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
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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%.

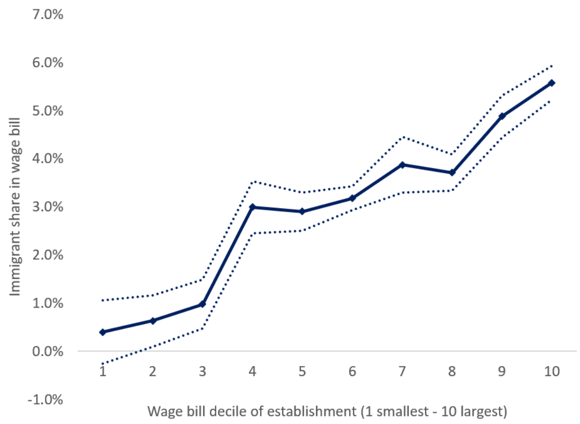
The relationship between employer size and immigrant intensity is not driven by specific confounders such as industry or labor markets. Large employers could be concentrated in industries that are more intensive in skills provided by immigrants. At the same time, immigrants might also concentrate in 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.

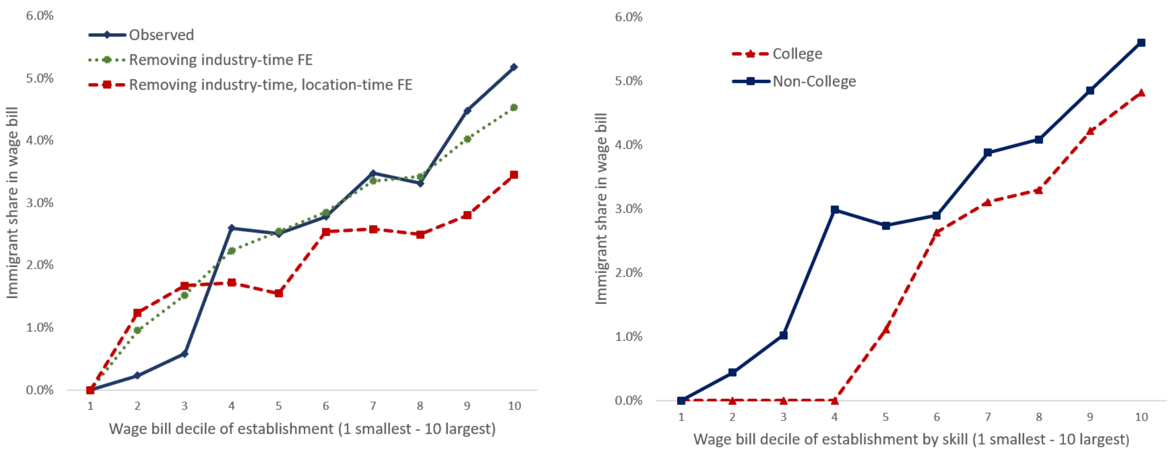
Our relationship of interest is also not driven by immigrant skills. Large firms tend to be more intensive in high-skill labor (Burstein and Vogel, 2017), and if immigration policy in Germany would be skewed toward workers with a specific education, this could drive the relationship between size and 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

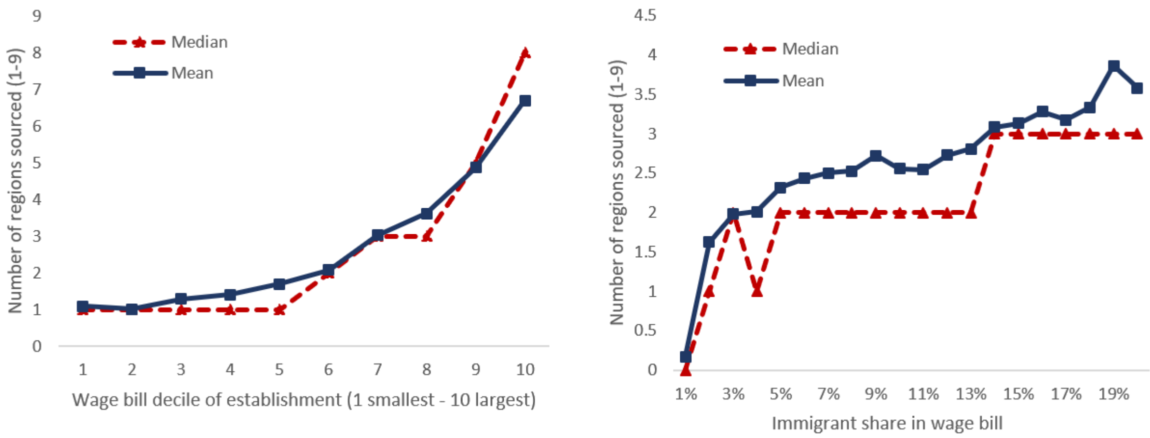
Size deciles	1	2	3	4	5	6	7	8	9	10
Share of firms	0.39	0.36	0.43	0.50	0.53	0.63	0.66	0.80	0.87	0.97

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 β is a sector-specific distributional parameter that captures the average intensity in immigrant labor, ϵ is common across sectors and captures the degree of substitution between native and immigrant workers within the firm, and ψ_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]

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

κ 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 Σ_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 δ_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 ψ_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 Σ_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 δ_o, such that firms will first source from the foreign country with the largest δ_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 δ_o is a random variable distributed Pareto with shape parameter ξ 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]

