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

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**Abstract**

We study the effects of U.S. restrictions on skilled immigration on the Canadian economy and on American workers' welfare. In 2017, a new policy tightened the eligibility criteria for U.S. visas and was immediately followed by a sharp increase in the number of skilled immigrant admissions to Canada. We use quasi-experimental variation introduced by this policy over time and across immigrant groups, along with U.S. and Canadian visa application data, to show that Canadian applications in 2018 were 30% larger than without the restrictions. We then study how the restrictions affected Canadian firms, using the universe of Canadian employer-employee-linked records, immigration records, and data on international trade in goods and services. We find that Canadian firms that were relatively more exposed to the inflow of immigrants increased production, exports, as well as employment of Canadian workers. Finally, we study the policy's impact on American and Canadian workers' welfare by incorporating immigration policy into a multi-sector model of international trade. We calibrate the model using our data and reduced-form estimates. 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 find that the welfare gains for American workers targeted for protection by the 2017 policy are up to 25% larger in a closed economy compared to an economy with the observed trade levels.

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# 1 Introduction

Restrictions on high-skilled immigration are becoming increasingly common in some developed countries that aim to protect domestic wages.[1] Other developed countries, however, are competing to attract high-skilled migrants, expecting their skills to meet the demands of key sectors, making these sectors more competitive in the global marketplace (Kerr, 2018). These conflicting policies alter the appeal of destinations for skilled workers. In fact, detractors of U.S. skilled immigration restrictions recently argued that such restrictions push skilled migrants to other more receptive developed countries.[2] If this is indeed the case, U.S. restrictions could make receptive countries more competitive in the global marketplace, ultimately affecting the U.S. through international trade. Despite the potential welfare implications for both the U.S. and 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 U.S. skilled visa laws since the early part of this century. This paper exploits a change in the interpretation of the law at the beginning of 2017 that tightened the eligibility criteria for college-educated immigrants applying for U.S. H-1B visas.[3] Immediately following this policy change, Canada experienced a surge in the number of skilled immigrant admissions, equivalent to 76,000 additional admissions in the period between 2018 and 2019.[4] This inflow represents 3.5% of the stock of college-educated immigrants in Canada, or about 2% of all workers in the high-skilled service sector. To what extent did the U.S. restrictions cause the increase in skilled immigration to Canada in the period following the 2017 policy? 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 from a Freedom of Information Act (FOIA) request, a novel Canadian visa application dataset, and Canadian administrative databases containing the universe of employer-employee-linked records, immigration records, and data on international trade in goods and services. Finally, we develop a new general equilibrium model of immigration and international trade to study the welfare effects of the policy and the role of international

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

[2] Jorge Loweree said "Until the U.S. government revamps its outdated employment-based immigration system, the U.S. economy will continue to fall behind in the global competition for skilled workers" in the U.S. Congress hearing *"How Outdated U.S. Immigration Policies Push Top Talent to Other Countries"* on July 13th, 2021.

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

[4] We refer to admissions granted under permanent residence programs commonly used by skilled workers, namely, the Canadian Experience Class, Skilled Worker, and Provincial Nominee Programs.

trade in the policy's efficacy.

The new policy was implemented through policy memorandums issued by U.S. Citizenship and Immigration Services (USCIS) in March 2017 and became effective immediately. By the end of 2018, the number of H-1B approvals had decreased by 140,000 (relative to the trend) and the spike in H-1B denial rates was unprecedented. 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. Intuitively, immigrant groups with a higher propensity to apply for U.S. visas were more affected by the new eligibility criteria in their respective occupations. We use this variation across time and immigrant groups to provide reduced-form evidence of the restrictions' effects on the Canadian economy and to estimate the parameters of 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.

We then document a large impact of the immigrant influx on Canadian firms, using our Canadian administrative dataset. To that end, we define a shift-share exposure measure that exploits the variation across firms due to the nationality composition of their workforce and the occupational composition of their industry.[5] We combine this variation across firms with the time variation of the policy within an event-study framework to estimate the effect of the policy. We find that firms that were relatively more exposed to the immigrant inflow paid a lower wage bill per worker and per native worker. We also find that these firms increased sales, exports, and the employment of Canadian workers. Our estimates imply that hiring an additional immigrant in 2017-2018 resulted in a 3.2% increase in sales for the median firm in the skilled service sector in 2018, amounting to C$112,000. Of this increase, approximately 40% can be attributed to the increase in export sales.[6] Our estimates also imply that, on average, a firm hired approximately 0.5 additional native workers per new immigrant hired due to the H-1B restrictions.

Finally, we develop a general equilibrium model to study the effects on Canadian workers' welfare associated with our empirical findings and the role of international trade in the effects on Amer-

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

[6]We interpret the results for firms in high-skilled service sectors because they are the most exposed sectors, but our sample is not limited to them.

ican workers' welfare. The international trade component of our model is based on a Ricardian model with multiple countries and sectors. Production features constant returns to scale and requires workers from different occupations and origin countries who are imperfect substitutes.[7] Motivated by our evidence, we incorporate immigration policy and migration decisions under uncertainty into an otherwise standard model of international migration. Immigration policy is represented as an exogenous probability of obtaining a visa and, given this uncertainty of obtaining visas, immigrants decide whether and to which destination country to migrate.

We use the model to derive an analytical expression for the impact of a reduction in the U.S. visa approval rate on American workers' welfare that is composed of a direct and indirect effect. The direct effect depends on how substitutable immigrants and American workers are and the extent to which U.S. sectors contract due to the lower availability of immigrant labor. This effect tends to be present in standard models of international migration. The indirect effect depends on how the restrictions affect workers' migration to other economies. An inflow of workers reduces production costs and increases production in the receiving economies, particularly in sectors that are immigrant-intensive (e.g., Rybczynski effect). 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 effects on American workers in a specific sector can be either positive or negative, depending on how the export prices of U.S. sectors and import prices for consumers adjust.

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

We find that a drop in H-1B visa approval rates, as observed in 2017, increases immigration to Canada in certain occupations, especially computer-related occupations, and leads to a 3.4% overall increase in immigrant labor. This inflow decreases the welfare of Canadian computer scientists because they are relatively close substitutes to the incoming immigrants but increases the welfare of workers in other occupations because Canadian sectors expand, especially high-

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

skilled service sectors. For instance, in these sectors, the welfare of computer scientists decreases by 2.9% and that of lower-skilled workers increases by 0.9% approximately.

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

**Related literature:** Our paper contributes to the extensive empirical literature studying the economic effects of immigration. Seminal papers include Card (1990, 2001), Borjas (2003, 2005), and Ottaviano and Peri (2012).[8] A stream of this literature studies the effects of skilled immigration on native-born workers' labor market outcomes.[9] Relatively few papers studied the effects of sudden and unexpected changes in the aggregate supply of skilled immigrants due to the limited number of such episodes (e.g., Hunt (1992), Friedberg (2001), Borjas and Doran (2012)). We contribute to the literature by offering direct evidence of the effects of an episode that has these characteristics and that is likely unrelated to the economic circumstances of the receiving economy, Canada. Also, we use our model to assess the corresponding effects on the *level* of native-born workers' wages and employment, accounting for general equilibrium effects.

Another related stream of this literature studies the impact of skilled immigration on firms (Dustmann and Glitz, 2015; Mitaritonna et al., 2017; Ottaviano et al., 2018; Brinatti and Morales, 2021; Egger et al., 2021; Mahajan, 2022; Dimmock et al., 2022; Arellano-Bover and San, 2023). Some of these papers are able to use quasi-experimental variation in the availability of skilled immigrants to firms but have often focused on a relatively small subset of firms (Kerr and Lincoln, 2010; Kerr et al., 2015; Doran et al., 2022). Relatively few papers use quasi-experimental variation to study the effects on a large number of firms (Beerli et al., 2021; Brinatti et al., 2023) but do not tend to assess the aggregate effects. We use quasi-natural variation in the aggregate supply of skilled workers to offer new evidence on the effects on the universe of firms in Canada

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

[9]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.

and to quantify the associated aggregate effects using a general equilibrium model.

We contribute to the empirical literature studying the labor market effects of immigration policies. Existing studies have predominantly studied the impact of immigration policies on the country imposing the restrictions (e.g., Peri et al. (2015), Clemens et al. (2018), Yoon and Doran (2020), 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 typically studied the effects of immigration policies on third countries. Glennon (2023) shows that U.S. multinational corporations (MNCs) experiencing H-1B visa constraints increased employment in their affiliates. Our paper contributes to this literature by offering quasi-experimental evidence of the effects of immigration policy on third countries. Relative to Glennon (2023), our results are robust to the exclusion of MNCs, suggesting that the effects on other countries may not require MNC linkages with the imposing country.

Our paper contributes to the international trade literature that studies the wage effects of changes in factor endowments dating back to Samuelson (1948) and Rybczynski (1955). According to Rybczynski's theorem, changes in factor endowments may not affect wages in a global economy with free trade. Several papers tested the empirical relevance of this theorem, such as Davis et al. (1997), Hanson and Slaughter (2002), Gandal et al. (2004), and Zimring (2019). We contribute to this literature by providing firm-level evidence consistent with Rybczynski's effect and quantifying the extent to which the wage effects predicted by Rybczynski's theorem hold in modern quantitative models with current levels of trade.

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

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

# 2 Data and institutional background

## 2.1 Assembly of a novel dataset

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

### 2.1.1 U.S. H-1B visa application data

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

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

### 2.1.2 Canadian Permanent Resident visa application data

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

### 2.1.3 Canadian administrative data

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

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

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

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

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

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

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

**Labor force survey (LFS)** This dataset provides information from a monthly survey conducted by Statistics Canada. In this survey, respondents report their country of birth, the sector and occupation of their main job, and the associated weekly earnings.

## 2.2 Institutional background

### 2.2.1 U.S. H-1B visa program

The H-1B visa program enables U.S. employers to hire highly skilled foreign workers in specialized occupations that demand advanced knowledge and a minimum of a bachelor's degree.[10] To

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

obtain an H-1B visa, an individual must have a qualifying job offer from a sponsoring firm. The firm is required to submit a Labor Condition Application (LCA) to the Department of Labor, which verifies that the employment offer meets the criteria of the H-1B visa program. Once the LCA is approved, the firm can file an I-129 petition with the USCIS, which makes the ultimate decision about the visa application. Initially valid for three years, the H-1B visa can be extended for an additional three years. An H-1B holder must submit a petition if they decide to renew their visa or if there are significant changes in their employment conditions such as a change of employer or occupation.

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

### 2.2.2 Canadian visa program: points-based system

The main channels for skilled immigration intake in Canada are through the permanent residence visa programs.[11] Prospective permanent resident visa applicants must fulfill core eligibility criteria to enter an application pool, where they are automatically ranked using a points system based on factors such as education, work experience, language proficiency, age, and having a valid job offer in place (See Appendix table E.3). There are no limits on the number of visas granted. Approximately every two weeks, the ministry announces the number of individuals who will receive an invitation to apply (ITA) for permanent residence. 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 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 qualification, 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.

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

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%). Secondly, immigrants in Canada and the U.S. appear to perform distinct tasks, a variation that our identification strategy will exploit. For example, while 83% of Indians applying for an H-1B are computer scientists and only 1% are managers, the respective fractions among Indians applying for a 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 H-1B policy change

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."[12]

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.[13] 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 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 not affected by this policy memorandum. These examples illustrate that this new policy memo effectively tightened the eligibility criteria for some occupations more than for others. Our empirical design will exploit the variation across occupations. Second, the USCIS required additional evidence when the complexity of the job duties was inconsistent with a petition for a low-wage position. Third, USCIS stopped giving deference to previously

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

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

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.[14]

Applications that failed to meet these new requirements were denied, leading to a sharp increase in denial rates and a decrease in H-1B approvals. Denial rates increased from 6% in 2016 to an unprecedented 16% in 2018 (see Figure 1) and H-1B approvals dropped by approximately 140,000 visas (relative to the trend) by the end of 2018.[15] Immediately following the policy change, Canada experienced a spike in the number of skilled immigrant admissions, with an average annual increase of approximately 30% relative to 2016. Between 2018 and 2019 there were about 76,000 additional admissions, representing a 3.5% increase in the number of college-educated immigrants, or about 2% of all workers in the high-skilled service sector in Canada.

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

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

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

### 3.2.1 Event-study framework

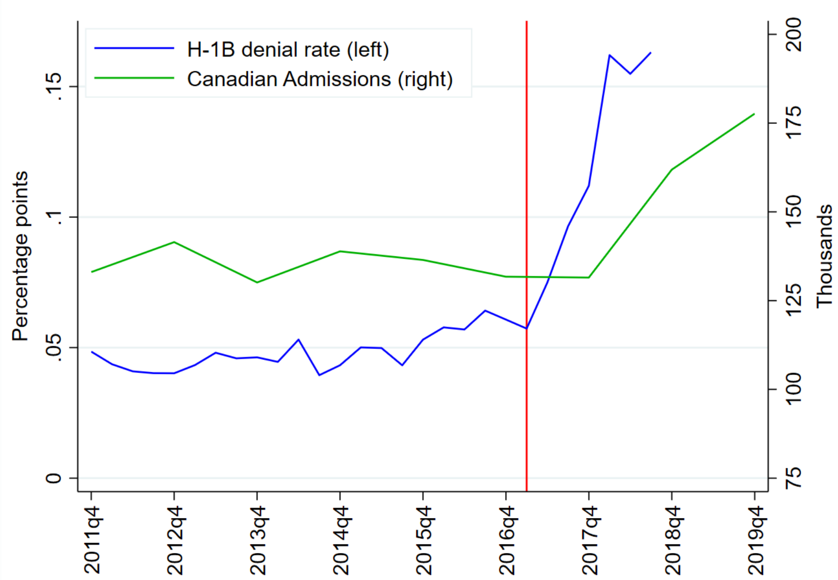
We estimate the effect of the policy on the change in Canadian applications before and after the introduction of the new policy for immigrant groups that were differently exposed. An immigrant group is defined by the combination of the applicant's country of origin and their occupation, denoted by $c$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

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

[14] 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.

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

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




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

where $Can\ App_{co,t}$ is the number of Canadian visa applications of immigrant group $co$ in year $t$, $\delta_{co}$ are the fixed effects at the immigrant group level, $\delta_{ot}$ are the fixed effects at the occupation-year level, $\delta_{ct}$ are the fixed effects at the country-of-birth-year level, and $\epsilon_{cot}$ is the error term, which we cluster at the immigrant group level. The coefficients $\theta_\tau$ measure the differences in the outcome variables between year $t$ and year 2016, our baseline year, for immigrant groups that are differently exposed to the new U.S. restrictions. Given that the new H-1B policy should affect outcomes only after the policy memorandums were introduced, we expect $\theta_\tau$ to be zero.

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

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

where "Initial" refers to the years before the introduction of the policy memos (i.e., FY2012-FY2015). The numerator can be interpreted as the number of immigrants with denied U.S. visas who could potentially consider migrating to Canada. The denominator proxies for the number of potential migrants to North America. $Intensity_{co}$ can be written as the interaction between the denial rate, denoted by $dr_o$, and the share of the total number of applications to North America that were submitted to the U.S., denoted by $\pi_{co,usa}$. The share $\pi_{co,usa}$ measures the propensity of an immigrant group to apply for a U.S. visa.[16] Our exposure measure predicts that relatively affected groups work in occupations with high denial rates and high propensity to apply for U.S. visas. This measure is based on our model as shown in section 4.5.

The choice of occupation as the level of variation of $dr_o$ is motivated by the instructions specified in the policy memorandum.[17] We compute these denial rates using only the applications for continuing H-1B visas and exclude applications for new H-1B visas.[18] We worry that if we include new H-1B applications, correlated shocks to the U.S. and Canada can affect both H-1B denial rates and 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 they live in the U.S., which reveals their preference for this country, and they have secured a job, which increases the (opportunity) cost of leaving the U.S. Consequently, applicants for continuing visas may be less likely to suddenly respond to demand shocks in Canada or their home country.[19]

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

We saturate the empirical model with a rich set of fixed effects to account for the effect of potential confounding factors. $\delta_{co}$ controls for pre-existing differences between groups such as

[16] To the extent to which $\pi_{co,usa}$ accurately predicts the post-treatment value, $Intensity_{co}$ can be interpreted as an accurate measure of the actual fraction of applicants denied. The empirical evidence on immigrant networks suggests that this fraction is likely to be stable over time because immigrants tend to follow the occupational choices of their compatriots (Bartel, 1989; Altonji and Card, 1991; Card, 2001; Patel and Velia, 2013).

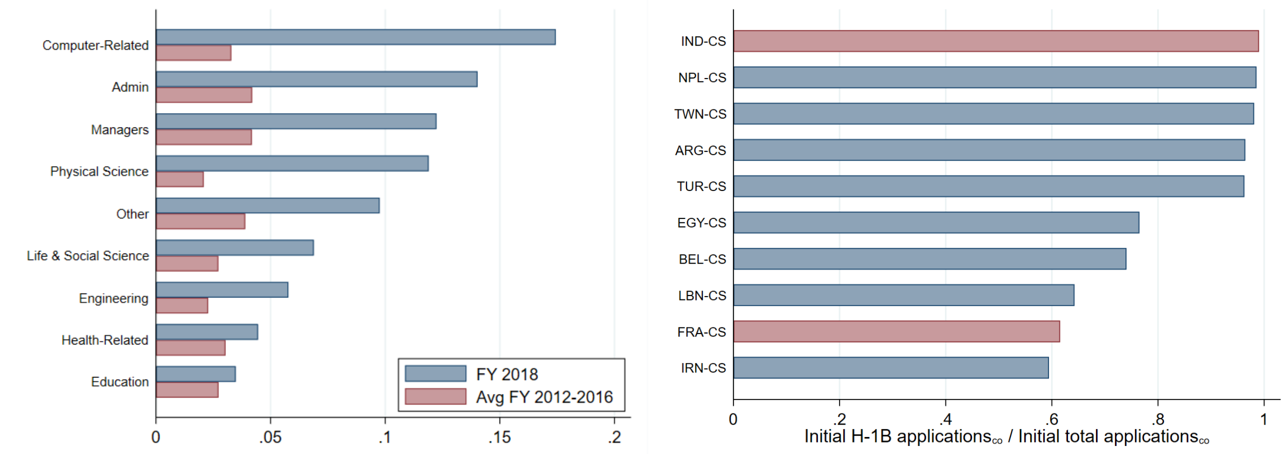
[17] We do not find evidence in the data, nor the policy memorandum, suggesting that the policy changed for immigrants from different nationalities conditional on working in the same occupations.

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

[19] In line with this hypothesis, Appendix Figure E.3 shows that immigrants living in the U.S. do not generally apply for Canadian visas. However, in 2017, there was a significant and sudden surge in applications. This pattern is consistent with a more restrictive U.S. immigration policy that left this group of immigrants with denied visas and no alternative but to leave the country.

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

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




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

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

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

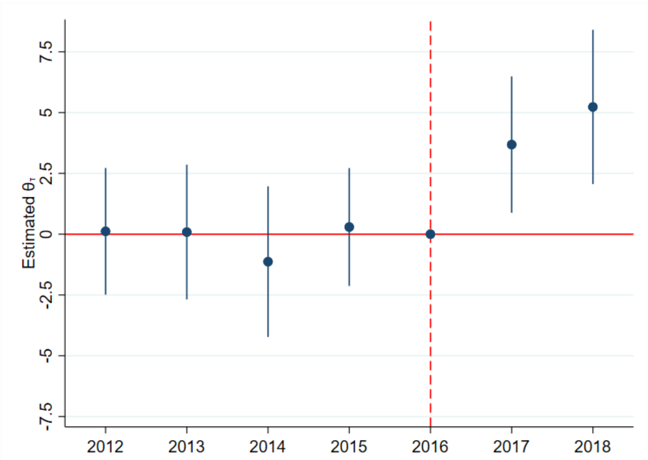
The identifying assumption is that the change in the outcome variable in the years 2017 and 2018 would have been the same in the absence of the policy change for immigrant groups that were differently exposed, conditional on the controls. We assess the plausibility of this assumption by formally testing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

### 3.2.2 Results

Figure 3 plots the estimates of $\theta_\tau$ for the years 2012-2018. It was only after the U.S. restrictions were imposed that Canadian visa applications of immigrants who were more exposed to the U.S. restrictions grew faster than less-exposed immigrant groups. The estimates for the years after the US shock, $\hat{\theta}_{2017}$ and $\hat{\theta}_{2018}$, are 3.7 (s.e.=1.4) and 5.2 (s.e.=1.6), respectively. They are statistically significant at conventional levels (1%) and economically large. Our estimates predict that Canadian applications in 2018 were 31% higher than what they would have been in the absence of the H-1B restrictions.[20]

Our event-study estimates can be also interpreted in terms of two statistics useful for policy analysis. First, an increase in H-1B denial rates by 10 percentage points increases applications to Canada by 30% given that the average exposure $\pi_{co,usa}$ of 0.57. This is equivalent to saying that a 10 percentage point increase in the fraction of immigrants who are affected increases applications to Canada in 2018 by 5.2%. Second, when we consider the response of Canadian applications and H-1B visa approvals, a back-of-the-envelope calculation suggests that roughly every 4 H-1B visa approvals forgone result in an increase of about one permanent resident application to Canada.[21]

Figure 3: Effect of H-1B Restrictions on Permanent Resident Applications to Canada




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

There are several reasons for this large response in the number of applications to Canada. First, potential migrants to the U.S. may choose Canada due to its economic opportunities, labor market integration, language, and cultural similarities. Secondly, the qualifications of a typical

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

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

H-1B visa applicant position them favorably to obtain a Canadian visa within the framework of the point-based Canadian immigration system. Third, American firms, which have long faced immigration challenges, are prepared to quickly relocate their employees to Canada.[22]

### 3.2.3 Discussion of threats to identification

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

## 3.3 Effects of skilled immigration on Canadian firms

This section documents how the inflow of skilled immigrants affected production in Canada and the labor market outcomes of native-born Canadian workers and explains how these facts motivate the assumptions of our quantitative model.

### 3.3.1 Event-study framework

To estimate the effect of the inflow of immigrants induced by the H-1B restrictions on Canadian firms, we construct a measure that predicts which firms are likely to absorb these immigrants. We expect that firms, like labor markets, serve as important channels for immigrant networks due to the vital role that co-nationals play in sharing information and providing referrals for immigrants (Egger et al., 2021). Thus, our measure builds on the assumption that a Canadian firm that typically hires x% of a given immigrant group in the Canadian market will absorb x% of the number of that immigrant group that migrates to Canada due to the U.S. policy. We combine this variation across firms with the time variation of the policy within the following event-study framework to estimate the effect of the policy. Our empirical model for outcome $y$ of firm $i$ in year $t$ is

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

where we consider several outcome variables $y_{it}$ that are scale-independent such as the logarithm of sales or, as is commonly done in the immigration literature, the number of Canadian workers

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

hired relative to the employment level in the baseline year. $Intensity_i$ is an exposure intensity measure of the H-1B policy change, which we describe shortly. The index $k$ refers to the industry where the firm operates, according to the 4-digit NAICS classification, and $m$ refers to the location of the firm. $\delta_i$ are firm-fixed effects, $\delta_{mt}$ are the labor markets' year-fixed effects, $X_{ikt}$ is a set of control variables that vary over time and across firms and industries, and $\epsilon_{it}$ is the error term, which we cluster at the firm level. The coefficients $\beta_\tau$ measure the difference in the outcome variable $y$ between year $\tau$ and year 2016, our baseline year, for firms that are differently exposed to the introduction of the policy memorandums. Given that the effect of the new H-1B policy should affect outcomes only after the policy memorandums were introduced, we expect $\beta_\tau$ to be zero for $\tau < 2016$ and to be different from zero for $\tau = \{2017, 2018\}$.

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

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

This exposure measure can be thought of as a Bartik exposure, with the shift given by $\frac{Flow_{co}^{post}}{L_{co}}$ and the share by $\frac{L_{coi}}{Li}$. According to this measure, relatively exposed firms have a workforce composition tilted to the immigrant groups that were relatively affected by the H-1B policy.

Given that we do not have occupation information at the firm level, we must approximate the firm-level share in (4). We first note that this share can be expressed as the multiplication of the share of nationality $c$ within occupation $o$ ($\frac{L_{coi}}{L_{oi}}$) and the occupation share in the firm's total workforce ($\frac{L_{oi}}{L_i}$). We then proxy $\frac{L_{coi}}{L_{oi}}$ with the overall nationality share ($\frac{L_{ci}}{L_i}$) and the occupational structure of the firm $\frac{L_{oi}}{L_i}$ with that of the industry where it operates ($\frac{L_{ok(i)}}{L_{k(i)}}$).

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

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

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

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

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

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

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

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

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

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

### 3.3.2 Results

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

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

The increase in total hiring is substantial. For reference, the average ratio of total hiring to employment in 2016 among exposed firms in the skilled service sector was 0.5%. Our estimates indicate that, for the average exposed firm in this sector, this ratio increased to 1.2% in 2017 and to 1.5% in 2018.

We also find that earnings per Canadian worker and median earnings dropped in firms that were relatively more exposed by approximately 0.5% in 2018 in the average exposed firm in the high-skilled service sector. This drop, along with the fact that more exposed firms are intensive in occupations that were more impacted by U.S. restrictions, suggests that earnings per native worker in more affected occupations decline compared to less affected ones.

**Effect on production and exports** Firms with higher exposure to the immigration restrictions exhibited a larger change in (log) sales compared to less-exposed firms, but only after the implementation of the restrictions (Figure 4d). The average exposed firm in the skilled service sector would be expected to register a 1% increase in sales than what it would have had in the absence of the H-1B restrictions. This estimate implies that an additional immigrant hired in 2017-2018 translated into an increase of C$112,000 earned in 2018 for the median firm in the skilled service sector, which represents 3.2% of pre-shock sales.[23] The rise in sales is likely indicative of an increase in production because we found no evidence of changes in mark-ups (see event studies in column 12 in Appendix Table E.6).

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

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

**Effect on domestic firms** Prior research found that American multinational corporations (MNCs) that have locations in both the U.S. and Canada, increased the employment in Canadian affiliates due to H-1B restrictions (Glennon, 2023). To understand whether our findings are attributed to the presence of MNCs or are a feature of domestic firms' responses, we esti-

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

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

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

mated equation (3) for the main outcome variables excluding MNCs and obtain estimates that are similar to our baseline estimates. These results imply that the effect of U.S. immigration restrictions extends beyond their direct impact on the affected (American) firms, as previously documented. This novel fact suggests that MNC linkages might not be needed for the U.S. restrictions to affect third countries.

### 3.3.3 Robustness exercises

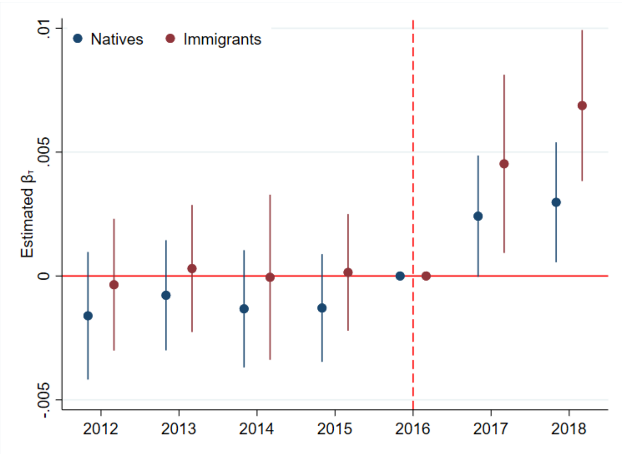
In Appendix section E, we address potential identification concerns and explain in detail the corresponding robustness exercises. First, we present estimates of the effect of the H-1B policy change that only uses the within-industry variation (e.g., we include industry-year fixed effects in our baseline specification). Second, we test the potential impact of the non-random assignment of $Intensity_i$ on our identification assumption. Third, we show the robustness of our estimates to foreign shocks by re-estimating equation 3, excluding importers and exporters. Finally, we show that our estimates are also robust to include additional control variables to account for changes in Canadian immigration policy leading up to the U.S. policy change.

### 3.3.4 Takeaways to designing the model

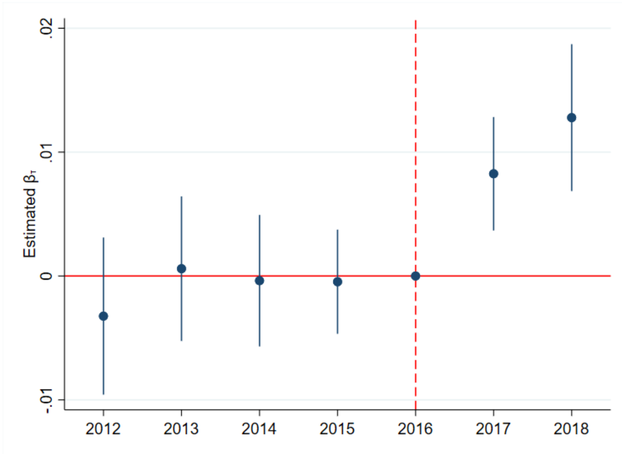
Our findings are consistent with a classic model with competitive labor markets where immigrants and Canadians working in different occupations are imperfect substitutes. In this framework, an inflow of immigrants affects the labor market outcome of Canadian workers in two ways. First, it can make hiring foreign labor cheaper compared to Canadian workers, inducing firms to substitute Canadians with immigrants. Second, it can drive down overall labor costs, inducing firms to expand their production scale. If the scale effect outweighs the substitution effect, we would expect firms to increase both Canadian and immigrant hiring. Additionally, this framework predicts that the wage effects of an immigrant inflow are less beneficial (or more detrimental) for Canadian workers who are closer substitutes to the immigrants. These predictions align with our finding of an increase in production, a drop in earnings per worker which is our closest proxy for labor costs (see column 7 in Appendix Table E.6), an increase in hiring of native workers and, if immigrants and Canadians working in the same occupation are closer substitutes than immigrants and Canadians working in different occupations, drop in earning per native worker.

The fact that sales per worker and earnings per native worker did not increase suggests that economies of scale may not be the primary driver of the increase in production. We will assume that there are constant returns to scale in production. However, we will allow for economies of scale in an extension of the baseline model because the empirical literature on skilled immigration found that skilled immigration often leads to economies of scale (Bound et al., 2017), especially in the long run.

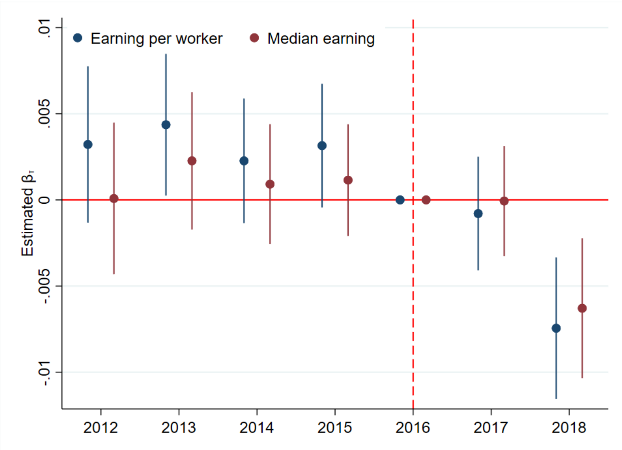
Figure 4: Effect of H-1B restrictions on Canadian firms



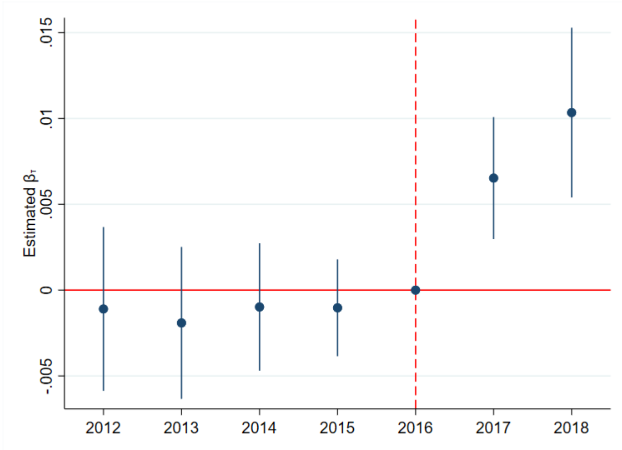

(a) Hiring relative to employment in 2016



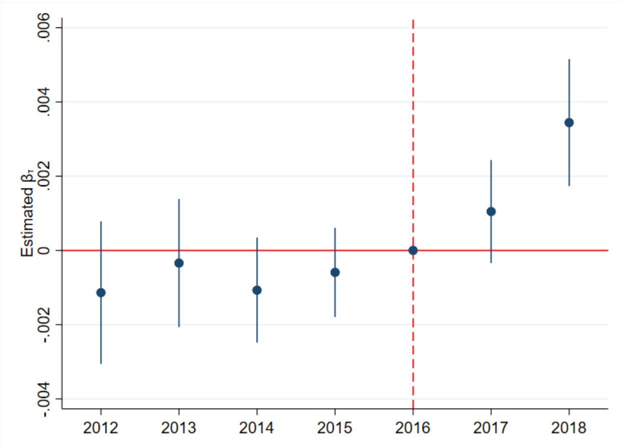

(b) Canadian employment (in log)



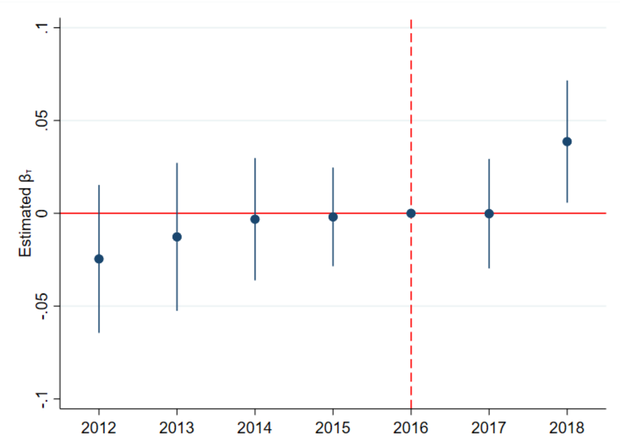

(c) Earning of native workers (in log)




(d) Sales (in log)




(e) Exports relative to total sales




(f) Exports (in log)

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

Our evidence on domestic firms suggests that the key mechanisms through which production adjusted to the inflow of skilled immigrants may not be specific to the ownership structure of MNCs. Accordingly, our model will not explicitly differentiate domestic firms from MNCs.

Additionally, the contribution of exports to the increase in sales suggests that international trade may be a relevant margin of adjustment of production.

Finally, our results on the (lack of) response to mark-ups are consistent with goods markets being perfectly competitive.

# 4 Theory: Immigration policy and international trade

We documented that U.S. immigration restrictions affected immigration to Canada, production and domestic workers' labor market outcomes. Our next goal is to understand the welfare effects on Canadian workers associated with our empirical findings and the role of international trade in the welfare effects of U.S. immigration policy on American workers. These goals ask for a quantitative general equilibrium model of international trade, international migration, and migration policy that rationalizes our empirical facts and can be quantified using our data. This section sets up the model and analytically studies how changes in the probability of granting U.S. visas spill over to other countries and affect the welfare of American workers. To that end, we introduce a new modeling assumption so that workers decide to migrate with uncertainty about whether they will obtain a visa.

## 4.1 Setup

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

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

**Workers** There is an exogenous mass of workers of group $co$, $L_{co}$, in each immigration-origin country $c \in \mathcal{C}^o$. Only an exogenous fraction $\psi_{co}^{emm}$ 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 the destination country $d \in \mathcal{C}^d$.

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

**Timing assumptions** All workers choose their sector of employment and only the fraction $\psi^{emm}_{co}$ 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 $\iota$ draws $\nu_{cod}(\iota)$ and then makes the migration decision. After this decision is made, they draw $a_{codk}(\iota)$ and then choose their sector of employment. This assumption allows us to solve the worker problem through backward induction. We first solve the choice of the sector given the country of residence and we then solve the migration decision.

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

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

where $P_c$ is the price index in country $c$, $w^f_{odk}$ and $w^n_{odk}$ represent the effective wage per efficient 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 the country $d$. We assume that workers can only apply for one visa.[27] If their visa application is denied, the workers have to stay in their home countries. To make the choice decision under

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

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

uncertainty tractable in general equilibrium, we bring the expected utility theory into an otherwise standard migration model. We model individuals as risk-averse agents by assuming that the payoff in each contingent state is given by the log of the utility in that state, $u_{cod}$.

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

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

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

**Consumption** Consumers have two-tier CES preferences over goods. The upper nest is a composite bundle of goods from different sectors $k$, with an elasticity of substitution $\alpha$. Each good is, in turn, a composite of a continuum of varieties $\omega$ with an elasticity of substitution $\sigma$.

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

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

where $l_{dk}(\omega)$ is the production of variety $\omega$, $z_{dk}(\omega)$ is the productivity level of the technology to produce variety $\omega$, $\psi_{dko}$ represents the efficiency units of occupation $o$, $l_{dko}(\omega)$ are the units of labor services of occupation $o$ used to produce $\omega$, 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).

The occupation's services are produced by combining effective units of native-born labor ($l^n_{dko}$) and foreign labor ($l^f_{dko}$) with an elasticity of substitution $\epsilon$. This modeling assumption follows a long tradition in the immigration literature, which understands immigrants and native-born workers as having comparative advantages in different tasks (Ottaviano et al., 2013; Peri and

Sparber, 2011, 2009). Specifically, the production function takes the following form:

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

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

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

## 4.2 Labor supply based on workers' migration and sector choices

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

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

and the expected real wage net of the migration costs in destination $d$ and at home are $u_{cod} = \Gamma_{\kappa} \frac{\zeta_{cod}\, \Phi_{cod}}{P_d}$ and $u_{coc} = \Gamma_{\kappa} \frac{\Phi_{coc}}{P_c}$, where $\Gamma_{\kappa}$ 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 $\iota$ chooses to stay in their home country is $\pi_{coc}$ and, conditioned on choosing to emigrate, the probability that they choose destination country $d$ is $\pi_{cod}$:

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

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, $\pi_{cod}$ and $\pi_{coc}$ are also the fractions of workers $co$ choosing destination country $d$ and home, respectively. Equation (10) shows how changes in the approval rate in destination country $d'$ affect migration patterns to other countries, $\pi_{cod}$ and $\pi_{coc}$, by directly affecting the expected value of emigrating $u_{coe}$.

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

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

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

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

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

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

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

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

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

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

## 4.3 Labor demand based on firms' hiring decisions

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

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

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

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

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

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

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

where $P_{ck} \equiv \Gamma\left(1 - \frac{\sigma-1}{\theta}\right)^{-1} \left(\sum_d T_{dk}(\tau_{dck}\; w_{dk})^{-\theta}\right)^{-\frac{1}{\theta}}$ is the price index in sector $k$ in country $c$. We assume that trade is balanced, implying that total spending equals total labor income, $Y_c \equiv \sum_k Y_{kc}$:[28]

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

## 4.4 Equilibrium

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

1. workers' migration decisions and sector allocations $\{\pi_{cod}, \pi_{codk}\}$;
2. firms' hiring decisions $\{s^f_{dko}, s^n_{dko}\}$;
3. aggregate quantities and prices $\{Y_c, Y_{dk}, LS^n_{dko}, LS^f_{dko}, LD^n_{dko}, LD^f_{dko}, P_c, w^f_{dko}, w^n_{dko}\}$;

such that

1. workers' migration decisions and sector allocations satisfy equations (9) and (10);
2. firms' hiring decisions satisfy equation (17); and

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

3. the markets for labor and goods all clear:

$$LD^x_{dko} = LS^x_{dko} \quad \forall x \in \{n,\ f\} \tag{20}$$
$$X_c = Y_c + D_c \quad \text{with} \quad D_c = 0 \tag{21}$$

## 4.5 Effects of U.S. immigration restrictions: comparative statics

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

### 4.5.1 Effects on third countries

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

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

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

where we assume that the average real wage in the U.S. net of 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 equations (23):

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

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

Therefore, U.S. immigration restrictions can either increase or decrease immigration to Canada, depending on the strength of these forces, as illustrated by equation (24)

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

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

Given our facts, we continue the narrative for the case of increasing immigration to country $d$.

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

**Drop in production costs** Immigrant workers $co$ in $d$ will sort themselves across various sectors based on their sectorial shares $\pi_{codk}$. This leads to a sector-specific expansion in the overall foreign labor supply of services from occupation $o$, $d\tilde{l}^{f}_{dko}$, which reduces their wages $\tilde{w}^{f}_{dko}$. The relative increase in the supply of immigrant labor also affects the wages of their native-born counterparts, depending on how substitutable immigrants and native-born workers are:

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

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

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

$$d\tilde{c}_{dk} = \sum_{o} s_{dko} \left( (1 - s^{f}_{dko})\, d\tilde{w}^{n}_{dko} + s^{f}_{dko}\, d\tilde{w}^{f}_{dko} \right) \tag{26}$$

This equation shows that sectors with a cost structure that is skewed towards workers with bigger wage reductions will experience greater unit cost reductions.

**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

$$d\tilde{Y}_{dk} = \sum_{c} \omega^{Y}_{dck} \Big( \underbrace{-\theta(d\tilde{c}_{dk} - \sum_{d} \lambda_{dck}\, d\tilde{c}_{dk})}_{d\tilde{\lambda}_{dck}} + \underbrace{-(\alpha-1)(d\tilde{P}_{ck} - d\tilde{P}_{c})}_{d\tilde{\alpha}_{ck}} + d\tilde{X}_{c} \Big) \tag{27}$$

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

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

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

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

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

$$w^{n}_{usa,ko} = p(\omega)_{usa,k}\; z(\omega) \left(\frac{l_{usa,ko}}{l_{usa,k}}\right)^{-1} \left(\frac{l^{n}_{usa,ko}}{l_{usa,ko}}\right)^{-\frac{1}{\epsilon}} \tag{28}$$

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

$$W^n_{usa,ko} = \frac{w^n_{usa,ko}}{P_{usa}} = \frac{Y_{usa,k} \quad l^{\frac{1}{\epsilon}-1}_{usa,ko} \quad (l^n_{usa,ko})^{-\frac{1}{\epsilon}}}{P_{usa}} \tag{29}$$

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*

$$\begin{aligned} d\tilde{W}^n_{usa,ko} = & \overbrace{-\left(1-\frac{1}{\epsilon}\right) s^f_{usa,ko}\, d\tilde{l}^f_{usa,ko}}^{\text{Substitution effect}_{usa,ko}} \\ & \overbrace{\overbrace{-\sum_k \alpha_{usa,k}\, \lambda_{usa,usa,k}\, d\tilde{c}_{usa,k}}^{\text{Price effect}_{usa}<0} \overbrace{-\,\theta \sum_j \omega^Y_{usa,jk}\, (1-\lambda_{usa,jk})\, d\tilde{c}_{usa,k}}^{\text{Competition effect}_{usa,k}<0}}^{\text{Domestic general equilibrium effects - increasing costs in the U.S.}} \\ & \underbrace{\underbrace{-\sum_k \alpha_{usa,k}\, \lambda_{c,usa,k}\, \tilde{c}_{ck}}_{\text{Price effect}_{usa}>0} + \underbrace{\theta \sum_j \omega^Y_{usa,jk}\, \lambda_{cjk}\, \tilde{c}_{ck}}_{\text{Competition effect}_{usa,k}<0}}_{\text{International general equilibrium effects - decreasing costs elsewhere}} + \epsilon_{usa,k} \end{aligned} \tag{30}$$

*where $\epsilon_{usa,k} = \sum_j \omega^Y_{usa,jk} \quad d\tilde{X}_j$ 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 $\varepsilon^f_{dko}$ 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 wages of an American worker due to the changes in the supply of immigrant labor in her occupation and sector of employment while holding the production scale constant. For a given reduction of 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 accounts for a larger share of the labor force $s^f_{usa,ko}$.

The "domestic general equilibrium effect" arises 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 increases the price index of the American consumption bundle according to the share of the good in total expenditures $\alpha_{usa,k}\lambda_{usa,usa,k}$, which reduces the purchasing power of American wages (Price Effect$_{usa} < 0$). Also, higher U.S. costs reduce the demand for U.S. goods and the sales of U.S. sector $k$. As a result, there is a corresponding decrease in the demand for all labor inputs in sector $k$ and a downward pressure on equilibrium wages (Competition Effect$_{usa,k} < 0$). Therefore, this standard general equilibrium effect unambiguously reduces the welfare of American workers.

The "international general equilibrium effect" arises when increasing migration to other countries that engage in international trade affects these countries' production costs. On one hand, decreasing costs in country $c$ reduces the price index of the American consumption bundle according to their share in expenditures $\alpha_{usa,k}\lambda_{c,usa,k}$, which increases the purchasing power of American wages (Price Effect$_{usa} > 0$).

On the other hand, a reduction in the production cost of country $c$ diminishes the international demand for American goods and their prices, in turn reducing the value of the marginal product of American workers and American wages. This competition effect is stronger when the overlap between the markets served by country $c$ and by the U.S. is larger. For example, immigrants migrating to Canada can have a greater adverse impact on American wages than those migrating to countries like the Philippines, which does not typically compete with the U.S. in international markets. This market overlap is captured by $\sum_j \omega^Y_{usa,jk}\lambda_{cjk}$ in equation (30), where $\lambda_{cjk}$ gauges the size of the expansion of producers from country $c$ in market $j$ due to the drop in costs $d\tilde{c}_{ck} < 0$ and $\omega^Y_{usa,jk}$ is the share of country $j$ in total U.S. sales.

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

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

# 5 Calibration based on our data and regression estimates

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

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

We inform the value of the structural parameters by extracting as much information as possible from our reduced-form regressions. As a result, we calibrate trade elasticity $\theta$, the elasticity of supply to sectors $\kappa$, and the elasticity of substitution of broad sectors $\eta$ to estimates from the literature; we estimate the elasticity of substitution between emigrating to the U.S. and Canada $\nu_d$ directly from a coefficient of a reduced-form regression derived from the model; and we calibrate the elasticity of substitution between emigrating and staying at home $\nu_h$, the elasticity of substitution across sectors $\alpha$, and the elasticity of substitution between immigrants and natives $\epsilon$ indirectly based on our event-study estimates. We proceed in two steps. We first calibrate $\Upsilon^E \equiv (\theta, \kappa, \eta, \nu_d)$ outside the model and, given $(\mathrm{P}, \Upsilon^E, \mathbf{S}^M, \mathbf{S}^{NM}, \mathbf{U}_u)$, then we calibrate $\Upsilon^I \equiv (\nu_h, \alpha, \epsilon)$ inside the model to match the impact of the spike in H-1B denial rates on Canada.

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

Table 1: Calibration

| Structural Parameters $\Upsilon$ | | | Value |
|---|---|---|---|
| $\theta$ | Trade elasticity | Romalis (2007) | 6.7 |
| $\eta$ | Elast. of subst. between occupations | Goos et al. (2014) | 0.9 |
| $\kappa$ | Elast. of supply to sectors | Galle et al. (2023) | 2.8 |
| $\nu_d$ | Elast. of subst. of emigrating to the U.S. vs Canada | IV estimation of regression (D.35) | 3.6 |
| | | | |
| $\nu_h$ | Elast. of subst. of emigrating vs staying at home | Indirect inference: target $\hat{\gamma}$ in equation (33) | 2.3 |
| $\epsilon$ | Elast. of subst. foreign- and native-born workers | Indirect inference: target $\hat{\gamma}$ in equation (34) for outcome $\log(\textit{Earning per native}_k)$ | 4.3 |
| $\alpha$ | Elast. of subst. across sectors | Indirect inference: target $\hat{\gamma}$ in equation (34) | 1.2 |

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

## 5.1 Instrumental variable approach: $\nu_d$

The novel part of our model is the migration decision. Standard quantitative models of immigration often assume that migrants face migration costs that are proportional to the real wage at their destination. Relative to these models, our model delivers a new prediction, given by equation 31, that becomes the starting point of our approach to estimating $\nu_d$. In our model, immigrant groups are differently affected by a common U.S. policy change depending on the value of obtaining a U.S. visa, which is immigrant group-specific. According to the country choice decision 4.1, the log of the number of workers in occupation $o$ from country $c$ choosing Canada relative to the U.S. is given by

$$\tilde{App}_{co,can,t} - \tilde{App}_{co,usa,t} = \nu_d \Bigg( p_{co,can,t}\Big(\tilde{u}_{co,can,t} - \tilde{u}_{coct}\Big) - p_{co,usa,t}\Big(\tilde{u}_{co,usa,t} - \tilde{u}_{coct}\Big)\Bigg) \tag{31}$$

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

$$\tilde{App}_{co,can,t} - \tilde{App}_{co,usa,t} = \nu_d \, p_{co,usa,t} \, \tilde{w}_{co,usa,t} + \eta_{cot} \tag{32}$$

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

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

## 5.2 Estimates calibrated from the literature: $\theta$, $\kappa$ and $\eta$

Equation 27 shows that $\theta$ 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 $\eta$ regulates the response of occupational wages. Since we do not observe occupation information, we calibrate it from Goos et al. (2014). Similar to our setting, Goos et al. (2014) estimate the elasticity of substitution across broad occupations within sectors to be 0.9. Finally, we model the supply of labor to sectors within a country as in Galle et al. (2023), which offers estimates of the dispersion parameter of the Frechet distribution $\kappa$ for workers in the U.S. Our model assumes that $\kappa$ is the same for all worker groups, including those workers in the U.S., and the granularity of the sectorial classification is similar to theirs. Therefore, we set $\kappa = 2.79$, based on their estimates.

### 5.3 Indirect inference approach: $\nu_h, \alpha$, and $\epsilon$

To complete the calibration of the model, we must calibrate $\nu_h$, $\alpha$, and $\epsilon$. We jointly choose these values to match the cross-sectional responses to the H-1B policy change implied by our estimates from sections 3.2 and 3.3.

The parameter $\nu_h$ 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 $\pi_{coc}$ 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 $\nu_h$. However, equation (24) shows that the relationship between the response of the log of Canadian applications and $\pi_{co,usa} dp_{o,usa}$ across immigrant groups, contains information about the underlying value of $\nu_h$.[29] Therefore, we estimate this empirical regression and use an indirect inference approach to infer the value of $\nu_h$. We proceed as follows. We first fix $(\mathrm{P}, \Upsilon^E, \mathbf{S}, \mathbf{U}_u)$ and input the observed $dp_{o,usa}$ from the data into our model for a given set of parameters $\Upsilon^I$. We then solve the model and extract the value of the change in the number of Canadian applications by immigrant groups. Finally, we estimate the following regression using both real and model-generated data:

$$\widetilde{dApp}_{co,can} = \gamma\, \pi_{co,usa}\, dp_{o,usa} \;+\; \epsilon_{co} \tag{33}$$

To obtain the outcome variable from the real data that is comparable with that from the model, we must isolate the effects of the U.S. policy change from other factors that are absent in our model. We do so by computing the predicted change in Canadian applications due to the H-1B policy change according to our estimated equation (1). Given that the categories of immigrant groups in this empirical regression are more granular than those in the model, 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).

