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.

JEL: F16, F22, J61
Keywords: Immigration Policy, High-Skill Migration, International Trade

1   Introduction

Restrictions on high-skilled immigration are becoming increasingly common in some developed countries that aim to protect domestic wages. 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.[1] 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 these laws at the beginning of 2017, which tightened the eligibility criteria for college-educated immigrants applying for U.S. H-1B visas.[2] 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.[3] 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 incorporate immigration policy into a multi-sector quantitative model of international trade, calibrated using our novel data and reduced-form estimates, to study the welfare effects of the policy and the role of international trade in determining the policy's efficacy in increasing American wages.

The new policy was implemented through policy memorandums issued by U.S. Citizenship and

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[1] See the Congress hearing *"How Outdated U.S. Immigration Policies Push Top Talent to Other Countries."*

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

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

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 to 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 firms, using our Canadian administrative dataset. To that end, we derive a shift-share exposure measure, 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. 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% higher 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 more 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 nationalities and occupations. The international trade 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 are motivated by our evidence. These probabilities are the immigration policy tool. Workers also choose their sectors. Since worker types differ in their comparative advantages, 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 larger inflows.

We use the model to derive an expression for the impact of changes in the U.S. visa denial rate on American workers' welfare that is composed of a direct and an 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 reduction in 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 are 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 workers from the incoming immigrant groups. 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 the purchasing power of their wages. The overall indirect effect on American workers in a sector can be positive or negative, depending on how export prices of U.S. sectors and 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 emigrating to Canada, directly from a coefficient of an equation that we derive from the model. For this estimation, we use our novel 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 event-study estimates. In addition, 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.

Using the calibrated model, 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 approximately 0.9%. 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 primarily benefits American computer scientists but tends to harm American workers employed in other occupations, resulting in a near-zero overall welfare effect. For instance, in high-skilled service sectors, the welfare of computer scientists increases by 0.7% and that of lower-skilled workers decreases by 0.3%. We assess the importance of international trade in these welfare 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 the 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 the goods that embody the labor services of these immigrants.

Related literature: Our paper contributes to an extensive empirical literature studying the economic effects of immigration (seminal papers include Card (1990, 2001), Borjas (2003, 2005), and Ottaviano and Peri (2012)).[4] A stream of this literature studies the effects of skilled immigration on native-born workers' labor market outcomes.[5] Finding a clean source of exogenous changes in the 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 study the impact of sudden refugee inflows (e.g., Hunt (1992), Friedberg (2001), Borjas and Monras (2016)). However, the economic effects of refugee and economic migrant inflows may differ (Cortes, 2004). The stream of the literature studying the impact of skilled immigration on firms tends to face similar challenges.[6] Some studies address this by using random availability in the number of H-1B immigrants to individual firms (Kerr and Lincoln, 2010; Kerr et al., 2015; Dimmock et al., 2022; Doran et al., 2022; Brinatti et al., 2023). These papers do not tend to capture the impact of aggregate skilled immigration inflows because the *total* number of immigrants in these experiments remains unchanged.

We contribute to this literature in two ways. First, we construct a novel measure of an aggregate supply shock of skilled immigrant labor, useful to addressing a wide range of research questions.[7] Second, we offer a quantitative general equilibrium model that quantifies the aggregate effects of skilled immigration and enables *counterfactual policy analysis*.

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

[5]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.

[6]This stream of the literature includes Dustmann and Glitz (2015); Mitaritonna et al. (2017); Ottaviano et al. (2018); Beerli et al. (2021); Egger et al. (2021); Mahajan (2022); Arellano-Bover and San (2023).

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

We also contribute to the empirical literature studying the labor market effects of immigration policies. Existing papers mainly study 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.

This paper contributes 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 strong assumptions, including free trade and fixed prices, 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). We contribute to this literature by quantifying the extent to which current levels of international trade mitigate the wage effects of changes in immigrant labor endowments, using our quantitative model. This exercise also provides insight into how far we are from Rybczynski's predictions.

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. We contribute to this literature by developing a quantitative trade model with three valuable features. First, it incorporates migration policy and migration choice under uncertainty in a tractable way. Second, unlike common immigration models that require observing actual changes in migration flow levels due to policy changes, our model relies on observing changes in denial rates. This is crucial for accurately assessing the *level* of welfare changes due to the policy shock, as denial rates are observable while migration flow levels are intrinsically unobservable.[8] Third, by incorporating multiple sectors, our model allows for the impact of international trade on the welfare effects of immigration to be positive or negative.

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[8]One approach is to use regression analysis to estimate the changes in migration flows due to U.S. policy. However, while such a regression may identify changes in *relative* migration flows, it might not identify the *levels*.

The paper is organized as follows. Section 2 introduces the data and the institutional background. 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 international trade data for goods and services. This section describes the content of these datasets. Appendix A provides details on the datasets 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 were 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 an 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 has been reached. This lack of information regarding unprocessed new H-1B visas is one reason why we use continuing visas to measure the U.S. policy shock 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 by year, occupation (4-digit National Occupational Classification, (NOC)), country of citizenship, the 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.

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).

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 immigrant database 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 permanent residents 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 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 by trading partner country for 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 U.S. 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 U.S. Citizenship and Immigrant Services (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 meet core eligibility criteria prior to entering 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 F.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

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[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 working 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

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[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 an 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's 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 trend) by the end of 2018 (see Appendix Figure F.2).[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.

The timing of these events suggests that the U.S. policy change may have caused the increase in skilled immigration to Canada. However, other contemporaneous factors may have affected immigration to Canada, such as changes in U.S. trade policy, increased xenophobia in the U.S., positive demand shocks in Canada, or changes in Canadian immigration policy. The next section proposes an empirical strategy to isolate the effects of U.S. immigration policies on Canadian immigration from the impact of other factors that may correlate with the H-1B policy change.

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

We aim to identify the effects of the U.S. restrictions by combining the mentioned time variation with the cross-sectional variation introduced by the new policy and by controlling for the effects of unobservable factors with a comprehensive set of fixed effects.

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[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 the number of denials explains the spike in the denial rates.

Figure 1: Increasing H-1B restrictions and skilled immigration to Canada
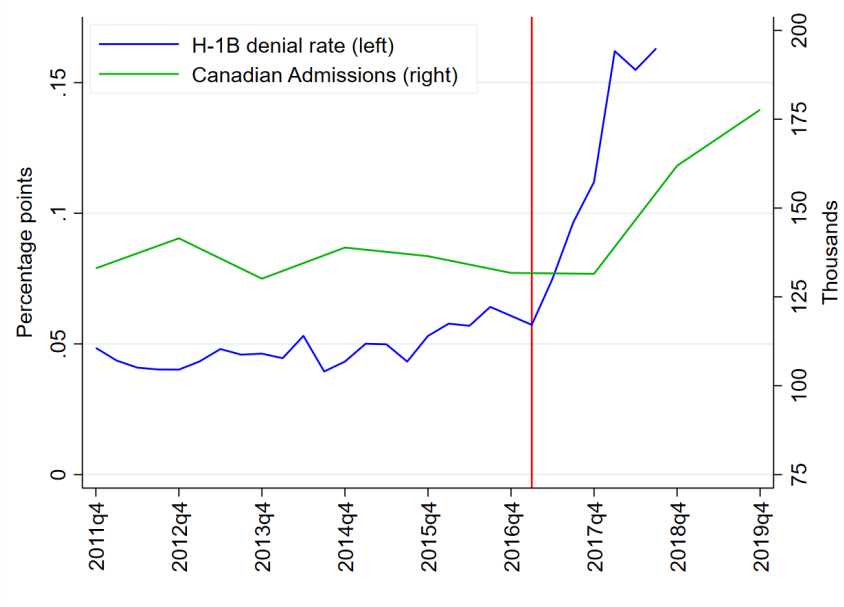
Notes: The blue line, which corresponds to the y-axis on the left-hand side of the figure, plots the number of denied H-1B applications divided by the total number of H-1B applications. It includes new and continuing H-1Bs. Given that the period to apply for new H-1B visa applications is during March 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, i.e., the Federal Skills Trades Program, Federal Skilled Worker (Express Entry), and Provincial Nominee Program (PNP).

3.2.1 Event-study framework

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 are 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 event-study model takes the following form:

$$log(Can\ App_{cot}) = \sum_{\tau \neq 2016} \theta_\tau \times \text{Fraction Affected}_{co} \times 1(t = \tau) + \delta_{co} + \delta_{ot} + \delta_{ct} + \epsilon_{cot} \quad (1)$$

where $Can\ App_{cot}$ is the number of Canadian visa applications of immigrant group co in year t, Fraction Affected$_{co}$ is the intensity of the treatment of the new eligibility criteria, given by the fraction of the immigrant group co whose H-1B visa applications were denied, δ_{co} are fixed effects at the immigrant group level, δ_{ot} are fixed effects at the occupation-year level, δ_{ct} are fixed effects at the country-of-birth-year level, and ϵ_{cot} is the error term, which we cluster at the immigrant group level. The coefficients θ_τ measure the differences in the outcome variables between year t and 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 have affected the outcomes

only after the policy memorandums were introduced, we expect θ_τ to be zero before 2016.

Immigrant group exposure to the H-1B restrictions   Motivated by our model, we measure Fraction Affected$_{co}$ as the fraction of the potential number of migrants to North America, either to the U.S. or to Canada, affected by the new policy:

$$\text{Fraction Affected}_{co} = \underbrace{\frac{\text{Denial Rate}_o^{2018} \quad \times \quad \text{US Applications}_{co}}{\text{CAN Applications}_{co} \quad + \quad \text{US Applications}_{co}}}_{\text{Denial Rate}_o^{2018} \times \text{US Share in Applications}_{co}} \qquad (2)$$

The numerator proxies for the number of immigrants with denied U.S. visas who could potentially consider migrating to Canada and the denominator proxies for the number of potential migrants to North America. For interpretation, Fraction Affected$_{co}$ can be re-written as the interaction between the denial rate and the U.S. share in the total number of applications to North America, denoted by $\pi_{co,usa}$. Thus, our measure suggests that while the policy changed differently across occupations, it effectively affected immigrants from different nationalities, depending on their propensity to apply for a U.S. visa.[15]

We compute the denial rates using only the applications for continuing H-1B visas and exclude applications for new H-1B visas.[16] 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 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 in their home country.[17] We measure $\pi_{co,usa}$ for the years before the introduction of the policy memorandum (i.e., FY2012-FY2015) to ameliorate the potential effects of confounding contemporaneous shocks.[18]

Figure 2 illustrates the sources of the variation of the fraction affected by the policy: Panel

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[15]The denial rate is not country-specific because we do not find evidence in the data or the memorandum indicating that the policy varied by nationality within occupations. Also, the results are very similar but noisier if we use the change in the denial rate rather than the level (see Subsection 3.2.3).

[16]Continuing visas account for 55% of all denials. See the spike in this denial rate in Appendix Figure F.3. Note that this does not mean that our estimates are restricted to the H-1B continuing visa applicants' responses.

[17]Appendix Figure F.4 shows that immigrants in the U.S. typically do not apply for Canadian visas. However, a sudden surge occurred in 2017, consistent with stricter U.S. policies forcing denied applicants to leave.

[18]We expect the pre-shock value of $\pi_{co,usa}$ to proxy well for the post-period value we would have observed had no other contemporaneous shock occurred, as immigrants tend to follow the occupational choices of their compatriots (Altonji and Card, 1991; Card, 2001; Patel and Velia, 2013).

Figure 2: Source of cross-sectional variation in Fraction Affected$_{co}$

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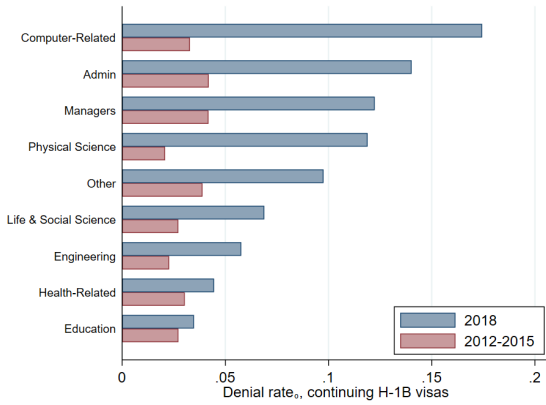
(b) Variation across nationalities: examples

Notes: Panel (a) plots the denial rates 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 are the denial rates for FY 2018. Panel (b) plots $\pi_{co,usa}$ for the top and bottom five countries in terms of $\pi_{co,usa}$ for computer scientists.

(a) shows denial rates for continuing H-1B visa applications by broad occupation, comparing a typical year (red bars) to a year following the policy 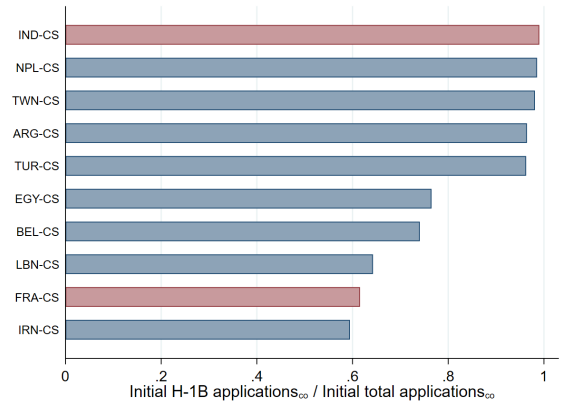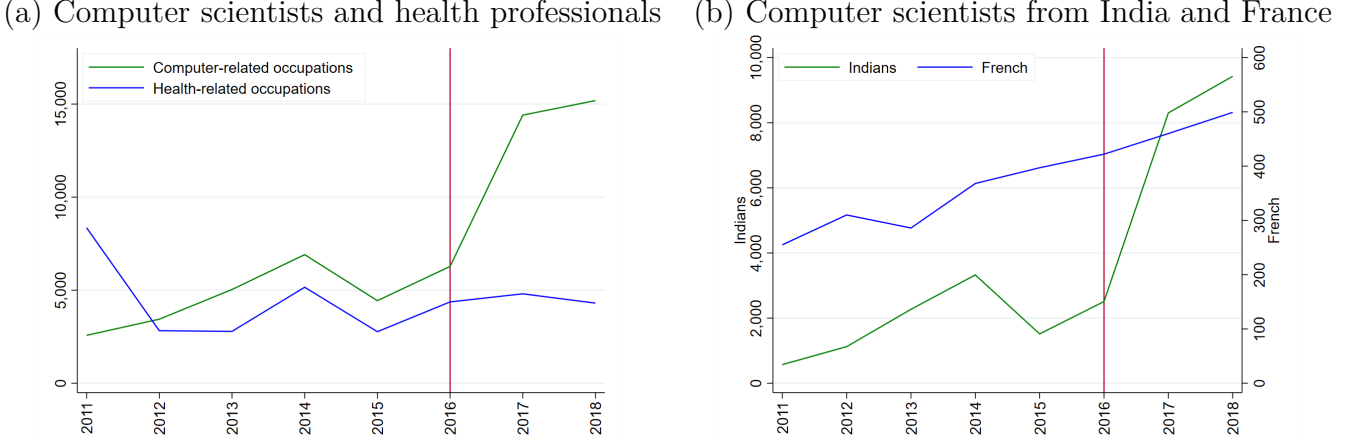memorandums (blue bars). In normal years, denial rates are similar across occupations, but large differences arise following the introduction of the policy memorandums. For example, computer-related occupations experienced an 18% denial rate (14.6 percentage points above average), while health-related occupations had a 4% denial rate (1.1 percentage points above average). Panel (b) highlights the variation across nationalities, 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. Consistent with the variation in Figure 2, Figure 3 shows a trend break in 2017 in the number of visa applications for computer scientists relative to health professionals (panel a) and of Indian computer scientists relative to French ones (panel b).

Fixed effects 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 size or preferences for the U.S. relative to Canada. δ_{ot} prevents attributing the effects of occupational shocks to the effects of the H-1B restrictions. This is important because some of the occupations that were more affected by the new eligibility criteria, such as computer-related occupations, had been growing relatively fast. Finally, immigration from certain countries such as India has been on an upward trend to several developed countries, including 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}.

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Figure 3: Canadian visa applications

(a) Computer scientists and health professionals   (b) Computer scientists from India and France

Notes: Panel (a) plots the time series of Canadian visa applications for computer- and health-related occupations. These are occupations that experienced relatively large and low denial rates respectively (see panel (a) of Figure 2). Panel (b) plots the number of computer-related occupations of nationals from India and France. These are immigrant groups with relatively high and low $\pi_{co,usa}$ according to panel (b) of Figure 2.

Identifying assumption   The 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 outcomes for immigrant groups that would 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 4 plots the estimates of θ_τ for the years between 2012 and 2018. It shows that Canadian visa applications of immigrants who were more exposed to the U.S. restrictions grew faster than the applications coming from less-exposed immigrant groups only after the U.S. restrictions were imposed. The estimates for the years after the U.S 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 suggest that Canadian applications in 2018 were 31% higher than what they would have been in the absence of the H-1B restrictions.[19] These (relative) effects are remarkably similar to those observed in the time series in Figure 1, which suggests a relatively large inflow of workers to the Canadian labor market.

Our event-study estimates can also be interpreted in terms of two statistics that are useful for policy analysis. First, an increase in H-1B denial rates of 10 percentage points increases the number of applications to Canada by 30%, given that the average exposure $\pi_{co,usa}$ is 0.57 (e.g.,

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

$0.57 \times 0.1 \times 5.2 = 0.30$). This is equivalent to saying that a 10 percentage point increase in Fraction Affected$_{co}$ 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 four forgone H-1B visa approvals results in an increase of about one permanent resident application to Canada.[20]

Figure 4: Effect of H-1B restrictions on permanent resident visa applications to Canada
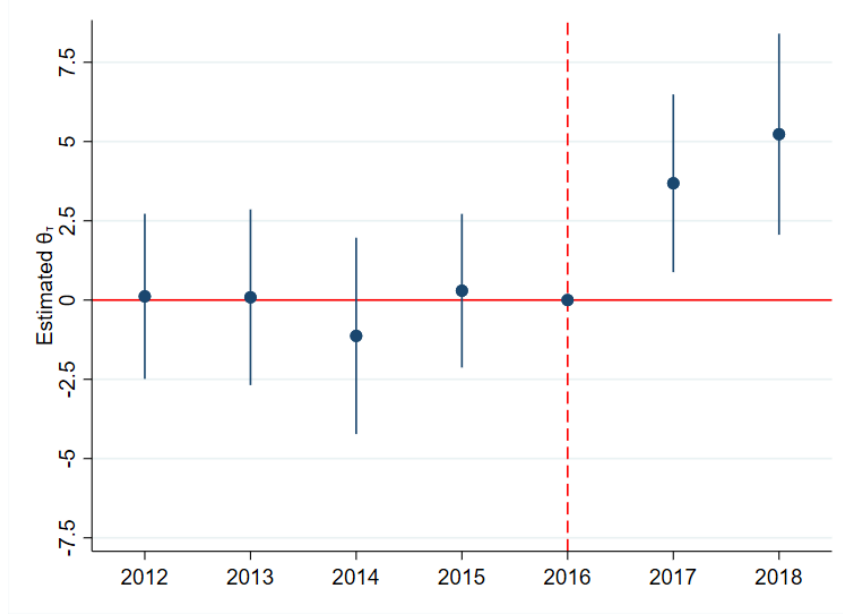
Notes: The y-axis plots the estimated event-study coefficient, θ_τ, of equation (1). The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The plotted coefficients correspond to column 1 in Appendix Table F.4. The omitted year is 2016.

There are several reasons for this large increase in immigration to Canada. First, potential migrants to the U.S. may choose Canada as their next-best alternative 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 their employees to Canada (see Envoy Global's 2019 Report).

3.2.3 Robustness exercises

Appendix Section B.1 elaborates on alternative specifications that assess the robustness of our results, and Appendix Table F.4 shows the estimated results. These alternative specifications address concerns such as the existence of confounding factors that correlate over time, which

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[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 $\hat{\theta}^{relative} \times \frac{Applications^{can}_{2012-2016}}{Aprovals^{H-1B}_{2012-2016}}$.

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 also estimate the baseline specification, using the change in the denial rate in Fraction Affected$_{co}$ rather than in the level in 2018. In addition, we test for linear trends that would violate our identification assumption (Roth, 2022) and whether the results are driven by outliers. Our results are robust to all of these alternative specifications.

3.3 Effects of increased skilled immigration on Canadian firms

Having established that the H-1B restrictions lead to a relatively large inflow of skilled immigrants to Canada, we aim to understand how this inflow of workers affected Canadian sectors' production and global competitiveness.[21] To do so, we estimate firm-level regressions that allow us to control for factors affecting firms within specific industries and still exploit the rich cross-sector (and within-sector) variation introduced by the U.S. policy change. This section documents how the inflow of skilled immigrants affected Canadian production, and the next section quantifies the aggregate implications of these facts.