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

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 σ_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 ℓ 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 ℓ. 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 ℓ 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 ℓ, 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 ω_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 Γ is a function that depends on the joint distribution of firm-level market shares (ω_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 ϵ 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 (ϵ) and the elasticity of substitution across firms or goods (σ). 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 (ϵ^{agg}) is a weighted average between the elasticity of substitution within the firm (ϵ) and the elasticity of substitution across firms (σ):

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

where π, and hence ϵ^{agg}, depend on the distribution of s_{dj}. The weight π 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 ϵ and σ. 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 ω_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 $\{s_{dj}\}$, ϵ^{agg} is independent from ω_j, meaning that ϵ^{agg} is not informed by *which* firm benefits by how much (e.g., the joint distribution of $\{s_{dj}, \omega_j\}$). Consequently, ϵ^{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 ϵ, σ, 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 σ) and the export markup (depending on σ_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 σ_x using our estimated value of σ.

OLS would yield biased estimates of ϵ, 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 ϵ 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 ϵ 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 (β_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 β_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 ι, 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
$\mathbb{V}ar(log(rev_j)\|s_{d,j}, exporter_j)$, T	1.38	1.38	Share of firms hiring immigrants, NT	0.63	0.61
$\mathbb{V}ar(log(rev_j)\|s_{d,j})$, 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	β_T	0.84	Covariance of ψ and f_j, NT	$\sigma_{\psi,f,NT}$	8.17
Share of natives, NT	β_{NT}	0.86	Fixed cost of immigrants, T	$f_{imm,T}$	3.41E-04
Dispersion in ψ_j, T	$\sigma_{\psi,T}$	1.02	Fixed cost of immigrants, NT	$f_{imm,NT}$	9.66E-04
Dispersion in ψ_j, NT	$\sigma_{\psi,NT}$	0.35	Productivity in RoW	ψ_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	τ	1.49
Covariance of ψ and f_j, T	$\sigma_{\psi,f,T}$	-2.65	Elasticity s_d to n	ι	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 θ_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)
θ_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)
θ_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 ϵ^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

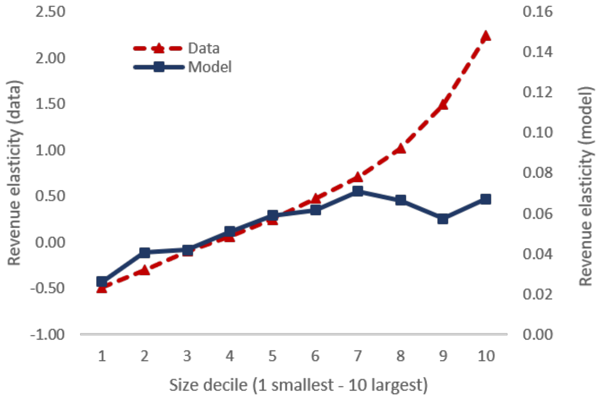
As a final step, we assess whether our model can generate counterfactual predictions that match the observed heterogeneous treatment effects across employer sizes estimated in Table 5. This is a key validation of the model as the reduced form estimates in this section have not been targeted at all for 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

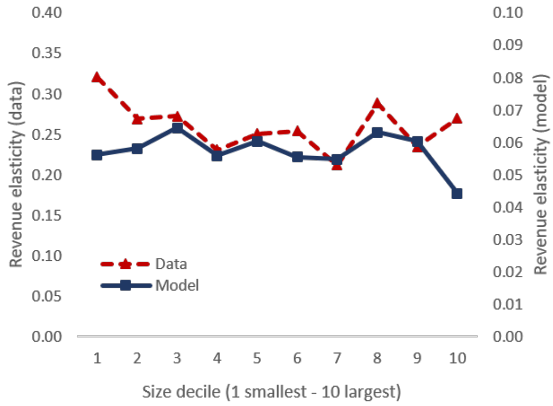
[19]Similar to the counterfactual discussed in Section 7, we lower migration costs to each sector such that the total number of immigrants in Germany increases by 1%.

Figure 4: Predicted treatment effects: Model vs data

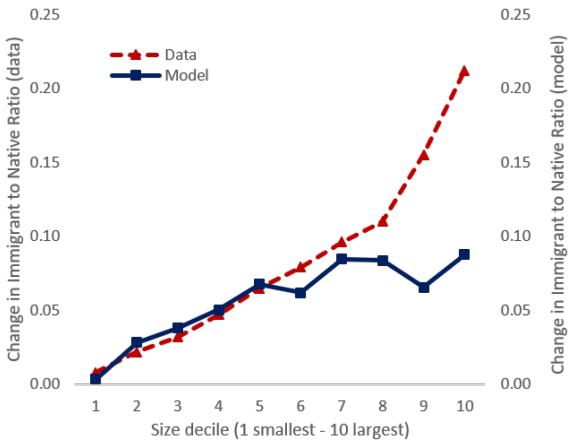
(a) Revenues - Tradable sector



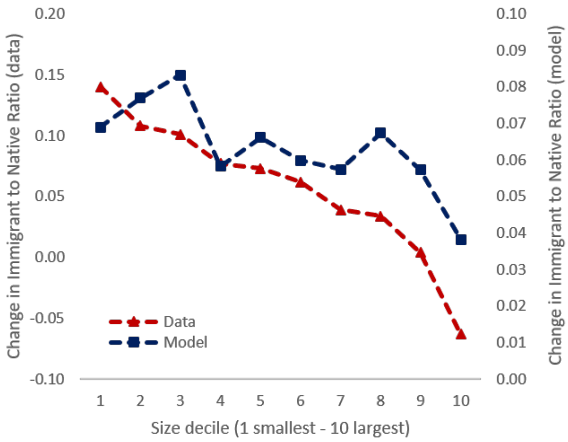
(b) Revenues - Non-Tradable sector



(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.

