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

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Abstract

We document significant heterogeneity in immigrant share across employers in Germany, with large firms spending a higher share of their wage bill on immigrants than small firms. We show that fixed costs of hiring immigrants, partly policy-induced, are a likely explanation for the observed heterogeneity. We show analytically and quantitatively 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 firms with heterogeneous productivities choose their immigrant share given fixed costs to hire immigrants. When firms are heterogeneous in their immigrant shares, two new adjustment mechanisms arise. First, native workers reallocate across firms, which affects the competition effect between immigrants and natives in the labor market. Second, larger firms, which have a greater weight in consumers' consumption baskets, experience a stronger drop in production costs and prices. These mechanisms are quantitatively important in the aggregate. Our model without within-sector firm heterogeneity in the immigrant share underestimates native workers' welfare gains from immigration by approximately 50%.

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 in many dimensions such as size, productivity, export behavior, and demand for labor. In this paper, we ask whether such heterogeneity across firms matters for understanding 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 larger firms are more immigrant-intensive, the marginal cost gains are predominantly concentrated among the most productive firms, which induces a stronger aggregate price decline. We find that if we ignore this within sector firm heterogeneity, the welfare gains from an increase in immigration would be underestimated by 54%.

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 find a systematic relationship between employer size and immigrant intensity, with the median establishment among firms with more than 500 employees spending 5.6% of their wage bill on immigrants, while the median establishment with fewer than 10 employees spends zero. We consider several explanations that could account for this heterogeneity in immigrant intensity and its systematic relationship with firm size. Our findings suggest that fixed costs associated with hiring immigrant workers may be a key explanatory factor. We show causal evidence for this margin by using the episode when Germany opened its labor market to EU New Member States (NMS) in 2011 as a natural experiment that lowered fixed costs to hire immigrants. Using an event study approach, we show that small firms expanded more than large firms in terms of hiring NMS workers relative to similar workers from non-EU countries, consistent with the existence of fixed costs for hiring migrants before 2011.[1]

[1]We also find evidence suggesting that immigrants may have comparative advantages in performing

Next, we set up a model where firms differ in their primitive productivity and their (endogenous) immigrant share 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). Consumers have CES preferences over goods in each sector. Each good is produced by a firm that can use immigrant and native workers, who are imperfect substitutes (Peri and Sparber, 2009, 2011).

To model the immigrant hiring decision, we closely follow the intermediate input sourcing literature (Blaum, 2024; Blaum et al., 2018). 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 a 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. 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 observed relationships between firm size and immigrant intensities, the model allows for firm-specific fixed costs of hiring immigrants, drawn from a joint distribution with innate productivity.

We use a simplified one-sector 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 of a model with and without heterogeneity in immigrant intensities (but with heterogeneity in productivity). 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 goods different from those of 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 opposite occurs when the substitution effect is weaker than the scale effect. The *magnitude of the bias* depends on the elasticity of demand, the elasticity of substitution between immigrants and natives, but also on the joint distribution between firm productivity and immigrant-hiring costs. When larger firms are more immigrant-intensive, these firms experience a stronger drop in unit cost and price. This means that the associated drop in the price index is stronger,

different tasks than native coworkers, providing a rationale for firms willing to pay the fixed cost.

as larger firms have a disproportionate weight in consumers' consumption baskets.

We estimate the elasticity of demand from the average firms' markups, following Oberfield and Raval (2014). 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 bill between immigrants and natives on relative employment, following an IV approach as in Ottaviano and Peri (2012). We extend their approach to allow for heterogeneity in workers' abilities, as suggested by our model, and use a model-based firm-level instrument. At a 1% confidence level, our estimates suggest that the elasticity of substitution between immigrants and natives within firms exceeds the elasticity of demand. Thus, the observed heterogeneity in immigrant share is expected to generate larger welfare gains from immigration. We calibrate other parameters jointly to match key targeted micro- and macro-level moments in Germany between 2003 and 2011. The observed distribution of immigrant share and firm revenues discipline the parameters of the joint distribution of productivities and hiring costs.