3.3.1 Event-study framework

To study the effect of the H-1B restrictions on Canadian firms, we predict which firms are likely to absorb the incoming immigrants and estimate if these firms started to perform better than others after the U.S. policy change. We implement this idea in an event-study framework, where the regression for outcome y of firm i in year t is

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

Intensity$_i$ measures the exposure intensity of firm i to the inflow of immigrants migrating to Canada due to the H-1B policy change, which we describe shortly. The index k refers to the industry according to its 4-digit NAICS classification, and m to the main commuting zone of the firm. δ_i are firm fixed effects, δ_{mt} are labor markets-year fixed effects, X_{ikt} is a set of control variables that vary over time and across firms and industries, and ϵ_{it} is the error term, which we cluster at the firm level.[22] The coefficient β_τ measures the difference in the outcome variable y between year τ and 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 not have

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[21]In principle, this could be accomplished with sector-level regressions. However, using firm-level data allows us to isolate better the effects of the U.S. policy change from other factors affecting industries differently, such as immigration for reasons other than the U.S. policy change.

[22]The statistical significance of our estimates is robust to clustering errors by industry and labor market (see Appendix Table F.7).

affected firms' outcomes before the policy memorandums were introduced, we expect β_τ to be zero for $\tau < 2016$. Appendix Section B.2 provides details on the measurements of the variables and the samples.

Firm exposure to the H-1B restrictions   We propose a measure to predict which firms hire the immigrants that migrate to Canada due to the H-1B restrictions. This 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.[23] This assumption is motivated by our model and the vital role that immigrant networks play in sharing information and providing referrals for immigrants (Egger et al., 2021).

Let ΔL_{co}^{pol} be the flow 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 Canadian labor market of workers co. Suppose that the inflow ΔL_{co}^{pol} is assigned to firms according to this share. Then the number of co workers assigned to firm i relative to its initial number of workers, L_i, is

$$\frac{Hires_i^{pol}}{L_i} \approx \sum_{co} \frac{L_{coi}}{L_{co}} \frac{\Delta L_{co}^{pol}}{L_i} = \sum_{co} \frac{L_{coi}}{L_i} \frac{\Delta L_{co}^{pol}}{L_{co}} \tag{4}$$

The right-hand side of the equation can be thought of as a Bartik exposure, with the shift given by $\frac{\Delta L_{co}^{pol}}{L_{co}}$ and the share by $\frac{L_{coi}}{L_i}$. 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, $\frac{L_{coi}}{L_i}$. We first note that this share can be expressed as the share of nationality c within occupation o at firm i $(\frac{L_{coi}}{L_{oi}})$ times the share of occupation o in the firm's total workforce $(\frac{L_{oi}}{L_i})$. We proxy $\frac{L_{coi}}{L_{oi}}$ with the overall nationality share $(\frac{L_{ci}}{L_i})$ and the occupational structure of the firm $\frac{L_{oi}}{L_i}$ with that of the industry in which it operates $(\frac{L_{ok(i)}}{L_{k(i)}})$.

We must also proxy the shift component $\frac{\Delta L_{co}^{pol}}{L_{co}}$ because the flow of immigrants *due to the U.S. policy* ΔL_{co}^{pol} is intrinsically unobservable. We rewrite $\frac{\Delta L_{co}^{pol}}{L_{co}}$ as $\frac{\Delta L_{co}^{pol}}{Flow_{co}} \times \frac{Flow_{co}}{L_{co}}$, where $Flow_{co}$ is the number of workers co migrating to Canada in the pre-shock period, and we assume that the growth in the inflow of immigrants due to the U.S. policy is proportional to the growth of their applications (e.g., $\frac{\Delta L_{co}^{pol}}{Flow_{co}} \propto \Delta log(CanApp_{co})$). This assumption allows us to use our previous empirical model to measure the growth of applications due to the H-1B policy (e.g., $\Delta log(CanApp_{co}) \approx \theta$ Fraction Affected$_{co}$).

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[23]This assumption does not impose specific restrictions on the degree of worker substitution in production. For example, it can arise from assumptions about the primitives governing the workers' comparative advantage.

Thus, $Intensity_i$ is proportional to the right-hand side of (4) and is given by

$$Intensity_i \equiv \sum_{co} \underbrace{\frac{L_{ci}}{L_i} \frac{L_{ok(i)}}{L_{k(i)}}}_{\approx \frac{L_{coi}}{L_i}} \underbrace{\text{Fraction Affected}_{co} \frac{Flow_{co}}{L_{co}}}_{\propto \frac{\Delta L_{co}^{pol}}{L_{co}}} \tag{5}$$

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

<u>Variation in $Intensity_i$</u>: Appendix Table F.5 provides summary statistics for $Intensity_i$ that highlight the cross-sectional variation that, together with the time variation of the policy, is used to identify the effect of interest. This empirical measure exhibits rich variation across industries and across firms within relatively exposed industries but it exhibits only limited variation due to the policy change across firms within relatively unexposed industries. The most-exposed sectors, given by the top quartile of sectors in terms of the average $Intensity_i$, are information and cultural industries, 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 and exposure to the U.S. policy change.

We also include labor market-year fixed effects, δ_{mt}, to address reverse causality concerns, which arise when immigrants choose where to locate. If migrants choose to locate in markets that are growing, this growth may cause immigration to increase rather than the reverse. Including labor market-year fixed effects implies that β_τ is identified by comparing firms that are located in the same labor market but are differently exposed to the H-1B restrictions. Note that these fixed effects also absorb the consumption effect of immigration, which arises because immigrants are consumers of goods produced by firms located in the market where they settle.

We also control for the effect of potential confounders, by including firm-year controls in X_{ikt}. As hinted earlier, an important confounding factor is the ongoing immigration inflow. Firms that typically hire immigrants might experience relatively faster growth due to ongoing immigration inflows, even in the absence of the H-1B restrictions. To isolate these effects from the effect of interest, we compare firms with similar reliance on immigrant labor but with different exposure to the H-1B policy change. To do so, we control for firms' immigrant share of the wage bill and the log of one plus the number of likely skilled immigrants in 2016, both interacted with year dummies.

Another threat to identification is the confounding effects of the contemporaneous changes in

U.S. trade policy. For example, if the trade war between the U.S. and China during President Trump's administration diverted trade towards (or away from) the 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 we interact them with year dummies: the share of exports in total sales, and the share of service exports in total exports. See Section 3.3.3 for related robustness exercises.

Additionally, we control for potential industry-level confounders by incorporating industry-year control variables in X_{ikt}. We include sector-specific trends because some industries that were already growing faster, such as the IT sector, happened to be intensive in the occupations affected by the rise in the number of H-1B denials. We also control for global industry-specific shocks by including the number of jobs created in the U.K. in each industry year, as the correlation of employment between the U.K. and Canada is approximately 0.95 (see Appendix Figure F.9). We also include the industry's employment growth in 2011 interacted with the year fixed effects to account for the effects of domestic factors that correlate over time.

Finally, it is worth explicitly explaining why our baseline specification does not include industry-year fixed effects. First, the paper aims to understand the impact of the U.S. policy change, which was intrinsically a sectorial shock, on the comparative advantage and global competitiveness of Canadian sectors. This requires accounting for the cross-sector variation introduced by the policy. Second, as noted under "Variation of $Intensity_i$", the U.S. policy led to limited variation in $Intensity_i$ across firms within relatively unexposed industries. If we include industry-year fixed effects, our estimate would capture the average impact of the policy within unaffected industries (e.g., zero effect) and truly affected industries, which is not our effect of interest. In a robustness exercise, however, we include industry-year fixed effects and show that our results are robust (see Subsection 3.3.3).

Identification assumption Similar to Abramitzky and Boustan (2017), the identification assumption of our empirical strategy is that firms with a higher or lower share of immigrants from the affected groups would not have diverged after 2016 in the absence of the U.S. policy change. We provide evidence supporting the parallel trends assumption by, among others, testing whether β_τ for $\tau < 2016$ are zero.[24]

3.3.2 Results

Figure 5 plots the event-study estimates for the main outcomes of interest such as sales, exports, and Canadian workers' earnings and employment. We relegate to the appendix the event-study

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[24]Our analysis shares some features with shift-share instruments because it relies on initial shares to determine the firm's exposure to the U.S. policy. This motivates us to include specific controls (e.g., firm's immigrant share interacted with year dummies) and perform some robustness exercises (see Subsection 3.3.3).

estimates of additional variables including the share of immigrants in the wage bill, total cost, and mark-ups measured as sales relative to total costs (see Appendix Table F.6).

Hiring of foreign-born workers We begin the analysis by showing that the H-1B restrictions increased the hiring of immigrant workers relative to the employment level in the baseline year (see panel (d)). This fact is reassuring because the outcome variable is the left-hand side of equation (4), which motivated the construction of $Intensity_i$.[25]

Effect on production and exports Panel (a) shows that firms with higher exposure to the U.S.'s immigration restrictions increased sales compared to less-exposed firms, only after the implementation of the restrictions. For reference, our estimates suggest that the average-exposed firm in the skilled service sector registered a 1% larger increase in sales than it would have in the absence of the H-1B restrictions. Our estimates imply that an additional immigrant hired in 2017-2018 translated into an increase in sales in 2018 of C$112,000 for the median firm in the skilled service sector, which represents 3.2% of pre-shock sales.[26] The rise in sales is likely indicative of an increase in production because we found no evidence of changes in mark-ups (see estimates in column 14 in Appendix Table F.6).

Exports play an important role in this expansion. Panel (b) 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 approximately 38% of the increase in sales.[27] Some of the destination countries for these exports are markets typically served by American firms, such as the U.S. market. Panel (c) offers supporting evidence by focusing on exports to the U.S. as a share of total sales. This fact provides more direct evidence that the expansion of Canadian firms' production could have increased the competition American firms faced in both domestic and international markets and, thus, ultimately have affected American wages. We will formalize how this adjustment of Canadian production and exports influenced the intended effects of the U.S. immigration policy on American wages in the following section.

Effects on Canadian workers Firms that were relatively more exposed hired not only more immigrants but also more native-born workers, as shown in panel (d). The ratio of the estimated responses of hiring Canadian and immigrant workers suggests that, on average, a firm hires approximately 0.5 additional Canadian workers per immigrant hired due to the H-1B restrictions.

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[25]It is worth mentioning that the firm's responses are likely driven by the increase in both the number of immigrants and their average ability level compared to typical immigrants to Canada (see Appendix Figure F.10 for supporting evidence).

[26]We approximate the change in sales and hiring of immigrants to its 2016 employment level as follows: $\Delta y_i \approx \hat{\beta}^y \, Intensity_i \, y_{i\,2016}$. Then $\frac{\Delta sales}{\Delta hiring\,imm} = \frac{\beta_{2018}^{log(sales)}}{\beta_{2017}^{HireImm} + \beta_{2018}^{HireImm}} \times \frac{sales_{2016}}{empl_{2016}}$. We use the estimates from panels (a) and (d) and the median value for the ratio of sales to employment in the skilled service sector.

[27]This increase in the share of exports in total sales is mainly explained by an increase in the exports of firms that were already exporting (see the event studies of the log of exports in Appendix Table F.4).

The impact is also detectable when we study the response of the stock of native-born workers, as shown in panel (e). This increase in the employment of native-born workers is consistent with a strong increase in the scale of the production of firms that absorbed immigrant workers.

We also find that earnings per Canadian worker and median earnings dropped in firms that were relatively more exposed (see panel (f)).[28] This relative 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 declined in more-exposed occupations (e.g. computer-related occupations) compared to less-exposed ones (e.g. unskilled occupations).

We will then use our quantitative model, which matches these employment and earnings effects on native-born workers, to assess the welfare implications of these facts.
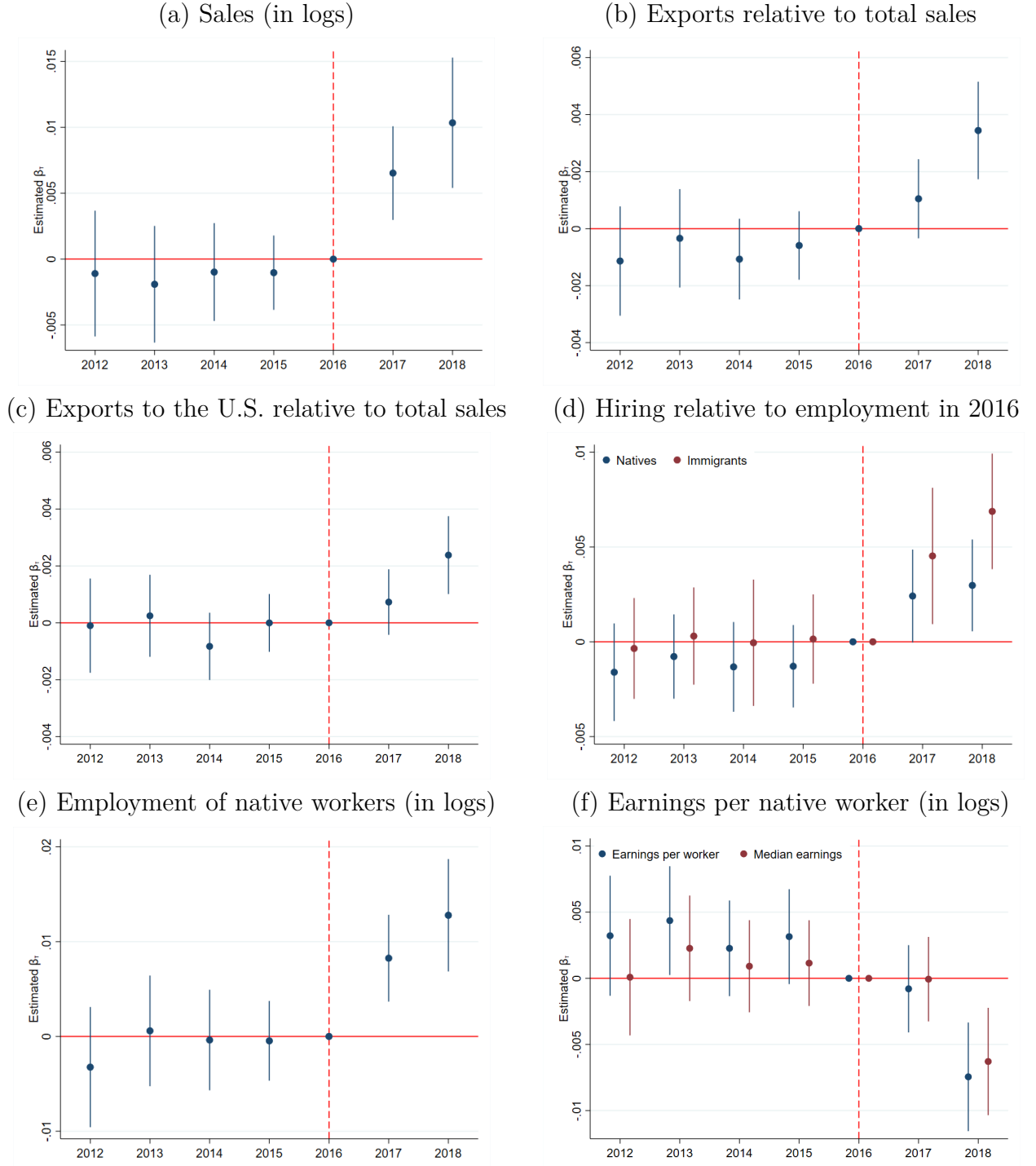
Taking stock Our estimates suggest that firms may have responded by scaling up inputs of production (labor and non-labor) and output in similar proportions. For reference, the average ratio of total hiring to employment in 2016 among exposed firms in the skilled service sector was 0.5% and, based on estimates from panel (d), it increased to 1.2% in 2017 and to 1.5% in 2018 due to the U.S. policy change. These estimates and those from panel (a) suggest that labor and production increased in similar proportions. Moreover, while we do not observe non-labor input quantities, our estimates for the response of total costs are consistent with other inputs responding in a similar proportion (see column 10 in Appendix Table F.6).

The Bank of Canada's Business Outlook Survey, used to monitor the economy, suggests two reasons for the quick response. First, skilled labor is scarce in Canada, especially with many skilled workers retiring during this period. Second, firms reported that if they had to increase output, they would face no difficulties due to the weak past demand that left them operating below normal levels and to the low oil prices that kept production costs low.

Effect on domestic firms Prior research has found that American MNCs with locations in both the U.S. and Canada increased employment in their Canadian affiliates due to H-1B restrictions (Glennon, 2023). To determine whether our findings are attributed to the presence of MNCs or whether they are also a feature of domestic firms' responses, we estimated equation (3) for the main outcome variables excluding MNCs and obtained estimates that are similar to those of our baseline (see Appendix Table F.9 and Figure F.11). 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.

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[28]Estimates in Appendix Table F.6 shows the drop in earnings per worker, including all workers.

Figure 5: Effect of H-1B restrictions on Canadian firms

(a) Sales (in logs)

(b) Exports relative to total sales

(c) Exports to the U.S. relative to total sales

(d) Hiring relative to employment in 2016

(e) Employment of native workers (in logs)

(f) Earnings per native worker (in logs)

Notes: 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 the log sales (panel a), exports relative to total sales (panel b), exports to the U.S. relative to total sales (panel c), net hiring of immigrants and Canadians with respect to the employment level in 2016 (panel d), log number of Canadian workers (panel e), log earnings per native worker (panel f), and log of the median earnings of native workers (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 F.6.

3.3.3 Robustness exercises

Appendix section B.3 presents robustness exercises that address potential identification concerns. First, we re-estimate equation 3 including industry-year fixed effects and allowing for the effects of firms in the most- and least-exposed sectors to differ. The estimates for the most-exposed sector show that more-exposed firms hired more immigrants and expanded production relative to less-exposed firms within the same industry. However, as expected, this pattern does not hold for firms in the unexposed industries. This exercise suggests that our estimates are likely not driven by unobserved industry-specific shocks. Second, we test the potential impacts of the non-random assignment of $Intensity_i$ on our identification assumption by controlling for the pre-shock firm characteristics interacted with the year dummies. 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.

3.3.4 Comparing our results with the literature

The empirical literature studying the effects of high-skilled immigration on firms and native-born workers have reached conflicting conclusions. Appendix Section B.4 discusses how our results align with the most closely related papers, namely Beerli et al. (2021), Doran et al. (2022) and Brinatti et al. (2023).

4 Theory: Immigration policy and international trade

Our next goal is to understand the welfare effects on the 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. Achieving these goals requires a quantitative general equilibrium model of international trade, international migration, and migration policy that rationalizes our empirical facts and can be quantified using our data. This section sets up such a model and analytically examines 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 develop a tractable general equilibrium model where immigration policy is modeled as an exogenous probability of granting visas. This assumption has two advantages relative to the alternative approach of modeling immigration policy as a migration cost. First, it allows us to assess the welfare changes resulting from actual policy changes, as the probability of granting visas is observable in the data. Second, it enables counterfactual policy analysis.

4.1 Building blocks of the model based on empirical facts

The starting point is a standard multi-sector multi-country model where international trade is driven by countries' comparative advantages in producing different goods.[29]

We use evidence from the previous sections 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 and employment increase in similar proportions 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.

The increase in the hiring of native-born workers and the decrease in the earnings per native worker are consistent with a classic model with competitive labor markets, where immigrants and Canadians working in different occupations are imperfect substitutes. For clarity, consider two occupations: skilled computer scientists and unskilled workers. An inflow of immigrant computer scientists affects the labor market outcomes of Canadian workers in two ways. First, it puts downward pressure on the wages of Canadian workers, especially those who are closer substitutes for these immigrants. If foreign computer scientists are closer substitutes for Canadian computer scientists than for unskilled Canadian workers, then this influx will lower the wages of Canadian computer scientists relative to unskilled Canadians, as documented in the previous section. Second, the inflow can reduce overall labor costs, inducing firms to increase their scale of production and input demand. For Canadian workers where the scale effects outweigh the substitution effects, the inflow increases the demand for and hiring of these Canadian workers. Consequently, firms that are intensive in computer scientists are expected to expand relative to those intensive in unskilled workers, which can lead to a relative increase in native employment. Thus, a classical model can potentially rationalize an increase in native employment and a drop in earnings per native worker.

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 to immigration-destination countries. Workers in occupation o who move from c to d lose a fraction $(1 - \zeta_{cod})$

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[29]There will be no concept of the firm, mainly because we lack the U.S. firm-level data relevant for calibration.

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 $d \in \mathcal{C}^d$.

We assume that workers are heterogeneous due to their preferences for applying for visas from different countries, for staying in their home countries, and for their productivity across sectors and countries. Each worker ι from group co draws preference shocks $v_{cod}(\iota)$ from distribution F_{cod}^v, and a number of efficiency units $a_{codk}(\iota)$ from distribution F_{codk}^a.

Timing assumptions All workers choose their sector of employment, but 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 $v_{cod}(\iota)$ and then makes their 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 sector, given the country of residence, and we then solve the migration decision.

Workers' choice of sector Consider workers living in country d. Each worker ι 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.[30] Workers choose the sector that yields the highest utility, $u_{codk}(\iota)$, which is given by the real income net of the migration costs:

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

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

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.[31] If their visa application is denied, the worker has to stay in their home country. To make the choice decision under uncertainty tractable in general equilibrium, we bring the expected utility theory into an otherwise

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[30]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.