The parameter $\alpha$ 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 4.5.1, the drop in relative unit costs is the result of the sector-specific immigrant labor supply shock. We thus expect the strength of the empirical relationship between the change in sales across sectors facing different immigrant labor supply inflows to contain information about $\alpha$. We use this empirical relationship to discipline

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

the value of $\alpha$. We follow an approach similar to that for $\nu_h$, with the difference being that the regression is at the sector level and is given by equation (34)

$$\widetilde{dSales}_k = \gamma \underbrace{\sum_{co} \omega^{wb}_{cok} \left(1 - \psi^{imm}_{co}\right) \pi_{co,usa} \, dp_{o,usa}}_{Intensity_k} + \epsilon_k \tag{34}$$

where $\omega^{wb}_{cok}$ is the share of immigrant group $co$ in the wage bill of sector $k$, and $Intensity_k$ proxies the predicted change in efficiency in the unit of labor in sector $k$.[30] Given that our causal estimates for the sales response are at the firm-level, we aggregate the firm-level responses to the sector level.

Finally, $\epsilon$ determines the extent to which an inflow of immigrants in a specific labor market (e.g., occupation-sector) reduces the earnings of native-born workers in the labor market. While we do not have information on occupations at the firm level, we observe the overall earnings of native-born workers by sector. Therefore we establish an empirical relationship between the earnings per native-born worker and the immigrant supply shock faced by each sector. We then use this empirical relationship to calibrate $\epsilon$ using a similar approach as for sales. We simply replace sales in regression (34) with the earnings per native-born worker, and use the corresponding causal estimates from section 3.

Our calibrated values are $\nu_h = 2.28, \epsilon = 4.30, \alpha = 1.16$, which fall within the range reported in the literature. Regarding $\nu_h$, our nested structure for immigrants' country of choice follows Allen et al. (2019), who explore how Mexican workers make migration decisions when selecting locations within the U.S. Their estimated values, $\hat{\nu_d} = 4.3$ (s.e.= 0.8) and $\widehat{(\frac{\nu_h}{\nu_d})} = 0.4$ (s.e = 0.17), closely align with our estimates. Regarding $\epsilon$, our modeling assumption follows Burstein et al. (2020), who estimate an elasticity of substitution between immigrants and natives within occupations to be 4.6.[31] Finally, our calibrated value for the elasticity of substitution across our eight sectors ($\alpha$) falls within the range of previous estimates in the literature, which varies depending on whether the categories are narrower or more general. For instance, in narrower categories like the 3-digit SITC sectors, Broda and Weinstein (2006) found a median estimate of 2.2. In contrast, for broader categories such as agriculture, manufacturing, and services, estimates tend to be around 0.5 (Cravino and Sotelo, 2019; Herrendorf et al., 2013; Comin et al., 2021).

[30] That is, $d\widetilde{LS}_k = \sum_{co} \omega^{wb}_{cok} \left(1 - \psi^{imm}_{co}\right) d\widetilde{App}_{co,can}$ and we use $\pi_{co,usa} dp_{o,usa}$ to measure the variation in $d\widetilde{App}_{co,can}$ in the data and in the model. Therefore, the $Intensity_k$s in the regressions with the empirical data and the model-generated data are identical.

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

## 5.4 Validation of the calibrated model

We validate the model by examining the matching of moments that were not targeted in the internal calibration procedure. The untargeted moments include the relative responses of shares of exports in total sales across sectors and the logarithm of native-born employment. In Table 2, we present the coefficients of the regressions (33) and (34), using real and model-generated data. A comparison between these coefficients suggests that the model matches well the cross-sectional response of the Canadian economy along targeted and untargeted dimensions.

Table 2: Parameter values

| | $d\widetilde{\text{App}}_{co,can}$ | $d\widetilde{\text{Sales}}_k$ | $d\text{Export share}_k$ | $d\text{Earnings}\widetilde{\text{ per }}\text{native}_k$ | $d\text{Native-}\widetilde{\text{born}}\text{ empl.}_k$ |
|---|---|---|---|---|---|
| Targeted? | Yes | Yes | No | Yes | No |
| Coefficient $\hat{\gamma}$ from data | 3.1 | 2.0 | 0.7 | -1.1 | 1.9 |
| Coefficient $\hat{\gamma}$ from model | 2.9 | 2.0 | 0.7 | -1.1 | 1.6 |

# 6 Quantitative effects of the 2017 US restrictions

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

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

Table 3: Variations across occupations

| Change in | All | CS | Engineers | Bss Prof. | Managers | Other H1B | Non H1B |
|---|---|---|---|---|---|---|---|
| US denial rate, $p_{o,usa}$ | | 18.76 | 6.22 | 13.80 | 11.40 | 6.37 | 0.00 |
| Immigrant empl. Canada (%) | 3.40 | 11.40 | 4.25 | 6.50 | 2.62 | 2.23 | 0.44 |
| Immigrant empl. US (%) | -1.56 | -4.55 | -2.23 | -4.55 | -2.42 | -0.73 | -0.02 |

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

## 6.1 Effects on Canada

**Production and exports** We find that the U.S. policy shift increases immigrant labor in Canada by 3.4%, with the largest increase being among computer scientists (see Table 3). Once in Canada, these immigrants sort into sectors according to their sectorial shares $\pi_{codk}$, leading to sector-specific expansions in the foreign labor supply. As a result, the sectors that experienced relatively stronger growth in their immigrant labor force are those where the immigrant workforce composition is skewed toward the occupation with a larger growth of immigrant inflow. The first row of Table 4 shows that the immigrant labor force increases in all sectors but the increase is especially strong in high-skilled service sectors (e.g., information and culture, business professional services, and finance and insurance). This increase in the immigrant labor force reduces labor costs and induces an aggregate expansion of production of 0.8%. Even though all sectors expand, they do not do so at the same rate. Notably, production in high-skilled service sectors responds the most due to the larger increase in the supply of immigrant labor and also these sectors' higher reliance on immigrants. To a first-order approximation, for a given labor supply of native-born workers, the expansion of a sector is approximately the increase in its immigrant labor supply, weighted by the immigrant share in the total cost $s^f_{dk}$, expressed as $d\tilde{y}_{dk} = s^f_{dk}\, d\tilde{l}^f_{ds}$.

Although total sales increase in all sectors, export sales increase only in high-skilled service and manufacturing sectors (e.g., Rybczynski's effect). This is because U.S. immigration restrictions alter the number of workers in all countries and, as a result, production costs of U.S. sectors increase relative to those of other economies, leading to a reallocation of production across sectors and countries. The U.S. reallocates production away from sectors that are relatively skilled and immigrant intensive, such as skilled-service sectors and high-tech manufacturing, towards sectors with lower dependence on skilled immigrant labor, such as agriculture, wholesale and retail trade, and low-tech manufacturing industries. Conversely, economies like Canada, which experiences an inflow of skilled immigrants, shift their production composition in the opposite direction.[32] The increase in Canadian exports to the U.S. contributed significantly to its export growth: it explained 45% of Canada's growth in exports of high-skilled services sectors and 75% of the increase in high-tech manufacturing exports.

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

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

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

| | Aggregate | By sectors | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | IC | BPS | FIN | High-Tech | Ag & Min | WRT | Low-Tech | Other |
| Immigrant labor force, $l_{dk}^{f}$ | 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 |
| Export | 0.23 | 3.94 | 5.99 | 5.39 | 0.6 | -0.39 | 0.13 | -0.35 | -0.81 |

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

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

The differences in 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 immigrant inflow and the resulting substitution effect is occupation-specific.[33]

The differences in the welfare effects on Canadian workers across sectors are mainly explained by two factors, depending on the occupation of the worker. Canadian computer scientists in sectors that are immigrant computer scientists-intensive experience a stronger substitution effect. For instance, the welfare losses of computer scientists in the the sector with largest and lowest $s_{can,ko}^{f}$ are 3.42% and 2.52% respectively (see Figure 6a). The cross-sector differences in the welfare effects of Canadian workers in less-exposed occupations are largely affected by the extent to which the sector expands due to the overall inflow of immigrants to the sector. To illustrate this point, Figure 6b plots the change in the welfare among managers, low-skilled workers, and workers in Other H-1B occupations and the first-order approximation to the employment growth $L_{dk}$, 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 absorbed a relatively larger number of immigrants. As the sector expands, the marginal revenue product of workers increases, increasing wages in the sector.

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

[33] 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 5: Change in real wage of Canadian workers (%)

| | CS | Bss Prof. | Engineers | Managers | Other H-1B | Non-H-1B |
|---|---|---|---|---|---|---|
| BPS | -2.59 | 0.09 | 0.26 | 0.86 | 0.81 | 1.10 |
| IC | -2.71 | 0.06 | -0.05 | 0.82 | 0.77 | 0.99 |
| FIN | -3.42 | -0.15 | 0.27 | 0.69 | 0.65 | 0.91 |
| High-Tech | -2.89 | -0.26 | -0.17 | 0.53 | 0.39 | 0.74 |
| WRT | -3.09 | -0.28 | -0.29 | 0.44 | 0.34 | 0.64 |
| Other | -2.74 | -0.34 | -0.15 | 0.42 | 0.34 | 0.59 |
| Low-Tech | -2.52 | -0.34 | -0.21 | 0.35 | 0.24 | 0.51 |
| Ag & Min | -3.04 | -0.35 | -0.18 | 0.33 | 0.28 | 0.50 |

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

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

(a) Computer scientists (b) Least exposed occupations


*Note.* 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 $s^f_{odk}$ in the x-axis. The right-hand panel plots the real wage change of Canadian workers in the less-exposed occupations in the y-axis and the first order approximation to the change in $L_{dk}$ in the x-axis.

## 6.2 Effects on the U.S.

**Production and exports** The drop in the observed visa approval rates causes a 1.6% decline in total immigrant labor, with the largest drop among computer scientists and business professionals (see Table 3). The drop in the immigrant labor force induces a drop in production of 0.25% in aggregate production. Compared to the effects on the Canadian economy, the magnitude of the effects on the U.S. economy are smaller. There are two reasons for this difference. First, the change in the immigrant labor force is relatively smaller in the U.S., given the larger size of its overall labor force compared to Canada's. Second, Canadian sectors are significantly more immigrant-intensive than U.S. sectors. For instance, the immigrant share in the wage bill in the U.S.'s high-skilled service sectors is 15% approximately, about half of that in Canada.

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

Table 5: Aggregate and sector-level adjustment in the U.S. (%)

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

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

**American workers' welfare** The welfare effects on American workers vary substantially across occupations and sectors, with differences in the welfare effects being particularly pronounced across occupations. The immigration restrictions increase the welfare of computer scientists and, to a lesser extent, business professionals, because the policy reduces relatively more of the supply of immigrant services in these occupations. Even though the drop in the immigrant labor force in these two occupations is similar, computer scientists are relatively more protected by the policy because this occupation is particularly immigrant intensive.[34] Workers in other occupations face a more moderate impact from the drop in immigrant competition, leading the policy to modestly increase or decrease their welfare.

The impact on American workers' welfare is also affected by the extent of the contractions in their employment sectors. For those occupations with the smallest drop in the immigrant labor force, like non-H-1B and other H-1B occupations or managers, the colors in Figure 7 turn to blue or darker blue as we move from the sectors on the bottom to those on the top. This implies that the policy has a less-beneficial or more detrimental effect on those working in sectors with

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

greater contractions. For instance, the drop in welfare of lower-skilled workers in the information and cultural sector is twice as strong as for their counterparts in the low-tech manufacturing sector.

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

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

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

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

## 6.3 Efficacy of the restrictions: the role of international trade

The welfare outcomes of American workers, shown in Figure 7, are the result of a substitution effect and general equilibrium effects, with some of the latter operating via international trade. We are interested in quantifying the role of international trade in these welfare effects. To that end, we quantify the effects of the same policy change $dp_{o,usa}$ assuming that the U.S. is a closed economy. We compare the change in the real wage of American workers in this counterfactual exercise, denoted by $\hat{w}^{CE}$, with our baseline results, denoted it by $\hat{w}^{BL}$. We interpret the difference in the wage changes as the impact of immigration policy on American workers due to international trade. To compute $\hat{w}^{CE}$, we proceed in two steps. First, we eliminate international trade by raising trade costs and solving for the equilibrium. This equilibrium, characterized by the absence of international trade, serves as the starting point for our implementation of the change in U.S. immigration policy. We then introduce the observed $dp_{o,usa}$ and calculate the new equilibrium.[35]

Figure 8 plots the ratio $\hat{w}^{CE}/\hat{w}^{BL}$ for American computer scientists working in different sectors. The plot focuses on computer scientists because the restrictions may be intended to protect their wages as computer-related occupations account for approximately 65% of all H-1B visas. These results show that international trade dampens the welfare gains of American computer scientists, particularly in high-skilled service sectors and high-tech manufacturing. For example, in a closed economy, the welfare gains of computer scientists in the business professional services sector are approximately 25% higher than in a world economy with current levels of international trade. There are two factors at play in a global economy that are absent in a closed economy. First, the U.S. restrictions reduce the number of immigrants coming into the U.S. and increase this factor elsewhere, leading to a relative increase in U.S. production costs. As a result, the economies that absorb these immigrants expand in sectors that compete with U.S. sectors in international markets. This competition in the goods markets drives American wages down and diminishes the benefits of immigration restrictions, compared to autarky. On the positive side, American workers in a globalized economy can get access to relatively cheaper imported goods, which increases their purchasing power. If the negative competition effect is stronger than the positive price effect, the welfare gains in a closed economy would be larger than in a globalized economy, as found in Figure 8. Therefore, these results imply that U.S. immigration restrictions may avoid direct competition between immigrants and American workers in the U.S. labor market, but they could still indirectly compete through international goods markets. If policymakers overlook the general equilibrium effects of international trade, they might overestimate the efficacy of the policy.

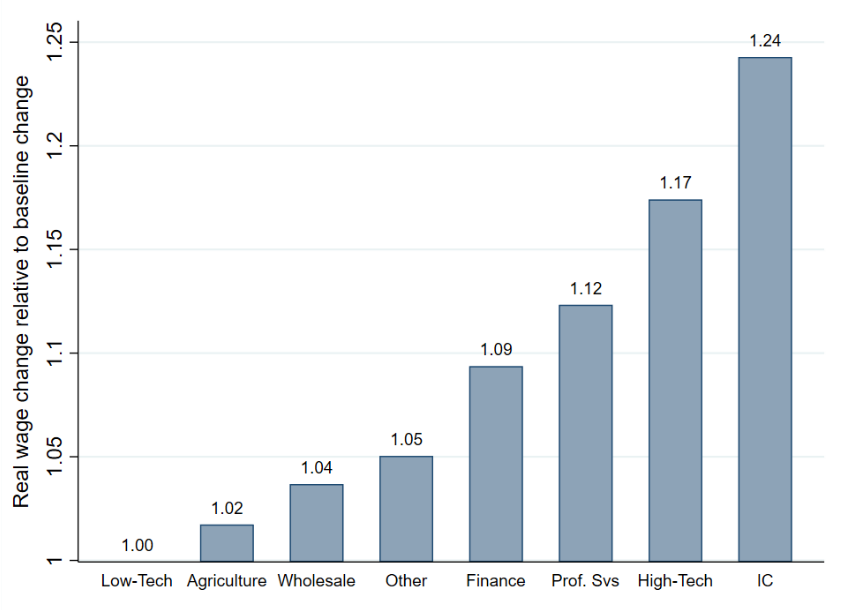
# 7 Conclusion

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

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

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

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




*Note.* We compute the changes in the equilibrium outcomes resulting from the observed change in the approval rate of H-1B visas, $dp_{o,usa}$, assuming that the U.S. is a closed economy. The y-axis is the ratio between the change in the real wage of American computer scientists in a closed economy, denoted by $\hat{w}^{CE}$, and in the baseline economy (see Figure 7), denoted by $\hat{w}^{BL}$. "*IC*" refers to the information and culture sector.

immigration to Canada and had significant effects on production, especially in the high-skilled service sector.

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

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# Appendix

# A Data

## A.1 Cross-walk of occupation codes

The H-1B dataset contains 106 occupation codes that follow the Dictionary of Occupational Titles (DOT) and the PR dataset contains 177 3-digit NOC codes.[36] We construct a crosswalk between these occupations and, when necessary, we appeal to the information provided by the fourth digit of the NOC classification. For some NOC codes, there were no DOT codes in the H-1B dataset (e.g., cashiers or any low-skill occupation) and for some DOT codes, there were no NOC codes (e.g., osteopaths). Among the matched cases, for some NOC occupations, there was more than one corresponding DOT code (e.g., NOC 0124 corresponds to DOT 164 and 165), for some DOT codes there was more than one corresponding NOC code (e.g., NOC 224 and 2133 correspond to 003) and for a few cases, the match was from many to many (e.g., 2175 corresponds to 030 and 039; and 2171, 2173, 2174 and 2283 correspond to 030). We thus define a grouping given by the smallest possible mutually exclusive sets of matches that yield 74 distinct groups (see Table E.2).[37] With this crosswalk at hand, we can aggregate the number of PR and H-1B applications at the new grouping level according to the corresponding NOC codes and DOT codes, respectively.

## A.2 Firm-level regression: measurement and sample

### A.2.1 Construction of firm-level shocks

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

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

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

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

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

### A.2.2 Construction of the variables used as controls

**Firm-level shares of skilled immigrant employment** In the IMDB, we flag an immigrant as a skilled immigrant based on the available data on their education, occupation, and visa program information. The IMDB includes two separate data files: permanent-resident (PR) records and non-permanent-resident (non-PR) records. In the PR records, an immigrant is flagged as a skilled immigrant if they satisfy one of the following three conditions:

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

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

**Local labor market** Each local labor market corresponds to a census metropolitan area (CMA) or a census agglomeration (CA), equivalent to a metropolitan area in the U.S.[38] Statistics Canada provides a mapping between each postal code and a geographical location group. Most of the postal codes are directly part of a CMA/CA. The postal codes for the remote areas do not directly belong to a specific CMA/CA, so we assign them to a CMA/CA that has the most influence on this postal code area, based on the information provided by Statistics Canada. By combining the postal code information from the T1-PMF and the employer-employee-link records, we measure each firm's employment composition by the local labor market. Then we assign the local labor market for a firm according the one accounting for the largest share of its employment. This location measure is analogous to the commuting zone commonly used for the U.S.

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

### A.2.3 Sample selection

We first construct the regression sample by dropping the non-profit firms, firms with lifetime maximum employment of less than 5, and the firms from the following sectors: agriculture, forestry, fishing and hunting, mining, quarrying, oil and gas extraction, utilities, construction, public administration, and other services except for public administration (NAICS code 11, 21, 22, 23, 91 and 81 respectively). Then, we exclude 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 $Intensity_i$, i.e., 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 the year 2017 or 2018, so that each firm in the sample has enough pre- and post-shock information for us to conduct the event study.

## A.3 Data sources used in the quantitative model

*Sources of data from Canada:*

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

*Sources of data from the U.S.:*

We use the income data by nativity, occupation, and sector in the American Community Survey (ACS 1-year data corresponding) to the year 2015 to compute the sectorial shares for the U.S. ($s^n_{dso}$, $s^f_{dso}$, and $f_{dso}$).

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

To compute $\psi_{gd}^{imm}$, we use the total number of immigrants by group and those who arrived in the U.S. during the last year. We then use an extrapolation method to assign a value for a six-year period. Specifically, we infer the six-year period for the U.S. as follows: $\psi_{gu}^{imm} = \frac{\psi_{gc}^{imm}}{\psi_{gc}^{imm}} \psi_{gu}^{imm}$, where we use Canadian data to compute the ratio or extrapolation factor.
We use the H-1B data described in section 2.1 to compute the admission probability of each skilled occupation, and we use official reports of I-129 petitions for H-2A and H-2B visas for the probability of lower-skilled occupations.[39] 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 $\epsilon_{cot}$ 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 $\epsilon_{oct}$ may be mitigated. We assess the plausibility of this correlation by controlling for the elements used to compute $\pi_{co,usa}$ interacted with year dummies (e.g., $App_{co,usa} \times \delta_t$ and $App_{co,can} \times \delta_t$). These estimates, reported in column 2 of Appendix Table E.4, are not statistically different from our baseline estimates, reported in column 1. This suggests that unobserved factors affecting $\pi_{co,usa}$ and $\epsilon_{oct}$ are unlikely to drive our estimates. Note that the correlation over time of unobserved factors either at the occupation level only or at the country level only do not threaten identification, due to the inclusion of $\delta_{ot}$ and $\delta_{ct}$.

The second potential concern is that the policy change was indeed the response to factors specific to certain immigrant groups (e.g., nationality and occupation). For example, critics of the program have argued that some outsourcing firms that provide IT and other business services are flooding the program with applications and are misusing the H-1B program. Many of the accused firms are intensive in computer-related occupations and tend to source most of their immigrant workforce from India. Given that during his campaign, former President Donald Trump expressed his intentions to end the misuse of the H-1B program, the policy may have aimed to stop the increasing inflow of computer scientists from India. If the new restrictions targeted immigrant groups that were growing, our estimates would suffer from reverse causality

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

issues and would be upward biased. To address this concern, we re-estimate the model by excluding India and China, the two largest nationalities of immigrants, and computer-related occupations, the largest occupation for the same group. The estimates, reported in columns 3 and 4 of Appendix Table E.4, are not lower than our baseline estimates, suggesting that this concern may not affect our estimates.

A third concern is that immigrant groups affected by the U.S. policy change may have been affected by contemporaneous changes in Canadian immigration policy. Changes in Canadian immigration policy at the nationality or occupation level are controlled by $\delta_{ct}$ and $\delta_{ot}$, 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 the Canadian policy responded to the new U.S. policy, our reduced-form estimates would incorporate these effects, and we should consider them when interpreting the coefficients.

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

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

## B.2 Firm-level evidence

### B.2.1 Robustness exercises

**Within-sector effects** Our empirical strategy for estimating $\beta_\tau$ leverages both inter-firm variation within the same industry and variation across different industries. One concern is that our industry-level controls do not fully account for potential demand or supply shocks that are specific to different industries. In such a case, the effect of these factors may confound the industry-level effect of the H-1B policy restrictions and, consequently, bias our estimates.

If such unobserved factors drive our estimates, we would expect to observe no effect on firm growth when using only within-industry variation to estimate $\beta_\tau$. 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 compete with these American counterparts may have expanded compared to other Canadian firms, even if they have not hired immigrants. If our estimates of $\beta_\tau$ are driven by differences in the demand for goods and services induced by the H-1B policy change, we would expect a less pronounced effect when estimating the differential hiring responses of Canadian firms within the same industry. To assess the plausibility of these concerns, we estimate the effects of the H-1B policy within the affected industries using only within-industry variation. To do so, we categorize sectors into "exposed" and "non-exposed." Specifically, we rank broad sectors according to the average firm exposure (see Appendix Table E.5) and define the top quartile as the "exposed" group of sectors. That is, the "exposed" sectors coincide with what we refer to in the main text as the "high-skilled service sector." The remaining sectors constitute the "non-exposed" sectors. Then we estimate the following event study:

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

where $1(\text{k} = \text{high-skilled service sector})$ is a dummy variable that equals one if the industry where the firm operates belongs to one of the "exposed" sectors and zero otherwise. We compare the estimates of $\beta_\tau^E$, which do not use variation across sectors for identification, with those from equation (3). Appendix Figure E.8 shows this comparison for the hiring of immigrants and for sales and export performance (Appendix Table E.7 reports all of the estimates and estimation details.) The pairwise comparison of the estimates of these variables shows that the within-industry estimates are noisier but, overall, the point estimates are similar in magnitude to those documented in Figure 4. Given this evidence, we consider that it is likely that our estimates are identifying the effects of H-1B restrictions due to the increase in the supply of immigrant labor to firms.

**Firm characteristics** Our empirical model allows the exposure of the firm $Intensity_i$ to be assigned non-randomly based on firm characteristics that affect the level of the outcome but that require the exposure to be mean independent of the factors that affect the trend in the outcome (Roth et al., 2023). This requirement is violated if, for instance, firm size matters more in the economic context of the Canadian economy in the years prior to 2016 than in the year after. To assess whether it is plausible that this requirement is violated, we re-estimate the model adding pre-shock firm characteristics interacted with year dummies. The firm characteristics that we add are firm size measured by revenues (in logs) and the labor intensity of the firm measured by the wage bill in total cost. All of these regressions include the pre-shock firm characteristics included in the baseline specification (e.g., the immigrant share in the wage bill, the share of exports in total sales, and the share of service exports in total exports). Appendix Figure E.9 plots the event studies of 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 export nor import in 2016. Appendix figure E.11 shows the event study and suggests that the baseline results are robust to this subsample of firms.

**Effect of Canadian immigration** The Canadian firms that use this program to source immigrants from abroad may also be those that are more exposed to the H-1B policy change. For instance, computer scientists were the most prevalent professionals among immigrants to be admitted under the Express Entry program. Therefore, firms that tend to employ computer scientists may have benefitted from the introduction of the Express Entry program in 2015 and the following years. We assess whether our estimates may confound the effect of the Express Entry program by re-estimating the model with an additional control variable. This variable is the interaction between the year dummies and the share of workers in 2016 who were admitted to Canada through this program. The estimates of immigrant and native hiring and firms' expansion in terms of sales and exports are robust to the inclusion of this control (see Appendix Figure E.10). Given these results, it is plausible that the effects of the Express Entry program do not confound with the effects of the H-1B restrictions.

### B.2.2 Additional results

**Effect on firms depending on whether they hired immigrants who resided in the U.S.** Our firm-level exposure measure was motivated by the influence of immigrant networks based on the country of birth . Immigrant networks can develop not only through shared birthplaces but also through shared locations of residence. To illustrate this, consider two immigrants, one from India and one from China, who previously resided in the United States. Suppose that one of them had relocated to Canada while the other had remained in the U.S. It is plausible that if the U.S. imposes immigration restrictions, the immigrant still living in the U.S. might seek assistance from the one residing in Canada to facilitate their plan to move to Canada. Based on this idea, we divided firms into two distinct groups based on the residence of their immigrant employees. Specifically, our data on immigration records allows us to track the country of residence for each immigrant employee before they relocated to Canada. Based on this information, we categorize firms into two groups: those that had employed immigrants who had previously lived in the United States and those that had not. We then modified our equation (3) to accommodate a heterogeneous treatment effect. In particular, we allow the $\beta_\tau$ coefficient to vary for firms belonging to each of these two groups (e.g., we incorporate a dummy interacting $Intensity_i$). Appendix Figure E.13 plots these pairs of coefficients $\beta_\tau$ for the main outcome variables. Our findings about the hiring of immigrants align with the idea of networks formed based on the locations of the previous residences. We observe that, on average, firms that had hired immigrants who had previously resided in the United States exhibited a more pronounced response in terms of increased immigrant hiring. Interestingly, these firms seem to play a pivotal role in the responses related to exports and the share of exports in total sales documented in Figure 4.

# C Model

## C.1 Solving for equilibrium

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$\hat{X}_{c} = \sum_{k} \omega^{X}_{ck}\,\hat{Y}_{ck} + \omega^{X}_{cD} \tag{C.19}$$

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

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

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

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

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

**Labor market clearing conditions**

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

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

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

## C.2 Analytical results

### C.2.1 Applications for Canadian visas

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

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

The change in the log of the pplications is

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

where the change in the log of emigrating is

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

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

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

### C.2.2 Welfare of American workers

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

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

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

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

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

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

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

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

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

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

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

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

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

The log differentiation of these expressions yields the following conditions:[40]

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

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

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

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

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

Log differentiating $Y_{usa,k}$ yields

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

where $\omega^{Y}_{usa,jk}$ is the share of country $j$ in the U.S. sales of sector $k$.[41]
Under the assumption that preferences are Cobb-Douglas, the change in the share of each sector in total expenditures is zero ($\tilde{\alpha}_{jk} = 0$). The change in the U.S. market share within a sector takes the following form:

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

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

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

Step 4: 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:

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

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

$$\tilde{l}_{usa,ko} = s^{f}_{usa,ko} \, \tilde{l}^{f}_{usa,ko} \tag{C.31}$$
$$\tilde{l}_{usa,k} = \sum_{o} s_{usa,ko} \, s^{f}_{usa,ko} \, \tilde{l}^{f}_{usa,ko} \tag{C.32}$$

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

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

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

The change in the unit cost of production is

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

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

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

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

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

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

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

# D Quantification

## D.1 Calibration

$p_{od}$: For the U.S., we compute the approval rate of each skilled occupation using the H-1B data. For the lower-skilled occupation, we use official reports of I-129 petitions for H-2A and H-2B visas.[43] For Canada, we use publicly available data from the IRCC on the approval rate by PR visa program. We assign a common approval rate to all occupations within skilled occupations because the data is not disaggregated by occupation.

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

Table D.1: Calibration

| | Description | Source |
|---|---|---|
| Immigration policy: P | | |
| $p_{od}$ | Approval rate | H-1B application data, USCIS, IRCC |
| Earning per worker in the US relative to home: $\mathbf{U_u}$ | | |
| $w^n_{odk}, w^f_{odk}$ | Nominal wages | H-1B application data for the US, NSS for India and IPUMS int'l for RoW |
| $P_d$ | Consumption price level | Hanson and Groegger and CEPII data |
| | Exchange rate | Penn World Table |
| $\zeta_{cod}$ | Migration costs | Hanson and Groegger and CEPII data |
| Migration-related shares: $\mathbf{S^M}$ | | |
| $\pi_{cod}$ | Share applying to $d$ | H-1B application data and PR application data |
| $\pi_{coc}$ | Share staying at home | Inferred using H-1B application data and IAB dataset |
| $1-\psi^{imm}_{cod}$ | Immigrant flow share | ACS for the US, and LFS for Canada |
| $1-\psi^{emm}_{co}$ | Share making migration decision | NSS for India and IPUMS int'l for RoW |
| Non migration-related shares: $\mathbf{S^{NM}}$ | | |
| $\pi_{codk}$ | Share choosing sector $k$ | ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW |
| $s_{dko}$ | Cost share of occupation $o$ | ACS for the US, LFS for Canada, NSS for India, IPUMS int'l for RoW |
| $s^f_{dko}$ | Cost share of immigrants | ACS for the US, and LFS for Canada |
| $\lambda_{dck}$ | Expenditure shares within sector | Trade in Value Database from the OECD (TiVA)[42] |
| $\alpha_{dk}$ | 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.

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

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

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

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

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

Here, $co$ represents Indian computer scientists, and the left-hand side denotes the proportion of Indian computer scientists remaining in their home country. Although data on the global distribution of Indians by occupation is unavailable, education group data from the IAB 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 $\pi_{coc}$ consistent with condition (D.33) is 0.4.[44] 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 $\pi_{coc}$ as a function of the data and the inferred value for $\pi_{ind,cs,ind}$. Given that we do not observe $L_{co}$ for the RoW, we proxy the last fraction of the right-hand side with the relative number of total employees. Finally, we apply the condition (D.33) for lower-skilled workers, where we used the data for the non-college population from the IAB.

## D.2 Instrumental variable approach: $\nu_d$

To go from equation (31) to an estimating equation that we can take to the data, we introduce four changes. First, we rewrite (31) as follows:

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

where $\eta_{cot}$ is a structural error that includes the effect of immigration policy in Canada ($p_{co,can,t}$), wages and prices in Canada and the cost to migrate to Canada (through $\tilde{u}_{co,can,t}$), wages and prices at home (through the average wage $u_{coct}$), prices in the U.S. ($P_{usa,t}$), and costs to migrate to the U.S. $\tilde{\zeta}_{co,usa}$. Second, motivated by the policy memorandum and our data, we make the probability $p_{co,usa,t}$ occupation specific, as opposed to occupation-nationality specific. Third, we set $\tilde{w}_{co,usa,t}$ at its pre-shock average value because it jumps around over time for immigrant groups that are relatively small. By making $\tilde{u}_{co,usa}$ time invariant, we eliminate random noise and increase the precision of the estimate. Additionally, this ensures that the identification of $\nu_d$ 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 $\eta_{cot}$. We include a group-specific fixed effect, $\delta_{co}$, to control for time-invariant factors such as preferences, migration costs, or long-run wage differences between

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

the U.S. and Canada. We include occupation-year fixed effects, $\delta_{ot}$, 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 $\delta_{ct}$ to control for changes in economic conditions at home that may push immigrants to migrate disproportionally more towards Canada or the U.S. The estimating equation becomes

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

where we measure $App_{co,can,t}$ and $App_{co,usa,t}$ as the number of PR applications and H-1B applications of immigrant group $co$ in year $t$ for $2012 \leq t \leq 2017$, $p_{o,usa,t}$ as the share of H-1B applications in occupation $o$ that were approved, and $\tilde{w}_{co,usa}$ as the log of the average H-1B wage by immigrant group $co$ for the pre-shock years 2012-2016.[45]

The OLS estimate of $\nu_d$ may be subject to omitted variable problems. Increases in the number of applications for H-1B cap-subject visas may decrease the approval rate $p_{ot}$, regardless of the U.S. policy stance. Thus, any factor that induced immigrants to apply to Canada and to apply for cap-subject H1B visas would bias our estimate of $\nu_d$ 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 $\nu_d$ towards zero.

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

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

## D.3 Indirect inference approach

Our goal is to obtain the outcome variable from real data that is comparable with that from the model. To that end, we must isolate the effect of the policy change on the outcomes of interest

[45] 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.

and then follow an aggregation step.[46]

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

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

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

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

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

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

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

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

Finally, we use the estimate of the year 2018 to construct the target moments for the model because 2018 is the last year in our sample. Thus, our measure of the outcome variable of the data-regression (33) is $log\Big(\sum_{g \in G} \omega^{app}_g e^{\hat{\beta}_{2018} Intensity_g}\Big)$.

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

# E Additional tables and figures

[46]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.

Table E.2: Crosswalk of classification of occupations

| New | NOC (Classification in PR) | | DOT (Classification in H-1B dataset) | |
|---|---|---|---|---|
| group | Code | Description | Code | Description |
| 1 | 0111 | Financial managers | 161 | Budget and management systems analysis occupations |
| 2 | 0112 | Human resources managers | 166 | Personnel administration occupations |
| 3 | 0113 | Purchasing managers | 162 | Purchasing management occupations |
| 4 | 0121 | Insurance, real estate and financial brokerage managers | 186 | Finance, insurance, and real estate managers and officials |
| 5 | 0124 | Advertising, marketing and public relations managers | 164 | Advertising management occupations |
| 5 | 0124 | Advertising, marketing and public relations managers | 165 | Public relations management occupations |
| 6 | 041 | Managers in public administration | 188 | Public administration managers and officials |
| 7 | 060 | Corporate sales managers | 163 | Sales and distribution management Occupations |
| 8 | 065 | Managers in customer and personal services, n.e.c. | 187 | Service industry managers and officials |
| 9 | 073 | Managers in transportation | 184 | Transportation, communication, and utilities industry Managers and officials |
| 10 | 081 | Managers in natural resources production and fishing | 180 | Agriculture, forestry, and fishing industry managers and officials |
| 10 | 081 | Managers in natural resources production and fishing | 181 | Mining industry managers and officials |
| 11 | 111 | Auditors, accountants and investment professionals | 160 | Accountants, auditors, and related occupations |
| 11 | 124 | Office administrative assistants - general, legal and medical | 169 | Other occupations In administrative specializations |
| 12 | 2111 | Physicists and astronomers | 021 | Occupations in astronomy |
| 12 | 2111 | Physicists and astronomers | 023 | Occupations in physics |
| 13 | 2112 | Chemists | 022 | Occupations in chemistry |
| 14 | 2114 | Meteorologists and climatologists | 025 | Occupations in meteorology |
| 15 | 2121 | Biologists and related scientists | 049 | Other occupations in life sciences |
| 15 | 2121 | Biologists and related scientists | 041 | Occupations in biological sciences |
| 16 | 2123 | Agricultural representatives, consultants and specialists | 040 | Occupations in agricultural sciences |
| 17 | 2131 | Civil engineers | 005 | Civil engineering occupations |
| 18 | 2132 | Mechanical engineers | 007 | Mechanical engineering occupations |
| 19 | 2134 | Chemical engineers | 008 | Chemical engineering occupations |
| 20 | 2141 | Industrial and manufacturing engineers | 012 | Industrial Engineering Occupations |
| 21 | 2142 | Metallurgical and materials engineers | 011 | Metallurgy and metallurgical engineering occupations |
| 21 | 2142 | Metallurgical and materials engineers | 006 | Ceramic engineering occupations |
| 22 | 2143 | Mining engineers | 010 | Mining and petroleum engineering occupations |
| 23 | 2144 | Geological engineers | 014 | Marine engineering occupations |
| 23 | 2253 | Drafting technologists and technicians | 017 | Drafters |
| 24 | 2146 | Aerospace engineers | 002 | Aeronautical engineering occupations |
| 25 | 2148 | Other professional engineers, n.e.c. | 015 | Nuclear engineering occupations |
| 25 | 2148 | Other professional engineers, n.e.c. | 013 | Agricultural engineering occupations |
| 25 | 2148 | Other professional engineers, n.e.c. | 019 | Other occupations in architecture, engineering, and surveying |
| 26 | 215 | Architects, urban planners and land surveyors | 001 | Architectural occupations |
| 27 | 216 | Mathematicians, statisticians and actuaries | 020 | Occupations in mathematics |
| 28 | 2171 | Information systems analysts and consultants | 030 | Occupations in systems analysis and programming |
| 28 | 2175 | Web designers and developers | 039 | Other computer-related occupations |
| 29 | 2172 | Database analysts and data administrators | 031 | occupations in data communications and networks |

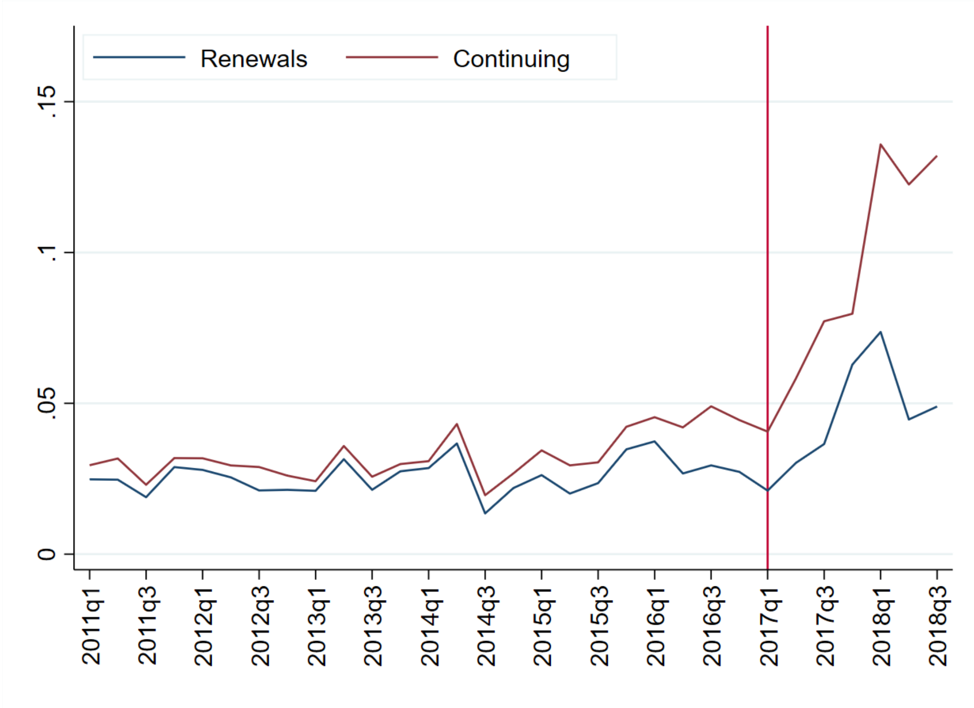
| New group | NOC (Classification in PR) Code | Description | DOT (Classification in H-1B dataset) Code | Description |
|---|---|---|---|---|
| 30 | 2212 | Geological and mineral technologists and technicians | 024 | Occupations in geology |
| 31 | 224 | Technical occupations in electronics and electrical engineering | 003 | Electrical/electronics engineering occupations |
| 32 | 2251 | Architectural technologists and technicians | 001 | Architectural Occupations |
| 33 | 2254 | Land survey technologists and technicians | 018 | Surveying/cartographic occupations |
| 34 | 2282 | User support technicians | 032 | Occupations in computer system user support |
| 35 | 301 | Professional occupations in nursing | 075 | Registered nurses |
| 36 | 3111 | Specialist physicians | 070 | Physicians and surgeons |
| 37 | 3112 | General practitioners and family physicians | 079 | Other Occupations in medicine and health |
| 38 | 3113 | Dentists | 072 | Dentists |
| 39 | 3114 | Veterinarians | 073 | Veterinarians |
| 40 | 3131 | Pharmacists | 074 | Pharmacists |
| 41 | 3132 | Dietitians and nutritionists | 077 | Dietitians |
| 42 | 314 | Therapy and assessment professionals | 076 | Therapists |
| 43 | 321 | Medical technologists and technicians (except dental health) | 079 | Other occupations in medicine and health |
| 44 | 322 | technical occupations in dental health care | 078 | Occupations in medical and dental technology |
| 45 | 401 | University professors and post-secondary assistants | 090 | Occupations in college and university education |
| 46 | 402 | College and other vocational instructors | 090 | Occupations in college and university education |
| 47 | 403 | Secondary and elementary school teachers and educational counsellors | 091 | Occupations in secondary school education |
| 47 | 403 | Secondary and elementary school teachers and educational counsellors | 092 | Occupations in preschool, primary school, and kindergarten education |
| 48 | 4111 | Judges | 110 | Lawyers |
| 49 | 4112 | Lawyers and Quebec notaries | 111 | Judges |
| 50 | 415 | Social and community service professionals | 045 | Occupations in psychology |
| 51 | 421 | Paraprofessional occupations in legal, social, community and education services | 119 | Other occupations in law and jurisprudence |
| 52 | 5111 | Librarians | 100 | Librarians |
| 53 | 5112 | Conservators and curators | 102 | Museum curators and related occupations |
| 54 | 5113 | Archivists | 101 | Archivists |
| 55 | 5121 | Authors and writers | 131 | Writers |
| 56 | 5122 | Editors | 132 | Editors: publication, broadcast, and script |
| 57 | 5123 | Journalists | 137 | Interpreters and translators |
| 58 | 5125 | Translators, terminologists and interpreters | 137 | Interpreters and translators |
| 59 | 5132 | Conductors, composers and arrangers | 152 | Occupations in music |
| 60 | 5133 | Musicians and singers | 152 | Occupations in music |
| 61 | 5134 | Dancers | 151 | Occupations in dancing |
| 62 | 5135 | Actors and comedians | 150 | Occupations in Dramatics |
| 63 | 5136 | Painters, sculptors and other visual artists | 144 | Fine arts |
| 64 | 5211 | Library and public archive technicians | 100 | Librarians |
| 65 | 5212 | Technical occupations related to museums and art galleries | 102 | Museum curators and related occupations |
| 66 | 5221 | Photographers | 143 | occupations in photography |
| 67 | 5222 | Film and video camera operators | 194 | Sound and film |
| 68 | 5225 | Audio and video recording technicians | 194 | Sound and film |
| 69 | 523 | Announcers and other performers, n.e.c. | 159 | Other occupations in entertainment and recreation |
| 70 | 525 | Athletes, coaches, referees and related occupations | 153 | Occupations in athletics and sports |
| 71 | 621 | Retail sales supervisors | 185 | wholesale and retail trade managers and officials |
| 72 | 652 | Occupations in travel and accommodation | 197 | Ship captains |
| 73 | 720 | Contractors and supervisors, industrial, electrical and construction trades and related workers | 182 | Construction industry managers and officials |
| 74 | 922 | Supervisors, assembly and fabrication | 183 | Manufacturing industry managers and officials |

Table E.3: Canadian points system

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

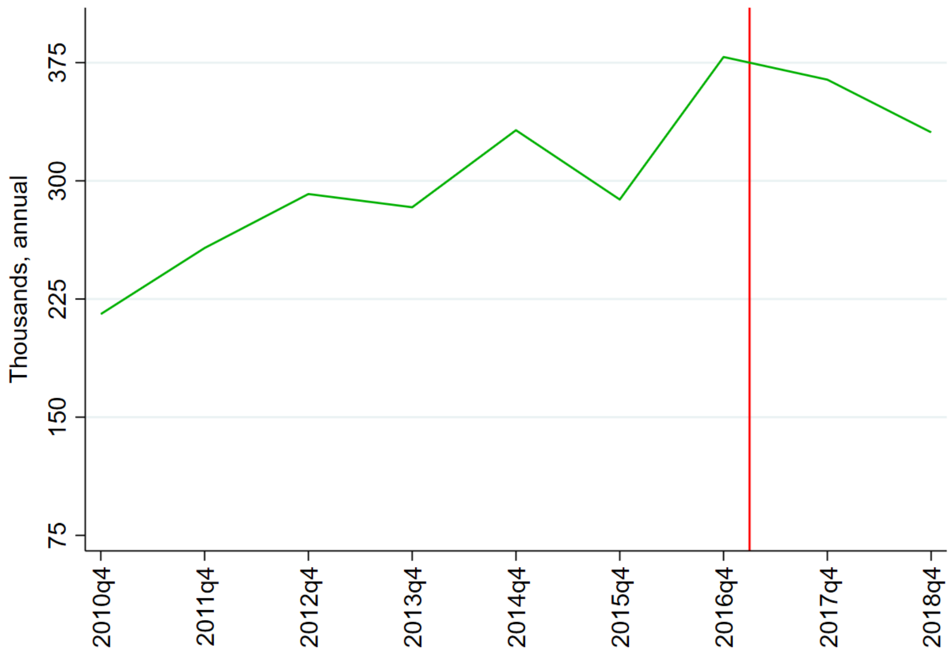
*Source:* IRCC's website Website (link), accessed June 2023.

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



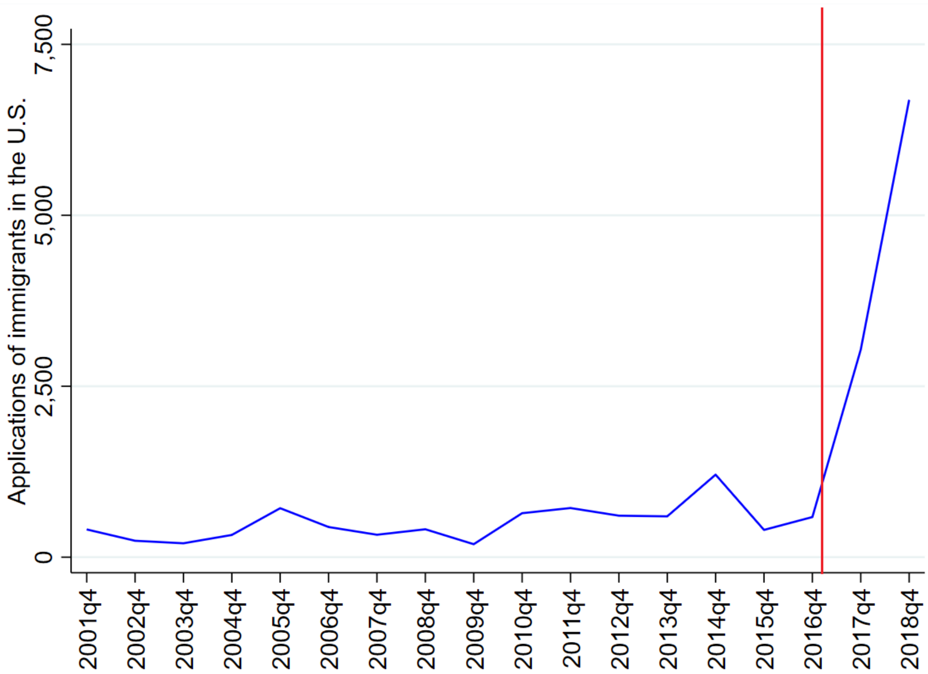

*Note. Figure E.1 plots the number of denied H-1B applications divided by the total number of H-1B applications. The red line includes continuing H-1Bs and the blue lines only renewals.*

Figure E.2: Annual number of H-1B approvals




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

Figure E.3: Canadian visa applications of immigrants who previously resided in the U.S.




