, which acts as the weight of the average value of emigrating, and on the value of securing a U.S. visa $(\tilde{u}_{co,usa} - \tilde{u}_{coc})$:

$$d\widetilde{u}_{coe} = \pi_{co,usa}\, (\tilde{u}_{co,usa} - \tilde{u}_{coc})\, dp_{co,usa} \tag{22}$$

where we assume that the average real wage in the U.S. net of the migration costs is larger than that at home, $\tilde{u}_{co,usa} > \tilde{u}_{coc}$, which is consistent with our data. The reduction in $\tilde{u}_{coe}$ directly affects the migration flows to other countries, according to equation (23):

$$d\widetilde{\pi}_{cod} = -\nu_d\, d\widetilde{u}_{coe} + \epsilon_{cod} \quad , \quad d\widetilde{\pi}_{coe} = \nu_h\, \pi_{coc}\, d\widetilde{u}_{coe} + \epsilon_{coe} \tag{23}$$

where ϵ_{cod} and ϵ_{coe} group the effects of changes in the equilibrium wages around the world due to the U.S. policy (see Appendix C.2.1 for details of the derivation). The equation on the left shows that when the average value of emigrating declines due to the U.S. restrictions, the relative attractiveness of emigrating to country d increases, leading to a larger proportion of workers who desire to emigrate choosing country d ($d\widetilde{\pi}_{cod} > 0$). This effect is stronger when country d and the U.S. are close substitutes for emigration (higher ν_d). The equation on the right shows that a drop in the expected benefits from emigrating, all else equal, increases the relative value of staying home and decreases the proportion of workers seeking to emigrate ($d\widetilde{\pi}_{coe} < 0$). This effect is stronger when home and abroad are closer substitutes (higher ν_h) and when home tends to be a relatively good option (e.g., higher initial probability of choosing home π_{coc}).

Therefore, the direction and size of the effect of U.S. immigration restrictions on immigrating to country d depend on the strength of these forces, as illustrated by equation (24)

$$d\widetilde{App}_{cod} = d\widetilde{\pi}_{cod} + d\widetilde{\pi}_{coe} = (\nu_h\, \pi_{coc} - \nu_d)\, \pi_{co,usa}\, (\tilde{u}_{co,usa} - \tilde{u}_{coc})\, dp_{co,usa} + \eta_{cod} \tag{24}$$

where $\eta_{cod} \equiv \epsilon_{cod} + \epsilon_{coe}$.

Increase in immigrant labor force An inflow of workers shifts the immigrant supply of labor co in country d according to $d\widetilde{L}_{cod} = (1 - \psi^{imm}_{cod})\, d\widetilde{App}_{cod}$, where $(1 - \psi^{imm}_{cod})$ is the fraction of workers of nationality c in occupation o working in destination country d accounted for by the flow of new immigrants.

Drop in production costs Immigrant workers co in country d will sort themselves across various sectors based on their sectorial shares π_{codk}. This leads to a sector-specific expansion in the overall foreign labor supply of services from occupation o: $d\tilde{l}^f_{dko} = \sum_{o,c\neq d} s^f_{ocdk}\, d\tilde{L}_{ocd}$, where s^f_{ocdk} is the share of nationals from country c in the immigrant wage bill of occupation o in sector k in country d. This immigrant labor supply shock reduces their wages $\tilde{w}^f_{dko}$. The relative increase in the supply of immigrant labor also affects the wages of their native-born counterparts, depending on how substitutable immigrants and native-born workers are:

$$d\tilde{w}^n_{dko} = d\tilde{w}^f_{dko} + \frac{1}{\epsilon}(d\tilde{l}^f_{dko} - d\tilde{l}^n_{dko}) \tag{25}$$

In the limiting case of perfect substitution, $\epsilon \to \infty$, the drop in native-born workers' wages is as strong as that of immigrant wages. This decline in immigrant and native-born workers' wages reduces the cost of services from occupation o, w_{dko}, which drives down the wages of other occupations $o' \neq o$, $w_{dko'}$, depending on the elasticity of substitution between occupations η.

Finally, the drop in the wages of the various types of workers affects unit costs, depending on the share of each labor input in the total cost of the sector:

$$d\tilde{c}_{dk} = \sum_{o} s_{dko} \left(s^{n}_{dko}\, d\tilde{w}^{n}_{dko} + s^{f}_{dko}\, d\tilde{w}^{f}_{dko} \right) \tag{26}$$

This equation shows that sectors with a cost structure that is skewed towards workers with bigger wage reductions will experience greater unit cost reductions. Moreover, we can rewrite the change in the unit cost as follows:

$$d\tilde{c}_{dk} \propto \underbrace{\sum_{o,c} s_{ocdk}\, d\tilde{L}_{ocd}}_{\text{Shift-share exposure}_k} + u_{kd} \tag{27}$$

where s_{ocdk} is the share of labor input co (including $c = d$) in the wage bill of sector k in country d, and u_{kd} is a structural error given by the weighted average of deviations of the elasticity $\frac{d\tilde{w}^{x}_{dko}}{d\tilde{l}^{x}_{dko}}$ relative to the average elasticity. This shift-share exposure measure, which resembles the empirical exposure measure (4), shows that sectors whose workforce compositions tilted towards the nationalities and occupations affected by the policy experienced a larger drop in production costs.

Increase in production and exports The reduction in production costs decreases consumption prices and consumers adjust their spending patterns by favoring relatively cheaper varieties. The resulting change in sales is given by

$$d\tilde{Y}_{dk} = \sum_{c} \omega^{Y}_{dck} \left(\underbrace{-\theta(d\tilde{c}_{dk} - \sum_{j} \lambda_{jck}\, d\tilde{c}_{jk})}_{d\tilde{\lambda}_{dck}} + \underbrace{-(\alpha-1)(d\tilde{P}_{ck} - d\tilde{P}_{c})}_{d\tilde{\alpha}_{ck}} + d\tilde{X}_{c} \right) \tag{28}$$

where ω^{Y}_{dck} is the share of country c in the total sales of sector k in country d. $d\tilde{\lambda}_{dck}$ measures the reallocation of expenditures (and sales) across varieties within the same sector and depends on how substitutable the varieties produced by sellers from different countries are (i.e., the trade elasticity θ). $d\tilde{\alpha}_{ck}$ measures the reallocation of expenditures across sectors and depends on the elasticity of substitution of goods from different sectors, α. $d\tilde{X}_{c}$ captures the change in the overall market size of country c.

In summary, our model predicts that a reduction in the probability of granting U.S. visas can increase immigration to a third country if immigrants consider it a close substitute to the U.S. This inflow of immigrants reduces the unit cost of production, resulting in an increase in sales and exports. These mechanisms are consistent with the evidence presented in sections 3.2 and 3.3.

4.6.2 Effects of U.S. immigration restrictions on American workers' welfare

We now study the channels through which the U.S. restrictions affect the welfare of American workers, highlighting the effects of increasing migration to other countries. We derive an expression for the effects of infinitesimal changes in the immigrant labor supply l^f_{dko} in a simplified version of our model where we assume that the labor supply is exogenous, the domestic labor supply l^n_{dko} is fixed, the preferences are Cobb Douglas with shares α_{dk}, and the occupation nest in equation (7) is a Cobb Douglas ($\eta = 1$) with shares s_{dko}.

The change in the welfare of a native-born worker in the U.S. working in occupation o in sector k, denoted by $W^n_{usa,ko}$, coincides with the change in the real wage because trade is balanced. The worker's wage is the marginal revenue product of their labor because labor markets are perfectly competitive. Therefore, the wages of American workers associated with the production function (7)-(8) are

$$w^n_{usa,ko} = p(\omega)_{usa,k}\ z(\omega) \left(\frac{l_{usa,ko}}{l_{usa,k}}\right)^{-1} \left(\frac{l^n_{usa,ko}}{l_{usa,ko}}\right)^{-\frac{1}{\epsilon}} \tag{29}$$

We can replace $p(\omega)_{usa,k}\ z(\omega)$ with $\frac{Y_{usa,k}}{l_{usa,k}}$ because goods markets are perfectly competitive and total costs equal total sales; that is, $p(\omega)_{usa,k} = \frac{c_{usa,k}}{z(\omega)}$ and $c_{usa,k}\ l_{usa,k} = Y_{usa,k}$. We then obtain the following expression for the welfare of American workers:

$$W^n_{usa,ko} = \frac{w^n_{usa,ko}}{P_{usa}} = \frac{Y_{usa,k}\quad l^{\frac{1}{\epsilon}-1}_{usa,ko}\quad (l^n_{usa,ko})^{-\frac{1}{\epsilon}}}{P_{usa}} \tag{30}$$

where $Y_{usa,k} = \sum_j\ \lambda_{usa,jk}\ \alpha_{jk}\ X_j$, where country j includes the U.S.

Proposition:

Suppose that the U.S. imposes restrictions that lead to infinitesimal changes in the immigrant labor supply in the U.S. $\tilde{l}^f_{usa,ko} < 0$ *and in a third country c* $\tilde{l}^f_{cko} > 0$*. The log change in the* *welfare of an American worker in occupation o in sector k is*

$$d\tilde{W}^{n}_{usa,ko} = \overbrace{-\left(1-\frac{1}{\epsilon}\right) s^{f}_{usa,ko}\, d\tilde{l}^{f}_{usa,ko}}^{\text{Substitution effect}_{usa,ko}}$$

$$\overbrace{\overbrace{-\sum_{k}\alpha_{usa,k}\,\lambda_{usa,usa,k}\;\; d\tilde{c}_{usa,k}}^{\text{Price effect}_{usa}<0}\overbrace{-\,\theta\sum_{j}\omega^{Y}_{usa,jk}\,(1-\lambda_{usa,jk})\,d\tilde{c}_{usa,k}}^{\text{Competition effect}_{usa,k}<0}}^{\text{Domestic general equilibrium effects - increasing costs in the U.S.}} \tag{31}$$

$$\underbrace{\underbrace{-\sum_{k}\alpha_{usa,k}\,\lambda_{c,usa,k}\;\; d\tilde{c}_{ck}}_{\text{Price effect}_{usa}>0} + \underbrace{\theta\sum_{j}\omega^{Y}_{usa,jk}\,\lambda_{cjk}\,d\tilde{c}_{ck}}_{\text{Competition effect}_{usa,k}<0}}_{\text{International general equilibrium effects - decreasing costs elsewhere}} + \epsilon_{usa,k}$$

where $\epsilon_{usa,k} = \sum_j \omega^{Y}_{usa,jk}\;\; d\tilde{X}_j$ *is the change in the market size faced by U.S. sectors, and* $d\tilde{c}_{dk} = \sum_o s_{dko}\,\varepsilon_{dko}\,d\tilde{l}^{f}_{dko}$ *where* $\varepsilon_{dko} \equiv \varepsilon^{f}_{dko} + \frac{s^{n}_{dko}}{\epsilon}$*, and* ε^{f}_{dko} *is the elasticity of the immigrant wage* w^{f}_{dko} *with respect to the supply of immigrants* l^{f}_{dko}*,* $\varepsilon_{dko} \equiv \frac{d\tilde{w}_{dko}}{d\tilde{l}^{f}_{dko}}$.

Proof: See Appendix C.2.2.

The "substitution effect" shows the change in the wages of an American worker due to the changes in the supply of immigrant labor in their occupation and sector of employment, while holding the production scale constant. For a given reduction of the immigrant labor force, $d\tilde{l}^{f}_{usa,ko} < 0$, there will be a stronger increase (or weaker decrease) in the American worker's wage when the elasticity of substitution between American workers and immigrants is higher or when immigrants account for a larger share of the labor force $s^{f}_{usa,ko}$.

The "domestic general equilibrium effects" arise when the lower availability of immigrant labor in the U.S. increases the production costs of U.S. sectors ($d\tilde{c}_{usa,k} > 0$). Increasing U.S. costs increase the price index of the American consumption bundle according to the share of the good in total expenditures $\alpha_{usa,k}\lambda_{usa,usa,k}$, which reduces the purchasing power of American wages (Price Effect$_{usa} < 0$). Also, higher U.S. costs reduce the demand for U.S. goods and the sales of U.S. sector k. 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 (competition effect$_{usa,k} < 0$). Therefore, this standard general equilibrium effect unambiguously reduces the welfare of American workers.

The "international general equilibrium effects" arise when increasing migration to other countries that engage in international trade affects these countries' production costs. On one hand, decreasing costs in country c reduce the price index of the American consumption bundle according to their share in expenditures $\alpha_{usa,k}\lambda_{c,usa,k}$, which increases the purchasing power of

American wages (Price Effect$_{usa} > 0$).

On the other hand, a reduction in the production cost of country c diminishes the international demand for American goods and their prices, in turn reducing the value of the marginal product of American workers and American wages. This competition effect is stronger when the overlap between the markets served by country c and by the U.S. is larger. For example, immigrants migrating to Canada can have a greater adverse impact on American wages than those migrating to countries like the Philippines, which does not typically compete with the U.S. in international markets. This market overlap is captured by $\sum_j \omega^Y_{usa,jk} \lambda_{cjk}$ in equation (31), where λ_{cjk} gauges the size of the expansion of producers from country c in market j due to the drop in costs $d\tilde{c}_{ck} < 0$ and $\omega^Y_{usa,jk}$ is the share of country j in total U.S. sales.

In summary, migration to other countries affects American workers' welfare through international trade by affecting the export prices of goods produced in U.S. sectors and the import prices of consumption goods. The overall effects can be either positive or negative depending on whether the positive price effect or the negative competition effect dominates.

In the next section, we explain how we calibrate the model, focusing on the parameters driving the welfare effects of U.S. immigration restrictions.

5 Calibration based on our data and regression estimates

We quantify the effects of U.S. immigration restrictions by solving the model in proportional changes following the "hat algebra" approach pioneered by Dekle et al. (2008). This procedure requires data on initial visa approval probabilities, earnings per worker in the U.S. 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 D describes the calibration of $\mathrm{P}, \mathbf{U}_u, \mathbf{S}^M$, and $\mathbf{S}^{NM}$ and the "hat algebra" approach.

Given the data requirements on $\mathbf{U}_u, \mathbf{S}^M$, and $\mathbf{S}^{NM}$, we group countries, occupations, and sectors into broad categories. We group countries into four categories: the U.S., Canada, India, and a constructed rest of the world (RoW); occupations into six categories: business professionals, computer scientists, engineers, managers, other H-1B occupations, and non-H-1B occupations; and sectors into eight categories: agriculture and mining (Ag & Min), finance (FIN), information and cultural sector (IC), business and professional services (BPS), high-tech manufacturing sectors, low-tech manufacturing sectors, a wholesale and retail trade sector (WRT), and a constructed sector that includes the remaining sectors. Following Galle et al. (2023), we exclude from the analysis the non-profit and public administration sectors.

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 trade elasticity θ, the elasticity of supply to sectors κ, and the elasticity of substitution of broad sectors η to estimates from the literature; we estimate the elasticity of substitution between emigrating to the U.S. and Canada ν_d directly from a coefficient of a reduced-form regression derived from the model; and we calibrate the elasticity of substitution between emigrating and staying at home ν_h, the elasticity of substitution across sectors α, and the elasticity of substitution between immigrants and natives ϵ, indirectly based on our event-study estimates. We elaborate on this decision in the following subsections.

We proceed in two steps. We first calibrate $\Upsilon^E \equiv (\theta, \kappa, \eta, \nu_d)$ outside the model. Second, we fix $(\mathrm{P}, \Upsilon^E, \mathbf{S^M}, \mathbf{S^{NM}}, \mathbf{U}_u)$ and input the observed $dp_{o,usa}$ from the data into our model. We solve the equilibrium for a given set of parameters Υ^I. We choose $\Upsilon^I \equiv (\nu_h, \alpha, \epsilon)$ so that the equilibrium response in the model matches the response implied by our reduced-form estimates from sections 3.2 and 3.3.