[31]This assumption allows us to derive an equation to estimate ν_d, which we can take directly to the data. Our estimate would be biased towards zero if the correctly specified model is with multiple applications.

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; that is, $u_{cod} \equiv \mathbb{E}_a \Big(max_k \, u_{codk}(\iota) \Big)$. 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 to better match the data.[32] In particular, this allows the elasticity of substitution between home and foreign countries, ν_h, to differ from the elasticity of substitution between two foreign countries, ν_d. These distributional assumptions lead us to a tree extreme value model of choice, where the "tree" has an upper nest between the home and the foreign countries and an inner nest between the foreign countries.

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) (henceforth BHTV). 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 occupation-sector-country-specific productivity, $l_{dko}(\omega)$ 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).[33]

Occupation services are produced by combining the effective units of native-born labor (l_{dko}^n) and foreign labor (l_{dko}^f) 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

---

[32]This modeling assumption follows Allen et al. (2019).

[33]The model can flexibly account for the agglomeration effects, for example, by allowing total factor productivity to depend on the number of skilled labor efficiency units in the sector (Bound et al., 2017).

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:

$$\pi_{codk} = \begin{cases} \left(\dfrac{a_{codk}\, w^f_{dko}}{\Phi_{cod}} \right)^{\kappa} & \text{with} \quad (\Phi_{cod})^{\kappa} \equiv \sum_k a^{\kappa}_{codk}\, (w^f_{dko})^{\kappa} & \text{if} \quad d \neq c \\[2ex] \left(\dfrac{a_{cock}\, w^n_{cko}}{\Phi_{coc}} \right)^{\kappa} & \text{with} \quad (\Phi_{coc})^{\kappa} \equiv \sum_k a^{\kappa}_{cock}\, (w^n_{cko})^{\kappa} & \text{if} \quad d = c \end{cases} \tag{9}$$

Due to the law of large numbers, π_{codk} is also the fraction of workers co in d choosing sector k. The expected real wage net of the migration costs in destination d and at home are

$$u_{cod} = \Gamma_{\kappa} \frac{\zeta_{cod}\, \Phi_{cod}}{P_d} \qquad u_{coc} = \Gamma_{\kappa} \frac{\Phi_{coc}}{P_c},$$

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

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, denoted by 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 emigrate to d. The actual number of workers who emigrate to d is the fraction of the workers whose visas are approved times the number of those who apply:

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

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)

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

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

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

Native-born labor supply The stock of workers that supplies labor at home in 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:

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

For immigration-destination countries, $L_{coc} = L_{co}$. The supply of efficiency units of labor in occupation o in sector k is

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

4.4 Labor demand based on firms' hiring decisions

The demand for efficiency units of native-born and foreign labor is the wage bill the sector pays for each type of labor divided by the wage level

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

where s_{dko} is the share of occupation o in the wage bill of sector k in country d, s_{dko}^x is the share of labor type x in that occupation, and Y_{dk} is the sales, which equal the wage bill of the sector because firms earn zero profits in equilibrium. Given the nested CES production function, these shares are given by

$$
\begin{aligned}
s_{dko}^n &= \frac{\beta_{dko}^\epsilon w_{dko}^{n\,1-\epsilon}}{w_{dko}^{1-\epsilon}} & w_{dko}^{1-\epsilon} &= \beta_{dko}^\epsilon w_{dko}^{n\,1-\epsilon} + (1-\beta_{dko})^\epsilon w_{dko}^{f\,1-\epsilon} \\
s_{dko} &= \frac{\psi_{dko}^\eta w_{dko}^{1-\eta}}{c_{dk}^{1-\eta}} & c_{dk}^{1-\eta} &= \sum_o \psi_{dko}^\eta w_{dko}^{1-\eta},
\end{aligned}
\tag{17}
$$

where w_{dko} is 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. Country c's expenditures on goods produced by sector k in country d 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}:

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

where $P_{ck} \equiv \Gamma\left(1 - \frac{\sigma-1}{\theta}\right)^{-1} \left(\sum_d T_{dk}(\tau_{dck}\,c_{dk})^{-\theta}\right)^{-\frac{1}{\theta}}$ is the price index in sector k in country c. We assume that trade is balanced, implying that total spending equals total labor income:[34]

$$
X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \quad \text{and} \quad Y_c \equiv \sum_k Y_{ck}
\tag{19}
$$

4.5   Equilibrium

Given the set of fundamentals $\Omega \equiv \{\zeta_{cod}, a_{codk}, \psi_{co}^{emm}, \psi_{dko}, \beta_{dko}, L_{co}, \bar{L}_{coc}, \bar{L}_{cod}, D_c, T_{dk}, \tau_{dck}\}$, the set of parameters $\{\nu_d, \nu_h, \alpha, \epsilon, \eta, \theta, \kappa, \sigma\}$, and the visa approval rates $\mathrm{P} \equiv \{p_{cod}\}$, an equilibrium is a collection of the labor supply $\{LS_{dko}^f, LS_{dko}^n\}$, the labor demand $\{LD_{dko}^f, LD_{dko}^n\}$, and wages $\{w_{dko}^f, w_{dko}^n\}$ such that the labor supply is consistent with the workers' migration decisions and sector choices, as specified in Section 4.3; the labor demand is consistent with the firms' hiring decisions, specified in Section 4.4; and labor markets clear: $LD_{dko}^n = LS_{dko}^n$ and $LD_{dko}^f = LS_{dko}^f$.

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

4.6 Comparative statics: effects of U.S. immigration restrictions

In this section, we study analytically the effects of a drop in U.S. visa approval rates on other economies and on 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, respectively.

4.6.1 Effects on third countries

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

1st. Change in applications A reduction in the probability of obtaining a U.S. visa, $p_{co,usa}$, reduces the average value of emigrating, $\widetilde{u}_{coe}$. This depends 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, $(\tilde{u}_{co,usa} - \tilde{u}_{coc})$:

$$d\widetilde{u}_{coe} = \pi_{co,usa} \left(\tilde{u}_{co,usa} - \tilde{u}_{coc} \right) dp_{co,usa}, \tag{20}$$

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 (21):

$$d\widetilde{\pi}_{cod} = -\nu_d \, d\widetilde{u}_{coe} + \epsilon_{cod} \qquad d\widetilde{\pi}_{coe} = \nu_h \, \pi_{coc} \, d\widetilde{u}_{coe} + \epsilon_{coe}, \tag{21}$$

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-hand side 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 the 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-hand side 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., a higher initial probability of choosing home, π_{coc}).

Therefore, the direction and size of the effect of U.S. immigration restrictions on the number of workers applying to emigrate to country d depend on the strength of these forces, as illustrated

by equation (22)

$$d\widetilde{App}_{cod} = d\tilde{\pi}_{cod} + d\tilde{\pi}_{coe} = (\nu_h \, \pi_{coc} - \nu_d) \, \pi_{co,usa} \, (\tilde{u}_{co,usa} - \tilde{u}_{coc}) \, dp_{co,usa} + \eta_{cod} \qquad (22)$$

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

2nd. Increase in the immigrant labor force An inflow of workers shifts the immigrant supply of labor co in country d according to $d\widetilde{L}_{cod} = (1 - \psi_{cod}^{imm}) \, d\widetilde{App}_{cod}$, where $(1 - \psi_{cod}^{imm})$ is the fraction of workers of nationality c in occupation o working in destination country d accounted for by the flow of new immigrants.

3rd. Drop in production costs Immigrant workers co in country d will sort themselves across sectors based on their initial sectorial shares, π_{codk}. This leads to a sector-specific expansion in the overall foreign supply of labor services from occupation o: $d\tilde{l}_{dko}^{f} = \sum_{o,c \neq d} s_{dkoc}^{f} \, d\widetilde{L}_{cod}$, where s_{dkoc}^{f} 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, $\tilde{w}_{dko}^{f}$. 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 within occupation

$$d\tilde{w}_{dko}^{n} = d\tilde{w}_{dko}^{f} + \frac{1}{\epsilon}(d\tilde{l}_{dko}^{f} - d\tilde{l}_{dko}^{n}). \qquad (23)$$

In the limiting case of perfect substitution, $\epsilon \to \infty$, the drop in native-born workers' wages is as strong as that of immigrants' wages. The downward pressure on w_{dko}^{n} and w_{dko}^{f} 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:

$$d\tilde{c}_{dk} = \sum_{o} s_{dko} \left(s_{dko}^{n} \, d\tilde{w}_{dko}^{n} + s_{dko}^{f} \, d\tilde{w}_{dko}^{f} \right) \qquad (24)$$

This equation shows that sectors with factor shares skewed towards workers with bigger wage reductions will experience greater unit cost reductions. Moreover, we can rewrite the change in the unit cost in terms of factor endowment changes:

$$d\tilde{c}_{dk} \propto \underbrace{\sum_{o,c} s_{dkoc} \, d\widetilde{L}_{cod}}_{\text{Shift-share exposure}_k} + u_{dk} \qquad (25)$$

where s_{dkoc} is the share of labor input co (including $c = d$) in the wage bill of sector k in country d ($s_{dkoc} = s_{dko} \, s_{dko}^{f} \, s_{dkoc}^{f}$ if $d \neq c$ or $s_{dkoc} = s_{dko} \, s_{dko}^{n}$ if $d = c$), and u_{dk} is a structural error given

by the weighted average of the 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 with a workforce compositions tilted towards the nationalities and occupations affected by the policy experienced a larger drop in production costs.

4th. 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

$$d\tilde{Y}_{dk} = \sum_c \omega^Y_{dck} \Big(\underbrace{-\theta(d\tilde{c}_{dk} - \sum_j \lambda_{jck}\, d\tilde{c}_{jk})}_{d\tilde{\lambda}_{dck}} + \underbrace{-(\alpha-1)(d\tilde{P}_{ck} - d\tilde{P}_c)}_{d\tilde{\alpha}_{ck}} + d\tilde{X}_c \Big), \qquad (26)$$

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 the 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 the 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 an adjustment that is consistent with the evidence presented in sections 3.2 and 3.3. 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. In the next subsection we show how these third-country effects ultimately affect American workers' welfare.

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 increased 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, in which we assume that the labor supply is exogenous, the domestic labor supply l^n_{dko} is fixed, preferences are Cobb Douglas with shares α_{dk}, and the occupation nest in equation (7) is Cobb Douglas ($\eta = 1$) with shares s_{dko}.

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, as labor markets are perfectly competitive. Therefore, the wages of American workers associated with the production function

(7)-(8) are

$$w^n_{usa,ko} = p(\omega)_{usa,k} \; z_{usa,k}(\omega) \left(\frac{l_{usa,ko}}{l_{usa,k}} \right)^{-1} \left(\frac{l^n_{usa,ko}}{l_{usa,ko}} \right)^{-\frac{1}{\epsilon}} \tag{27}$$

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

$$W^n_{usa,ko} = \frac{w^n_{usa,ko}}{P_{usa}} = \frac{Y_{usa,k} \; l^{\frac{1}{\epsilon}-1}_{usa,ko} \; (l^n_{usa,ko})^{-\frac{1}{\epsilon}}}{P_{usa}} \tag{28}$$

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

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

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

$$\underbrace{\underbrace{- \sum_k \alpha_{usa,k} \; \lambda_{c,usa,k} \; d\tilde{c}_{ck}}_{\text{Price effect}_{usa} > 0} + \underbrace{\theta \; \sum_j \omega^Y_{usa,jk} \; \lambda_{cjk} \; d\tilde{c}_{ck}}_{\text{Competition effect}_{usa,k} < 0} + \; \epsilon_{usa,k}}_{\text{International general equilibrium effects - decreasing costs in country } c} \tag{29}$$

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, $s_{usa,ko}^{f}$.

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$_{usa,k} < 0$).

The "international general equilibrium effects" arise when increased migration to other countries that engage in international trade affects these countries' production costs. On one hand, lower 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 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 $\sum_{j} \omega_{usa,jk}^{Y}\lambda_{cjk}$ in equation (29), 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 $\omega_{usa,jk}^{Y}$ is the share of country j in total U.S. sales.

It is worth mentioning that while the proposition highlights the effect of increasing immigrant labor in third countries, it can be easily extended to include similar effects from increasing labor in home countries. The main takeaway is that migration to other countries influences American workers' welfare through international trade by affecting U.S. export prices and consumer import prices. The overall effects can be positive or negative, depending on whether the positive price effect or the negative competition effect prevails.

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 P, U_u, S^M, S^{NM} and Υ, respectively. This section discusses the calibration of the elasticities, Υ,

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summarized in Table 1. Appendix D describes the calibration of 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 (Bss. Prof.), computer scientists (CS), 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 Υ by extracting as much information as possible from our data and reduced-form regressions. 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 using our novel cross-boarder application data. We cannot estimate the elasticity of substitution between emigrating and staying at home, ν_h, the elasticity of substitution across sectors, α, or the elasticity of substitution between immigrants and natives ϵ, directly from a coefficient of an equation derived from the model, as we did for ν_d, due to data limitations. 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, 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 $(P, \Upsilon^E, \mathbf{S}^M, \mathbf{S}^{NM}, \mathbf{U}_u)$ and input the observed $dp_{o,usa}$ from the data into our model.[35] We solve the equilibrium for a given set of parameters $\Upsilon^I \equiv (\nu_h, \alpha, \epsilon)$. We choose Υ^I so that the equilibrium response in the model matches the response implied by our reduced-form estimates.

$$\Upsilon \equiv \{ \underbrace{\theta, \kappa, \eta}_{\text{Calibrated from the literature}} \quad , \quad \underbrace{\nu_d}_{\text{IV approach}} \quad , \quad \underbrace{\nu_h, \alpha, \epsilon}_{\text{Indirect inference approach}} \}$$

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

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[35]Consistent with our empirical evidence, the change in the approval probability does not vary across origin countries so, in the rest of the paper, we use the notation $dp_{o,usa}$ for simplicity.

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

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

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 that becomes the starting point of our approach to estimating ν_d (equation 30). 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

$$\widetilde{App}_{co,can,t} - \widetilde{App}_{co,usa,t} = \nu_d \left(p_{co,can,t} \left(\tilde{u}_{co,can,t} - \tilde{u}_{coct} \right) - p_{co,usa,t} \left(\tilde{u}_{co,usa,t} - \tilde{u}_{coct} \right) \right) \quad (30)$$

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. We can estimate the parameter ν_d through the following equation:

$$\widetilde{App}_{co,can,t} - \widetilde{App}_{co,usa,t} = \nu_d \, p_{co,usa,t} \, \tilde{\tilde{w}}_{co,usa,t} + \eta_{cot} \quad (31)$$

where $\bar{w}_{co,usa,t}$ is the average wage of workers co in the U.S. in t, and η_{cot} is a structural error that includes the effects 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. $(\tilde{P}_{usa,t})$, and the costs of migrating to the U.S. $\tilde{\zeta}_{co,usa}$.

As $p_{co,usa,t} \, \tilde{\tilde{w}}_{co,usa,t}$ correlates with this structural term, we include immigrant-group fixed effects δ_{co}, occupation-year fixed effects δ_{ot}, and nationality-year fixed effects δ_{ct}, and instrument the regressor with Fraction Affected$_{co}$ $1(t \geq 2017)$, where Fraction Affected$_{co}$ is the same regressor as defined in (2). Appendix D.2 explains in detail the IV approach, including how the model suggests that the relevant condition for the instrument is met. The IV estimate is 3.6 (s.e: 1.3). Appendix Table F.11 includes the estimation details and robustness exercises.

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

The trade elasticity 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 set $\kappa = 2.79$, following estimates from Galle et al. (2023), for three reasons. First, we model the supply of labor to sectors within a country similarly to their approach, and the structural parameter (e.g., the Frechet dispersion parameter κ) aligns with ours. Second, the sectoral granularity in their study is comparable to ours. Third, they provide careful estimates of this parameter for U.S. workers, which our model assumes holds for all worker groups, including those in the U.S.

5.3 Indirect inference approach: $\nu_h, \alpha,$ and ϵ

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 (22) 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.[36] 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:

$$\widetilde{dApp}_{co,can} = \gamma_{\nu_h} \ \pi_{co,usa} \ dp_{o,usa} \ + \ \epsilon_{co} \tag{32}$$

A challenge in estimating this equation with real data is that Canadian applications might be affected by factors other 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. To do so, we proceed in two steps. First, we compute the predicted change in Canadian applications due to the H-1B policy change, using our estimate of θ_{2018} in equation (1).[37] Second, given that the categories of

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

[37]Our estimate of the response of Canadian applications to the U.S. restrictions and ν_d is likely to be conservative if the estimates of δ_{ot} and δ_{ct} in equation (1) account for part of the effect of the U.S. policy.

immigrant groups in this empirical regression are more granular than those in the model (and in equation (32)), 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 of these steps. The y-axis in panel (a) of Figure 6 shows $\widetilde{dApp}_{co,can}$ (relative to the mean), using real and model-generated data; the x-axis shows $\pi_{co,usa} \, dp_{o,usa}$, which are identical in the model and in the real data; and the slopes are the corresponding coefficient estimates of γ_{ν_h}.

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 empirical relationship, which is given by equation (33), to discipline the value of α:

$$\widetilde{dSales}_k = \gamma_\alpha \underbrace{\sum_{o,c} s_{can,koc} \left(1 - \psi_{co}^{imm}\right) \pi_{co,usa} \, dp_{o,usa}}_{Intensity_k} + \epsilon_k, \tag{33}$$
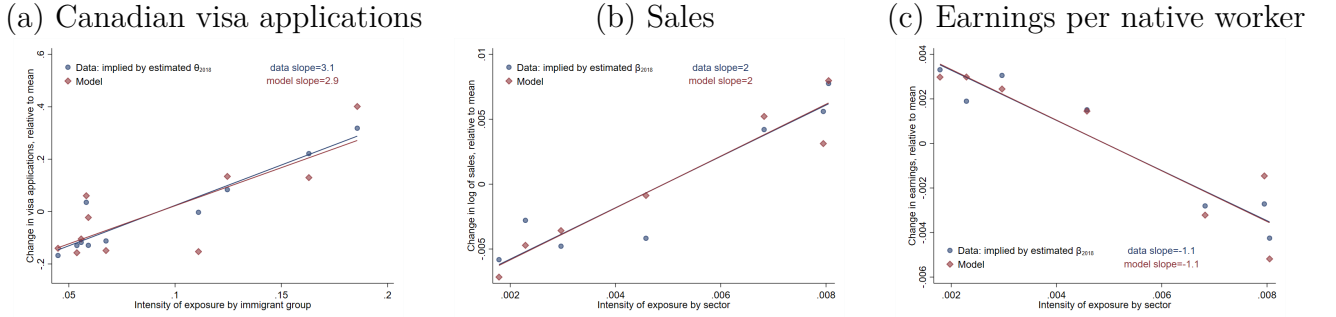
where $s_{can,koc}$ is the share of immigrant group co in the wage bill of Canadian sector k, and $Intensity_k$ proxies the shift-share exposure measure in equation (25). Again, we use our event-study regressions to isolate the causal effect of the policy change on sales. Since our empirical estimates for the sales response are at the firm level, we aggregate the firm-level responses to the sector level. Panel (b) of Figure 6 shows the scatter plot and coefficient estimates corresponding to (33) 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 each sector faces. We then use this empirical relationship to calibrate ϵ using a similar approach as for sales. We simply replace the sales in regression (33) with the earnings per native-born worker and use the corresponding causal estimates from Section 3. Panel (c) of Figure 6 shows the corresponding scatter plot and coefficient estimates.

We complement the analytical results suggesting that γ_{ν_h}, γ_α and γ_ϵ are informative about ν_h, α, and ϵ in Appendix Figure F.17. This figure plots the estimates of γ_{ν_h}, γ_α 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.

Our jointly calibrated values are $\nu_h = 2.3, \alpha = 1.2, \epsilon = 4.3$, 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 explores 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 $\widehat{\left(\frac{\nu_h}{\nu_d}\right)} = 0.4$ (s.e = 0.17), closely align with our estimates. Regarding ϵ, our modeling assumption follows Burstein et al. (2020), who estimates an elasticity of substitution of 4.6 between immigrants and natives within occupations.[38] Finally, previous estimates of *alpha* in the literature vary depending on the granularity of the categories used. For instance, for narrower categories than ours, 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).

Figure 6: 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

Notes: 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 the mean) respectively. The triangles represent model-generated data for $(\nu_h, \alpha, \epsilon) = (2.3, 1.2, 4.3)$, and the 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 (32), and in (b) and (c) the exposure measure as defined in equation (33). 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 the model 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 on the other event-studies in 5, namely, exports relative to total sales, and exports to the U.S. relative to total sales and native-born employment. Figure 7, which is analogous to Figure 6, shows that the model matches well the Canadian economy's sectorial adjustment along these dimensions.

6 Quantitative effects of the 2017 US restrictions

We feed the observed increase in H-1B denial rates (e.g., $-dp_{o,usa}$) directly into our calibrated model and study its quantitative effects. Being able to directly input the size of the shock into

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[38]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.