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

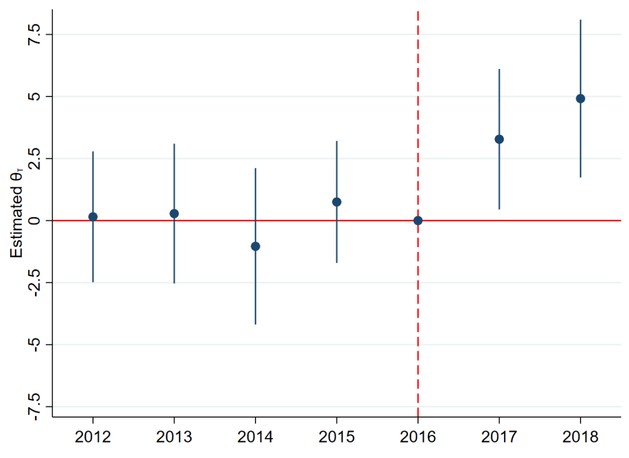
Table E.4: Effect of increasing H-1B denial rates on Canadian immigration

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

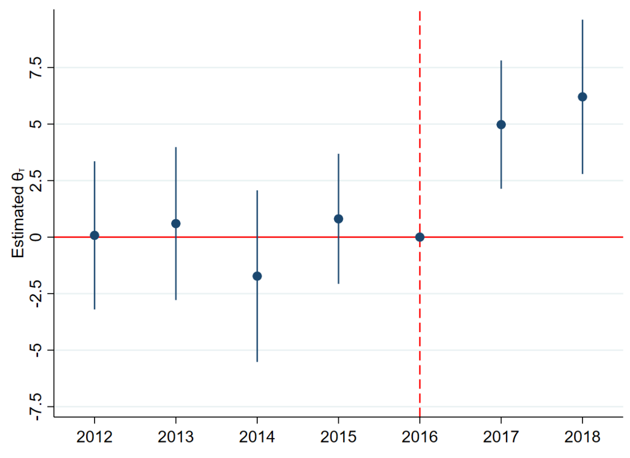
*Note.* $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. All columns include occupation-nationality fixed effects, occupation-year fixed effects, and nationality-year fixed effects. Standard errors are clustered at the occupation level. Column (1) is the baseline specification given by 1. Column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

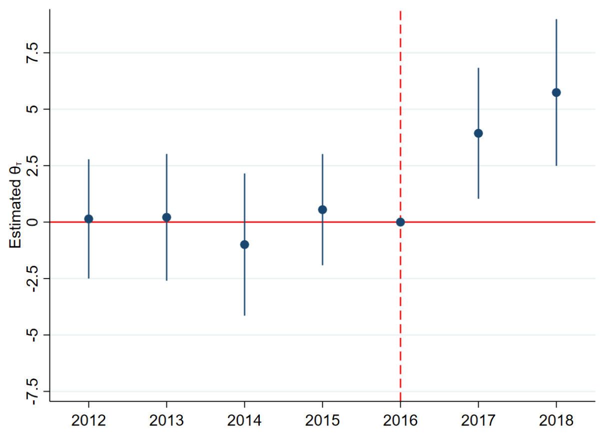
Figure E.4: Effect of increasing H-1B denial rates on Canadian Immigration

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

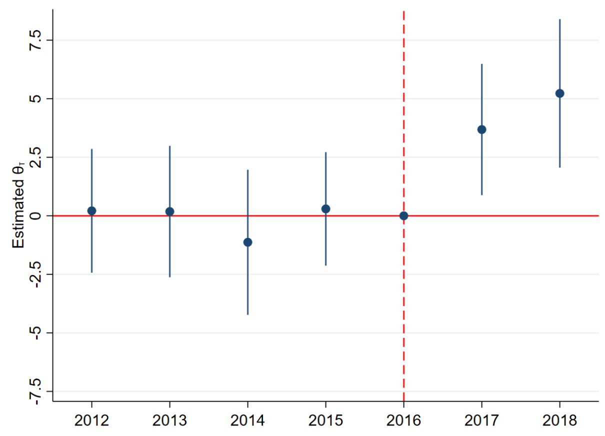



(b) Excluding apps. from India and China



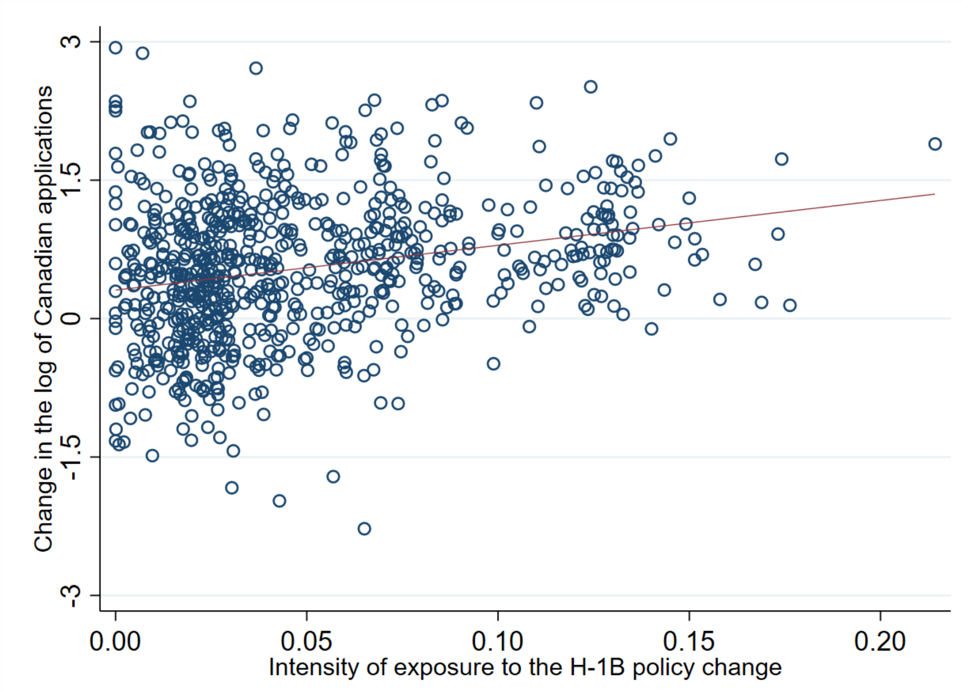

(c) Excluding apps. of computer scientists




(d) Including Express Entry control variables

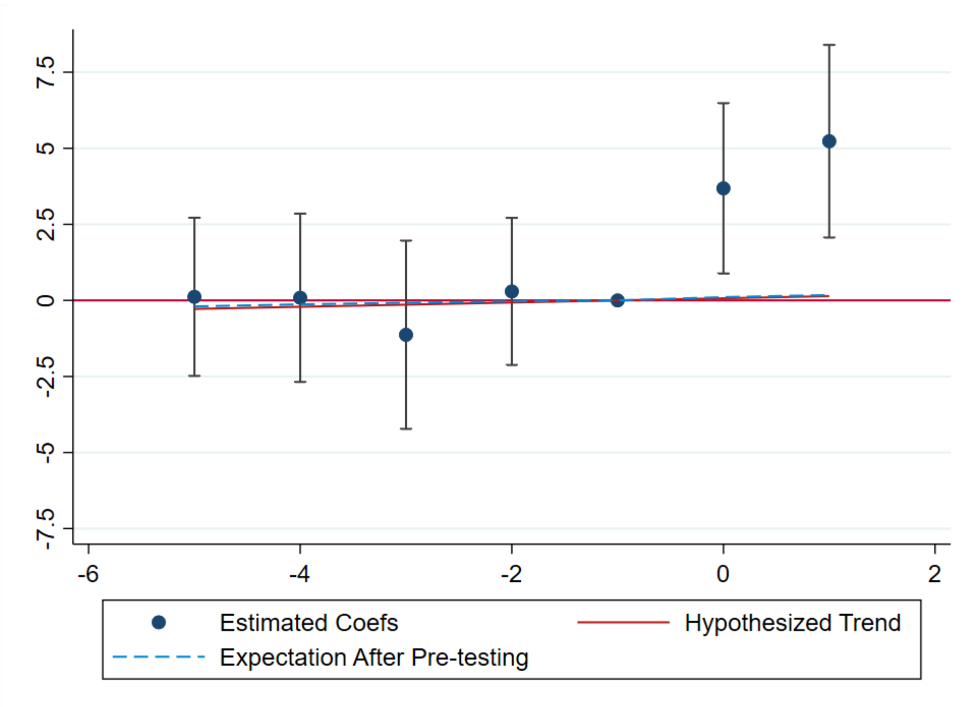
*Note. The y-axis plots the estimated event-study coefficients corresponding to columns 2-4 from Appendix Table E.4.*

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



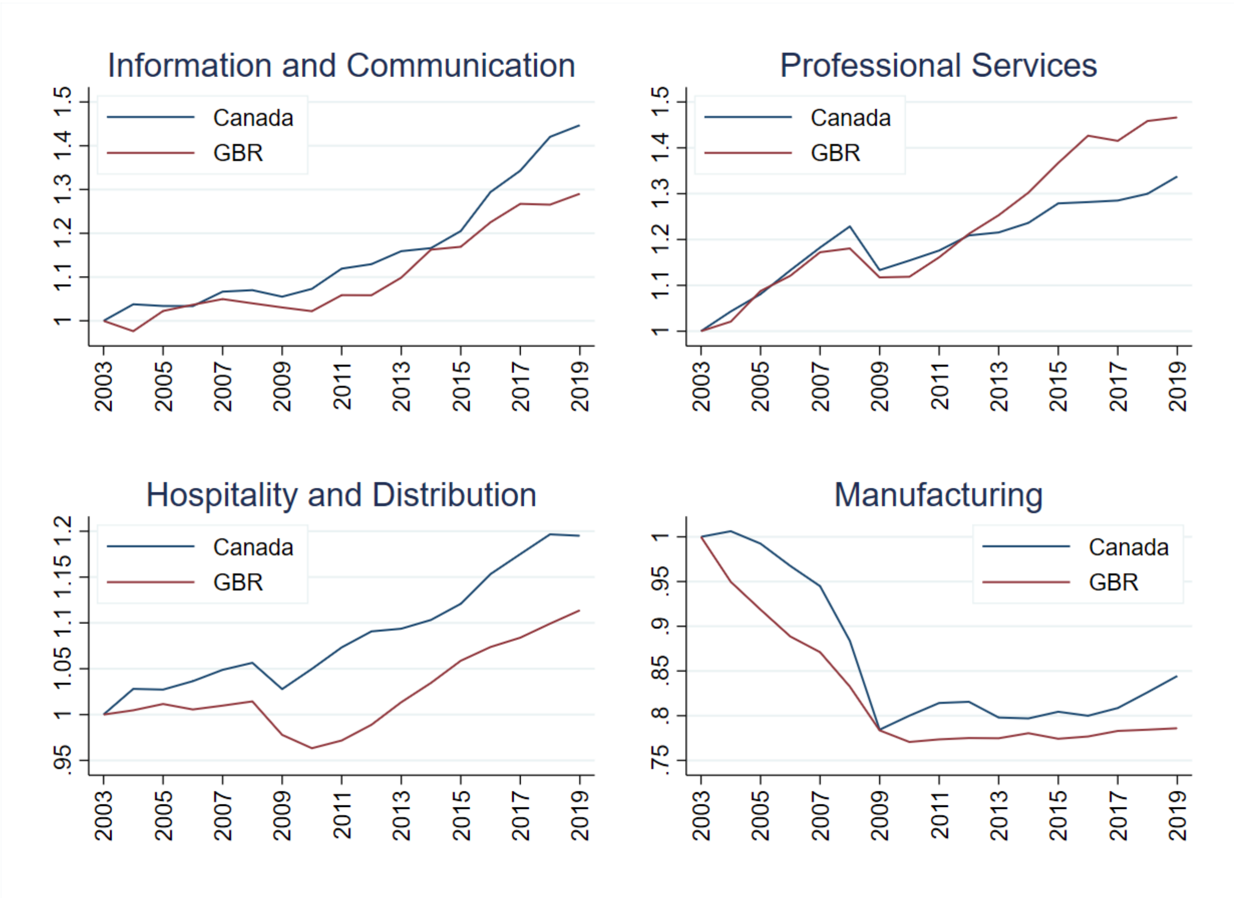

*Note.* The y-axis is computed as $\frac{\sum_{t=2017}^{2018} log(App_{co,can,t})}{2} - \frac{\sum_{t=2012}^{2016} log(App_{co,can,t})}{5}$ and the x-axis is $Fraction\ of Affected_{co}$ in equation (2). An observation is an immigrant group $co$ where $c$ and $o$ stand for the country of birth and occupations,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

Figure E.6: Test for linear trends




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

Figure E.7: Number of working hours relative to the year 2003




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

Table E.5: Distribution of the firm-level intensity of treatment

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

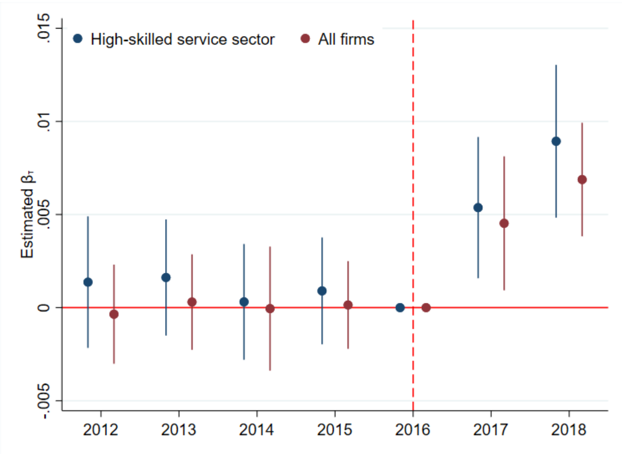
*Note.* This table reports the summary statistics of $Intensity_i$, normalized by the overall standard deviation. The statistics reported in the columns from left to right are the mean, standard deviation, median, 10th percentile, 90th percentile, and the number of firms, among the firms with positive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

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

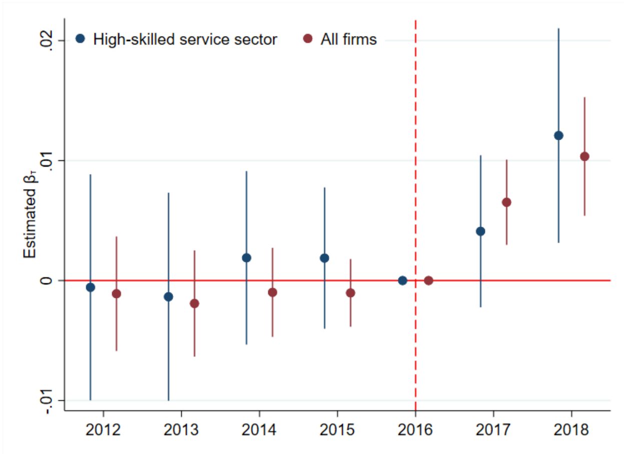
| | Log of Revenues | Export-Rev ratio | Net hiring of imm. | Net hiring of native-born workers | Log of Native-born empl. | Log of Total empl. | Log of earnings per worker | Immigrant Share | Log of markup | Log of cost | Log median earn. native-born worker | Log of earnings per native-born worker |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

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

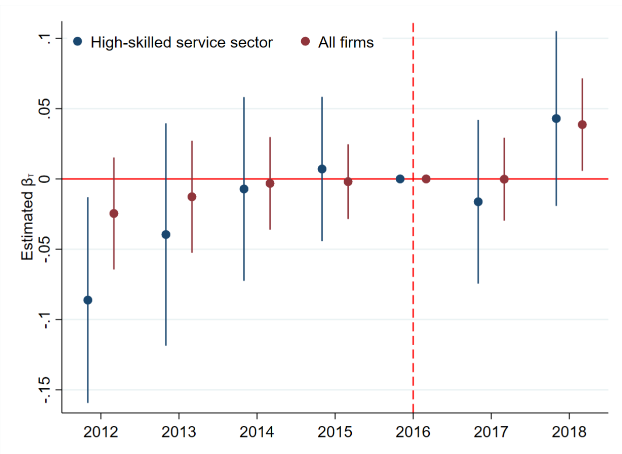
Figure E.8: Effect of increasing H-1B denial rates on Canadian firms



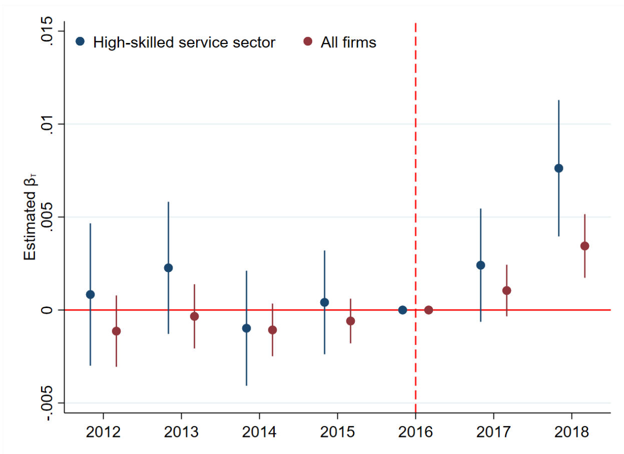

(a) Hiring of imm. relative to emp




(b) Sales (in log)




(c) Exports (in log)




(d) Exports relative to total sales

*Note.* The y-axis plots the estimated event-study coefficients $\beta_\tau$ of equation 3 and $\beta_\tau^E$ of equation B.1, multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals. The estimated coefficients $\beta_\tau$ plotted correspond to Appendix Table E.4, and the estimated coefficients $\beta_\tau^E$ plotted correspond to $SS = 1$ in Appendix Table E.7.

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

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

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

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

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

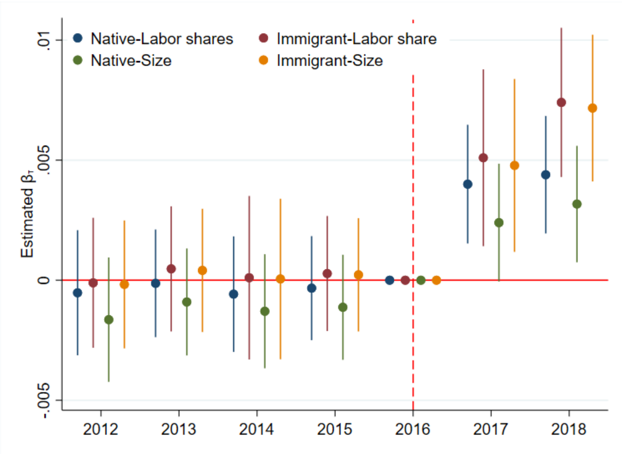
*Note.* The table displays the estimated event-study coefficients, $\beta_\tau$, of equation (3) multiplied by the average value of $Intensity_i$ in the high-skilled service sector, for ease of interpretation. The sample includes only domestic firms and excludes MNCs. We plot these coefficients in Appendix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

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

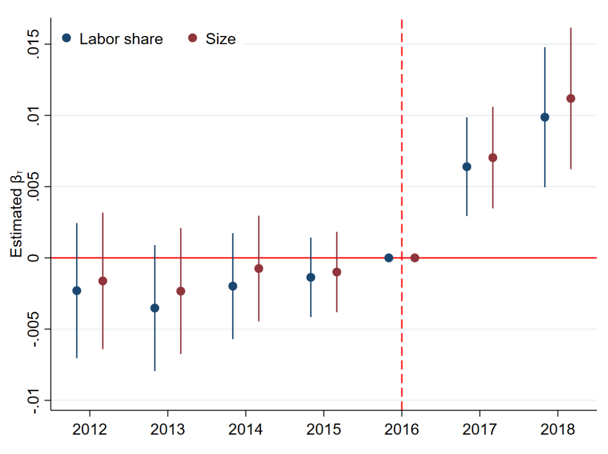
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$ | $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$ | $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$ | $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$ | $log(\frac{app_{co,can,t}}{app_{co,usa,t}})$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

*Note.* $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. All columns include occupation-nationality fixed-effects, occupation-year fixed effects, and nationality-year fixed effects. Standard errors are clustered at the occupation level. Column (1) shows the OLS estimates of the baseline specifications given by (D.35). Columns (2)-(6) show 2SLS estimates. Column (2) estimates the baseline specification. Column (3) controls for the elements used to compute $\pi_{co,usa}$ interacted with the year dummies (e.g., $\pi_{co,can} \times \delta_t$ and $\pi_{co,usa} \times delta_t$). Column (4) excludes applications of immigrants from India and China. Column (5) excludes applications of computer scientists. Column (6) includes $Share^{EE}_{oc2015} \times 1(t \geq 2015)$ and $Share^{EE}_{oc2016} \times 1(t \geq 2016)$ where $Share^{EE}_{oct}$ is the share of applications of an immigrant group $oc$ in year $t$ accounted for by the Express Entry program.

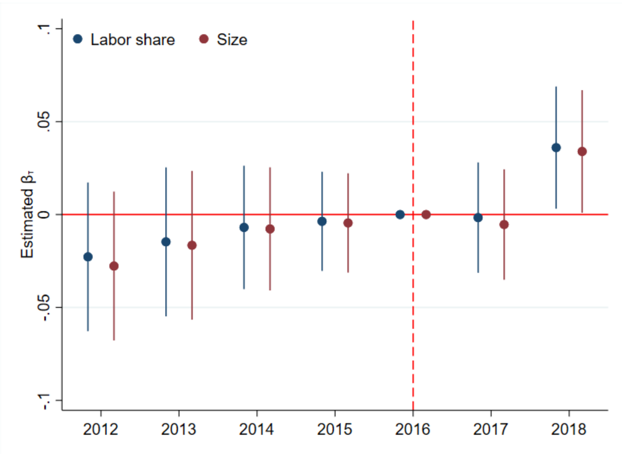
Figure E.9: Robustness exercise to control for the effects of firm characteristics



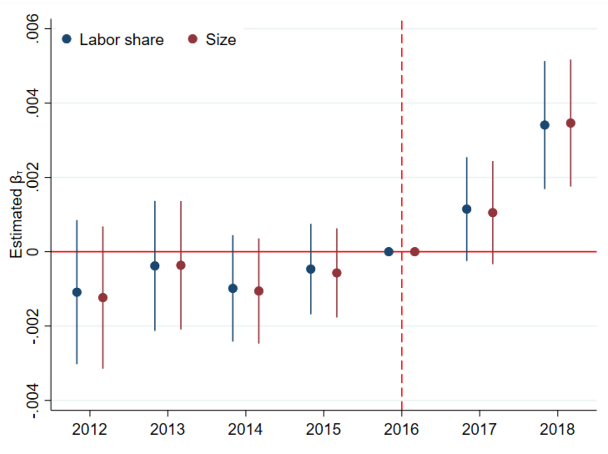

(a) Hiring relative to employment in 2016




(b) Sales (in log)



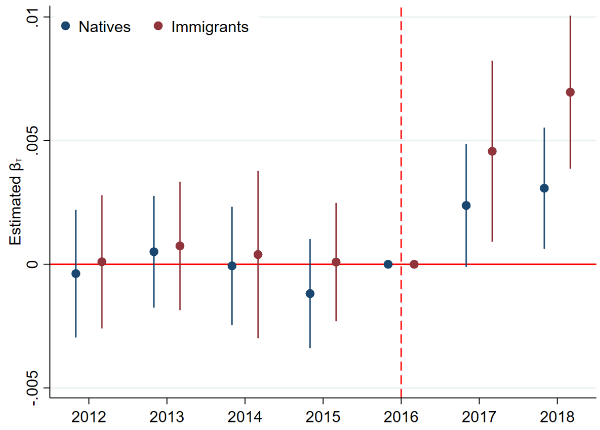

(c) Exports (in log)



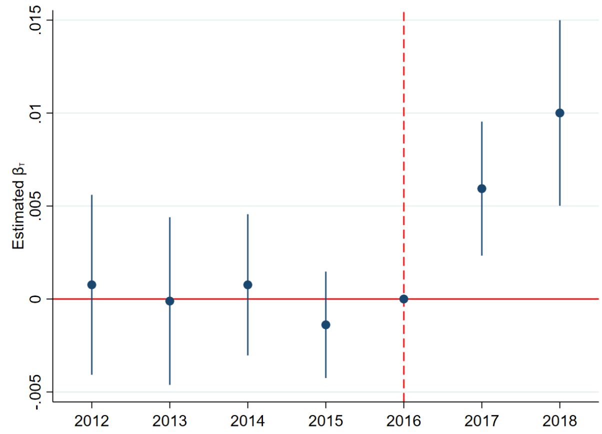

(d) Exports relative to total sales

*Note.* The y-axis plots the estimated event-study coefficients, $\beta_\tau$, 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 these regressions include the pre-shock firm characteristics included in the baseline specification. The event is defined as the spike in the H-1B denial rate in 2017. The vertical lines reflect the 95% confidence intervals.

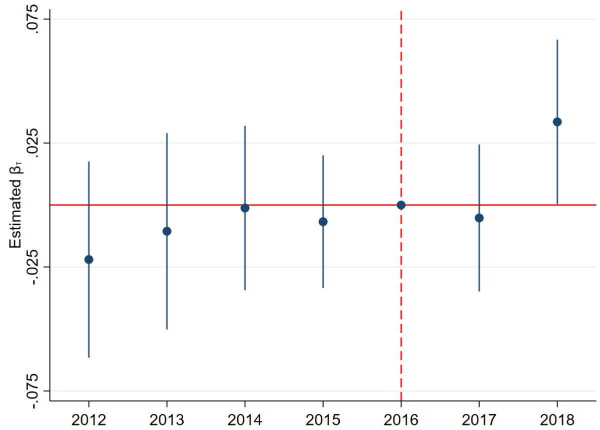
Figure E.10: Robustness exercise to control for the effect of the Express Entry program



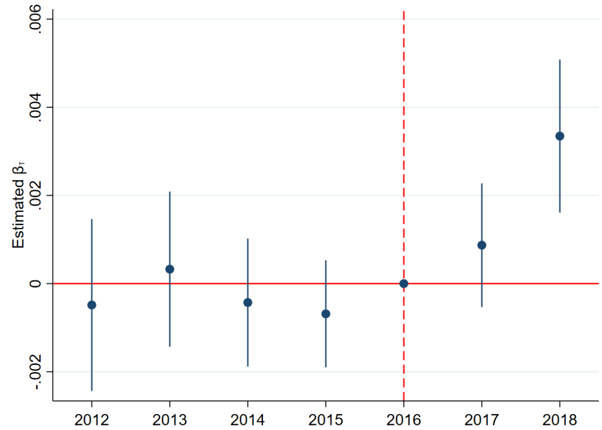

(a) Hiring relative to employment in 2016




(b) Sales (in log)



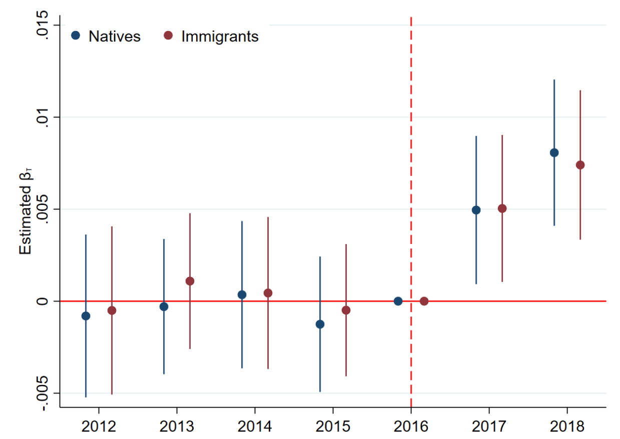

(c) Exports (in log)



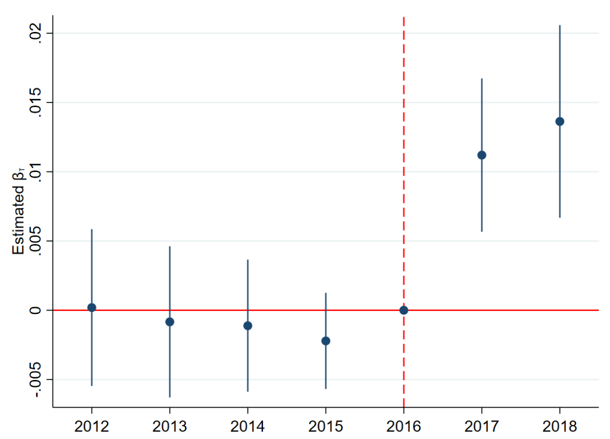

(d) Exports relative to total sales

*Note.* The y-axis plots the estimated event-study coefficients, $\beta_\tau$, 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 the 95% confidence intervals.

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



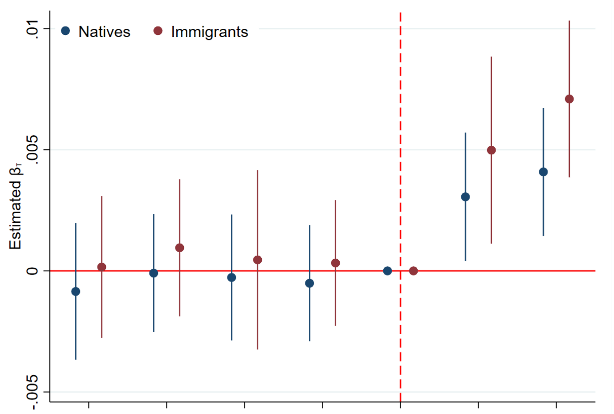

(a) Hiring relative to Employment in 2016



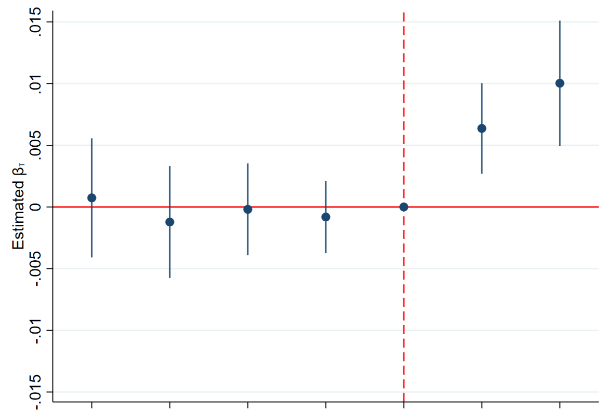

(b) Sales (in log)

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

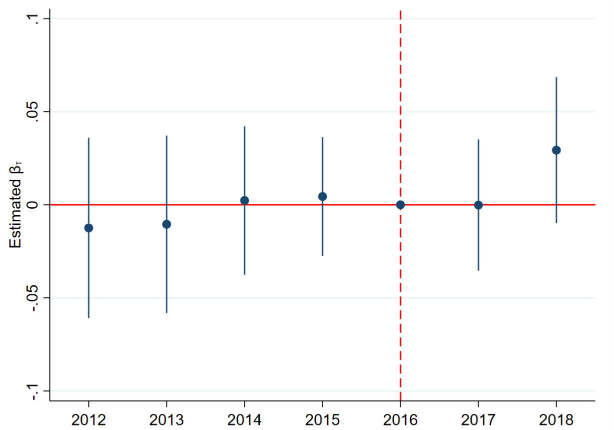
Figure E.12: Effects on domestic firms



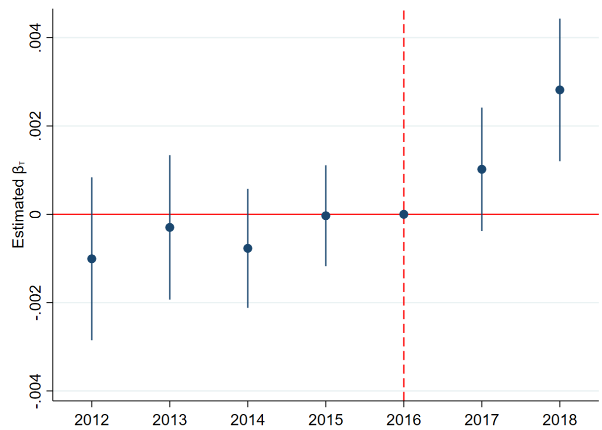

(a) Hiring relative to employment in 2016




(b) Sales (in log)



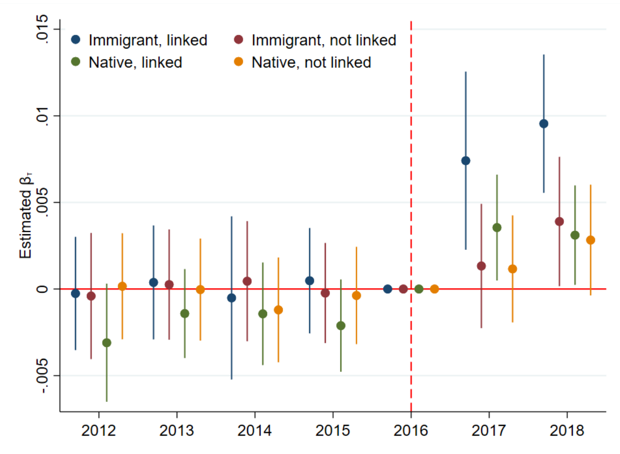

(c) Exports (in log)



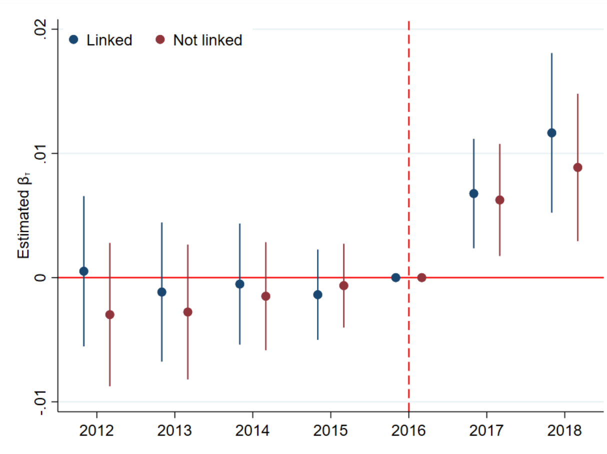

(d) Exports relative to total sales

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

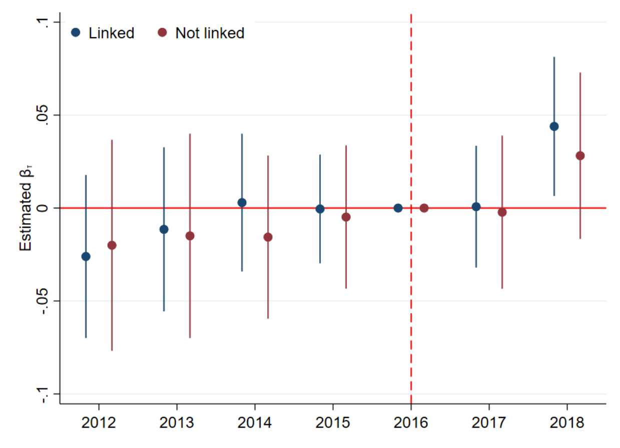
Figure E.13: Effects on firms based on the share of workers who lived in the US



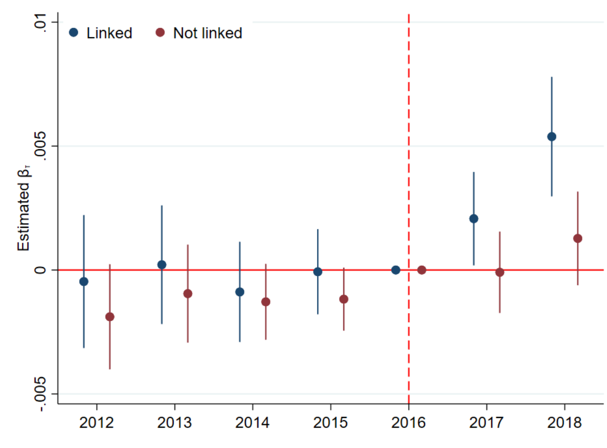

(a) Hiring relative to employment in 2016




(b) Sales (in log)



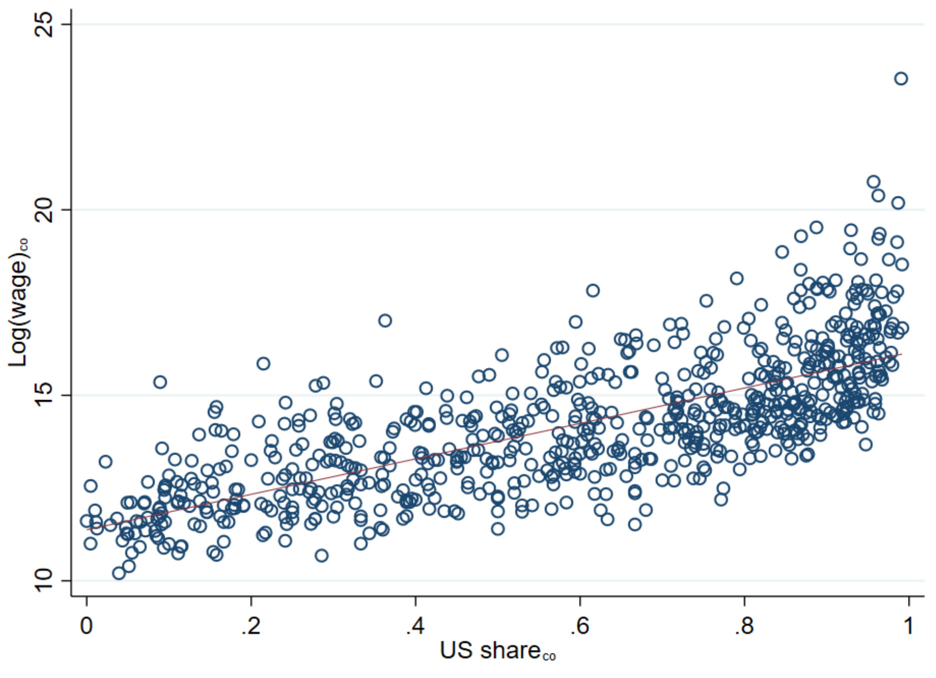

(c) Exports (in log)




(d) Exports relative to total sales

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

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




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

Table E.10: Crosswalk of classification of occupations

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

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

# Firm Heterogeneity and the Impact of Immigration: Evidence from German Establishments*

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**Abstract**

We use a detailed establishment-level dataset from Germany to document a new dimension of firm heterogeneity: large firms spend a higher share of their wage bill on immigrants than small firms. We show analytically that ignoring this heterogeneity in the immigrant share leads to biased estimates of the welfare gains from immigration. To do so, we set up and estimate a model where heterogeneous firms choose their immigrant share and then use it to quantify the welfare effects of an inflow of immigrants in Germany. When firms are heterogeneous in their immigrant shares, a new adjustment mechanism arises. Native workers reallocate across firms, which mitigates the competition effect between immigrants and natives in the labor market. If we ignore the heterogeneity in the immigrant share across firms, we would underestimate the welfare gains of native workers by 11%.

*JEL:* F16, F22, J24, J61
*Keywords:* Heterogeneous Firms, Migration, International Trade

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# 1 Introduction

During the past two decades, the number of immigrants in developed countries increased by more than 80%, which has fueled the academic and public debate regarding the impact of immigration on native workers. To study this question, most of the literature has assumed, implicitly or explicitly, that a representative firm exists. However, firms are heterogeneous along many dimensions such as size, productivity, export behavior, and demand for labor. In this paper, we ask whether such heterogeneity across firms matters to understand the effect of immigration on the welfare of native workers.

We start by using a detailed establishment-level dataset from Germany to document a new dimension of heterogeneity: large employers are more immigrant-intensive than small employers. We then show analytically and quantitatively that ignoring this heterogeneity leads to biased welfare gains from immigration. First, when firms are homogeneous, the elasticity of substitution between immigrants and natives in the labor market coincides with the within-firm elasticity. However, when firms are heterogeneous, the aggregate immigrant-native substitution elasticity depends on the within-firm elasticity and the elasticity of substitution across firms or goods. Thus, having different immigrant-intensities across firms allows for natives and immigrants to specialize in working for different employers, which makes them less substitutable in the labor market. Second, when firms are heterogeneous, the marginal cost gains are predominantly concentrated among the largest firms, which induces a stronger aggregate price decline. We find that if we ignore this heterogeneity, the welfare gains from an increase in immigration would be underestimated by 11%.

To characterize the relationship between employer size and immigrant intensity, we use a comprehensive employer-employee matched dataset of social security records in Germany between 2003 and 2011. We show that the median establishment in the top wage bill decile spends 5.6% of their wage bill on immigrants, while the median establishment in the fifth decile spends almost half of that (2.9%), and the median establishment in the bottom decile spends even less (0.4%). This relationship is stronger in the tradable sector, where the immigrant share of the top decile is 8%, while the immigrant share at the bottom decile is zero. We explore the mechanisms behind this relationship and provide evidence suggesting that firms may incur fixed hiring costs to start recruiting immigrants. We also rule out confounders such as differences in worker skills, production technologies, and local labor markets.

Next, we set up a model with heterogeneous firms to quantify the general equilibrium adjustment and welfare implications of an influx of immigrants. The model incorporates a tradable and non-tradable sector, the decision to export (Melitz, 2003), and crucially, the decision to hire immigrant labor. Consumers have preferences over a set of goods in each sector, which are aggregated in a CES fashion. Each good is produced by a single firm that can use immigrant and native labor as inputs, which we consider imperfect substitutes in production (Peri and Sparber, 2009, 2011).

We model the immigrant hiring decision following the input-sourcing literature (Antràs et al., 2017; Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015). Firms can choose to hire immigrant labor, but to do so they must incur two types of fixed costs: an initial fixed cost to start hiring immigrants, and an additional fixed cost for any new country they source immigrants from. Such fixed cost structure has two implications supported by the data. First, larger and more productive firms will be more likely than small firms to hire immigrants in equilibrium. Second, larger firms will also find it profitable to recruit immigrants from more countries and spend a larger share of their wage bill on immigrants. To fully capture the rich relationships between size and immigrant intensities across firms observed in the data, the model allows for two sources of firm heterogeneity: innate productivity and the cost of hiring immigrants, which are both drawn from a joint distribution.

We use a simplified version of this model to analytically show that the welfare predictions of a model that ignores the relationship between firm size and immigrant share are biased. To this end, we compare the welfare gains between our model with full heterogeneity and a model without heterogeneity in immigrant intensities. The sign of the bias depends on whether the elasticity of substitution between immigrants and natives is larger or smaller than the elasticity of demand, which regulates the change in the scale of production. When the substitution effect is stronger than the scale effect, immigrants crowd-out natives at immigrant-intensive firms who are reallocated toward native-intensive firms. By specializing in producing different goods than immigrants, natives become less substitutable in the labor market, and the downward pressure on wages induced by competition with immigrants is weaker than when natives do not reallocate across firms. Such reallocation across firms implies that the aggregate elasticity of substitution in the model with full heterogeneity is lower than in the model without heterogeneity, which makes the welfare gains from immigration larger.

The *magnitude of the bias* depends on the elasticity of demand, the elasticity of substitution between immigrants and natives, and the joint distribution between firm-level productivity and firm-level immigrant-hiring costs. Following Oberfield and Raval (2014), we estimate the elasticity of demand from the average firms' markups (i.e., the ratio of revenue to total costs). The substitution between immigrants and natives is structurally estimated using the firm's first-order condition with respect to immigrant and native labor. We regress the firm-level relative wage between immigrants and natives on relative employment, following an IV approach as in Ottaviano and Peri (2012). Since the quantities in our model are in effective units of labor, we provide a model-based method to back out the effective units from data on labor quantities and wages.

Given the estimates of these two elasticities, we estimate the joint distribution of productivities and costs to match the observed dispersion and correlation between firm-level revenues and immigrant-intensities in the data. These parameters are jointly estimated with the remaining parameters of the model through a Simulated Method of Moments (SMM) approach to match key targeted micro- and macro-level moments in Germany between 2003 and 2011. We show that the estimated model is capable of replicating the cross-sectional distribution of immigrant intensities across firms, even for important untargeted moments in the distribution.

We validate the model by comparing our model-predicted treatment effects of an increase in immigration across firm sizes with the observed treatment effects estimated independently from the model. Specifically, we regress firm revenues and the relative wage bill between immigrants and natives on the share of immigrants in the local labor market and its interaction with firm size. To identify the causal effect, we follow Ottaviano and Peri (2012) and instrument the share of immigrants in a labor market with a shift-share instrument that exploits country-of-origin variation in the initial network of immigrants across regions. For establishments in the tradable sector, we find that a 1% increase in the share of immigrants in the local labor market increases revenues for firms in the top decile by 2.16%, while it decreases revenues in the bottom decile by 0.42%. We also show that large establishments in the tradable sector become more immigrant-intensive than small establishments. For establishments in the non-tradable sector, we find weak heterogeneous effects in their response to immigration. The model does a good job in replicating the observed relative responses to immigration across firms in both sectors.

We use the estimated model to measure the welfare effects of a 20% increase in the total number of immigrants, which is what happened in Germany between 2011 to 2017 after the country unified its labor market with other EU countries. We find that native workers in both sectors benefit from immigration since wages are higher due to larger domestic and international demand, and prices are lower due to lower production costs. Revenues and profits increase for both sectors, but more so in the tradable sector, where firms are more intensive in immigrant labor. Natives reallocate within sector toward less immigrant-intensive firms and across sectors toward the non-tradable sector. In monetary terms, welfare gains from immigration amount to \$4 billion for native workers and \$15 billion for firm owners.

Finally, for our welfare results, we quantify the significance of accounting for the heterogeneity in the immigrant share. To do so, we keep the same estimates of the elasticity of substitution and the elasticity of demand, and re-estimate the remaining parameters of our model for the case where all firms spend the same share of their wage bills on immigrants. Such model is equivalent to a quantitative model estimated without firm-level data on immigrant labor, a data limitation commonly faced by the literature. Overall, the model without heterogeneity understates the change in welfare of natives by 11%, which is driven by an underestimation of both the drop in the price level and the increase in wages caused by immigration. The bias can be explained by two main components. First, the aggregate elasticity of substitution between immigrants and natives in the heterogeneous model is lower than when ignoring heterogeneity in the immigrant share. Second, even when using the same aggregate elasticity in both models, the largest and most productive firms, by being immigrant-intensive, benefit the most from the endogenous productivity gains generated by immigrants. As a result, their unit cost of production and the aggregate price drops by more than when ignoring heterogeneity.

Our paper contributes to the literature in three main ways. First, while some notable papers use general equilibrium models to study the impact of immigration (Burstein et al., 2020; Caliendo et al., 2021; Desmet et al., 2018; di Giovanni et al., 2015; Khanna and Morales, 2018; Morales, 2019), they tend to follow a neoclassical approach, where firms are assumed to be homogeneous in their immigrant hiring decisions. Relative to the existing quantitative models, we add the novel feature of firms endogenously choosing their immigrant intensities by following the literature on intermediate input sourcing (Antràs et al., 2017; Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015). This approach allows us to consider the firm as a fundamental channel where aggregate production and labor adjust to immigration. We document a large heterogeneity in the immigrant share across firms and, in light of this heterogeneity, we find that it matters for quantifying the aggregate impact of immigration.

Second, we also speak to an emerging literature that uses firm-level data to provide reduced-form evidence on the effect of immigration on firms (Arellano-Bover and San, 2020; Beerli et al., 2021; Brinatti et al., 2023; Brinatti and Guo, 2023; Card et al., 2020; Dustmann and Glitz, 2015; Egger et al., 2022; Kerr et al., 2015; Mahajan, 2020; Mitaritonna et al., 2017; Orefice and Peri, 2020). We contribute to this literature by documenting new facts regarding the relationship between firm size and immigration and by assessing the aggregate consequences of immigration with a general equilibrium model. In Section 8, we further discuss how our results compare to the findings of this literature and how the institutional context of Germany matters for our conclusions.

Third, we contribute to the literature that studies the importance of firm heterogeneity for aggregate outcomes. In the context of international trade, Arkolakis et al. (2012)

show that, conditional on having the same trade elasticity, the welfare gains from trade are the same for a class of heterogeneous and homogeneous firm models. As opposed to that class of heterogeneous firm models, we allow firms to be heterogeneous in their input shares and, building on Oberfield and Raval (2021), we show how this heterogeneity affects the *aggregate* elasticity of substitution between immigrants and natives.[1] Our new insight is that if firms are heterogeneous in their immigrant share, immigration induces a reallocation of *natives* across firms. Such reallocation affects the aggregate substitution between natives and immigrants and, in turn, the welfare gains from immigration.

# 2 Data

We use a detailed, employer-employee matched dataset from Germany provided by the Research Data Center (FDZ) of the Federal Employment Agency in the Institute for Employment Research (IAB). The main data source is the Longitudinal Establishment Panel (LIAB), which includes records for a large sample of establishments over the period 2003-2011.[2] The dataset contains full employment trajectories for each employee who worked at least one day for one of the establishments in the sample during the period. It also includes employee information on citizenship, occupation, education, and daily wage. Regarding citizenship, countries are grouped into ten regions: 1) Germany, 2) France, United Kingdom, Netherlands, Belgium, Austria, Switzerland, Finland, and Sweden, 3) Italy, Spain, Greece, and Portugal, 4) countries that joined the EU after 2004, 5) countries of former Yugoslavia not in the EU, 6) Turkey, 7) all other European countries including Russia, 8) Asia-Pacific, 9) Africa and Middle East, and 10) the Americas. On the establishment side, the dataset contains information on industry, location, and establishment-level financials such as revenues, investment, and material use, among others. More information on LIAB can be found in Heining et al. (2016).

A key variable needed for our analysis is workers' immigration status at a given establishment, but the German social security data records citizenship as opposed to country of birth. Since we are interested in country of birth, we redefine this key variable to make sure we count immigrants properly. The most common recoding is when observing individuals with a foreign citizenship become Germans the next period. If a worker is recorded as a foreigner for at least two periods, we classify them as an immigrant from

[1] Oberfield and Raval (2021) show that the aggregate elasticity between two inputs of production, labor and capital, depends on the elasticity of substitution within a firm and the reallocation of *market shares* across firms that employ capital and labor differently.

[2] The data basis of this paper is the Longitudinal Model (version 1993–2014) of the Linked Employer-Employee Data from the IAB. The data were accessed on-site at the Research Data Centre of the Federal Employment Agency at the Institute for Employment Research (FDZ) and/or via remote data access at the FDZ.

the initial citizenship country.[3]

It is important to note that the German administrative data is at the establishment level, and it is not possible to link multiple establishments to a single firm. Throughout the paper, we will use establishment and firm interchangeably. Also, while LIAB is not directly a representative sample of the population, we apply survey weights to get representative aggregates whenever necessary. For establishment location within Germany, our data includes an administrative sub-division of German states into districts called "Kreis." For part of our analysis, we also group districts into local labor market areas following the analysis of Kropp and Schwengler (2011), who use commuting flows to delineate functional labor markets. We complement the German administrative data with publicly available datasets from the World Bank to deflate wages and compute exchange rates, the World Input-Output tables for data on trade and international GDP, and the OECD for aggregate migration data.

# 3 Firms Are Heterogeneous in Their Immigrant Share

We present a series of facts that provide insight on how employers have different intensities on immigrants and use these facts to ground our model.[4] As a first step, we document that larger employers are more intensive in immigrant labor. We rank the establishments in our sample into wage bill deciles, where decile 1 includes the smallest establishments, and decile 10 includes the largest.[5] For each decile, we plot the median share of immigrant labor in the establishment wage bill to capture the firm-level intensity on immigrants. As shown in Figure 1, there is a monotonic and increasing relationship between employer size and immigrant intensity. The median establishment in decile 10 spends 5.6% of their wage bill on immigrants, while the median establishment in decile 5 spends only 2.9%, and the median establishment in the lowest decile spends even less, 0.4%.

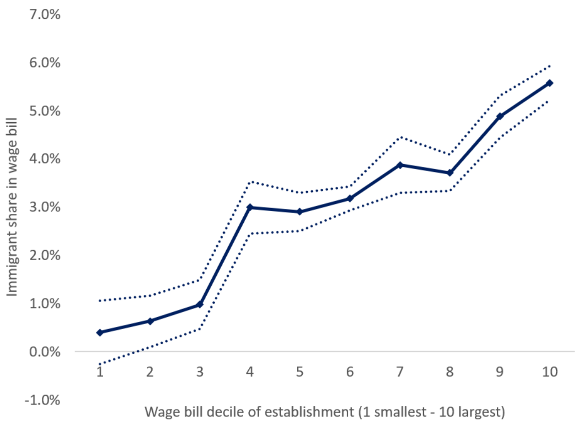
The relationship between employer size and immigrant intensity is not driven by specific confounders such as industry or labor markets. Large employers could be concentrated in industries that are more intensive in skills provided by immigrants. At the same time, immigrants might also concentrate in large cities where immigrant networks are larger, which also happens to be where large employers are located. However, none of these

[3] A second challenge is that some workers might join the labor market with a foreign citizenship, but they may have grown up in Germany to foreign parents. Our results are robust to recoding workers as natives if they have foreign citizenship and either join the labor force at age 20 or younger without a college degree, or join the labor force at age 25 or younger with a college degree.

[4] In Appendix A, we present summary statistics on the sample of establishments, and the distribution of immigrants across sectors and origin regions.

[5] We use wage bill as our main measure to rank establishments, but results are robust to using employment or revenues. We focus on establishments with more than 10 employees, but the relationship between size and immigrant intensity is still positive and strong when including smaller establishments.