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

Table 1: Calibration

Structural Parameters Υ			Value
θ	Trade elasticity	Romalis (2007)	6.7
η	Elast. of subst. between occupations	Goos et al. (2014)	0.9
κ	Elast. of supply to sectors	Galle et al. (2023)	2.8
ν_d	Elast. of subst. of emigrating to the U.S. vs Canada	IV estimation of regression (see section 5.1)	3.6
ν_h	Elast. of subst. of emigrating vs staying at home	Indirect inference: match the response of Canadian visa applications (see section 5.3)	2.3
ϵ	Elast. of subst. foreign- and native-born workers	Indirect inference: match the response of earnings per Canadian worker (see section 5.3)	4.3
α	Elast. of subst. across sectors	Indirect inference: match the response of sales (see section 5.3)	1.2

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

5.1 Instrumental variable approach: ν_d

The novel part of our model is to incorporate immigration policy in a way that is directly observable in the data without losing tractability in general equilibrium. This allows us to estimate the migration decision parameter ν_d directly from our data using observed immigration policy changes.

Standard quantitative models of immigration often assume that migrants face migration costs that are proportional to the real wage at their destination. Relative to these models, our model delivers a new prediction, given by equation 32, that becomes the starting point of our approach to estimating ν_d. In our model, immigrant groups are differently affected by a common U.S. policy change, depending on the value of obtaining a U.S. visa, which is immigrant-group-specific.

According to the country choice decision 4.2, the log of the number of workers in occupation o from country c choosing Canada relative to the U.S. is given by

$$\tilde{App}_{co,can,t} \;-\; \tilde{App}_{co,usa,t} = \nu_d \Bigg(\; p_{co,can,t} \Big(\tilde{u}_{co,can,t} - \tilde{u}_{coct} \Big) \;-\; p_{co,usa,t} \Big(\tilde{u}_{co,usa,t} - \tilde{u}_{coct} \Big) \Bigg) \tag{32}$$

where the relative difference between the number of applications to Canada and those to the U.S. is determined by the relative payoff difference of residing in one country versus the other. Since $\tilde{u}_{codt} = \tilde{w}_{codt} - \tilde{P}_{dt}$, we can estimate the parameter ν_d through the following equation:

$$\tilde{App}_{co,can,t} \;-\; \tilde{App}_{co,usa,t} = \nu_d \; p_{co,usa,t} \; \tilde{w}_{co,usa,t} + \eta_{cot} \tag{33}$$

where η_{cot} is a structural error that includes the effect of Canadian immigration policy ($p_{co,can,t}$), wages and prices in Canada, and the cost to migrate to Canada (through $\tilde{u}_{co,can,t}$), wages and prices at home (through the average wage $\tilde{u}_{coct}$), prices in the U.S. ($P_{usa,t}$), and the costs of migrating to the U.S. $\tilde{\zeta}_{co,usa}$.

As $p_{co,usa,t} \; \tilde{w}_{co,usa,t}$ correlates with this structural term, we include immigrant-group fixed effects d_{co}, occupation-year fixed effects d_{co}, and nationality-year fixed effects d_{co}, and follow an IV approach. The instrument is $Intensity_{co}\; 1(t \geq 2017)$, where $Intensity_{co}$ is given by the interaction of the denial rates of continuing H-1B visas dr_o and the fraction $\pi_{co,usa}$ (see Section 3.2.1), and the IV estimate is 3.6 (s.e: 1.3). Appendix Table E.9 includes the estimation details and robustness exercises. In the Appendix D.2 we explain in detail the IV approach, including how the model suggests that the relevant condition for the instrument is met.

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

Equation 28 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 E.U. imports from Canada and it exploits plausible exogenous variation in the change in the tariff preference that the U.S. 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 U.S., and the granularity of the sectorial classification is similar to theirs. Therefore, we set $\kappa = 2.79$, based on their estimates.

5.3 Indirect inference approach: ν_h, α, and ϵ

Due to data limitation, we can not estimate ν_h, α, and ϵ directly from a coefficient of an equation derived from the model as we did for ν_d. Instead, we calibrate these values jointly to match the effect of the H-1B policy change on Canadian visa applications, sales, and earnings per native-born worker respectively.

The parameter ν_h regulates the change in the relative number of immigrants choosing to stay at home relative to emigrating $\frac{\pi_{coc}}{1-\pi_{coc}}$ due to changes in $p_{co,usa}$. Given that we do not observe π_{coc} directly from the data, we cannot use the relationship between $\frac{\pi_{coc}}{1-\pi_{coc}}$ and $p_{co,usa}$ to estimate a reduced-form coefficient and directly recover the value of ν_h. However, equation (24) shows that the relationship between the response of the log of Canadian applications and $\pi_{co,usa} dp_{o,usa}$ across immigrant groups contains information about the underlying value of ν_h.[30] Therefore, we estimate this empirical regression using both real and model-generated data and follow an indirect inference approach to infer the value of ν_h:

$$d\widetilde{App}_{co,can} = \gamma_{\nu_h}\ \pi_{co,usa}\ dp_{o,usa}\ +\ \epsilon_{co} \tag{34}$$

A challenge in estimating this equation with real data is that Canadian applications might be affected by other factors than the H-1B policy change. We must isolate the effects of the U.S. policy change from other factors that are absent in our model to obtain the outcome variable from the real data that is comparable with that from the model. We do so by computing the predicted change in Canadian applications due to the H-1B policy change using our estimate of θ_{2018} in equation (1). Given that the categories of immigrant groups in this empirical regression are more granular than those in the model (and in equation (34)), we aggregate the predicted effects to the level of granularity that is consistent with the model. See Appendix section D.3 for a detailed explanation. Figure 5a shows the scatter plot and coefficient estimates corresponding to (34) using real and model-generated data.

Parameter α regulates the change in sales across sectors due to changes in their relative prices or unit costs. The challenge is that while we have data on sales, we do not observe prices or unit costs. However, as explained in subsection 4.6.1, the drop in unit costs is stronger for sectors with a higher (shift-share) exposure to the inflow of immigrants induced by the policy change. We thus expect the strength of the empirical relationship between the change in sales across sectors with different shift-share exposure to contain information about α. We use this

[30] $\pi_{co,usa}\ dp_{o,usa}$ is the portion of the expression (24) that we can measure directly in the data.

empirical relationship, which is given by equation (35), to discipline the value of α:

$$\widetilde{dSales}_k = \gamma_\alpha \underbrace{\sum_{co} \omega^{wb}_{cok} \left(1 - \psi^{imm}_{co}\right) \pi_{co,usa}\, dp_{o,usa}}_{Intensity_k} + \epsilon_k \tag{35}$$

where ω^{wb}_{cok} is the share of immigrant group co in the wage bill of sector k, and $Intensity_k$ proxies the shift-share exposure measure in (27).[31] Again, we use our event-study regressions to isolate the causal effect of the policy change on sales. Since our empirical estimates for the sales response are at the firm level, we aggregate the firm-level responses to the sector level. Figure 5b shows the scatter plot and coefficient estimates corresponding to (35) using real and model-generated data on sales.

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-born workers in the labor market. While we do not have information on occupations at the firm level, we observe the overall earnings of native-born workers by sector. Therefore we establish an empirical relationship between the earnings per native-born worker and the immigrant supply shock faced by each sector. We then use this empirical relationship to calibrate ϵ using a similar approach as for sales. We simply replace sales in regression (35) with the earnings per native-born worker and use the corresponding causal estimates from section 3. Figure 5c shows the corresponding scatter plot and coefficient estimates.

Our calibrated values are $\nu_h = 2.3, \epsilon = 4.3, \alpha = 1.2$, which fall within the range reported in the literature. Regarding ν_h, our nested structure for immigrants' country of choice follows Allen et al. (2019), who explore how Mexican workers make migration decisions when selecting locations within the U.S. 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 of 4.6.[32] Finally, our calibrated value for the elasticity of substitution across our eight sectors (α) falls within the range of previous estimates in the literature, which varies depending on whether the categories are narrower or more general. For instance, in narrower categories such as 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).

Appendix Figure E.15 shows how the response of Canadian visa applications, sales, and earnings per native worker guide our choice of ν_h, α, and ϵ. These figures plot the estimates of γ_{ν_h}, γ_α

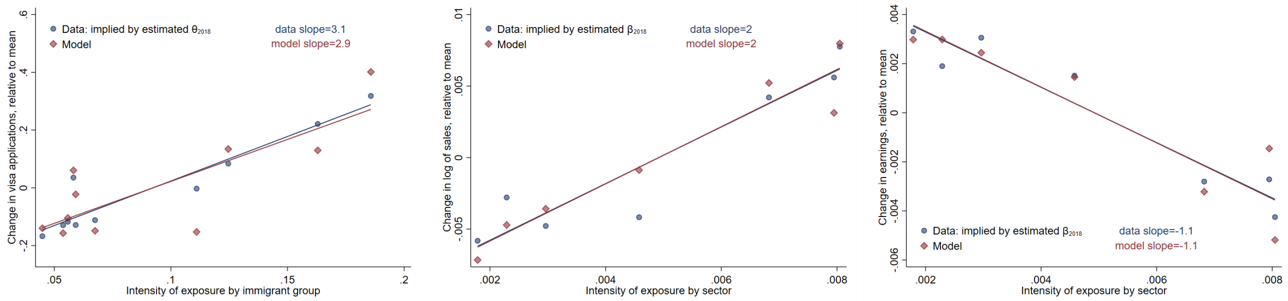
[31]Note that, by construction, $Intensity_k$ in the data and model regressions are identical.

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

and γ_ϵ using model-generated data against the value of the corresponding structural parameter while fixing all other parameters at their baseline values. As suggested by our analytical results, the coefficients γ_{ν_h}, γ_α and γ_ϵ are responsive to ν_h, α, and ϵ, respectively.

Figure 5: Calibration of $\Upsilon^I \equiv (\nu_h, \alpha, \epsilon)$ to match slopes using real data

(a) Canadian visa applications (b) Sales (c) Earnings per native worker



Note. The y-axis values of (a), (b) and (c) are the change in the logarithm of $App_{co,can}$, $Sales_k$ and $Earnings\ per\ native\ worker_k$ (relative to mean) respectively. Triangles represent model-generated data for $(\nu_h, \alpha, \epsilon) = (2.3, 1.2, 4.3)$, and circles represent the values implied by our actual data and event-study estimates. The x-axis in (a) is the exposure measure of immigrant groups given by $\pi_{co,usa}\ dp_{o,usa}$ as in equation (34), and in (b) and (c) is the exposure measure of sectors given by $Intensity_k$ as defined in equation (35). The values of the x-axis in the data and the model are identical by construction. The values of the parameters $(\nu_h, \alpha, \epsilon)$ are chosen jointly to minimize the difference between the data and mmodel slope in (a), (b), and (c).

5.4 Validation of the calibrated model

We validate the model by examining the matching of moments that were not targeted in the internal calibration procedure. In particular, we focus on the response of exports relative to total sales and native-born employment. Figure 6, which is analogous to Figure 5, shows that the model matches well the sectorial adjustment of the Canadian economy along these untargeted dimensions.

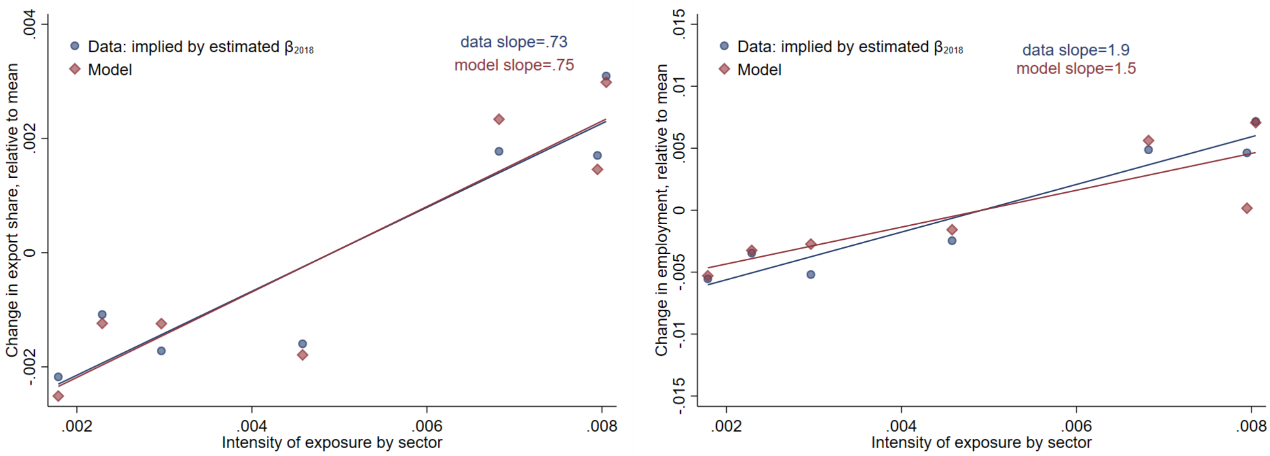
6 Quantitative effects of the 2017 US restrictions

We feed the observed increase in H-1B denial rates directly into our calibrated model and study its quantitative effects. Consistent with our empirical setup, the change in H-1B approval rates only varies by occupation, $dp_{co,usa} = dp_{o,usa}$. We keep unchanged the denial rate of non-H-1B occupations and the stock of immigrant workers that are already in the U.S. and Canada, $\bar{L}_{co,usa}$ and $\bar{L}_{co,can}$. Thus, the results in this section should be interpreted as the long-term effects of permanently decreasing the U.S. visa approval rates $dp_{o,usa}$, which affects the six-year flow of immigrants working in skilled occupations, on a permanent basis.

This change in the U.S. immigration policy alters global production and welfare in the U.S. and Canada by essentially reducing the number of immigrants in the U.S. and increasing the number

Figure 6: Untargeted coefficients

(a) Share of exports in total sales (b) Native-born employment



Note. The y-axis values of (a) and (b) are the change in $\frac{Exports_k}{Sales_k}$ and the logarithm of $Native\ Employment_k$ (relative to mean) respectively. Triangles represent model-generated data for $(\nu_h, \alpha, \epsilon) = (2.3, 1.2, 4.3)$, and circles represent the values implied by our actual data and event-study estimates. The x-axis is the exposure measure of sectors given by $Intensity_k$ as defined in equation (35). The values of the x-axis in the data and the model are identical by construction.

in Canada, which we discuss in the following two sections. We then shift the focus and discuss the extent to which international trade influences the effects of this policy change on American workers' welfare.

Table 2: Variations across occupations

Change in	All	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 (%)	3.40	11.40	4.25	6.50	2.62	2.23	0.44
Immigrant empl. US (%)	-1.56	-4.55	-2.23	-4.55	-2.42	-0.73	-0.02

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

6.1 Effects on Canada

Production and exports We find that the U.S. policy shift increases immigrant labor in Canada by 3.4%, with the largest increase being among computer scientists (see Table 2). Once in Canada, these immigrants sort into sectors according to their sectorial shares π_{codk}, leading to sector-specific expansions in the foreign labor supply. As a result, the sectors that experienced relatively stronger growth in their immigrant labor force are those where the immigrant workforce composition is skewed toward the occupation with a larger growth of immigrant inflow. The first row of Table 3 shows that the immigrant labor force increases in all sectors but the increase is especially strong in high-skilled service sectors (e.g., information and culture, business professional services, and finance and insurance). This increase in the immigrant labor force reduces labor costs and induces an aggregate expansion of production of 0.8%. Even though all sectors expand, they do not do so at the same rate. Notably, production in high-skilled service sectors responds the most due to the larger increase in the supply of immigrant labor and also these sectors' higher reliance on immigrants. To a first-order approximation, for a given labor supply of native-born workers the expansion of a sector is approximately the increase in its immigrant labor supply weighted by the immigrant share in the total cost s^f_{dk}, expressed as $d\tilde{y}_{dk} = s^f_{dk}\, d\tilde{l}^f_{dk}$.