Figure 7: Untargeted coefficients

(a) Exports/sales	(b) Exports to the U.S./sales	(c) Native-born employment
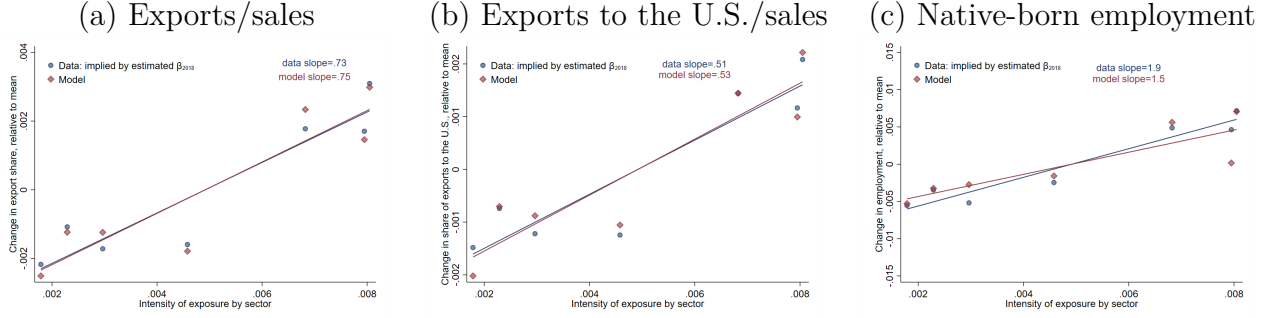
Notes: The y-axis values of (a), (b), and (c) are the change in $\frac{\text{Exports}_k}{\text{Sales}_k}$, $\frac{\text{Exports to the U.S.}_k}{\text{Sales}_k}$ and the logarithm of $Native\ Employment_k$ (relative to mean) respectively. The triangles represent model-generated data and the circles represent the values implied by our actual data and event-study estimates. The x-axis is the exposure measure of sectors, given by the exposure measure as defined in equation (33). The values of the x-axis in the data and the model are identical.

the model helps us to accurately assess the *level* of the economic outcome changes due to the policy shock.[39] 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 effects of a permanent drop in U.S. visa approval rates, $dp_{o,usa}$, which affects the (six-year) flow of immigrants working in skilled occupations.

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 of workers elsewhere, which we discuss in the following two sections. We then 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
U.S. 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. U.S. (%)	-1.56	-4.55	-2.23	-4.55	-2.42	-0.73	-0.02

Notes: 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 for computer scientists (see Table 2). Once in Canada,

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[39]If we were to use a standard quantitative model of immigration, where policy changes could be modeled as changes in migration costs, we would need to calibrate it to the actual changes in the migration flows *due to the U.S. policy*. These changes cannot be observed and would need to be estimated from a regression. While such a regression may identify relative effects, it might not identify the level effect of the shock (see a discussion of "The Missing Intercept Problem" by Nakamura and Steinsson (2014) and Wolf (2023)).

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, sectors with an immigrant workforce composition skewed toward occupations with larger growth in immigrant inflows experienced relatively stronger immigrant labor force growth. 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 their supply of immigrant labor and also their higher reliance on immigrants.[40]

Although total sales increase in all sectors, export sales increase only in high-skilled service and manufacturing sectors (e.g., consistent with 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, and 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. The increase in Canadian exports to the U.S. contributes significantly to its export growth, explaining 45% of Canada's growth in exports from high-skilled service sectors and 75% of the increase due to 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_{dk}^f	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
Exports	0.23	3.94	5.99	5.39	0.6	-0.39	0.13	-0.35	-0.81

Notes: 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_{dk}^f is measured in efficient units. The sectors' labels are as in Section 5.

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'

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[40]To a first-order approximation, for a given labor supply of native-born workers, the expansion of a sector is the increase in its immigrant labor supply, weighted by the immigrant share in the total cost, s_{dk}^f: $d\tilde{y}_{dk} = s_{dk}^f \, d\tilde{l}_{dk}^f$.

corresponding sectors of employment. The substitution effect can potentially counteract the expansion effect for workers who directly compete with incoming immigrants in the labor market, resulting in negative welfare effects. Figure 8 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 effects is occupation-specific.[41]

The differences in the welfare effects on Canadian workers across *sectors* are mainly explained by two factors, depending on the occupation of the worker. For occupations with a large influx of immigrants, cross-sector differences in the welfare effects are partially explained by differences in $s_{can,ko}^f$. For instance, the welfare losses of computer scientists in the sector with the largest and lowest $s_{can,ko}^f$ are 3.42% and 2.52%, respectively (see panel (a) of Figure 9).

For less-exposed occupations, the cross-sector differences in the welfare effects of Canadian workers are largely affected by the extent to which the sector expands due to the overall inflow of immigrants to that sector. To illustrate this point, panel (b) of Figure 9 plots the change in the welfare among managers, low-skilled workers, and workers in other H-1B occupations, against the measure of the sector's exposure to the inflow of immigrants, 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. This is because as the sector expands, the workers' marginal revenue products increase, increasing wages in the sector.

In summary, the U.S. policy change leads to large and heterogeneous welfare effects on Canadian workers. Canadian workers in occupations experiencing a significant influx of immigrants often experience losses due to direct labor market competition. However, workers from other occupations in expanding sectors benefit from the higher marginal revenue productivity of their labor. Overall, the policy increases the welfare of Canadian workers by about 0.2%.

6.2 Effects on the U.S.

Production and exports The drop in visa approval rates causes a 1.6% decline in total immigrant labor in the U.S., with the largest drop among computer scientists and business

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[41]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 8: Change in the real wage of Canadian workers $\tilde{W}^n_{can,ko}$ (%)

	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

Notes: 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. The labels of sectors and occupations are as in Section 5.

Figure 9: Differences in welfare effects of Canadian workers across sectors

(a) Computer scientists

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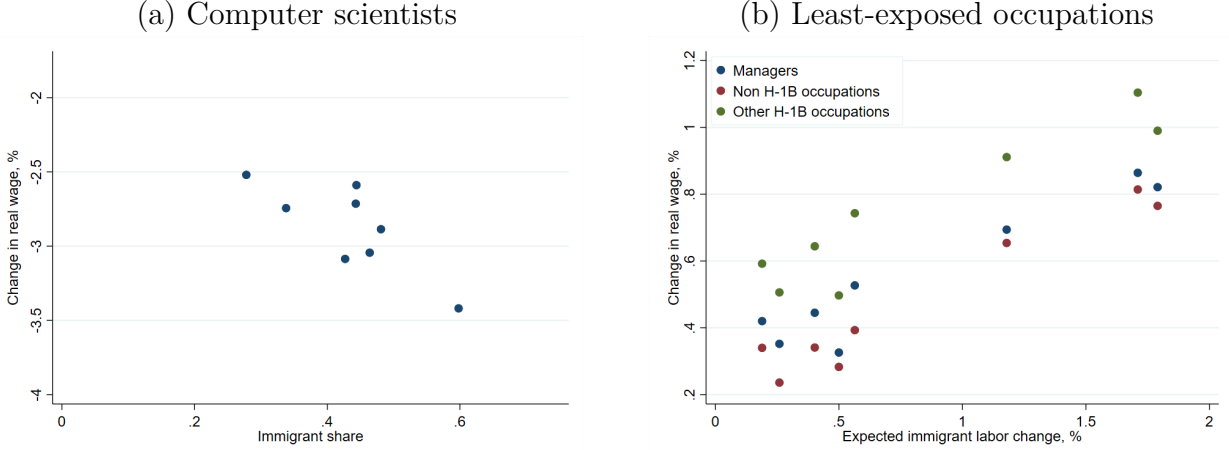
Notes: The left-hand panel plots the real wage change of Canadian computer scientists in the y-axis and the immigrant share within the occupation across sectors s^f_{dko} in the x-axis. The right-hand panel plots the real wage change of Canadian workers in the less-exposed occupations against the first-order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

professionals (see Table 2). The drop in the immigrant labor force induces a 0.25% drop in aggregate production. Compared to the effects on the Canadian economy, the magnitude of the effects on the U.S. economy are smaller for two reasons. First, 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 high-skilled service sectors is approximately 15% in the U.S. and 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 occurs in part because they are losing markets to international competitors. For instance, exports of the information and culture and business professional services sectors drop by approximately 1.4% and high-tech manufacturing exports fall 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_{dk}^f	-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

Notes: 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_{dk}^f is measured in efficient units. The labels of sectors are as in Section 5.

American workers' welfare The welfare effects on American workers vary substantially across occupations and sectors, with differences 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 labor 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.[42] Workers in other occupations face a more moderate impact from the drop in immigrant competition, leading the policy to either modestly increase their welfare or to decrease it.

The impact on American workers' welfare is also affected by sectorial contractions. For those occupations with the smallest drop in the immigrant labor force, such as managers, non-H-1B and other H-1B occupations, the colors in Figure 10 turn to blue or darker blue as we move from the sectors at the bottom to those at 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 welfare drop for unskilled 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 the rise in U.S. denial rates benefits primarily American computer scientists but tends to harm American workers employed in other occupations, with a near-zero overall welfare effect. Moreover, given that lower-skilled workers and other H-1B workers, who are negatively affected by the policy, account for approximately two-thirds of the native-born workforce, the restrictions improve the welfare of a relatively small number of American workers at the expense of a significantly larger group.

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

Figure 10: Change in real wage of American workers $\tilde{W}_{usa,ko}^n$ (%)

	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

Notes: We compute the changes in the equilibrium outcomes resulting from the observed change in the approval rates 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. The labels of the sectors and occupations are as in Section 5.

6.3 Efficacy of the restrictions: The role of international trade

Fundamental theorems of international trade (Rybczynski, 1955; Samuelson, 1948) suggest that immigration does not affect wages because economies can fully accommodate the cross-country reallocation of workers by adjusting their trade flows and production. These theorems are insightful but impose strong assumptions, such as fixed international prices and free trade, which challenge their quantification in the data. Our model, in contrast, can be taken to the data and used to quantify the role of international trade in the wage adjustment to immigration.

We do so by quantifying the welfare effects of the same policy change, $dp_{o,usa}$, under the counterfactual scenario in which the U.S. is a closed economy,[43] denoted by $\tilde{W}^{CE}$, and compare it with our baseline results, denoted by $\tilde{W}^{BL}$. We interpret the difference in the wage changes as the impact of the immigration policy on American workers due to international trade. To compute $\tilde{W}^{CE}$, we proceed in two steps. First, we eliminate international trade by raising trade costs and solving for 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.

Figure 11 plots the ratio $\tilde{W}^{CE}/\tilde{W}^{BL}$ 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 results show that international trade dampens the welfare gains of American computer

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[43]A closed-economy framework serves as a natural benchmark as it is commonly employed in the existing literature that uses quantitative general equilibrium models to study the effects of U.S. immigration policy (Allen et al., 2019; Burstein et al., 2020).

scientists, particularly in high-skilled service sectors and high-tech manufacturing. For example, the welfare gains of computer scientists in the information and cultural sector are approximately 25% higher in the counterfactual closed economy than in our baseline economy.

There are two factors at play in a global economy that are absent in a closed economy. First, the U.S. restrictions increase production costs in the U.S. and reduce them in economies that absorb these workers. As a result, the economies that absorb these workers expand in sectors that compete with U.S. sectors in international markets. This competition in goods markets drives American wages down and diminishes the benefits of immigration restrictions, compared to autarky. Second, American workers in an open economy have access to 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 are larger than in the open economy, as found in Figure 11.[44]

Our results imply that U.S. immigration restrictions may avoid direct competition between immigrants and American workers in the U.S. labor market, but immigrants can still indirectly compete through international goods markets. If policymakers overlook the effects of international trade, they might significantly overestimate the efficacy of the policy.

7 Conclusion

Immigration restrictions are increasingly common in developed countries. We study the effects of U.S. immigration policy in a global economy, using a quasi-natural experiment given by a sudden tightening of the eligibility criteria of U.S. visas for college-educated immigrants.

We study the effects of these U.S. immigration restrictions on the Canadian economy. First, we document that the restrictions increased skilled immigration to Canada. Second, we find that Canadian firms that were relatively more exposed to the inflow of immigrants increased production, with exports playing an important role in this expansion. Third, we show that the inflow of immigrants had a significant impact on the welfare of Canadian workers, with effects ranging from approximately -3% to 1% and an overall effect of 0.2%.

We also examine the effects of the restrictions on American workers' welfare. Using our novel quantitative model, we find that the restrictions had a near-zero effect on overall welfare but resulted in distributional consequences. The policy positively affected a small group of American

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[44]As discussed in the previous literature (e.g. Burstein et al. (2020)), international trade can attenuate the benefits of American workers from immigration restrictions if it increases the elasticity of output to prices. Our paper proposes a novel mechanism through which international trade affects the impact of immigration restrictions that arise due to labor reallocation across countries. See the explanation of equation (29). In Appendix E, we conduct counterfactual analyses to assess the quantitative relevance of this novel mechanism and our results highlight the important role of labor reallocation in determining the effects of international trade. For example, in IC sectors, labor reallocation contributes about 70% of the overall effect of international trade.

Figure 11: Change in the real wage of American computer scientists: $\tilde{W}^{CE}/\tilde{W}^{BL}$
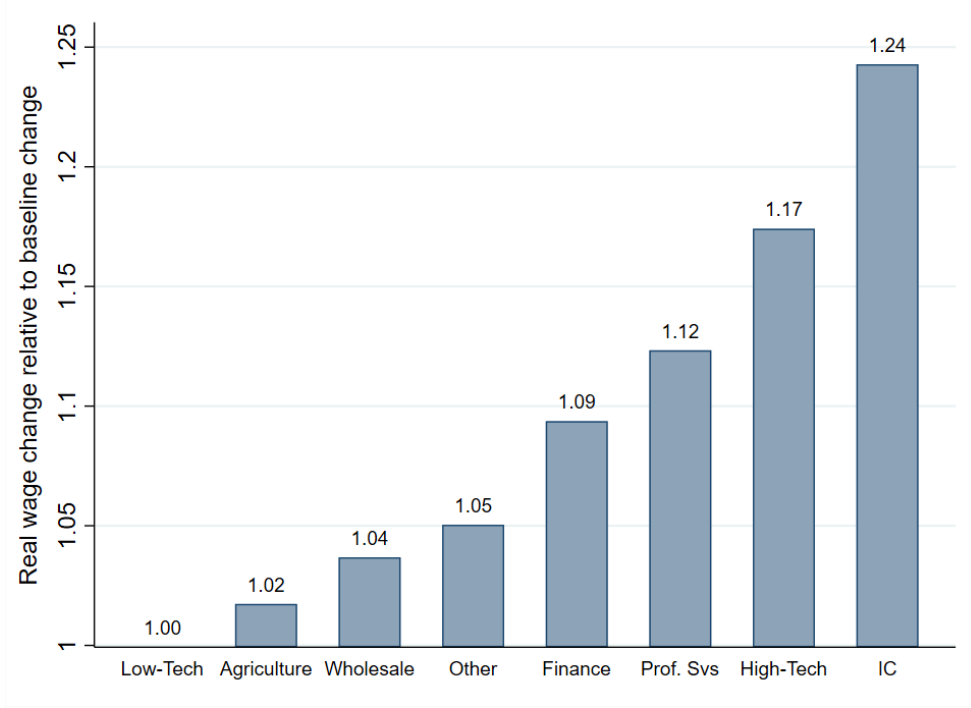
Notes: The y-axis is the ratio between the change in the real wage of American computer scientists in a closed economy, denoted by $\tilde{W}^{CE}$, and in the baseline economy, denoted by $\tilde{W}^{BL}$ (see Figure 10). The labels of sectors are as in Section 5.

workers who competed directly with immigrants in the labor market. However, the policy negatively affected American workers employed in other occupations in sectors that contracted.

Finally, we study the role of international trade in mitigating the intended wage effects of immigration restrictions. We find that the welfare gains for American workers targeted for protection are up to 25% larger in a closed economy compared to our baseline economy, which is calibrated to observed trade levels. This is because when the U.S. restricts immigration, immigrants seek to migrate to other economies. Because these receiving economies compete with the U.S. in international markets, this tougher competition drives down prices for American goods and lowers American workers' wages, undermining the intended goal of job protection. If policymakers overlook the general equilibrium effects of international trade, they may significantly overestimate the policy's efficacy. 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 to high-skilled immigration but can be adapted to different settings.

References

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

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

Abramitzky, R. and L. Boustan (2017). Immigration in american economic history. *Journal of economic literature 55*(4), 1311–1345.

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

Akcigit, U., J. Grigsby, and T. Nicholas (2017). Immigration and the rise of american ingenuity. *American Economic Review 107*(5), 327–331.

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

Arellano-Bover, J. and S. San (2023). The role of firms and job mobility in the assimilation of immigrants: Former soviet union jews in israel 1990-2019.

Arkolakis, C., S. K. Lee, and M. Peters (2020). European immigrants and the united states' rise to the technological frontier. In *2019 Meeting Papers*, Volume 1420.

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

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

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

Borjas, G. J. and J. Monras (2016). The labor market consequences of refugee supply shocks. Technical report, National Bureau of Economic Research.

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

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

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

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

Burchardi, K. B., T. Chaney, T. A. Hassan, L. Tarquinio, and S. J. Terry (2020). Immigration, innovation, and growth. Technical report, National Bureau of Economic Research.

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

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

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

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

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

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

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

Coluccia, D. M. and L. Spadavecchia (2021). The economic effects of immigration restriction policies-evidence from the italian mass migration to the us.

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

Cortes, K. E. (2004). Are refugees different from economic immigrants? some empirical evidence on the heterogeneity of immigrant groups in the united states. *Review of Economics and Statistics 86*(2), 465–480.

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

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

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

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

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

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

Dimmock, S. G., J. Huang, and S. J. Weisbenner (2022). Give me your tired, your poor, your high-skilled labor: H-1b lottery outcomes and entrepreneurial success. *Management Science 68*(9), 6950–6970.

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

Dustmann, C. and A. Glitz (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics 33*(3), 711–750.

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

Egger, D., D. Auer, and J. Kunz (2021). Effects of migrant networks on labor market integration, local firms and employees.

Friedberg, R. M. (2001). The impact of mass migration on the israeli labor market. *The Quarterly Journal of Economics 116*(4), 1373–1408.

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

Gandal, N., G. H. Hanson, and M. J. Slaughter (2004). Technology, trade, and adjustment to immigration in israel. *European Economic Review 48*(2), 403–428.

Ghosh, A., A. M. Mayda, and F. Ortegae (2014). The Impact of Skilled Foreign Workers on Firms: an Investigation of Publicly Traded U.S. Firms. *Working paper*. IZA Discussion Paper 8684.

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

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

Grogger, J. and G. H. Hanson (2011). Income maximization and the selection and sorting of international migrants. *Journal of Development Economics 95*(1), 42–57.

Hanson, G. H. (2009). The economic consequences of the international migration of labor. *Annu. Rev. Econ. 1*(1), 179–208.

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

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

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

Hunt, J. (1992). The impact of the 1962 repatriates from algeria on the french labor market. *ILR Review 45*(3), 556–572.

Hunt, J. and M. Gauthier-Loiselle (2010). How Much Does Immigration Boost Innovation? *American Economic Journal: Macroeconomics 2:2*.

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

Kerr, W. (2020). Global talent and us immigration policy. *Harvard Business School Entrepreneurial Management Working Paper* (20-107).

Kerr, W. R. (2018). *The gift of global talent: How migration shapes business, economy & society.* Stanford University Press.

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

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

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

Lewis, E. and G. Peri (2015). Immigration and the economy of cities and regions. In *Handbook of regional and urban economics*, Volume 5, pp. 625–685. Elsevier.

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

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

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

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

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

Muñoz, M. (2023). Trading nontradables: The implications of europe's job-posting policy. *The Quarterly Journal of Economics*, qjad032.

Nakamura, E. and J. Steinsson (2014). Fiscal stimulus in a monetary union: Evidence from us regions. *American Economic Review 104*(3), 753–792.

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

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

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

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

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

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

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

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

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

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

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

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

Wolf, C. K. (2023). The missing intercept: A demand equivalence approach. *American Economic Review 113*(8), 2232–2269.

Yoon, C. and K. Doran (2020). Immigration and invention: Evidence from the quota acts.

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

Appendix

A Data

A.1 Cross-walk of Canadian and U.S. 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.[45] 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., for cashiers or any low-skill occupation); and for some DOT codes, there were no NOC codes (e.g., for 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 F.2).[46] With this crosswalk at hand, we can aggregate the number of PR and H-1B applications at the new grouping level according to the corresponding the NOC and the DOT codes, respectively.

A.2 Data sources used in the quantitative model

A.2.1 Sources of data from Canada

We use income data by country of birth, occupation, and sector from the Canadian Labour Force Survey Data (LFS) for the period 2012-2016 to compute the sectorial shares (s^n_{dko}, s^f_{dko}, and f_{dko}) and we use the number of immigrants by landing year to compute ψ^{imm}_{cod}. 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.

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

[46]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).