Figure 1: Immigrant share of the wage bill across establishments




*Note.* We divide all establishments with more than 10 employees into total wage bill deciles, with 1 being the smallest establishments and 10 the largest. For each decile, we plot the median immigrant share of the total establishment wage bill. We calculate the 95% confidence interval using 200 bootstrap repetitions.

channels seem to explain the observed heterogeneity in immigrant intensities. As shown in the dashed lines in Figure 2a, the pattern remains strong after controlling for three-digit industry fixed effects and local labor market fixed effects, indicating that differences in production technologies or geographic destinations of immigrants alone cannot explain the observed relationship between size and immigrant-intensity.

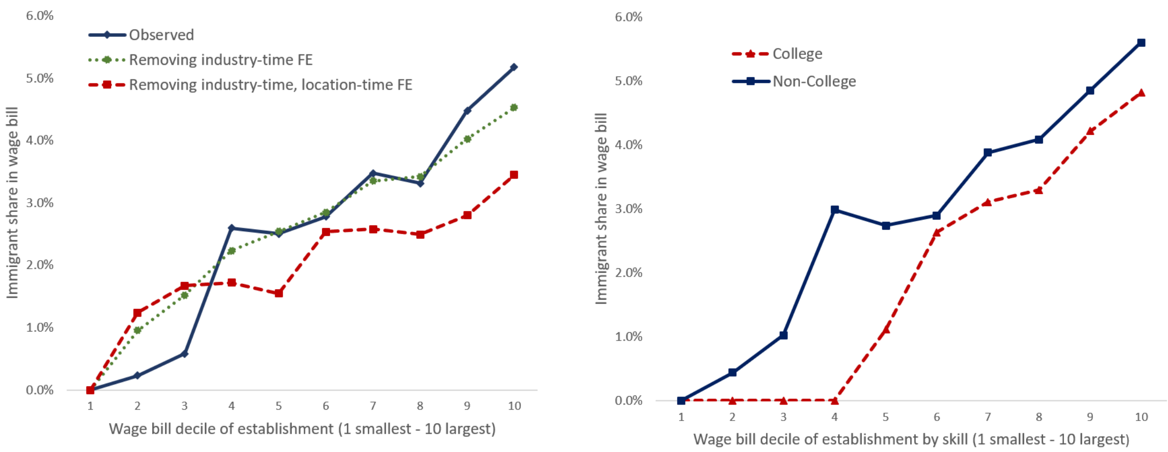
Our relationship of interest is also not driven by immigrant skills. Large firms tend to be more intensive in high-skill labor (Burstein and Vogel, 2017), and if immigration policy in Germany would be skewed toward workers with a specific education, this could drive the relationship between size and immigrant intensity. As shown in Figure 2b, the relationship between size and immigration holds for workers with and without a college education. Additionally, we corroborate that the observed patterns are not driven by the establishment being foreign-owned, or being part of a multi-unit firm. In the remainder of this Section, we discuss a possible origin of these observed patterns.

## Fixed costs to hire immigrants

The evidence presented thus far is consistent with the existence of fixed costs to hire immigrants, which act as a barrier to recruit immigrants and are particularly constraining for small firms. These fixed costs can capture different features of the hiring process. For instance, firms might need to train their staff into the administrative and legal hurdles of hiring immigrants. Once incurred, firms can start considering immigrant candidates as part of their hiring decisions. A separate type of costs can be related to a specific group of immigrants. For example, immigrants from specific countries might need to go through different visa application processes depending on their nationality. At the

Figure 2: Immigrant share across industries, labor markets, and skill groups

(a) All establishments (b) By education group




*Note.* We divide all establishments with more than 10 employees into total wage bill deciles, with 1 being the smallest establishments and 10 the largest. For each decile, we plot the median immigrant share of the total establishment wage bill. Decile 1 is normalized to 0. Left panel: we plot the observed median immigrant share, the residual median share after removing industry-time fixed effects, and the residual median share after we remove industry-time and location-time fixed effects. Right panel: we divide all establishments with more than 10 college and non-college employee, respectively, into total wage bill deciles. For firms in each decile, we plot the median immigrant share of total wage bill spent in each education group.

same time, screening and evaluating resumes might require country-specific knowledge or connections. Once firms begin hiring from a given origin, hiring costs from that origin are likely to become smaller due to the newly acquired information on the foreign labor market and access to the new immigrant's network (Egger et al., 2022).

Germany, is a good example of a setting where firms incur in such hiring costs to recruit immigrants. Before the EU labor market integration in 2011, most immigrants were required to have a guaranteed employment offer to migrate to the country which placed the responsibility of searching for candidates and incurring in recruitment and administrative expenses on the employer sponsoring the immigrant visa.[6] These obligations, however, were particularly challenging for smaller firms, which often operate with limited resources.

The OECD and the German Chamber of Commerce and Industry (DIHK) ran an employer survey in 2010 that provides qualitative evidence in support of an environment where small firms find it harder to hire immigrants (OECD, 2013). According to the report, despite widespread claims of labor shortages, relatively few employers in Germany have attempted to recruit labor migrants. The top three reasons for this trend are the

[6]Our framework is well suited to study cases where firms have an active role in finding and sponsoring immigrants. The US H-1B program where firms sponsor workers' visas is another example of such framework.

lack of German language skill of candidates, unclear and complex administrative procedures, and difficulties to contact candidates abroad. While law firms can help overcome the complexity of the immigration system and the administrative barriers, hiring their services is particularly costly for Small and Medium Enterprises (SMEs) with occasional needs, or first-time users.

Moreover, the German Employment Agency needs to verify that the employer petition to hire immigrants is legitimate and whether the working conditions offered to the foreign worker are not below those offered to German employees in the same occupation. These checks tend to be more severe when the employer is not well-known, as tends to be the case for SMEs. Finally, SMEs experience more difficulties in matching with candidates. For instance, in contrast to large firms, SMEs lack the option to recruit via intra-company transfer, and have fewer international connections.

The difficulty of SMEs to hire immigrants has even been the subject of public policy in Germany. Recently, the Ministry of Economics and Technology established a *"competence center for securing qualified labor for SMEs"* which provides, among other things, information and administrative support for the recruitment of foreign labor for SMEs.

We complement this anecdotal evidence with direct evidence from our data consistent with the presence of fixed costs to hire immigrants. As shown in Table 1, there is a significant mass of small firms that do not hire any immigrants. If immigrants and natives are imperfect substitutes, as documented extensively in the literature (Peri and Sparber, 2009, 2011), all firms would optimally choose to hire a strictly positive level of natives and immigrants, which contradicts the results in Table 1. However, firms need to pay a fixed cost to hire immigrants, profits earned by SMEs may not be enough to afford such fixed costs, limiting their choice to the hiring exclusively native workers.

Table 1: Share of firms that hire immigrants by firm size decile

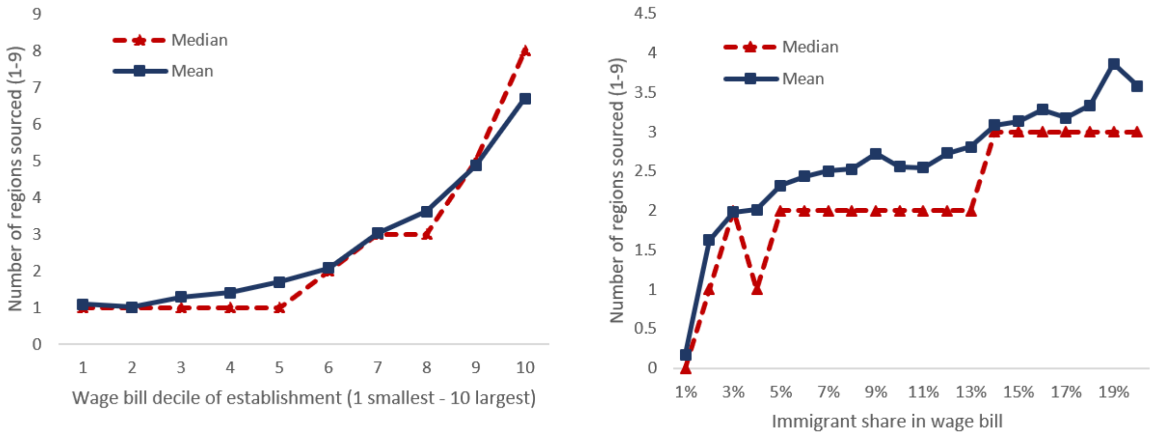
| Size deciles | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Share of firms | 0.39 | 0.36 | 0.43 | 0.50 | 0.53 | 0.63 | 0.66 | 0.80 | 0.87 | 0.97 |

*Note.* We divide all establishments with more than 10 employees into total wage bill deciles, with 1 being the smallest establishments and 10 the largest.

The relationship between size and immigrant intensity is directly related to the number of origin regions where firms hire from. As shown in Figure 3a, larger firms not only are more intensive on immigrants but also hire from more origins. Similarly, when firms expand their immigrant share, they seem to do so by hiring from additional regions as shown by Figure 3b. Such differences are not driven by large firms hiring a higher number of immigrants. A variance decomposition analysis suggests that 75% of the explained variation in the immigrant share across firms can be attributed to differences in the number of origin countries while the remaining 25% is explained by the number of immigrants hired.

Figure 3: Number of origin regions where firms hire from.

(a) By size (b) By immigrant share




*Note.* Panel (a) We divide all establishments with more than 10 employees into total wage bill deciles, with decile 1 including the smallest establishments and 10 the largest. Panel (b) We group all establishments with more than 10 employees by the share of the wage bill spent on immigrants into 20 bins (those who spend 0-1%, 1-2%, etc.). For firms in each bin, we plot the mean and median number of origin countries. In our sample, we have 9 immigrant origin regions, which are listed in section 2.

In Appendix B.1, we provide additional evidence that the fixed hiring costs are likely related to origin-specific costs borne by firms. Our data shows that when firms expand their origin countries, they typically do so incrementally by incorporating immigrants from just one additional origin at a time, rather than from multiple origins simultaneously. We also find that there is lumpiness in the hiring process. The year that the firm adds an additional country, there is a discrete *jump* in the number of employees hired employees from that country. These patterns are consistent with firms paying a *fixed* cost for each additional country they hire from. If this were not the case and the costs were variable, firms would start hiring small quantities of those immigrants and begin hiring from many origins simultaneously.

The relationship between immigrant share and firm size could also be explained by recent theories on the internal organization of firms, as in Caliendo et al. (2015). If larger firms with more layers of management can supervise and hire more immigrants than smaller firms, it could also rationalize the patterns in Figure 1. Alternatively, large firms could have a technology that is biased toward immigrants, which would also rationalize these patterns. However, these theories would not rationalize that larger firms also hire workers from more countries, and expand their immigrant share by increasing the number of source countries. The institutional setting in Germany also points to the existence of fixed costs to hire immigrants, which are particularly binding for smaller firms.

# 4 The Model

Our quantitative model has two main components: the labor demand and the labor supply. On the labor demand side, heterogeneous firms choose their optimal immigrant share, following the setup proposed by the literature on importing intermediate inputs (Antràs et al., 2017; Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015). Firms also choose whether to export their goods by paying a fixed cost as in Melitz (2003). The labor supply side is based on the combination of Eaton and Kortum (2002) model of comparative advantage with Roy (1951), commonly referred to as EK-Roy models.[7] We focus on the main components of the model and relegate derivations to Appendix C.

**Consumption:**

Domestic workers (indexed by $i$), supply $L_d$ effective units of labor inelastically and have Cobb-Douglas preferences for goods from two sectors indexed by $k$:

$$U_i = (Y_i^T)^\alpha (Y_i^{NT})^{1-\alpha} \tag{1}$$

where $Y^T$ stands for a tradable sector and $Y^{NT}$ for the non-tradable sector. Each sector $k$ is composed by a CES aggregate of varieties indexed by $z$ as in equation 2:

$$Y_i^k = \left( \int_{J_z} (y(z)_i^k)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where $J_z$ represents the set of varieties available in the country, and $\sigma > 1$ is the elasticity of demand. We focus on the tradable and non-tradable sector following Burstein et al. (2020). The tradability of the output produced by immigrants is a key feature to account for, as immigrants are absorbed differently in the labor market when working in tradable versus non-tradable occupations. Tradable sectors face a more elastic demand and can expand output more than non-tradable sectors in response to immigration. As shown in Appendix Figure 6, establishments in the tradable sector are more intensive in immigrants than similar sized establishments in the non-tradable sector. The tradable sector presents a stronger relationship between size and immigrant intensity than the non-tradable sector.

[7] The so-called EK-Roy models have been used to model individual choices across sectors (Lagakos and Waugh, 2013; Lee, 2020) and across countries to migrate (Morales, 2019), among many other applications.

**Production:**

In each industry $k$, there is a mass of N firms indexed by $j$ that produce a specific variety. Firms employ only labor inputs, which can be native "domestic" workers or immigrants. There is a long tradition in immigration literature to think about immigrants and natives as imperfect substitutes in production, as they have different comparative advantages across tasks and specialize in different occupations (Peri and Sparber, 2009, 2011). We assume that firms combine domestic and foreign effective units of labor ($d_j$ and $x_j$, respectively) in a CES manner as shown in equation 3. For simplicity, we omit the subscript $k$ from the equations below, but all parameters except for the elasticities are industry-specific:

$$y_j = \psi_j \left( \beta d_j^{\frac{\epsilon-1}{\epsilon}} + (1-\beta) x_j^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \tag{3}$$

where $\beta$ is a sector-specific distributional parameter that captures the average intensity in immigrant labor, $\epsilon$ is common across sectors and captures the degree of substitution between native and immigrant workers within the firm, and $\psi_j$ is an firm-specific productivity draw. Using CES properties, the unit cost can be written as in equation 4:

$$u_j = \left( \beta^{\epsilon} w_d^{1-\epsilon} + (1-\beta)^{\epsilon} W_{x,j}^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}} \tag{4}$$

where $w_d$ and and $W_{x,j}$ are the wage per effective unit of native and immigrant labor, respectively. Following CES properties for the expenditure share in a given input, we can write the domestic share as in equation 5:

$$s_{d,j} = \frac{\beta^{\epsilon} w_d^{1-\epsilon}}{\beta^{\epsilon} w_d^{1-\epsilon} + (1-\beta)^{\epsilon} W_{x,j}^{1-\epsilon}} = \frac{\beta^{\epsilon} w_d^{1-\epsilon}}{u_j^{1-\epsilon}} \tag{5}$$

If the wage per effective unit of immigrant labor, $W_{x,j}$, was the same across firms, the unit cost of production would also be the same. In that case, all firms, regardless of their productivity or size, would have the same immigrant and domestic shares. However, as shown in Section 3, the data suggests that the immigrant share is not constant across firms, and large firms have a larger intensity in immigrants than small firms. To incorporate this into the model, we need a theory on why firms hire different shares of immigrants and face different immigrant costs $W_{x,j}$.

As discussed in Appendix B.1, we find multiple features in the data that suggest that firms face fixed costs of hiring immigrants, and part of it seems to be dependent on the origin region of the immigrants hired. Larger firms are not only more intensive on immigrants than small firms, but also hire immigrants from more countries. Additionally, there is lumpiness in the observed hiring patterns when firms start hiring immigrants from a given region. Finally, the immigrant share of the firm has a strong correlation with the number of regions that the firm recruits from, even after controlling for the total number of immigrants hired. These features of the data are consistent with firms investing resources into learning how to recruit immigrants from additional origin regions.

**Environment to Recruit Immigrants:**

To theorize on the firm choice of its immigrant share that accommodates those facts and remains tractable in a general equilibrium framework, we follow Blaum et al. (2018) and Blaum (2019), who develop a theory of how firms choose their intermediate input share. We assume that the immigrant input of labor, $x_j$, is a composite of labor from different origin countries (indexed by $o$) as in equation 6:[8]

$$x_j = \left( \int_{\Sigma_j} \delta_o x_{j,o}^{\frac{\kappa-1}{\kappa}} d_o \right)^{\frac{\kappa}{\kappa-1}} \tag{6}$$

$\kappa$ is the elasticity of substitution between origin countries, such that every additional origin country the firm hires from will have a positive impact on productivity and lower the effective immigrant unit cost $W_{x,j}$ faced by firm $j$. The hiring strategy of the firm, denoted by $\Sigma_j$, represents those countries where the firm hires immigrants from, out of a total of $O$ origins. We denote the share of each origin in the production function by $\delta_o$.

Following the evidence presented in Section 3, we assume firms must pay a fixed cost $f_{imm}$ to begin hiring immigrants from abroad and a firm-specific fixed cost $f_j$ for each additional origin country it wants to hire from. For example, if the firm hires immigrants from two origins, it spends $w_d \times (f_{imm} + 2 \times f_j)$ in hiring costs. One interpretation is that the fixed cost $f_{imm}$ captures the costs of setting up a legal department or training HR staff in order to start hiring immigrants. The cost $f_j$ captures the learning cost that is country-specific, such as understanding foreign education credentials and labor experience necessary to screen workers.

We assume that hiring costs $f_j$ are jointly drawn with the firm-specific productivities $\psi_j$,

[8] Immigrants from different countries are assumed to be different inputs in the production function. Such differences can come from specialization across occupations due to differences in comparative advantages across origins (Hanson and Liu, 2023) or differences in cultural values across origins (Ek, 2023), among others.

from a multivariate sector-specific log normal distribution with mean $[\mu_\psi, \mu_f]$, dispersion $[\sigma_\psi, \sigma_f]$, and covariance between firm productivity draws and hiring costs of $\sigma_{\psi,f}$.

Choosing $\Sigma_j$ becomes computationally challenging because it requires computing profits for $2^O$ possible combinations of countries. To overcome this difficulty, we make a series of simplifications. First, we assume that foreign countries are perfectly ranked in terms of productivity $\delta_o$, such that firms will first source from the foreign country with the largest $\delta_o$ and move down the ladder as they source from more countries. This assumption simplifies the sourcing problem as it now boils down to choosing the mass of countries, $n \in [0, 1)$, to hire from. Second, we assume $\delta_o$ is a random variable distributed Pareto with shape parameter $\xi$ and scale parameter $\bar{\delta}$. This assumption allows us to get a closed form expression for the wage index of immigrants as in equation 7:[9]

$$W_{x,j} = w_x \underbrace{\frac{1}{\bar{\delta}^{\frac{\kappa}{\kappa-1}}} \left(\frac{\xi}{\xi - \kappa}\right)^{\frac{1}{1-\kappa}}}_{\bar{z}} n_j^{\overbrace{-\frac{1}{\kappa-1}\frac{\xi-\kappa}{\xi}}^{\iota}} \tag{7}$$

where $\iota > 0$ can be interpreted as the elasticity of the immigrant unit cost to expanding the mass of countries the firm hires from. The wage per effective unit of immigrant labor is denoted by $w_x$ and $\bar{z}$ stands for a combination of parameters. Intuitively, imperfect substitution of immigrants generates productivity gains from hiring immigrants from additional origins. This reduces the wage index of immigrants and the unit cost of production.

**Pricing Decision:**

For a given domestic share (and unit cost of production), firms choose the price that maximizes variable profits. Given that consumers have CES preferences, the optimal price is a constant markup over the marginal cost:

$$p_j = \frac{\sigma}{\sigma - 1} \frac{u_j}{\psi_j} \tag{8}$$

where $p_j$ is the price charged in the domestic market.

**Optimal Domestic Share:**

An advantage of this setup is that we can write the unit cost $u_j$, price $p_j$, and the optimal

[9]The specific implementation of these assumptions can be found in Appendix C.

mass of countries $n_j$ as a function of the key object $s_{d,j}$, as in equations 9 and 10:

$$p_j = \frac{\sigma}{\sigma-1}\frac{1}{\psi_j}\underbrace{\beta^{\epsilon} w_d^{1-\epsilon} s_{d,j}^{\epsilon-1}}_{u_j} \tag{9}$$

$$s_{d,j} = \frac{\beta^{\epsilon} w_d^{1-\epsilon}}{\beta^{\epsilon} w_d^{1-\epsilon} + (1-\beta)^{\epsilon} w_x^{1-\epsilon} (\bar{z})^{1-\epsilon} n_j^{\iota(\epsilon-1)}} \longrightarrow n(s_{d,j}) = \bar{\chi}\left(\frac{1}{s_{d,j}} - 1\right)^{\frac{1}{\iota(\epsilon-1)}} \tag{10}$$

where $\bar{\chi}$ is a combination of parameters and wages $w_d$, $w_x$. Equation 9 follows from equation 4 and the consumer's optimization problem. Equation 10 follows from equations 4, 5, and 7.

Firms maximize their profits by choosing the optimal native share $s_{d,j}$, as shown in equation 11:

$$\max_{s_{dj}} \Pi_j = \underbrace{\left(p_j(s_{d,j}) - \frac{u_j(s_{d,j})}{\psi_j}\right) y_j}_{\text{profits}} - \underbrace{n_j(s_{d,j}) f_j w_d - w_d f_{imm} \mathbb{I}(n_j(s_{d,j}) > 0)}_{\text{Sourcing cost}} \tag{11}$$

The main takeaways of the model are as follows: firms benefit from an immigration inflow because the wage of immigrants drops and so does the unit cost of production. The size of the drop in the unit cost of production is firm-specific, and it depends on the firm's domestic share.[10] In other words, the domestic share acts as a firm-exposure to a common immigration shock and becomes the key empirical object to learn about how much each firm (and the economy as a whole) benefits from immigration. The native share $s_{d,j}$ can be directly observed in our firm-level data and is the fundamental link between the model and the data.

How do firms choose their optimal domestic share? They face a trade-off between the drop in the marginal cost of production induced by complementarity of hiring from an additional country and the fixed cost to source from that additional country. Given their scale of production, larger firms earn higher profits and can afford paying $f_j$ more times than small firms. Thus, larger firms hire immigrants from more countries than small firms, and they become more immigrant-intensive.

**Export Decision and the Rest of the World (RoW):**

[10] Note that the benefit from the drop in unit cost of production is also firm-specific and depends on the firms size. For each percentual drop in the *unit* cost of production, larger firms benefit more than smaller firms because they produce more units.

Consumers in the RoW are assumed to have identical preferences over local and German varieties as in equation 2 with elasticity of demand $\sigma_x$.

German firms in the tradable sector can decide to export their goods by paying a fixed cost $f_x$, as in Melitz (2003). Therefore, a firm will choose to export if the variable profits from export sales are larger than $f_x$. The exporters choose the price to charge abroad to maximize export profits. The optimal price in that market is again a constant markup over total marginal cost, which now includes an iceberg cost $\tau > 1$ that represents a fraction of the good that gets "lost" in transit as in equation 12:

$$p_j^x = \frac{\sigma_x}{\sigma_x - 1} \frac{u_j \tau}{\psi_j} \tag{12}$$

Finally, conditional on its export decision, the firm chooses $s_{d,j}$ by solving a problem analogous to 11.[11]

Since our focus is the German economy, we make several simplifications to the modeling of the RoW. We assume it has a single tradable sector, foreign firms are equally productive, and use only domestic labor to produce with a constant return to scale production function $y_j^x = \bar{\psi}^x d_j^x$. Foreign firms also pay the iceberg trade costs to export their goods but do not have to pay a fixed cost to export.

**Labor Supply:**

Consumers are either firm owners, whose income are firms' profits, or workers who earn wages. We treat workers as heterogeneous in their sectorial skills by combining tools from the Eaton and Kortum (2002) model of trade and the Roy (1951) model of occupational selection. Specifically, we assume that each country $o = \{g, x\}$ has an exogenous number of workers born in $o$ ($N_o$). Each worker $i$ from $o$ draws a sector $k$, location $\ell$ specific ability ($\eta^o_{i,\ell,k}$) from a Frechet distribution with shape parameter $\nu > 1$, and scale parameter $A_{o,k}$ as in equation 13:

$$F(\eta) = exp\left(-\sum_k A_{o,k}(\eta)^{-\nu}\right) \tag{13}$$

where $A_{o,k}$ can be interpreted as the comparative advantage of workers from $o$ in industry $k$. Workers within a country are ex-ante identical but ex-post heterogeneous due to

[11] The model predicts that firms that hire immigrants are more likely to export, which provides a micro foundation for the empirical literature looking at the relationship between exports and immigration (Bonadio, 2020; Cardoso and Ramanarayanan, 2019; Gould, 1994; Hiller, 2013).

different ability draws across sectors, while workers from different countries also differ in that they draw their abilities from different distributions. Workers choose the industry and country that yield the highest utility as shown in equation 14:

$$U^o_{i,\ell,k} = \frac{w_{\ell,k}\eta^o_{i,\ell,k}}{P_\ell}\phi^{-1}_{o,\ell,k} \tag{14}$$

where $\frac{w_{\ell,k}\eta^o_{i,\ell,k}}{P_\ell}$ is the real wage, and $\phi_{k,o,\ell}$ are iceberg frictions for workers from country $o$ to work in industry $k$ and country $\ell$. The iceberg cost captures both the cost of working in a given sector and the migration cost of moving. For example, if Germany is very restrictive in letting migrants into the country, $\phi_{k,o=x,\ell=g}$ will be very high. For simplicity, we will assume the cost of migration out of Germany is infinity, such that German workers are immobile across countries. Following the properties of the Frechet distribution, the fraction of workers from country $o$ who choose to work in industry $k$ in destination location $\ell$ can be expressed as in equation 15:

$$\pi_{o,k,\ell} = \frac{A_{o,k}\left(\frac{w_{\ell,k}}{P_\ell}\right)^\nu \phi^{-\nu}_{o,\ell,k}}{\sum_{\ell,k} A_{o,k}\left(\frac{w_{\ell,k}}{P_\ell}\right)^\nu \phi^{-\nu}_{o,\ell,k}} \tag{15}$$

This expression shows that reducing migration costs from any $o$ to Germany increases the supply of immigrants into the country.

**Equilibrium and Market Clearing:**

The equilibrium in this model can be defined as a set of prices, wages, and labor allocations such that: workers optimally choose the industry and destination country $\ell, k$ to work for, consumers choose how much of each variety to purchase to maximize utility, firms choose the sourcing strategy and export status to maximize profits, labor markets clear, and trade is balanced. Appendix C includes the main equilibrium conditions.

## 4.1 Firm Heterogeneity and Welfare Gains

In this section, we show that ignoring heterogeneity in the immigrant share across firms may lead to biased estimates of the welfare gains of immigration. To that end, we compare the analytical welfare gains of a simplified version of our fully heterogeneous model with that of a model that ignores heterogeneity in immigrant share (but allows for heterogeneity in innate productivity).[12] We will refer to these models as the "heterogeneous model" and the "homogeneous model," respectively. The homogeneous model can be a special case of the heterogeneous model with $f_{imm} = f_j = 0$, or any model in the class of heterogeneous and homogeneous models following the Arkolakis et al. (2012) framework. Alternatively, it could be a model with CES preferences over goods coupled with the canonical production framework of immigration, with constant elasticity of substitution between immigrants and natives (Card, 2009; Dustmann and Glitz, 2015; Ottaviano and Peri, 2012; Peri and Sparber, 2009).

To simplify the model, we focus on a closed economy with one sector. We assume that native workers are homogeneous and set $f_{imm} = 0$, but leave the firm-specific fixed cost $f_j$ unrestricted. In this model, the welfare gains of immigration are given by the increase in real wages $\frac{w_d}{P}$ as shown in equation 16:

$$dlog\left(\frac{w_d}{P}\right) = -\frac{\sum_j \omega_j dlog(s_{dj})}{\epsilon - 1} = -\underbrace{\frac{dlog(S^{agg})}{\epsilon - 1}}_{\substack{\text{Prediction without} \\ \text{heterogeneity in } s_{dj}}} \frac{1}{1 + (\sigma - \epsilon)\underbrace{\Gamma(\{s_{dj}, \omega_j\})}_{\geq 0}} \tag{16}$$

where $\omega_j$ is the market share of firm $j$ ( $\omega_j \equiv \frac{p_j y_j}{\int p_j y_j dj}$) and measures firm $j$'s weight in the consumption basket, $S^{agg}$ stands for the immigrant share in the total wage bill in the economy, while $\Gamma$ is a function that depends on the joint distribution of firm-level market shares ($\omega_j$) and native shares ($s_{dj}$).

The first component of expression 16 coincides with the welfare prediction of models that ignore heterogeneity in $s_{dj}$. In these models, immigration reduces the unit cost of production for all firms and, as firms become more competitive, they increase their scale of production, demand for native labor, and wages. The size of these gains depends on the size of the inflow and on $\epsilon$ as it regulates how substitutable immigrants and natives are in the labor market. The more substitutable immigrants and natives are, the lower the productivity gains for firms, and the lower the welfare gains for natives.

The welfare predictions of the homogeneous model may be biased if there is heterogeneity in the presence of immigrants across firms. Under heterogeneity, a new adjustment mechanism arises, because native workers reallocate across firms with different immigrant intensities. Such reallocation has two main implications. First, when firms are heterogeneous, the aggregate elasticity of substitution between immigrants and natives depends on the within-firm elasticity ($\epsilon$) and the elasticity of substitution across firms or goods ($\sigma$). Thus, having different immigrant-intensities across firms allows natives to specialize in working for specific employers, which can make them more or less substitutable with

[12] All derivations are included in Appendix D.

immigrants in the aggregate labor market. Second, there is a complementarity between firm efficiency and the firm-specific endogenous productivity gains from immigration. As these gains are largely concentrated among the largest and most productive employers, there is an additional aggregate productivity gain that is not present in the homogeneous model. Hence, even if we estimate the homogeneous model with the same aggregate elasticity than the one predicted by the heterogeneous model, there can still be first-order differences between their welfare predictions.

When firms are heterogeneous in their immigrant share, the *aggregate* elasticity of substitution between immigrants and natives ($\epsilon^{agg}$) is a weighted average between the elasticity of substitution within the firm ($\epsilon$) and the elasticity of substitution across firms ($\sigma$):

$$\epsilon^{agg} = (1-\pi)\,\epsilon + \pi\,\sigma \tag{17}$$

where $\pi$, and hence $\epsilon^{agg}$, depend on the distribution of $s_{dj}$. The weight $\pi$ is proportional to the cost-weighted variance of immigrant shares and lies between zero and one (see Oberfield and Raval (2021) for a derivation), taking the value of zero if firms employ the same immigrant share. The first term, $(1-\pi)\,\epsilon$, measures the substitution effect within firms; whereas the second term, $\pi\,\sigma$, measures a reallocation effect across firms with different immigrant-intensities.

In the edge case of $\epsilon = \sigma$, the substitution and scale effects cancel out, immigrants do not crowd-in or crowd-out native workers, and native employment at the firm level does not change.[13] Given that the reallocation of natives across firms is muted, the demand response for native labor and welfare gains are the same as those predicted by the homogeneous model.

When the elasticity of substitution within the firm is stronger than the elasticity of demand ($\epsilon > \sigma$), immigrants crowd-out natives from immigrant-intensive firms, and natives are reallocated toward native-intensive firms. Such increase in specialization between natives and immigrants in producing different varieties makes them less substitutable in the labor market than when natives do not reallocate across firms. Given that this reallocation adjustment is absent if firms employ the same immigrant share, the increase in both, the aggregate demand for natives and welfare are larger in the heterogeneous world.

[13]The relative change in employment of natives across firms is proportional to the change in immigrant share. Let $\tilde{x} \equiv dlog(x)$, then $\tilde{d}_j - \tilde{d}_{j'} = \frac{\epsilon-\sigma}{\epsilon-1}\left(\tilde{s}_{dj} - \tilde{s}_{dj'}\right)$ and, to a first order approximation, $\tilde{s}_{dj} \approx (\epsilon-1)(1-s_{dj})(\tilde{w}_{imm} - \tilde{w}_d)$. Thus, the drop in relative wage of immigrants induced by an immigration inflow reallocates natives toward native-intensive firms if $\epsilon > \sigma$ and toward immigrant-intensive firms if $\epsilon < \sigma$.

When the elasticity of substitution is weaker than the elasticity of demand ($\epsilon < \sigma$), the opposite happens. Immigrants crowd-in natives toward immigrant-intensive firms, and this reallocation pattern increases the concentration of immigrants and natives in producing a similar set of varieties. As a result, immigrants and natives become more substitutable in the labor market when compared to the homogeneous world, and the increase in real wages and welfare are lower.

Overall, equation 16 shows that the sign of the bias depends on the race between $\epsilon$ and $\sigma$. In Section 5, we estimate these elasticities and find that $\hat{\epsilon} > \hat{\sigma}$, suggesting that welfare gains predicted by the homogeneous model are downward biased. Equation 16 also shows that the size of the bias depends not only on these two elasticities, but also on the joint distribution of firm size and immigrant share through $\Gamma(\{s_{dj}, \omega_j\})$. We estimate our model to match moments on the joint distribution of $s_{dj}$ and $\omega_j$ and find that the homogeneous model underestimates welfare by 11%.[14]

As noted by Arkolakis et al. (2012), there is a class of heterogeneous and homogeneous models where, if calibrated to the same aggregate elasticity and change in aggregate domestic trade share, would yield the same welfare gains. In our case, however, we would still expect a bias even if we assign the same aggregate elasticity to both models. The reason is that the endogenous productivity gains generated by firms choosing their $s_{dj}$ are stronger for larger and more productive firms, an adjustment channel that is absent in the homogeneous model. Intuitively, conditioning on $\{s_{dj}\}$, $\epsilon^{agg}$ is independent from $\omega_j$, meaning that $\epsilon^{agg}$ is not informed by *which* firm benefits by how much (e.g., the joint distribution of $\{s_{dj}, \omega_j\}$). Consequently, $\epsilon^{agg}$ will not capture the first-order heterogeneous response and resulting reallocation of natives across firms that arises when firms are heterogeneous.

The discussion on whether the fully heterogeneous firm model provides new welfare implications of immigration has similarities and differences with the discussion offered by Melitz and Redding (2015) about the welfare implications of trade. Similar to their paper, our heterogeneous model differs from the homogeneous model in that the elasticity (of substitution) is endogenous, and the homogeneous model does not capture the extra adjustment mechanism that arises when we allow for heterogeneity. However, opposite of their paper, the differences in welfare predictions in our setup are of first-order importance and do not vanish for small immigration inflows.[15]

[14] Additionally, equation 16 shows that the size of immigration shock does not affect the size of the bias, which we also corroborate quantitatively in Appendix G.3.

[15] In Section 7.2, we show quantitatively that the welfare prediction of the homogeneous model with the aggregate elasticity generated by the heterogeneous model reduces, but does not eliminate the bias. Such bias remains large even for inflows of immigrants as small as 0.1%.

# 5 Estimation

As discussed in Section 4.1, the key parameters of the model are $\epsilon$, $\sigma$, and parameters that determine the joint distribution of firm productivities and fixed costs to hire immigrants. In this section, we explain how we use German administrative data to estimate these key parameters of the model.

### Elasticity of Demand

We use micro-data to identify the elasticity of demand that firms face. Following Oberfield and Raval (2014), we infer the demand elasticity from firms' markups, i.e., the ratio of revenue to total costs. According to the model, the following condition holds for every firm $j$:

$$\frac{Revenue_j}{Cost_j} = \frac{\sigma_j}{\sigma_j - 1}$$

where $Revenue_j$ stands for the revenues of firm $j$, and $Cost_j$ denotes production costs. Although the model assumes that the only production costs are labor costs, we compute total cost as the sum of wage bill and material bill. The average markup is 1.4, which implies that the elasticity of demand is 3.08. This estimate is consistent with the values used in the literature, where this parameter takes values between 3 and 4.

We use data on markups for exporters relative to non-exporters in the tradable sector to back out the implied demand elasticity from the RoW. The observed markup for exporters can be expressed as a weighted average between the domestic markup (depending on $\sigma$) and the export markup (depending on $\sigma_x$). Using the exports as a share of revenues as weights, we calibrate $\sigma_x = 3.62$.[16]

### Elasticity of Substitution Between Native Workers and Immigrants

In the model, firm $j$'s demand of immigrants relative to natives is given by (18):

$$ln\Big(\frac{w_j^d}{w_j^x}\Big) = ln\Big(\frac{\beta^k}{1-\beta^k}\Big) - \frac{1}{\epsilon} ln\Big(\frac{d_j}{x_j}\Big) \tag{18}$$

where $w_j^d$ is the effective wage paid by firm $j$ to native workers, and $d_j$ is native employment in effective units, $w_j^x$ is the effective wage paid for the immigrant labor bundle, and $x_j$ is the composite immigrant labor defined by 6.

Estimating equation (18) presents a number of challenges. First, effective wages and quantities are not observed directly in the data. Second, estimating equation (18) by

[16] More specifically, we use the following equation: markup exporters = share exports $\times \frac{\sigma_x}{\sigma_x - 1} + (1 -$ share exports$) \times \frac{\sigma}{\sigma - 1}$. As we observe the markup for exporters and export share in the data, we can back out $\sigma_x$ using our estimated value of $\sigma$.

OLS would yield biased estimates of $\epsilon$, since unobserved demand shocks at the firm level can affect the relative quantities of immigrants and natives and the wages firms pay to each labor type.

To address these challenges, we proceed sequentially. First, as we explain in Appendix E.2, we use the structure of the model to estimate the immigrant composite $x_j$ based on observed data on labor quantities and wages across origin countries and industries. Second, we propose an instrument to structurally estimate $\epsilon$ from equation (18).

To summarize our empirical strategy, we construct a shift-share instrument that exploits immigrant networks to create a supply push at the local labor market level that is plausibly independent from demand shocks at the firm level. The first stage is strong with an F-stat above 20, and our preferred estimate for $\epsilon$ is 4.28, which is close to the estimates of Burstein et al. (2020), who find an elasticity of substitution between immigrants and natives within occupations of 5. Appendix E.2 describes the dataset construction, instruments, and results in detail.

**Additional Parameters**

Given the estimates for the elasticity of demand and the elasticity of substitution between immigrants and native workers, we calibrate the parameters of the model by simulated method of moments to match micro- and macro-level moments. This approach serves as a bridge between aggregate data on trade and immigration and what we have learned about firm heterogeneity from the firm-level data.

As a first step, we proceed to do some normalizations, since not all parameters can be separately identified. The mean fixed costs of hiring immigrants ($\mu_{f,k}$), the mean productivity of immigrants ($A_{o,k}$), and the migration cost ($\phi_{o,\ell,k}$) cannot be separately identified from the immigrant share in the production function ($\beta_k$), so we normalize the first one to 0 and the remaining two to 1. We assume the mean productivities in each sector are equal to 1 ($\mu_{\psi,k} = 1$) and set the elasticity of labor supply $\nu = 6.17$ following Morales (2019). Finally, we calibrate the Cobb Douglas parameter $\alpha = 0.68$ to match the domestic expenditures in the tradable and non-tradable sectors using World Input-Output Tables (WIOT).

As a second step, we are left with fourteen parameters, which we jointly estimate using a SMM approach by minimizing the distance between fourteen moments simulated by the model and fourteen empirical moments computed from the data. While all parameters are estimated together, there is strong intuition regarding which parameters identify which moments. The variance of log revenues conditional on the immigrant share and exporter status is used to identify the dispersion parameter on productivities $\sigma_{\psi,k}$. The observed variance of the immigrant-share relative to the domestic share identifies the variability of fixed costs $\sigma_{f,k}$, while the difference in the mean of $s_{d,j}$ between firms in percentile 90 relative to percentile 50 are used to identify the correlation between productivities and hiring costs $\sigma_{\psi,f,k}$. These three parameters for each sector estimate the joint distribution between size and immigrant intensity, a key ingredient for the quantitative model.

For the remaining parameters, we use the aggregate immigrant share by sector to identify $\beta_k$, the distributional share parameter in the production function. The fraction of firms that hire immigrants helps identify the base fixed hiring costs $f_{imm,k}$. The average immigrant share across all firms and sectors is used to identify $\iota$, the elasticity on how the immigrant cost changes with the mass of countries the firm hires from. For trade moments, we match the mean ratio of export to domestic revenues for exporters to identify the iceberg cost and the fraction of firms that export in the tradable sector to match the fixed cost of exporting $f_x$. Finally, we use aggregate data to compute the relative GDP per capita between Germany and the RoW, which helps identify the mean productivity of the RoW $\bar{\psi}^x$.

Table 2 shows the fourteen moments that are targeted in the estimation, their observed values in the data and the ones generated by the model. For all fourteen moments, the model does a good job in approximating their observed values. Table 3 contains the final calibration of the fourteen parameters that minimize the distance between simulated and empirical moments.

While the model matches the targeted moments, we want to make sure it also matches non-targeted moments that are relevant to our main mechanisms. As shown in Appendix E.2, the model does a good job in matching the cross-sectional means and medians of the immigrant share by size decile.

Table 2: Simulated vs data moments

| Moment description | Simulated | Data | Moment description | Simulated | Data |
|---|---|---|---|---|---|
| Aggregate $s_{d,T}$ | 0.91 | 0.91 | $\mathbb{E}(s_{d,NT,p90}) - \mathbb{E}(s_{d,NT,p50})$ | 0.009 | 0.008 |
| Aggregate $s_{d,NT}$ | 0.93 | 0.93 | Share of firms hiring immigrants, $T$ | 0.57 | 0.62 |
| $\mathbb{V}ar(log(rev_j)\vert s_{d,j}, exporter_j)$, T | 1.38 | 1.38 | Share of firms hiring immigrants, $NT$ | 0.63 | 0.61 |
| $\mathbb{V}ar(log(rev_j)\vert s_{d,j})$, NT | 1.23 | 1.29 | GDP per capita RoW to Germany | 0.32 | 0.32 |
| $\mathbb{V}ar((1-s_{d,T})/s_{d,T})$ | 1.36 | 1.39 | Share of firms exporting, T | 0.34 | 0.37 |
| $\mathbb{V}ar((1-s_{d,NT})/s_{d,NT})$ | 1.48 | 1.58 | $\mathbb{E}$(Export to Domestic Rev$_j$), T | 0.80 | 0.79 |
| $\mathbb{E}(s_{d,T,p90}) - \mathbb{E}(s_{d,T,p50})$ | 0.015 | 0.021 | $\mathbb{E}(s_d)$ | 0.93 | 0.93 |

Table 3: Parameter estimates using Simulated Method of Moments

| Parameter description | Parameter | Estimate | Parameter description | Parameter | Estimate |
|---|---|---|---|---|---|
| Share of natives, $T$ | $\beta_T$ | 0.84 | Covariance of $\psi$ and $f_j$, NT | $\sigma_{\psi,f,NT}$ | 8.17 |
| Share of natives, $NT$ | $\beta_{NT}$ | 0.86 | Fixed cost of immigrants, T | $f_{imm,T}$ | 3.41E-04 |
| Dispersion in $\psi_j$, T | $\sigma_{\psi,T}$ | 1.02 | Fixed cost of immigrants, NT | $f_{imm,NT}$ | 9.66E-04 |
| Dispersion in $\psi_j$, NT | $\sigma_{\psi,NT}$ | 0.35 | Productivity in RoW | $\psi_x$ | 1.52 |
| Dispersion in $f_j$, T | $\sigma_{f,T}$ | 1048 | Fixed cost of exporting | $f_g$ | 0.011 |
| Dispersion in $f_j$, NT | $\sigma_{f,NT}$ | 1710 | Iceberg trade cost | $\tau$ | 1.49 |
| Covariance of $\psi$ and $f_j$, T | $\sigma_{\psi,f,T}$ | -2.65 | Elasticity $s_d$ to $n$ | $\iota$ | 0.013 |

# 6 Model Validation: Heterogeneous Response

Before quantifying the aggregate implications of a change in the number of immigrants in Germany, we evaluate whether the data validates the main mechanisms proposed by the model. First, the model predicts that large firms, who are more immigrant-intensive than small firms, will experience a larger increase in terms of revenues. Second, given that $\hat{\epsilon} > \hat{\sigma}$, larger firms will increase their immigrant share relative to smaller firms. Such heterogeneity in the response to immigration is expected to be larger in the tradable sector, where the relationship between size and immigrant intensity is stronger.

We begin by estimating a regression as shown in equation 19:

$$ln(y_{j,m,k,t}) = \theta_1 \ S^{agg}_{m,t} \ + \theta_2 \ S^{agg}_{m,t} \ log(emp_{j,t-1}) \ + \theta_3 \ X_{j,t} \ + \delta_j \ + \delta_{k,t} \ + \delta_m t \ + \epsilon_{j,m,k,t} \quad (19)$$

where $y_{j,m,k,t}$ is an establishment-level outcome such as sales, for establishment $j$ located in labor market $m$, industry $k$, in year $t$. The regressor $S^{agg}_{m,t}$ is the share of immigrants in the total wage bill of labor market $m$ in year $t$, $emp_{j,t-1}$ is establishment size measured by employment, and $X_{j,t}$ are establishment-level control variables. This model allows for labor markets to be in different linear trends as captured by $\delta_m t$. It also includes industry-time fixed effects to control for factors affecting all establishments in an industry over time and an establishment fixed effect to control for unobservable characteristics that are time-invariant.

We define the immigrant shock $S^{agg}_{m,t}$ at the local labor market level as we aim to understand how different establishments adjust within a labor market whenever there is an immigration influx. The key parameter of interest is $\theta_2$: if positive, it implies that a rise in the share of immigrants in a labor market promotes faster growth for larger establishments compared to smaller ones in the same market. Thus, $\theta_2 > 0$ will suggest that larger establishments respond more to immigration than small establishments.

Even though the fixed effects and controls included in the empirical specification aim to capture unobservable shocks and establishment heterogeneity, ordinary least squares (OLS) estimates will be upward biased if, for example, productivity shocks at the local labor market level improve establishment outcomes and attract migration inflows into the region. To address these endogeneity concerns, we follow an IV approach inspired by Card (2001) and Ottaviano et al. (2018), and define a shift-share instrument as shown in equation 20:

$$Z_{m,t} = \sum_{o} \frac{\text{Wage Bill}_{o,m,2003}}{\text{Wage Bill}_{m,2003}} \frac{1+\gamma_{o,t}^{GER}}{1+\gamma_{t}^{GER}} \tag{20}$$

where $\text{Wage Bill}_{o,m,2003}$ is the wage bill earned by immigrants from origin country $o$ in labor market $m$ in our initial year 2003. $\text{Wage Bill}_{m,2003}$ is the total wage bill spent across all foreign origin countries in 2003 ($\sum_o \text{Wage Bill}_{o,m,2003}$). The initial share is interacted with a time-shifter that captures the national growth rate, from 2003 to year $t$, of immigrants from origin $o$ relative to the working-age population growth in Germany. Thus, this shift-share instrument interacts country-specific flows of migration with their initial differential presence in local labor markets in Germany. The validity of this instrument relies on the assumption that the geographic distribution of immigrants by origin in 2003 is not correlated with local economic conditions in any year $t$ once we control for fixed effects that capture unobservable differences across establishments, industries, and local labor markets. The interaction term is instrumented by $Z_{mt}\ log(emp_{j,2003})$.

For the sake of the economic interpretation of the effect of an immigration shock, we compute the elasticity or semi-elasticity of $y_{j,m,k,t}$ to $S_{m,t}^{agg}$, denoted as $\epsilon_{j,m,k,t}^{y}$, as follows:

$$\epsilon_{j,m,k,t}^{y} \equiv \Big(\theta_1\ + \theta_2\ log(emp_{j,t-1})\Big) S_{m,t}^{agg} \tag{21}$$

when the outcome variable of the regression is $log(y)$, $\epsilon_{j,m,k,t}^{y}$ equals the elasticity of $y$, and when the regression outcome variable is $y$, it equals the semi-elasticity.[17] The elasticity of firm $j$'s outcome $y_{j,m,k,t}$ to an immigration shock depends on both its size and the share of immigrants in the labor market where it operates.

[17]Specifically, equals $\frac{\partial y_{j,m,k,t}}{\partial S_{m,t}^{agg}} \frac{S_{m,t}^{agg}}{y_{j,m,k,t}}$ and $\frac{\partial y_{j,m,k,t}}{\partial S_{m,t}^{agg}} S_{m,t}^{agg}$, respectively.

## 6.1 Results

We present the estimates of equation 19 using total revenues and the ratio of immigrant to native wage bill as the outcome variable to show that larger firms expand more and become more immigrant-intensive in response to an immigration shock.

Table 4 presents estimates for total revenues for the full sample in columns 1 to 3 and separately for the tradable and non-tradable sectors in columns 4 and 5. Columns 6 to 8 present results using the immigrant to native wage bill ratio as the outcome. The OLS estimate in column 1 shows that, on average, establishments in local labor markets with larger increases in the share of immigrants register larger revenue growth. Column 2 shows that the 2SLS estimate is lower than the OLS estimate consistent with the hypothesis that OLS estimates are upward biased.[18] The 2SLS estimate suggests that immigration into a local labor market has no statistically significant impact on establishments' revenues. However, the average effect masks significant heterogeneity, uncovered in column 3. After accounting for the heterogeneous effect across establishment sizes, the average effect is negative and strong. That is, an increase in the share of immigrants in the labor market shrinks firms' revenues on average, and increases the revenue of large establishments relative to small establishments. The implied threshold size of the establishment, above which the elasticity is positive, is 71 employees.

Columns 4 and 5 show that the heterogeneity in size is driven primarily by establishments in the tradable sector, where large establishments grow their revenues significantly more than small establishments. Establishments in the non-tradable sector do not seem to differentially respond to the immigration shock, consistent with the patterns in Figure 6, where establishments in the non-tradable sector presented a low correlation between immigrant share and size.

Columns 6 to 8 show the the 2SLS estimates for the firm-level ratio between immigrant and native wage bill. Column 6 suggests that immigration into a local labor market has no impact on the immigrant intensity of establishments, but once again, this result masks significant heterogeneity across sectors. Column 7 shows that large firms in the tradable sector increase their immigrant-intensity relative to small firms: firms with more than 33 employees increase their immigrant-intensity, while smaller firms become more native-intensive. However, Column 8 shows that this heterogeneous effect across firm size is absent in the non-tradable sector, as expected based on the relatively flat relationship between firm size and the immigrant-share shown in Figure 6.

Table 5 presents the results in terms of elasticities by firm size and sector, which will be used to compare the elasticities implied by our quantitative model. In the tradable

[18] First stages can be found in Appendix Table 15.

sector, a 1% increase in the immigrant share decreases establishments' revenues in the lowest size decile by 0.42% while increasing establishments' revenues in the highest decile by 2.16%. The elasticity of revenues in the non-tradable sector, on the other hand, seems to be similar across establishments of different size.

We find a similar pattern in each sector when looking at the response of the relative wage bill between immigrants and natives across size deciles. In the tradeable sector, a 1% increase in the share of immigrants in the labor market would increase the ratio of an establishment in the lowest decile by 0.01 while increasing the ratio for an establishment in the highest decile by 0.21. The elasticities across deciles in the non-tradable sector seem to be decreasing with size but are not statistically significant.