Although total sales increase in all sectors, export sales increase only in high-skilled service and manufacturing sectors (e.g., Rybczynski's effect). This is because U.S. immigration restrictions alter the number of workers in all countries and, as a result, production costs in U.S. sectors increase relative to those in other economies, leading to a reallocation of production across sectors and countries. The U.S. reallocates production away from sectors that are relatively skilled and 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 trade, and low-tech manufacturing industries. Conversely, an economy like Canada's, which experiences an inflow of skilled immigrants, shifts its production composition in the opposite direction.[33] The increase in Canadian exports to the U.S. contributed significantly to its export growth: this explains 45% of Canada's growth in exports of high-skilled services sectors and 75% of the increase in high-tech manufacturing exports.

Table 3: 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 the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$, using the world sales as the numeraire. l^f_{dk} is measured in efficient units. "*IC*", "*BPS*", "*FIN*", "*High-Tech*", "*Ag & Min*", "*WRT*", and "*Low-Tech*" refer to information and culture, business professional services, finance and insurance, high-tech manufacturing sectors, agriculture and mining, retail trade, and low-tech manufacturing sectors respectively.

Canadian workers' welfare The welfare effects on Canadian workers are large and vary substantially across occupations and sectors of employment. Two factors drive this variation: the direct substitution effect, which is specific to each occupation and sector, and the domestic and international general equilibrium effects that determine the expansion of the workers' corresponding sectors of employment. The substitution effect can potentially counteract the

[33]For some sectors like finance, exports grew at a high rate mostly due to their small initial size. The size of Canada's exports was only USD8 billion in 2016, which only accounted for 1.7% of Canada's total exports for that year.

expansion effect for workers who directly compete with incoming immigrants in the labor market, resulting in negative welfare effects. Figure 7 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 are arranged in descending order of the production change, from largest to smallest, and occupations are organized from left to right, based on the average welfare change.

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

The differences in the welfare effects on Canadian workers across sectors are mainly explained by two factors, depending on the occupation of the worker. Canadian computer scientists in sectors that are immigrant-computer-scientist-intensive experience a stronger substitution effect. For instance, the welfare losses of computer scientists in the the sector with the largest and lowest $s^f_{can,ko}$ are 3.42% and 2.52% respectively (see Figure 8a). The cross-sector differences in the welfare effects of Canadian workers in less-exposed occupations are largely affected by the extent to which the sector expands due to the overall inflow of immigrants to the sector. To illustrate this point, Figure 8b plots the change in the welfare among managers, low-skilled workers, and workers in other H-1B occupations, against the measure the sector's exposure to the inflow of immigrants $Intensity_k$, which is computed using only observable initial shares and $dp_{o,usa}$. The figure highlights that the inflow of immigrants is more beneficial for workers employed in sectors that are more exposed to the overall inflow of immigrants because as the sector expands, the marginal revenue product of workers increases, increasing wages in the sector.

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

6.2 Effects on the U.S.

Production and exports The drop in the observed visa approval rates causes a 1.6% decline in total immigrant labor, with the largest drop among computer scientists and business professionals (see Table 2). The drop in the immigrant labor force induces a 0.25% drop in production in aggregate production. Compared to the effects on the Canadian economy, the magnitude of the effects on the U.S. economy are smaller. There are two reasons for this difference. First,

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

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

	CS	Bss Prof.	Engineers	Managers	Other H-1B	Non-H-1B
BPS	-2.59	0.09	0.26	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	-0.26	-0.17	0.53	0.39	0.74
WRT	-3.09	-0.28	-0.29	0.44	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 the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$. Positive values are depicted in red, while negative values are represented in blue, with the intensity of the color reflecting the magnitude of the value. Sectors are arranged in descending order of production change, from largest to smallest, and occupations are organized from left to right, based on the average welfare change. "*IC*", "*BPS*", "*FIN*", "*High-Tech*", "*Ag & Min*", "*WRT*", and "*Low-Tech*" refer to information and culture, business and professional services, finance and insurance, high-tech manufacturing sectors, agriculture and mining, retail trade, and low-tech manufacturing sectors respectively. "*CS*" and "*Bss Prof*" refer to computer scientists and business professionals.

Figure 8: 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 computer scientists in the y-axis and the immigrant share within the occupation across sectors s^f_{odk} in the x-axis. The right panel plots the real wage change of Canadian workers in the less-exposed occupations against the first-order approximation to $d\tilde{L}_{dk}$, which is the exposure of the sector to the U.S. policy change $Intensity_k$.

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

While all U.S. sectors are affected, the impact on production is most pronounced in the high-skilled service and high-tech manufacturing sectors. Production in these sectors decreases by approximately 0.5%. The contraction of these sectors is, in part, because they are losing markets to international competitors. For instance, exports of the information and culture and business professional service sectors dropped by approximately 1.4% and high-tech manufacturing exports fell by 0.5%.

Table 4: Aggregate and sector-level adjustment in the U.S. (%)

	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
Exports	-0.07	-1.56	-1.25	-0.65	-0.50	0.42	0.39	0.60	1.15

Note. We compute the changes in the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$, using the world sales as the numeraire. l^f_{dk} is measured in efficient units. "*IC*", "*BPS*", "*FIN*", "*High-Tech*", "*Ag & Min*", "*WRT*", and "*Low-Tech*" refer to information and culture, business professional services, finance and insurance, high-tech manufacturing sectors, agriculture and mining, retail trade, and low-tech manufacturing sectors respectively.

American workers' welfare The welfare effects on American workers vary substantially across occupations and sectors, with differences in the welfare effects being particularly pronounced across occupations. The immigration restrictions increase the welfare of computer scientists and, to a lesser extent, business professionals because the policy reduces relatively more of the supply of immigrant services in these occupations. Even though the drop in the immigrant labor force in these two occupations is similar, computer scientists are relatively more protected by the policy because this occupation is particularly immigrant intensive.[35] Workers in other occupations face a more moderate impact from the drop in immigrant competition, leading the policy to modestly increase or decrease their welfare.

The impact on American workers' welfare is also affected by the extent of the contractions in their employment sectors. For those occupations with the smallest drop in the immigrant labor force, like non-H-1B and other H-1B occupations or managers, the colors in Figure 9 turn to blue or darker blue as we move from the sectors on the bottom to those on the top. This implies that the policy has 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 information and cultural sector is twice as strong as for their counterparts in the low-tech manufacturing sector.

Overall, the results for American workers suggest that the policy improves the welfare of certain worker groups, presumably those it aims to protect, but it does 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-born workforce, the restrictions improve the welfare of

[35] Immigrants account for 28% of the wage bill for computer scientists and 12% for business professionals.

a relatively small number of American workers at the expense of a larger number of American workers.

Figure 9: Change in real wage of American workers (%)

	CS	Bss Prof.	Managers	Engineers	Other H-1B	Non-H-1B
IC	0.68	0.04	-0.11	-0.03	-0.29	-0.36
BPS	0.76	0.14	-0.02	-0.02	-0.22	-0.29
High-Tech	0.73	0.12	-0.05	-0.01	-0.23	-0.32
FIN	0.76	0.13	-0.03	0.06	-0.19	-0.27
WRT	0.76	0.20	0.03	0.10	-0.13	-0.21
Ag & Min	0.83	0.22	0.06	0.13	-0.09	-0.19
Other	0.71	0.21	0.02	0.07	-0.13	-0.21
Low-Tech	0.70	0.21	0.05	0.07	-0.09	-0.17

Note. We compute the changes in the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$. Positive values are depicted in red, while negative values are represented in blue, with the intensity of the color reflecting the magnitude of the value. Sectors are arranged in descending order of the production change, from largest to smallest, and occupations are organized from left to right, based on the average welfare change. *IC*, *BPS*, *FIN*, *High-Tech*, *Ag & Min*, *WRT*, and *Low-Tech* refer to information and culture, business and professional services, finance and insurance, high-tech manufacturing sectors, agriculture and mining, retail trade, and low-tech manufacturing sectors respectively. "*CS*" and "*Bss Prof*" refer to computer scientists and business professionals.

6.3 Efficacy of the restrictions: the role of international trade

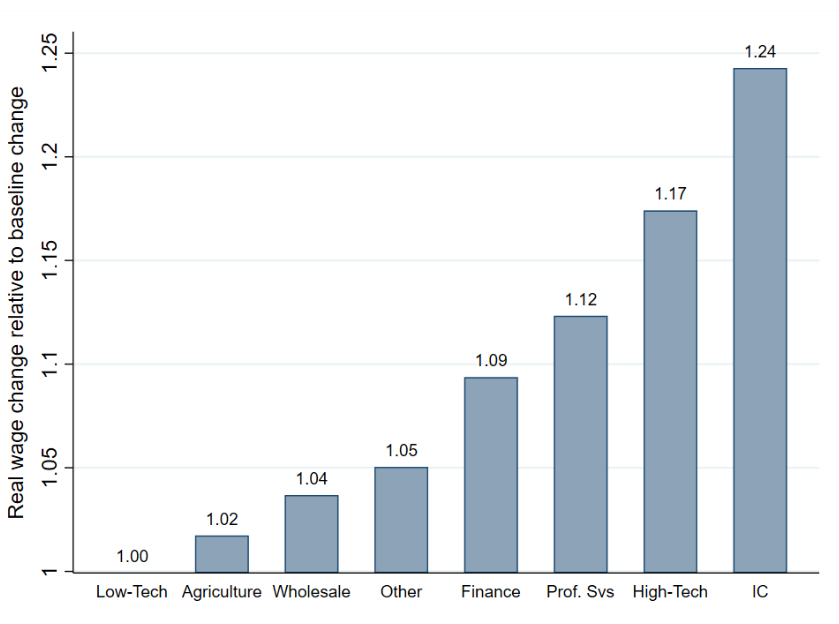
The welfare outcomes of American workers, shown in Figure 9, are the result of a substitution effect and general equilibrium effects, with some of the latter operating via international trade. We are interested in quantifying the role of international trade in these welfare effects. To that end, we quantify the effects of the same policy change $dp_{o,usa}$, assuming that the U.S. 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, denoted by $\hat{w}^{BL}$. We interpret the difference in the wage changes as the impact of the 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 solving for the equilibrium. This equilibrium, characterized by the absence of international trade, serves as the starting point for our implementation of the change in U.S. immigration policy. We then introduce the observed $dp_{o,usa}$ and calculate the new equilibrium.[36]

Figure 10 plots the ratio $\hat{w}^{CE}/\hat{w}^{BL}$ for American computer scientists working in different sectors. The plot focuses on computer scientists because the restrictions may be intended to protect their wages, as computer-related occupations account for approximately 65% of all H-1B visas. These

[36] We implement an alternative counterfactual exercise to the closed economy, which yields similar quantitative results. In this counterfactual exercise, we implement the same $dp_{o,usa}$ in an open economy and we adjust bilateral trade costs to keep bilateral trade flows unchanged.

results show that international trade dampens the welfare gains of American computer scientists, particularly in high-skilled service sectors and high-tech manufacturing. For example, in a closed economy, the welfare gains of computer scientists in the business and professional services 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 U.S. restrictions reduce the number of immigrants coming into the U.S. and increase this factor elsewhere, leading to a relative increase in U.S. production costs. As a result, the economies that absorb these immigrants expand in sectors that compete with U.S. sectors in international markets. This competition in the goods 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 10. Therefore, these results imply that U.S. immigration restrictions may avoid direct competition between immigrants and American workers in the U.S. labor market, but they could still indirectly compete through international goods markets. If policymakers overlook the general equilibrium effects of international trade, they might overestimate the efficacy of the policy.

Figure 10: Change in the real wage of American computer scientists: $\hat{w}^{CE}/\hat{w}^{BL}$



Note. We compute the changes in the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$, assuming that the U.S. is a closed economy. The y-axis is the ratio between the change in the real wage of American computer scientists in a closed economy, denoted by $\hat{w}^{CE}$, and in the baseline economy (see Figure 9), denoted by $\hat{w}^{BL}$. *IC* refers to the information and culture sector.

7 Conclusion

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

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

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

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Appendix

A Data

A.1 Cross-walk of occupation codes

The H-1B dataset contains 106 occupation codes that follow the Dictionary of Occupational Titles (DOT) and the PR dataset contains 177 3-digit NOC codes.[37] We construct a crosswalk between these occupations and, when necessary, we appeal to the information provided by the fourth digit of the NOC classification. For some NOC codes, there were no DOT codes in the H-1B dataset (e.g., cashiers or any low-skill occupation); and for some DOT codes, there were no NOC codes (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 correspond to 003); and for a few cases, the match was from many to many (e.g., 2175 corresponds to 030 and 039; and 2171, 2173, 2174 and 2283 correspond to 030). We thus define a grouping given by the smallest possible mutually exclusive sets of matches that yield 74 distinct groups (see Table E.2).[38] With this crosswalk at hand, we can aggregate the number of PR and H-1B applications at the new grouping level according to the corresponding NOC codes and DOT codes respectively.

A.2 Firm-level regression: measurement and sample

A.2.1 Construction of firm-level shocks

Firm-level country composition Combining the T4-ROE records and the IMDB database, we compute the country share of each firm i by the pooled total employment between 2010 and 2013. In the 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 the 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 individuals working in sector s. Here, the wage bill is measured by the reported weekly earnings and the statistical weight provided in the LFS is applied to the aggregation.

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

[38]Most of these distinct groups have associated with 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 these groups have one NOC code and 4 groups have two NOC codes).

Share of flow within the population of immigrants from country c In the LFS, we define individuals not born in Canada as immigrants. Then we measure this flow share by dividing the number of immigrants from country c who have been permanent residents for no more than one year or who were not permanent residents in 2016 by the number of all immigrants from country c in 2016. When calculating the number of headcounts, the statistical weight provided in the LFS is applied.

A.2.2 Construction of the variables used as controls

Firm-level shares of skilled immigrant employment In the IMDB, we flag an immigrant as a skilled immigrant based on the available data on their education, occupation, and visa program information. The 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 they satisfy one of the following three conditions:

1. have an education level above a bachelor's degree;
2. are admitted through the Express Entry (EE) program;
3. qualify 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 they are reported to have an education level above a bachelor's degree or are in the occupation category of Managerial, Professional, or Skilled and Technical. We flag an immigrant as skilled if they are flagged as a skilled immigrant in the 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 U.S.[39] Statistics Canada provides a mapping between each postal code and a corresponding geographical location group. Most of the postal codes are directly part of a CMA/CA. The postal codes for 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 the T1-PMF and the employer-employee-link records, we measure each firm's employment composition by the local labor market. Then we assign the local labor market for a firm according the one accounting for the largest share of its employment. This location measure is analogous to the commuting zone commonly used for the U.S.

[39]There are 151 CMAs/CAs 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.

A.2.3 Sample selection

We first construct the regression sample by dropping the non-profit firms, firms with lifetime maximum employment of less than 5, and 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 from the sample firms with a lifetime maximum annual employment growth rate above 2000% 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 $Intensity_i$; that is, firms with an $Intensity_i$ level above the 99% percentile of those with positive $Intensity_i$. Finally, we restrict the sample to only include firms with an observation in the baseline year 2016, at least two observations before 2016, and at least one observation in either 2017 or 2018, so that each firm in the sample has enough pre- and post-shock information for us to conduct the event study.

A.3 Data sources used in the quantitative model

Sources of data from Canada

We use income data by country of birth, 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 publicly available data from IRCC's website on the approval rate by PR visa program for Canada for 2016. We assign a common approval rate to all occupations within a 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 the Provincial Nominee program under Express Entry, the Quebec-selected Skilled Workers program, and the Canadian Experience Class. For the lower-skilled group, we include the Provincial Nominee program under the non-express entry and the Caregiver Program.