We verify that the calibrated model properly captures the mechanisms through which firm heterogeneity in immigrant share affects welfare. Our analytical results show that the heterogeneity in immigrant shares matters because it leads to heterogeneity in the elasticity of sales and the elasticity of the immigrant-to-native wage bill ratio to immigrant labor inflows. Therefore, we validate the model by comparing its predicted changes in firms' sales and the immigrant-to-native wage bill ratio due to an exogenous immigrant inflow with the data counterparts. To that end, we need empirical estimates of the causal effect of immigration, which we obtain by regressing firm revenues and the relative wage bill ratio on the share of immigrants in the local labor market and its interaction with firm size. We use these reduced-form estimates to compute the effect of a 1% increase in the share of immigrants in the labor market for firms in different size deciles and find the model does a good job of matching the data counterparts.

We use the estimated model to measure the real wage (or welfare) effects of a 20% increase in the total number of immigrants, motivated by the inflow experienced by Germany between 2011 to 2017. We find that native workers in both sectors benefit from immigration despite lower wages, as domestic prices drop significantly due to lower production costs. This suggests that focusing solely on wage effects may lead to opposite conclusions about immigration's welfare impact. Revenues and profits increase for both sectors, but more so in the tradable sector, where firms are more intensive in immigrant labor. Firms in the top size decile of the tradable sector, being the most immigrant-intensive, absorb a large share of incoming immigrants, leading to the reallocation of many native workers to other firms. Given their size, large firms in the non-tradable sector absorb a significant portion of these native workers. This reallocation between firms explains most of the cross-sector reallocation of native workers. Natives also reallocate within sector toward less immigrant-intensive firms. Overall, welfare gains of native-born workers and firm owners are 0.10% and 1.23%, respectively. In monetary terms, these gains amount to $1.5 billion for native workers and $15.3 billion for firm owners.[2]

We find that firm heterogeneity in immigrant share within sector plays a quantitatively important role in the native-born welfare effects of immigration. Specifically, our model with the same primitive productivities and structural parameters but without fixed costs to hiring immigrants predicts that firms within a sector would employ the same immigrant share and the welfare gains for native-born workers would be approximately 50% lower. The bias is due to both a weaker drop in wages and a stronger drop in the price index in the model with heterogeneous immigrant share, with the latter explaining 80% of the bias. These results highlight that immigration induces a reallocation of resources across firms with significant aggregate implications. We also find that this heterogeneity is important to understand how international trade mitigates immigration gains. In addition to commonly known "terms of trade effects", which are absent under trade autarky, trade shapes the equilibrium relationship between immigrant share and firm size, affecting how immigration reallocates resources across firms. In a counterfactual trade autarky economy, welfare gains from immigration are 27% larger, with 85% of the dampening effect due to the reallocation of resources across firms.

Finally, we use our model to study alternative immigration policies that reduce immigrant hiring costs for a subset of firms. Policies targeting smaller firms in the economy, mainly benefit non-tradable sector firms because they face higher hiring frictions.[3] Small tradable sector firms are not similarly affected, as the cost reduction does not offset productivity differences with large competitors in the sector. The effects on native workers are positive but small. We find that lowering fixed costs for high-productivity firms in the tradable sector has the largest aggregate welfare effects for natives as firms affected face a more elastic demand, and can expand production without crowding out many natives.

Our paper contributes to the literature on the economic effects of immigration on the receiving economy. A challenge in this literature, which is primarily empirical, is estimating immigration's impact on the *levels* of *real* wages because reduced-form coefficients do not tend to identify general equilibrium effects, and data availability limits price index computation. Some papers address this challenge by using general equilibrium models that do not require price data to quantify immigration's effects (Burstein et al., 2020; Caliendo et al., 2021; Desmet et al., 2018; di Giovanni et al., 2015; Khanna and Morales,

[2]These effects are relatively large. For reference, estimates of the U.S. welfare gains from China's rise in world trade range from 0.03% to 0.2% (Caliendo et al., 2019; Hsieh and Ossa, 2016).

[3]Germany implemented the Competence Center for Securing a Skilled Workforce to help small and medium firms hire immigrants (see here for more details). This policy motivated our counterfactual.