Table 4: Heterogeneous benefits of immigration

| | Log of Revenues | | | | | Immigrant-Native Wage Bill | | |
|---|---|---|---|---|---|---|---|---|
| Sector | All | All | All | Tradable | Non-Tradable | All | Tradable | Non-Tradable |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\theta_1$ | 5.83*** | 2.99 | -31.86*** | -57.56*** | 6.81 | 0.2 | -3.13* | 6.14 |
| | (1.98) | (3.29) | (11.47) | (16.95) | (17.78) | (1.7) | (1.72) | (4.12) |
| $\theta_2$ | | | 7.49*** | 13.28*** | -0.44 | 0.18 | 0.9** | -1.07 |
| | | | (2.46) | (3.66) | (3.48) | (0.36) | (0.43) | (0.78) |
| Average $\epsilon^y$ | | | 0.28 | 0.54 | 0.26 | 0.06 | 0.08 | 0.05 |
| N observations | 3507 | 3507 | 3507 | 1974 | 1533 | 3507 | 1974 | 1533 |
| N establishments | 949 | 949 | 949 | 532 | 417 | 949 | 532 | 417 |
| Estimation | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS |
| 1st stage F-stat | | 372.23 | 35.85 | 29.47 | 15.53 | 35.85 | 29.47 | 15.53 |

*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employees.

In Appendix F, we also show that export revenues are more elastic than domestic revenues, as predicted by the model. These estimates imply that for every 1% increase in the immigrant share of the labor market, domestic revenues increase by 0.44%, whereas export revenues increase by 1.15%. Since the response of export revenues is stronger than domestic revenues, this channel can explain part of the heterogeneous effects found in Table 4. Large establishments, which are more likely to be exporters, may adjust more to the immigration shock because they are able to expand their export revenues, whereas for small firms, expansion is constrained by the size of the domestic market.

Appendix F also shows alternative specifications of equation 19, where we remove the industry-time fixed effects, the local labor market time trends, and the firm controls.

Table 5: Response to immigration by firm size

| | Size deciles | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Tradeable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Revenues | -0.42 | -0.28 | -0.06 | 0.03 | 0.2 | 0.41 | 0.57 | 0.81 | 1.41 | 2.16 |
| Relative Immigrant WB | 0.01 | 0.02 | 0.03 | 0.05 | 0.07 | 0.08 | 0.1 | 0.11 | 0.16 | 0.21 |
| Non-Tradeable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Revenues | 0.25 | 0.23 | 0.24 | 0.13 | 0.22 | 0.22 | 0.21 | 0.21 | 0.2 | 0.27 |
| Relative Immigrant WB | 0.14 | 0.11 | 0.1 | 0.08 | 0.07 | 0.06 | 0.04 | 0.03 | 0 | -0.06 |

*Note.* We rank establishments in terms of employment and for each decile, compute the mean elasticity of revenues and semi-elasticity of spending in immigrants relative to natives in response to a 1 percent change in the local labor market immigrant share. We compute the average of 21 for each decile using the same sample as in Table 4.

Overall, the qualitative implications of our results hold under the alternative specifications. We also run a set of specification tests to verify the validity of our instrument following the recent literature on shift-share instruments as suggested by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2021), among others. We find no evidence of pre-trends, and other labor market characteristics drive little variation in the initial shares used to construct the shift-share instrument.

## 6.2 Predicted Treatment Effects: Data vs. Model

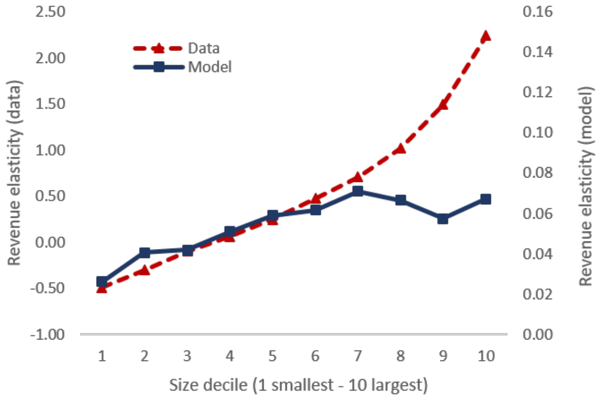
As a final step, we assess whether our model can generate counterfactual predictions that match the observed heterogeneous treatment effects across employer sizes estimated in Table 5. This is a key validation of the model as the reduced form estimates in this section have not been targeted at all for the estimation of the model. First, we use our estimated model to compute, for each firm, the revenue and relative wage bill elasticities in response to a 1% change in the immigrant share in each sector. Then, we divide the firms in the model into size deciles and calculate the mean elasticity for each decile.[19] Second, we take the estimated elasticities by decile from Table 5 and compare them to the estimated elasticities in the model.

As shown in Figure 4, the model does a good job in replicating the relative treatment effects from our empirical exercise. The changes in the tradable sector predicted by the model replicate the revenue responses in the data almost exactly until decile seven and predict a more conservative response to immigration for firms in the highest three deciles. For the non-tradable sector, the model does a good job in replicating the treatment effects in the data across deciles, where establishments of different sizes do not respond

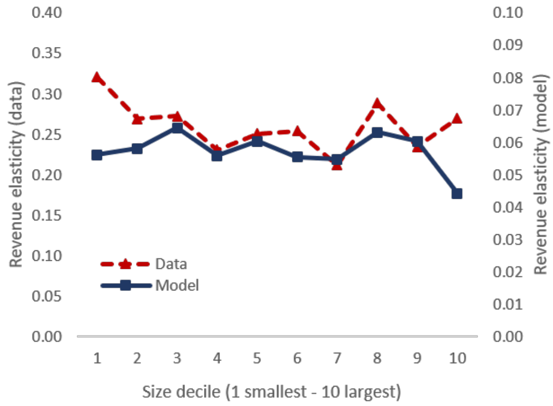
[19] Similar to the counterfactual discussed in Section 7, we lower migration costs to each sector such that the total number of immigrants in Germany increases by 1%.

Figure 4: Predicted treatment effects: Model vs data

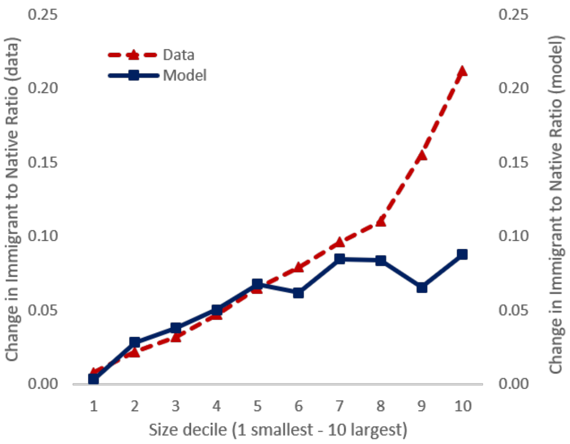
(a) Revenues - Tradable sector



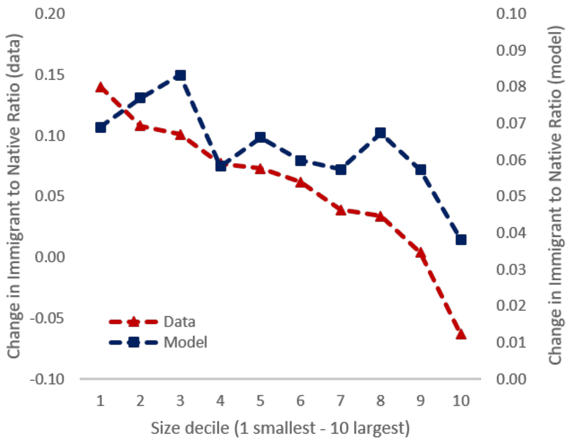

(b) Revenues - Non-Tradable sector




(c) Relative Wage Bill - Tradable sector




(d) Relative Wage Bill - Non-Tradable sector




*Note.* For the model, we rank establishments in terms of revenues into 10 deciles, with decile 1 being the establishments with lowest revenues. In the top two panels, we compute the elasticity of revenues to a 1% increase in the immigrant share and calculate the mean elasticity for firms in each decile. For the data, we use the sector-specific elasticities by size decile presented in Table 5. In the bottom two panels, we calculate, for each establishment, the change in the ratio between the wage bill of immigrants and the wage bill of natives in response to a 1% change in the immigrant share. We then compute the average for each size decile in both the data and the model.

differently to the immigration shock. The model also captures that large firms become more immigrant-intensive than small firms, particularly in the tradable sector.[20]

[20]The model-generated elasticities include general equilibrium changes in prices and quantities due to immigration, while in the data, we control for aggregate changes through industry-time fixed effects and local labor market trends. Given this discrepancy, we should not expect the *levels* of the elasticities to necessarily match between model and data. Instead, the key object to compare when judging whether the model can replicate the heterogeneous responses observed in the data is the *relative* elasticity across size deciles.

# 7 Aggregate implications

We proceed to quantify the economic and welfare consequences of an inflow of immigrants into Germany. Section 7.1 evaluates the main forces shaping the adjustment of the economy to the immigration shock. Section 7.2 quantifies the bias in the estimated welfare gains for native workers when using a model that does not capture the observed heterogeneity in the immigrant share across firms. Finally, Section 7.3 discusses the role of trade for our quantitative results.

## 7.1 Quantitative Exercise

The economic adjustment to the immigration shock takes the form of equilibrium changes in prices, wages, welfare, and the reallocation of workers across sectors and firms. The size of the shock mimics the magnitude of the immigration wave that occurred in Germany between 2011 and 2017. According to the OECD, the total number of immigrants in Germany went from 10.55 million in 2011 to 12.74 million in 2017, a 20.7% increase. While our data ends in 2011, we can use the model to calculate the new equilibrium when the total number of immigrants in Germany increases exogenously by 20%. To do so, we change the migration cost from the RoW to Germany, $\phi_{k,x,g}$, such that it increases the total stock of immigrants by 20%.[21] For our quantitative results, we set the numeraire to be the wage in the RoW, $w_x$.

We define welfare of natives, denoted by $W_g$, as their real labor income:

$$W_g = \frac{\sum_k (L_{g,k} w_{g,k})/N_g}{P_g} \tag{22}$$

As shown in Table 6, the welfare of native workers would increase by 0.24%, which represents \$113 per native worker every year or \$4 billion for the aggregate economy. Such welfare gains are mainly explained by the drop in the cost of the consumption basket: 70% of the gains can be explained by the drop in the price index, while only 30% is explained by the increase in per capita labor income. The decrease in the price index is mainly driven by the tradable sector because its price index drops more strongly than the non-tradable sector, and because it accounts for a larger share of the consumption basket of Germans (almost 70%). Welfare also increases because wages are higher due to immigration, as the increase in the scale of production and associated demand for native labor offsets the substitution effect between natives and immigrants.

The welfare gains of firm owners is significantly larger than for native workers because

[21] In Appendix G, we show our results for different changes in the stock of immigrants.

they experience the same price decreases but do not compete with immigrants in the labor market. Their real income from firm profits increase by 1.22% due to the drop in production costs and increase in profits induced by immigration, amounting to a gain of $15 billion.

Table 6: Effect of immigration on welfare

| | Real Income | Price Index | Nominal Income | Monetary Gains |
|---|---|---|---|---|
| Native Workers | 0.24% | -0.17% | 0.07% | $4B |
| Firm Owners | 1.22% | -0.17% | 1.04% | $15B |

*Note.* We compute the changes on the key endogenous variables of going from the observed equilibrium to an equilibrium where the number of immigrants is 20% higher. Income refers to wages for workers and profits for firm owners. Monetary gains are computed using average wages PPP adjusted at 2019 dollars and total workforce numbers from the OECD. We use data from LIAB to separate the share of the wage bill by sector.

Table 7 narrows the analysis to the sector level and shows the sectoral effects on employment and wages in terms of labor units (i.e., number of workers) and effective units. The influx of immigrants decreases the relative wage between immigrants and natives, and both sectors become more immigrant-intensive. As they become more competitive, both sectors expand their production and total employment in terms of effective units. Employment of native workers decreases in the tradable sector as the least productive native workers are substituted by immigrants, and they reallocate to the non-tradable sector. This result differs from the well-known Rybczynski (1955) theorem, which predicts that production of the immigrant-intensive sector increases and production of the native-intensive sector decreases, so natives reallocate from the native-intensive sector to the immigrant-intensive sector. This theorem builds on the assumption that the domestic share of labor does not respond to an immigration shock, which does not hold in our setting. In our model, the domestic share decreases in both sectors but decreases more in the immigrant-intensive sector. Thus, even though output increases more in the immigrant-intensive sector than in the native-intensive sector, the immigrant-intensive sector does it by hiring more immigrants. Some of these immigrants replace less productive native workers, who are now reallocated to the native-intensive sector.

Wages per native worker increase in both sectors. In the tradable sector, this is due to selection as lower ability natives reallocate to the non-tradable sector, and those natives who stay in the tradable sector are, on average, of higher ability. In the non-tradable sector, there are two counteracting effects. On one hand, lower ability natives get in the sector decreasing average wages. On the other hand, the additional domestic demand created by the new immigrants increases demand for the sector pushing effective wages up. Overall, the latter effect dominates, and workers in both sector earn higher wages due to immigration.

Table 7: Effect of immigration on employment and wages

| | Labor units | | Effective units | |
|---|---|---|---|---|
| **Employment** | Tradable | Non-Tradable | Tradable | Non-Tradable |
| Total | 2.49% | 2.09% | 4.49% | 3.78% |
| Native | -0.11% | 0.23% | -0.09% | 0.20% |
| Immigrant | 20.01% | 20.01% | 16.51% | 16.51% |
| **Wages** | | | | |
| Natives | 0.07% | 0.07% | 0.05% | 0.11% |
| Immigrants | -6.32% | -6.26% | -3.51% | -3.45% |

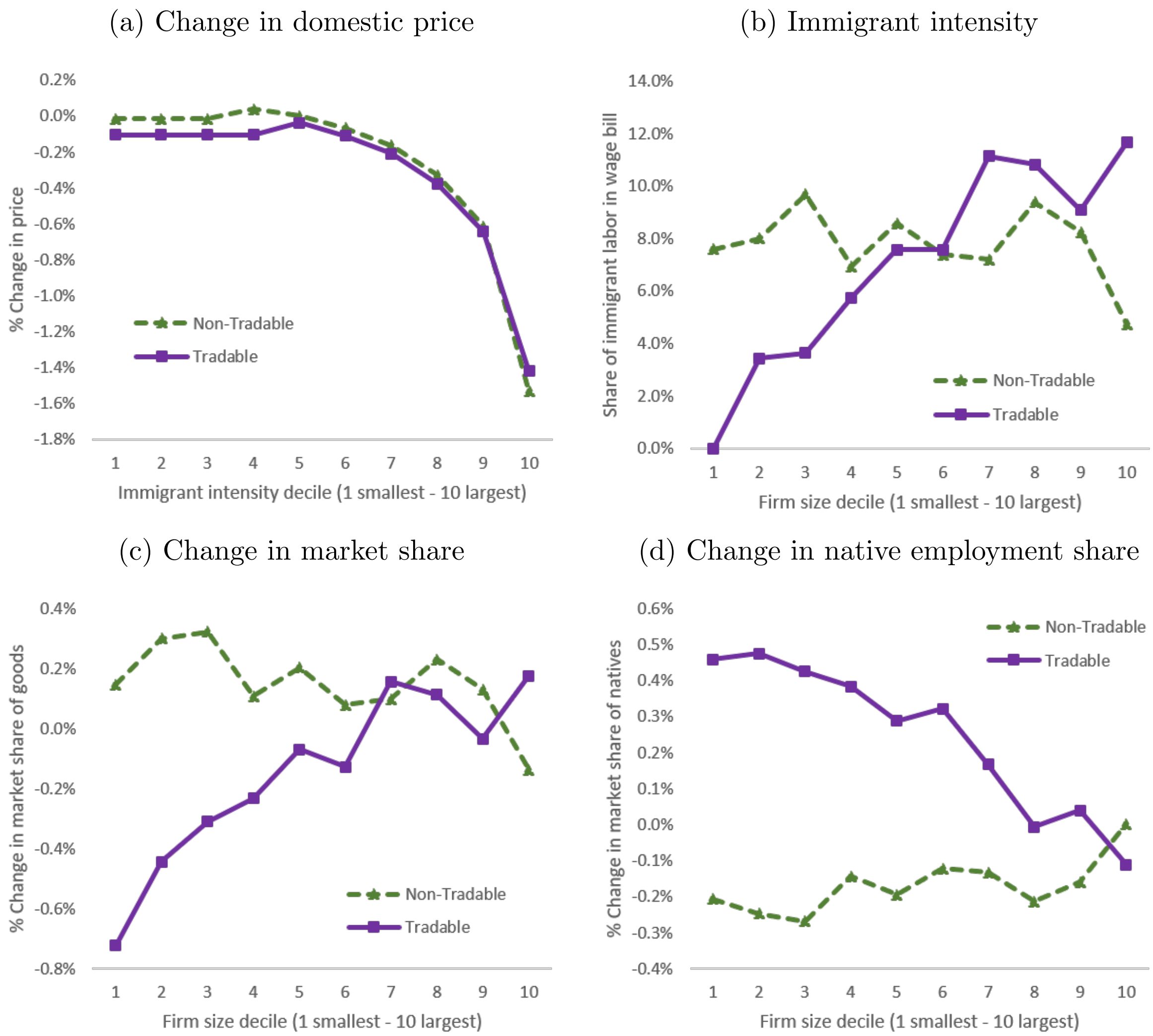
*Note.* We compute the changes on the key endogenous variables of going from the observed equilibrium to an equilibrium where the number of immigrants is 20% higher.

The benefit of immigration for firms is large in the aggregate, but it masks significant heterogeneity for firms of different sizes in the tradable sector. From the top panel of Figure 5, three facts stand out. First, there is a large dispersion in the within-sector price responses and the initial exposure to the immigration shock, which can be a quantitatively important determinant of the aggregate results described before. Second, the cross-sectional differences in the initial exposure $(1 - s_{dj})$ go a long way in explaining differences in price responses (Figure 5a). Third, the exposure to the shock is significantly higher for larger firms (Figure 5b). Thus, the positive relationship between firm size and immigrant intensity, as observed in the data, drives the positive relationship between firm size and price decrease in the model. Larger firms, by virtue of being immigrant-intensive, are more exposed to the decrease in immigrant wage than smaller firms, and their unit cost of production and price decrease more than the cost of small firms. As a result of immigration, larger firms increase their market share. Even though larger firms gain market share to small firms (Figure 5c), they reduce their share in the labor market of natives (Figure 5d) because immigrants crowd-out natives at immigrant-intensive firms (large firms), and these natives are reallocated to native-intensive firms (small firms).

## 7.2 Role of Heterogeneity in Immigrant Share

In this section, we asses the importance of the documented heterogeneity in quantifying the adjustment of the German economy to an immigration inflow. To that end, we compare the model predictions to the same immigration shock across two models: the *heterogeneous model* and the *homogeneous model*. The heterogeneous model is the general model presented in Section 4, whereas the homogeneous model is a particular case where the parameters generating the heterogeneity in immigrant share are turned off. Importantly, both models are recalibrated to match the same aggregate moments and are

Figure 5: Responses to immigration across sectors and firms.




*Note:* The x-axis of figure 5a groups firms into deciles in terms of their immigrant intensity $(1 - s_{dj})$, and the ex-axis of figure 5b, 5c, and 5d does it in terms of their total revenues. The y-axis in all figures measures the average change in the variable in the counterfactual equilibrium where immigrant stock increases by 20% relative to the initial equilibrium.

subject to the same immigration shock (20% increase in the stock of immigrants).[22] The homogeneous model, however, does not match the observed cross-sectional heterogeneity in the immigrant share; that is, $\mathbb{V}ar(s_{dj})$, $\mathbb{C}ov(s_{dj}, rev_j)$, and the share of firms hiring immigrants. To estimate the homogeneous model, we impose the following restrictions: $\sigma_{f,T} = \sigma_{f,NT} = \sigma_{\psi,f,T} = \sigma_{\psi,f,NT} = f_{imm,T} = f_{imm,NT} = 0$.

As shown in the last row of Table 8, the homogeneous model underestimates the welfare gains by 11% because it predicts a weaker increase in workers' income and a weaker drop in the price index. As explained in section 4.1, the increase in real wages is stronger in

[22] In terms of equation 16, it means that in both economies, $dlog(S^{agg})$ is the same. The estimates of parameters that are not estimated by SMM (e.g. $\epsilon$ and $\sigma$) are the same in both models. Appendix G.3 presents the recalibrated parameters under homogeneity.

the heterogeneous model because firms choose different immigrant shares. Hence, immigration increases the specialization of immigrants and natives in producing different varieties, which makes them less substitutable in the aggregate. Since the competition faced by natives in the labor market due to immigration is weaker, there is a lower downward pressure on the wages of natives. The stronger drop in prices in the heterogeneous model, especially in the tradable sector, is explained by larger firms being more immigrant-intensive: large firms, by virtue of being immigrant-intensive, experience a relatively strong drop in the price of the good they produce and, given that they account for a larger share of the consumption basket, their price drops affect the aggregate price index of the economy.

Table 8: Welfare effects with and without firm heterogeneity on the immigrant share

| | Welfare Workers | Nominal Wage | Price Index | Price Index Tradable | Price Index Non tradable |
|---|---|---|---|---|---|
| Heterogeneous | 0.24% | 0.07% | -0.17% | -0.18% | -0.15% |
| Homogeneous | 0.22% | 0.06% | -0.16% | -0.16% | -0.15% |
| Homog/Heterog | 89% | | | | |

*Note.* For both models, we compute the changes on the key endogenous variables of going from the observed equilibrium to an equilibrium where the number of immigrants is 20% higher. The heterogeneous model is our baseline model. The homogeneous model is an alternative model where all firms are equally intensive on immigrants.

The results of this section highlight the importance of firm-level hiring decisions in understanding the consequences of immigration. Immigration leads to within-industry reallocations of native workers across firms. One reason why this reallocation matters in the aggregate is that it affects the (endogenous) immigrant-native elasticity of substitution. However, even with the same aggregate elasticity, the homogeneous model would underestimate the welfare gains of immigration. In Appendix G, we quantify the welfare gains of the homogeneous model with the same aggregate elasticity that the one implied by the heterogeneous model, and show that the bias is not eliminated and remains large (8% approx.). Thus, even after conditioning on the same change in domestic labor share and aggregate native-immigrant elasticity of substitution, the micro structure of the economy affects the measurement of the welfare gains from immigration.

## 7.3 The Quantitative Role of Trade

Exports and trade have a key role in the quantitative results of increasing immigration and the size of the bias. We compare our baseline model with an alternative model where Germany and the RoW are in autarky, such that trade is not allowed between countries. This model is analogous to a model where the fixed cost of selecting into trade goes to infinity (e.g., $f_x \to \infty$).

As shown in Table 9, if countries cannot engage in international trade, the price decrease induced by immigration is too strong. The model with no trade overstates the decrease in the price index by more than double the decrease predicted by the baseline model. Both trade and migration lower the marginal cost of production and, in turn, the price index. When trade is not allowed, migration becomes more important as a source of reducing the cost for consumers as they cannot adjust their consumption through trade.

However, the relationship between trade and welfare goes in the opposite direction when considering the wage component. In the baseline model with trade, demand is more elastic, and total production expands more than in the no-trade model in response to immigration. The more elastic product demand increases labor demand for both immigrants and natives and partially compensates the competition effect in the local labor market. As shown in Table 9, the model with no-trade predicts a negative impact on wages, as demand does not respond as much, and the competition effect between natives and immigrants dominates. As explained by Burstein et al. (2020), if immigrants work for a sector where goods are traded, immigration imposes less of a downward pressure on wages because the demand is more inelastic. While both effects are at play, the change in price index dominates the quantitative difference in terms of real wages between the baseline and the no-trade model. The model with no trade overstates the welfare gains of immigration by 41%.

Finally, we compare the no-trade model with a model with no trade and homogeneous immigrant intensities. The homogeneous model underestimates the gains from immigration by 9%, which is lower than the bias in the model with trade (11%). Trade amplifies the inequality in sizes across firms in the tradable sector, which in turn, amplifies the differences in immigrant intensities across firms.

Table 9: Comparing the baseline model with a model no-trade model

| | Welfare | Nominal Wage | Price Index | Revenues |
|---|---|---|---|---|
| Baseline | 0.24% | 0.07% | -0.17% | 1.05% |
| No Trade | 0.34% | -0.04% | -0.37% | 0.98% |
| No Trade and homogeneous | 0.31% | -0.02% | -0.33% | 0.98% |

*Note.* The values represent the percent change of key variables after a 20% increase in the stock of migrants.

# 8 Comparing our results with the literature

To put our results into context, it is important to understand the institutional framework in Germany during our study period. We focus on the years between 2003 and 2011, before Germany unified its labor market with other EU countries. Hence, this is a period where a majority of immigrants needed a guaranteed employment offer in order to migrate. Such policy context is important because firms had a fundamental role in determining what immigrants came into the country. Similar setup can be found in the United States, the largest destination country of immigrants, through the H-1B, H-2B, and L-1 visa programs, among others. In these programs, firms need to sponsor workers' visas for them to be able to migrate to the country. The Canadian immigration system is similar with its point-based system, where immigrants with a guaranteed employment offer get substantially more points to qualify for immigration.

Differences in immigration policy across countries can reconcile why firm-level studies find, what at first may seem contradictory. Mitaritonna et al. (2017) find that larger French firms are more immigrant-intensive, but small and low-productivity firms experience the most gains from immigration. Arellano-Bover and San (2020) find that immigrants in Israel initially select into small firms, while Mahajan (2020) finds that high-productivity firms in the United States benefit the most from immigration. In the context studied by Mitaritonna et al. (2017) and Arellano-Bover and San (2020), immigrants were easily available to firms, while in our setup and Mahajan (2020), migration policy required firms to invest resources for recruiting and sponsoring immigrants. Therefore, our framework is well suited to study immigration whenever migrants are not easily available in the labor market, and firms have an active role in deciding which immigrants come into the country.

In terms of the magnitude of our findings, our quantitative estimates are somewhat larger than those estimated by Caliendo et al. (2021), who predict immigration after the EU labor market integration increases welfare for the original EU members by just 0.04%. Our larger gains can be explained due to allowing immigrants and natives to be imperfect substitutes, while in Caliendo et al. (2021) they are considered perfect substitutes within skill group. Their estimates also are mainly driven by the UK, which opened their goods and labor market simultaneously. They conclude that a phased policy like Germany, where the labor market was opened in a later period, would likely have created higher welfare gains.

## 9 Conclusion

In this paper, we document a large degree of heterogeneity across employers regarding their immigrant share, and revisit the old question of the impact of immigration on the welfare of native workers. When immigration increases by 20%, our model predicts that both the tradable and non-tradable sectors expand in terms of revenues and profits due to the drop in unit cost induced by the inflow of immigrants. This expansion is more pronounced in the tradable sector, where firms are more intensive in immigrant labor. The immigration inflow also induces the tradable sector to become more immigrant-intensive, which triggers a reallocation of the least productive natives from the tradable sector toward the non-tradable sector. We find that native workers and firm owners in both sectors experience higher wages and profits, respectively, and lower prices due to immigration. The welfare gains amount to $4 billion for native workers and $15 billion for firm owners.

Most of the literature has assumed that firms are homogeneous in terms of hiring decisions of immigrants, which is at odds with the data and leads to biased welfare gains from immigration. First, when firms are homogeneous, the elasticity of substitution between immigrants and natives in the labor market coincides with the within-firm elasticity. However, when firms are heterogeneous, the aggregate immigrant-native elasticity of substitution depends on the within-firm elasticity and the elasticity of substitution across firms or goods. Thus, having different immigrant-intensities across firms allows for natives and immigrants to specialize in working for different employers, which makes them less substitutable in the aggregate labor market. Second, when firms are heterogeneous, the gains are largely concentrated among the largest and most productive employers, which induces an additional aggregate productivity gain. These two forces lead to potentially large biased estimates of the welfare gains from immigration. We find that if we ignore this heterogeneity, the welfare gains from an increase in immigration would be underestimated by 11%.

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# A Summary statistics

In Table 10, we present the average employment, college employment, and immigrant distribution by origin region for our sample. We split the establishments in the sample into the tradable and non-tradable sectors and calculate summary statistics for years 2003 and 2011.

Table 10: Descriptive Statistics

| | Tradable | | Non-Tradable | |
|---|---|---|---|---|
| | 2003 | 2011 | 2003 | 2011 |
| N establishments (unweighted) | 1,530 | 1,426 | 2,148 | 2,379 |
| Mean Employment | 45.0 | 45.9 | 39.2 | 36.5 |
| Mean Employment - College | 4.5 | 5.8 | 3.0 | 2.9 |
| Share of employment by origin region | | | | |
| Germany | 90.97% | 91.15% | 92.66% | 91.13% |
| EU (FR, GB, NL, BE, AT, CH, FI, SE) | 1.03% | 0.97% | 0.74% | 0.70% |
| EU (ES, IT, GR, PT) | 1.94% | 1.69% | 1.22% | 1.40% |
| EU, joined after 2004 | 0.63% | 0.74% | 0.68% | 1.22% |
| Europe, other | 0.80% | 1.10% | 0.73% | 1.02% |
| Turkey | 2.73% | 2.55% | 1.71% | 2.06% |
| Former Yugoslavia | 0.79% | 0.61% | 0.73% | 0.70% |
| Asia - Pacific | 0.41% | 0.52% | 0.76% | 0.64% |
| Africa and Middle East | 0.52% | 0.46% | 0.63% | 0.75% |
| Americas | 0.16% | 0.21% | 0.14% | 0.36% |

*Note:* The sample is restricted to establishments with more than 10 employees.

# B Empirical Facts - Extensions

## B.1 Empirical Evidence for Fixed Cost Assumptions

This section presents additional stylized facts that motivate the modeling assumption that firms face fixed costs to hire immigrants and that these costs have to be paid whenever the firm expands the set of countries where it hires immigrants from. In the data, countries of origin are grouped in nine blocks as explained in Section 2.

Firms that increase the number of sourcing countries tend to do it by adding a single additional origin, as opposed to multiple origins at the same time. Each row in Table 11 shows the number of countries that an establishment sourced immigrants from in period $t-1$ ($Nc_{t-1}$), each column shows that number for period $t$ ($Nc_t$), and each cell contains the number of establishments that keep or increase the number of countries between $t-1$

and $t$. Establishments that increase the number of origins where they hire immigrants from are more likely to go from $Nc_{t-1}$ to $Nc_{t-1}+1$ than to any other number of countries. This fact would not arise if firms were supposed to pay a fixed cost to source immigrants from any origin as firms would optimally start hiring from all countries after paying that cost. However, if firms were supposed to pay a cost for every *additional* origin they source immigrants from, they would start hiring from one country at a time.

Table 11: Number of immigrant origin countries

| $Nc_{t-1}$ | | | | | $Nc_t$ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| 0 | 5,108 | 368 | 41 | * | * | * | * | * | * | * |
| 1 | | 2,014 | 319 | 64 | * | * | * | * | * | * |
| 2 | | | 1,160 | 259 | 47 | * | * | * | * | * |
| 3 | | | | 766 | 179 | 40 | * | * | * | * |
| 4 | | | | | 512 | 144 | 33 | * | * | * |
| 5 | | | | | | 125 | 372 | 106 | 26 | * |
| 6 | | | | | | | 332 | 107 | 26 | * |
| 7 | | | | | | | | 310 | 88 | * |
| 8 | | | | | | | | | 436 | 70 |
| 9 | | | | | | | | | | 406 |

*Note.* Sample is restricted to establishments with more than 10 employees. $Nc_t$ stands for the number of regions the establishment hires immigrants from at time $t$. Number of regions can go from 1 to 9. Cells with an "*" have less than 20 observations and cannot be disclosed.

Second, the year that the firm adds an additional country, it starts hiring a large number of employees from that country. This *jump* in the number of employees hired from the additional country is consistent with firms paying a *fixed* cost for any additional sourcing country. If this were not the case and the cost were variable, firms would tend to start hiring small quantities of those immigrants. Table 12 shows the distribution of the number of new hires with respect to the size of the workforce of the firm for two sample of firms. The first sample ("All") is the sample of firms that started hiring from a new source country, and the second sample ("Top 5 deciles") is the subsample of them that are in the top 5 deciles of the employment size distribution. The first row of the following table shows that the average number of employees from the new source is 3.8% of the total employment of the firm, and there is a significant mass of firms (10%) that hire approximately 10% or more of their employment in new-country immigrants. These results do not seem to be driven by firms hiring only few workers that still represent a large share of their small workforce because results remain in the subsample of the Top 5 deciles.

Third, firms hiring immigrants from more countries tend to be more immigrant-intensive. This is exactly what the model predicts in equation 10 and is corroborated by Figure 3b,

Table 12: Immigrants from new source as a share of firm total employment

| Sample | Mean | Percentiles | | | | | | | | | N |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1% | 5% | 10% | 25% | 50% | 75% | 90% | 95% | 99% | |
| All | 3.80 | 0.00 | 0.06 | 0.10 | 0.27 | 0.87 | 2.98 | 9.02 | 16.85 | 44.63 | 3617 |
| Top 5 deciles | 3.90 | 0.00 | 0.05 | 0.9 | 0.24 | 0.75 | 2.93 | 10.00 | 18.55 | 46.57 | 3224 |

Note: An observation is an establishment-year. We rank establishments who start hiring from a new origin region in terms of the employment from the new region relative to the establishment's total employment. The sample "All" includes those observations that increase the number and the sample "Top 5 deciles" contains the subsample of firms that belong to the top 5 deciles in terms of employment.

where we group firms by the percentage of their payroll spent on immigrants. Figure 3b shows that firms that are more intensive on immigrants also source immigrants from more countries.

There may be a mechanical correlation between the number of sourcing countries and the number of immigrants, as the total number of immigrants that the firm hires can drive the observed relationship between number of countries and immigrant share. To suggest that the changes in immigrant share are mainly associated to the number of sources countries, Table 13 shows that, even after controlling for the total number of immigrants hired, the correlation between immigrant share and the number of countries is significant and strong. Moreover, a variance decomposition based on these estimates suggests that 10% of the variance in the immigrant share is explained by differences in the extensive margin (number of countries), and only 3% is explained by the intensive margin (number of immigrants).

Table 13: Immigrant share: Intensive vs Extensive Margin: OLS estimate

| | Immigrant share | Immigrant share |
|---|---|---|
| N countries | 0.016*** | 0.012*** |
| | (0.0008) | (0.0009) |
| N immigrants | | 5.23e-03 |
| | | (1.07e-06) |
| N observations | 17,501 | 17,501 |
| N establishments | 2,485 | 2,485 |

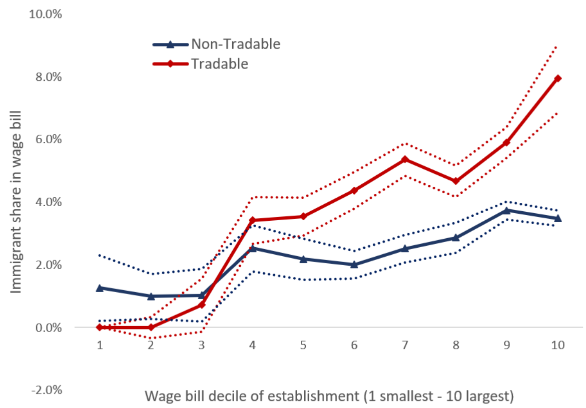
*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We control for 2-digit industry-time fixed effects and local labor market time trends. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 10 employees.

To conclude, we interpret these stylized facts as evidence in favor of an environment where large firms are more immigrant-intensive than small firms because they can afford to pay more fixed costs to hire immigrants from different origins.

## B.2 Differences Across Tradable and Non-Tradable Sectors

We evaluate how immigrant intensity varies across firms for the tradable and non-tradable sectors. Our definition for the tradable sector considers manufacturing, professional services, and wholesale trade. While immigrants do concentrate in some small establishments in the non-tradable sector (e.g., restaurants), the representative establishment captured by the median tends to have a low immigrant intensity. As shown in Figure 6, establishments in the tradable sector are more intensive in immigrants than similar sized establishments in the non-tradable sector. The tradable sector presents a stronger relationship between size and immigrant intensity than the non-tradable sector.

Figure 6: Tradable and non-tradable sector.




*Note.* We divide all establishments with more than 10 employees into total wage bill deciles, with 1 being the smallest establishments and 10 the largest. For each decile, we plot the median immigrant share of the total establishment wage bill. We separate establishments in each decile on whether they belong to the tradable or non-tradable sectors. We calculate the 95% confidence interval using 200 bootstrap repetitions.

# C Model Derivations

## C.1 Sourcing Decision Details

In this section, we describe step by step how we get to the immigrant wage index expression in equation 7. Following equation 6, we know the price index for foreign labor is as in equation 23:

$$W_{x,j} = \left( \int_{\Sigma_j} \delta_o^{\kappa} w_x^{1-\kappa} do \right)^{\frac{1}{1-\kappa}} \tag{23}$$

where $\delta_o$ is a source-country specific productivity assumed to be a Pareto random variable with the following cumulative distribution and density function:

$$F(\delta) = 1 - \left(\frac{\bar{\delta}}{\delta}\right)^{\xi} \quad \text{and} \quad g(\delta) = \xi \bar{\delta}^{\xi} \delta^{-\xi-1} \tag{24}$$

where $\bar{\delta}$ and $\xi$ are the scale and shape parameters, respectively. Since the firm needs to pay a fixed cost $f_j$ for each additional country they hire from, they will just hire from countries with a $\delta > \delta_j^*$, for a given $\delta_j^*$. The mass of countries that the firm hires from is then $n_j = F(\delta > \delta_j^*) = \bar{\delta}^{\xi}(\delta_j^*)^{-\xi}$. With this result, we can calculate the price index of foreign labor as in equation 25:

$$\begin{aligned} W_{x,j} &= \left(w_x^{1-\kappa} \int_{\delta_j^*}^{\infty} \delta_o^{\kappa} \xi \bar{\delta}^{\xi} \delta^{-\xi-1} d\delta\right)^{\frac{1}{1-\kappa}} = w_x \left(\left[\frac{\xi \bar{\delta}^{\xi}}{\kappa - \xi} \delta^{\kappa-\xi}\right]_{\delta_j^*}^{\infty}\right)^{\frac{1}{1-\kappa}} = \\ &= w_x \left(\frac{\xi \bar{\delta}^{\xi}}{\xi - \kappa} (\delta_j^*)^{-(\xi-\kappa)}\right)^{\frac{1}{1-\kappa}} \text{ if } \xi - \kappa > 0 \end{aligned} \tag{25}$$

Since the mass of countries the firm sources from is $n_j = \bar{\delta}^{\xi}(\delta_j^*)^{-\xi}$, we can now compute the foreign price index as in equation 26:

$$W_{x,j} = w_x \underbrace{\frac{1}{\bar{\delta}^{\frac{\kappa}{\kappa-1}}} \left(\frac{\xi}{\xi - \kappa}\right)^{\frac{1}{1-\kappa}}}_{\bar{Z}} n^{\underbrace{-\frac{1}{\kappa - 1} \frac{\xi - \kappa}{\xi}}_{\iota}} \tag{26}$$

## C.2 Equilibrium Equations

The equilibrium in this model is defined as a set of prices, wages, and labor allocations such that: workers optimally choose the industry and destination country $d, k$ to work for, consumers in each location choose how much of each variety to purchase to maximize utility, firms choose the sourcing strategy and export status to maximize profits, labor markets clear, and trade is balanced. We set the wage in the RoW ($w_x$) to be the numeraire. Formally, the equilibirum conditions are the following:

1) Consumer budget constraint. In a given country, natives and immigrants have identical preferences. The total expenditure in Germany ($Y_g$) and RoW ($Y_x$) are shown in equation 27:

$$Y_g = \sum_k \left( w_{g,k} L_{g,k} + w_{g,x,k} L_{g,x,k} + \Pi_{g,k} \right) \quad Y_x = w_x L_x + \Pi_x \tag{27}$$

where $L_{g,k}$ is the total number of German effective units of labor in sector $k$, $L_{g,x,k}$ is the number of effective immigrant units in Germany working in sector $k$, and $w_{g,k}$, $w_{g,x,k}$ are the respective effective wages. $\Pi_{g,k}$ are the total profits in sector $k$ in Germany. $w_x$, $L_x$, and $\Pi_x$ are the effective wages, effective labor, and total profits in RoW.

2) Trade balance. Total income from exports in Germany is equal to the total import expenditure as in equation 28:

$$\sum_j \mathbb{1}\left(exporter_{g,j} = 1\right) p^T_{j,x,g} y^T_{j,x,g} = \sum_j \mathbb{1}\left(exporter_{x,j} = 1\right) p_{j,g,x} y_{j,g,x} \tag{28}$$

3) Total labor market clearing. In each industry, the expenditure of labor by industry $k$ equals the number of effective units supplied by the labor market times the effective wage paid by that industry. The market clearing conditions 29-31 require that demand for effective units of native and immigrant labor equals supply in each industry and country:

$$\sum_j d_{j,k} = A^{\frac{1}{\nu}}_{g,k} \left(\pi_{g,k}\right)^{\frac{\nu-1}{\nu}} \bar{H} N_g \tag{29}$$

$$\sum_j \sum_o x_{j,o,k} = \left( A^{\frac{1}{\nu}}_{x,k} \left(\pi_{x,g,k}\right)^{\frac{\nu-1}{\nu}} \bar{H} \right) N_x \tag{30}$$

$$\sum_j d_{j,x} = \left( A^{\frac{1}{\nu}}_{x,k} \left(\pi_{x,x,k}\right)^{\frac{\nu-1}{\nu}} \bar{H} \right) N_x \tag{31}$$

Equation 29 stands for the market clearing condition for natives in Germany, equation 30 for the market clearing condition for immigrants in Germany, and equation 31 for the market clearing of workers that stay in RoW. The parameter $\bar{H}$ stands for the Gamma function evaluated at $1 - \frac{1}{\kappa}$

# D Welfare Response to Immigration

We focus on a closed economy with one sector, we choose the wage of natives as the numeraire, and assume that the fixed cost $f_{imm}$ is zero (but the firm-specific fixed cost

$f_j$ is unrestricted). We present the expression for the change in the welfare of natives workers in four steps.

**Step 1:** Express $dlog(s_{dj})$ as proportional to $dlog(s_{d1})$.

The profit function and the corresponding first order condition with respect to $s_{dj}$ are:

$$\begin{aligned} \Pi_j &= A\psi_j^{\sigma-1}s_{dj}^{\chi} - Bf_j(s_{dj}^{-1}-1)^{\theta+1} \\ \psi_j^{\sigma-2}s_{dj}^{-\chi+1+\theta} &= f_jC(1-s_{dj})^{\theta} \end{aligned}$$

where $A, B,$ and $C$ are general equilibrium variables that are common to all firms, $\chi = \frac{\sigma-1}{\epsilon-1} > 0$ and $\theta = \Big(\iota(\epsilon-1)\Big)^{-1} - 1 > 0$ .

The first order condition for firm $j$ and firm 1 implies that:

$$(\chi + 1 + \theta + \frac{\theta}{1-s_{dj}})\ dlog(s_{dj}) = (\chi + 1 + \theta + \frac{\theta}{1-s_{d1}})\ dlog(s_{d1})$$

or

$$dlog(s_{dj}) = \frac{\alpha_j}{\alpha_1}\ dlog(s_{d1}) \quad with \quad \alpha_j = \frac{1}{\chi + 1 + \theta + \theta(1-s_{dj})^{-1}} > 0 \tag{32}$$

**Step 2:** Express $dlog(s_{dj})$ as proportional to $dlog(S_d^{agg})$.

By definition, the aggregate domestic share is the total wage bill spent on natives divided by the total wage bill:

$$S_d^{agg} = \frac{\sum_j WB_{dj}}{\sum_j WB_j} = \sum_j \underbrace{\frac{WB_j}{\sum_j WB_j}}_{\omega_j^{WB}=\omega_j} s_{dj} = \sum_j \omega_j s_{dj}$$

where $\omega_j^{WB}$ is the share of firm $j$ in the wage bill of natives and happens to also be the share in revenues, $\omega_j$. In what follows, we use this fact and keep the notation as $\omega_j$.

The change in the aggregate domestic share is then given by:

$$dlog(S_d^{agg}) = \sum_j \underbrace{\frac{\omega_j s_{dj}}{\sum_j \omega_j s_{dj}}}_{\omega_j^S} \Big(dlog(\omega_j) + dlog(s_{dj})\Big) \tag{33}$$

where $\omega_j^S$ is the share of firm $j$ in the aggregate domestic share.

Next, we find an expression for $dlog(\omega_j)$ as a function of $dlog(s_{dj})$. To that end, we use firm $j$'s optimal demand for natives and the definition of $\omega_j$:

$$\begin{aligned} WB_j = \frac{\sigma-1}{\sigma} r_j = \frac{D}{\psi_j} s_{dj}^{-\chi} \quad &\rightarrow \quad dlog(WB_j) = dlog(D) - \chi dlog(s_{dj}) \\ \omega_j = \frac{WB_j}{\sum_l WB_l} \quad &\rightarrow \quad dlog(\omega_j) = dlog(WB_j) - \sum_l \omega_l dlog(WB_l) \end{aligned}$$

where D is a general equilibrium variable common to all firms.
The expression of $dlog(\omega_j)$ as a function of $dlog(s_{dj})$ follows from combining these last two expressions:

$$dlog(\omega_j) = -\chi\Big(dlog(s_{dj}) - \sum_l \omega_l \; dlog(s_{dl})\Big) \tag{34}$$

This expression, together with 32 and 33, implies that the change in aggregate share can be expressed as a function of the change in $s_{d1}$:

$$\begin{aligned} dlog(S_d^{agg}) &= \sum_j \omega_j^S (-\chi\Big(dlog(s_{dj}) - \sum_l \omega_l \; dlog(S_{dl})\Big) + dlog(s_{dj})\Big) \\ dlog(S_d^{agg}) &= \sum_j \omega_j^S \Big( -\chi(\alpha_j - \sum_l \omega_l \alpha_l) + \alpha_j\Big) dlog(s_{d1}) \end{aligned} \tag{35}$$

In a more compact way, it reads as:

$$dlog(S_d^{agg}) = \sum_j \omega_j^S \underbrace{\Big( -\chi(\alpha_j - \bar{\alpha}) + \alpha_j\Big)}_{\beta_j} dlog(s_{d1}) \tag{36}$$

with $\bar{\alpha} \equiv \sum_l \omega_l \alpha_l$.[23]

Expressions 37 and 32 let us express individual changes in domestic share as a function of the aggregate change:

$$dlog(s_{dj}) = \frac{\alpha_j}{\beta} dlog(S_d^{agg}) \quad with \quad \beta = \sum_l \beta_l \tag{37}$$

**Step 3:** Express welfare change into a component observable with aggregate data and a component that requires micro-level data.

The welfare gains from immigration in this simplified model are given by the drop in the price index induced by immigration. The change in the price index (relative to the numeraire good) is a weighted average of the changes of individual prices which, in turn,

[23] If all firms choose the same immigrant-share, $dlog(S_d^{agg}) = dlog(s_{dj})$.

are proportional to the change in the domestic share:

$$\begin{aligned}
dlog(P) &= \sum_j \omega_j^{rev} dlog(p_j) \\
&= \sum_j \omega_j^{rev} dlog(u_j) \\
&= \sum_j \omega_j^{rev} \Big( dlog(w_d) + \frac{dlog(s_{dj})}{\epsilon - 1} \Big) \\
&= dlog(w_d) + \frac{\sum_j \omega_j dlog(s_{dj})}{\epsilon - 1}
\end{aligned} \tag{38}$$

where we used the fact that $\omega_j = \frac{p^{1-\sigma}}{P^{1-\sigma}}$, $\sum_j \omega_j^{rev} = 1$, and equations 5 and 8.

We can express the change in the price index as a function of the change of the aggregate share and an additional factor by plugging equation 37 into equation 38.

The last two expressions and the optimal pricing implies:

$$dlog\Big(\frac{P}{w_d}\Big) = \frac{dlog(S_d^{agg})}{\epsilon - 1} \underbrace{\sum_j \omega_j \frac{\alpha_j}{\beta}}_{\tilde{\Gamma}\Big(\{s_{dj}, \omega_j\}; \sigma, \epsilon\Big)}$$

This expression shows that the change in the price index can be computed only if firm-level data on the market share and immigrant intensity are available.

**Step 4:** Determine if the bias is larger or smaller than one.

For the sake of the mathematical exposition, we work with the inverse of $\tilde{\Gamma}$, which takes the following shape:

$$\tilde{\Gamma}\Big(\{s_{dj}, \omega_j\}; \sigma, \epsilon\Big)^{-1} = \frac{\sum_j \omega_j^S \beta_j}{\sum_j \omega_j \alpha_j} = \frac{\sum_j \omega_J^S \Big( - \chi(\alpha_j - \bar{\alpha}) + \alpha_j \Big)}{\bar{\alpha}}$$

and can be rewritten as in 39 by adding and subtracting $\sum_J \omega_j^S \bar{\alpha}$:

$$\tilde{\Gamma}\Big(\{s_{dj}, \omega_j\}; \sigma, \epsilon\Big)^{-1} = 1 + \frac{\epsilon - \sigma}{\epsilon - 1} \frac{\sum_j \omega_j^s \alpha_j - \sum_j \omega_j \alpha_j}{\sum_j \omega_j \alpha_j} \tag{39}$$

The bias will be higher or lower than one, depending on whether $\epsilon$ is larger than $\sigma$, as the sign of the second term on the right side is always negative. To see this, notice that there is a tight relationship between $\omega_j$ and $\omega_j^S$:

$$\omega_j^S = \omega_j \frac{s_{dj}}{\sum_j \omega_j s_{dj}}$$

which implies that the weighting system $\omega^s$ assigns lower weight to immigrant-intensive firms than the weighting system $\omega$. Given that $\alpha_j$ is strictly increasing in the immigrant-share of the firm, the average of $\alpha_j$ under the weighting system $\omega^s$ must be lower than that under $\omega_j$ and

$$\frac{\sum_j \omega_j^s \alpha_j - \sum_j \omega_j \alpha_j}{\sum_j \omega_j \alpha_j} < 0$$

Thus, if $\epsilon > \sigma$, equation 39 shows that $\tilde{\Gamma}\Big(\{s_{dj}, \omega_j\}; \sigma, \epsilon\Big)^{-1}$ is lower than one and vice versa.