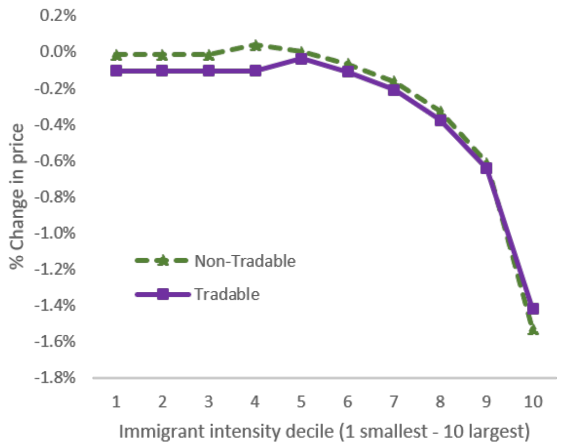
The benefit of immigration for firms is large in the aggregate, but it masks significant heterogeneity for firms of different sizes in the tradable sector. From the top panel of Figure 5, three facts stand out. First, there is a large dispersion in the within-sector price responses and the initial exposure 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

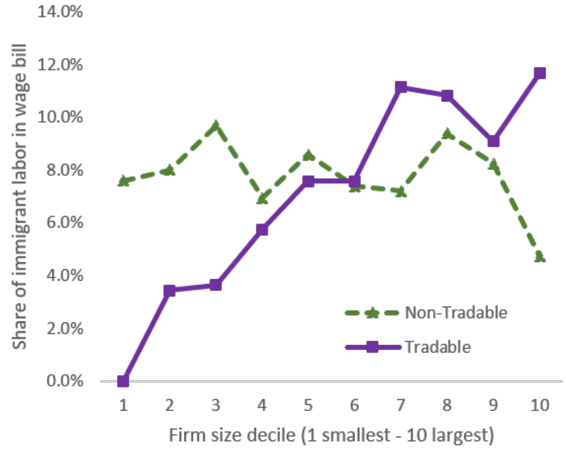
In this section, we asses the importance of the documented heterogeneity in quantifying the adjustment of the German economy to an immigration inflow. To that end, we compare the model predictions to the same immigration shock across two models: the *heterogeneous model* and the *homogeneous model*. 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.

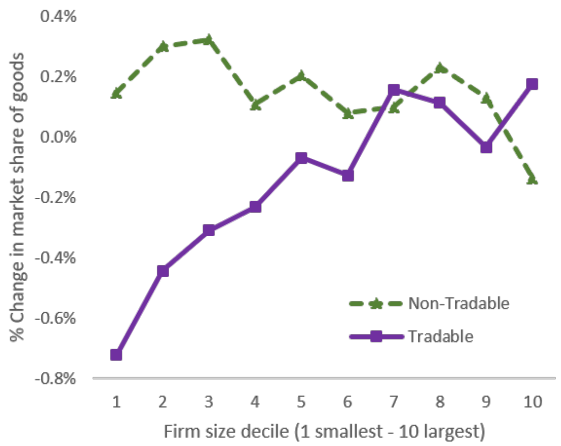
(a) Change in domestic price



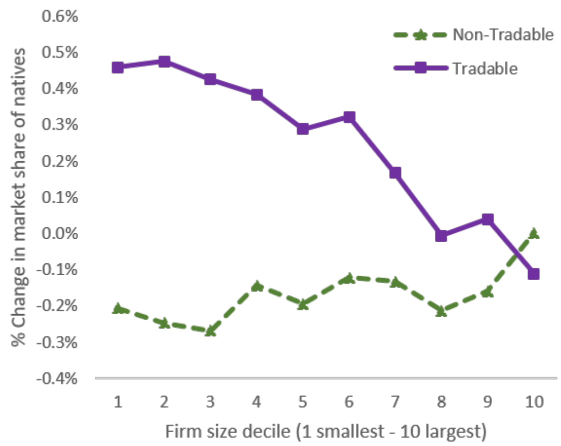
(b) Immigrant intensity



(c) Change in market share



(d) Change in native employment share



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. ϵ and σ) 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

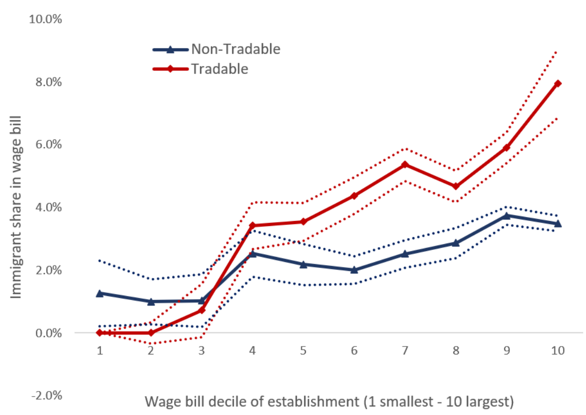
Note. $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. We control for 2-digit industry-time fixed effects and local labor market time trends. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 10 employees.