A.2.2 Sources of data from the U.S.

We use the income data by nativity, occupation, and sector from the American Community Survey (ACS 1-year data) corresponding to the year 2015 to compute the sectorial shares for the U.S. (s_{dko}^{n}, s_{dko}^{f}, and f_{dko}).

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_{dko} according to the distribution of income across occupations and sectors of immigrants from the RoW living in the U.S.

To compute ψ_{cod}^{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.

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.[47] 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., *US App*$_{co}$ × δ_t and *Can App*$_{co}$ × δ_t). These estimates, reported in column 2 of Appendix Table F.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 does 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

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

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 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 F.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, an alternative measure of Fraction Affected$_{co}$, which is consistent with the model, uses the change in denial rates by occupation rather than the level of the denial rate in the period after the introduction of the new policy. Figure F.6 shows the estimated event-study coefficients corresponding to a regression analogous to the baseline regression 1, with the only difference being that Fraction Affected$_{co}$ is computed using the change in the denial rate by occupation between 2016 and 2018. The estimates imply a similar economic effect to the baseline regression. For instance, these estimates suggest that Canadian visa applications in 2018 were 29% higher than what they would have been in the absence of the H-1B restrictions.[48]

Fifth, 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

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[48]The scale of these estimates are different from the baseline estimates because the scales of the regressors are also different.

linear trend, as per the 2016-2017 immigration plan. We reject this trend at the 1% significance level, as plotted by Appendix Figure F.7, indicating that our estimates may not capture pre-shock differential trends. 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 F.8, 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 Fraction Affected$_{co}$), 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 regressions: measurement and sample

B.2.1 Construction of firm exposure measure $Intensity_i$

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.

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.

B.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.[49] 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 as 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.

B.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. Finally, we restrict the sample of firms in the log of export regression to those with a exports

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[49]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.

above a threshold to increase the precision of our estimates. In practice, these restriction drops those firms with sporadic exports. We set the threshold to be the first percentile of the positive total export distribution, which around 800 CAD.

B.3 Firm-level evidence: robustness exercises

Within-industry effects Our empirical strategy for estimating β_τ uses 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 a smaller 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 estimate equation (B.1) which, relative to equation (3), incorporates industry-year fixed effects and allows for the effects on the exposed and unexposed sectors to differ (e.g., $\beta_\tau^E \neq \beta_\tau^{NE}$).

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

Here, $1(k = \text{high-skilled service sector})$ 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 F.12 shows this comparison for the hiring of immigrants and for sales and export performance (Appendix Table F.10 reports the estimates of β_τ^E and β_τ^{NE}). 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 5. 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.

Non-random assignment of treatment   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 the 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 F.13 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 F.14 shows the event study and suggests that the baseline results are robust to this subsample of firms.

Canadian immigration policy   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 benefited from the introduction of the Express Entry program in 2015 and the years that followed. 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 F.15). 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.4 Comparing our results with the literature

The empirical literature studying the effects of high-skilled immigration on firms and native-born workers have reached conflicting conclusions.[50] The closest work to ours is by Beerli et al. (2021), who study the effect on firms of an aggregate inflow of skilled immigrants resulting from a reform granting European cross-border workers free access to the Swiss labor market. Using data that spans roughly a decade post-reform, they find that this inflow of immigrants increased both employment and wages for college-educated native workers at firms that were more exposed. This was driven by an expansion in the size, productivity, and innovation performance of skill-intensive incumbent firms, along with the attraction of new firms, which collectively raised the demand for highly educated native workers. Similarly, we find that relatively more-exposed Canadian firms expanded in size and increased their native-born employment. However, we do not observe increases in labor productivity or native-born wages. One plausible explanation is that the underlying mechanism in Beerli et al. (2021) may require more time to manifest and, unlike their study, we only have data covering two years after the policy change.

Our findings complement a set of papers that use quasi-experimental variation from the random allocation of new H-1B visas to examine the impact of skilled immigrants hired by firms on firm-level outcomes. Like our study, Doran et al. (2022) and Brinatti et al. (2023) study the effects on employment and the wage bill per worker. Doran et al. (2022) find that hiring one additional H-1B worker reduces total employment by 0.5, while Brinatti et al. (2023) find an increase in total employment by 0.83. This discrepancy may be explained by the extent to which other immigrants are displaced, as both studies suggest some degree of crowding out of immigrants, though neither finds a definitive impact on native-born workers.[51] Our findings also support the conclusion that skilled immigrants do not displace native workers and suggest a stronger positive effect on total employment, with an increase of 1.5 employees for each additional immigrant.

When it comes to the wage bill per native-born worker, while these two papers find no statistically significant effect, we observe a negative impact. Several factors could explain this difference. First, we analyze the effects of an aggregate change in the number of immigrants, while their experiments change the availability of immigrants to individual firms without changing the overall number of immigrants. If wages are partly determined at the market level, our approach is presumably more likely to detect wage changes.[52] In addition, as opposed to the Canadian immigration context, the H-1B program imposes a high wage floor, which may limit

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[50]For instance, Ghosh et al. (2014) and Kerr and Lincoln (2010) find that greater access to H-1B workers generally increases the size, productivity, and innovation performance of firms that rely heavily on H-1B visas. Conversely, Doran et al. (2022) find that an additional H-1B worker has no effect on patenting and firm size but does increase profits and reduce total employment. Kerr et al. (2015) findings suggest that hiring young skilled immigrants increases firms' skill intensity, but their evidence regarding firm size is inconclusive.

[51]See Table 4 and Appendix Table 13 in Doran et al. (2022), and Figures 4 and 5 in Brinatti et al. (2023).

[52]Even if their shock changes local market wages, their empirical strategy primarily relies on market variation.

the downward pressure of immigration on wages. This difference in the response of the wage bill per worker is consistent with our findings of a relatively stronger increase in firm production and, thus, of total employment and native employment.

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 (Ω, Υ, P), the equilibrium changes that are induced by a change in the probability of granting a U.S. visa $dp_{co,usa} \equiv p'_{co,usa} - p_{co,usa}$ 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.

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

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

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

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

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

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

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

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

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

where $1 - \psi_{cod}^{imm}$ is the fraction of workers of nationality c in occupation o working in destination country d accounted for by the flow of new immigrants; ψ_{co}^{emm} 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

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

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

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

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

$$\hat{w}_{dko}^{1-\epsilon} = s_{dko}^n \left(\hat{w}_{dko}^n\right)^{1-\epsilon} + s_{dko}^f \left(\hat{w}_{dko}^f\right)^{1-\epsilon} \tag{C.14}$$

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

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, and $\omega^X_{cD} = 0$ for any $c \in \mathcal{C}$, the aggregated prices are given by

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

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

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

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

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

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

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

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 dp_{cod} and the general equilibrium variables $d\tilde{u}_{cod}$, $d\tilde{u}_{co,usa}$ and $d\tilde{u}_{coc}$. 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_{dko}^x 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 $\tilde{l}_{usa,ko}^f$. The change in the welfare of an

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

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

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

Proof: The proof proceeds in the following five steps.

Step 1: 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)

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

Given that the goods market is perfectly competitive, $p(\omega)_{dk} = \frac{c_{dk}}{z_{dk}(\omega)}$. Therefore, we can replace $p(\omega)_{dk} \; z_{dk}(\omega)$ 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:

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

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:

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

<u>Step 2</u>: 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:[53]

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

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 $d\tilde{P}_u$ simplifies to

$$d\tilde{P}_{usa} = \sum_k \alpha_{usa,k}\left(\lambda_{usa,usa,k}\, d\tilde{c}_{usa,k} + \lambda_{c,usa,k}\, d\tilde{c}_{ck}\right) \quad \text{(C.28)}$$

<u>Step 3</u>: Expression for the change in the sales of sector k in the U.S., $Y_{usa,k}$ in C.27.
Log differentiating $Y_{usa,k}$ yields

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

where $\omega^Y_{usa,jk} \equiv \frac{\lambda_{usa,jk}\, \alpha_{jk}\, X_j}{\sum_d \lambda_{udk}\, \alpha_{dk}\, X_d}$ is the share of country j in the U.S. sales of sector k.
Under the assumption that preferences are Cobb Douglas, the change in the share of each sector in total expenditures is zero ($d\tilde{\alpha}_{jk} = 0$). The change in the U.S. market share within a sector takes the following form:

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

We can then write the change in the U.S. sales of sector k as a weighted average of the change

---

[53]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).

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

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

(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:

$$d\tilde{l}_{usa,ko} = s^n_{usa,ko} \, d\tilde{l}^n_{usa,ko} + s^f_{usa,ko} \, d\tilde{l}^f_{usa,ko}$$
$$d\tilde{l}_{usa,k} = \sum_o s_{usa,ko} \, d\tilde{l}_{usa,ko}$$

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

$$d\tilde{l}_{usa,ko} = s^f_{usa,ko} \, d\tilde{l}^f_{usa,ko} \tag{C.31}$$
$$d\tilde{l}_{usa,k} = \sum_o s_{usa,ko} \, s^f_{usa,ko} \, d\tilde{l}^f_{usa,ko} \tag{C.32}$$

Step 5: Expression for $\tilde{c}_{ck}$ in C.27 as a function of l^f_{cko}.
The change in the unit cost of production is

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

Given that the optimal labor demand of immigrants relative to native-born workers is

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

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:

$$d\tilde{c}_{dk} = \sum_o s_{dko} \left(s_{dko}^n (d\tilde{w}_{dko}^f + \frac{1}{\epsilon} d\tilde{l}_{dko}^f) + s_{dko}^f d\tilde{w}_{dko}^f \right)$$

$$= \sum_o s_{dko} \left(d\tilde{w}_{dko}^f + \frac{s_{dko}^n}{\epsilon} d\tilde{l}_{dko}^f \right)$$

$$= \sum_o s_{dko} \left(\varepsilon_{dko}^f d\tilde{l}_{dko}^f + \frac{s_{dko}^n}{\epsilon} d\tilde{l}_{dko}^f \right)$$

$$= \sum_o s_{dko} \ \varepsilon_{dko} \ d\tilde{l}_{dko}^f$$

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

D Quantification

D.1 Calibration

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_{dko}^n, w_{dko}^f	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
$1 - \psi_{cod}^{imm}$	Immigrant flow share	ACS for the US, and LFS for Canada
ψ_{co}^{emm}	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_{dko}^f	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)[54]
α_{dk}	Expenditure shares across sectors	Trade in Value Database from the OECD (TiVA)

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

p_{od}: For the 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.[55] For Canada, we use publicly available data from the IRCC on the approval rate by PR

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

visa program. We assign a common approval rate to all occupations within skilled occupations because the data is not disaggregated by occupation.

w_{dko}^n, w_{dko}^f: 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:

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

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.[56] 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

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[56]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 $\pi_{cs,ind,usa}$ is given by $\left(\frac{w_{ind,cs,usa}^f}{w_{cs,ind}^n} \right)^{p_{cs,usa} \nu}$. 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.

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_{cod}^{imm}: We compute ψ_{cod}^{imm} 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.2. 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_{dko}^{f}: 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_{co}^{emm}: Given that the shares ψ_{co}^{emm} 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.

D.2 Instrumental variable approach: ν_d

To go from equation (30) to an estimating equation that we can take to the data, we introduce four changes. First, we rewrite (30) as follows:

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

where $\bar{w}_{co,usa,t}$ is the average wage of immigrants in group co working in the U.S. in year t, and 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 $\tilde{\bar{w}}_{co,usa,t}$ at its pre-shock average value because it jumps around overtime 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

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

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.[57]

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 reduce 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 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 Fraction Affected$_{co} \times 1(t > 2016)$. In Section 3.2, we explain why Fraction Affected$_{co} \times 1(t > 2016)$ 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 F.16 shows empirically that this relationship is significantly strong.

Columns 1 and 2 of Appendix Table F.11 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.

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[57]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.

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.[58]

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

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

where $\theta_{2016} = 0$, 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., Fraction Affected$_{co}$ = 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.[59] 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 θ_t Fraction Affected$_{co}$.

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 $App_{G,can,t} = \sum_{g \in G} App_{g,can,t}$, we can then compute the log change in the applications of group G as follows:

$$
\begin{aligned}
\widetilde{App}_{G,can,t} - \widetilde{App}_{G,can,2016} &= log\Big(\frac{\sum_{g \in G} App_{g,can,t}}{\sum_{g \in G} App_{g,can,2016}} \Big) \\
&= log\Big(\sum_{g \in G} \frac{App_{g,can,2016} e^{\theta_t \text{Fraction Affected}_g}}{\sum_{g \in G} App_{g,can,2016}} \Big) \\
&= log\Big(\sum_{g \in G} \omega_g^{app} e^{\theta_t \text{Fraction Affected}_g} \Big)
\end{aligned}
$$

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

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[58]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.

[59]Our estimate of the response of Canadian applications to the U.S. restrictions is likely to be conservative if the estimates of δ_{ot} and δ_{ct} account for part of the effect of the U.S. policy.

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 (32) is $log\left(\sum_{g \in G} \omega_g^{app} e^{\hat{\beta}_{2018} \text{Fraction Affected}_g}\right)$.

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   Quantitative results

In this section, we perform two counterfactual analyses to evaluate how labor reallocation across countries influences the overall impact of international trade on the welfare of American workers targeted for protection by the U.S. immigration restrictions.

Our first analysis is directly motivated by equation (29). We exogenously fix the labor supply in Canada and the two origin countries while reducing the immigrant labor supply in the U.S. by the same amount as in the baseline open economy. In this counterfactual economy, the welfare change of American workers $\tilde{W}^{\text{fixed labor supply}}$ only accounts for the effects of the reduction in U.S. immigrant labor, so $\tilde{W}^{\text{fixed labor supply}}/\tilde{W}^{\text{BL}}$ is informative about the effects contributed by ignoring labor reallocation across countries. The left panel of Figure E.1 plots this ratio for American computer scientists in each sector, showing that their welfare gains are up to 18% higher than our baseline result. Our results imply that, for instance, for American computer scientists in the IC sector, 76% of the international trade's attenuation effects on their welfare gains is due to the labor reallocation across countries (i.e., 18%/24% = 0.76). This importance of labor reallocation holds similarly across other highly exposed sectors.

Our second analysis is motivated by the insight from Burstein et al. (2020), who point out that international trade can attenuate the native wage effect of immigration by affecting the *elasticity* of native labor demand.[60] To separate the role of international trade into this and our novel mechanism, we proceed as follows. We first recalibrate the closed economy to match the elasticity of American computer scientist wages to labor supply ($\frac{\partial \ln w_{usa,k,cs}^n}{\partial \ln l_{usa,k,cs}^n}$) in the baseline open economy.[61] Then we compute the welfare effect of the U.S. immigration restrictions on American workers $\tilde{W}^{\text{fixed wage elasticity}}$. Since this recalibrated closed economy features the same wage responsiveness to labor supply within the U.S. as in the baseline open economy,

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[60]Specifically, they show that if trade increases the elasticity of output to prices, the native wage effect of immigration may be weaker.

[61]As characterized in Burstein et al. (2020), this elasticity captures the elasticity of labor demand. To compute this wage elasticity, we fit an exogenous infinitesimal change in the labor supply of native computer scientists into the model, while keeping the labor supply in all the other countries and occupations fixed and goods and labor market markets cleared. We conduct counterfactual analyses separately for each sector k. In each of the analyses, we recalibrate the substitution elasticity between occupations η in the closed economy to match the wage elasticity of the baseline open economy and calculate the response of American computer scientists working in this specific sector.

$\tilde{W}^{\text{matched wage elasticity}}/\tilde{W}^{\text{BL}}$ measures the effect of international trade that due to ignoring the increase in labor to other countries. The right panel plots this measure and show that the results are remarkably similar to those in the left panel. For example, 70% of the role of international trade for American computer scientists in the IC sector can be attributed to the labor reallocation mechanism. The similarity in results between these two counterfactual analyses is reassuring and suggests a significant role of labor reallocation across countries in shaping the overall impact of international trade.

Figure E.1: Contribution of labor reallocation to the effects of international trade

(a) $\tilde{W}^{\text{fixed labor supply}}/\tilde{W}^{\text{BL}}$ (b) $\tilde{W}^{\text{matched wage elasticity}}/\tilde{W}^{\text{BL}}$
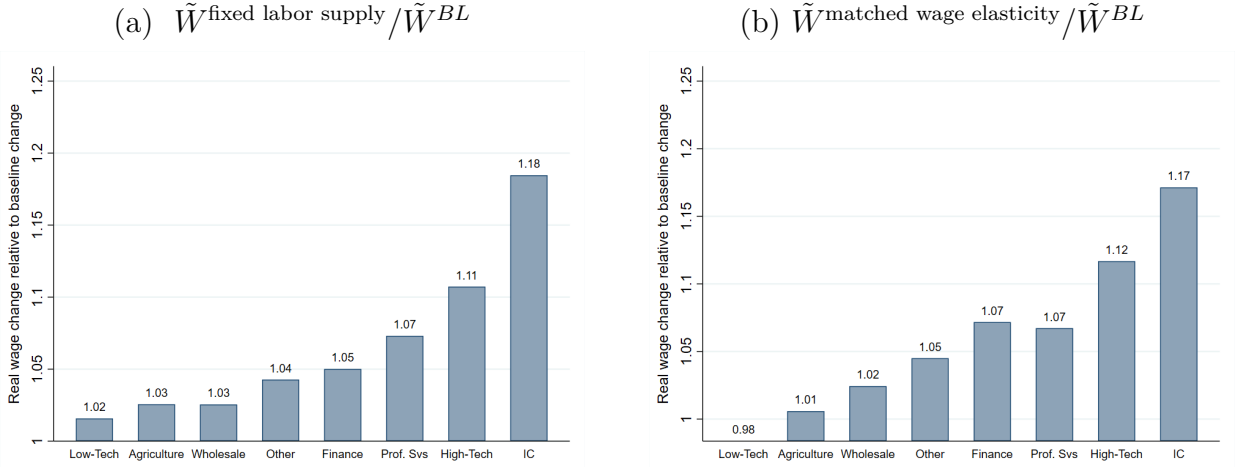
Notes: The y-axis in the left- and right-hand figures are $\tilde{W}^{\text{fixed labor supply}}/\tilde{W}^{BL}$ and $\tilde{W}^{\text{match wage elasticity}}/\tilde{W}^{BL}$ respectively, where $\tilde{W}^{\text{fixed labor supply}}$, $\tilde{W}^{\text{match wage elasticity}}$ and $\tilde{W}^{BL}$ are the wage changes due to the policy change $dp_{o,usa}$ in an open economy that only accounts for the reduction in U.S. immigrant labor, a closed economy that matches the labor demand elasticity $dlog(w^n_{usa,k,cs})/dlog(l^n_{usa,k,cs})$ corresponding to the baseline open economy, and the baseline open economy (see the description in Section 6.3). The labels of sectors are as in Section 5.

F   Additional tables and figures

Table F.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	Code	NOC (Classification in PR) Description	Code	DOT (Classification in H-1B dataset) 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 F.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

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

Table F.4: Effects of increasing H-1B denial rates on Canadian immigration

	(1)	(2)	(3)	(4)	(5)
Fraction Affected$_{co}$ $1(t = 2012)$	0.117	0.153	0.078	0.142	0.213
	(1.326)	(1.342)	(1.669)	(1.345)	(1.347)
Fraction Affected$_{co}$ $1(t = 2013)$	0.086	0.282	0.600	0.212	0.182
	(1.411)	(1.435)	(1.723)	(1.430)	(1.429)
Fraction Affected$_{co}$ $1(t = 2014)$	-1.131	-1.038	-1.726	-0.996	-1.131
	(1.578)	(1.605)	(1.933)	(1.604)	(1.579)
Fraction Affected$_{co}$ $1(t = 2015)$	0.295	0.751	0.810	0.551	0.295
	(1.234)	(1.253)	(1.465)	(1.254)	(1.234)
Fraction Affected$_{co}$ $1(t = 2017)$	3.683**	3.279**	4.977***	3.933***	3.684**
	(1.428)	(1.442)	(1.445)	(1.477)	(1.428)
Fraction Affected$_{co}$ $1(t = 2018)$	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

Notes: *** $= p < 0.01$,** $= p < 0.05$,* $= p < 0.1$. The outcome variable is all columns is $log(Can\ App_{cot})$ and 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., $Can\ App_{co} \times \delta_t$ and $US\ App_{co} \times \delta_t$). 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.