It also follows that $\Gamma\Big(\{s_{dj}, \omega_j\}\Big)$ in Section 4.1 is always positive:

$$\Gamma\Big(\{s_{dj}, \omega_j\}\Big) \equiv -\frac{1}{\epsilon - 1} \frac{\sum_j \omega_j^s \alpha_j - \sum_j \omega_j \alpha_j}{\sum_j \omega_j \alpha_j} > 0$$

# E Estimation of $\epsilon$

## E.1 Dataset Description

To estimate the elasticity of substitution between native and immigrant effective units, $\epsilon$, we use an alternative administrative dataset called SIAB, which is also provided by the German Social Security Administration.[24] SIAB contains the full labor biographies for 2% of the German workforce between 1975 to 2014 and includes information on employer size, citizenship, workplace, industry, occupation, and other covariates similar to the labor market component of our main dataset LIAB. A few advantages of SIAB include a representative sample of the German workforce, a longer time span, and a significantly larger sample size. As will be explained in section E.2, the estimation procedure requires constructing generated regressors at the firm-time-origin level and control for a rich set of time-varying fixed effects. Given these constraints, this alternative dataset allows us to exploit the larger sample size and longer time panel.

One limitation of the SIAB dataset is that it does not contain information on every employee at the establishments in the sample. Since we need the migrant and native

[24]The data basis of this section of the paper is the weakly anonymous Sample of Integrated Labour Market Biographies (SIAB) 1975 - 2014. The data were accessed on-site at the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and/or via remote data access at the FDZ. For more information on SIAB please check Antoni et al. (2016).

employment at the establishment level, we group establishments in SIAB into bins by time, geographic district, three-digit industry, and size quartile. We then construct our firm level dataset by considering all employees in the sample working for establishments in a given bin as if they would work for the same "synthetic" firm.

## E.2 Estimation Details

To get an expression for the immigrant composite, we start from the supply side of the model. Using the Frechet properties, we can write the number of effective units supplied to firm $j$ in industry $k$ by workers from origin country $o$ as in equation 40.:

$$x_{j,o} = \underbrace{A_{o,k}^{\frac{1}{\nu}} \left(\pi_{o,k,\ell}\right)^{-\frac{1}{\nu}} \bar{H}}_{\gamma_{o,k}} N_j^o \tag{40}$$

where $N_j^o$ is the number of workers employed at firm $j$, and the expression $\gamma_{o,k}$ is the average ability per worker from $o$ at firm $j$.

Using the first order condition of profits from firm $j$ with respect to each $x_{j,o}$ relative to the first order condition with respect to a base origin country $o'$, $x_{j,o'}$, and using equation 40, we can get an expression as in equation 41:

$$Ln\left(\frac{w_o x_{j,o}}{w_{o'} x_{j,o'}}\right) = Ln\left(\frac{\delta_{o,k}}{\delta_{o',k}}\right) + \frac{\kappa-1}{\kappa} Ln\left(\frac{\gamma_{o,k} N_j^o}{\gamma_{o',k} N_j^{o'}}\right) \tag{41}$$

Using equation 41 and assigning a value for $\kappa$, we can get to the first estimating equation, 42, which gives us an estimate for the average effective units provided by each migrant worker at firm $j$:[25]

$$Ln\left(\text{Wage bill}_{o,j}\right) - \frac{\hat{\kappa}-1}{\hat{\kappa}} Ln(N_j^o) = \underbrace{Ln(\delta_{o,k}) + \frac{\kappa-1}{\kappa} Ln(\gamma_{o,k})}_{\zeta_{o,k} \text{ Origin-Industry FE}} + \underbrace{Ln(\delta_{o',k}) - Ln(\gamma_{o',k} N_j^{o'})}_{\text{Firm FE}} \tag{42}$$

To estimate equation 42, we pool all years between 1995 until 2014 and run a regression at the firm-origin-time level. We include origin-industry-time and firm-time fixed effects,

[25] $\kappa$ stands for the degree of substitution across immigrant origin countries for production. We assume $\kappa = 20$, close to the upper bound of the elasticity of substitution between immigrants and natives estimated by Ottaviano and Peri (2012). We show results are very robust to other values of $\kappa$ between 10 and 30.

such that we only exploit the cross-sectional variation to estimate the fixed effects. From equation 42, we obtain the fixed effects $\zeta_{o,k}$, which will allow us to compute the immigrant composite at the firm level using data on the number of immigrants by country, the $\zeta_{o,k}$ estimates, and the assigned value of $\kappa$ as shown in equation 43:

$$\hat{x}_j = \left(\sum \delta_o x_{j,o}^{\frac{\hat{\kappa}-1}{\hat{\kappa}}}\right)^{\frac{\hat{\kappa}}{\hat{\kappa}-1}} = \left(\sum \delta_o (\gamma_{o,k} N_j^o)^{\frac{\hat{\kappa}-1}{\hat{\kappa}}}\right)^{\frac{\hat{\kappa}}{\hat{\kappa}-1}} = \left(\sum e^{\hat{\zeta}_{o,k}} \left(N_j^o\right)^{\frac{\hat{\kappa}-1}{\hat{\kappa}}}\right)^{\frac{\hat{\kappa}}{\hat{\kappa}-1}} \tag{43}$$

Once we calculate $\hat{x}_j$, we can proceed to estimate our key elasticity $\epsilon$. We can use the firm first order condition with respect to the number of native effective units $d_j$ and the immigrant composite $x_j$ to get to estimating equation 44:

$$\underbrace{Ln\left(\frac{w_{j,t}^d d_{j,t}}{w_{j,t}^x x_{j,t}}\right)}_{\text{Relative wage bill}} = Ln\left(\frac{\beta^k}{1-\beta^k}\right) + \frac{\epsilon-1}{\epsilon} Ln\left(\frac{\gamma_{d,k} N_j^d}{\hat{x}_{j,t}}\right) \tag{44}$$

With some additional structure, we reach estimating equation 45, as shown in Section 5. We proceed to take logs and reorganize equation (18) into estimating equation 45:

$$Ln\left(\frac{\text{Wage bill Natives}_{j,t}}{\text{Wage Bill Immig}_{j,t}}\right) = \frac{\epsilon-1}{\epsilon} Ln\left(\frac{N_j^d}{\hat{x}_{j,t}}\right) + \underbrace{Ln\left(\frac{\beta_t^k}{1-\beta_t^k}\right) + Ln(\gamma_{d,k,t})}_{\text{Industry-time FE}} + \zeta_j + \xi_{j,t} \tag{45}$$

We assume the error term can be written as a firm fixed effect $\zeta_j$ and an unobserved component $\xi_{j,t}$. We also use the labor supply property that the number of effective units of native workers can be expressed as an interaction between an industry-time constant $\gamma_{d,k,t}$ and the observed number of German workers at firm $j$, $N_j^d$ as in equation 40. While the model is static, once again we add time subscripts as we pool several years of data to maximize our sample size.

The OLS estimates will not provide a consistent estimate of the elasticity of substitution under the presence of unobservable shocks affecting both the relative labor demand and relative wage. If, for example, firms face productivity shocks that are biased to immigrants, the OLS estimate will be upward biased. To address endogeneity concerns, we instrument the firm's relative demand of workers with the following shift-share instrument:

$$Z^f_{j,m,t} = \sum_o \frac{\text{Wage Bill}_{o,m,1995}}{\text{Wage Bill}_{m,1995}} \frac{\text{Employment}^{Imm}_{o,t}}{\text{Employment}^{Ger}_t} \tag{46}$$

The initial share component of the instrument is the wage bill of immigrants from origin $o$ in market $m$ in year 1995 relative to the total wage bill in market $m$ in 1995.[26] We use "kreis" as the market concept ($m$) of this instrument, which is the finest geographical area in our dataset. The shift component of the instrument captures the employment level of immigrants from country $o$ relative to Germans in market $m$ in year $t$. This instrument exploits country-of-origin-driven variation in the relative supply of immigrant across markets and "assigns" the increase of immigrants from each origin in that market to firms according to their market-share in 1995.

The validity of the instrument depends on this market share not being correlated with shocks determining the relative wage that firms pay in period $t$. Larger firms tend to have a larger market share and may also tend to pay systematically different average wages to immigrants relative to natives. Even though we control for time-invariant firm heterogeneity, there may be serially correlated time-varying productivity shocks that affect the relative size of firms in 1995 and their hiring decisions in the future. This would bias the 2SLS estimate upward. The time-industry fixed effect will help control for unobserved time-varying shocks. Finally, we cluster standard errors at the firm level to account for the correlation within firm over time.

Table 14 presents the OLS and the 2SLS estimates of 45. The OLS estimate of $\frac{\epsilon-1}{\epsilon}$ is larger than 1 and implies an unreasonable elasticity of substitution between immigrants and natives of -35.1. The 2SLS estimate in column 2 is lower than one and statistically significant. This estimate implies that the elasticity of substitution between immigrants and native workers within the firm is 4.28. As expected, the OLS estimate is upward biased, since the error term includes demand-side shocks that positively affect the wages and employment of immigrants relative to natives. The instrument is strong, as shown by the F-stat in Table 14.

[26] While the data is available since 1975, we use 1995 as our base year since administrative data for East Germany only becomes available after 1993.

Table 14: Estimates for $\epsilon$

| | OLS | 2SLS | | First stage |
|---|---|---|---|---|
| Estimate for $(\epsilon-1)/\epsilon$ | 1.029*** | 0.81*** | Instrument | -0.00025*** |
| | (0.003) | (0.355) | | (0.00005) |
| Number of observations | 458,308 | 458,308 | | 458,308 |
| Implied $\epsilon$ | -35.1 | 4.28 | 1st stage F-stat | 21.29 |

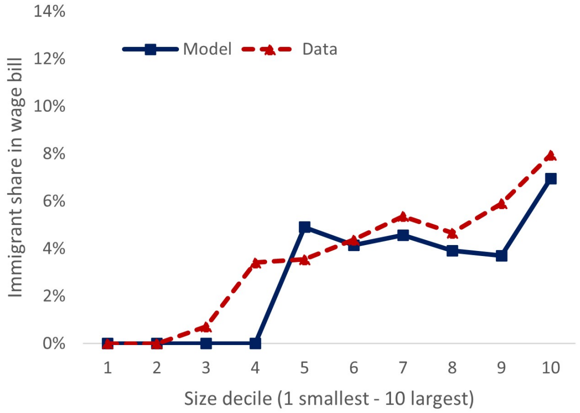
*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. OLS and 2SLS estimates for equation 45. We include industry-time and firm fixed effects. Industry-time FEs are defined according to our tradable and non-tradable industries used in the model. Standard errors are clustered at the firm level and bootstrapped with 200 repetitions. Time period used is 1995 to 2014.

### Model Fit

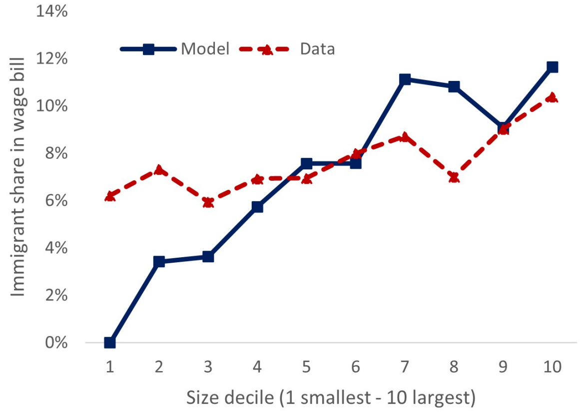
While the model matches the targeted moments, we want to make sure it also matches nontargeted moments that are relevant to our main mechanisms. As shown in Figure 7, the model does a good job in matching the cross-sectional means and medians of the immigrant share by size decile. The medians are completely untargeted by the estimation routine, and the model does a good job in replicating the positive slope in the tradable sector and somewhat misses the slight increasing slope in the non-tradable sector. However, the observed correlation between size and immigrant share in the non-tradable sector is weak and the model captures the levels reasonably well. The means are also informative of the distribution within decile. These are not completely untargeted since we are matching the mean immigrant share across all establishments in our estimation routine as well as the difference in the means of P90 and P50 for each sector. However, we are not targeting the mean by sector nor the relationship between any deciles other than 5 and 9. As shown in Figure 7, the model does a good job matching both means but underestimates the mean for the first deciles in the tradable sector.

Figure 7: Immigrant share across establishments: model vs data

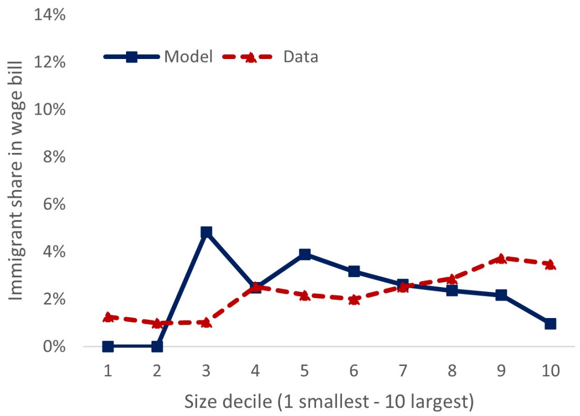
(a) Median Tradable



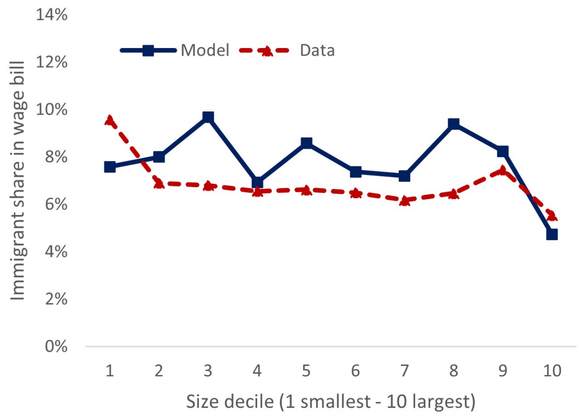

(b) Mean Tradable




(c) Median Non-Tradable




(d) Mean Non-Tradable




*Note:* We divide establishments in the model and the data into size deciles, where 1 groups the smallest establishments. We plot the mean and median for each decile and each sector as shown by the data as in Figure 1. For the model, we plot the size distribution predicted by our estimated model.

# F Empirical Results Details

## F.1 Heterogeneous Response to Immigration: Additional Results

Table 15: First stage regressions

| | Full sample | | Tradable sector | | Non-Tradable sector | |
|---|---|---|---|---|---|---|
| | $s^{agg}_{m,t}$ | $s^{agg}_{m,t} \times log(\text{size})$ | $s^{agg}_{m,t}$ | $s^{agg}_{m,t} \times log(\text{size})$ | $s^{agg}_{m,t}$ | $s^{agg}_{m,t} \times log(\text{size})$ |
| $Z_{m,t}$ | 1.49*** | 0.59 | 1.35*** | -0.86 | 1.50*** | 2.79 |
| | (0.256) | (1.420) | (0.374) | (2.013) | (0.377) | (1.918) |
| $Z_{m,t} \times log(\text{size})$ | -0.02 | 1.15*** | 0.02 | 1.45*** | -0.07 | 0.61 |
| | (0.05) | (0.298) | (0.069) | (0.413) | (0.074) | (0.241) |
| N | 3507 | | 1974 | | 1533 | |
| Kleinberg-Paap F-stat | 35.86 | | 29.48 | | 15.53 | |

*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market-time trends, and lagged firm level controls such as log employment and investment. Sample is restricted to establishments with more than 30 employees. Standard errors are clustered at the establishment level.The Kleibergen-Paap F-stat tests for the joint significance of both instruments. The first two columns are the first stages for the full sample, columns 3 and 4 restrict the sample to establishments in the tradable sector, and columns 5 and 6 to the non-tradable sector.

Table 16 evaluates how the controls added to the regression affect our estimates. Column 2 removes the firm-level controls, column 3 removes the industry-time FEs, and column 4 removes the local labor market trends.

Table 17 presents the heterogeneous effects of the immigration shock on profits, total employment, and labor productivity. Profits are measured as revenues net of wage bill and material bill, and labor productivity is measured as the ratio between revenues and employment. The 2SLS estimates in Table 17 reassures the previous findings on the heterogeneous effect of immigration. Relative to small establishments, larger establishments hire more workers and show a larger labor productivity (columns 2 and 3). Estimates for profits are imprecisely estimated, so we cannot reject a null effect of changes in response to the immigrant share.

## F.2 Export Revenues vs Domestic Revenues

A second prediction is that the drop in unit costs generated by immigration would expand export revenues more than domestic revenues because an exporter faces a demand curve from the RoW that is more elastic than its domestic demand.

Table 16: Robustness exercises for main specification

| | Baseline | No firm-level controls | No industry-time FEs | No local labor time trends |
|---|---|---|---|---|
| $\theta_1$ | -31.86*** | -37.39** | -52.91*** | -25.32** |
| | (11.47) | (15.41) | (12.79) | (10.99) |
| $\theta_2$ | 7.49*** | 8.56*** | 12.38*** | 5.93** |
| | (2.46) | (3.28) | (2.74) | (2.4) |
| N observations | 3507 | 3507 | 3507 | 3507 |
| N establishments | 949 | 949 | 949 | 949 |
| 1st stage F-stat | 35.85 | 8.76 | 33.67 | 18.18 |

*Note.*$^{***} = p < 0.01, ** = p < 0.05, * = p < 0.1$. Dependent variable in all cases is log revenues. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 10 employees. Column 1 shows the baseline specification with full controls. Column 2 removes the firm-level controls. Column 3 removes the industry-time fixed effects and controls only for time fixed effects. Column 4 removes the local labor time-trends.

Table 17: The impact of immigration on other outcomes

| | Log Profits | Log employment | Log Revenue per employee |
|---|---|---|---|
| $\theta_1$ | -136.7 | -4.82 | -26.99** |
| | (101.31) | (6.43) | (11.4) |
| $\theta_2$ | 29.6 | 1.64 | 5.83** |
| | (17.35) | (1.4) | (2.51) |
| Average $\epsilon^y$ | 0.47 | 0.18 | 0.09 |
| Threshold size | 101 | 19 | 102 |
| N observations | 2901 | 3507 | 3507 |
| N establishments | 853 | 949 | 949 |
| Estimation | 2SLS | 2SLS | 2SLS |
| 1st stage F-stat | 30 | 35.86 | 35.85 |

*Note.*$* * * = p < 0.01, ** = p < 0.05, * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employees

Table 18 presents the estimated results of regression 19 for domestic revenues and export revenues for the sample of exporters. The average response of export revenues is stronger than domestic revenues, and in both cases, the heterogeneous effect significantly favors large establishments relative to small establishments. These estimates imply that by each 1% increase of the labor market immigration share, domestic revenues increase by

0.44%, whereas export revenues increases by 1.15%. Since the response of export revenues is stronger than domestic revenues, this channel can explain part of the heterogeneous effects found in Table 4. Large establishments, which are more likely to be exporters, may adjust more to the immigration shock because they are able to expand their export revenues whereas for small firms, expansion is constrained by the size of the domestic market.

Table 18: Revenue regressions by sector and exporter status

| | Log Export Revenues | Log Domestic Revenues |
|---|---|---|
| $\theta_1$ | -87.99** | -78.45*** |
| | (39.31) | (29.77) |
| $\theta_2$ | 20.64** | 16.6*** |
| | (8.07) | (5.92) |
| Average $\epsilon^y$ | 1.15 | 0.44 |
| Threshold size | 71 | 113 |
| N observations | 1654 | 1654 |
| N establishments | 466 | 466 |
| Estimation | 2SLS | 2SLS |
| 1st stage F-stat | 20.72 | 26 |

*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market-time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employess and that report positive export revenues.

To summarize our findings, the reduced-form evidence presented in this section shows that larger employers benefit more from an increase in the immigrant share of the local labor market than small establishments. Establishments' export revenues are more responsive than its domestic revenues. This evidence is consistent with the mechanisms put forward in the model: given that large firms are more immigrant-intensive than small firms (Figure 2a), large firms face a larger drop in the labor cost of production than small firms when the economy receives a new wave of immigrants. This drop in the cost of production drives large firms to expand their production at the expense of putting downward pressure on the market price of the good they sell. This downward pressure is weaker the more elastic the demand. Given that large firms are likely to export and foreign demand is more elastic, they find it optimal to increase production to all markets and especially to export markets. As a result, an influx of immigrants is mostly absorbed by large firms that find it profitable to expand production.

## F.3 Shift-share Instrument Diagnostics

Our instrument falls into the category of shift-share instruments, and as such, we run a series of diagnostics suggested by the literature on the validity of shift-share instruments (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020). Our setup is not exactly the standard shift-share case because in addition to the shift-share instrument, we have an interaction between the instrument and the log size of the establishment. However, we can still use the guidance of these methodological papers to understand the variation driving our instruments.

As a first step, we follow the suggestions in Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2021) and test for pre-trends. The shift-share design implies that the common shock is the main driver of the observed changes, so we need to make sure there were no preexisting differences explaining such observed changes. As shown in Table 19, we lag the outcome 5 years and 1 year and use them as outcomes in our baseline regression. The instrument is still strong, but the second stage coefficients are not significant. This corroborates that the observed changes are not driven by preexisting differences across establishments. Borusyak et al. (2021) also suggest that if the sum of the initial shares does not add up to one within local labor market, we should control for the sum of the exposure shares in our regression. We do so in a non-parametric fashion by including an establishment fixed effect in our regressions which would absorb the sum of initial shares at the local labor market level.

Table 19: Pre-trends tests

| | Log Total Revenues $t-5$ | Log Total Revenues $t-1$ |
|---|---|---|
| $\theta_1$ | 2.51 | -7.48 |
| | (9.28) | (9.61) |
| $\theta_2$ | -1.29 | 2.09 |
| | (1.93) | (1.99) |
| N observations | 3329 | 3434 |
| N establishments | 907 | 937 |
| 1st stage F-stat | 41.16 | 40.85 |

*Note.* $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employess. The first column includes the outcome variable lagged by 5 periods, the second column includes the outcome variable lagged by one period.

As a second step, we focus on the case of testing for exogenous shares, and run a set of diagnostics proposed by Goldsmith-Pinkham et al. (2020). We perform the tests for a simplified version of equation 19, where we do not include the size interaction term nor the industry-time fixed effects and labor market trends. While the regression is different than our main specification, the analysis is still useful to understand what is driving the main shift-share instrument.

In our case, we can write the first stage coefficient on the shift-share instrument as a combination of the estimates of nine separate first stage regressions. Each of these "just identified" regressions uses an instrument that is constructed with the initial share and shock of only one of our nine origin regions. The weights in which each of these nine instruments affects the overall IV are called Rottemberg weights. We proceed to use the code provided by Goldsmith-Pinkham et al. (2020) to calculate such weights and denote them $\alpha$. Each origin region is affected each year by a national level shock we denote by $G$. The just identified coefficients are denoted by $\beta$.

As shown in panel A of Table 20, 89% of the Rottemberg weights are positive, meaning that our regression is likely not subject to misspecification. In panel B, we show the correlation between the weights, the shocks, and the just-identified coefficients. Panel C shows the top five origin regions in terms of the Rottemberg weights. For the time period between 2003-2011, countries of former Yugoslavia have the largest weight with 0.28. These are followed by Asia-Pacific (0.24), other non-EU countries which include predominantly Russian immigrants (0.17), Africa and Middle East (0.15), and Turkey (0.07). These regions are expected to drive most of the variation in our instrument. It is reassuring however, that no single region accounts for a large majority of the variation in our instrument.

Finally, we look into the correlation between the initial shares used in the instrument and other covariates at the local labor market in the initial period. The intuition behind this exercise is that the variation in the initial shares should not be explained by other covariates that can also affect the change in outcomes at the regional level. As shown in Table 21, key characteristics at the regional level only explain 4.4% of the total variation in the shares, indicating that the shares are not significantly driven by other observables.

Table 20: Shift-share diagnostics

| Panel A | Sum | Mean | Share |
|---|---|---|---|
| $\alpha_s \leq 0$ | -0.014 | -0.014 | 0.111 |
| $\alpha_s > 0$ | 1.014 | 0.127 | 0.889 |
| **Panel B** | $\alpha_s$ | $G$ | $\beta_s$ |
| $\alpha_s$ | 1 | - | - |
| $G$ | 0.149 | 1 | - |
| $\beta_s$ | 0.013 | -0.402 | 1 |
| **Panel C** | $\alpha$ | $G$ | $\beta$ |
| Countries of former Yugoslavia | 0.28 | 0.98 | 1.54 |
| Asia-Pacific | 0.24 | 1.11 | 4.46 |
| Europe other | 0.17 | 1.23 | 3.89 |
| Africa and Middle East | 0.15 | 1.13 | 3.97 |
| Turkey | 0.07 | 0.83 | 1.47 |

*Note.*We run the shift-share diagnostics suggested by Goldsmith-Pinkham et al. (2020). Panel A shows the share of Rottemberg weights that are positive and negative. Panel B shows the correlation between the Rottemberg weights, the time-shifter shock $G$, and the just-identified coefficients $\beta$. Panel C summarizes $\alpha$, $G$, and $\beta$ for the top 5 origin regions in terms of weights.

# G Additional Quantitative Results

## G.1 Size of the Inflow of Immigrants

Table 22: Change in real wages for alternative counterfactuals

| | Percent change in immigrant stock | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0.1% | 1% | 5% | 10% | 20% | 30% | 50% |
| Real wages | 0.001% | 0.01% | 0.06% | 0.12% | 0.24% | 0.36% | 0.58% |
| Homogeneous/Heterogeneous | 0.82 | 0.88 | 0.90 | 0.89 | 0.89 | 0.89 | 0.89 |
| Homogeneous (agg)/Heterogeneous | 0.63 | 0.88 | 0.91 | 0.91 | 0.92 | 0.91 | 0.92 |
| Aggregate Elasticity | 4.154 | 4.216 | 4.224 | 4.206 | 4.203 | 4.202 | 4.185 |

*Note.*We compute real wage changes for different aggregate changes in the number of immigrants. The row "Homogeneous/Heterogeneous" presents the relative real wage changes between the homogeneous model and our baseline heterogeneous model. The row Homogeneous (agg)/Heterogeneous, computes the relative real wage changes between a homogeneous model and our baseline model, where the homogeneous model has the same aggregate elasticity than the one predicted by the heterogeneous model. The aggregate elasticity is the endogenous elasticity of substitution between immigrants and natives in the baseline heterogeneous model.

Table 21: Correlation between initial shares and observables

| | Initial share 03 |
|---|---|
| Avg Age | -0.0008 |
| | (0.0003) |
| Share Female | -0.0086 |
| | (0.007) |
| Share College | 0.0207 |
| | (0.014) |
| Share Manual Occupation | 0.0096 |
| | (0.009) |
| Share Services Occupation | 0.0129 |
| | (0.007) |
| Share Manufacturing | -0.004 |
| | (0.002) |
| Average Wage | 4.60E-07 |
| | (1.08E-07) |
| N | 936 |
| R-sq | **0.0436** |

*Note.*We pool 104 local labor market and 9 origin regions. Regressions include an origin region FE, but results are consistent to not controlling for origin FEs or running a separate regression for each origin. As covariates, we include average age, share of women, share of college graduates, share in manual and services occupations, share in manufacturing industry, and average wage. Key statistic for analysis is the R-squared.

## G.2 Homogeneous Model

This section presents the estimates of the parameters estimated by simulated method of moments for the homogeneous model, conditioning on $\hat{\epsilon} = 4.28$, $\hat{\sigma} = 3.08$, and $\hat{\sigma_x} = 3.62$.

Table 23: Simulated vs data moments

| Moment description | Simulated | Data | Moment description | Simulated | Data |
|---|---|---|---|---|---|
| Aggregate $s_{d,T}$ | 0.91 | 0.91 | GDP per capita RoW to Germany | 0.32 | 0.32 |
| Aggregate $s_{d,NT}$ | 0.93 | 0.93 | Share of firms exporting, T | 0.37 | 0.37 |
| $\mathbb{V}ar(log(rev_j)\|s_{d,j}, exporter_j)$, T | 1.38 | 1.38 | $\mathbb{E}$(Export to Domestic Rev$_j$), T | 0.79 | 0.79 |
| $\mathbb{V}ar(log(rev_j)\|s_{d,j})$, NT | 1.29 | 1.29 | $\mathbb{E}(s_d)$ | 0.93 | 0.93 |

Table 24: Parameter estimates using simulated method of moments

| Parameter description | Parameter | Estimate | Parameter description | Parameter | Estimate |
|---|---|---|---|---|---|
| Share of natives, $T$ | $\beta_T$ | 0.82 | Productivity in RoW | $\psi_x$ | 1.64 |
| Share of natives, $NT$ | $\beta_{NT}$ | 0.84 | Fixed cost of exporting | $f_g$ | 0.014 |
| Dispersion in $\psi_j$, T | $\sigma_{\psi,T}$ | 1.03 | Iceberg trade cost | $\tau$ | 1.55 |
| Dispersion in $\psi_j$, NT | $\sigma_{\psi,NT}$ | 0.38 | Elasticity $s_d$ to $n$ | $\iota$ | 0.014 |

## G.3 Homogeneous Model with aggregate elasticity

This section presents the estimates of the parameters estimated by simulated method of moments for the homogeneous model, conditioning on the aggregate elasticity of substitution implied by the heterogeneous model ($\hat{\epsilon} = 4.20$) and, as before, $\hat{\sigma} = 3.08$, and $\hat{\sigma_x} = 3.62$. We compute the aggregate elasticity of substitution implied by the heterogeneous model as the weighted average of the elasticity in the labor market for tradable and for non-tradable sector. The weights are given by the number of firms in each sector and equal to 0.5. The elasticity in each labor market is computed as follows:

$$\epsilon = \frac{d\ ln\ L_g/L_{g,x}}{d\ ln\ w_{g,x}/w_g}$$

Table 25: Simulated vs data moments

| Moment description | Simulated | Data | Moment description | Simulated | Data |
|---|---|---|---|---|---|
| Aggregate $s_{d,T}$ | 0.91 | 0.91 | GDP per capita RoW to Germany | 0.32 | 0.32 |
| Aggregate $s_{d,NT}$ | 0.93 | 0.93 | Share of firms exporting, T | 0.37 | 0.37 |
| $\mathbb{V}ar(log(rev_j)\|s_{d,j}, exporter_j)$, T | 1.38 | 1.38 | $\mathbb{E}$(Export to Domestic Rev$_j$), T | 0.79 | 0.79 |
| $\mathbb{V}ar(log(rev_j)\|s_{d,j})$, NT | 1.29 | 1.29 | $\mathbb{E}(s_d)$ | 0.92 | 0.93 |

Table 26: Parameter estimates using simulated method of moments

| Parameter description | Parameter | Estimate | Parameter description | Parameter | Estimate |
|---|---|---|---|---|---|
| Share of natives, $T$ | $\beta_T$ | 0.82 | Productivity in RoW | $\psi_x$ | 1.64 |
| Share of natives, $NT$ | $\beta_{NT}$ | 0.84 | Fixed cost of exporting | $f_g$ | 0.008 |
| Dispersion in $\psi_j$, T | $\sigma_{\psi,T}$ | 1.03 | Iceberg trade cost | $\tau$ | 1.56 |
| Dispersion in $\psi_j$, NT | $\sigma_{\psi,NT}$ | 0.38 | Elasticity $s_d$ to $n$ | $\iota$ | 0.014 |

# The International Price of Remote Work*

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**Abstract**

We study how the price of remote work is determined in a globalized labor market using data from a large web-based job platform, where workers from around the world compete for remote jobs. Despite the global nature of the platform, we find that remote wages are higher for workers in regions with higher income per-capita. This correlation is not accounted for by differences in workers' observable characteristics, occupations, or differences in the employers' locations. Instead, data on wage-histories indicate that remote wages are partly determined by the conditions that workers face in their local labor markets. We also show that remote wages expressed in local currency move strongly with the dollar exchange rate of the worker's country and are highly sensitive to foreign competition. Finally, we identify occupations at high-risk of being offshored based on the prevalence of cross-border contracts.

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*JEL Codes: F1, F2, F4, F6*

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# 1 Introduction

An increasing number of jobs are being done remotely, a trend that accelerated dramatically during the COVID pandemic.[1] Remote work can be done from anywhere, even across international borders, which can make these jobs easier to offshore.[2] By globally integrating labor markets, the rise of remote work can have a profound impact on the levels and dynamics of wages across the world.[3] Will wages be equalized across remote workers located in different countries? How will such wages respond to international shocks? Which remote jobs are more likely to be offshored? While these questions are crucial for understanding the future of wages in both developing and developed countries, there is limited research on how the price of remote work is determined in globalized labor markets.

This paper uses new data from a large web-based job platform to shed light on these questions. Web-based job platforms match employers and workers located around the world who trade tasks that are delivered remotely, providing a window into a globalized market for remote work. The number of such platforms has tripled over the past decade. By 2020, hundreds of web-based job platforms had facilitated millions of international transactions totaling over 50 billion US$ (ILO 2021). The emergence of these platforms coincided with the dramatic growth in ICT-Enabled Service trade, which quadrupled in the US since the year 2000 and now accounts for 70% (800 billion US$) of all US service trade.[4]

Our dataset is sourced from one of the largest platforms in the market today. It has several features that make it particularly well suited for our purposes. First, workers are located around the world and compete for the same jobs. These jobs can be done remotely, require little capital other than a computer, and encompass a wide range of occupations, ranging from accountants to web developers. This makes the platform the ideal marketplace for studying the international price of remote work. Second, the dataset is very rich: in addition to hourly wages, it contains extensive information on worker characteristics such as experience, earnings, quality ratings, and standardized test scores and certifications. This information is essential for understanding cross-country wage differences, as it facilitates the comparison of workers around the world. Third, the data record the workers' job histories in the platform (wages, earnings, and start date of each job), which are necessary

[1] Bloom et al. (2022), Aksoy et al. (2022), and Hansen et al. (2022).

[2] Blinder and Krueger (2013).

[3] Baldwin (2016, 2019) and ILO (2021).

[4] U.S. Bureau of Economic Analysis, Table 3.1. International Services (accessed Sept 30, 2021).

for understanding how remote wages respond to shocks. Finally, the job histories contain the employers' identities and locations, which in conjunction with the workers' locations, allow us to identify which jobs are being offshored.

We first document large differences in remote wages across workers located in different countries. For example, the wages of Indian workers are, on average, a third of those of US workers. In fact, the country of the workers accounts for at least a quarter of the variance of wages in the data. Furthermore, remote wages are strongly correlated with the GDP per capita in the worker's country: the elasticity of wages to GDP per capita is 0.22. We document a very similar elasticity between remote wages and GDP per capita across US states. These elasticities are not accounted for by observable differences in worker and job characteristics, differences in the employers' locations, or the fact that workers work for different employers. We show, however, that remote wages are more equalized across countries than non-remote wages.

We propose a model of a global remote labor market that rationalizes these observations. In the model, workers from different locations are imperfect substitutes and can choose to work either in their local or in the remote labor market.[5] Equilibrium remote wages vary across locations if workers have different productivities or face different local wages. We disentangle these two alternative hypotheses by estimating a model-based exchange rate pass-through (ERPT) regression. We show that the partial elasticity of dollar wages with respect to the exchange rate between the dollar and the currency in the worker's location is 0.20, which is in line with the cross-country elasticity of remote wages to GDP per capita. Under the assumption that changes in exchange rates affect local wages denominated in dollars but are uncorrelated to changes in remote workers' productivity, this result indicates that remote wages are tied to the conditions that workers face in their local labor markets.

We also study how remote wages respond to other international shocks. Our estimates imply that (partial) ERPT into local currency wages is 80%. This is in sharp contrast to non-remote wages, which typically do not respond to movements in exchange rates at short horizons.[6] We further show that a worker's wage reacts strongly to changes in the wages of other workers on the platform. Guided by the model, we regress the change in a worker's wage on an index measuring the changes in wages of a worker's competitors. To overcome endogeneity issues, we exploit that workers in different sectors face com-

[5] Alternatively, we can assume that workers are perfect substitutes but specialize in different tasks, as shown in Appendix A.4.

[6] This finding is not mechanically accounted for by remote wages being sticky in dollars, as we obtain a similar elasticity when focusing on a subsample of dollar wages that do change in a particular period.

petitors from different countries, and construct a model-based instrument for changes in competitors' wages that uses variation in the inflation and exchange rate changes in the competitors' countries. We find that workers adjust their wages in response to changes in their competitors' wages with an elasticity of 0.74. Since most of our workers work from outside the US, this means that US remote workers are exposed to shocks that affect their foreign competitors.

Finally, we use our data to shed light on which occupations are more likely to be offshored. Existing measures of 'offshorability' typically hinge on subjective judgments of the different attributes of a job. Such judgments are often based on whether a job can be performed remotely. For example, Blinder and Krueger (2013) establish that a job is easily offshorable if it involves extensive use of computers/email, processing information/data entry, talking on the telephone, or analyzing data. Instead, we directly measure the frequency with which US jobs are offshored by computing the share of US contracts in an occupation in which the worker is located outside the US. The data on cross-border contracts reveal that whether a job is done remotely is an imperfect proxy for whether a job is actually being offshored. For instance, less than a third of grant writer jobs in the platform are offshored, even though all of them are performed remotely. We show that wages are less dispersed across countries in occupations that are more frequently offshored.

Our paper relates to various strands of the literature. First, it is related to a rapidly growing literature that studies the rise of remote work and its consequences. Hansen et al. (2022) document a three-fold increase in vacancy postings for remote work between 2019 and 2022. Aksoy et al. (2022) use data from 27 countries to document work-from-home patterns around the world in 2022. Barrero et al. (2022) use survey data to estimate that remote work can moderate wage-growth pressures in the US by 2 percentage points over two years.[7] We contribute to this literature by documenting cross-country differences in wages across workers in a globalized market for remote work.

Second, we contribute to a large literature on international price and wage comparisons. The main source of international price comparisons is the Penn World Table (see Feenstra et al. 2015), while more recent papers make international price comparisons using online data (see, e.g., Cavallo et al. 2014, Gorodnichenko and Talavera 2017, and Cavallo et al. 2018). Data on international wages are more limited. Ashenfelter (2012) documents

[7]There is a separate literature that uses data from remote job platforms to study topical questions in Labor Economics. Horton (2017) and Barach and Horton (2021) use experimental data from a large platform to study how minimum wages and compensation histories affect labor market outcomes. Stanton and Thomas (2015) use data from oDesk (now Upwork) to show that outsourcing agencies that intermediate between workers and employers have emerged in that market, while Dube et al. (2020) use data from Amazon Mechanical Turk to study monopsony power.

cross-country wage differentials for McDonalds' employees. Hjort et al. (2019) document that multinationals' wages around the world are anchored to wage levels at headquarters, while Hjort et al. (2022) use a database covering compensation for 300,000 middle managers to show that their wages vary little across countries. Inside the US, Hazell et al. (2022) show that large firms post similar wages across locations. We contribute to this literature by providing international wage comparisons for remote workers. We show that despite the global nature of this marketplace, there is pervasive dispersion in wages across observationally-equivalent workers that are located in different countries.

Third, our paper contributes to an extensive literature on exchange rate pass-through (see Burstein and Gopinath 2015 and the papers cited therein). Gopinath et al. 2020 show that in most countries, goods export prices in dollars are stable, and local currency export prices move with the dollar exchange rate. Due to data limitations, that literature has focused almost exclusively on exchange rate pass-through into goods prices. Our paper is the first to study pass-through into the price of tradeable services (remote jobs). We show that ERPT into dollar wages is low, so remote wages denominated in domestic currency move almost one-to-one with the dollar exchange rate. In this respect, the global market for remote workers behaves similarly to the global goods market.

Finally, our paper is related to a large literature on how wages are affected by foreign competition, either through trade (e.g. Goldberg and Pavcnik 2007, Autor et al. 2013, 2016), offshoring (e.g. Feenstra and Hanson 2003, Hummels et al. 2014), or international migration (e.g. Borjas 2014, Card and Peri 2016). Blinder (2009) and Blinder and Krueger (2013) classify occupations according to their offshorability, and consider jobs that can be done remotely as being easily offshorable. Our paper lies at the intersection of these topics, as the cross-border contracts in our platform can be simultaneously interpreted as trade in services, offshoring, or 'tele-migration'. We show that in a globalized market for remote work, a worker's wage responds strongly to changes in the wages of foreign competitors. We also measure the prevalence of cross-border remote work for different occupations, and document substantial heterogeneity in the frequency at which remote work is offshored across remote occupations.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 compares remote wages across countries. Section 4 studies how remote wages respond to international shocks. Section 5 measures which jobs are more frequently offshored, and the last section concludes.

# 2 Data

## 2.1 Data description

Web-based job platforms match workers and employers across the world who sell and buy services that are delivered online. We obtained our data from one of the largest web-based job platforms in the market today. We collected one snapshot in January 2019 and another in November 2020. The platform encompasses remote jobs from a wide range of industries, ranging from accountants to web developers, and has millions of registered workers and employers around the globe that transacted around 2 billion US$ in 2020.

Workers that register on the platform must create a profile and post an hourly wage at which they are willing to work. All wages in the platform are set and displayed to potential employers in US dollars.[8] Employers can post job listings, to which workers can apply, or alternatively search for workers that match their needs. Billing and payments are handled by the platform, and jobs are paid within two weeks of completion. The platform's revenues originate from fees charged to workers (in the form a percentage of their invoiced earnings) and clients (in the form of a percentage of all payments made to a worker).

We build our dataset by collecting data from the publicly-available profiles of workers in the platform. We focus our sample on 100,023 workers that have a completed profile and have positive earnings and job experience in the platform.[9] In addition to the worker's 'ask' hourly wage, the profiles contain the following information.

**General information:** The platform displays the name and location (country and city) of each worker.[10] It also reports the type of jobs or 'occupations' that each worker can perform, which are self-reported at the time the worker creates a profile and are selected from a predetermined list of 91 occupations. In addition, workers can specify their time availability, and provide a brief written description of their skills and interests in their profiles. We anonymize the dataset of all personal information and extract a worker's unique identifier along with their location, occupation, and time availability.

[8]All contracts are denominated in U.S. dollars. However, the platform offers clients the option to settle invoices denominated in U.S. dollars in the local currencies of several non-U.S. countries.

[9]Since creating a profile is easy and free of charge, a large fraction of profiles appear to be ghost accounts with no registered activity on the Platform. We exclude such inactive profiles from the analysis.

[10]The platform routinely sends freelancers and clients verification requests asking for documents that verify their residence (e.g., bank statements, credit card statements, and utility bills). The submitted address must match the location information that freelancers and clients entered on the Platform.

**Skills:** Workers can list several predetermined skills and take online examinations through the platform to certify their expertise in certain areas, such as 'English to Spanish Translation'. The platform offers more than 200 different tests. We observe the tests each worker takes, along with the scores and rank percentiles among the platform's population. We use the results from these tests as our primary measure of skills, as they are standardized across all workers.

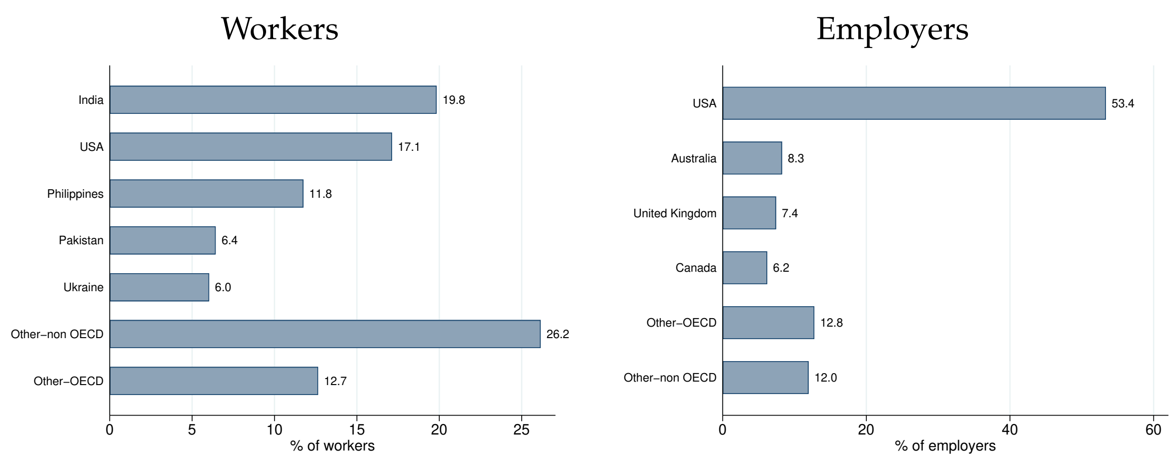
**Experience and quality:** In addition to the information provided by workers, the profiles record information that is based on the workers' interactions with the platform. Specifically, the platform records each worker's total earnings and total number of jobs completed. Additionally, it displays the average response time for each worker and the percentage of contracted jobs they have successfully finished, referred to as the 'success rate'. Finally, the Platform certifies experienced workers as 'Top-Rated.' To earn and maintain a Top Rated status, a worker must have, at a minimum, a completed profile, a job success rate of 90%, $1,000 in earnings in the previous year, and must have had some activity in the platform (i.e., accepted a job invitation or received earnings) in the past 90 days. Thus, the platform rewards its most active and successful workers by awarding them Top Rated status.

**Job histories in the platform:** For each job that a worker started, the platform reports a description of the job, the total payment and, if the contract was stipulated on an hourly basis, the transacted hourly rate and number of hours worked. It also reports the start date and, if the job is not still in progress, the end date of each job. Given the complexity of the process, we obtained a sample of the job histories for a subset of 30,520 workers. Finally, for a subsample of 348,000 of these jobs, we obtained information on the employer's identifier and location.

## 2.2 Summary statistics

The data collected include the profiles of more than 100,000 workers located across a total of 183 countries, although most workers are concentrated in a few countries. Overall, there are 26 countries with at least 500 workers, 65 countries with at least 100, and 90 countries with at least 50 workers. Figure 1 compares the geographical distribution of workers and employers in the data. Over 60% of the workers are concentrated in 5 countries: India, the US, Philippines, Pakistan, and Ukraine. Employers are even more concentrated—75% of employers are located in just 4 countries: the US (53.4%), Australia (8.3%), the UK (7.4%), and Canada (6.2%). While the US is a large source of both workers and employers, most employers (88%) are located in OECD countries, while most workers (70%) are located in non-OECD countries. This indicates that many workers from non-OECD countries work for employers in OECD countries. In fact, for 87% of the jobs in our sample, the worker and the employer are located in different countries.

Figure 1: Distribution of jobs across worker's and employer's locations

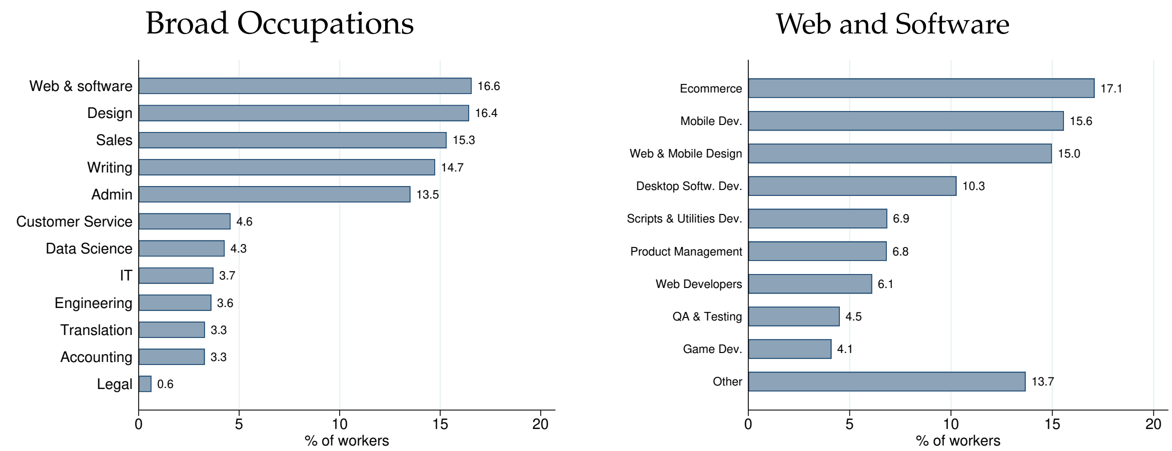



Notes: The figure shows the distribution of jobs across the workers' locations (left panel) and the employers' locations (right panel).

Figure 2 shows the distribution of workers across 12 broad occupations. In our sample, the largest occupations in terms of the number of workers are 'Web and Software', 'Design', and 'Sales', accounting for 16.6, 16.4, and 15.3 percent of the workers of our sample, respectively. In contrast, only 0.6 percent of the workers in our sample are listed in 'Legal'. Each broad occupation can be further disaggregated into detailed occupations. For example, the right panel of Figure 2 shows that within 'Web and software', 20 percent of workers are listed as 'E-commerce'. There are 91 detailed occupations in total, which we list in Appendix Table A1.

Table 1 reports summary statistics for some of the main variables that will be used in our analysis. Ask wages in the platform are high for international standards: the median and mean wages are 18 and 25 dollars, respectively. There is, however, a wide variation in wages: the gap between the 95th and 5th percentile of the wage distribution is 2.8 times as large as the mean. The average worker in the data has completed 69 jobs and earned 18,667 US dollars. The distribution of earnings exhibits large dispersion, with a 5th and 95th percentiles of 20 and 90,000 dollars, respectively. Although these numbers reflect cumulative earnings in the platforms, they are 6-9 times larger than the annual income

Figure 2: Workers by broad occupation




Notes: The left panel reports the share of the workers across the 12 broad occupations in the platform. The right panel reports the shares in each detailed occupation belonging to 'Web and Software'.

per capita in countries such as India, Pakistan, or the Philippines, and are also substantial in relation to the income per capita in the US. This suggests that a large number of workers are probably earning most of their income through the platform. Indeed, 42% of workers report being available more than 30 hours per week, and an additional 33% are available 'as needed'.

The platform allows workers to take standardized tests to signal their skills. The median (average) worker takes 3 (4) tests in the platform, and the standard deviation of (cross-test average) scores is 12% of the mean score. Finally, 41% of the workers in our sample are classified as 'Top Rated', and only 28% have a success rate of 100%.

**Comparability of ask vs. transacted wages:** As noted above, the dataset contains information on both the hourly 'ask' wage listed on the worker's profile and the hourly 'transacted' wage in each (hourly) job listed in the worker's job history. Figure A.1 in the Appendix shows a scatter plot of a worker's (log) ask wage in January 2019 and the workers' 2018-2019 average (log) hourly wage based on transactions recorded in their job histories. The figure shows that log transacted wages move close to one for one with log posted wages: The slope of the relationship is 0.91. The intercept in the relationship is -0.02, which means that on average, transacted wages are 2% lower than ask wages. Although this difference could naturally arise if, for example, employers bargain with workers before hiring them, the quantitative relevance of such mechanisms seem to be small.