2025; Morales, 2025). These models, as opposed to ours, do not allow for heterogeneity in immigrant shares. By introducing heterogeneous firms that endogenously choose their immigrant intensities given fixed costs to hire immigrants, we make three contributions. First, our results suggest that labor reallocation across firms within a sector is an important adjustment channel for aggregate production and labor markets. Second, the price effect, which tends to be empirically challenging to quantify, is important. In our setting, focusing solely on nominal wages or earnings would reverse the conclusion on whether immigration raises or lowers native welfare. Third, while aggregate elasticity of substitution estimates can be useful depending on the setting, they do not inform welfare effects when firm heterogeneity in immigrant share arises from fixed costs.[4]

We also contribute to the stream of the empirical literature studying the effect of immigration on firms (e.g., Mitaritonna et al. (2017), Arellano-Bover and San (2020), Mahajan (2024), Gyetvay and Keita (2024), Amior and Stuhler (2024), Mahajan et al. (2025)) by documenting new facts on the relationship between firm size and immigration and assessing the aggregate general equilibrium effects of immigration.[5]

Our work contributes to two strands of the international trade literature. The first relates to the role of trade in shaping the effects of immigration, dating back to Rybczynski (1955) and Samuelson (1948). Recent work quantifies the relevance of trade using modern quantitative models that abstract from firm heterogeneity (e.g., Caliendo et al. (2021) and Brinatti and Guo (2024)). We contribute to this literature by studying whether trade amplifies or dampens immigration gains due to a new mechanism, firm heterogeneity in immigrant shares. The second stream of the literature studies whether firm heterogeneity matters for the welfare effects of 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. Blaum et al. (2018) show that this result does not hold when firms have heterogeneous import intensities. Compared to Blaum et al. (2018), who study a context where factor shares and firm size are not systematically correlated, we analyze how the relationship between factor intensities and firm size affects welfare, uncovering a new mechanism.

This paper also contributes to the literature on the relationship between micro and macro elasticities. One strand of this work examines how firm heterogeneity in factor shares drives differences between the micro and macro elasticities of substitution between factors (e.g., Satō (1975), Oberfield and Raval (2021), Lashkari et al. (2024)). While this literature tends to focus on aggregate variables such as the labor share, it does not tend to

[4] Mehra and Shen (2022) and Mandelman et al. (2024) also propose models that include hiring costs to hire immigrants in the U.S. Their models are calibrated using mostly aggregate data.

[5] Other papers on the effect of immigrants on firms are Kerr et al. (2015), Dustmann and Glitz (2015), Orefice and Peri (2024), Card et al. (2023), Beerli et al. (2021), and Egger et al. (2022) among others.

analyze the implications for welfare. We contribute by linking firm heterogeneity in factor shares and micro elasticities to welfare. Specifically, we derive an expression for welfare as a function of a weighted average of micro elasticities, where weights depend on firms' immigrant and market shares. Additionally, we show that the macro elasticity alone may not be sufficient for welfare analysis. When firm heterogeneity in factor shares does not lead to firm heterogeneity in elasticity of substitution between factors of production, as in Oberfield and Raval (2021), the weighted average of micro elasticities coincides with the aggregate elasticity, making the latter sufficient for inferring welfare gains. However, in our setting, where factor share heterogeneity also leads to heterogeneous substitution elasticities, the two diverge. As a result, the aggregate elasticity is not informative about welfare effects because it does not fully capture the first-order impact of price changes. Thus, micro elasticities and firms' shares are needed for welfare analysis.

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.[6] 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) Europe high-income: France, United Kingdom, Netherlands, Belgium, Austria, Switzerland, Finland, and Sweden, 3) EU middle-income: Italy, Spain, Greece, and Portugal, 4) New member states: 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, material use, and export share 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

[6]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 remotely.

individuals with foreign citizenship become Germans in the next period. If a worker is recorded as a foreigner for at least two periods, we classify them as an immigrant from the initial citizenship country.[7]

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.