Table F.5: Summary statistics of the firm-level intensity of treatment, $Intensity_i$

NAICS code	Mean	Std	Median	10th	90th	N firms	All firms N firms
		Firms with $Intensity_i > 0$					
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

Notes: This statistics correspond to $Intensity_i$ 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 F.6: Effect of increasing H-1B denial rates on Canadian firms

	(1) Log of revenue	(2) Share of total export in revenue	(3) Log of total export	(4) Share of export to US in revenue	(5) Log of export to US	(6) Net hiring of immigrant workers	(7) Net hiring of native-born workers	(8) Log of native-born employment	(9) Log of total employment	(10) Log avg. wage of all workers	(11) Log avg. wage of native-born workers	(12) Log median wage of native-born workers	(13) Immigrant wage bill share	(14) Log of markup	(15) Log of cost
Intensity$_i$ ×1(τ = 2012)	-0.1092	-0.1137	-3.2124	-0.0106	-0.8368	-0.0349	-0.1607	-0.3244	0.2850	0.1880	0.3214	0.0076	0.0303	-0.1713	-0.1122
	(0.2441)	(0.0985)	(2.3604)	(0.0849)	(2.5651)	(0.1364)	(0.1319)	(0.3229)	(0.1941)	(0.1652)	(0.2320)	(0.2244)	(0.0713)	(0.1728)	(0.2001)
Intensity$_i$ ×1(τ = 2013)	-0.1910	-0.0334	-1.5054	0.0243	0.9142	0.0303	-0.0773	0.0591	0.3745**	0.2774	0.4366**	0.2274	-0.0227	-0.1622	-0.1577
	(0.2259)	(0.0879)	(2.3013)	(0.0743)	(2.4741)	(0.1304)	(0.1137)	(0.2971)	(0.1774)	(0.1516)	(0.2092)	(0.2031)	(0.0637)	(0.1380)	(0.1865)
Intensity$_i$ ×1(τ = 2014)	-0.0985	-0.1076	-0.8141	-0.0834	-0.9854	-0.0045	-0.1319	-0.0379	0.1956	0.1076	0.2274	0.0910	0.0076	-0.0182	-0.1622
	(0.1895)	(0.0728)	(1.8920)	(0.0606)	(2.0390)	(0.1698)	(0.1213)	(0.2699)	(0.1592)	(0.1349)	(0.1850)	(0.1774)	(0.0546)	(0.1258)	(0.1622)
Intensity$_i$ ×1(τ = 2015)	-0.1031	-0.0591	-0.0743	-0.0000	-0.6852	0.0152	-0.1289	-0.0470	0.0728	0.2335	0.3153	0.1152	0.0303	0.0061	-0.1289
	(0.1440)	(0.0606)	(1.5751)	(0.0515)	(1.7495)	(0.1198)	(0.1107)	(0.2138)	(0.1198)	(0.1349)	(0.1834)	(0.1652)	(0.0409)	(0.1061)	(0.1182)
Intensity$_i$ ×1(τ = 2017)	0.6519***	0.1046	0.7777	0.0728	1.4721	0.4533**	0.2410	0.8247***	0.5154***	-0.1395	-0.0788	-0.0061	0.0470	0.0561	0.5564***
	(0.1819)	(0.0713)	(1.7328)	(0.0591)	(1.8753)	(0.1834)	(0.1243)	(0.2335)	(0.1531)	(0.1182)	(0.1683)	(0.1622)	(0.0409)	(0.1046)	(0.1455)
Intensity$_i$ ×1(τ = 2018)	1.0339***	0.3441***	7.2375***	0.2380***	5.2287**	0.6883***	0.2971**	1.2780***	0.9414***	-0.4033***	-0.7444***	-0.6291***	0.1895***	0.1319	0.9157***
	(0.2517)	(0.0879)	(1.9193)	(0.0697)	(2.1618)	(0.1561)	(0.1228)	(0.3032)	(0.2092)	(0.1425)	(0.2092)	(0.2077)	(0.0606)	(0.1304)	(0.2107)
Number of observations	537585	537585	87420	537585	79225	537585	537585	537585	537585	408640	408640	408640	537585	532015	532115
Number of firms	79430	79430	15935	79430	14600	79430	79430	79430	79430	65950	65950	65950	79430	78955	78955
R^2	0.9837	0.9006	0.8993	0.8922	0.8946	0.1302	0.1457	0.9639	0.9711	0.9342	0.9219	0.9116	0.9649	0.6730	0.9877

Notes: 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. For ease of reading, we further multiply the coefficients by 100. The event is defined as the spike in the H-1B denial rate in 2017. Standard errors are clustered at the firm level (*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$). Compared with other regressions, the samples in columns (3), (5), (10), (11), (12), (14), and (15) are smaller. The regression samples in columns (3) and (5) are smaller because we exclude the observations with exports below the first percentile of the positive exports, which is about 800 CAD. The regression sample in columns (10), (11), and (12) is smaller due to our restrictions on the employer-employee records in computing the firm-level statistics of workers' annual earnings. To compute these firm-level statistics, we first restrict the sample of workers to those who work for only one firm and do not have separation records in a given year; then, we drop the records that report an annual earning less than the annual earning implied by the minimum wage of the corresponding provinces; finally, we keep the firms with at least 5 records of workers in a given year in the regression sample. The regression sample in columns (14) and (15) is smaller because some firms in the full sample have missing records of their total costs.

Table F.7: Effect of increasing H-1B denial rates on Canadian firms: standard error clustered at sector and local labor market level

	(1) Log of revenue	(2) Share of total export in revenue	(3) Log of total export	(4) Share of export to US in revenue	(5) Log of export to US	(6) Net hiring of immigrant workers	(7) Net hiring of native-born workers	(8) Log of native-born employment	(9) Log of total employment	(10) Log avg. wage of all workers	(11) Log avg. wage of native-born workers	(12) Log median wage of native-born workers	(13) Immigrant wage bill share	(14) Log of markup	(15) Log of cost
Intensity$_i$ ×1(τ = 2012)	-0.1092	-0.1137	-3.2124	-0.0106	-0.8368	-0.0349	-0.1607	-0.3244	0.2850	0.1880	0.3214	0.0076	0.0303	-0.1713	-0.1122
	(0.3047)	(0.1137)	(2.5317)	(0.1031)	(2.9320)	(0.1668)	(0.1440)	(0.4381)	(0.2880)	(0.1895)	(0.2532)	(0.2365)	(0.0955)	(0.1925)	(0.2350)
Intensity$_i$ ×1(τ = 2013)	-0.1910	-0.0334	-1.5054	0.0243	0.9142	0.0303	-0.0773	0.0591	0.3745	0.2774	0.4366	0.2274	-0.0227	-0.1622	-0.1577
	(0.2774)	(0.1016)	(2.7849)	(0.0819)	(3.2003)	(0.1546)	(0.1228)	(0.3911)	(0.2426)	(0.1743)	(0.2304)	(0.2077)	(0.0803)	(0.1546)	(0.2122)
Intensity$_i$ ×1(τ = 2014)	-0.0985	-0.1076	-0.8141	-0.0834	-0.9854	-0.0045	-0.1319	-0.0379	0.1956	0.1076	0.2274	0.0910	0.0076	-0.0182	-0.1622
	(0.2350)	(0.0758)	(1.9071)	(0.0652)	(2.0406)	(0.2031)	(0.1334)	(0.3684)	(0.1971)	(0.1637)	(0.2183)	(0.2213)	(0.0622)	(0.1364)	(0.1910)
Intensity$_i$ ×1(τ = 2015)	-0.1031	-0.0591	-0.0743	-0.0000	-0.6852	0.0152	-0.1289	-0.0470	0.0728	0.2335	0.3153	0.1152	0.0303	0.0061	-0.1289
	(0.1713)	(0.0728)	(1.6722)	(0.0682)	(2.0209)	(0.1304)	(0.1319)	(0.2517)	(0.1410)	(0.1561)	(0.2168)	(0.1925)	(0.0440)	(0.1198)	(0.1349)
Intensity$_i$ ×1(τ = 2017)	0.6519***	0.1046	0.7777	0.0728	1.4721	0.4533**	0.2410	0.8247***	0.5154***	-0.1395	-0.0788	-0.0061	0.0470	0.0561	0.5564***
	(0.2107)	(0.0743)	(1.8799)	(0.0682)	(2.0375)	(0.1986)	(0.1334)	(0.2729)	(0.1652)	(0.1349)	(0.1804)	(0.1880)	(0.0485)	(0.1243)	(0.1607)
Intensity$_i$ ×1(τ = 2018)	1.0339***	0.3441***	7.2375***	0.2380***	5.2287**	0.6883***	0.2971**	1.2780***	0.9414***	-0.4033**	-0.7444***	-0.6291**	0.1895***	0.1319	0.9157***
	(0.2805)	(0.1016)	(2.1588)	(0.0803)	(2.4120)	(0.1698)	(0.1440)	(0.3790)	(0.2562)	(0.1683)	(0.2547)	(0.2623)	(0.0743)	(0.1743)	(0.2577)
Number of observations	537585	537585	87420	537585	79225	537585	537585	537585	537585	408640	408640	408640	537585	532015	532115
Number of firms	79430	79430	15935	79430	14600	79430	79430	79430	79430	65950	65950	65950	79430	78955	78955
R^2	0.9837	0.9006	0.8993	0.8922	0.8946	0.1302	0.1457	0.9639	0.9711	0.9342	0.9219	0.9116	0.9649	0.6730	0.9877

Notes: 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. For ease of reading, we further multiply the coefficients by 100. The event is defined as the spike in the H-1B denial rate in 2017. Standard errors are clustered at the sector (3-digit NAICS) and local labor market level (*** = $p < 0.01$,** = $p < 0.05$,* = $p < 0.1$). Compared with other regressions, the samples in columns (3), (5), (10), (11), (12), (14), and (15) are smaller. The regression samples in columns (3) and (5) are smaller because we exclude the observations with exports below the first percentile of the positive exports, which is about 800 CAD. The regression sample in columns (10), (11), and (12) is smaller due to our restrictions on the employer-employee records in computing the firm-level statistics of workers' annual earnings. To compute these firm-level statistics, we first restrict the sample of workers to those who work for only one firm and do not have separation records in a given year; then, we drop the records that report an annual earning less than the annual earning implied by the minimum wage of the corresponding provinces; finally, we keep the firms with at least 5 records of workers in a given year in the regression sample. The regression sample in columns (14) and (15) is smaller because some firms in the full sample have missing records of their total costs.

Table F.8: Effect of increasing H-1B denial rates on Canadian firms: without sector-year controls

	(1) Log of revenue	(2) Share of total export in revenue	(3) Log of Total export	(4) Share of export to US in revenue	(5) Log of export to US	(6) Net hiring of immigrant workers	(7) Net hiring of native-born workers	(8) Log of native-born employment	(9) Log avg. wage of all workers	(10) Log avg. wage of native-born workers
Intensity$_i$ ×$\mathbf{1}$(τ = 2012)	-0.0182	-0.1092	-2.8850	-0.0045	-0.9612	-0.0273	-0.1577	-0.2092	0.1471	0.2850
	(0.2426)	(0.0985)	(2.3635)	(0.0849)	(2.5484)	(0.1349)	(0.1319)	(0.3229)	(0.1652)	(0.2304)
Intensity$_i$ ×$\mathbf{1}$(τ = 2013)	-0.1334	-0.0349	-1.2977	0.0243	0.6534	0.0349	-0.0803	0.1364	0.2486	0.4093**
	(0.2259)	(0.0879)	(2.2907)	(0.0743)	(2.4590)	(0.1304)	(0.1137)	(0.2971)	(0.1501)	(0.2077)
Intensity$_i$ ×$\mathbf{1}$(τ = 2014)	-0.0212	-0.0970	-0.5640	-0.0743	-0.9945	0.0045	-0.1182	0.0606	0.0803	0.1956
	(0.1880)	(0.0728)	(1.8859)	(0.0606)	(2.0193)	(0.1698)	(0.1198)	(0.2699)	(0.1349)	(0.1834)
Intensity$_i$ ×$\mathbf{1}$(τ = 2015)	-0.0515	-0.0500	0.1895	0.0091	-0.5822	0.0197	-0.1122	0.0061	0.2107	0.2926
	(0.1440)	(0.0606)	(1.5827)	(0.0515)	(1.7495)	(0.1198)	(0.1092)	(0.2138)	(0.1334)	(0.1819)
Intensity$_i$ ×$\mathbf{1}$(τ = 2017)	0.6701***	0.1198	0.4624	0.0803	1.0263	0.4548**	0.2426	0.8520***	-0.1471	-0.0849
	(0.1819)	(0.0697)	(1.7358)	(0.0591)	(1.8738)	(0.1834)	(0.1243)	(0.2335)	(0.1182)	(0.1683)
Intensity$_i$ ×$\mathbf{1}$(τ = 2018)	1.0779***	0.3684***	6.8933***	0.2532***	4.6117**	0.6959***	0.3123**	1.3265***	-0.4033***	-0.7428***
	(0.2532)	(0.0864)	(1.9087)	(0.0697)	(2.1679)	(0.1546)	(0.1243)	(0.3032)	(0.1440)	(0.2107)
Number of observations	537585	537585	87420	537585	79225	537585	537585	537585	408640	408640
Number of firms	79430	79430	15935	79430	14600	79430	79430	79430	65950	65950
R^2	0.9837	0.9001	0.8984	0.8918	0.8936	0.1297	0.1446	0.9638	0.9340	0.9218

Notes: The table displays the estimated event-study coefficients, β_τ, of equation (3) without the sector-specific trends, the number of jobs created in the U.K. in each sector and year, and the interacted term between sector employment growth in 2011 and year fixed effects. We multiply the coefficients by the average value of Intensity$_i$ in the high-skilled service sector for ease of interpretation. For ease of reading, we further multiply the coefficients by 100. The event is defined as the spike in the H-1B denial rate in 2017. Standard errors are clustered at the firm level (*** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$). Compared with other regressions, the samples in columns (3), (5), (9), and (10) are smaller. The regression samples in columns (3) and (5) are smaller because we exclude the observations with exports below the first percentile of the positive exports, which is about 800 CAD. The regression sample in columns (9) and (10) is smaller due to our restrictions on the employer-employee records in computing the firm-level statistics of workers' annual earnings. To compute these firm-level statistics, we first restrict the sample of workers to those who work for only one firm and do not have separation records in a given year; then, we drop the records that report an annual earning less than the annual earning implied by the minimum wage of the corresponding provinces; finally, we keep the firms with at least 5 records of workers in a given year in the regression sample.

Table F.9: Effect of increasing H-1B denial rates on domestic firms

	(1) Log of revenue	(2) Net hiring of immigrant workers	(3) Net hiring of native-born workers	(4) Share of total export in revenue	(5) Share of export to US in revenue
Intensity$_i$ ×$\mathbf{1}(\tau = 2012)$	0.0743	0.0167	-0.0849	-0.1001	-0.0197
	(0.2456)	(0.1501)	(0.1440)	(0.0940)	(0.0803)
Intensity$_i$ ×$\mathbf{1}(\tau = 2013)$	-0.1228	0.0955	-0.0091	-0.0303	0.0106
	(0.2320)	(0.1440)	(0.1243)	(0.0834)	(0.0697)
Intensity$_i$ ×$\mathbf{1}(\tau = 2014)$	-0.0197	0.0455	-0.0273	-0.0773	-0.0606
	(0.1895)	(0.1895)	(0.1319)	(0.0682)	(0.0576)
Intensity$_i$ ×$\mathbf{1}(\tau = 2015)$	-0.0819	0.0334	-0.0515	-0.0030	0.0152
	(0.1501)	(0.1319)	(0.1228)	(0.0576)	(0.0485)
Intensity$_i$ ×$\mathbf{1}(\tau = 2017)$	0.6367***	0.4988**	0.3062**	0.1016	0.0637
	(0.1880)	(0.1971)	(0.1349)	(0.0713)	(0.0591)
Intensity$_i$ ×$\mathbf{1}(\tau = 2018)$	1.0036***	0.7095***	0.4078***	0.2820***	0.1789***
	(0.2592)	(0.1652)	(0.1349)	(0.0819)	(0.0652)
Number of observations	510685	510685	510685	510685	510685
Number of firms	75470	75470	75470	75470	75470
R^2	0.9809	0.1275	0.1437	0.8958	0.8878

Notes: The table displays the estimated event-study coefficients, β_τ, of equation (3). To facilitate the interpretation, we multiply the coefficients by the average value of $Intensity_i$ in the high-skilled service sector. For ease of reading, we further multiply the coefficients by 100. The sample includes only domestic firms and excludes MNCs. We plot these coefficients in Appendix Figure F.11. Standard errors are clustered at the firm level (*** = $p < 0.01$,** = $p < 0.05$,* = $p < 0.1$).

Table F.10: Robustness exercise. Within-industry estimates

	(1) Log of revenue	(2) Net hiring of immigrant workers	(3) Share of total export in revenue	(4) Share of export to US in revenue
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2012)$	-0.1001	-0.1683	-0.2744**	-0.1182
	(0.2668)	(0.1895)	(0.1152)	(0.0955)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2012)$	-0.0561	0.1364	0.0834	0.1380
	(0.4806)	(0.1804)	(0.1956)	(0.1592)
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2013)$	-0.1092	-0.0061	-0.2850***	-0.0879
	(0.2517)	(0.1941)	(0.1046)	(0.0864)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2013)$	-0.1349	0.1622	0.2274	0.1637
	(0.4427)	(0.1592)	(0.1819)	(0.1410)
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2014)$	-0.1107	0.0622	-0.1001	-0.0288
	(0.2213)	(0.2714)	(0.0834)	(0.0667)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2014)$	0.1895	0.0303	-0.0985	-0.1001
	(0.3684)	(0.1592)	(0.1577)	(0.1213)
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2015)$	-0.1850	-0.0273	-0.1531**	-0.0318
	(0.1698)	(0.1743)	(0.0697)	(0.0561)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2015)$	0.1880	0.0894	0.0409	0.0500
	(0.3002)	(0.1471)	(0.1425)	(0.1092)
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2017)$	-0.2456	0.2168	-0.0910	-0.0394
	(0.2517)	(0.2926)	(0.0758)	(0.0606)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2017)$	0.4108	0.5367***	0.2410	0.1167
	(0.3229)	(0.1941)	(0.1561)	(0.1152)
$Intensity_i \times \mathbf{1}(SS=0) \times \mathbf{1}(\tau=2018)$	-0.9081***	0.2441	-0.0970	-0.0273
	(0.3290)	(0.2213)	(0.0910)	(0.0743)
$Intensity_i \times \mathbf{1}(SS=1) \times \mathbf{1}(\tau=2018)$	1.2083***	0.8929***	0.7626***	0.4715***
	(0.4563)	(0.2092)	(0.1865)	(0.1334)
Number of observations	537585	537585	537585	537585
Number of firms	79430	79430	79430	79430
R^2	0.9839	0.1317	0.9021	0.8938

Notes: The table displays the estimated event-study coefficients, β_τ, of equation B.1. To facilitate the interpretation, we multiply the coefficients by the average value of $Intensity_i$ in the high-skilled service sector. For ease of reading, we further multiply the coefficients by 100. $SS=1$ 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. We plot these coefficients in Appendix Figure F.12. Standard errors are clustered at the firm level (*** = $p < 0.01$,** = $p < 0.05$,* = $p < 0.1$).

Table F.11: Estimate of the elasticity of substitution between the U.S. and Canada

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

Notes: *** = $p < 0.01$,** = $p < 0.05$,* = $p < 0.1$. 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 $Share_{oc2015}^{EE} \times 1(t \geq 2015)$ and $Share_{oc2016}^{EE} \times 1(t \geq 2016)$ where $Share_{oct}^{EE}$ is the share of applications from an immigrant group oc in year t accounted for by the Express Entry program.

Table F.12: Categorization of industries into broad sectors in the model

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

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

Figure F.2: Annual number of H-1B approvals
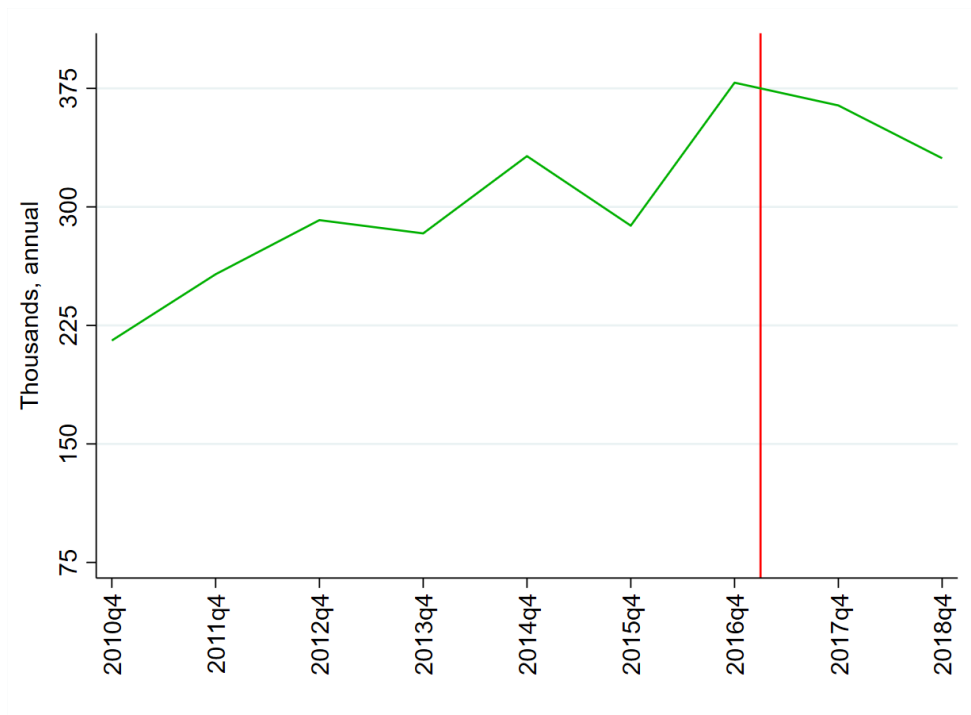
Notes: We use our H-1B dataset to compute the number of H-1B approvals until 2018q3 and complement the data for 2018q4 from an additional FOIA request. The number of approvals in 2018 was approximately 47,000 fewer than in 2016 and 140,000 fewer than its linear trend.