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 δ_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 ξ 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 δ_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:

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

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

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

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:

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

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 ϵ is larger than σ, 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 ω_j and ω_j^S:

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

which implies that the weighting system ω^s assigns lower weight to immigrant-intensive firms than the weighting system ω. Given that α_j is strictly increasing in the immigrant-share of the firm, the average of α_j under the weighting system ω^s must be lower than that under ω_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 ϵ

E.1 Dataset Description

To estimate the elasticity of substitution between native and immigrant effective units, ϵ, 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 κ, 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] κ 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 κ 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 κ 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 ϵ. 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 ζ_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 ϵ

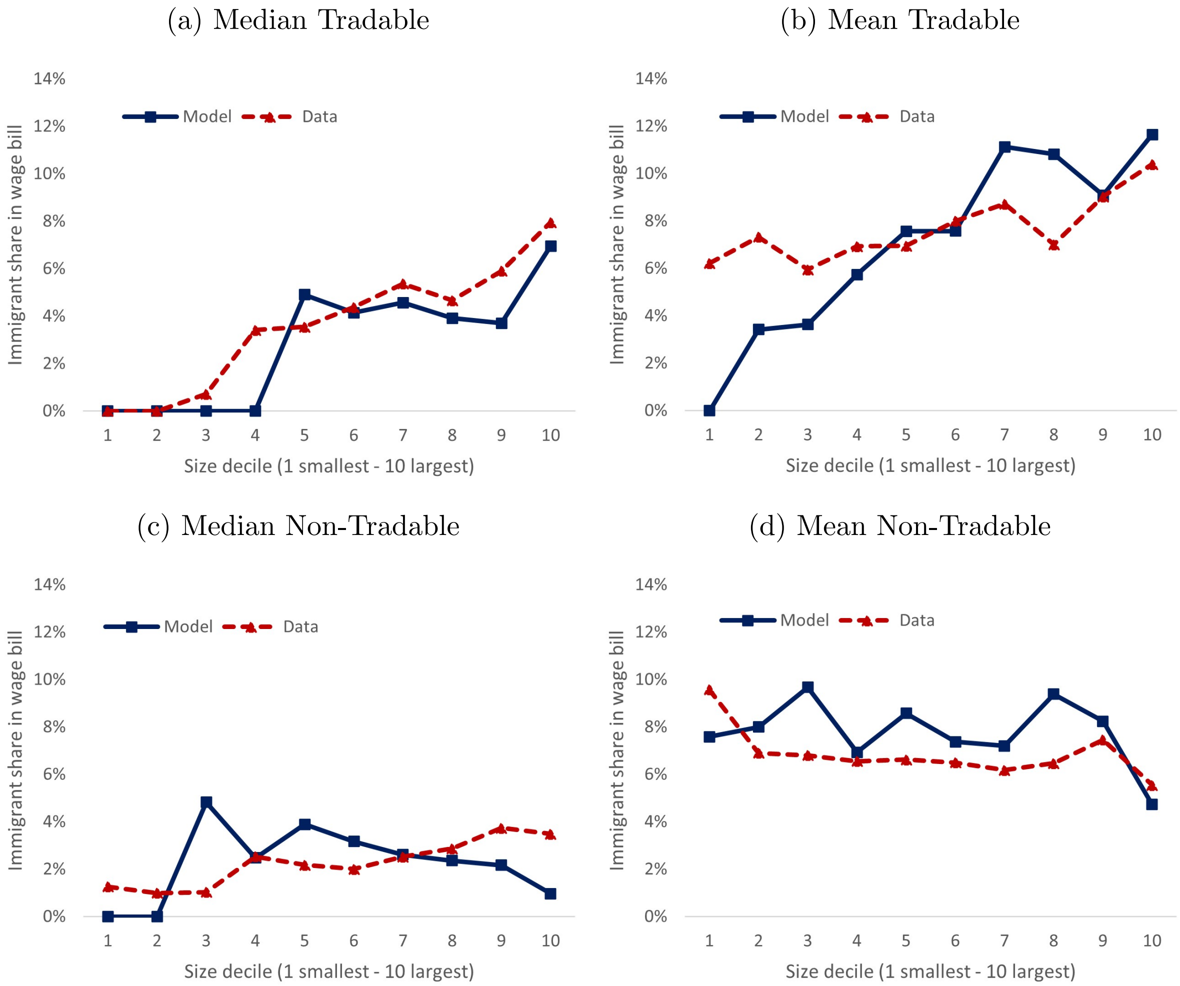
	OLS	2SLS		First stage
Estimate for $(\epsilon-1)/\epsilon$	1.029***	0.81***	Instrument	-0.00025***
	(0.003)	(0.355)		(0.00005)
Number of observations	458,308	458,308		458,308
Implied ϵ	-35.1	4.28	1st stage F-stat	21.29

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



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
θ_1	-31.86***	-37.39**	-52.91***	-25.32**
	(11.47)	(15.41)	(12.79)	(10.99)
θ_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
θ_1	-136.7	-4.82	-26.99**
	(101.31)	(6.43)	(11.4)
θ_2	29.6	1.64	5.83**
	(17.35)	(1.4)	(2.51)
Average ϵ^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
θ_1	-87.99**	-78.45***
	(39.31)	(29.77)
θ_2	20.64**	16.6***
	(8.07)	(5.92)
Average ϵ^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 $t-1$
θ_1	2.51	-7.48
	(9.28)	(9.61)
θ_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 α. Each origin region is affected each year by a national level shock we denote by G. The just identified coefficients are denoted by β.