Sources of data from the U.S.

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 U.S. (s^n_{dso}, s^f_{dso}, and f_{dso}).
We also use this data to calibrate the occupational structure of sectors in the RoW, due to the lack of disaggregated data by occupation and sector of the largest countries included in the RoW. In particular, we calibrate f_{dso} according to the distribution of income across occupations and sectors of immigrants from the RoW living in the U.S.

To compute ψ_{gd}^{imm}, we use the total number of immigrants by group and those who arrived in the U.S. during the last year. We then use an extrapolation method to assign a value for a six-year period. Specifically, we infer the six-year period for the U.S. as follows: $\psi_{gu}^{imm} = \frac{\psi_{gc}^{imm}}{\psi_{gc}^{imm}}\psi_{gu}^{imm}$, where we use Canadian data to compute the ratio or extrapolation factor.
We use the H-1B data described in section 2.1 to compute the admission probability of each skilled occupation, and we use official reports of I-129 petitions for H-2A and H-2B visas for the probability of lower-skilled occupations.[40] Specifically, we compute the admission probability for the lower-skilled occupations as the weighted average of the approval rate of the H-2A and H-2B visas for the fiscal year 2016.

B Reduced-form evidence

B.1 Immigration to Canada: robustness exercises

Correlation over time of confounding factors may threaten identification as it will imply that ϵ_{cot} correlates with past applications and, hence, $\pi_{co,usa}$. It is plausible that $\pi_{co,usa}$ may be in part determined by pre-existing immigration conditions such as historical events (e.g., Canada was a French colony), cultural factors (e.g., French is an official language of Canada), and institutional aspects of the immigration systems (e.g., the majority of sponsoring firms in the U.S. are Indian affiliates due to the IT boom in the 2000s). If these factors significantly contribute to determining $\pi_{co,usa}$, concerns regarding its correlation with ϵ_{oct} may be mitigated. We assess the plausibility of this correlation by controlling for the elements used to compute $\pi_{co,usa}$ interacted with the year dummies (e.g., $App_{co,usa} \times \delta_t$ and $App_{co,can} \times \delta_t$). These estimates, reported in column 2 of Appendix Table E.4, are not statistically different from our baseline estimates, reported in column 1. This suggests that unobserved factors affecting $\pi_{co,usa}$ and ϵ_{oct} are unlikely to drive our estimates. Note that the correlation over time of unobserved factors either at the occupation level only or at the country level only do not threaten the 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 some 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 of their immigrant workforce 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

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

issues and would be upward biased. To address this concern, we re-estimate the model by excluding India and China, the two largest nationalities of immigrants, and computer-related occupations, the largest occupations for the same group. The estimates, reported in columns 3 and 4 of Appendix Table E.4 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. Changes in Canadian immigration policy at the nationality or 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 of the 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 for the Express Entry program in the years 2015 and 2016, interacted with a dummy that equals 1 for the years 2015 through 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 U.S. restrictions. It is worth mentioning that if Canadian policy responded to the new U.S. policy, our reduced-form estimates would incorporate these effects, and we should consider them when interpreting the coefficients.

Fourth, we perform additional tests of the identifying assumption recommended by the recent research on difference-in-differences design (Roth, 2022). We test the hypothesis of a 7% annual linear trend, as per the 2016-2017 immigration plan. At the 1% significance level, we reject this trend, indicating that our estimates may not capture pre-shock differential trends (see estimation details in Appendix Figure E.6). We also test for steeper slopes up to 30%, yielding the same qualitative results.

Finally, we verify that our estimates are not driven by outliers. In Appendix Figure E.5, we plot the relationship between the change in the outcome variable and the main regressor (e.g., the change in $log(App_{co,can,t})$ and $Intensity_{co}$), using raw data. The distribution of the observations in the scatter plot suggests that it is unlikely that the outliers affect our estimates.

B.2 Firm-level evidence

B.2.1 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 effects of these factors may confound the industry-level effect of the H-1B policy restrictions and, consequently, 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 the changes in the demand for goods due to the H-1B restrictions. In particular, the adverse effects of restricting immigrant labor in the U.S. mainly affected American firms operating in the skilled-intensive service sector. Consequently, Canadian firms that competed with these American counterparts may have expanded compared to other Canadian firms, even if they had not hired immigrants. If our estimates of β_τ are driven by differences in the demand for goods and services induced by the H-1B policy change, we would expect a less pronounced effect when estimating the differential hiring responses of Canadian firms within the same industry. To assess the plausibility of these concerns, we estimate the effects of the H-1B policy within the 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 E.5) and define the top quartile as the "exposed" group of sectors. That is, the exposed sectors coincide with what we refer to in the main text as the "high-skilled service sector." The remaining sectors constitute the non-exposed sectors. Then we estimate the following event study:

$$
\begin{aligned}
y_{it} = & \sum_{\tau \neq 2016} \beta_\tau^E \times 1(\text{k} = \text{high-skilled service sector}) \times Intensity_i \times 1(t=\tau) \; + \\
& \sum_{\tau \neq 2016} \beta_\tau^{NE} \times Intensity_i \times 1(t=\tau) + \; \delta_i \; + \delta_{kt} + \delta_{mt} + \; \gamma' \; X_{ikt} \; + \epsilon_{it}
\end{aligned} \tag{B.1}
$$

where $1(\text{k} = \text{high-skilled service sector})$ is a dummy variable that equals one if the industry where the firm operates belongs to one of the exposed sectors and zero otherwise. We compare the estimates of β_τ^E, which do not use variation across sectors for identification, with those from equation (3). Appendix Figure E.8 shows this comparison for the hiring of immigrants and for sales and export performance (Appendix Table E.7 reports all of the estimates and estimation details.) The pairwise comparison of the estimates of these variables shows that the within-industry estimates are noisier but, overall, the point estimates are similar in magnitude to those documented in Figure 4. Given this evidence, we consider that it is likely that our estimates are identifying the effects 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 that require the exposure to be mean independent of the factors that affect the trend in the outcome (Roth et al., 2023). 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 years after. To assess whether it is plausible that 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 of these regressions include the pre-shock firm characteristics included in the baseline specification (e.g., the immigrant share in the wage bill, the share of exports in total sales, and the share of service exports in total exports). Appendix Figure E.9 plots the event studies of the 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 the effects associated with the firm characteristics that are affecting firm performance after 2016.

Foreign shocks Another concern is the potential confounding effects of international demand shocks in 2017 and 2018, especially because the U.S. is a large trading partner of Canada. To assess whether foreign shocks, including changes in U.S. trade policy, may be affecting our estimates of the effects of the H-1B restrictions, we re-estimate equation 3, restricting the sample to firms that neither exported nor imported in 2016. Appendix figure E.11 shows the event study and suggests that the baseline results are robust to this subsample of firms.

Effect of Canadian immigration The Canadian firms that use this program to source immigrants from abroad may also be those that are more exposed to the H-1B policy change. For instance, computer scientists were the most prevalent professionals among immigrants to be 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 the 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 firms' expansion in terms of sales and exports are robust to the inclusion of this control (see Appendix Figure E.10). Given these results, it is plausible that the effects of the Express Entry program do not confound with the effects of the H-1B restrictions.

B.2.2 Additional results

Effect on firms depending on whether they hired immigrants who resided in the U.S. Our firm-level exposure measure was motivated by the influence of immigrant networks based on the country of birth. 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 U.S. It is plausible that if the U.S. imposes immigration restrictions, the immigrant still living in the U.S. might seek assistance from the one residing in Canada to facilitate their plan to move there. 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 firms that had employed immigrants who had previously lived in the United States and those firms 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 E.13 plots these pairs 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 locations of the previous residences. 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 responses related to exports and the share of exports in total sales documented in Figure 4.

C Model

C.1 Solving for equilibrium

Following Dekle et al. (2008), we rewrite all of the equilibrium equations in the proportional changes of the different variables. Given $(\Omega, \Upsilon, \mathrm{P})$, the changes, in the equilibrium, that are induced by a change in the probability of granting a U.S. visa $\Delta p_{ocu} \equiv p^{'}_{co,usa} - p_{co,usa}$ can be summarized by equations (C.2)-(C.24). We divide these equations into three blocks: the equations determining the labor supply, 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.

$$\hat{\pi}_{cock} = \Big(\frac{\hat{w}^n_{cok}}{\hat{\Phi}_{coc}}\Big)^{\kappa}, \qquad \text{where } \hat{\Phi}^{\kappa}_{coc} = \sum_k \pi_{cock}(\hat{w}^n_{cok})^{\kappa} \tag{C.2}$$

$$\hat{\pi}_{codk} = \Big(\frac{\hat{w}^f_{dok}}{\hat{\Phi}_{cod}}\Big)^{\kappa} \quad \text{for } d \neq c, \qquad \text{where } \hat{\Phi}^{\kappa}_{cod} = \sum_k \pi_{codk}(\hat{w}^f_{dok})^{\kappa} \tag{C.3}$$

$$\hat{u}_{coc} = \frac{\hat{\Phi}_{coc}}{\hat{P}_c}, \quad \hat{u}_{cod} = \frac{\hat{\Phi}_{cod}}{\hat{P}_d} \quad \text{for } d \neq c \tag{C.4}$$

$$\hat{u}^{\nu_h}_{co} = \pi_{coe}\, \hat{u}^{\nu_h}_{coe} + \pi_{coc}\, \hat{u}^{\nu_h}_{coc} \tag{C.5}$$

$$\hat{u}^{\nu_d}_{coe} = \sum_{d \neq c} \pi_{cod}\, (\hat{u}^{p_{cod}}_{cod} \hat{u}^{1-p_{cod}}_{coc} u^{\Delta p_{cod}}_{cod} u^{-\Delta p_{cod}}_{coc})^{\nu_d} \tag{C.6}$$

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 or to stay in the 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 $\sum_{d \in \mathcal{C}^d} \pi_{cod} = 1$.

$$\hat{\pi}_{coc} = \Big(\frac{\hat{u}_{coc}}{\hat{u}_{co}}\Big)^{\nu_h}, \; \hat{\pi}_{coe} = \Big(\frac{\hat{u}_{coe}}{\hat{u}_{co}}\Big)^{\nu_h}, \; \hat{\pi}_{cod} = \Big(\frac{\hat{u}^{p_{cod}}_{cod} \hat{u}^{1-p_{cod}}_{coc} u^{\Delta p_{cod}}_{cod} u^{-\Delta p_{cod}}_{coc}}{\hat{u}_{coe}}\Big)^{\nu_d} \tag{C.7}$$

$$\widehat{LS}_{coc} = \Big(\big(\psi_{coc}\hat{\pi}_{coc} + \sum_{d \neq c} \psi_{cod}\, \widehat{(1 - p_{cod})} \hat{\pi}_{cod}\, \hat{\pi}_{coe}\big)(1 - \psi^{emig}_{co}) + \psi^{emig}_{co}\Big) \hat{\Phi}_{coc} \tag{C.8}$$

$$\widehat{LS}_{cod} = \big(\hat{p}_{cod}\hat{\pi}_{co,d}(1 - \psi^{imm}_{cod}) + \psi^{imm}_{cod}\big)\, \hat{\Phi}_{cod}, \text{ for } d \neq c \tag{C.9}$$

where $1 - \psi^{imm}_{cod}$ is the fraction of workers of nationality c in occupation o working in destination country d accounted for by the flow of new immigrants; $1 - \psi^{emig}_{coc}$ 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.

$$\widehat{LS}_{codk} = \hat{\pi}_{codk} \widehat{LS}_{cod} \tag{C.10}$$

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

$$\hat{s}^n_{dko} = \left(\frac{\hat{w}^n_{dko}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{C.11}$$

$$\hat{s}^f_{dko} = \left(\frac{\hat{w}^f_{dko}}{\hat{w}_{dko}}\right)^{1-\epsilon} \tag{C.12}$$

$$\hat{f}_{dko} = \left(\frac{\hat{w}_{dko}}{\hat{w}_{dk}}\right)^{1-\eta} \tag{C.13}$$

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

$$\hat{w}^{1-\epsilon}_{dko} = s^n_{dko}\left(\hat{w}^n_{dko}\right)^{1-\epsilon} + s^f_{dko}\left(\hat{w}^f_{dko}\right)^{1-\epsilon} \tag{C.14}$$

$$\hat{w}_{dk} = \left(\sum_o f_{dko}\,\hat{w}^{1-\eta}_{dko}\right)^{\frac{1}{1-\eta}} \tag{C.15}$$

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

$$\hat{Y}_{dk} = \sum_c \omega^Y_{cdk}\,\hat{\lambda}_{dck}\hat{\alpha}_{ck}\hat{X}_c \tag{C.16}$$

$$\hat{\alpha}_{dk} = \left(\frac{\hat{P}_{dk}}{\hat{P}_d}\right)^{1-\alpha} \tag{C.17}$$

$$\hat{\lambda}_{dck} = \frac{\hat{w}^{-\theta}_{dk}}{\sum_d \lambda_{dck}\,\hat{w}^{-\theta}_{dk}} \tag{C.18}$$

$$\hat{X}_c = \sum_k \omega^X_{ck}\,\hat{Y}_{ck} + \omega^X_{cD} \tag{C.19}$$

where ω^Y_{cdk} is the share of country c in the total sales of sector k in country d, ω^X_{ck} is the share of sales from sector k in the total expenditures of country c, and ω^X_{cD} is the share of the deficit in the total expenditures 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

$$\hat{P}^{-\theta}_{dk} = \sum_{i\in\mathcal{C}} \lambda_{idk}\left(\hat{w}_{is}\right)^{-\theta} \tag{C.20}$$

$$\hat{P}^{1-\alpha}_{d} = \sum_k \alpha_{dk}\,\hat{P}^{1-\alpha}_{dk} \tag{C.21}$$

With 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-born workers in sector k of country d is

$$\widehat{LD}^x_{dko} = \hat{s}^x_{dko} \hat{f}_{dko} \hat{Y}_{dk},\ \forall x \in \{n,\ f\} \tag{C.22}$$

Labor market clearing conditions

$$\widehat{LD}^f_{dko} = \sum_{c \neq d} \omega^{LS}_{codk} \widehat{LS}_{codk} \tag{C.23}$$

$$\widehat{LD}^n_{dko} = \widehat{LS}_{dodk} \tag{C.24}$$

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

C.2 Analytical results

C.2.1 Applications for Canadian visas

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 the applications is

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

where the change in the log of emigrating is

$$d\widetilde{\pi}_{cod} = \nu_d \left[\ p_{cod} d\widetilde{u}_{cod} + (1 - p_{cod}) d\widetilde{u}_{coc} + dp_{cod}(\tilde{u}_{cod} - \tilde{u}_{coc}) - d\tilde{u}_{coe}\ \right]$$

$$d\widetilde{\pi}_{coe} = \nu_h\ (1 - \pi_{coe}) \left(d\widetilde{u}_{coe} - d\widetilde{u}_{coc} \right)$$

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

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

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

$$d\widetilde{App}_{cod} = (\nu_h\ \pi_{coc} - \nu_d)\ \pi_{co,usa}\ dp_{co,usa}(\tilde{u}_{co,usa} - \tilde{u}_{coc}) + \eta_{cod} \tag{C.25}$$

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

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

C.2.2 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 U.S. imposes restrictions on skilled immigration that lead to infinitesimal (negative) changes in the immigrant labor supply $\tilde{l}^f_{usa,ko}$. The change in the welfare of an American worker in occupation o in sector k is ($d = usa$).