Finally, we obtained a complementary administrative dataset, the Sample of Integrated Employer-Employee Data (SIEED). This new data comes from a 1.5% random sample of the universe of German establishments, where we also access the entire labor market biographies of employees who worked at least one day in these establishments. Relative to LIAB, SIEED has the advantages of covering later years (until 2018) and having information on the citizenship country of workers. These two aspects of the data allow us to look at the EU enlargement episode in 2011 to test for the existence of fixed costs in Section 4.2.[8]

3 Firm Heterogeneity in Immigrant Share

We begin our analysis by establishing an empirical regularity: larger firms are more intensive on immigrant labor than smaller firms. To assess the implications of this firm-level heterogeneity for the welfare effects of immigration on native workers, we first need to understand the microfoundations that determine immigrant employment shares as suggested by the data. Accordingly, the second part of this section evaluates several explanations that could account for this heterogeneity. Our findings suggest that fixed costs associated with hiring immigrant workers constitute the primary explanatory factor

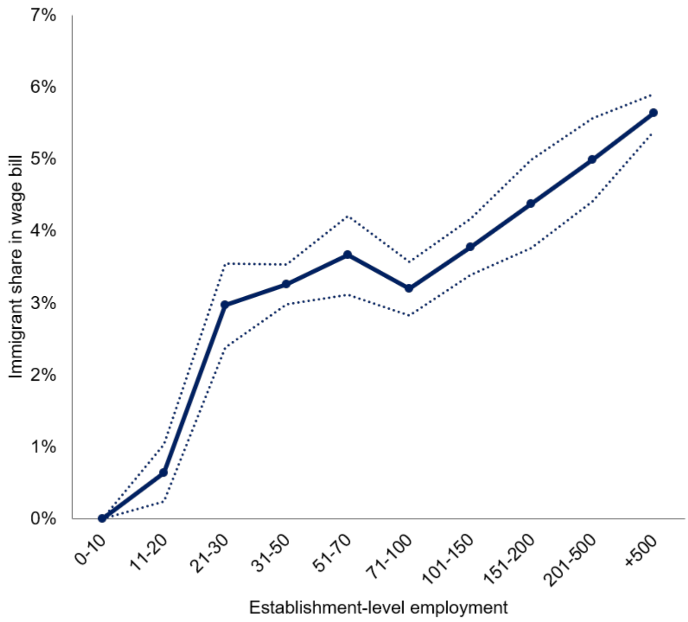
[7] A second challenge is that some workers might join the labor market with a foreign citizenship, but they may have grown up in Germany with foreign parents. Our results are robust to recoding workers as natives if they have foreign citizenship and either join the labor force at age 20 or younger without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

[8] We do not use SIEED for the rest of the analysis because it does not have firms' financial information.

of the observed systematic relationship between firm size and immigrant intensity.[9]

To illustrate the relationship between firm size and immigrant share, we classify the establishments in our sample into ten bins based on their total reported employment.[10] For each bin, we plot the median share of immigrant labor in the establishment wage bill to capture the firm-level intensity on immigrants. Figure 1 shows a systematic relationship between employer size and immigrant intensity. The median establishment among firms with more than 500 employees spends 5.6% of their wage bill on immigrants, while the median establishment with less than 10 employees spends zero.

Figure 1: Immigrant share across the establishment size distribution



Notes: We divide establishments into bins based on employment size and, for each bin, plot the median immigrant share of the wage bill. We compute 95% confidence intervals using 200 bootstrap repetitions.

We look into potential underlying mechanisms for the documented heterogeneity. 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, 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 the industry or geographic destinations of immigrants alone cannot explain the observed relationship between size and immigrant-intensity.

[9]Appendix A.1 presents summary statistics on the sample of establishments and the distribution of immigrants across sectors and origin regions.

[10]Our findings are robust to alternative bin classifications, including dividing the establishments into deciles of employment, revenues, or wage bill.