Table 1: Summary statistics

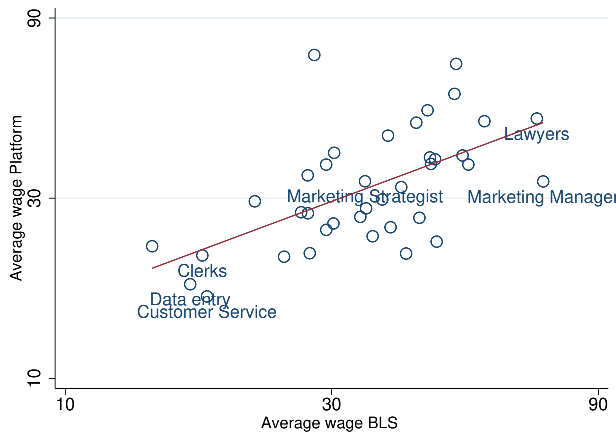
| | Mean | Median | St. Dev. | 5 pct | 95 pct |
|---|---|---|---|---|---|
| Ask hourly wage | 25 | 18 | 27 | 5 | 75 |
| Number of jobs | 69 | 10 | 642 | 1 | 147 |
| Total earnings | 18,667 | 4,000 | 62,558 | 20 | 90,000 |
| Number of tests | 4 | 3 | 4 | 1 | 10 |
| Average score | 4.23 | 4.25 | 0.50 | 3.38 | 5 |

| | Share of workers | Success rate | Share of workers |
|---|---|---|---|
| Top Rated | 0.41 | N/A | 0.42 |
| Agency | 0.15 | <70% | 0.02 |
| | | [70%,80%) | 0.03 |
| Available as needed | 0.33 | [80%,90%) | 0.07 |
| Available < 30 hs. per week | 0.13 | [90%,95%) | 0.07 |
| Available > 30 hs. per week | 0.42 | [95%,100%) | 0.11 |
| Availability N/A | 0.12 | 100% | 0.28 |

Notes: The top of the table reports moments of the distribution of worker characteristics. Hourly wage refers to the ask wage specified in the worker's profile. Number of jobs and total earnings refer to a worker's cumulative experience up to January 2019. Number of tests and average score refer to the standardized tests offered by the platform to workers to certify their skills. The bottom of the table reports the share of workers classified as 'Top Rated' by the platform, the share of workers that belong to an agency, the distribution of the time availability reported by workers and the distribution of success rates.

**Remote vs. traditional wages for US workers across occupations:** Finally, we compare remote to traditional wages for US workers in different occupations. We match the occupations in the platform to those in the Standard Occupational Classification (SOC) categories manually using the corresponding descriptions. Appendix Table A2 lists the concordance between the classifications. We obtain data on traditional wages by occupation for US workers from the U.S. Bureau of Labor Statistics (BLS). Figure 3 compares hourly wages in the platform to those provided by the BLS for 38 SOC occupations represented in our data. Remote wages are similar to traditional wages for US workers ranging between $20 and $80 per-hour depending on the occupation, though remote wages are more compressed than traditional wages. There is a strong positive relation between the two, suggesting that remote wages are in part shaped by what workers can earn in their local labor markers, an issue that we explore in detail in the following sections.

Figure 3: Remote vs. traditional wages for US workers




Notes: Each circle represents an occupation. The figure compares hourly average wages for US workers in the platform vs. wages in the BLS data for in different SOC occupations. The estimated slope is 0.55 (0.11) and the $R$-squared is 0.34.

# 3 Remote wages across locations

This section documents how remote wages vary across workers' and employers' locations. To do so, we estimate the following OLS regression using data on transacted wages:

$$w_{fi} = \mathbb{C}_i + \mathbb{D}_f + \mathbb{I}_{i=f} + \boldsymbol{\beta}'\boldsymbol{X_i} + \varepsilon_{fi}. \tag{1}$$

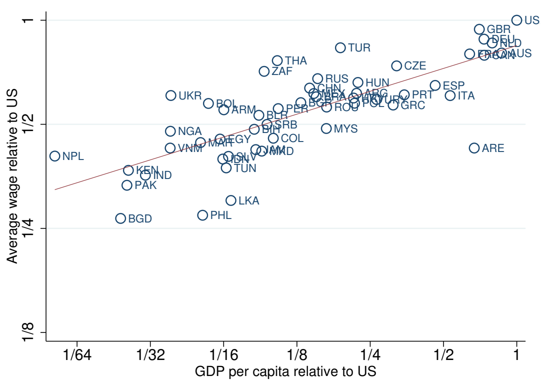
Here, $w_{fi}$ denotes the (log) wage paid by employer $f$ to worker $i$ in a given job. $\mathbb{C}_i$ and $\mathbb{D}_f$ are full sets of fixed effects for the workers' and the employers' countries, respectively. The omitted country category is the US, so these fixed effects measure the average wage earned by workers and paid by employers in each country relative to the US. $\mathbb{I}_{i=f}$ is an indicator variable that is equal to one if the employer and worker are in the same country. $\boldsymbol{X_i}$ is a vector of worker characteristics, containing experience variables (log earnings and number of jobs), skill variables (number of tests and the average score), quality ratings (whether the worker is Top Rated, and dummies for success rates), availability variables (dummies for full/part-time, and dummies for response time), dummies for the occupations listed in the worker's profile, and an indicator for whether the worker works in an agency (multi-worker or single worker).

A variance decomposition of equation (1) shows that the workers' locations account for 31% of the dispersion of wages, which is more than the variance accounted for by all other controls (this decomposition splits the contribution of the covariance terms equally across regressors). In contrast, employers' locations account for only 0.04% of the variance in wages, in part because employers are located in a few countries.[11]

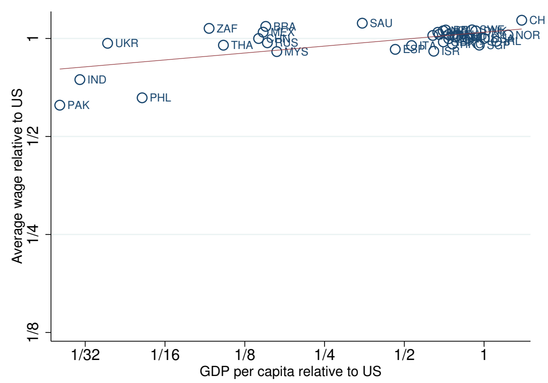
Figure 4a plots average wages across workers in each country relative to the US, obtained from the fixed effects $\mathbb{C}_i$ in equation (1), and the relative GDP per capita in each country with at least 100 workers with transacted wage data. There is a very strong and positive relationship between workers' remote wages and the GDP per capita in their country. The slope of this relationship is 0.22 (SE 0.03) and the R-squared is 0.58. These cross-country differences in average wages are not driven by observable worker characteristics nor by differences in the location of the employers. Appendix Figure A.2 shows similar results using the larger sample of workers with available ask wage data, and Appendix Figure A.3a shows a similar relationship between non-residualized wages and GDP per capita. Note that while cross-country differences in remote wages are pervasive, they are about one-fifth the size of the differences in GDP per capita.

Figure 4: Wages and GDP per capita relative to the US

(a) Average wage across workers




(b) Average wage across employers




Notes: The x-axes report the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). Panel (a) and panel (b) plot $\mathbb{C}_i$ and $\mathbb{D}_f$ relative to the US obtained from the country fixed effects estimated in equation (1). The red lines show the linear fit of the data. The estimated slope is 0.22 (0.03) in panel (a) and 0.07 (0.02) in panel (b), and the $R$-squared are 0.58 and 0.40, respectively.

Figure 4b plots the average wages across employers in each country relative to the US, obtained from the fixed effects $\mathbb{D}_f$ in equation (1), for countries with at least 100 employers.

[11] Appendix Table A3 reports the results of the estimation in equation (1), and Appendix Table A4 reports the full variance decomposition. A regression of log-wages on the set of country fixed effects $\mathbb{C}_i$ has an $R^2$ of 0.41, while the $R^2$ of estimating equation (1) with all the additional controls is 59%.

The figure shows a very weak relation between the remote wages paid by the employers and the level of GDP per capita in their country. This relationship is driven by a few outliers; only employers from Pakistan, India, and the Philippines appear to pay relatively lower wages than those in the US.

**Wage differences across US states:** We now document differences in remote wages across workers located in different US states. We follow the strategy in the previous analysis and compare average wages in each state after residualizing them for worker characteristics. Unfortunately, we do not observe the transacted wage for enough workers and employers in each of the US states to estimate (1) at the state level (there are only 12 states with more than 100 workers that report these data). Thus, we use data on ask wages for workers located in the US to estimate:

$$w_i = \mathbb{S}_i + \boldsymbol{\beta}'\boldsymbol{X_i} + \varepsilon_i. \tag{2}$$

Here, $w_i$ is the ask wage of worker $i$, and $\mathbb{S}_i$ is the full set of fixed effects for the workers' state. The omitted state is California—the state with the most workers in our sample—so the state fixed effects measure average wages in each state relative to the average wage earned in California. Since equation (2) is estimated on the ask wage data, we cannot control for the location of the employer (workers only post one ask wage in their profiles).

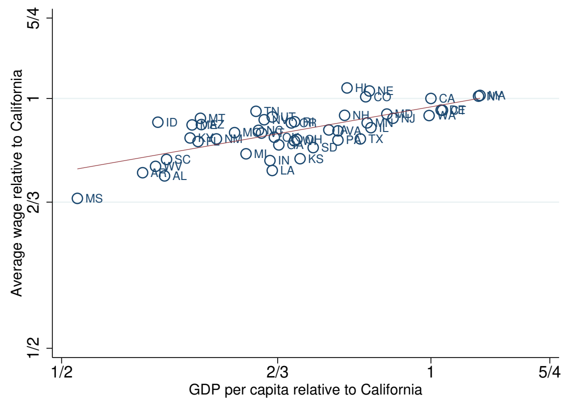
Figure 5 compares relative wages to the relative GDP per capita of each of the 47 states with at least 30 workers in our sample.[12] It shows that the pattern across US states is similar to the one we observe across countries: Workers from richer states earn on average higher wages. The slope of this relation is 0.26 (SE 0.04) and the R-squared is 0.48. These patterns are remarkably similar to the cross-country patterns documented above.[13]

Wage differences across remote workers located in different countries and US states suggest that the worker's location plays a large role in shaping wages, even in remote jobs that do not require the worker to be present at a specific location. Below, we empirically evaluate some potential explanations for this phenomenon.

[12] We exclude North Dakota, Wyoming, and Alaska since they only have 18, 25, and 26 workers, respectively in our sample.

[13] Non-residualized wages in each state are reported in Appendix Figure A.3b.

Figure 5: Wages and GDP per capita across US states (ask wages)




Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the Bureau of Economic Analysis. The figure plots the average ask wage in each state relative to California, obtained from state fixed effects in equation (2). The red line shows the linear fit of the data. The estimated slope is 0.26 (0.04) and the $R^2$ is 0.48.

## 3.1 Disentangling sources of cross-country wage differences

**Trade costs:** One potential reason for wages to vary with the worker's location is that employers may find it more costly to work with workers from distant countries. With this in mind, Appendix Figures A.4a and A.4b plot average wages across workers' and employers' locations obtained from a version of (1) that incorporates controls for the time difference and geographical distance between the employer's and the worker's countries, and for whether the countries share a common language, currency, and legal origin. The figure shows that these controls do not affect the main results in Figures 4a and 4b.

**Comparison with non-remote wages and local prices:** Differences in GDP per capita may not be representative of the cross-country differences in non-remote wages for the type of occupations that are traded in the platform. With this in mind, we obtain data on non-remote wages for occupations that are similar to those represented in the platform from the International Comparison Program (ICP) from the World Bank.[14] Appendix Figure A.5a shows that the relation between remote wages and non-remote wages from similar occupations resemble that in Figure 4a. Appendix Figure A.5b compares remote wages to local price levels, and shows that remote wages are higher for workers living in more expensive countries.

[14] We include the following occupations included in the ICP database: Accounting and Bookkeeping Clerks, HR Professionals, Computer Operators, Data Processing Managers, and Database Administrators.

**Controlling for employer fixed effects:** The wage gaps we observe could potentially be driven by differences in the employers that hire workers in different countries. Figure 4a plots the dummies $\mathbb{C}_i$ in equation (1), which also controls for the country of employer fixed-effects $\mathbb{D}_f$. We can also estimate an analogous equation that uses unique employer identifiers to control for employer fixed-effects. We estimate this regression using the sample of employers for which we observe more than one worker, which accounts for 42% of the observations (unfortunately, we do not observe all the workers hired by each employer). Appendix Figure A.6a plots the average wage in each location residualized with employer fixed-effects. The figure continues to show a strong relationship between the (residual) remote wages and the GDP per capita of the location of the workers, although the slope of this relation drops to 0.15 (SE 0.02). This shows that even when working for the same employer, remote workers from richer countries earn higher wages.

**Controlling for worker fixed effects:** Finally, we evaluate whether workers price to market, that is, whether the wage earned by a particular worker depends on the employer's location. With this in mind, we can estimate a version of (1) that includes worker fixed effects instead of all the worker-level controls. Appendix Figure A.6b plots the wages paid by employers from each country, obtained from the dummies $\mathbb{D}_f$ in this regression, for the set of countries that have more than 100 workers. Workers get paid somewhat more when working for employers from richer countries, although the relation is mild and driven by a only few countries (slope of 0.05 with a standard error of 0.02).

The results from this section show that remote wages are strongly correlated with the GDP per capita in the worker's locations. This finding is not accounted for by any observable differences in workers', jobs, or employer characteristics, though it may be in part driven by unobserved differences in worker characteristics. The following section uses data on wage changes to further understand this relationship and to study how remote wages respond to international shocks.

# 4 Remote wages and international shocks

This section first proposes a model of a remote labor market where remote wages can differ across locations due to differences in workers' characteristics (productivities) or differences in local conditions. It then uses the model and data on wage changes to disentangle these two alternatives and to study how remote wages respond to international shocks.

### 4.1 Conceptual framework

**Remote labor demand:** We consider a market for remote labor populated by a continuum of workers who live in different locations indexed by $c$ and work in different sectors indexed by $j$. The market is competitive: a representative firm hires workers from different locations and sectors to produce a final good, taking wages as given. The production function for the final good is:

$$Y_t = \left[ \sum_j \left[ Y_t^j \right]^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}, \tag{3}$$

where $Y_t^j$ denotes output from sector $j$. Cost minimization implies

$$Y_t^j = \left[ \frac{\Omega_t^j}{P_t} \right]^{-\eta} Y_t, \tag{4}$$

where $\Omega_t^j$ and $P_t$ are prices of the sectorial and final output. The sectorial output is produced according to

$$Y_t^j = \left[ \sum_c \left[ A_{ct}^j L_{ct}^j \right]^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}. \tag{5}$$

Here, $L_{ct}^j$ denotes the efficiency units of labor from location $c$ in sector $j$, $A_{ct}^j$ is a factor-augmenting technology term that acts as a demand shifter, and $\rho$ is the elasticity of substitution across workers from different locations. Equation (5) assumes that efficiency units of labor from the same location are perfect substitutes. On the other hand, units from different locations can be imperfect substitutes if $\rho < \infty$. An alternative to assuming that workers from different locations are imperfect substitutes is to assume that they specialize in different tasks that are necessary to produce the sectorial good. Appendix A.4 derives such an alternative model and shows that it is isomorphic to the one presented here.

Let $\Omega_{ct}^j$ denote the dollar remote wage per efficiency unit of labor from location $c$ in sector

$j$. Cost minimization implies that the demand for labor is given by

$$L_{ct}^{j} = \left[A_{ct}^{j}\right]^{\rho-1}\left[\frac{\Omega_{ct}^{j}}{\Omega_{t}^{j}}\right]^{-\rho} Y_{t}^{j}, \tag{6}$$

and that the unit cost of production in sector $j$ is

$$\Omega_{t}^{j} = \left[\sum_{c}\left[\Omega_{ct}^{j}/A_{ct}^{j}\right]^{1-\rho}\right]^{\frac{1}{1-\rho}}. \tag{7}$$

**Remote labor supply:** Each location is inhabited by a continuum of workers indexed by $i$, each of which specializes in one sector $j$. Each worker is endowed with $Z_{it}^{j}$ efficiency units of labor in one of the sectors, and can work in the remote or in the local labor market. In the local labor market, workers earn a wage given by $Z_{it}^{j} \times B_{ct}^{j}/H_{i}^{j}$, where $B_{ct}^{j}$ is the wage per efficiency unit of labor in the local labor market denominated in dollars, and $H_{i}^{j}$ is a worker-specific cost for working in the local labor market, which can be interpreted as the fraction of time that a worker must spend commuting.[15] We assume that $B_{ct}^{j}$ is exogenously determined.[16] A worker chooses to work remotely if and only if the wage for remote labor exceeds the wage paid in the local labor market. Thus, there exists a cutoff

$$H_{i}^{j} \geq \underline{H}_{ct}^{j} \equiv B_{ct}^{j}/\Omega_{ct}^{j}, \tag{8}$$

such that workers with $H_{i}^{j}$ above this cutoff choose to work remotely. We assume that $Z_{it}^{j}$ and $H_{i}^{j}$ are independently distributed and that the c.d.f. of $H$ is $G\left(H\right) = 1 - \left[\frac{\kappa_{c}^{j}}{H}\right]^{\theta}$ with support $[\kappa_{c}^{j}, \infty)$. Let $N_{ct}^{j}$ denote the number of workers in location $c$. Then, the supply of remote labor in sector $j$ from location $c$ is given by

$$L_{ct}^{j} = N_{ct}^{j} \times Z_{ct}^{j} \times \left[1 - G(\underline{H}_{ct}^{j})\right] = \tilde{N}_{ct}^{j}\left[\frac{\Omega_{ct}^{j}}{B_{ct}^{j}}\right]^{\theta}, \tag{9}$$

[15] More generally, $1/H_{i}^{j}$ is the relative cost of working in the remote vs. in the local labor market. $H_{i}^{j}$ could be smaller than one, in which case workers perceive working in the local labor market as advantageous, other things equal.

[16] We make this simplifying assumption since our interest is on how local wages affect remote wages, and, while rapidly growing, remote labor markets are still small relatively to local labor markets.

where $Z^j_{ct} \equiv \mathbb{E}_c\left[Z^j_{it}\right]$ denotes the average efficiency units of labor across all workers from location $c$ in sector $j$, and $\tilde{N}^j_{ct} \equiv N^j_{ct} Z^j_{ct}\left[\kappa^j_c\right]^\theta$ collects supply shifters other than $B^j_{ct}$. Equation (9) states that the labor supply elasticity is given by $\theta$.

**Equilibrium:** Combining equations (6) and (9) with (4), and using lowercase to denote variables in logs ($\omega^j_{ct} \equiv ln\Omega^j_{ct}$, and $\omega^j_t = ln\Omega^j_t$), we obtain the equilibrium wage per efficiency unit of remote labor for sector $j$ in location $c$:

$$\omega^j_{ct} = \frac{\theta}{\rho+\theta} b^j_{ct} + \frac{\rho-\eta}{\rho+\theta}\omega^j_t + \frac{1}{\rho+\theta}\varphi^j_{ct}, \tag{10}$$

$$\tag{11}$$

$$var_c\left[\omega^j_{ct}\right] = \left[\frac{\theta}{\rho+\theta}\right] var[b^j_{ct}] + \frac{1}{\rho+\theta} var\left[\left[\rho-1\right] a^j_{ct} - \tilde{n}^j_{ct}\right] \tag{12}$$

where $\varphi^j_{ct} \equiv [\rho-1]\, a^j_{ct} - \tilde{n}^j_{ct} + \eta p_t + y_t$ collects aggregate and location-sector-specific supply and demand shifters.

**Remote wages and workers' locations:** We now evaluate wage differences across remote workers. Let $w^j_{it} \equiv \omega^j_{ct} + z^j_{it}$ denote the log wage per unit of time of remote worker $i$ in location c and sector $j$ (i.e., the equivalent of hourly wages in the platform). Then,

$$w^j_{it} = \frac{\theta}{\rho+\theta} b^j_{ct} + \frac{\rho-\eta}{\rho+\theta}\omega^j_t + \frac{1}{\rho+\theta}\varphi^j_{ct} + z^j_{it}. \tag{13}$$

Equation (13) states that wage differences across workers in the same sector can arise from differences in local wages, $b^j_{ct}$, location-specific demand and supply shifters, $\varphi^j_{ct}$, and workers' efficiency units, $z^j_{it}$.[17] Note that if workers from different locations are perfect substitutes, $\rho \to \infty$, demand is perfectly elastic and wage differences arise only due to differences in $z^j_{it}$. If, instead, labor supply is close to being perfectly elastic, $\theta \to \infty$, wage differences are given by differences in local wages $b^j_{ct}$ and differences in $z^j_{it}$. For finite values of $\rho$ and $\theta$, the elasticity of remote wages with respect to local wages is positive but less than one, $\frac{\theta}{\rho+\theta} < 1$. Equation (13) underscores that, while our model is highly stylized, remote wages will be tied to local labor market conditions insofar as both: (i) the labor demand from individual locations is downward sloping; and (ii) the labor supply from those locations is upward sloping (see Enrico 2011 and Card et al. 2018 for a discussion of

[17]Note that if local wages $b^j_{ct}$ are correlated with local prices, the model also predicts that remote wages should be higher in more expensive locations.

similar determinants of wage differences in the context of domestic local labor markets). Appendix A.4 provides alternative micro-foundations for such conditions.

We can use equation (13) to interpret the results from Section 3. If local wages can be proxied by the GDP per capita in a location, equation (13) suggests that the partial elasticity of wages with respect to GDP per capita is $\frac{\theta}{\rho+\theta}$. If the unobserved supply and demand shifters and productivities in equation (13) ($\varphi_c$, and $Z_c$) are uncorrelated with GDP per capita, then the evidence from Section 3 suggests that $\frac{\theta}{\rho+\theta} \simeq 0.2$. This orthogonality condition can be violated if, for example, workers in richer countries have more efficient units $z^j_{it}$, and differences in $z^j_{it}$ are not fully captured in the controls in equation (2). The following section uses time variation in wages to distinguish these alternative interpretations.

**Wage changes:** We now evaluate the model's predictions for wage changes. We denote the change in a variable $x_t$ by $dx_t$. Since we do not observe changes in local wages at short frequencies, we write the change in local wages expressed in dollars as

$$db^j_{ct} = \gamma^j_{ct} + \pi_{ct} + de_{ct}, \tag{14}$$

where $\gamma^j_{ct}$ is the growth of local wages in constant local currency units, $\pi_{ct}$ is the inflation rate, and $de_{ct}$ is the change in the exchange rate denominated in dollars per unit of local currency.[18]

Let $dx^j_t \equiv \sum s^j_{ct} dx_{ct}$ denote the (sector-specific) cross-country average change in a variable, with weights $s^j_{ct}$ corresponding to a country's cost share in a sector. Differentiating equations (7) and (13) and substituting yields:

$$dw^j_{it} = \frac{\theta}{\rho+\theta}\left[de_{ct} + \pi_{ct}\right] + \frac{\rho-\eta}{\rho+\theta} dw^j_t + d\psi^j_{ct} + dz^j_{it}, \tag{15}$$

with

$$dw^j_t = \frac{\theta}{\theta+\eta}\left[de^j_t + \pi^j_t\right] + d\phi^j_t. \tag{16}$$

Here, $dw^j_t \equiv \sum_c s^j_{ct} \mathbb{E}_c \left[dw^j_{it}\right]$ is an index of wage changes in the remote market, while $d\psi^j_{ct}$ and $d\phi^j_t$ collect supply and demand shifters (See Appendix A.3 for a derivation.).

[18]Equation (14) states that, to obtain the (log) change in local wages expressed in dollars, we add the inflation and the change in the exchange rate to the change in real wages. Since we do not have data on local wage inflation at short frequencies, we approximate it with price inflation in the next section.

Equations (15) and (16) state that the partial exchange rate pass-through elasticity is $\frac{\theta}{\rho+\theta}$, and that wages respond to average wages in the remote market with an elasticity of $\frac{\rho-\eta}{\rho+\theta}$.

## 4.2 Estimation

This section uses data on the workers' job histories to estimate how wages respond to international shocks.

### 4.2.1 Preliminaries

The job histories cover a sample of 641,679 jobs performed between January 2012 and January 2020. As noted in Section 2, for each job in the data, we observe the start date, the total payment, the worker's identifier and country, and a job description. For 85,095 jobs, we also observe the sector to which the job was assigned in the platform. We aggregate these sectors into four broad sectors: 'Admin and Sales,' 'Design,' 'Web and Programing,' and 'Writing.' We then assign sectors to the remaining jobs using the information from the job descriptions using a machine-learning algorithm.[19]

We restrict our analysis to jobs that were billed on an hourly basis, and thus an hourly wage is observable (along with the number of hours worked).[20] The start date of the job is reported at a monthly frequency, though a worker can start multiple jobs in the same month. We collapse the data at the monthly level so that the unit of observation is a worker-sector-month. After taking the difference between two consecutive jobs, this leaves a sample of 88,399 wage changes.

Finally, not all workers are observed each month-sector, both because workers may not start new jobs in a sector in a particular month, and because our data only contains a subset of the jobs in the platform. With this caveat in mind, we denote by $\Delta_s w^j_{it} \equiv w^j_{it} - w^j_{it-s}$ the log-change in the wage of a worker in sector $j$ that is observed in months $t$ and $t-s$ (and not in between). More generally, we denote the $s$-period change in a variable by $\Delta_s x_t \equiv x_t - x_{t-s}$, and refer to the period itself as time-spell $t_s$. We summarize the distribution of wage changes in Appendix Table A5. In the following analysis, we use

[19] The algorithm assigns a probability that a job belongs to each sector based on keywords from the job descriptions. For example, a job with the description 'looking for a grant writer' will likely be assigned to the sector 'writing' based on the keyword 'writer.' We detail the algorithm in Appendix A.2.

[20] About 50% of the jobs in the job-level dataset are billed as a 'fixed price' job, in which workers charge a predetermined price for completing a job. For these jobs, we observe how much workers are paid but not how many hours they work. We exclude these jobs from the analysis in this section.

data on monthly exchange rate changes and CPI inflation obtained from the International Financial Statistics.

### 4.2.2 Estimating partial exchange rate pass-through elasticities

We start by describing how to estimate partial pass-through elasticities from equation (15). Note that $\Delta_s w_t^j$ varies across time spells and sectors, so that we can estimate the equation as:

$$\Delta_s w_{it}^j = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{t_s}^j + \epsilon_{it_s}^j. \tag{17}$$

Here, $\mathbb{C} \times \mathbb{J} \times s$ is the product between country fixed effects, sector fixed effects, and the duration $s$ of the time-spell, which controls for the country-sector-specific linear trends in the demand and supply shifters $\psi_{ct}^j$. $\mathbb{T}_{t_s}^j$ is a set of fixed effects for each period by spell-duration by sector combination ($t \times s \times j$) which control for the aggregate and sector-specific shifters in $\psi_{ct}^j$. The error term is given by $\epsilon_{it_s}^j \equiv \Delta_s \tilde{z}_{it}^j + \Delta_s d\tilde{\psi}_{ct}^j$, where the notation $\tilde{x}$ denotes the deviation of a variable from the sector-time-spell average and its country trend. Equation (17) is similar to the medium-run exchange rate pass-through regressions estimated by Gopinath et al. (2010). The coefficients $\beta_1$ and $\beta_2$ are identified from both time and country variation in exchange rates and inflation.

Estimating (17) by OLS yields consistent estimates of $\beta_1$ if the error term $\epsilon_{ijt_s}$ is orthogonal to changes in exchange rates and inflation across countries, i.e. $cov(\Delta_s \tilde{z}_{it}^j + \Delta_s \tilde{\psi}_{ct}^j, \Delta_s e_{ct}) = 0$. This exclusion restriction requires changes in exchange rates to be uncorrelated to trend deviations in sectoral productivity and supply and demand shifters at monthly frequencies. An extensive literature on the 'exchange rate disconnect' shows empirically that this restriction holds at short frequencies.[21] Finally, we note that we will test the restriction imposed by the model $\beta_1 = \beta_2$ empirically rather than imposing it in our estimation.

### 4.2.3 Estimating the effect of competitors' wages

According to equation (15), wages respond to changes in competitors' wages with an elasticity of $\frac{\rho-\eta}{\rho+\theta}$. We cannot test this implication using equation (17), since $\Delta_s w_t^j$ is absorbed

[21] See, e.g., Itskhoki and Mukhin (2017).

by the fixed-effects $\mathbb{T}^j_{t_s}$. We thus estimate the following equation:

$$\Delta_s w^j_{it} = \beta_1 \Delta_s e_{ct} + \beta_2 \pi_{ct_s} + \beta_3 \Delta_s w^j_t + \mathbb{C} \times \mathbb{J} \times s + \mathbb{T}_{t_s} + \varepsilon^j_{it_s}, \tag{18}$$

where $\varepsilon^j_{it_s} \equiv \Delta_s \hat{z}^j_{it} + \Delta_s \hat{\psi}^j_{ct}$, and $\hat{x}$ denotes the deviation of a variable from the time-spell average and the country-sector trend. Here, $\mathbb{T}_{t_s}$ denotes a set of fixed effects of each period by spell-duration combination ($t \times s$). To implement equation (18), we need to construct an index of average wage changes in each sector, $\Delta_s w^j_t \equiv \sum_c s^j_{ct} \mathbb{E}_c \left[\Delta_s w^j_{it}\right]$. Obtaining such an index is not straightforward since, as mentioned above, the set of workers observed in our data changes from period to period. Thus, for any given time spell $t_s$, data on $\Delta_s w^j_{it}$ is not observed for many workers.

With this in mind, we approximate $\Delta_s w^j_t$ as the change in the average of wages observed in periods $t - s$ and $t$, after controlling for the composition of workers over time. More specifically, we estimate

$$w^j_{it} = \delta^j_i + \delta^j_t + v^j_{it},$$

where $\delta^j_i$ and $\delta^j_t$ are two sets of worker-sector and time-sector fixed-effects, respectively. We construct a series of the wage index as the series of the estimated time fixed effects, i.e., $\Delta_s w^j_t = \Delta_s \delta^j_t$.[22]

Finally, the OLS estimates of (18) are inconsistent if $\Delta_s w^j_t$ is correlated with $\varepsilon^j_{it_s}$, which would be the case if the detrended aggregate shifters $\Delta_s \hat{\phi}^j_t$ and $\Delta_s \hat{\psi}^j_{ct}$ are correlated. We thus pursue an IV approach. From equation (16), a natural instrument for $\Delta_s w^j_t$ is

$$\Delta_s \Theta^j_t \equiv \pi^j_{t_s} + \Delta_s e^j_t, \tag{19}$$

which correlates with $\Delta_s w^j_t$ but is orthogonal to $\varepsilon^j_{it_s}$ under the exclusion restriction. In building the instrument in (19), we proxy $s^j_{ct}$ by the share of jobs performed by workers from country $c$ in sector $j$ throughout our sample. Figure A.7 in the Appendix reports that there is substantial variation in $s^j_{ct}$ across sectors.

[22]This procedure recovers up to a first-order approximation the time series of $dw^j_t$. To see this, note that from equations (15) and (16) we have:

$$\begin{aligned} d\delta^j_t &= \frac{\theta}{\rho+\theta}\left[de_t + \pi_t\right] + \frac{1}{\rho+\theta}\left[d\varphi^j_t + \theta\gamma^j_t\right] + \frac{\theta+\eta}{\rho+\theta} dz^j_t + \frac{\rho-\eta}{\rho+\theta}\frac{1}{1-\rho} da^j_t + \frac{\rho-\eta}{\rho+\theta} dw^j_t \\ &= \frac{\theta+\eta}{\rho+\theta} dw^j_t + \frac{\rho-\eta}{\rho+\theta} dw^j_t = dw^j_t. \end{aligned}$$

#### 4.2.4 Results

We present our estimates in Table 2. Column 1 shows the results from estimating equation (17) by OLS, which in addition to $\Delta_s e_{ct}$ and $\pi_{ct_s}$ includes country-sector-specific trends and sector-time-spell fixed effects. We cluster standard errors at the sector-time-spell and country level. The estimated partial pass-through elasticity is $\hat{\beta}_1 = 0.203$ and is estimated to be statistically different from zero. This indicates that while dollar wages respond to changes in the dollar exchange rate, the corresponding elasticity is low. This, in turn, shows that wages in local currency move in tandem with the dollar exchange rate (with an elasticity of 0.797). The coefficient on inflation is similar, $\hat{\beta}_2 = 0.227$, though we cannot reject the null hypothesis that it is equal to zero at a 1% significance level. In addition, we cannot reject the null hypothesis that $\beta_1 = \beta_2$. Under the assumption that changes in exchange rates affect local wages denominated in dollars but are uncorrelated to changes in the workers' productivity, this result suggests that remote wages are tied to the conditions that workers face in their local labor markets.

Column 2 shows the results from estimating equation (18) by OLS, which controls for country-sector-specific linear trends and time-spell fixed effects but includes $\Delta_s w_t^j$ instead of the sector-time-spell fixed effects $\mathbb{T}_{t_s}^j$. Standard errors are clustered at the sector-time-spell and country level. The coefficients on the dollar exchange rate and inflation are very close to those in Column 1 and given by $\hat{\beta}_1 = 0.212$ and $\hat{\beta}_2 = 0.197$, respectively. The coefficient on the aggregate wage index is $\hat{\beta}_3 = 0.781$ and is statistically different from zero.

Column 3 reports the 2SLS estimates in which we use $\pi_{t_s}^j$ and $\Delta_s e_t^j$ separately as instruments for $\Delta_s w_t^j$. The estimated coefficient on the exchange rates and inflation are almost identical to those in Column 2. More importantly, the coefficient on $\Delta_s w_t^j$ is 0.741, and is statistically significant at the 1% level. The bottom of Table 2 reports the F-statistic of the first stage, which is well above conventional critical values. Appendix Table A6 reports the first-stage regression in Column 1 and shows that the coefficients on $\pi_{t_s}^j$ and $\Delta_s e_t^j$ are statistically significant and contribute to the variation in $\Delta_s w_t^j$. These results show that dollar wages do respond to changes in competitors' wages driven by changes in foreign inflation and exchange rates. In particular, the estimates imply that a 1% increase in the wages in country $c' \neq c$ increases wages in country $c$ by $0.741 \times \left[s_{c'}^j \times 1\%\right]$.[23]

[23]Table A7 in the Appendix reports the results obtained after imposing the constraint $\beta_1 = \beta_2$.

Table 2: Wage changes and international shocks

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ |
| $\Delta_s e_{ct}$ | $0.203^{***}$ | $0.212^{***}$ | $0.213^{***}$ |
| | (0.058) | (0.052) | (0.053) |
| $\pi_{c,t_s}$ | $0.227^{*}$ | $0.197^{*}$ | $0.196^{*}$ |
| | (0.120) | (0.103) | (0.103) |
| $\Delta_s w_{jt}$ | | $0.781^{***}$ | $0.741^{***}$ |
| | | (0.073) | (0.252) |
| Observations | 88399 | 88399 | 88399 |
| Test $\beta_1 = \beta_2$ | 0.84 | 0.87 | 0.85 |
| Specification | OLS | OLS | 2SLS |
| F stat 1st stage | | | 39.8 |

Notes: Column (1) reports the OLS estimates from equation (17), which contains period by spell-duration by sector fixed effects. Columns (2) and (3) report the OLS and 2SLS estimates from equation (18) respectively, and include period-by-spell-duration fixed effects. All columns include country by sector by spell-duration fixed-effects. The nominal exchange rate $e_{ct}$ is measured in US$ per unit of local currency. Standard errors are clustered at the sector-time-spell and country level*: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

## 4.3 Robustness

This section presents several robustness exercises that complement the results presented above.

**Conditioning on a wage change:** The conceptual framework in Section 4.1 assumes that workers' wages are flexible, which is a good approximation in the context of cross-country wage comparisons in Section 3. However, if wages are sticky in the short run, our time series estimates can be biased toward zero. In fact, Appendix Table A5 shows that wages do not change between subsequent jobs in around 25% of our observations.

To address this concern, we reproduce our regression analysis using the subsample of jobs for which we observe a non-zero wage change. Column 3 in Appendix Table A7 reports the results. The coefficient on the change in the domestic exchange rate increases from the baseline value of 0.213 to 0.251, and the coefficient in domestic inflation increases from 0.196 to 0.240. Overall, the analysis of non-zero wage changes reveals that wages are indeed more responsive. However, the quantitative differences relative to our baseline analysis are small.

**Alternative measures of competitors' wages:** A potential source of concern is that the aggregate wage index $\Delta_s w_t^j$ is, by definition, a function of each worker's wage and is thus correlated with the error term in equation (15). In the model of Section 4.1, there is a continuum of workers, so this dependence vanishes. To further reduce concerns about the endogeneity of our regressor, we reestimate equation (15) using the leave-one-out index for the competitors' wages, $\Delta_s w_{-it}^j \equiv \sum_{l \neq i} \frac{s_{lt}^j}{1-s_{it}^j} \Delta_s w_{lt}^j = \left[\Delta_s w_t^j - s_{it}^j \Delta_s w_{it}^j\right] / \left[1 - s_{it}^j\right]$, where $s_{it}^j$ is the market share of worker $i$ in sector $j$.[24] Note also that if all workers have small market shares $s_{it}^j \to 0$ (as they do in practice), then $\Delta_s w_{-it}^j \to \Delta_s w_t^j$. The results of this alternative estimation are presented in Column 4 of Appendix Table A7, and coincide with our baseline estimation.

**Placebo analysis:** In our baseline estimates, we classified jobs into four broad sectors using the jobs' descriptions and a machine-learning algorithm, and assumed that a worker's wage depends on the wages of other workers in the same sector. To validate this approach, we conduct a placebo analysis in which we evaluate if workers respond to changes in the wages of remote workers from other sectors. We would expect workers to respond more strongly to competitors in their sector than to remote workers from different sectors. With this in mind, we match each job to its 'most distant' sector in the following way. For each job, the algorithm estimates the likelihood that the job belongs to each of the four broad sectors. In our baseline analysis, we assigned each job to the sector with the highest estimated likelihood. For this placebo analysis, we also assign a 'most distant' to each job, which is given by the sector with the lowest estimated likelihood. We then extend the estimating equation (18) to include the average wage change in the job's most distant sector as an additional regressor.

Column 5 of Table A7 in the Appendix reports the results. The inclusion of this additional wage change barely affects the coefficient on the competitors' wages. In contrast, the co-

[24] Note that equation (15) can also be written as

$$dw_{it}^j = \frac{\theta}{\tilde{\rho}_{it} + \theta + s_{it}^j \eta} \left[de_{ct} + \pi_{ct}\right] + \frac{\tilde{\rho}_{it}^j - \eta \left[1 - s_{it}^j\right]}{\tilde{\rho}_{it}^j + \theta + s_{it}^j \eta} dw_{-it}^j + \frac{d\psi_{ct}^j + dz_{it}^j}{\tilde{\rho}_{it}^j + \theta + s_{it}^j \eta}, \tag{20}$$

where $\tilde{\rho}_{it}^j \equiv \rho \left[1 - s_{it}^j\right]$ and $dw_{-it} \equiv \sum_{l \neq i} \frac{s_{lt}}{1-s_{it}} dw_{lt}$. Note that if all workers have small market shares, $s_{it}^j \to 0$, then $\tilde{\rho}_{it}^j \to \rho$.

efficient on the wage changes of the most distant competitors is much smaller in absolute value and is not statistically different from zero, as expected.

**Alternative assumptions on country-trends:** Columns 6 and 7 in Appendix Table A7 re-estimate equations (17) and (18) using alternative controls for the country-specific trends. Column 6 does not control for country-sector-specific trends. Column 7 does not control for time-spell fixed effects. The table shows that our results are robust to the different ways we control for country-specific trends.

**Estimation on the worker-level data:** Finally, we reestimate partial ERPT elasticities using data on ask wages. As detailed in Section 2, these data are in a more conventional format as the wage posted by each worker is observed twice, once in January 2019 and once in November 2020. Workers are listed across (possibly more than one of) the 91 occupations in the platform described in Table A1 in the Appendix. The regression sample contains 226,569 pairs of worker-sector observations corresponding to 60,840 workers who have posted wages in both periods. We can estimate the partial pass-through elasticities from equation

$$\Delta w_i^j = b_1 \Delta e_c + b_2 \pi_c + \mathbb{S}^j + \mu_i^j, \tag{21}$$

where $\Delta x$ represents the change in a variable between the two periods, and $\mathbb{S}^j$ is a vector of sector fixed effects. We omitted time subscripts to highlight that we only observe one wage change per-worker. Here, the coefficients are identified from the country variation in exchange rates and inflation. An important difference with equation (17) is that, since exchange rates only vary at the country level, we cannot include country fixed effects to control for country-specific trends. Nonetheless, $b_1$ can be consistently estimated by OLS if changes in exchange rates are orthogonal to sector-specific supply and demand shocks.

We report our results in Column 8 of Appendix Table A7. We cluster standard errors at the country level. The estimated pass-through coefficient is 0.084, and the coefficient for inflation is 0.095. The coefficients are smaller than those estimated with the job data, reinforcing our conclusion that there is low pass-through into dollar wages. This occurs in part because ask wages are more sticky than transacted wages, and a large fraction of ask wages that do not change during our period. As in the previous section, we cannot reject the null hypothesis that $\beta_1 = \beta_2$.

# 5 Which remote jobs are more frequently offshored?

This section documents how frequently are jobs offshored in different occupations. While existing measures of job offshorability typically hinge on subjective judgments of how to classify the different attributes of a job (Blinder and Krueger 2013), we measure which jobs are actually offshored using data on the prevalence of cross-border contracts in an occupation.

## 5.1 Measurement

We define a job as offshored if the employer and the worker are located in different countries. As noted in Section 2, the US is the country with the majority of employers in the data. In what follows, we use the US as our benchmark country and measure the share of jobs that US employers offshore in each occupation. With this in mind, we assign the jobs in the workers' job-histories to occupations listed in the workers profiles. For each of the 91 detailed occupations in the worker-profiles, we compute the value share of US jobs performed by non-US workers:

$$\mathcal{O}^j = \frac{\text{value of jobs in } j \text{ where cty. employer} = \text{US and cty. worker} \neq \text{US}}{\text{value of all jobs in } j \text{ where cty. employer} = \text{US}}. \tag{22}$$

The expression in (22) measures the share of the wage bill that is offshored from the US to the rest of the world in occupation $j$.[25] Appendix A.5 reports an alternative measure that captures the share of jobs that are offshored. The results are consistent across measures.

## 5.2 Results

Table 3 reports the measure in (22) for the most and least frequently offshored occupations in the platform. The data on cross-border contracts suggests that whether a job can be performed remotely is an imperfect proxy of the likelihood that the job is offshored. For example, only 24% of corporate law jobs are offshored, even though all of them are performed remotely. In fact, there is substantial heterogeneity across occupations. For

[25] In Section 4.1, we denoted the share of the wage bill earned by US workers as $s^j_{us}$. In this section, we write $\mathcal{O}^j$ instead of $1 - s^j_{us}$ to highlight that our empirical measure in (22) is based on jobs whose employers are in the US (i.e., those that are offshored from a US perspective). We note that, in the model, the remote good is perfectly tradeable, so the model is consistent with employers being located anywhere, including the US.

example, Technical Support jobs are three times more likely to be offshored than Grant Writers jobs. Again, this is in spite of the fact that all the jobs in the platform are performed remotely. We compute how frequently are jobs offshored for the Standard Occupational Classification (SOC) categories represented in our data, and report these results in Appendix Table A9.

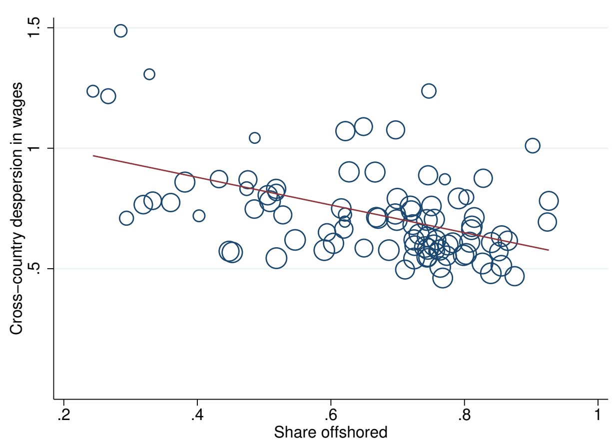
Table 3: Most and least offshored occupations

| Most offshored | | Least offshored | |
|---|---|---|---|
| Technical Support Representatives | 0.93 | Corporate Law | 0.24 |
| ERP / CRM Specialists | 0.92 | Contract Law | 0.29 |
| Medical Translators | 0.88 | Grant Writers | 0.29 |
| Legal Translators | 0.87 | Intellectual Property Law | 0.33 |
| Mobile Developers | 0.86 | Resumes & Cover Letters Writer | 0.33 |

Notes: The Table reports the measure defined in equation (22) for the Top 5 and Bottom 5 occupations.

Figure 6 plots the value share of jobs offshored (x-axis) and the cross-country standard deviation in log wages within each occupation (y-axis). There is a clear negative relationship between the two: Wages are less dispersed across countries in more frequently offshored occupations. This correlation suggests that offshoring may play a role in equalizing remote wages across countries.

Figure 6: Offshoring and cross-country wage dispersion




Notes: Each circle represents an occupation. The figure compares the measure in equation (A.5.1) to the cross-country standard deviation in average (log) wages within each occupation. Circle sizes represent the number of countries with workers in the occupation. The estimated slope is -0.47 (0.11) and the $R$-squared is 0.18.

# 6 Conclusion

This paper uses novel data from a large web-based job platform to study how the price of remote work is determined in a globalized labor market. Despite the global nature of the platform, we find large wage gaps that are strongly correlated with the GDP per capita of the workers' country, and are not accounted for by differences in workers' characteristics, occupations, or by differences in the employers' locations. Data on wage changes suggests that this correlation is driven by differences in the wages and prices that remote workers face in their local labor markets. We also document that remote wages in local currency move with the dollar exchange rate of the worker's country, and are highly sensitive to changes in the wages of foreign competitors. Finally, we provide a new measure of which jobs are more frequently offshored based on the prevalence of actual cross-border contracts rather than subjective job characteristics.

These findings have profound implications on how the rise of remote work may impact wages across the world. First, remote wages are more equalized than local wages across countries, but the wage gaps across locations are still large. Second, there is a high pass-through from the exchange rate to local currency remote wages in countries other than the US. These two facts are strikingly similar to findings obtained in the literature that looks at tradable goods prices, suggesting that remote work can potentially integrate service markets in similar ways that trade has tended to globalize goods markets. Finally, we show that whether a job is performed remotely is an imperfect proxy for whether a job is at risk of being offshored. Future work on how to measure offshorability should take this into account.