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

where $\epsilon_{usa,k} = \left(\frac{1}{\eta} - 1\right)\tilde{l}_{usa,k} + \sum_j \omega^Y_{usa,jk}\;\; \tilde{X}_j$, $\tilde{l}_{usa,k} = \sum_o s_{usa,ko}\; s^f_{usa,ko}\; \tilde{l}^f_{usa,ko}$ and $\tilde{c}_{dk}$ is the change in the production costs of sector k in country d induced by the U.S. 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 the following five steps.

<u>Step 1</u>: Expression for the welfare of American workers.
Given that trade is balanced, the change in a worker's real wage coincides with the change in their utility. The nominal wage earned by a worker is the marginal revenue product of their labor because labor markets are perfectly competitive. Therefore, the wage of worker $x \in \{f, n\}$ in occupation o in sector k in country d, w^x_{dko}, is given by (C.26)

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

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

After substituting these equilibrium conditions into (C.26), we obtain the following expression for the welfare of an American worker in occupation o working in sector k:

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

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

$$\tilde{W}^n_{usa,ko} = \tilde{Y}_{usa,k} + \left(\frac{1}{\eta} - 1\right)\tilde{l}_{usa,k} + \left(\frac{1}{\epsilon} - \frac{1}{\eta}\right)\tilde{l}_{usa,ko} - \frac{1}{\epsilon}\ \tilde{l}^n_{usa,ko} - \tilde{P}_{usa} \tag{C.27}$$

Step 2: Expression for the change in the price level in (C.27).

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

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

The log differentiation of these expressions yields the following conditions:[41]

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

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

$$\tilde{P}_{usa} = \sum_k \alpha_{usa,k}\ (\lambda_{usa,usa,k}\ \ \tilde{c}_{usa,k} + \lambda_{c,usa,k}\ \ \tilde{c}_{ck}) \tag{C.28}$$

Step 3: Expression for the change in the sales of sector k in the U.S., $Y_{usa,k}$ in C.27.

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

Log differentiating $Y_{usa,k}$ yields

$$\tilde{Y}_{usa,k} = \sum_{j \in \mathcal{C}} \omega^{Y}_{usa,jk} \left(\tilde{\lambda}_{usa,jk} + \tilde{\alpha}_{jk} + \tilde{X}_j \right) \tag{C.29}$$

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

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

We can then write the change in the U.S. 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:

$$\tilde{Y}_{usa,k} = -\theta \sum_{j} \omega^{Y}_{usa,jk} \left(1 - \lambda_{usa,jk}\right) \tilde{c}_{usa,k} \;\; + \;\; \theta \sum_{j} \omega^{Y}_{usa,jk} \lambda_{cjk} \, \tilde{c}_{ck} \;\; + \;\; \sum_{j} \omega^{Y}_{usa,jk} \; \tilde{X}_j \tag{C.30}$$

Step 4: The expression for the change in the labor bundle $l_{usa,ko}$ and $l_{usa,k}$ is found in equation (C.27). Log differentiating (7) and using additional optimal conditions yields the following conditions:

$$\begin{aligned} \tilde{l}_{usa,ko} &= s^{n}_{usa,ko} \, \tilde{l}^{n}_{usa,ko} + s^{f}_{usa,ko} \, \tilde{l}^{f}_{usa,ko} \\ \tilde{l}_{us} &= \sum_{o} s_{usa,ko} \, \tilde{l}_{usa,ko} \end{aligned}$$

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

$$\tilde{l}_{usa,ko} = s^{f}_{usa,ko} \, \tilde{l}^{f}_{usa,ko} \tag{C.31}$$

$$\tilde{l}_{usa,k} = \sum_{o} s_{usa,ko} \, s^{f}_{usa,ko} \, \tilde{l}^{f}_{usa,ko} \tag{C.32}$$

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

Step 5: Expression for $\tilde{c}_{ck}$ in C.27 as a function of l^{f}_{cko}.

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

The 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 native-born workers 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-born 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 the immigrant wage with respect to the supply of immigrants. We do not provide an explicit solution for ε^f_{cko}; rather, we assume that the parameter values guarantee that the following law of demand is satisfied: All else equal, an increase in the immigrant labor supply reduces immigrants' wages $\varepsilon^f_{cko} < 0$.
This simplification allows us to express native-born workers' wages as follows:

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

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

D Quantification

D.1 Calibration

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

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

Table D.1: 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	CEPII data
	Exchange rate	Penn World Table
ζ_{cod}	Migration costs	Grogger and Hanson (2011) and CEPII data
Migration-related shares: $\mathbf{S^M}$		
π_{cod}	Share applying to d	H-1B application data and PR application data
π_{coc}	Share staying at home	Inferred using H-1B application data and IAB dataset
$1-\psi^{imm}_{cod}$	Immigrant flow share	ACS for the US, and LFS for Canada
$1-\psi^{emm}_{co}$	Share making migration decision	NSS for India and IPUMS int'l for RoW
Non migration-related shares: $\mathbf{S^{NM}}$		
π_{codk}	Share choosing sector k	ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW
s_{dko}	Cost share of occupation o	ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW
s^f_{dko}	Cost share of immigrants	ACS for the US, and LFS for Canada
λ_{dck}	Expenditure shares within sector	Trade in Value Database from the OECD (TiVA)[43]
α_{dk}	Expenditure shares across sectors	Trade in Value Database from the OECD (TiVA)

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

w^n_{odk}, w^f_{odk}: We compute the nominal wage of each worker group, based on the H-1B dataset, the NSS survey, and IPUMS international database.

P_d and the exchange rate: To convert the nominal wage dominated in different currencies into the real wage dominated in U.S. dollars, we use the consumption price level from CEPII data and the exchange rate data from the Penn World Table.

ζ_{cod}: We compute the bilateral migration cost as a share of the wage earned in the U.S., based on estimates from Table 4 from Grogger and Hanson (2011) and CEPII data.

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

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

$$\frac{L_{coc}}{L_{co}} = \left(\pi_{coc} + \sum_{d\neq c}(1-p_{cod})\cdot\pi_{cod}\,(1-\pi_{coc})\right)\,(1-\psi^{emm}_{coc}) + \psi^{emm}_{coc} \tag{D.33}$$

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 the Institute for

Employment Research (IAB), Nürnberg, is accessible. Therefore, we approximate the left-hand side share for Indian computer scientists with the share of college-educated Indians. Given this data, the value of π_{coc} consistent with condition (D.33) is 0.4.[45] Second, we infer the shares of other high-skilled occupations based on the computed share for Indian computer scientists. To that end, we use the model's equation for the number of applications to the U.S. of each immigrant group relative to computer scientists from India $\pi_{ind,cs,u}$:

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

This equilibrium condition allows us to recover the remaining π_{coc} as a function of the data and the inferred value for $\pi_{ind,cs,ind}$. Given that we do not observe L_{co} for the RoW, we proxy the last fraction of the right-hand side with the relative number of total employees. Finally, we apply condition (D.33) for lower-skilled workers, where we use the data for the non-college population from the IAB.

ψ^{imm}_{cod}: We compute ψ^{imm}_{cod} as the proportion of immigrants from origin country c employed in occupation o in country $d \neq c$ who had arrived in the country within the previous six years. We choose a six-year window to align it with the H-1B visa's validity period. For the U.S., 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 A.3. In the case of Canada, we rely on data from the 2012-2016 waves of the Canadian Labor Force Survey Data (LFS).

π_{codk}, s_{dko}, and s^f_{dko}: We construct these statistics of labor market composition using different data sets for each country. For the U.S. and Canada, we use the ACS data and LFS data, respectively. For the statistics on the Indian labor market composition, we use the NSS data. For the rest of the world, we use the IPUMS data.

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 in skilled occupations. For lower-skilled occupations, we only impose age restrictions.

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

D.2 Instrumental variable approach: ν_d

To go from equation (32) to an estimating equation that we can take to the data, we introduce four changes. First, we rewrite (32) as follows:

$$\tilde{App}_{co,can,t} \; - \; \tilde{App}_{co,usa,t} = \nu_d \, p_{co,usa,t} \, \tilde{w}_{co,usa,t} + \eta_{cot} \tag{D.34}$$

where η_{cot} is a structural error that includes the U.S. immigration policy's effects in Canada ($p_{co,can,t}$), wages and prices in Canada and the cost to migrate to Canada (through $\tilde{u}_{co,can,t}$), wages and prices at home (through the average wage u_{coct}), prices in the U.S. ($P_{usa,t}$), and the cost to migrate to the U.S. $\tilde{\zeta}_{co,usa}$. Second, motivated by the policy memorandum and our data, we make the probability $p_{co,usa,t}$ occupation specific, as opposed to occupation-nationality specific. Third, we set $\tilde{w}_{co,usa,t}$ at its pre-shock average value because it jumps around over time for immigrant groups that are relatively small. By making $\tilde{u}_{co,usa}$ time invariant, we eliminate random noise and increase the precision of the estimate. Additionally, this 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 in 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 U.S. 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 U.S. We include country-specific fixed effects δ_{ct} to control for changes in economic conditions at home that may push immigrants to disproportionately migrate either more towards Canada or towards the U.S. The estimating equation becomes

$$\tilde{App}_{co,can,t} \; - \; \tilde{App}_{co,usa,t} = -\nu_d \, p_{o,usa,t} \, \tilde{w}_{co,usa} + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot} \tag{D.35}$$

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

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 U.S. 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 from emigrating and affect the pool of immigrants applying to the U.S. If the pool of applicants improves, approval

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

rates would likely decrease, which would bias our estimate of ν_d towards zero.

To address endogeneity concerns of the OLS estimate, we pursue an instrumental variable approach where we instrument $p_{o,usa,t}\ \tilde{w}_{co,usa}$ with $Intensity_{co} \times 1(t > 2016)$. In section 3.2, we explain why $Intensity_{co} \times 1(t > 2016)$ provides the plausible exogenous variation introduced by the H-1B policy change. It is worth mentioning that the model suggests the relevance condition of this instrument. In the model, higher U.S. wages increase the value of securing a job in the U.S., leading to a larger share of immigrants choosing to apply to the U.S. (e.g., larger $\pi_{co,usa}$). Appendix Figure E.14 shows empirically that this relationship is significantly strong.

Columns 1 and 2 of Appendix Table E.9 show that the OLS is not distinguishable from zero and that it is biased towards zero, as the 2SLS estimate is 3.6 (s.e=1.3). Columns 3-6 perform the same robustness exercises as discussed in section 3.2 and show that the 2SLS estimate is robust to these alternative specifications. Thus, we set $\nu_d = 3.6$ in the calibration of the model.

D.3 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 interest and then follow an aggregation step.[47]

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

$$\widetilde{App}_{co,can,t} \ = \ \beta_t \ Intensity_{co} \ + \delta_{co} \ + \ \delta_{ot} \ + \ \delta_{ct} + \ \epsilon_{cot}$$

with $\beta_{2016} = 0$, given that 2016 is our reference year. We use the same model to construct the counterfactual number of the 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

$$\widetilde{App}_{co,can,t} = \delta_{co} \ + \ \delta_{ot} \ + \ \delta_{ct} + \ \epsilon_{cot}$$

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

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

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

change in the applications of group G as follows:

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

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

Finally, we use 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 (34) 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 earnings per native worker by sector, implied by our estimates from equation (3).

E Additional tables and figures

Table E.2: 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

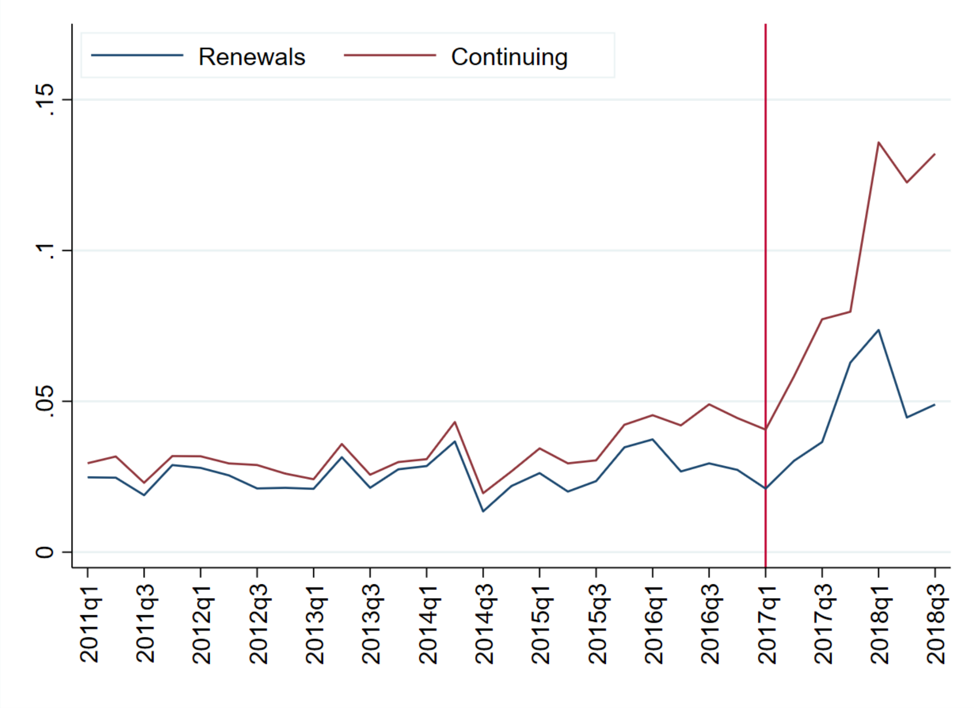
New group	NOC (Classification in PR)		DOT (Classification in H-1B dataset)	
	Code	Description	Code	Description
30	2212	Geological and mineral technologists and technicians	024	Occupations in geology
31	224	Technical occupations in electronics and electrical engineering	003	Electrical/electronics engineering 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 E.3: Canadian points 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

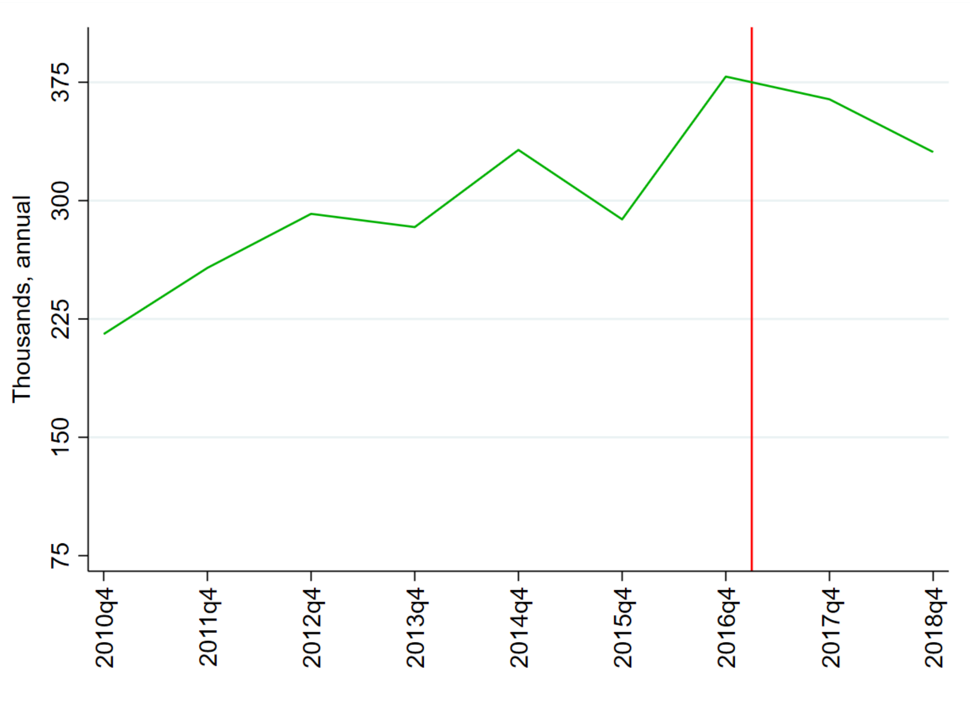
Source: IRCC's website (link), accessed June 2023.