Figure F.3: Denial rates of continuing H-1B visas and renewals by quarter
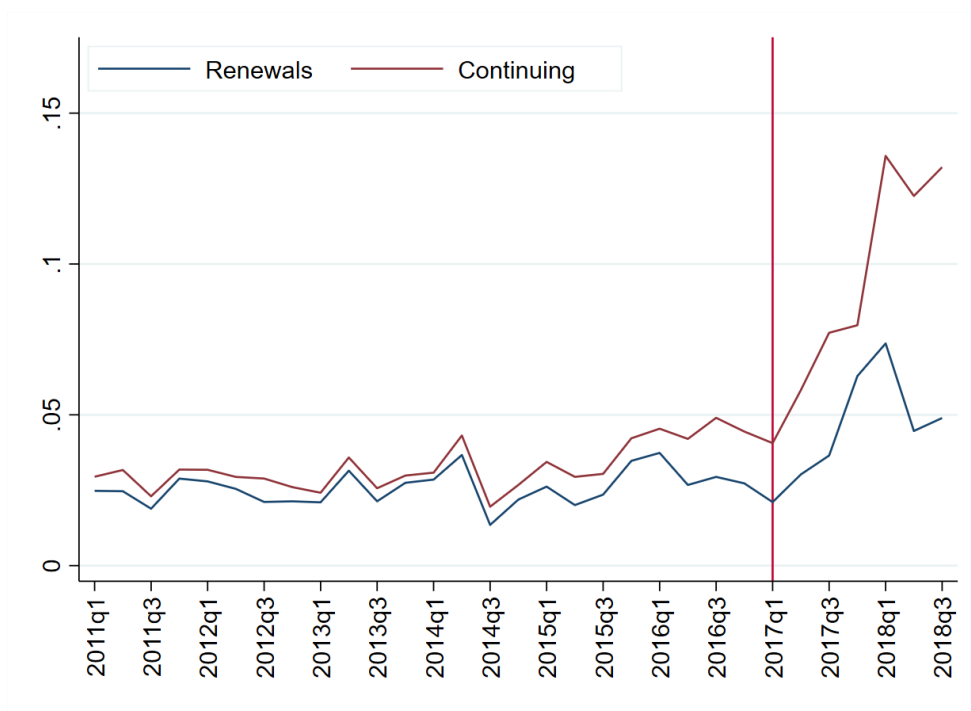
Notes: The denial rate is computed as the number of denied H-1B applications divided by the total number of H-1B applications. The red line includes continuing H-1B visas, and the blue line includes the subset of continuing visas that are renewals.

Figure F.4: Canadian visa applications of immigrants living in the U.S.
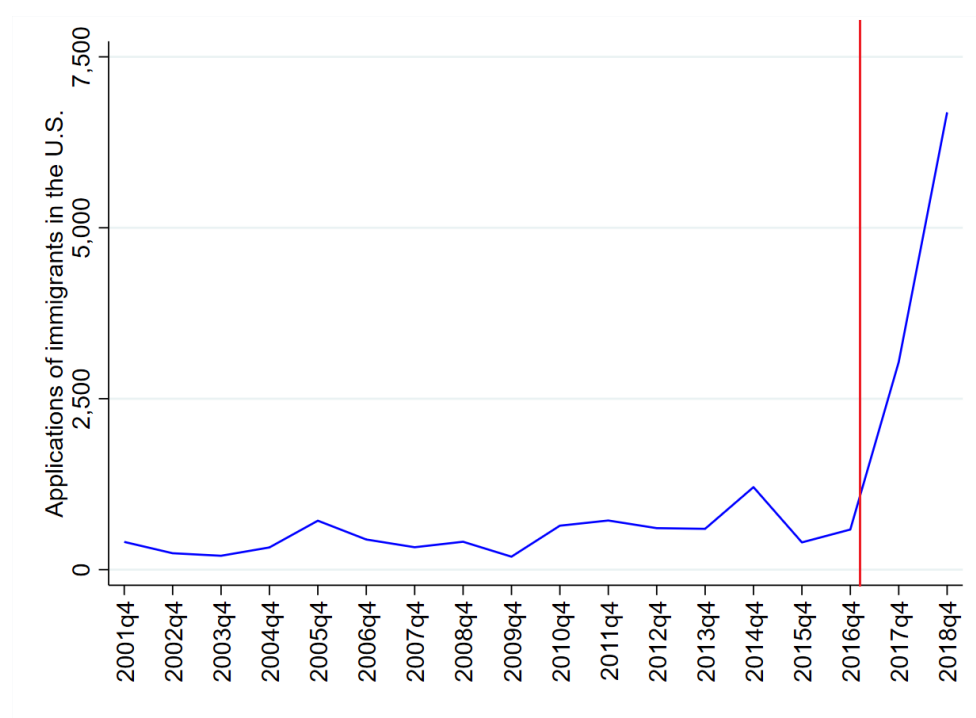
Notes: The y-axis represents the number of applications for Canadian permanent residence visas from applicants residing in the U.S., excluding American applicants.

Figure F.5: Effects on Canadian Immigration. Robustness exercises

(a) Controlling for the elements in $\pi_{co,usa}$
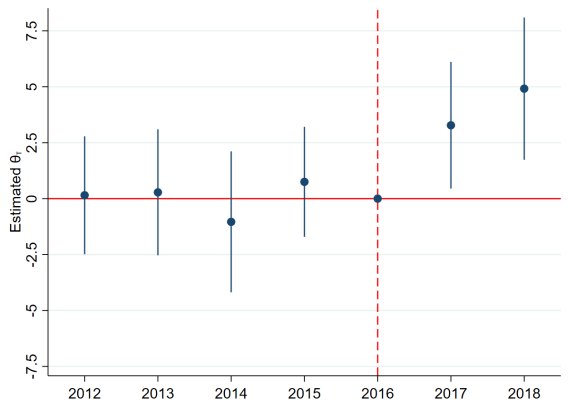
(b) Excluding apps. from India and China
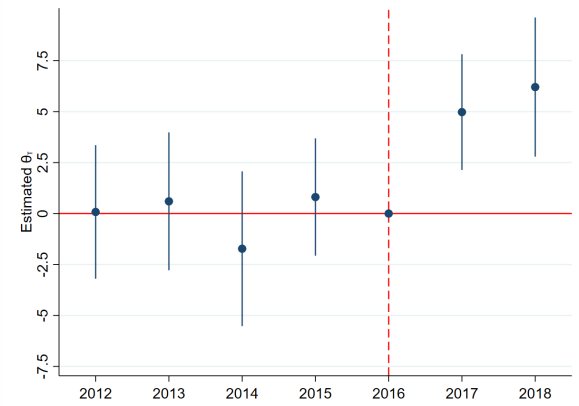
(c) Excluding apps. from computer scientists
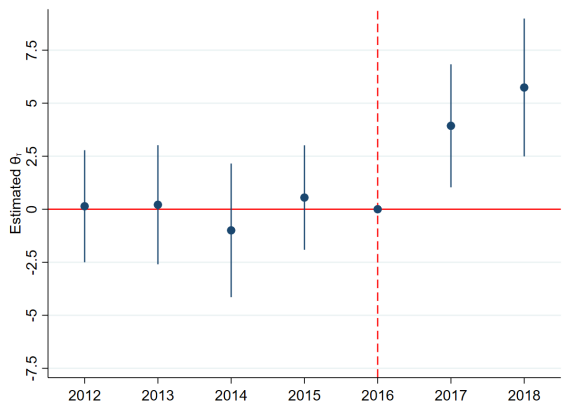
(d) Including Express Entry control variables
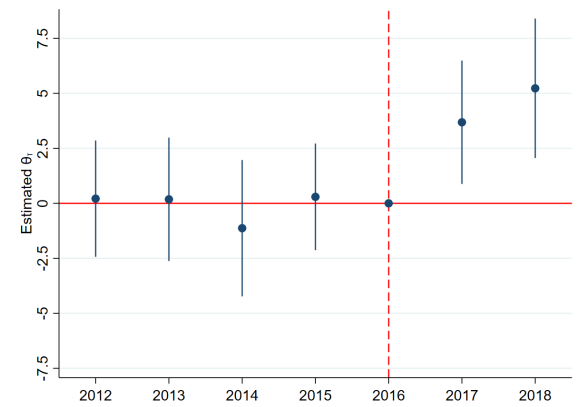
Notes: The y-axis plots the estimated event-study coefficients corresponding to columns 2-4 from Appendix Table F.4.

Figure F.6: Effect on Canadian visa applications using the change in denial rates
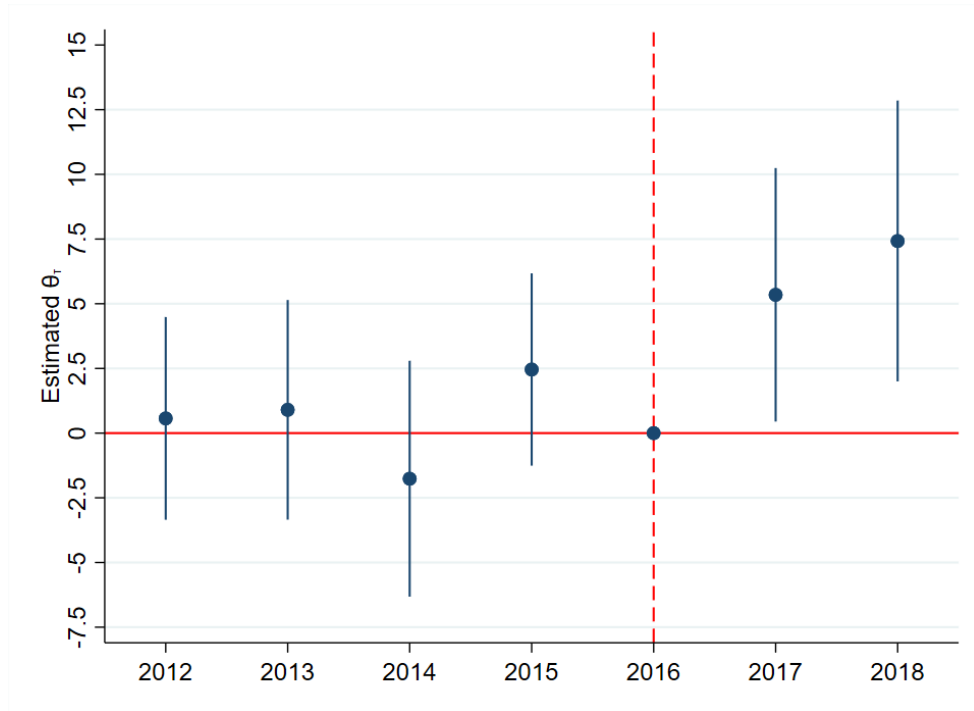
Notes: The y-axis plots the estimated event-study coefficients corresponding to a regression analogous to the baseline regression (1), with the only difference that Fraction Affected$_{co}$ is computed using the change in the denial rate by occupation between 2016 and 2018.

Figure F.7: Test for linear trends
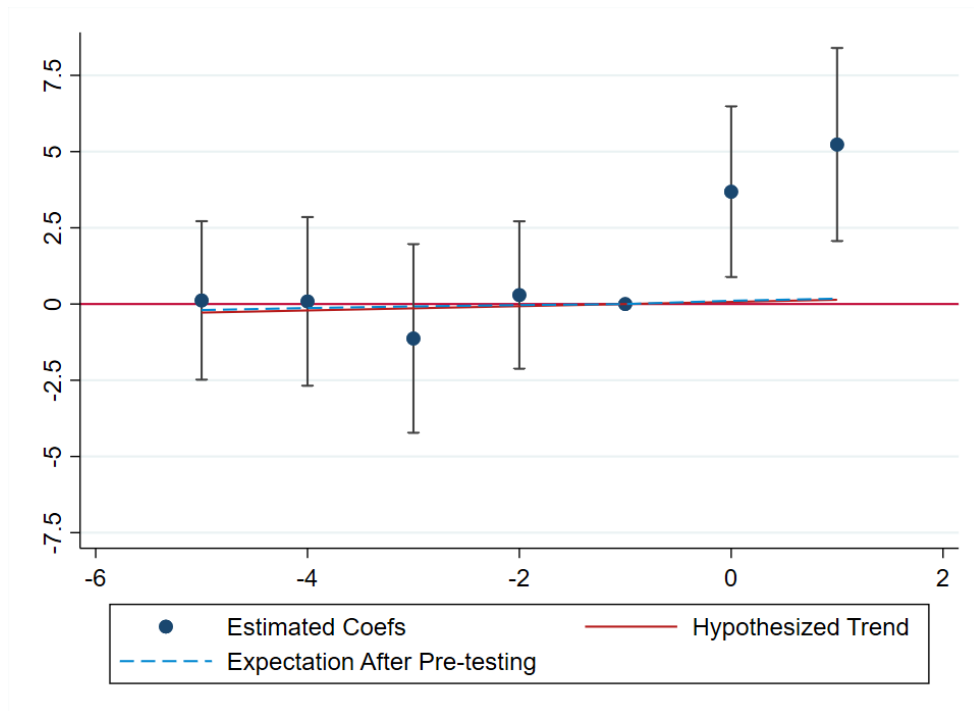
Notes: This plot shows our estimated coefficients along with the test of the hypothesis of linear trends with a slope of 7%, according to Roth (2022).

Figure F.8: Change in Canadian visa applications and exposure measure: raw data
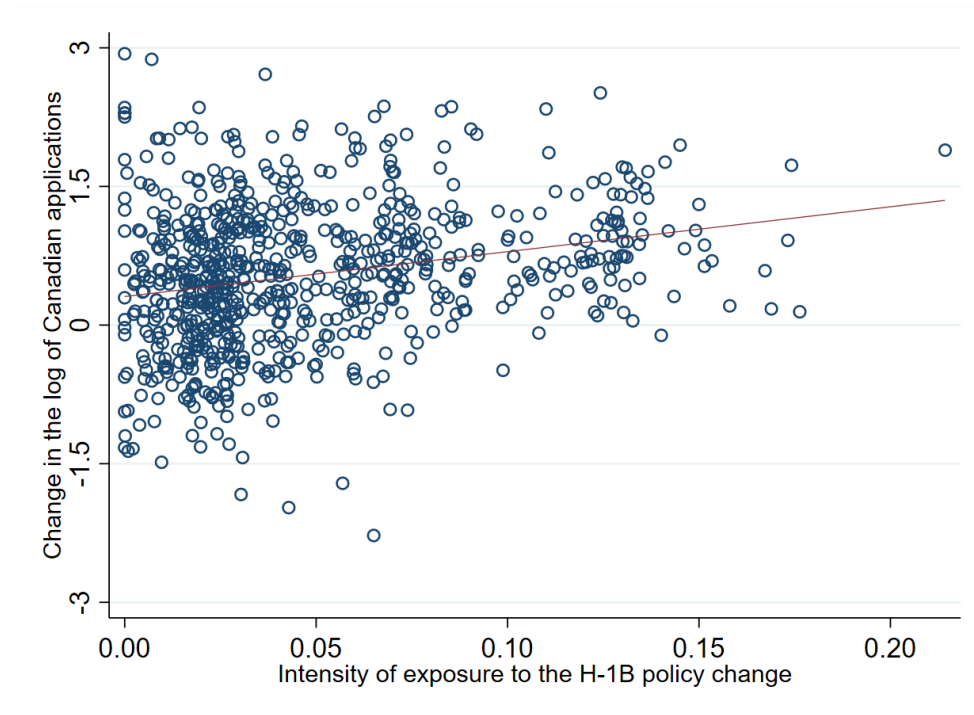
Notes: The y-axis is computed as $\frac{\sum_{t=2017}^{2018} log(App_{co,can,t})}{2} - \frac{\sum_{t=2012}^{2016} log(App_{co,can,t})}{5}$ and the x-axis is Fraction Affected$_{co}$ in equation (2). An observation is an immigrant group *co*.

Figure F.9: Number of working hours relative to the year 2003
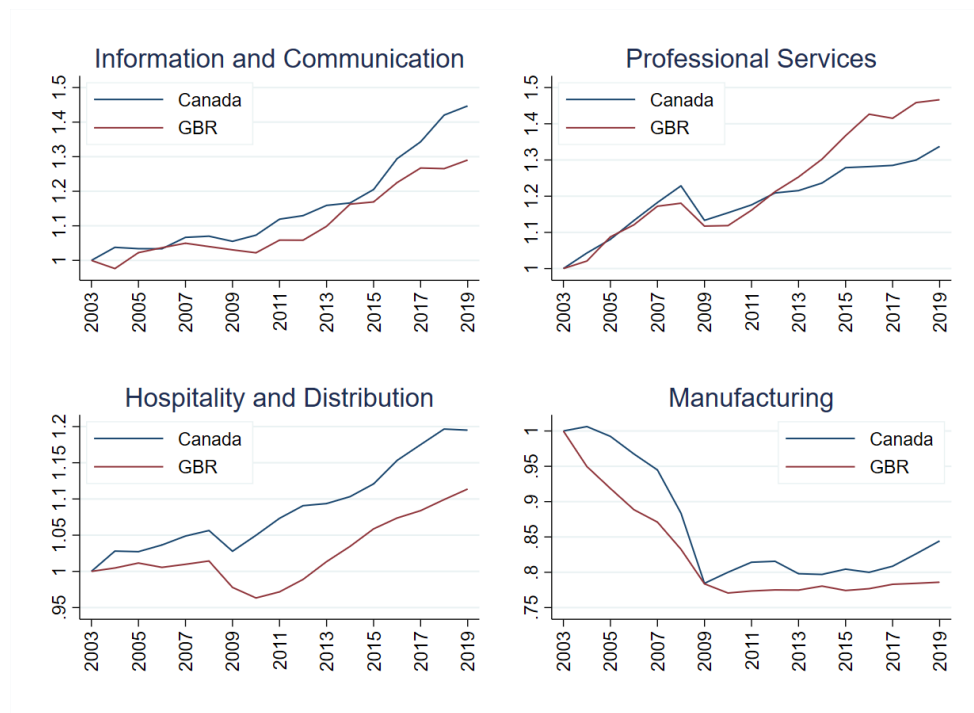
Notes: The y-axis measures the number of working hours relative to the year 2003, from the OECD database (variable name: EEM). The correlation of the time series for information and communications, professional services, hospitality and distribution, and manufacturing are 0.97, 0.95, 0.87, and 0.96, respectively.

Figure F.10: Increase in Immigrant Wages Relative to Native-Born Coworkers
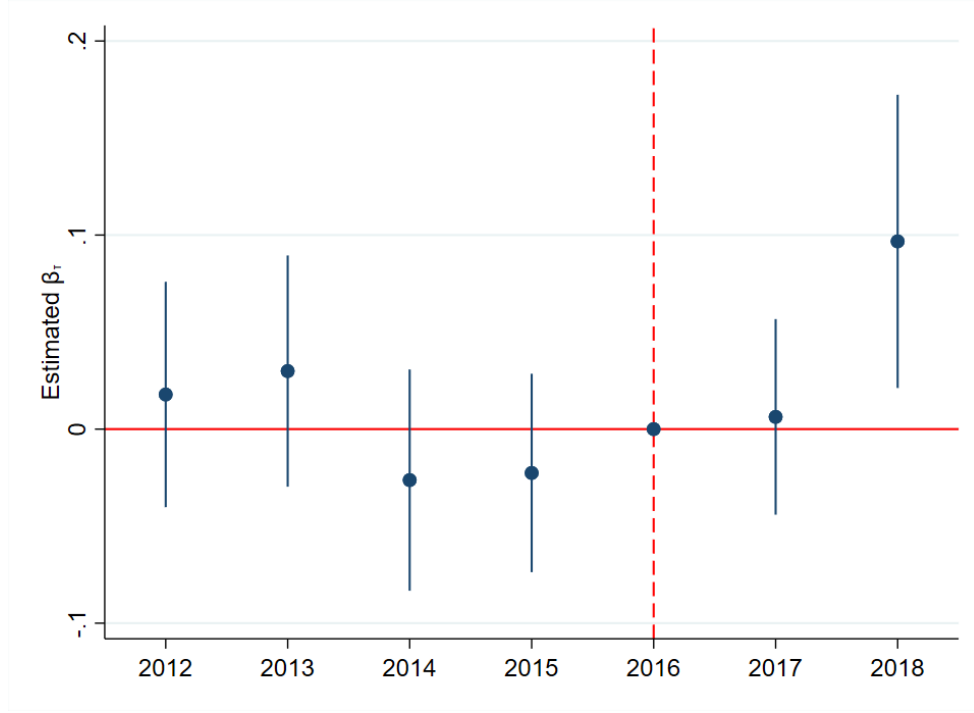
Notes: The y-axis plots the estimated coefficients of the following regression $\log\left(\frac{\text{Wage}_{i,t}}{\text{Avg. native wage within the same firm}_{i,t}}\right) = \sum_{\tau \neq 2016} \beta_\tau I_{\tau,i} + X_{i,t} + \epsilon_{i,t}$ where i stands for immigrant worker i, τ for cohort, t year, and the control variables in $X_{i,t}$ are age, age squared, nationality dummies, and tenure in Canada and at the firm level. Here, cohort refers to the year when an immigrant legally lands in Canada. The sample includes the immigrants in high-skilled service sectors with less than two years of Canadian tenure who work in the firms that do not have employment records of immigrants working before their earliest date to legally work in Canada. The sample period is 2012-2018. The figure suggests that the wage gap between the immigrants and their native-born coworkers is lower for the immigrants who arrived after the U.S. policy change relative to immigrants who arrived before.