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	α_s	G	β_s
α_s	1	-	-
G	0.149	1	-
β_s	0.013	-0.402	1
Panel C	α	G	β
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 β. Panel C summarizes α, G, and β 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	β_T	0.82	Productivity in RoW	ψ_x	1.64
Share of natives, NT	β_{NT}	0.84	Fixed cost of exporting	f_g	0.014
Dispersion in ψ_j, T	$\sigma_{\psi,T}$	1.03	Iceberg trade cost	τ	1.55
Dispersion in ψ_j, NT	$\sigma_{\psi,NT}$	0.38	Elasticity s_d to n	ι	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
$\mathbb{V}ar(log(rev_j)\vert s_{d,j}, exporter_j)$, T	1.38	1.38	$\mathbb{E}$(Export to Domestic Rev$_j$), T	0.79	0.79
$\mathbb{V}ar(log(rev_j)\vert s_{d,j})$, 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	β_T	0.82	Productivity in RoW	ψ_x	1.64
Share of natives, NT	β_{NT}	0.84	Fixed cost of exporting	f_g	0.008
Dispersion in ψ_j, T	$\sigma_{\psi,T}$	1.03	Iceberg trade cost	τ	1.56
Dispersion in ψ_j, NT	$\sigma_{\psi,NT}$	0.38	Elasticity s_d to n	ι	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.

Keywords: Remote Work, Offshoring, Wages, Exchange rates, PPP.
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.

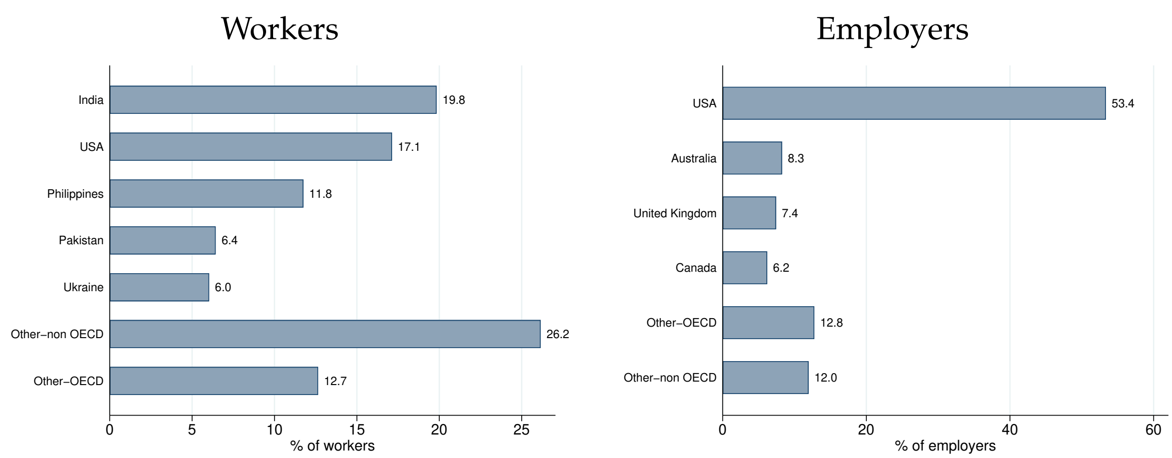
Experience and quality: In addition to the information provided by workers, the profiles record information that is based on the workers' interactions with the platform. Specifically, the platform records each worker's total earnings and total number of jobs completed. Additionally, it displays the average 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

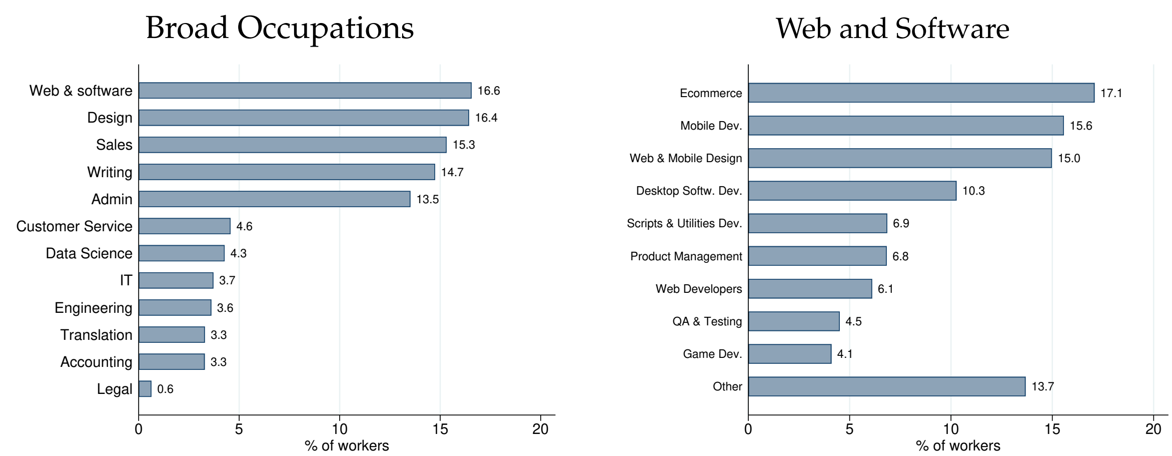


Notes: The figure shows the distribution of jobs across the workers' locations (left panel) and the employers' locations (right panel).