While the pattern of heterogeneity is not driven by specific sectors, we observe differences in tradable and non-tradable sectors.[11] Figure 2b shows that establishments in the tradable sector are more intensive in immigrants than similar-sized establishments in the non-tradable sector and the tradable sector presents a stronger relationship between size and immigrant intensity than the non-tradable sector. This fact could be explained if immigrants reduce trade costs between their origin and destination countries (Bonadio, 2023; Hiller, 2013; Ottaviano et al., 2018), which would be more relevant for large firms that tend to export. If this was the main driving factor, we would expect the relationship between size and immigrant intensity to be present primarily for exporters. However, Appendix Figure B1a shows that exporters and non-exporters present similar patterns, suggesting that reductions in firms' trade costs are unlikely to be the main explanation. The different patterns in the tradable and non-tradable sectors are consistent with the findings from Burstein et al. (2020), who show that tradable sectors face more elastic demand and can expand output more than non-tradable sectors in response to immigration. Motivated by this evidence, our model will allow firms in tradable sectors to face higher demand elasticity than those in non-tradable sectors, while assuming that immigrant hiring at the firm level does not directly reduce the cost of international trade.

We consider additional channels in Appendix B.1. For instance, we show that our relationship of interest is not driven by immigrant skills and large firms being more skill intensive, as we find the pattern holds within skill groups. Similarly, we show our pattern is not explained by the firm being a multinational or part of a multi-establishment firm. The data also provides evidence against exogenous immigrant-intensity or immigrant-biased technological differences across firms of different sizes. In these cases, the *elasticity* of immigrant intensity to immigration would be the same across firms, which is at odds with the evidence in Section 7.

4 Fixed costs to hire immigrants

4.1 Institutional aspects of the immigration system

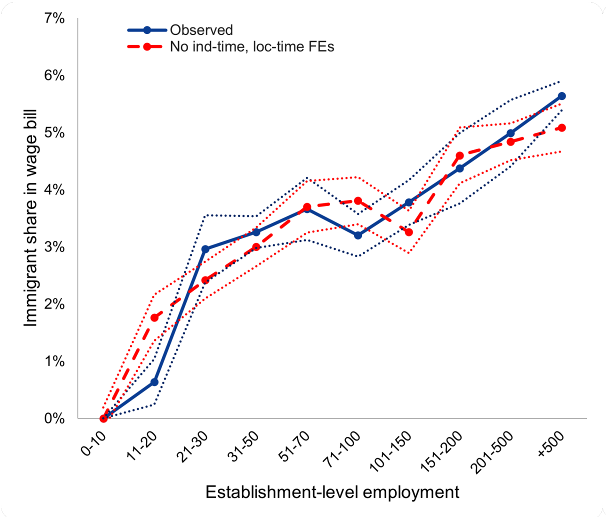
The institutional setting in Germany for nationals from non-EU countries required most immigrants to secure a job offer before migrating during our period of analysis. This system, similar to the U.S. system, places the burden of navigating administrative obstacles, as well as identifying and screening candidates, on sponsoring employers (see Appendix Section A.2 for more details).

In addition to these policy-induced fixed costs that firms need to overcome to start hiring

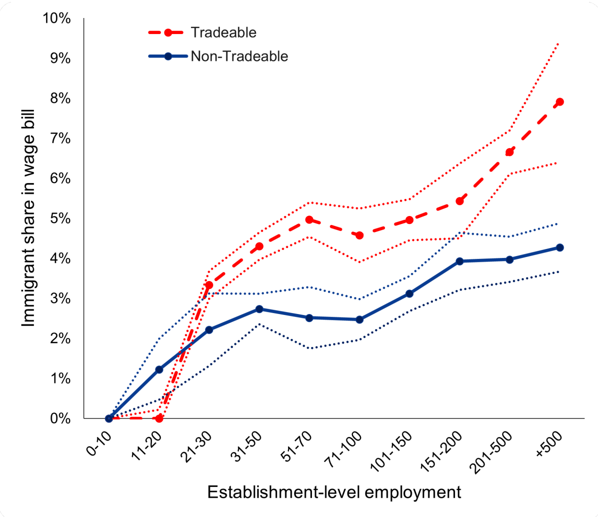
[11] The tradable sector is defined as manufacturing, professional services, and wholesale trade.