Figure F.11: Effect of increasing H-1B denial rates on domestic firms
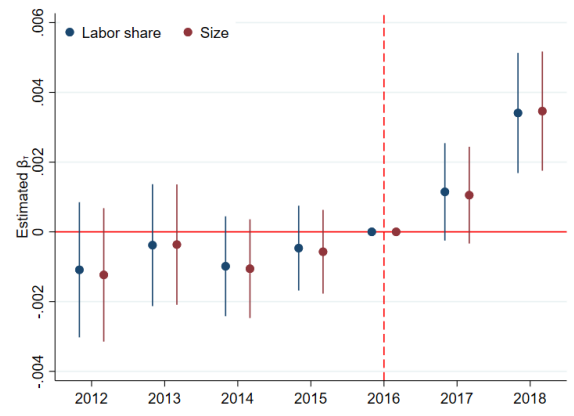
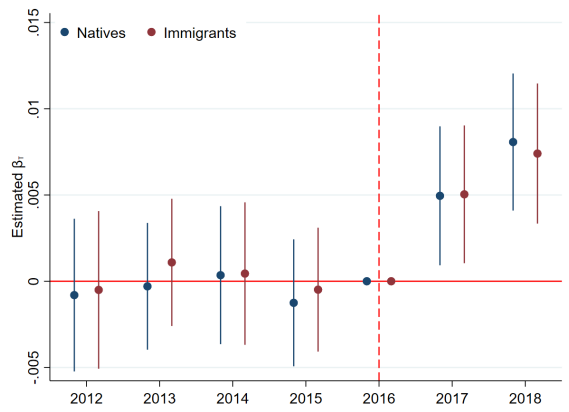(a) Hiring relative to employment in 2016
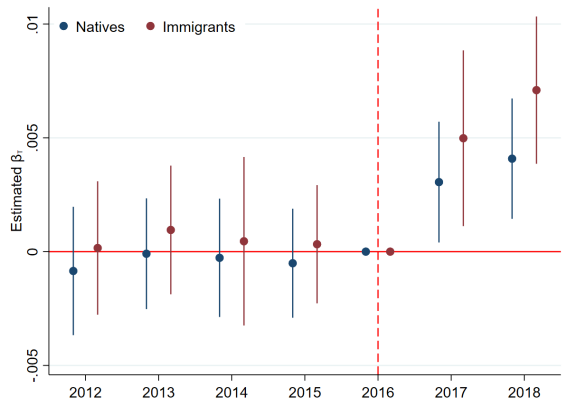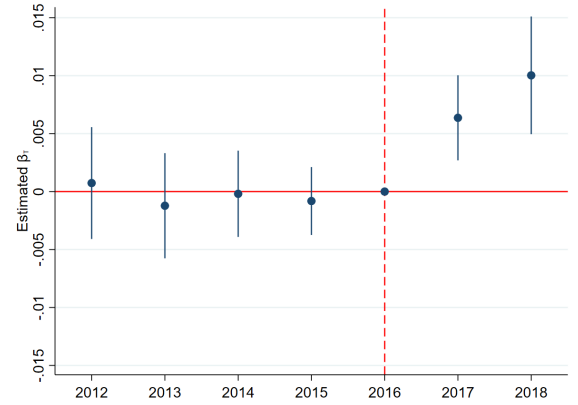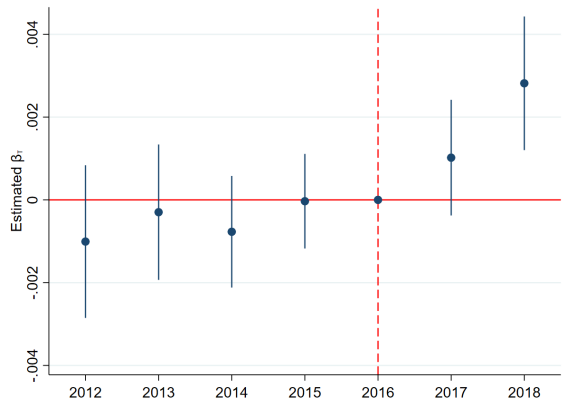
(b) Sales (in logs)

(c) Exports relative to total sales
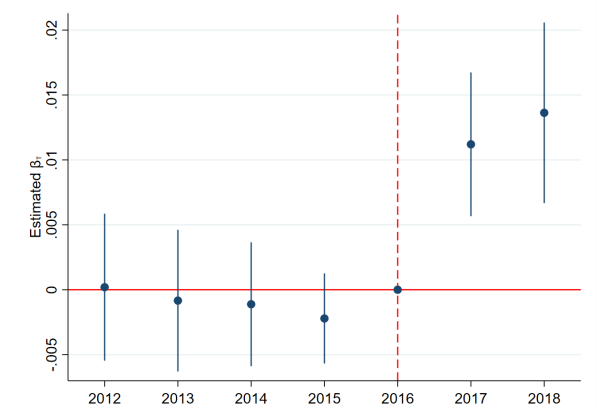
(d) Exports to the U.S. relative to total sales
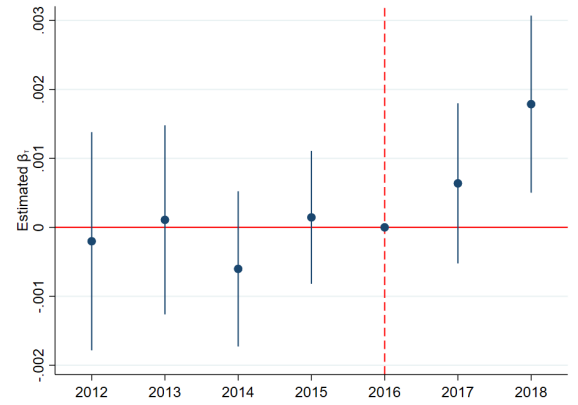
Notes: The y-axis plots the estimated event-study coefficients, multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The sample includes domestic firms and excludes all MNCs (we also exclude Canadian multinationals). The event is defined as 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 F.9.

Figure F.12: Robustness exercise. Baseline and within-industry estimates

(a) Hiring of imm. relative to emp
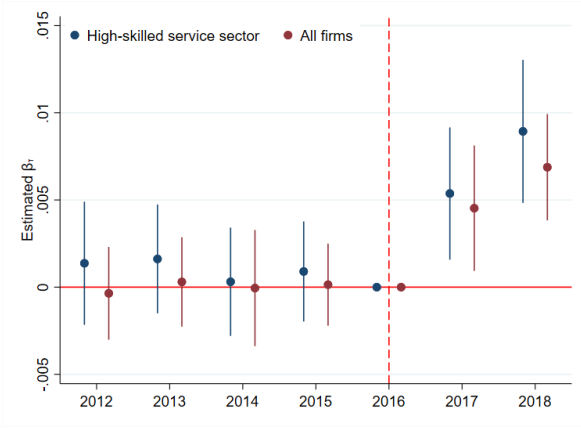
(b) Sales (in logs)
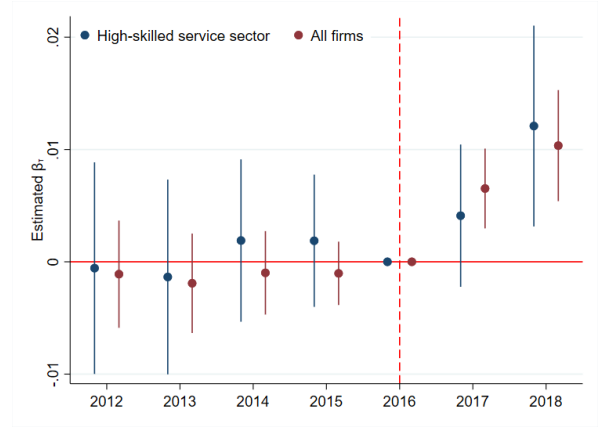
(c) Exports relative to total sales
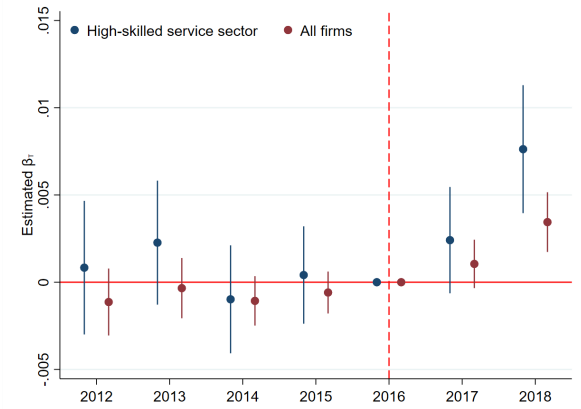
(d) Exports to the U.S. relative to total sales
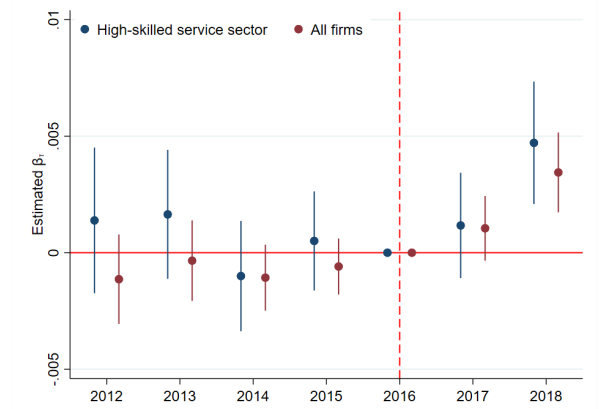
Notes: The y-axis plots the estimated event-study coefficients β_τ of equation 3, labeled as "All firms", and β_τ^E of equation B.1, labeled as "High-skilled service sector". The estimated coefficients β_τ plotted correspond to Appendix Table F.6, and the estimated coefficients β_τ^E plotted correspond to $SS = 1$ in Appendix Table F.10. The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals.

Figure F.13: Robustness exercise. Control for the effects of firm characteristics

(a) Hiring relative to employment in 2016
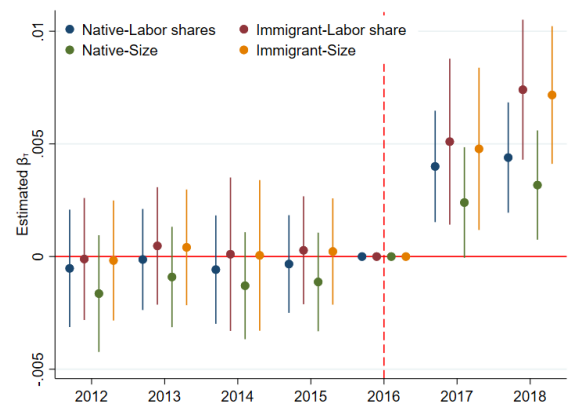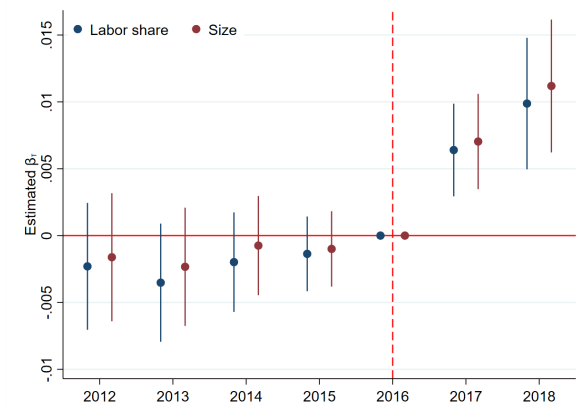
(b) Sales (in logs)

(c) Exports relative to total sales

(d) Exports to the U.S. relative to total sales
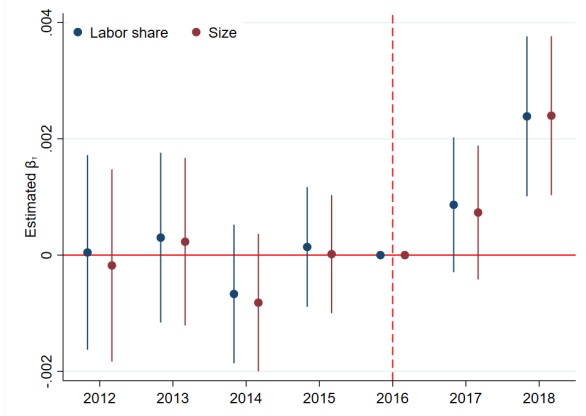
Notes: The y-axis plots the estimated event-study coefficients, β_τ, of equation 3 with additional control variables, multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. These variables are pre-shock firm characteristics interacted with year 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 outcome variables considered are the net hiring of immigrants and native workers with respect to the employment level in 2016 (panel a), the log sales (panel b), the log export sales (panel c), and export sales relative to total sales (panel d). The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect 95% confidence intervals.

Figure F.14: Robustness exercise. Excluding importers and exporters

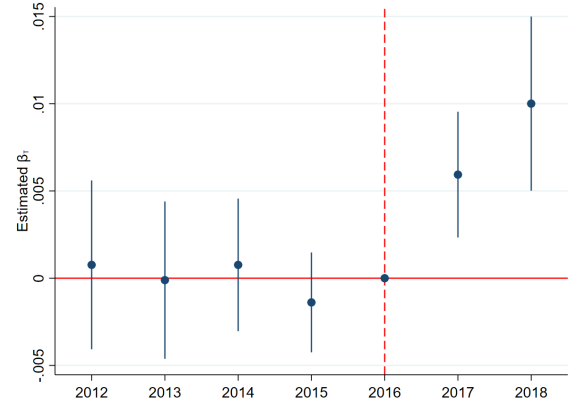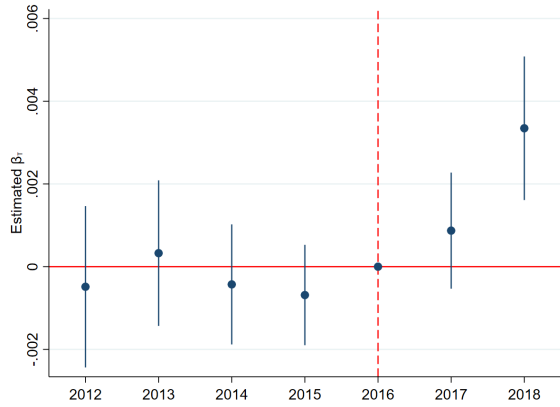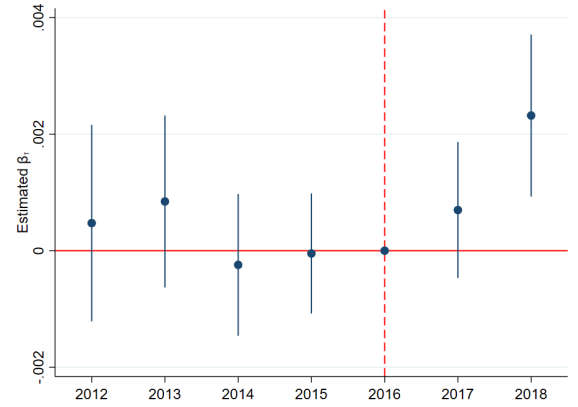(a) Hiring relative to Employment in 2016

(b) Sales (in logs)

Notes: 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 excludes 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 F.15: Robustness exercise. Control for the effects of the Express Entry visa program

(a) Hiring relative to employment in 2016
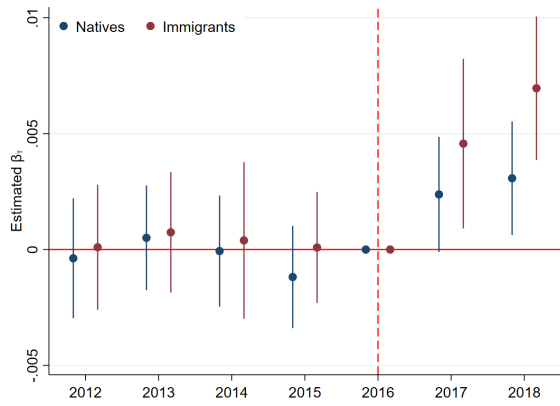
(b) Sales (in logs)

(c) Exports relative to total sales

(d) Exports to the U.S. relative to total sales

Notes: 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 F.16: U.S. wages and the share of immigrants choosing the U.S. over Canada
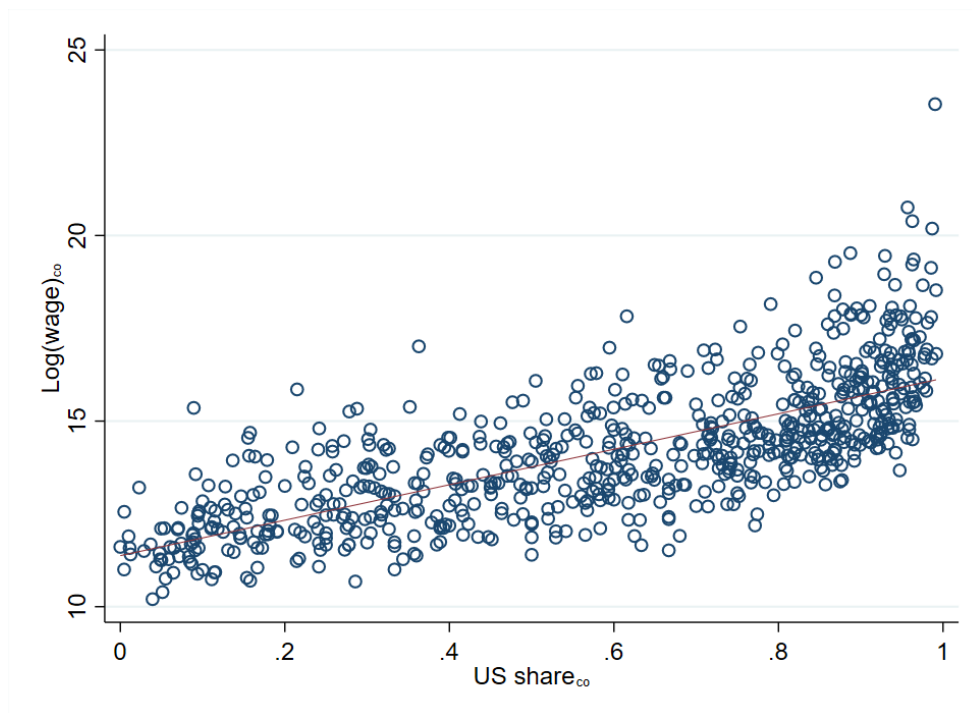
Notes: The y-axis is computed as the logarithm of the average annual earnings reported in the H-1B visa application dataset. The x-axis is the U.S. share in applications, $\pi_{co,usa}$. Both values are computed for the period before the introduction of the PM (2012-2015). An observation is an immigrant group *co*, where *c* and *o* stand for the country of birth and occupation, respectively.

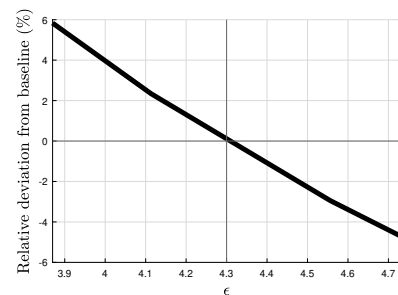Figure F.17: Identification of moments used for calibration
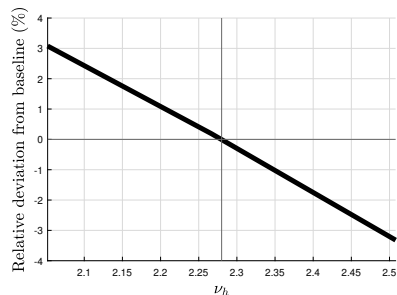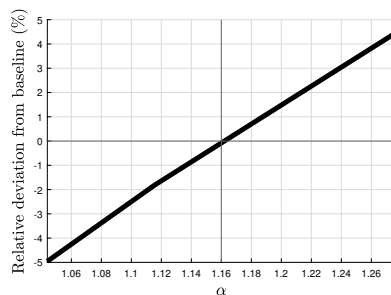
(a) Canadian visa applications   (b) Sales   (c) Earnings per native worker

Notes: 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 displays 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.