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

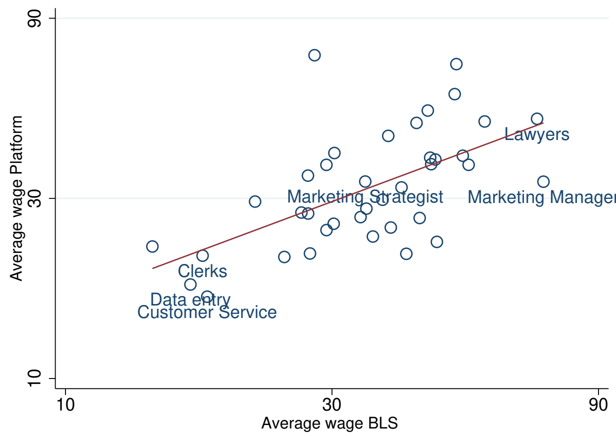
	Mean	Median	St. Dev.	5 pct	95 pct
Ask hourly wage	25	18	27	5	75
Number of jobs	69	10	642	1	147
Total earnings	18,667	4,000	62,558	20	90,000
Number of tests	4	3	4	1	10
Average score	4.23	4.25	0.50	3.38	5

	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).

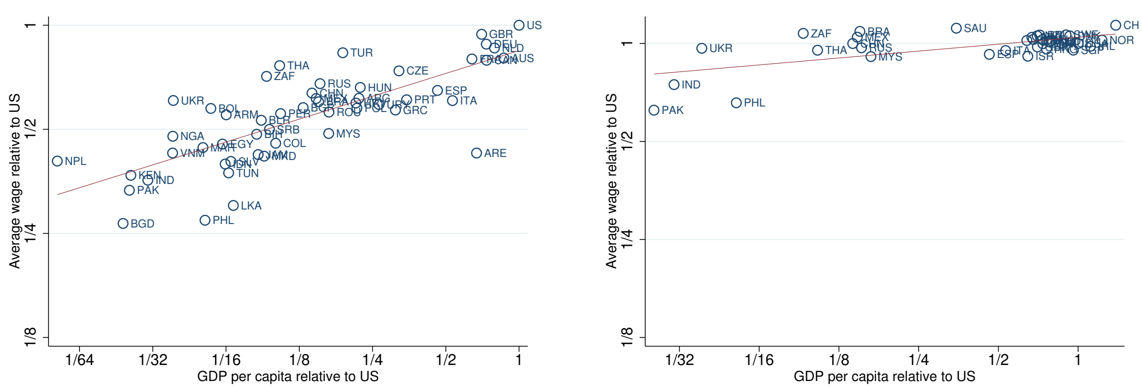
A variance decomposition of equation (1) shows that the workers' locations account for 31% of the dispersion of wages, which is more than the variance accounted for by all other controls (this decomposition splits the contribution of the covariance terms equally across regressors). In contrast, employers' 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).

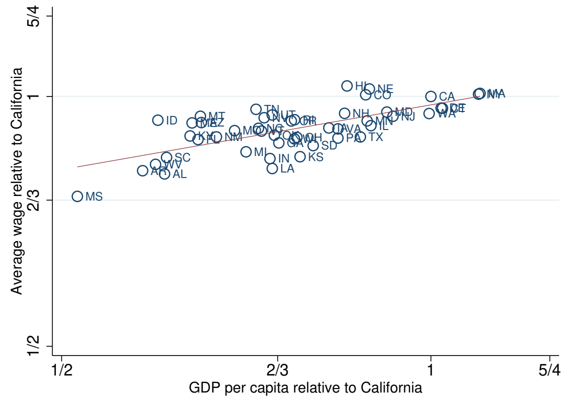
Figure 5 compares relative wages to the relative GDP per capita of each of the 47 states with at least 30 workers in our sample.[12] It shows that the pattern across US states is similar to the one we observe across countries: Workers from richer states earn on average higher wages. The slope of this 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 Ω_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 ρ 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 Ω_{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 θ.

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, φ^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 ρ and θ, 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) (φ_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 γ^j_{ct} is the growth of local wages in constant local currency units, π_{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 $\Delta_s w_{it}^j \equiv w_{it}^j - w_{it-s}^j$ 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 ψ_{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 ψ_{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 β_1 and β_2 are identified from both time and country variation in exchange rates and inflation.

Estimating (17) by OLS yields consistent estimates of β_1 if the error term ϵ_{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 δ^j_i and δ^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 π_{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)
π_{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 Δx 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.

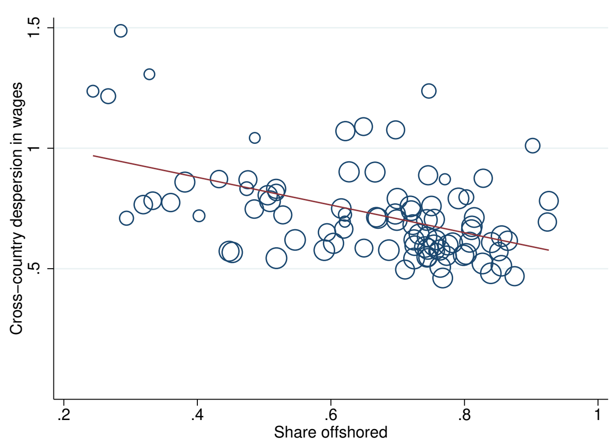
Table 3: Most and least offshored occupations

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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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)
π_{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)
π_{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 $\Delta_s W_{-ijt} \equiv \sum_{l \neq i} \frac{s_{ljt}}{1-s_{ijt}} \Delta_s w_{lt} = \left[\Delta_s W_{jt} - s_{ijt}\Delta_s w_{ijt}\right] / \left[1 - s_{ijt}\right]$. 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.