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



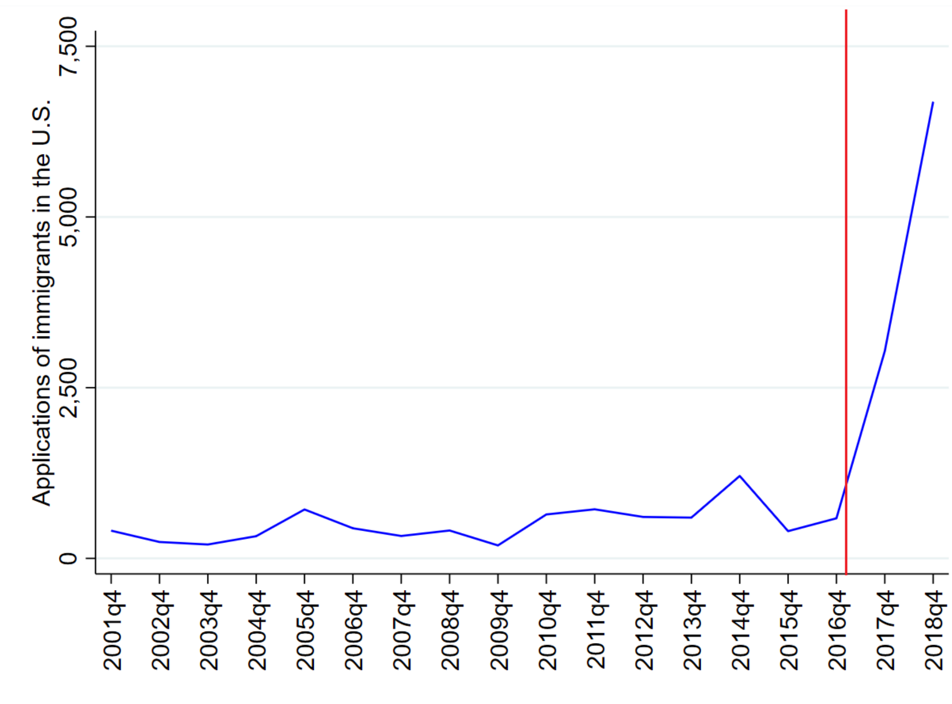
Note. Figure E.1 plots the number of denied H-1B applications divided by the total number of H-1B applications. The red line includes continuing H-1Bs and the blue lines only renewals.

Figure E.2: 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 than its linear trend.

Figure E.3: Canadian visa applications of immigrants who previously resided 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 E.4: Effects of increasing H-1B denial rates on Canadian immigration

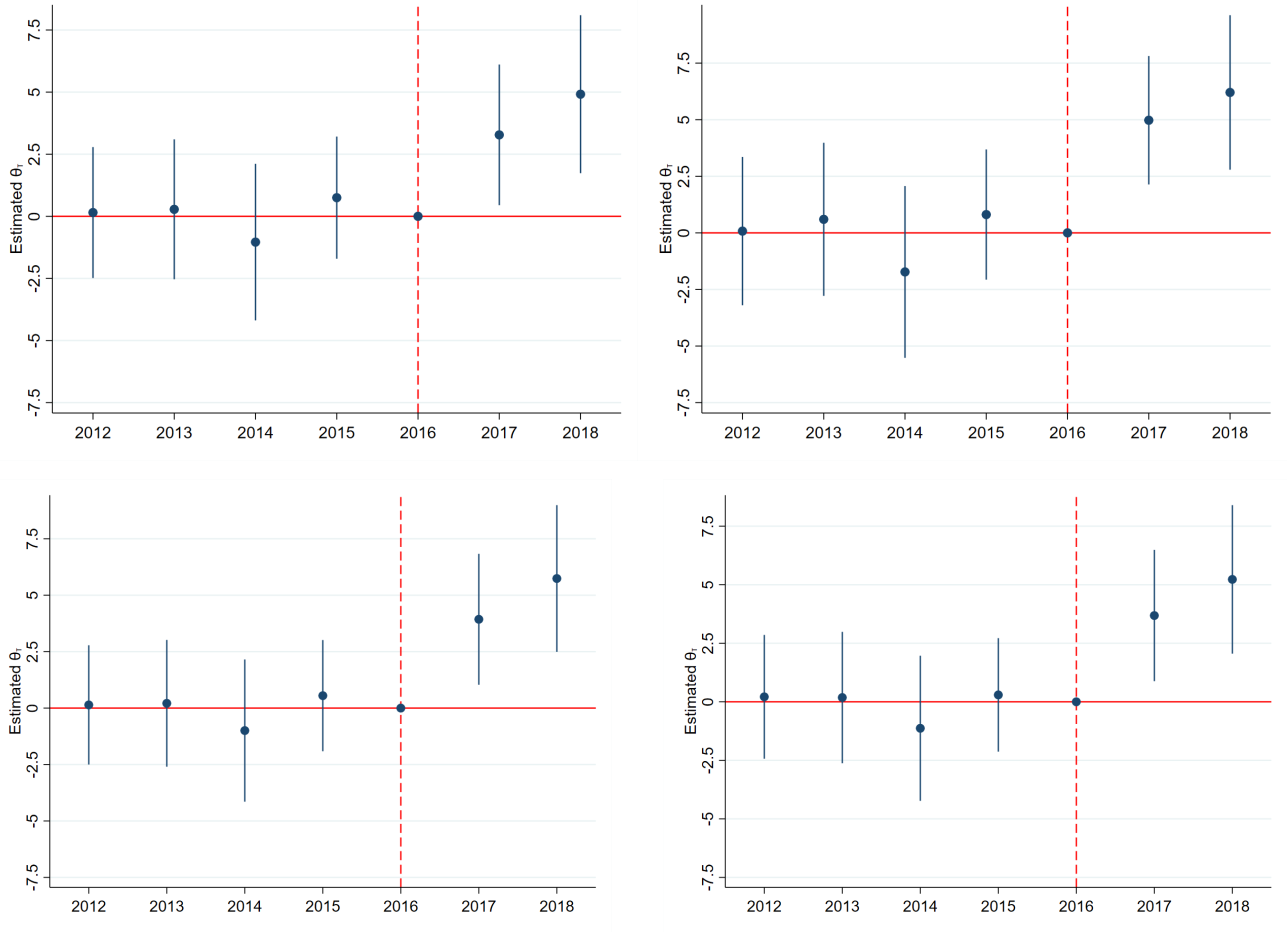
	(1) $log(App_{co,can,t})$	(2) $log(App_{co,can,t})$	(3) $log(App_{co,can,t})$	(4) $log(App_{co,can,t})$	(5) $log(app)^{can}_{cot}$
$Intensity_{co}$ $1(t = 2012)$	0.117	0.153	0.078	0.142	0.213
	(1.326)	(1.342)	(1.669)	(1.345)	(1.347)
$Intensity_{co}$ $1(t = 2013)$	0.086	0.282	0.600	0.212	0.182
	(1.411)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

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

Figure E.4: Effect of increasing H-1B denial rates on Canadian Immigration

(a) Controlling for the elements in $\pi_{co,usa}$

(b) Excluding apps. from India and China

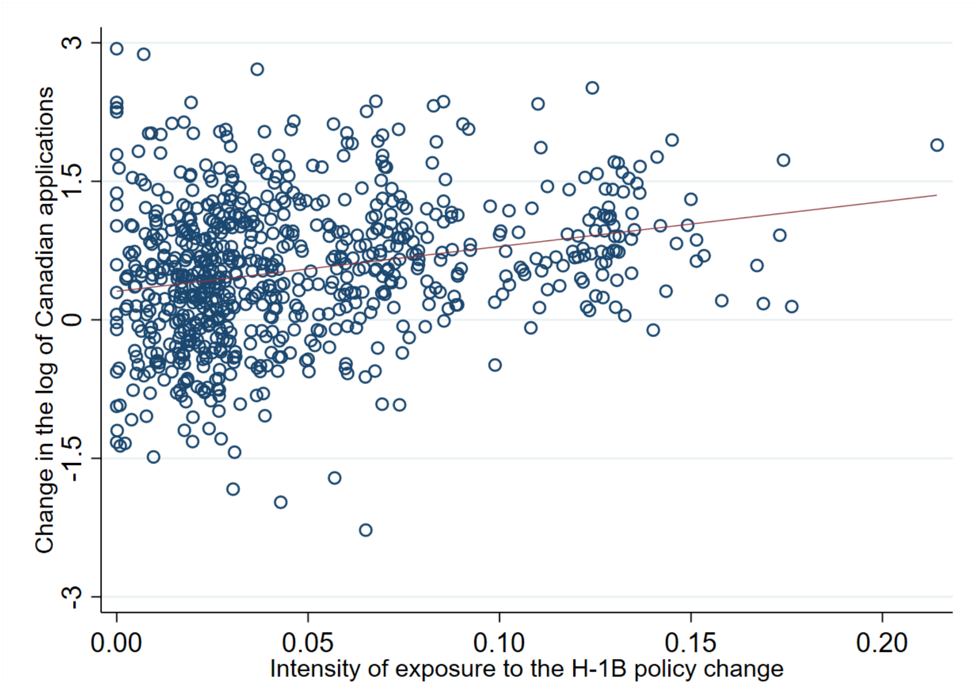


(c) Excluding apps. from computer scientists

(d) Including Express Entry control variables

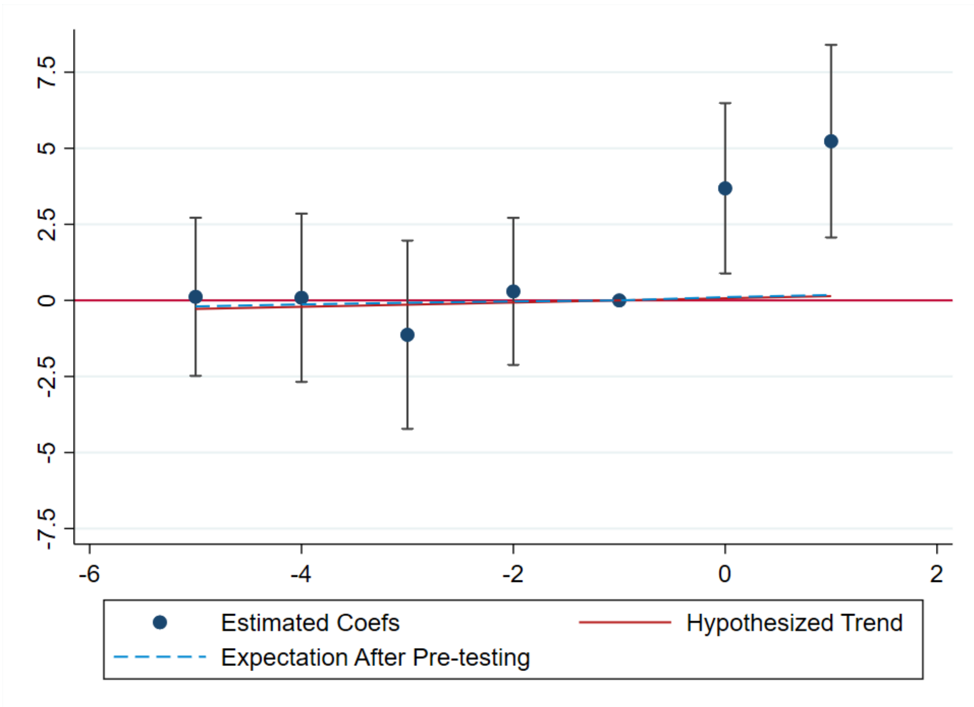
Note. The y-axis plots the estimated event-study coefficients corresponding to columns 2-4 from Appendix Table E.4.

Figure E.5: Change in Canadian applications and exposure measure: raw data



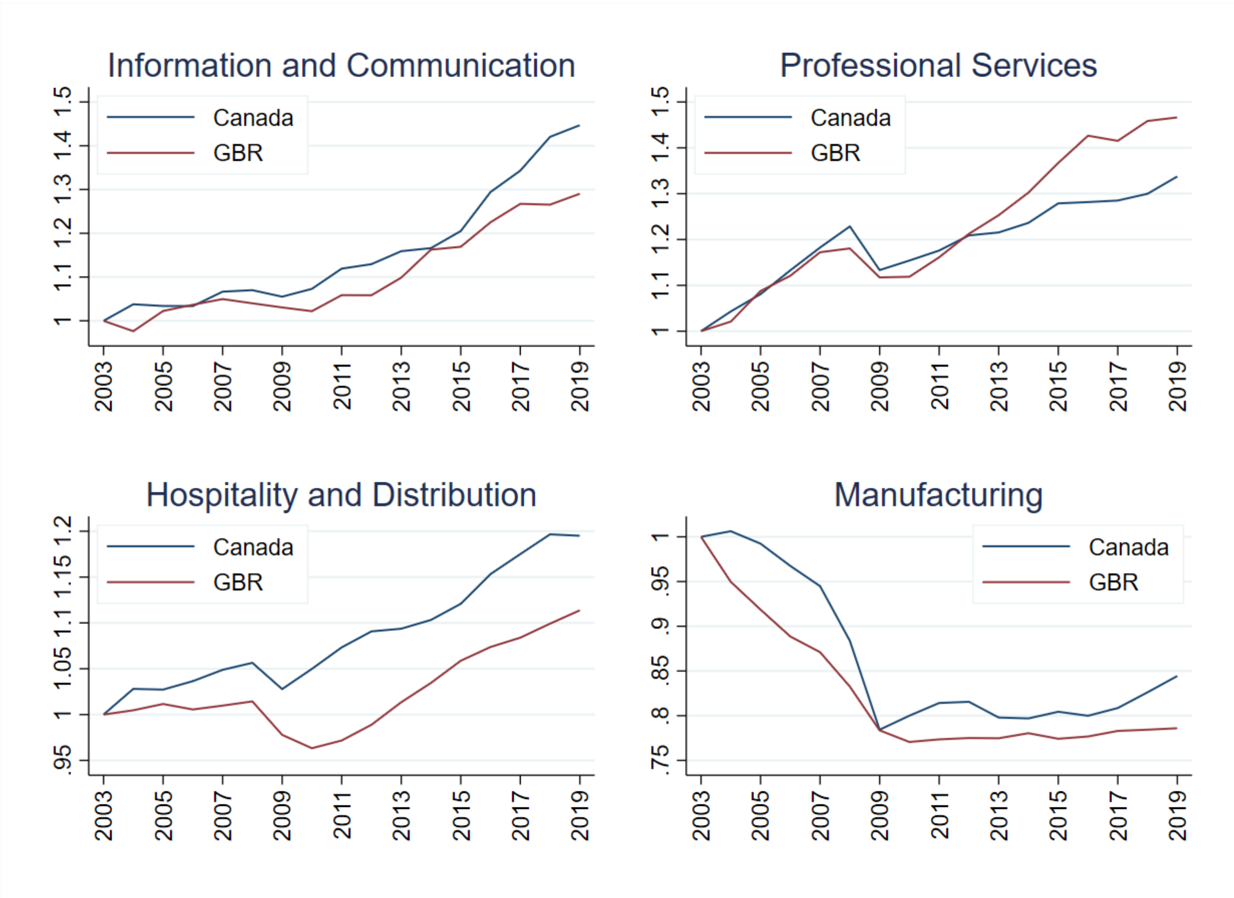
Note. The y-axis is computed as $\frac{\sum_{t=2017}^{2018} log(App_{co,can,t})}{2} - \frac{\sum_{t=2012}^{2016} log(App_{co,can,t})}{5}$ and the x-axis is $Fraction\ Affected_{co}$ in equation (2). An observation is an immigrant group co, where c and o stand for the country of birth and the occupations,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

Figure E.6: 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 E.7: 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 communications, professional services, hospitality and distribution, and manufacturing are 0.97, 0.95, 0.87, and 0.96, respectively.