Figure 2: Immigrant share across the establishment size distribution

(a) Controlling for industry and geography



(b) Tradable vs non-tradable sectors



Notes: We divide establishments into bins based on employment size and, for each bin, plot the median immigrant share of the wage bill. We compute 95% confidence intervals using 200 bootstrap repetitions. In Figure 2a, we first regress immigrant shares on 3-digit industry-year and labor market-year fixed effects and plot the median residual for each bin. We normalize the residual of the smallest bin to 0. In Figure 2b, we plot the median immigrant share for the tradable and non-tradable sectors separately.

immigrants, firms need to learn from specific origins to establish a reliable pipeline of workers they can hire. This learning process can take various forms. For example, firms may need to train their staff to assess foreign qualifications or language skills. Similarly, learning might imply hiring an initial worker from a given country to tap into their network for future recruitment. This is consistent with qualitative evidence from the OECD and the German Chamber of Commerce and Industry (DIHK), who ran an employer survey in 2010 asking for the reasons why firms with unfilled vacancies did not attempt to hire workers from abroad (OECD, 2013). The top three reasons for this trend are the lack of German language skills of candidates, unclear and complex administrative procedures, and difficulties contacting candidates abroad.

The survey also shows that these barriers disproportionately impact small and medium enterprises (SMEs). One reason is that SMEs have fewer resources than large firms to overcome these barriers. For instance, larger firms are better positioned to afford language and integration training for their employees and invest in specialized HR services that navigate the complexities of the immigration system and facilitate contacting candidates abroad. Moreover, the German Employment Agency needs to verify that the employer's 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. According to the OECD report, these checks tend to be more severe when the employer is not well-known, as tends to be the case for SMEs. 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.

4.2 Descriptive and causal evidence of fixed costs

We complement this anecdotal evidence with direct evidence from our data consistent with the presence of fixed costs to start hiring immigrants. First, 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 in the absence of fixed costs. This contradicts the results in Figure 3a, which shows that a significant fraction of firms do not hire immigrants. Moreover, the fact that this fraction increases with size, suggests that profits earned by SMEs may not be enough to afford such fixed costs. Second, we observe lumpiness in the immigrant hiring process. The year that firms start hiring immigrants, there is a jump in the immigrant share of new hires that later goes down to a lower and constant long-run value (see Appendix B3). Third, we show that the size-immigrant intensity pattern is stronger for workers who recently arrived in Germany and for younger workers, for which fixed costs of hiring are likely higher. See Appendix B.2 for additional descriptive analyses that are consistent with the existence of fixed costs.

Our data also suggests that there might be origin-specific fixed costs that firms need to pay to hire immigrants from additional origin countries. If immigrants from different origins are imperfect substitutes, as our data in the Appendix Section B.4 suggests, firms hiring immigrants would find it optimal to source immigrants from all origins. This contradicts Figure 3b, which shows that firms only the largest firms hire immigrants from all regions. Firms seem to increase the number of sourcing countries as they become more immigrant intensive.[12] In Appendix B.2, we show additional descriptive evidence that supports this.

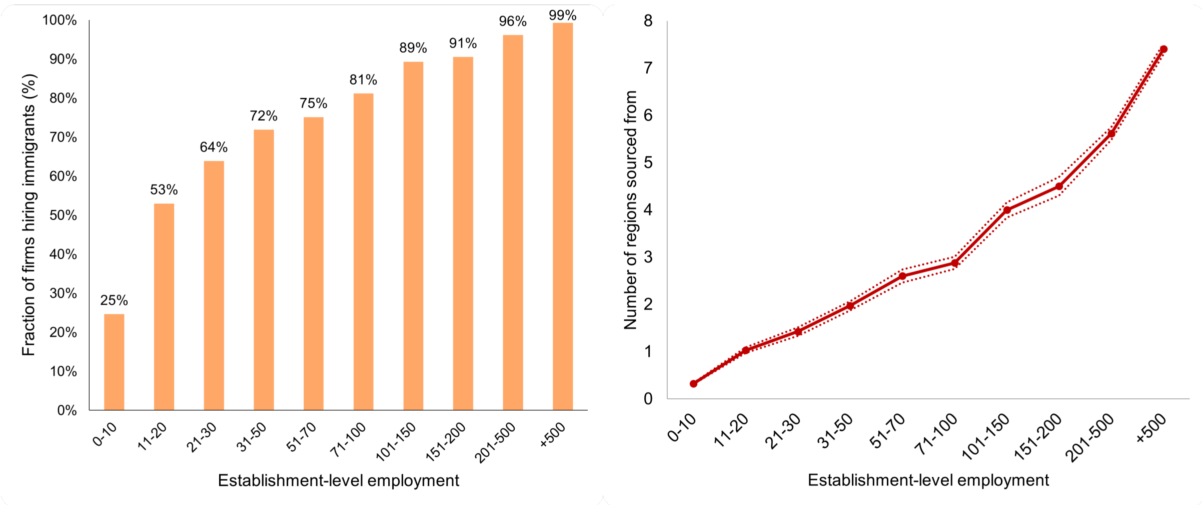
European Union Enlargement: reduction in fixed cost to hire immigrants