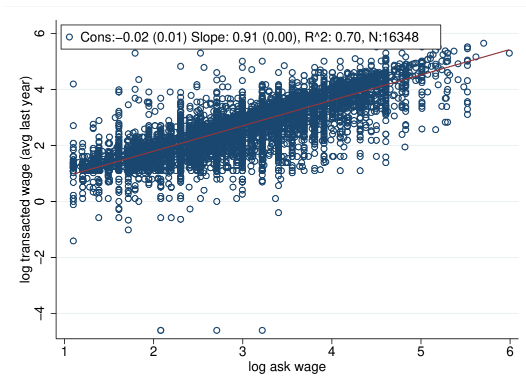
Table A8: Offshoring by occupation in the Platform

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

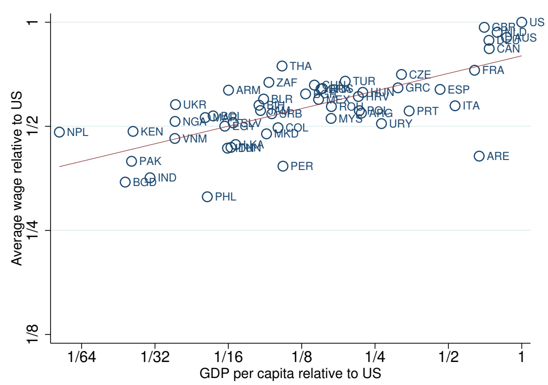
SOC code	SOC title	Value share offshored	SOC code	SOC title	Value share offshored
15-1232	Computer User Support Specialists	0.93	27-1011	Art Directors	0.72
15-1211	Computer Systems Analysts	0.92	13-1161	Search Marketing Strategists	0.72
27-3091	Interpreters and Translators	0.85	13-1161	Market Research 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

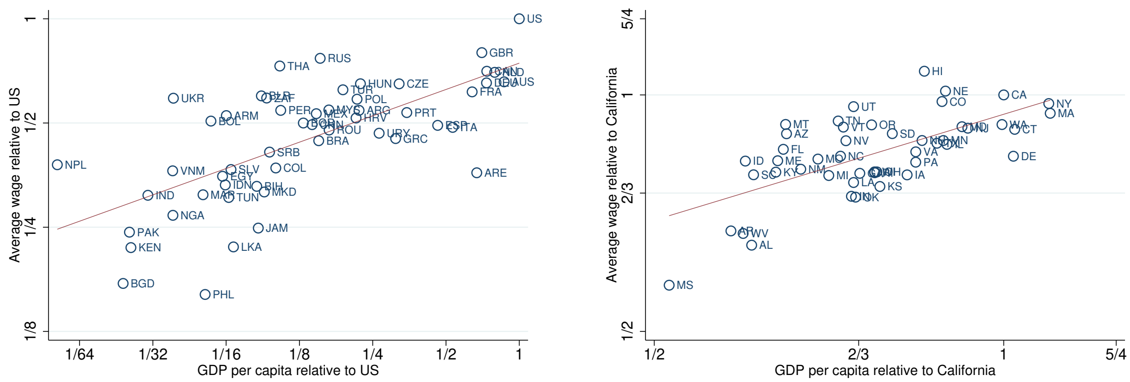


Notes: The x-axis reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). It plots the residualized average wage in each country relative to the US obtained from the worker's country fixed effects estimated in equation (1). The outcome variable 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

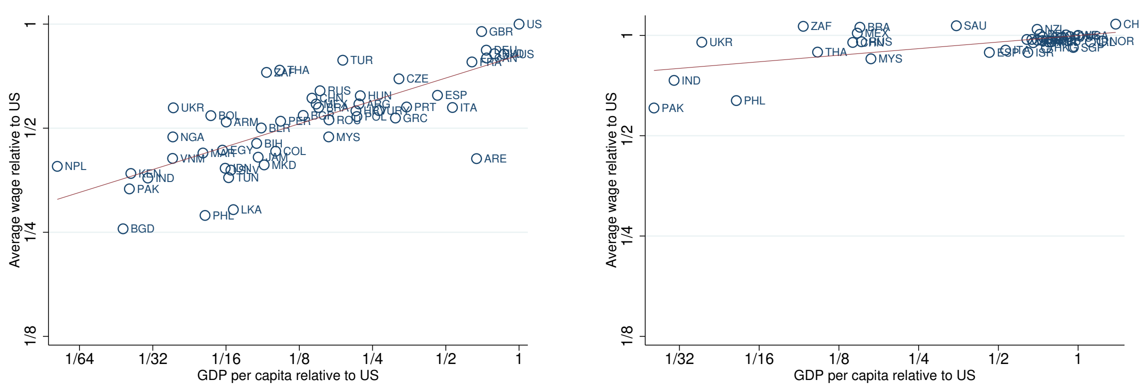


Notes: The x-axis in panel (a) reports the (log of) the relative GDP per capita in US dollars, taken from the World Development Indicators (WDI). The y-axis plots the average transacted wage in each country relative to the US. The estimated slope is 0.25 (0.04) and the R-squared is 0.47. The x-axis in 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.