Table E.5: 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

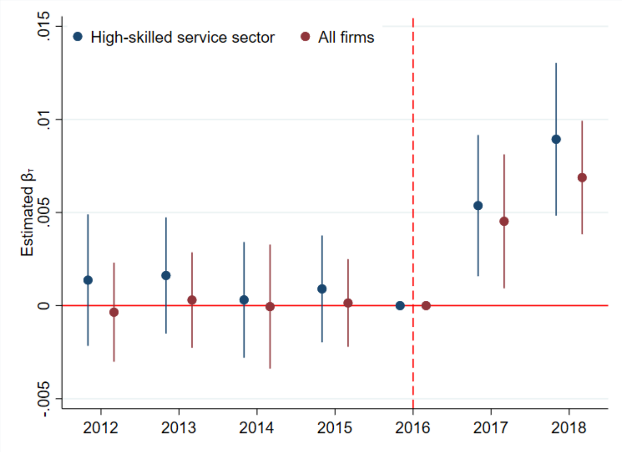
Note. This table reports the summary statistics of $Intensity_i$, normalized by the overall standard deviation. The statistics reported in the columns from left to right are the mean, standard deviation, median, 10th percentile, 90th percentile, and the number of firms, among the firms with positive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

Table E.6: Effect of increasing H-1B denial rates on Canadian firms

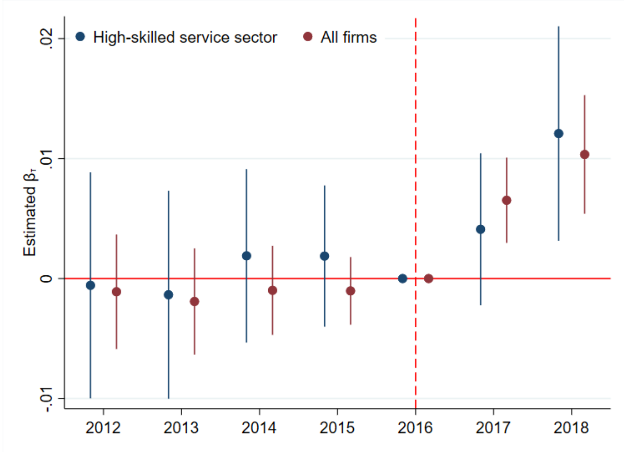
	Log of Revenues	Export-Rev ratio	Net hiring of imm.	Net hiring of native-born workers	Log of Native-born empl.	Log of Total empl.	Log of earnings per worker	Immigrant Share	Log of markup	Log of cost	Log median earn. native-born worker	Log of earnings per native-born worker	Log of Exports
$Intensity_i \times 1(\tau = 2012)$	-.0010915	-.001137	-.0003487	-.001607	-.0032443	.0028501	0.00124	.0003032	-.0017131	-.0011219	.0000758	0.00212	-.0245746
	.0024408	.0009854	.0013644	.0013189	.0032291	.0019405	-0.00109	.0007125	.0017283	.0020011	.0022437	-0.00153	.0203298
$Intensity_i \times 1(\tau = 2013)$	-.0019102	-.0003335	.0003032	-.0007732	.0005912	.0037446**	0.00183	-.0002274	-.0016221	-.0015767	.002274	0.00288**	-.0126891
	.0022589	.0008793	.0013038	.001137	.0029714	.0017737	-0.001	.0006367	.0013796	.0018647	.0020315	-0.00138	.0203298
$Intensity_i \times 1(\tau = 2014)$	-.0009854	-.0010764	-.0000455	-.0013189	-.000379	.0019557	0.00071	.0000758	-.0001819	-.0016221	.0009096	0.0015	-.0031685
	.001895	.0007277	.0016979	.0012128	.0026985	.0015918	-0.00089	.0005458	.0012583	.0016221	.0017737	-0.00122	.0168126
$Intensity_i \times 1(\tau = 2015)$	-.0010309	-.0005912	.0001516	-.0012886	-.00047	.0007277	0.00154	.0003032	.0000606	-.0012886	.0011522	0.00208	-.0019253
	.0014402	.0006064	.0011977	.0011067	.0021376	.0011977	-0.00089	.0004093	.0010612	.0011825	.0016525	-0.00121	.0135684
$Intensity_i \times 1(\tau = 2017)$	.0065189***	.0010461	.0045329**	.0024105	.0082471***	.0051545***	-0.00092	.00047	.0005609	.0055638***	-.0000606	-0.00052	-.0001971
	.0018192	.0007125	.0018344	.0012431	.0023347	.0015312	-0.00078	.0004093	.0010461	.0014554	.0016221	-0.00111	.0150541
$Intensity_i \times 1(\tau = 2018)$	.0103392***	.0034414***	.0068827***	.0029714**	.01278***	.0094145***	-0.00266***	.001895***	.0013189	.0091567***	-.0062915***	-0.00491***	.0386433**
	.0025166	.0008793	.0015615	.001228	.003032	.0020921	-0.00094	.0006064	.0013038	.0021073	.0020769	-0.00138	.0167975
Observations	537585	537585	537585	537585	537585	537585	408640	537585	532015	532115	408640	408640	79710
N firms	79430	79430	79430	79430	79430	79430	65950	79430	78955	78955	65950	65950	14345
R-squared	.9837	.9006	.1302	.1457	.9639	.9711	0.9342	.9649	.673	.9877	.9116	0.9219	.9068

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

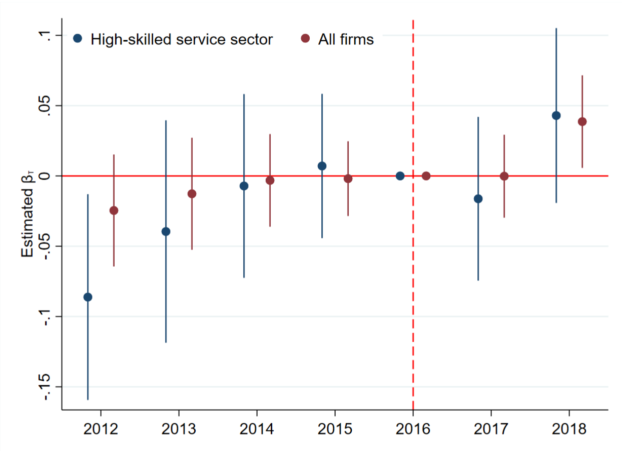
Figure E.8: Effect of increasing H-1B denial rates on Canadian firms



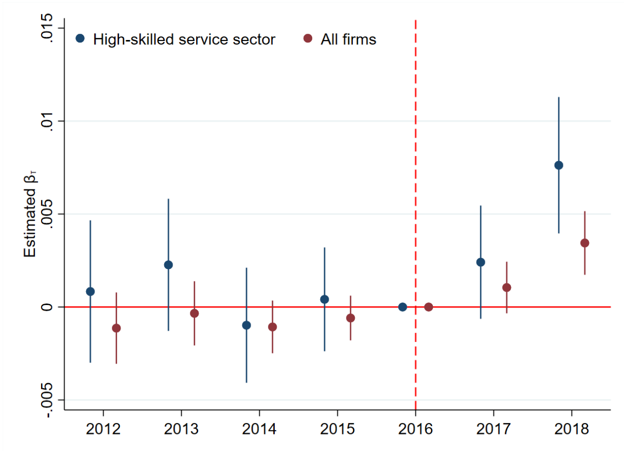
(a) Hiring of imm. relative to emp



(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_τ^E of equation B.1, multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals. The estimated coefficients β_τ plotted correspond to Appendix Table E.4, and the estimated coefficients β_τ^E plotted correspond to $SS = 1$ in Appendix Table E.7.

Table E.7: Effect of increasing H-1B denial rates on Canadian firms: within-sector estimates

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

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

Table E.8: Effect of increasing H-1B denial rates on domestic firms

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

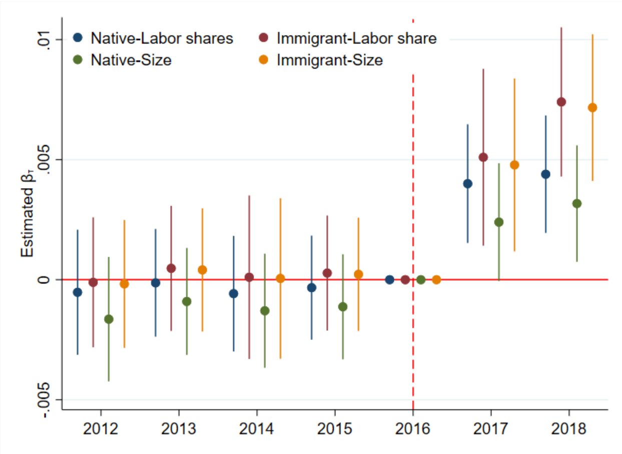
Note. The table displays the estimated event-study coefficients, β_τ, of equation (3) multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The sample includes only domestic firms and excludes MNCs. We plot these coefficients in Appendix Figure E.12. The event is defined as the spike in the H-1B denial rate in 2017. Standard errors are clustered at the firm level. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$

Table E.9: Estimate of the elasticity of substitution between the U.S. and Canada

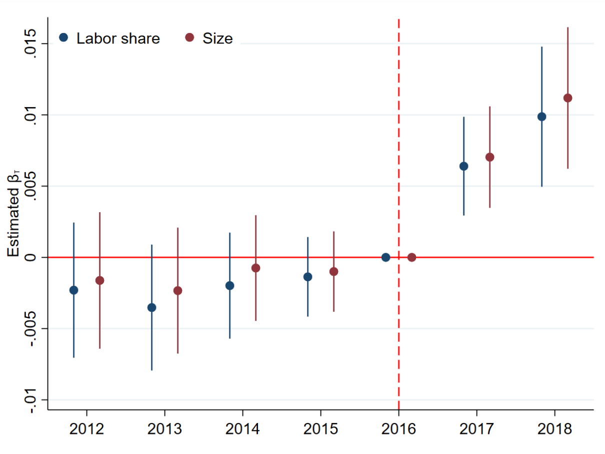
	(1)	(2)	(3)	(4)	(5)	(6)
	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$	$log(\frac{app_{co,can,t}}{app_{co,usa,t}})$
$p_{o,usa,t}\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

Note. $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. All columns include occupation-nationality fixed effects, occupation-year fixed effects, and nationality-year fixed effects. Standard errors are clustered at the occupation level. Column (1) shows the OLS estimates of the baseline specifications given by (D.35). Columns (2)-(6) show 2SLS estimates. Column (2) estimates the baseline specification. Column (3) controls for the elements used to compute $\pi_{co,usa}$ interacted with the year dummies (e.g., $\pi_{co,can} \times \delta_t$ and $\pi_{co,usa} \times delta_t$). Column (4) excludes applications from immigrants from India and China. Column (5) excludes applications from 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 from an immigrant group oc in year t accounted for by the Express Entry program.

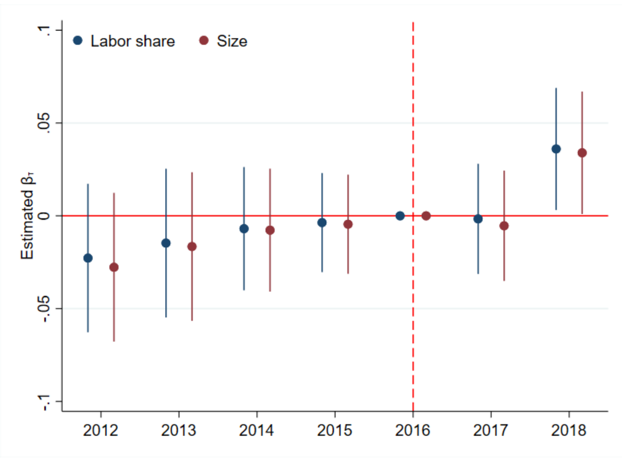
Figure E.9: Robustness exercise to control for the effects of firm characteristics



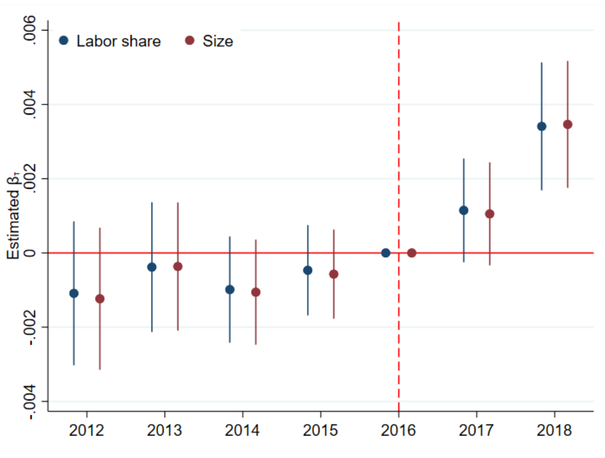
(a) Hiring relative to employment in 2016



(b) Sales (in log)



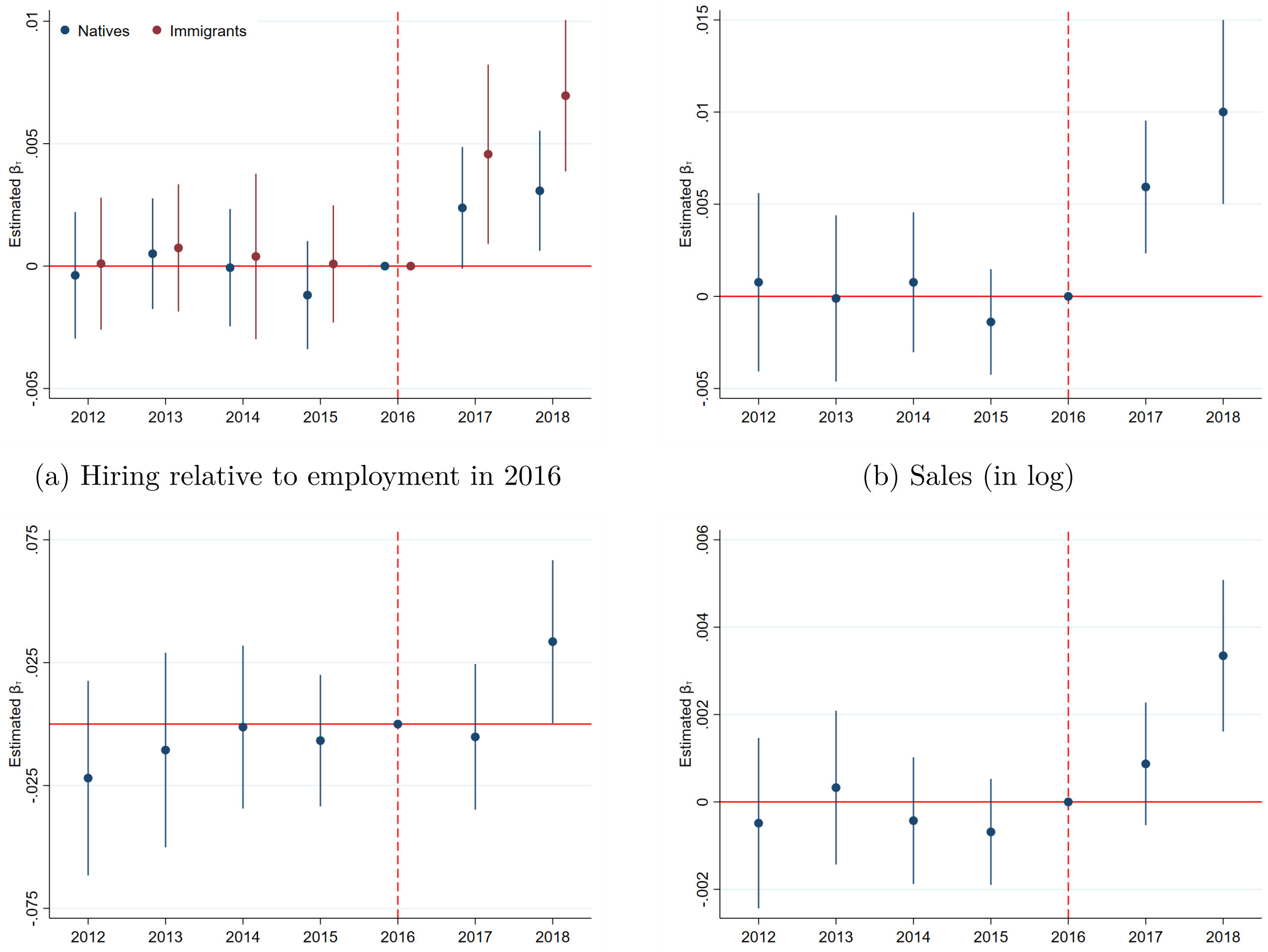
(c) Exports (in log)