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# The International Price of Remote Work

*Online Appendix*

## A.1 Additional Tables and Figures

Table A1: List of Occupations

| Detailed occupation | Broad Occ. | Detailed occupation | Broad Occ. |
|---|---|---|---|
| Accounting Freelancers | Accounting | Brand Identity Strategy Freelancers | Design |
| Financial Planners & Advisors | Accounting | Graphics Design Freelancers | Design |
| HR & Recruiting Professionals | Accounting | Logo & Brand Designers | Design |
| Management Consultants | Accounting | Motion Graphics Freelancers | Design |
| Other - Accounting & Consulting Specialists | Accounting | Other - Design & Creative | Design |
| Data Entry Specialists | Admin | Photographers | Design |
| Other - Admin Support Professionals | Admin | Physical Design Freelancers | Design |
| Project Managers | Admin | Presentation Designers & Developers | Design |
| Transcription Services Professionals | Admin | Video Production Specialists | Design |
| Virtual Assistants, Personal Assistants | Admin | Voice Talent Artists | Design |
| Web Research Specialists | Admin | 3D Modeling Cad Freelancers | Engineering |
| Customer Service & Tech Support Reps | Customer Service | Architects | Engineering |
| Other - Customer Service Specialists | Customer Service | Chemical Engineers | Engineering |
| Technical Support Representatives | Customer Service | Contract Manufacturers | Engineering |
| A/B Testing Specialists | Data Science | Electrical Engineers | Engineering |
| Data Extraction / ETL Specialists | Data Science | Interior Designers | Engineering |
| Data Mining Management Freelancers | Data Science | Mechanical Engineers | Engineering |
| Data Visualization Specialists & Analysts | Data Science | Other - Engineering & Architecture Specialists | Engineering |
| Machine Learning Specialists & Analysts | Data Science | Product Designers | Engineering |
| Other - Data Science & Analytics Professionals | Data Science | Structural & Civil Engineers | Engineering |
| Quantitative Analysis Specialists | Data Science | Database Administration Freelancers | IT |
| Animators | Design | ERP / CRM Implementation Specialists | IT |
| Art Illustration Freelancers | Design | Information Security Specialists & Consultants | IT |
| Audio Production Specialists | Design | Network & System Administrators | IT |
| | | Other - IT & Networking | IT |

Table A1: (cont.) List of Occupations

| Detailed occupation | Broad Occ. | Detailed occupation | Broad Occ. |
|---|---|---|---|
| Contract Law Freelancers | Legal | Desktop Software Developers | Web & soft. |
| Corporate Law Professionals & Consultants | Legal | E-commerce Programmers & Developers | Web & soft. |
| Criminal Law Professionals & Consultants | Legal | Game Developers | Web & soft. |
| Family Law Professionals & Consultants | Legal | Mobile Developers | Web & soft. |
| Intellectual Property Law Professionals & Consultants | Legal | Other Software Development Freelancers | Web & soft. |
| Other Legal Freelancers | Legal | Product Management Professionals & Consultants | Web & soft. |
| Paralegal Professionals | Legal | QA & Testing Specialists | Web & soft. |
| Display Advertising Specialists | Sales | Scripts & Utilities Developers | Web & soft. |
| Email & Marketing Automation Managers & Consultants | Sales | Web Designers, Mobile Designers | Web & soft. |
| Lead Generation Professionals | Sales | Web Developers | Web & soft. |
| Market Researchers, Customer Researchers | Sales | Academic Writers & Researchers | Writing |
| Marketing Strategy Freelancers | Sales | Article Blog Writing Freelancers | Writing |
| Other Sales & Marketing Specialists | Sales | Copywriters | Writing |
| Public Relations (PR) Professionals | Sales | Creative Writers | Writing |
| Search Engine Marketing (SEM) Specialists | Sales | Grant Writers | Writing |
| Search Engine Optimization (SEO) Specialists | Sales | Other Writing Services Professionals | Writing |
| Social Media Marketing (SMM) Specialists | Sales | Proofreaders & Editors | Writing |
| Telemarketing & Telesales Specialists | Sales | Resumes & Cover Letters Writers | Writing |
| General Translation Freelancers | Translation | Technical Writers | Writing |
| Legal Translation Professionals | Translation | Web Content Writers, Web Content Managers | Writing |
| Medical Translators Professionals | Translation | | |
| Technical Translation Professionals | Translation | | |

Table A2: Concordance between occupations in the Platform and SOC classification

| Occupation Platform | SOC code | SOC title | Occupation Platform | SOC code | SOC tittle |
|---|---|---|---|---|---|
| 3D Modeling Cad Freelancers | 27-1014 | Special Effects Artists and Animators | Logo & Brand Designers | 27-1024 | Graphic Designers |
| A/B Testing Specialists | 15-1250 | Software and Web Developers, Programmers | Machine Learning Specialists & Analysts | 15-2051 | Data Scientists |
| Accounting Freelancers | 13-2011 | Accountants and Auditors | Management Consultants | 13-1111 | Management Analysts |
| Animators | 27-1014 | Special Effects Artists and Animators | Market Researchers, Customer Researchers | 13-1161 | Market Research Analysts and Mktg Spec. |
| Architects | 17-1011 | Architects, Except Landscape and Naval | Marketing Strategy Freelancers | 13-1161 | Market Research Analysts and Mktg Spec. |
| Art Illustration Freelancers | 27-1013 | Fine Artists | Mechanical Engineers | 17-2141 | Mechanical Engineers |
| Article Blog Writing Freelancers | 27-3043 | Poets, Lyricists and Creative Writers | Medical Translators Professionals | 27-3091 | Interpreters and Translators |
| Audio Production Specialists | 27-4011 | Audio and Video Technicians | Mobile Developers | 15-1252 | Software Developers |
| Chemical Engineers | 17-2041 | Chemical Engineers | Network & System Administrators | 15-1244 | Network and Computer Systems Admin. |
| Contract Law Freelancers | 23-1011 | Lawyers | Other - Admin Support Professionals | 43-4151 | Order Clerks |
| Contract Manufacturers | 17-3011 | Architectural and Civil Drafters | Other Sales & Marketing Specialists | 13-1161 | Search Marketing Strategists |
| Copywriters | 27-3043 | Writers and Authors | Other Writing Services Professionals | 27-3043 | Writers and Authors |
| Corporate Law Professionals & Consultants | 23-1011 | Lawyers | Paralegal Professionals | 23-2011 | Paralegals and Legal Assistants |
| Creative Writers | 27-3043 | Poets, Lyricists and Creative Writers | Photographers | 27-4021 | Photographers |
| Customer Service & Tech Support Reps | 43-4051 | Customer Service Representatives | Presentation Designers & Developers | 27-1011 | Art Directors |
| Data Entry Specialists | 43-9021 | Data Entry Keyers | Product Management Professionals & Consultants | 13-1081 | Logistics Analysts |
| Data Extraction / ETL Specialists | 15-1243 | Data Warehousing Specialists | Project Managers | 13-1082 | Project Management Specialists |
| Data Mining Management Freelancers | 15-2051 | Data Scientists | Proofreaders & Editors | 27-3041 | Editors |
| Data Visualization Specialists & Analysts | 15-2051 | Data Scientists | Public Relations (PR) Professionals | 27-3031 | Public Relations Specialists |
| Database Administration Freelancers | 15-1242 | Database Administrators | QA & Testing Specialists | 15-1253 | Software Quality Assurance Analysts |
| Desktop Software Developers | 15-1252 | Software Developers | Quantitative Analysis Specialists | 15-2051 | Data Scientists |
| Display Advertising Specialists | 13-1161 | Search Marketing Strategists | Resumes & Cover Letters Writers | 21-1012 | Educational, Guidance, and Career Counselors |
| ERP / CRM Implementation Specialists | 15-1211 | Computer Systems Analysts | Scripts & Utilities Developers | 15-1251 | Computer Programmers |
| Ecommerce Programmers & Developers | 13-1161 | Search Marketing Strategists | Search Engine Marketing (SEM) Specialists | 13-1161 | Search Marketing Strategists |
| Electrical Engineers | 17-2071 | Electrical Engineers | Search Engine Optimization (SEO) Specialists | 13-1161 | Market Research Analysts and Mktg Spec. |
| Email & Marketing Automation Managers & Consultants | 13-1161 | Search Marketing Strategists | Social Media Marketing (SMM) Specialists | 13-1161 | Search Marketing Strategists |
| Family Law Professionals & Consultants | 23-1011 | Lawyers | Technical Support Representatives | 15-1232 | Computer User Support Specialists |
| Game Developers | 15-1255 | Video Game Designers | Technical Translation Professionals | 27-3091 | Interpreters and Translators |
| General Translation Freelancers | 25-1124 | Foreign Lang. and Literature Teachers, PSE | Technical Writers | 27-3042 | Technical Writers |
| Grant Writers | 13-1131 | Fundraisers | Telemarketing & Telesales Specialists | 41-9041 | Telemarketers |
| Graphics Design Freelancers | 27-1024 | Graphic Designers | Transcription Services Professionals | 27-4011 | Audio and Video Technicians |
| Information Security Specialists & Consultants | 15-1212 | Information Security Analysts | Video Production Specialists | 27-2012 | Producers and Directors |
| Intellectual Property Law Professionals & Consultants | 23-1011 | Lawyers | Virtual Assistants, Personal Assistants | 27-1014 | Special Effects Artists and Animators |
| Interior Designers | 27-1025 | Interior Designers | Voice Talent Artists | 27-2042 | Musicians and Singers |
| Lead Generation Professionals | 11-2021 | Marketing Managers | Web Designers, Mobile Designers | 15-1255 | Web and Digital Interface Designers |
| Legal Translation Professionals | 27-3091 | Interpreters and Translators | Web Research Specialists | 15-2051 | Data Scientists |

Table A3: Wage determinants

| | Coef. | Std. Err. | | Coef. | Std. Err. |
|---|---|---|---|---|---|
| **Experience** | | | **Quality ratings** | | |
| Earnings (in logs) | 0.0723*** | (0.00175) | Top rated | 0.132*** | (0.0048) |
| <=5 jobs | -0.0424*** | (0.00578) | SR <70% | -0.167*** | (0.0229) |
| [6,15) jobs | -0.0610*** | (0.00625) | SR [70%,80%) | -0.0745*** | (0.0165) |
| [15,50) jobs | -0.0390*** | (0.00771) | SR [80%,90%) | -0.0773*** | (0.0130) |
| >=50 jobs | -0.00258 | (0.0172) | SR [90%,95%) | -0.0497*** | (0.0128) |
| **Part time/full time** | | | SR [95%,100%) | -0.0380*** | (0.0124) |
| As needed | 0.141*** | (0.0108) | SR 100% | -0.100*** | (0.0120) |
| <= 30 hrs/week | 0.0982*** | (0.0117) | **Skills** | | |
| > 30 hrs/week | 0.0779*** | (0.0105) | # test | -0.0018*** | (0.0003) |
| **Response time** | | | Av. score | 0.0581*** | (0.00542) |
| < 24 hrs | -0.0415*** | (0.00861) | **Agency** | | |
| < 3 days | 0.0781*** | (0.00507) | Single worker | 0.148*** | (0.0125) |
| 3+ days | 0.0572*** | (0.0145) | Multi worker | -0.0437*** | (0.0134) |
| **Observations** | 90,550 | $\mathbf{R^2}$ | 0.551 | | |

Notes: The table reports the coefficients estimated from equation (1). The sample size includes the pairs worker-employer with available transacted wage data. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A4: Variance decomposition of wages

| Component | Share of variance |
|---|---|
| Country of worker | 0.23 |
| Country of employer | 0.004 |
| Controls | 0.17 |
| Cov (country of worker - controls) | 0.15 |
| Cov (country of employer - controls) | 0.0008 |
| Cov (country of employer - country of worker) | 0.002 |
| Residual | 0.45 |

Notes: The Table reports the variance decomposition of equation (1) using transacted wages. Rows (1)-(3) show the variance accounted by the country of worker $\mathbb{C}_i$, the country of employer $\mathbb{D}_f$, and the controls $\mathbb{I}_{i=f}$ and $\boldsymbol{\beta' X_i}$. Rows (4) and (5) show two times the covariance between $\mathbb{C}_i$ and controls and between $\mathbb{D}_f$ and controls, respectively. Rows (7) shows two times the covariance between $\mathbb{C}_i$ and $\mathbb{D}_f$. Row (7) is the variance not explained.

Table A5: Frequency of transacted wage changes

| Sample | Freq. Wage Changes | Share Wage Increases | Med. Wage Increase | Med. Wage Decrease |
|---|---|---|---|---|
| All | 0.76 | 0.64 | 0.25 | -0.22 |
| $\Delta T = 1$ | 0.69 | 0.58 | 0.22 | -0.22 |
| $\Delta T \leq med(\Delta T)$ | 0.71 | 0.60 | 0.22 | -0.22 |
| $\Delta T > med(\Delta T)$ | 0.82 | 0.68 | 0.29 | -0.22 |

Notes: The Table presents summary statistics about the distribution of transacted wage changes in between subsequent hourly jobs.

Table A6: Pass-through to transacted wages: First Stage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | $\Delta_s w_{jt}$ | $\Delta_s w_{jt}$ | $\Delta_s w_{jt}$ | $\Delta_s w_{-ijt}$ | $\Delta_s w_{jt}$ | $\Delta_s w_{jt}^{plac}$ | $\Delta_s w_{jt}$ | $\Delta_s w_{jt}$ |
| $\Delta_s e_{ct}$ | -0.003 | | -0.006 | -0.004 | -0.003 | 0.002 | -0.002 | 0.019 |
| | (0.017) | | (0.017) | (0.017) | (0.017) | (0.004) | (0.016) | (0.017) |
| $\pi_{c,t_s}$ | -0.010 | | -0.013 | -0.010 | -0.010 | 0.008 | -0.008 | -0.001 |
| | (0.026) | | (0.026) | (0.026) | (0.026) | (0.021) | (0.021) | (0.048) |
| $\pi_{c,t_s} + \Delta_s e_{ct}$ | | -0.003 | | | | | | |
| | | (0.017) | | | | | | |
| $\Delta_s e_t$ | 0.688*** | 0.688*** | 0.757*** | 0.691*** | 0.688*** | 0.028 | 0.552*** | 0.100*** |
| | (0.116) | (0.115) | (0.115) | (0.118) | (0.116) | (0.035) | (0.112) | (0.027) |
| $\pi_{t-s,t}$ | -0.178 | -0.187 | -0.109 | -0.162 | -0.178 | -0.347*** | -1.100*** | 0.470*** |
| | (0.175) | (0.170) | (0.182) | (0.177) | (0.175) | (0.065) | (0.143) | (0.146) |
| $\Delta_s e_t^{plac}$ | | | | | 0.000 | -0.009*** | | |
| | | | | | (0.000) | (0.002) | | |
| $\pi_{t-s,t}^{plac}$ | | | | | 0.001 | -0.351*** | | |
| | | | | | (0.003) | (0.045) | | |
| Observations | 88399 | 88399 | 66526 | 88399 | 88399 | 88399 | 88399 | 88399 |

Notes: Columns 1 reports the first stage corresponding to Column 3 in Table (2). Columns 2-4 report the first stage corresponding to Columns 2-4 in Table (A7). Columns 5-6 report the first stage corresponding to Column 5 in Table (A7). Columns 7-8 report the first stage corresponding to Columns 6-7 in Table (A7). Specifications in these columns include country-sector-specific linear trends but they are not reported. Standard errors are clustered at the sector-time-spell and country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level.

Table A7: Pass-through to transacted wages: Robustness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ | $\Delta_s w_{ijt}$ |
| $\Delta_s e_{ct}$ | | | 0.251*** | 0.214*** | 0.213*** | 0.183** | 0.232*** | 0.084*** |
| | | | (0.067) | (0.053) | (0.053) | (0.087) | (0.080) | (0.028) |
| $\pi_{c,t_s}$ | | | 0.240* | 0.195* | 0.196* | 0.217 | 0.248 | 0.095 |
| | | | (0.137) | (0.103) | (0.104) | (0.206) | (0.160) | (0.086) |
| $\pi_{c,t_s} + \Delta_s e_{ct}$ | 0.203*** | 0.213*** | | | | | | |
| | (0.058) | (0.053) | | | | | | |
| $\Delta_s w_{jt}$ | | 0.748*** | 0.804*** | | 0.737*** | 1.089*** | -0.398 | |
| | | (0.260) | (0.282) | | (0.250) | (0.230) | (0.544) | |
| $\Delta_s w_{-ijt}$ | | | | 0.741*** | | | | |
| | | | | (0.252) | | | | |
| $\Delta_s w_{jt}^{plac}$ | | | | | 0.062 | | | |
| | | | | | (0.103) | | | |
| Observations | 88399 | 88399 | 66526 | 88399 | 88399 | 88399 | 88399 | 226559 |
| Test $\beta_1 = \beta_2$ | | | 0.93 | 0.84 | 0.85 | 0.86 | 0.88 | 0.90 |
| Specification | OLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | 2SLS | OLS |
| F stat 1st stage | | 34.0 | 48.3 | 37.2 | 33.9 | 193.1 | 7.01 | |

Notes: Columns 1-2 reestimate Columns 1 and 3 from Table 2 imposing the restriction that $\beta_1 = \beta_2$. Column 3 reestimates Column 3 in Table 2 using the sample of non-zero wage changes. Column 4 reestimates Column 3 in Table 2 replacing the baseline wage index $\Delta_s W_{jt}$ for the leave-one-out wage index $\Delta_s W_{-ijt} \equiv \sum_{l \neq i} \frac{s_{ljt}}{1-s_{ijt}} \Delta_s w_{lt} = [\Delta_s W_{jt} - s_{ijt} \Delta_s w_{ijt}] \,/\, [1 - s_{ijt}]$. This alternative specification alleviates the concern that the aggregate wage index $\Delta_s W_{jt}$ is by definition a function of each worker's wage, and is thus correlated with the error term. Column 5 reestimates Column 3 in Table 2 and includes the change in wages of workers that are predicted to be the least likely competitors of a given worker. These columns include country-sector-specific linear trends. Column 6 reestimates the specification in Columns 3 of Table 2 without controlling for country-sector-specific trends. Column 7 reestimates the specification in Column 3 of Table 2 without controlling for time-spell fixed effects. In Columns 1-7, standard errors are clustered at the sector-time-spell and country level. Column 8 reports the results from estimating equation (21). Standard errors are clustered at the country level. *: significant at the 10% level, **: significant at the 5% level, *** significant at the 1% level. The corresponding first stage regressions are reported in Table A6.

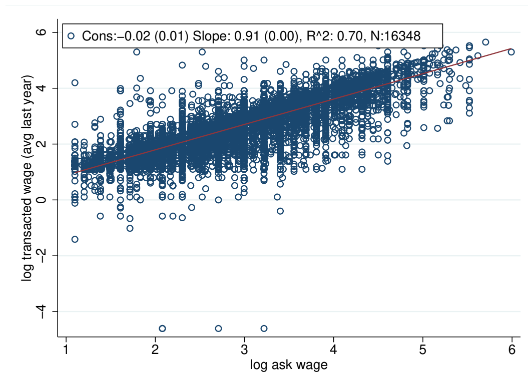
Table A8: Offshoring by occupation in the Platform

| Occupation Platform | Value share offshored | Quantity share offshored | Occupation Platform | Value share offshored | Quantity share offshored |
|---|---|---|---|---|---|
| Technical Support Representatives | 0.93 | 0.89 | Lead Generation Professionals | 0.72 | 0.87 |
| ERP / CRM Implementation Specialists | 0.92 | 0.95 | Presentation Designers & Developers | 0.72 | 0.82 |
| Medical Translators Professionals | 0.88 | 0.90 | Architects | 0.71 | 0.89 |
| Legal Translation Professionals | 0.86 | 0.88 | Video Production Specialists | 0.70 | 0.81 |
| Mobile Developers | 0.86 | 0.90 | Logo & Brand Designers | 0.70 | 0.81 |
| Interior Designers | 0.85 | 0.90 | Data Mining Management Freelancers | 0.70 | 0.89 |
| Technical Translation Professionals | 0.84 | 0.87 | Photographers | 0.70 | 0.83 |
| General Translation Freelancers | 0.84 | 0.88 | Project Managers | 0.69 | 0.79 |
| Machine Learning Specialists & Analysts | 0.83 | 0.89 | Email & Marketing Automation Managers & Consultants | 0.67 | 0.80 |
| Virtual Assistants, Personal Assistants | 0.83 | 0.88 | Market Researchers, Customer Researchers | 0.67 | 0.83 |
| QA & Testing Specialists | 0.81 | 0.80 | Audio Production Specialists | 0.67 | 0.76 |
| Web Research Specialists | 0.81 | 0.87 | Mechanical Engineers | 0.65 | 0.81 |
| Animators | 0.81 | 0.89 | Data Visualization Specialists & Analysts | 0.62 | 0.77 |
| Network & System Administrators | 0.81 | 0.87 | Contract Manufacturers | 0.62 | 0.80 |
| Information Security Specialists & Consultants | 0.80 | 0.88 | Chemical Engineers | 0.62 | 0.71 |
| Data Entry Specialists | 0.80 | 0.88 | Technical Writers | 0.62 | 0.64 |
| Desktop Software Developers | 0.80 | 0.87 | Marketing Strategy Freelancers | 0.60 | 0.76 |
| Ecommerce Programmers & Developers | 0.79 | 0.85 | Electrical Engineers | 0.59 | 0.80 |
| Scripts & Utilities Developers | 0.78 | 0.81 | Copywriters | 0.59 | 0.61 |
| Product Management Professionals & Consultants | 0.77 | 0.84 | Proofreaders & Editors | 0.55 | 0.56 |
| Family Law Professionals & Consultants | 0.77 | 0.56 | Accounting Freelancers | 0.53 | 0.68 |
| Customer Service & Tech Support Reps | 0.76 | 0.83 | Article Blog Writing Freelancers | 0.52 | 0.57 |
| 3D Modeling Cad Freelancers | 0.76 | 0.87 | A/B Testing Specialists | 0.52 | 0.76 |
| Other - Admin Support Professionals | 0.75 | 0.87 | Voice Talent Artists | 0.52 | 0.55 |
| Web Designers, Mobile Designers | 0.75 | 0.84 | Quantitative Analysis Specialists | 0.51 | 0.70 |
| Search Engine Marketing (SEM) Specialists | 0.75 | 0.83 | Display Advertising Specialists | 0.49 | 0.64 |
| Data Extraction / ETL Specialists | 0.75 | 0.87 | Creative Writers | 0.45 | 0.48 |
| Transcription Services Professionals | 0.75 | 0.78 | Other Writing Services Professionals | 0.45 | 0.51 |
| Telemarketing & Telesales Specialists | 0.74 | 0.85 | Paralegal Professionals | 0.40 | 0.36 |
| Social Media Marketing (SMM) Specialists | 0.74 | 0.86 | Public Relations (PR) Professionals | 0.38 | 0.57 |
| Graphics Design Freelancers | 0.74 | 0.82 | Management Consultants | 0.36 | 0.53 |
| Search Engine Optimization (SEO) Specialists | 0.74 | 0.83 | Resumes & Cover Letters Writers | 0.33 | 0.35 |
| Other Sales & Marketing Specialists | 0.73 | 0.84 | Intellectual Property Law Professionals & Consultants | 0.33 | 0.38 |
| Game Developers | 0.73 | 0.88 | Grant Writers | 0.29 | 0.30 |
| Database Administration Freelancers | 0.72 | 0.84 | Contract Law Freelancers | 0.29 | 0.33 |
| Art Illustration Freelancers | 0.72 | 0.79 | Corporate Law Professionals & Consultants | 0.24 | 0.33 |

## Table A9: Offshoring by SOC occupation

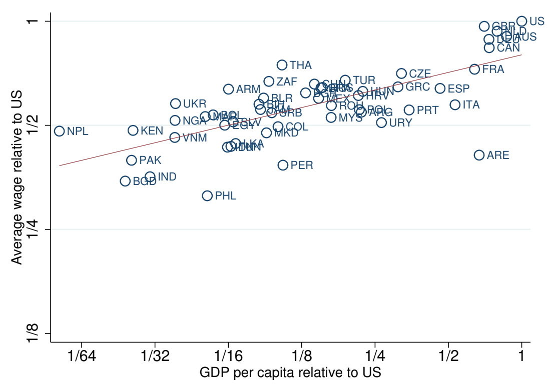
| SOC code | SOC title | Value share offshored | SOC code | SOC title | Value share offshored |
|---|---|---|---|---|---|
| 15-1232 | Computer User Support Specialists | 0.93 | 27-1011 | Art Directors | 0.72 |
| 15-1211 | Computer Systems Analysts | 0.92 | 13-1161 | Search Marketing Strategists | 0.72 |
| 27-3091 | Interpreters and Translators | 0.85 | 13-1161 | Market Research Analysts and Marketing Specialists | 0.72 |
| 27-1025 | Interior Designers | 0.85 | 17-1011 | Architects, Except Landscape and Naval | 0.71 |
| 25-1124 | Foreign Language and Literature Teachers, Postsecondary | 0.84 | 27-2012 | Producers and Directors | 0.70 |
| 15-1252 | Software Developers | 0.83 | 27-4021 | Photographers | 0.70 |
| 15-1253 | Software Quality Assurance Analysts and Testers | 0.81 | 13-1082 | Project Management Specialists | 0.69 |
| 27-1014 | Special Effects Artists and Animators | 0.81 | 17-2141 | Mechanical Engineers | 0.65 |
| 15-1244 | Network and Computer Systems Administrators | 0.81 | 17-3011 | Architectural and Civil Drafters | 0.62 |
| 15-1212 | Information Security Analysts | 0.80 | 17-2041 | Chemical Engineers | 0.62 |
| 43-9021 | Data Entry Keyers | 0.80 | 27-3042 | Technical Writers | 0.62 |
| 15-1251 | Computer Programmers | 0.78 | 17-2071 | Electrical Engineers | 0.59 |
| 13-1081 | Logistics Analysts | 0.77 | 27-3041 | Editors | 0.55 |
| 43-4051 | Customer Service Representatives | 0.76 | 13-2011 | Accountants and Auditors | 0.53 |
| 43-4151 | Order Clerks | 0.75 | 15-1250 | Software and Web Developers, Programmers, and Testers | 0.52 |
| 15-1255 | Video Game Designers | 0.75 | 27-2042 | Musicians and Singers | 0.52 |
| 15-1255 | Web and Digital Interface Designers | 0.75 | 27-3043 | Poets, Lyricists and Creative Writers | 0.50 |
| 15-1243 | Data Warehousing Specialists | 0.75 | 27-3043 | Writers and Authors | 0.50 |
| 41-9041 | Telemarketers | 0.74 | 23-2011 | Paralegals and Legal Assistants | 0.40 |
| 15-2051 | Data Scientists | 0.74 | 23-1011 | Lawyers | 0.39 |
| 27-1024 | Graphic Designers | 0.73 | 27-3031 | Public Relations Specialists | 0.38 |
| 15-1242 | Database Administrators | 0.72 | 13-1111 | Management Analysts | 0.36 |
| 27-1013 | Fine Artists, Including Painters, Sculptors, and Illustrators | 0.72 | 21-1012 | Educational, Guidance, and Career Counselors and Advisors | 0.33 |
| 27-4011 | Audio and Video Technicians | 0.72 | 13-1131 | Fundraisers | 0.29 |
| 11-2021 | Marketing Managers | 0.72 | | | |

Figure A.1: Ask vs. transacted wages




Notes: The figure shows the scatter plot between a worker's ask wage (x-axis) and the worker's average transacted wage (y-axis). Average transacted wages are computed using wages that were received within the year around the date of the ask wage.

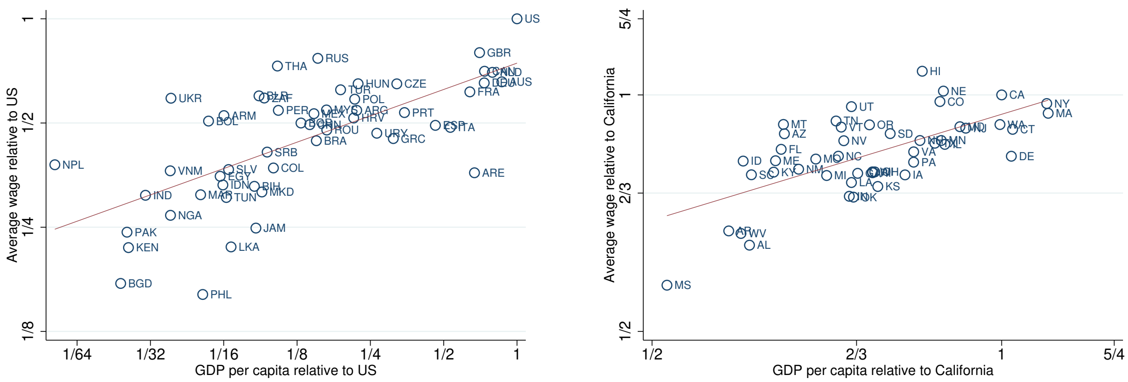
Figure A.2: Average wages across workers: Ask wages




Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). It plots the residualized average wage in each country relative to the US obtained from the worker's country fixed effects estimated in equation (1). The outcome variable is ask wages, as opposed to transacted wages. The red lines show the linear fit of the data. The estimated slope is 0.17 (0.03) and the $R^2$ is 0.50.

# Figure A.3: Average wages (non-residualized) across workers

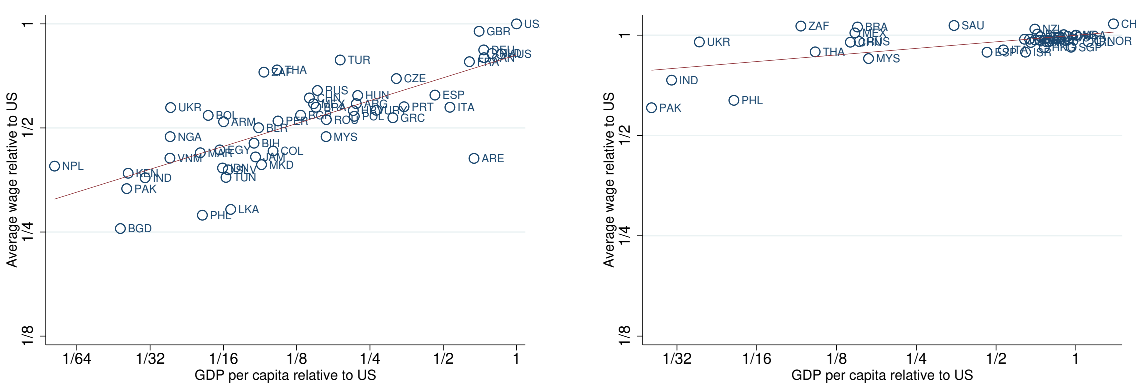
(a) By country (b) By US states




Notes: The x-axis in panel (a) reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). The y-axis plots the average transacted wage in each country relative to the US. The estimated slope is 0.25 (0.04) and the $R$-squared is 0.47. The x-axis in panel (b) reports the (log of) the relative GDP per capita in US dollars, taken from the Bureau of Economic Analysis. The y-axis plots the average transacted wage in each state relative to California. The estimated slope is 0.44 (0.09) and the $R$-squared is 0.43. The red lines show the linear fit of the data.

# Figure A.4: Wages and GDP per capita relative to the US: controlling for distance

(a) Country of worker (b) Country of employer

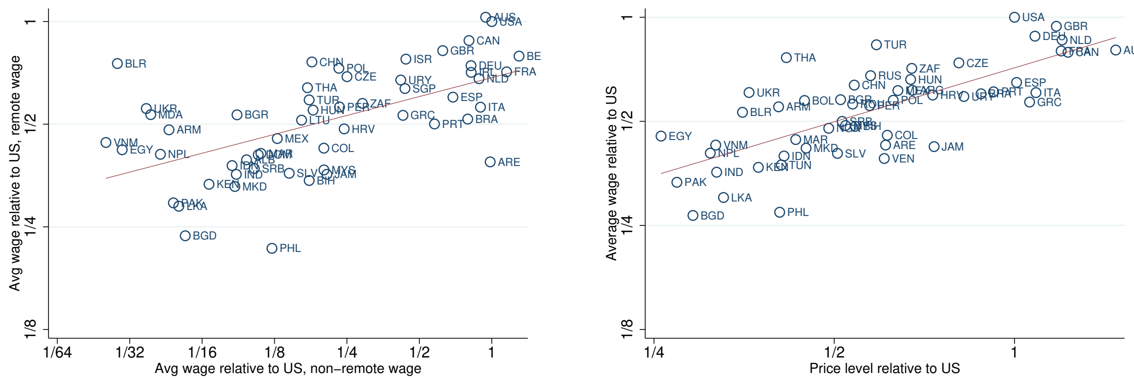



Notes: The x-axes report the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). The figure reports the average residualized wage in each country relative to the US obtained from the country fixed effects. These worker' and employer's country fixed effect are estimated according to equation (1) with the following additional control variables: a dummy variable for whether the country of the employer and worker are contiguous, have common language, have colony ties, common currency, and common legal origin. It also controls for the distance in kilometers between the capital cities of both countries weighted by the population size, and the number of hours difference between both countries. Panel (a) plots the worker's country fixed effects and panel (b) plots the employer's country fixed effects. The estimated slope in panel (a) is 0.22 (0.03) and the $R$-squared is 0.58. The estimated slope in panel (b) is 0.07 (0.02) and the $R$-squared is 0.36.

## Figure A.5: Real wages and comparison with non-remote wages

(a) Remote vs. non-remote wages

(b) Remote wages and domestic price levels

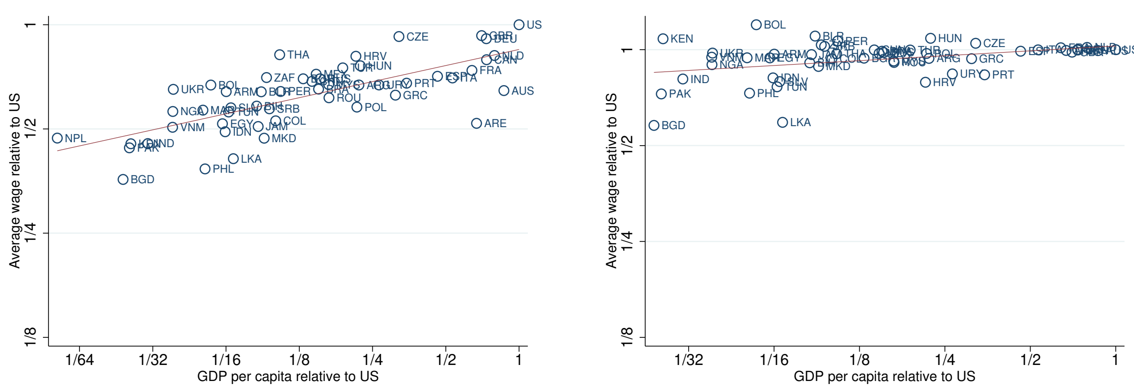



Notes: The x-axis of panel (a) reports the average (log of) compensation of employees in 2011 denominated in US dollars. The average compensation for each country is computed as the average among the following occupations included in the Comparison Program (ICP) from the World Bank: Accounting and Bookkeeping Clerks, HR Professionals, Computer Operator, Data Processing Manager, and Database Administrator. Panel (a) plots the average wage residualized in each country relative to the US. The x-asis of panel (b) reports the price level of output included in the ICP (PPP/XR, where the price level of output of USA in 2017 equals 1), relative to the US. The y-axes reports average residualized wage obtained are from the country fixed effects estimated in equation (1). The red lines show the linear fit of the data. The estimated slope is 0.18 (0.04) and the $R$-squared is 0.41 in panel a, the estimated slope is 0.52 (0.06) and the $R$-squared is 0.54.

## Figure A.6: Differences in wages within workers and employers

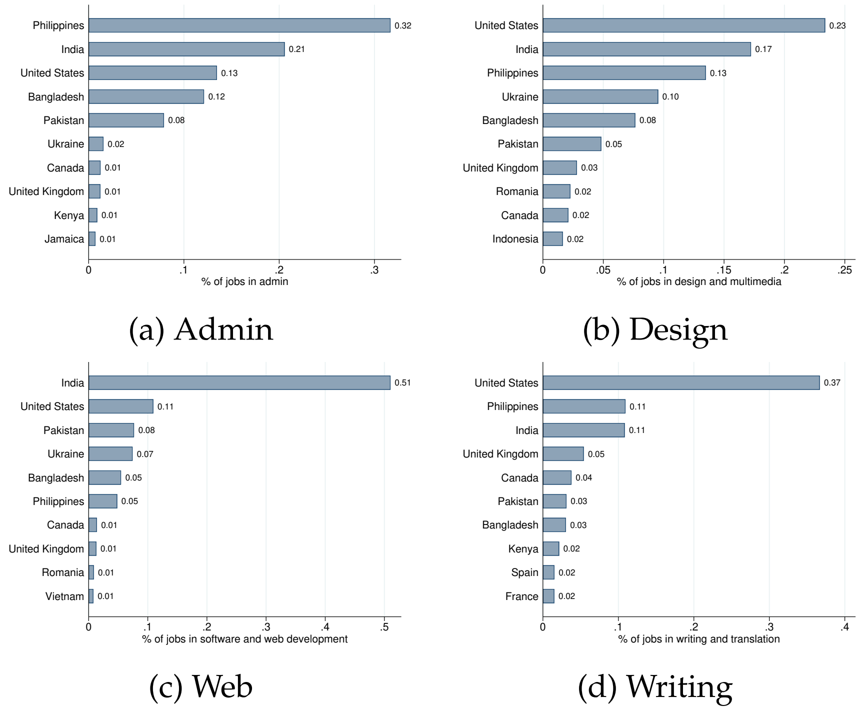
(a) Within employer

(b) Within worker




Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, which we take from the World Development Indicators (WDI). The y-axis in panel (a) reports the set of country-of-worker effect (relative to employers in the US) estimated according a version of equation (1) that controls for employer fixed effects. The estimated slope is 0.15 (0.02) with an $R$-squared of 0.53. The y-axis in panel (b) reports the set of country-of-employer fixed effect (relative to employers in the US) estimated according to a version of equation (1) that controls for worker fixed effects. The estimated slope is 0.05 (0.02) with an $R$-squared of 0.14.

# Figure A.7: Sectorial variation in instrumental variable




(a) Admin (b) Design

(c) Web (d) Writing

Notes: This figure reports the variation behind the sectoral shares $s^j_{ct}$ used to construct the instrumental variable $\sum_c s^j_{ct} [\pi_{ct_s} + \Delta_s e_{ct}]$.

## A.2 Data Appendix

**Additional data sources:** Our measure of GDP per capita in current US dollars is the variable gdp_pc_curr for year 2016 from the World Development Indicators (WDI). The GDP per capita in US dollars for each state is the variable SAGDP10N obtained from the U.S. Department of Commerce, Bureau of Economic Analysis for year 2017. The 'gravity' variables obtained from the The CEPII Gravity Database are the following: contig, comlang_off, distw, tdiff, colony, comcur, comleg_pretrans, tradeflow_imf_d, gdp_ppp_o, and gdp_ppp_d (for a detailed description see http://www.cepii.fr/DATA_DOWNLOAD/gravity/doc/Gravity_documentation.pdf). For non-remote wages, we use the compensation of employees for year 2001 from the International Comparison Program (ICP) from the World Bank for the following occupations: Accounting and bookkeeping clerks, HR professionals, Computer operator, Data processing manager, and Database administrator. We adjust the value of compensation by the current exchange rate to convert it into dollars. Finally, the exchange rate and inflation data used in section 4 is sourced from the International Financial Statistics (IFS) database from the IMF.

**Algorithm:** The data on job history used in section 4.2 specify the sector for a subset of jobs. We assign sectors to the remaining jobs using the information from the jobs' descriptions using a machine-learning algorithm. We first make the data suitable for analysis by removing a set of stop-words (e.g., "and", "the", etc.), punctuation marks and numbers from the job description, which is available for all jobs. Then, we keep the 3,000 most frequent words, which balances the desire to use as many words as possible in the prediction step without overfitting the data. Next, we keep 70% of jobs with occupation data as a training sample, and use the remaining 30% as a validation sample. We then train an artificial neural network on the training sample using a hyper-parameter optimization algorithm (see Chollet, 2021) to predict the broad occupation a given job belongs to based on the (cleaned) job description. To set the parameters of this algorithm, we follow a cross-validation exercise in order to achieve good prediction outcomes on the validation sample. Finally, we apply the estimated prediction model on the descriptions of jobs for which we do not have occupation data and obtain the likelihood that a given job belongs to each broad occupation. In our baseline analysis, we assign jobs to the occupation that obtains the highest likelihood.

## A.3 Derivation of Equations (15) and (16)

The change in worker's $i$ wage is:

$$dw_{it}^{j} = d\omega_{ct}^{j} + dz_{it}^{j}, \tag{A.3.1}$$

where the change in wages per efficiency units is given by

$$d\omega_{ct}^{j}=\frac{\theta}{\rho+\theta}db_{ct}^{j}+\frac{1}{\rho+\theta}d\varphi_{ct}^{j}+\frac{\rho-\eta}{\rho+\theta}d\omega_{t}^{j}+\frac{1}{\rho+\theta}\left[\eta dp_{t}+dy_{t}\right]. \tag{A.3.2}$$

Differentiating (7) yields

$$d\omega_{t}^{j}=\sum s_{ct}^{j}d\omega_{ct}^{j}-\sum s_{ct}^{j}da_{ct}^{j},$$

which substituting for (A.3.2) can be rewritten as

$$d\omega_{t}^{j}=\frac{\theta}{\theta+\eta}db_{t}^{j}+\frac{1}{\theta+\eta}d\varphi_{t}^{j}-\frac{\rho+\theta}{\theta+\eta}da_{t}^{j}+\frac{1}{\theta+\eta}\left[\eta dp_{t}+dy_{t}\right]. \tag{A.3.3}$$

Substituting (14) into (A.3.2) and (A.3.3) yields:

$$d\omega_{ct}^{j}=\frac{\theta}{\rho+\theta}\left[de_{ct}+\pi_{ct}\right]+\frac{1}{\rho+\theta}\left[d\varphi_{ct}+\theta\gamma_{ct}^{j}\right]+\frac{\rho-\eta}{\rho+\theta}\omega_{t}^{j}+\frac{1}{\rho+\theta}\left[\eta p_{t}+y_{t}\right].$$

and

$$d\omega_{t}^{j}=\frac{\theta}{\theta+\eta}\left[de_{ct}+\pi_{ct}\right]+\frac{1}{\theta+\eta}\left[d\varphi_{t}^{j}-\left[\rho+\theta\right]da_{t}^{j}+\theta\gamma_{t}^{j}+\eta dp_{t}+dy_{t}\right],$$

Let $dz_{t}^{j}\equiv\sum s_{ct}^{j}\mathbb{E}_{c}dz_{it}^{j}$. Then, we can write:

$$\begin{aligned}d\omega_{t}^{j}&=\sum_{c}s_{ct}^{j}\mathbb{E}_{c}\left[d\omega_{ct}^{j}+dz_{it}^{j}\right]-dz_{t}^{j}-da_{t}^{j},\\&=-da_{t}^{j}-dz_{t}^{j}+\sum_{c}s_{ct}^{j}\mathbb{E}_{c}\left[dw_{it}^{j}\right],\end{aligned}$$

Finally, we define the index of wage changes as:

$$dw_{t}^{j}\equiv\sum_{c}s_{ct}^{j}\mathbb{E}_{c}\left[dw_{it}^{j}\right].$$

Note that we can write:

$$d\omega_{t}^{j}=dw_{t}^{j}-dz_{t}^{j}-da_{t}^{j}, \tag{A.3.4}$$

and

$$dw_{t}^{j}=\frac{\theta}{\theta+\eta}\left[de_{ct}+\pi_{ct}\right]+\frac{1}{\theta+\eta}\left[\theta\gamma_{ct}^{j}+d\varphi_{t}^{j}-\left[\rho-\eta\right]da_{t}^{j}+\eta dp_{t}+dy_{t}\right]+dz_{t}^{j}, \tag{A.3.5}$$

Substituting (A.3.2), (A.3.4), and (A.3.5) into (A.3.4), we obtain expressions (15) and (16)with

$$d\psi^j_{ct} \equiv \frac{1}{\rho+\theta}\left[d\varphi_{ct}+\theta\gamma^j_{ct}\right]-\frac{\rho-\eta}{\rho+\theta}\left[da^j_t+dz^j_t\right]+\frac{1}{\rho+\theta}\left[\eta p_t+y_t\right].$$

and

$$d\phi^j_t = \frac{1}{\theta+\eta}\left[\theta\gamma^j_{ct}+d\varphi^j_t-[\rho-\eta]\,da^j_t+\eta dp_t+dy_t\right]+dz^j_t.$$

## A.4 Alternative occupation production function

This Appendix derives the structural equations used in our estimation in Section 4 from an alternative model in which workers from different locations are perfect substitutes, but can specialize in the production of different tasks. In particular, we modify the framework in Section 4.1 by assuming that the output of sector $j$ in year $t$ is produced by combining the output of a continuum of tasks indexed by $\omega \in [0,1]$:

$$Y_t^j = \left[\int_0^1 y_t^j(\omega)^{\frac{\sigma_j - 1}{\sigma_j}} d\omega\right]^{\frac{\sigma_j}{\sigma_j - 1}}. \tag{A.4.1}$$

Each task $\omega$ can be produced remotely by workers in different locations $c$. The cost of purchasing task $\omega$ from location $c$ is $\Omega_{ct}^j / x_c^j(\omega)$, where $\Omega_{ct}^j$ is the wage per efficient unit of labor from location $c$ in sector $j$ and $x_c^j(\omega)^{-1}$ are the number of efficiency units of labor from location $c$ required to produce task $\omega$. This number can be location-task specific, indicating that labor from different locations can be relatively more productive for the production of different tasks. We assume that efficiency units of labor from different locations are perfect substitutes in the production of a task, so tasks are supplied by the lowest cost location. Consequently, the price actually paid in the platform for task $\omega$ in sector $j$ is then $p_t^j(\omega) = min\left\{\frac{\Omega_{1t}^j}{x_1^j(\omega)}, ..., \frac{\Omega_{Nt}^j}{x_N^j(\omega)}\right\}$.

We assume that $x_c^j(\omega)$ is a random variable drawn independently for each $\omega$ from a Frechet distribution given by

$$F_c^j(x) \equiv Pr\left(x_c^j(\omega) \leq x\right) = e^{-\tilde{A}_c^j x^{1-\rho}},$$

with shape parameter $\rho > 2$ , and scale parameter $\tilde{A}_c^j > 0$. A lower value of $\rho$ implies that the draws $x_c^j(\omega)$ are more dispersed across tasks, so that differences in comparative advantage across tasks is stronger. A larger value of $\tilde{A}_c^j$ implies that workers from a location are likely to be more productive across all tasks.

The distributional assumption implies that the distribution of prices in the platform for task $\omega$, $p_t^j(\omega)$, is also Frechet. This distribution, denoted by $G_t^j(p)$, is given by

$$G_t^j(p) = 1 - \prod_c Pr\left(\frac{\Omega_{ct}^j}{x_c^j(\omega)} > p\right) = 1 - e^{-\Phi_t^j p^{\rho-1}},$$

with $\Phi_t^j \equiv \sum_c \tilde{A}_c^j \left[\Omega_{ct}^j\right]^{1-\rho}$.

We can now compute the cost function associated to the CES production function (A.4.1). The cost function of sector $j$ in year $t$ is a weighted average of tasks' prices given by

$$\Omega_t^j = \gamma_j \left[\Phi_t^j\right]^{\frac{-1}{\rho-1}}, \tag{A.4.2}$$

where $\gamma_j \equiv \Gamma\left(\frac{\rho-\sigma_j}{\rho-1}\right)^{\frac{1}{1-\sigma_j}}$, and $\Gamma(\cdot)$ is the Gamma function assuming $\sigma_j < \rho$.[26]

The probability that a task with labor requirement $x_c^j(\omega)$ is supplied by location $c$ in sector $j$ is

$$Pr\left(\frac{\Omega_{ct}^j}{x_c^j(\omega)} \leq min_{s\neq c}\left\{\frac{\Omega_{st}^j}{x_s^j(\omega)}\right\}\right),$$

which is equal to

$$\prod_{s\neq c} Pr\left(\frac{\Omega_{st}^j}{x_s^j(\omega)} \geq \frac{\Omega_{ct}^j}{x_c^j(\omega)}\right) = \prod_{s\neq c} e^{-\tilde{A}_s^j\left[\frac{\Omega_{st}^j}{\Omega_{ct}^j}x_c^j(\omega)\right]^{1-\rho}}$$
$$= e^{\left[x_c^j(\omega)\right]^{1-\rho}\left[\tilde{A}_c^j - \Phi_t^j\left[\Omega_{ct}^j\right]^{\rho-1}\right]}$$

Integrating across all possible values of $x_c^j(\omega)$, we obtain the probability that location $c$

[26] Given that the production function of sector $j$ combines tasks with a CES technology, the cost function is given by:

$$\left[\Omega_t^j\right]^{1-\sigma_j} = \int_0^1 p_j(\omega)^{1-\sigma_j} d\omega.$$

The moment generating function for $y = -ln(p)$ is $\mathbb{E}\left(e^{ty}\right) = \Gamma\left(1-\frac{t}{\rho-1}\right)\left[\Phi_t^j\right]^{\frac{t}{\rho-1}}$. Then, $\mathbb{E}\left(e^{-t}\right)^{-1/t} = \Gamma\left(1-\frac{t}{\rho-1}\right)^{-1/t}\left[\Phi_t^j\right]^{\frac{-1}{\rho-1}}$. The expression for the cost function follows by replacing $t$ with $\sigma_j - 1$ (see Eaton and Kortum, 2002).

supplies the task:[27]

$$s_{ct}^{j} = \frac{\tilde{A}_{c}^{j} \left[\Omega_{ct}^{j}\right]^{1-\rho}}{\Phi_{t}^{j}}.$$

Under our distributional assumptions, the probability that a location supplies an individual task coincides with the share of spending on tasks performed from the location (see Eaton and Kortum, 2002). That is,

$$\frac{\tilde{A}_{c}^{j} \left[\Omega_{ct}^{j}\right]^{1-\rho}}{\Phi_{t}^{j}} = s_{ct}^{j} = \frac{\Omega_{ct}^{j} L_{ct}^{j}}{\Omega_{t}^{j} Y_{t}^{j}}.$$

Substituting (A.4.2), we obtain the demand for efficiency units of labor from location $c$ in sector j:

$$L_{ct}^{j} = \tilde{A}_{c}^{j} \gamma_{j}^{\rho-1} \left[\frac{\Omega_{ct}^{j}}{\Omega_{t}^{j}}\right]^{-\rho} Y_{t}^{j},$$

which coincides with equation (6) with $A_{c}^{j} = \left[\tilde{A}_{c}^{j}\right]^{\frac{1}{\rho-1}} \gamma_{j}$.

[27]This integral is given by

$$\begin{aligned} s_{ct}^{j} &= \int_{0}^{\infty} e^{x^{1-\rho}\left[\tilde{A}_{c}^{j} - \Phi_{t}^{j}\left[\Omega_{ct}^{j}\right]^{\rho-1}\right]} \tilde{A}_{c}^{j} x^{-\rho} \left[\rho-1\right] e^{-\tilde{A}_{c}^{j} x^{1-\rho}} dx \\ &= \int_{0}^{\infty} e^{-x^{1-\rho}\Phi_{t}^{j}\left[\Omega_{ct}^{j}\right]^{\rho-1}} \tilde{A}_{c}^{j} x^{-\rho} \left[\rho-1\right] dx \\ &= \tilde{A}_{c}^{j} \left[\rho-1\right] \int_{0}^{\infty} x^{-\rho} e^{-x^{1-\rho}\Phi_{t}^{j}\left[\Omega_{ct}^{j}\right]^{\rho-1}} dx. \end{aligned}$$

Define $y \equiv \left[\Omega_{ct}^{j}\right]^{\rho-1} \Phi_{t}^{j} x^{1-\rho}$. Then, $dy = -\left[\Omega_{ct}^{j}\right]^{\rho-1} \Phi_{t}^{j} \left[\rho-1\right] x^{-\rho} dx$. This implies that the previous expression can be rewritten as follows:

$$s_{ct}^{j} = \frac{\tilde{A}_{c}^{j}}{\left[\Omega_{ct}^{j}\right]^{\rho-1} \Phi_{t}^{j}} \int_{0}^{\infty} e^{-y} dy = \frac{\tilde{A}_{c}^{j} \left[\Omega_{ct}^{j}\right]^{1-\rho}}{\Phi_{t}^{j}}.$$

## A.5 Alternative measures of offshoring by occupation

### A.5.1 Quantity based measures

Section 5 measures the share of jobs that are offshored in terms of values. Here, we present an alternative measure that computes the share in the number (rather than the value) of jobs that are offshored. In particular, we compute

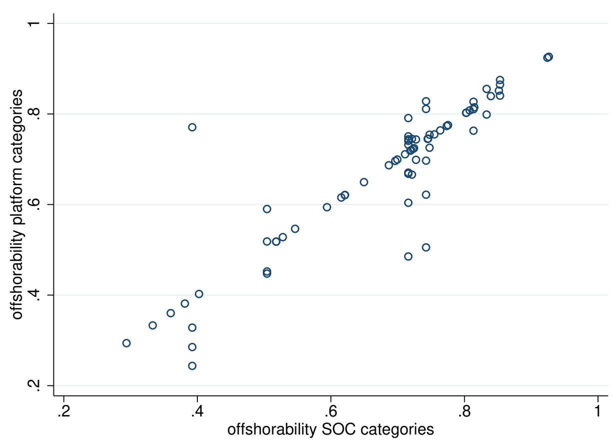
$$\widetilde{\mathcal{O}}^j = \frac{\text{jobs in } j \text{ where cty. employer=US and cty. worker}\neq\text{US}}{\text{All jobs in } j \text{ where cty. employer=US}}. \tag{A.5.1}$$

Appendix Table A8 reports this measure and shows that it is very similar to that in equation (5).

### A.5.2 Offshoring across categories in the SOC system

To make our measure easier to use in future research, we compute the fraction of jobs offshored for the SOC categories represented in our data. Figure A.8 plots the measure in (5) when computed for the categories in the platform (y-axis) vs. the SOC categories (x-axis). The categories in the platform are often more disaggregated than those in the SOC, so that the figures often contain many occupations in the y-axis corresponding to one point in the x-axis. The figure shows that, while the measures are positively correlated, the SOC categories are often too broad and mask substantial heterogeneity in the extent that different occupations are being offshored. For example, the SOC category 'Search Marketing Strategists' includes a wide range of more specific occupations in the platform. Within this SOC category, we observe a difference of 30% in the probability of offshoring jobs between 'Ecommerce Programmers and Developers' and 'Display Advertising Spcecialists' ($\mathcal{O}^j = 0.79$ and $\mathcal{O}^j = 0.50$, respectively). This also suggests that having more disaggregated job categories than those currently available in official statistics can help capture better the degree to which different jobs are offshored, and other important dimensions of international labor transactions.

Figure A.8: Offshoring within SOC categories




Notes: Each circle represents an occupation. The figure compares the frequency with which jobs are offshored using equation (22) for SOC categories vs. platform categories.