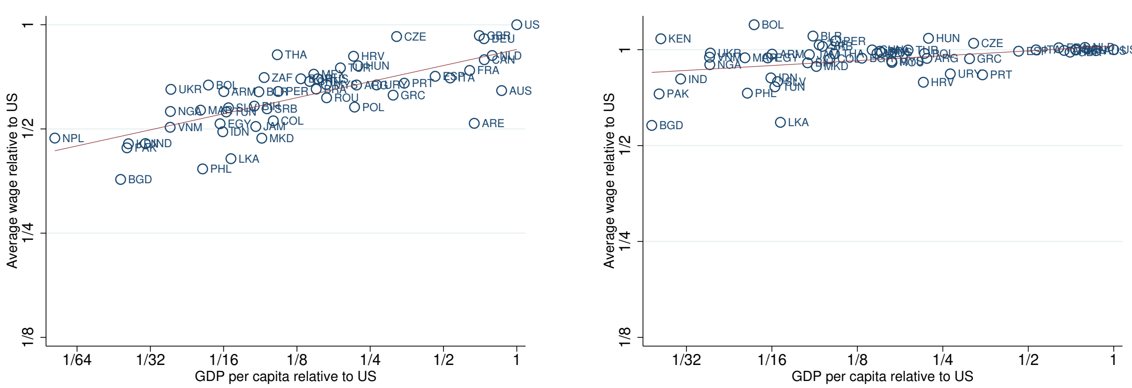
Figure A.5: Real wages and comparison with non-remote wages

(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.

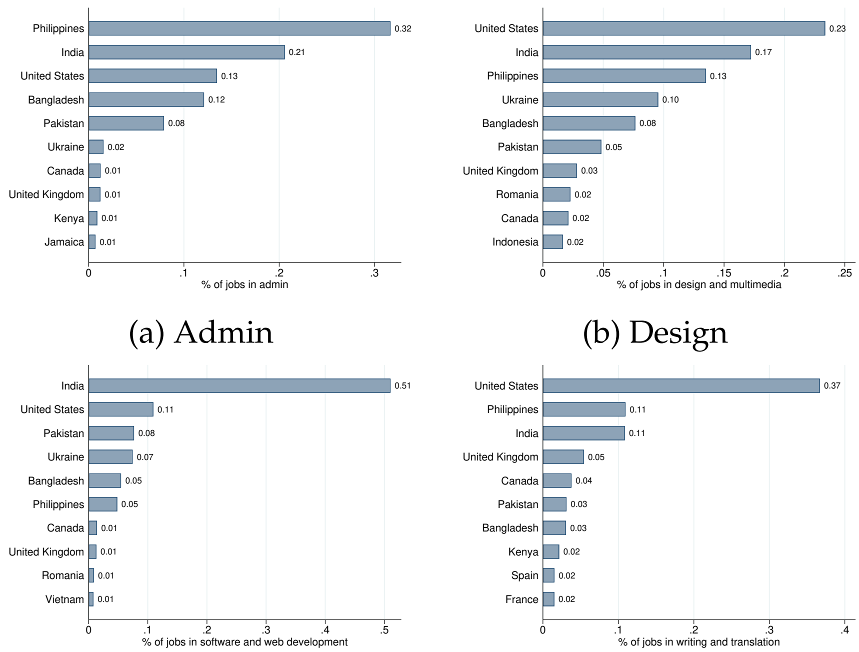
Figure A.6: Differences in wages within workers and employers

(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

$$d\psi_{ct}^{j} \equiv \frac{1}{\rho+\theta}\left[d\varphi_{ct}+\theta\gamma_{ct}^{j}\right]-\frac{\rho-\eta}{\rho+\theta}\left[da_{t}^{j}+dz_{t}^{j}\right]+\frac{1}{\rho+\theta}\left[\eta p_{t}+y_{t}\right].$$

and

$$d\phi_{t}^{j}=\frac{1}{\theta+\eta}\left[\theta\gamma_{ct}^{j}+d\varphi_{t}^{j}-[\rho-\eta]\,da_{t}^{j}+\eta dp_{t}+dy_{t}\right]+dz_{t}^{j}.$$

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 ω can be produced remotely by workers in different locations c. The cost of purchasing task ω from location c is $\Omega_{ct}^j / x_c^j(\omega)$, where Ω_{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 ω. 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 ω 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 ω 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 ρ 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 ω, $p_t^j(\omega)$, 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

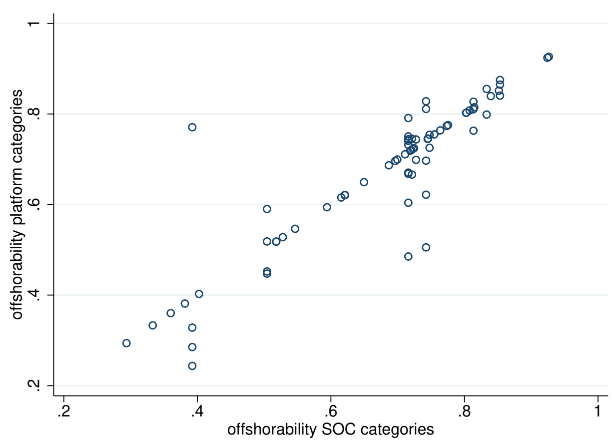
$$\widetilde{\mathcal{O}}^j = \frac{\text{jobs in } j \text{ where cty. employer=US and cty. worker} \neq \text{US}}{\text{All jobs in } j \text{ where cty. employer=US}}. \tag{A.5.1}$$

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.