(d) Exports relative to total sales

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

Figure E.10: Robustness exercise to control for the effects of the Express Entry program



(a) Hiring relative to employment in 2016

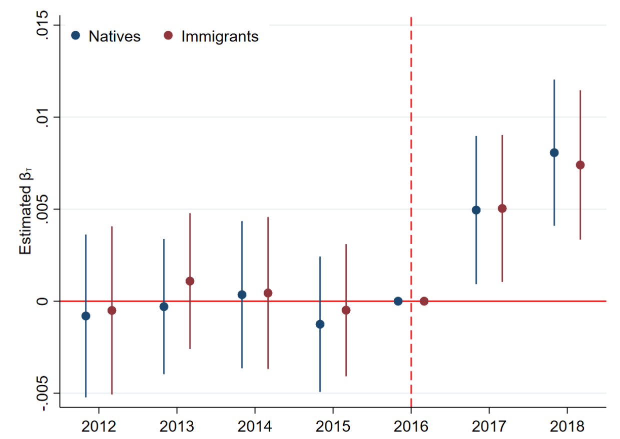
(b) Sales (in log)

(c) Exports (in log)

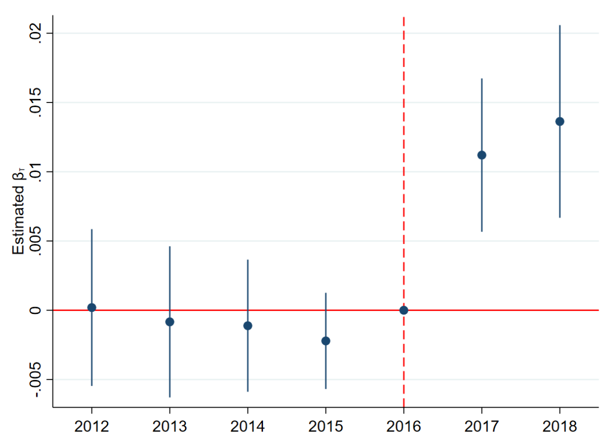
(d) Exports relative to total sales

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

Figure E.11: Robustness exercise to control for effects through international trade



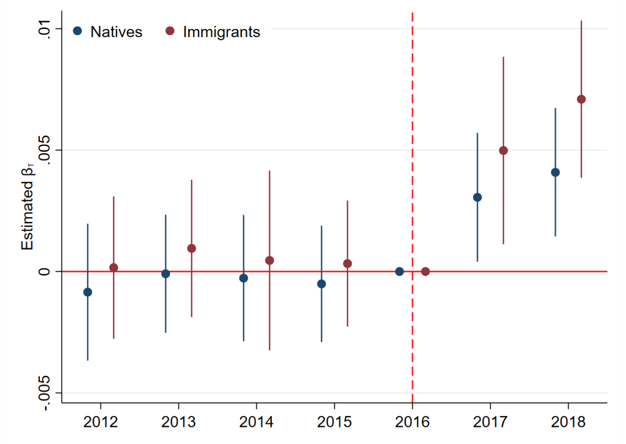
(a) Hiring relative to Employment in 2016



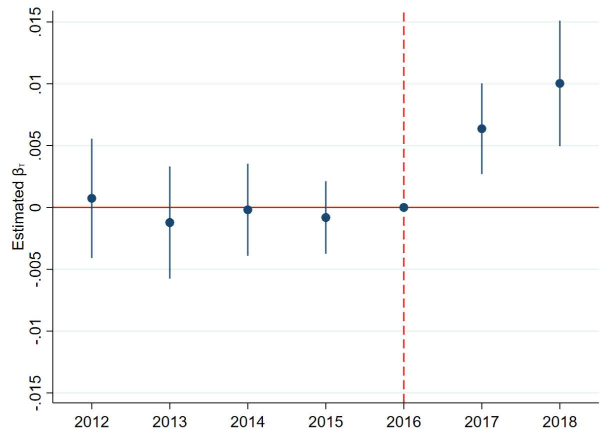
(b) Sales (in log)

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

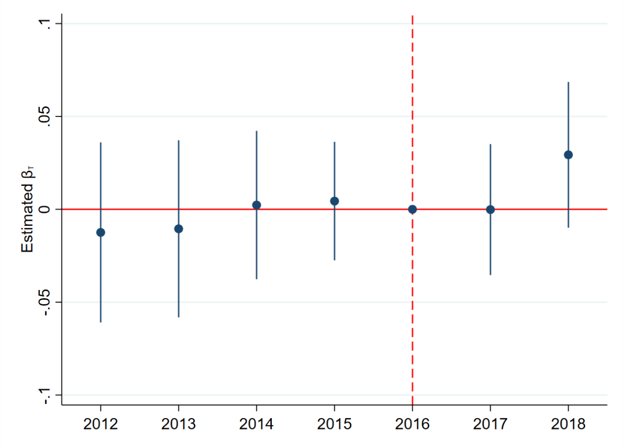
Figure E.12: Effects on domestic firms



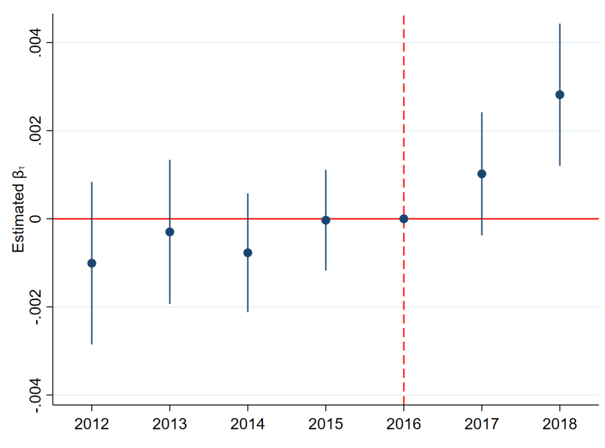
(a) Hiring relative to employment in 2016



(b) Sales (in log)



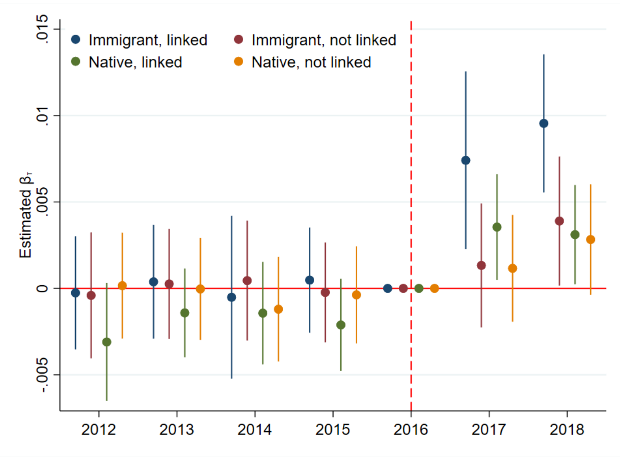
(c) Exports (in log)



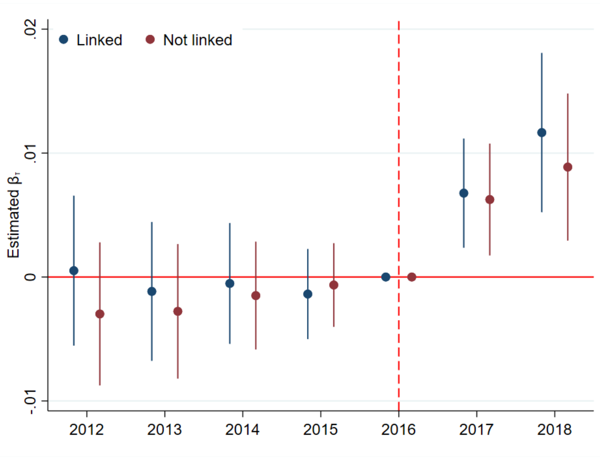
(d) Exports relative to total sales

Note. The y-axis plots the estimated event-study coefficients, multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The sample includes domestic firms and excludes all MNC (we also exclude Canadian multinationals). The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals. This figure corresponds to the estimates in Table E.8

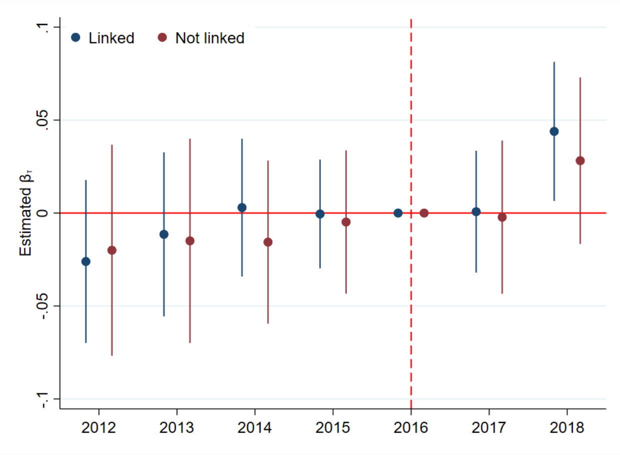
Figure E.13: Effects on firms based on the share of workers who lived in the U.S.



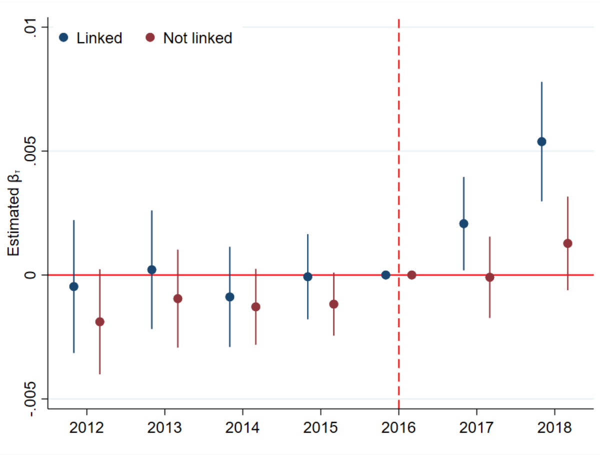
(a) Hiring relative to employment in 2016



(b) Sales (in log)



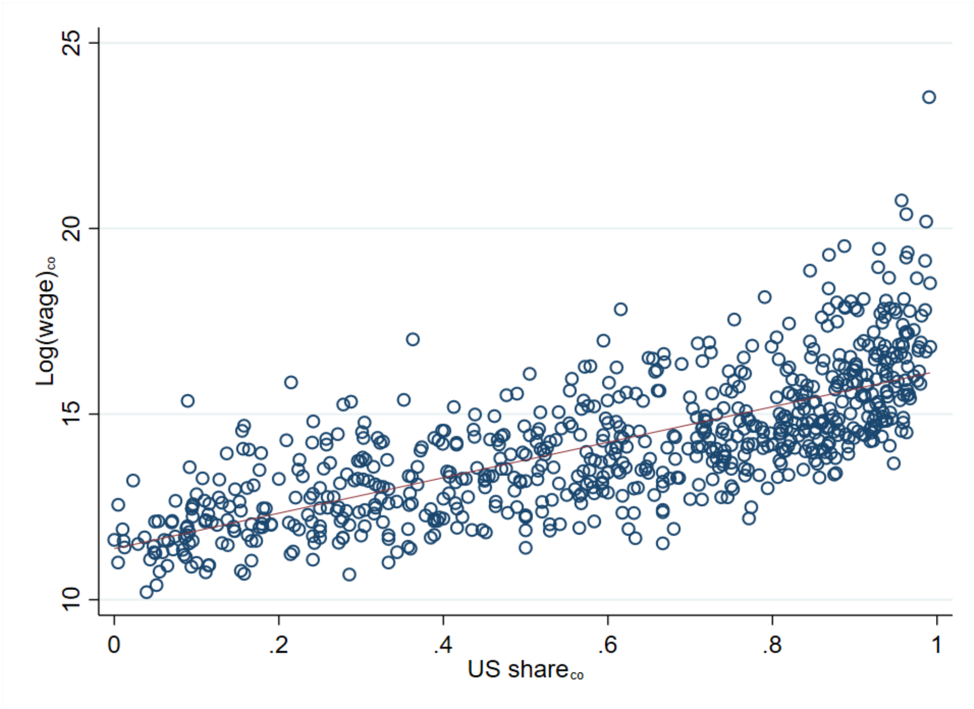
(c) Exports (in log)



(d) Exports relative to total sales

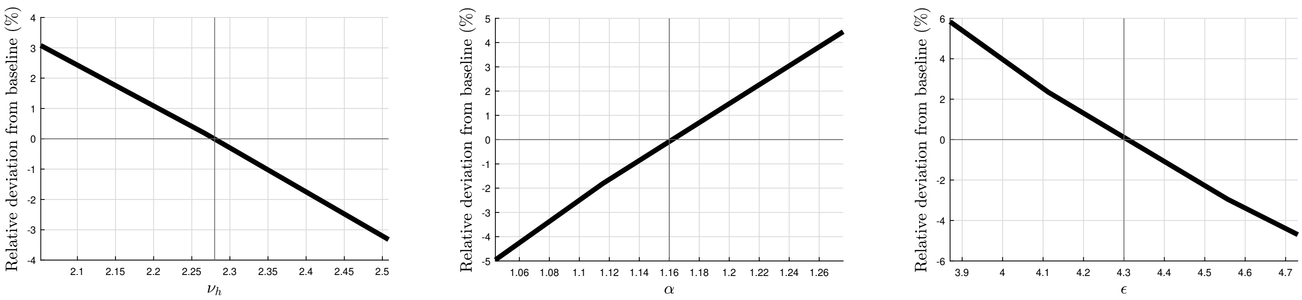
Note. The y-axis plots the estimated event-study coefficients of a modified version of equation 3, where we allow for heterogeneous treatment effects. In particular, we allow for β_τ to be different for firms in two different groups. We split firms into two groups: those that had employed immigrants 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 the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals.

Figure E.14: U.S. wages and the share of immigrants choosing the U.S. over Canada



Note. The y-axis is computed as the logarithm of the average annual earnings reported in the H-1B visa application dataset. The x-axis is the U.S. 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 stand for the country of birth and occupations, respectively.

Figure E.15: Identification of moments used for calibration



(a) Canadian visa applications (b) Sales (c) Earnings per native worker

Note. Each panel illustrates how a target moment varies with a corresponding parameter, holding all other parameters at their baseline levels. The x-axis represents the value of the corresponding parameter and the vertical line denotes its baseline value (i.e. $\nu_h = 2.3$, $\alpha = 1.2$, and $\epsilon = 4.3$). The y-axis display the model-implied coefficient of the regressions on the logarithm of Canadian visa applications, sales, and earnings per native-born worker, respectively, as a relative deviation from their values under the baseline calibration in percentage points.

Table E.10: Crosswalk of classification of occupations

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 been sub-categorized by technological intensity according to the United Nations Industrial Development Organization (UNIDO).