While this anecdotal and cross-sectional evidence is suggestive of the existence of fixed effects, it does not isolate the effect of fixed costs on the immigrant hiring decisions of firms of different sizes. To make progress in this direction, we use the 2011 incorporation of the New Member States (NMS) into the EU, which granted citizens from Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia

[12] Alternatively, in Appendix Figure B4 we show that as firms increase their immigrant share, they hire workers from more regions.

Figure 3: Evidence consistent with the existence of fixed costs

(a) Extensive margin of hiring (b) Number of regions sourced from



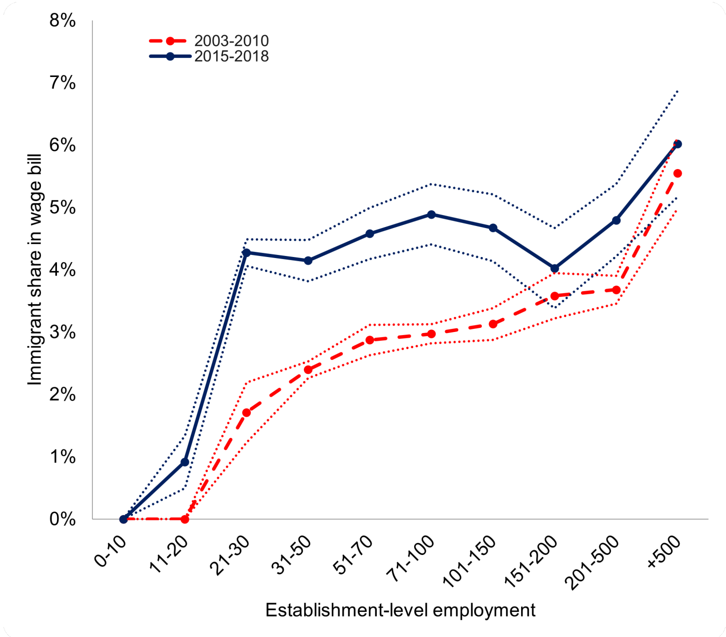
Notes: We divide establishments into bins based on employment size. In Figure 3a, we plot the fraction of firms in each bin that hire at least one immigrant. In Figure 3b, we plot for each bin the average number of regions from the rest of the world that the firm hires workers from (see Section 2 for details).

unrestricted access to the German labor market. These countries joined the EU in 2004 but only gained access to the labor market in Germany in 2011. This policy change serves as a natural experiment, reducing fixed costs for hiring NMS immigrants while leaving restrictions for non-EU nationals unchanged. If the policy lowered fixed hiring costs for NMS nationals, we expect smaller firms that are more constrained by these costs to be more impacted than larger firms.

To use time and cross-section variation introduced by this policy change, we use SIEED data which includes several years after the policy change and country nationality (see Section 2 for details). Using this new data, Figure 4 plots the relationship between immigrant share and firm size for the period before the policy change in red (analogous to Figure 1 which uses our baseline dataset) and for the period after the policy change in blue. Two facts emerge. First, the firm size threshold above which firms begin hiring immigrants decreases after the immigration restrictions are lifted, shifting from the 21–30 size bin to the 11–20 size bin. Second, while the median firm in the top three deciles does not exhibit a significant increase in immigrant share, firms in other deciles show the largest increases. These facts are consistent with the policy reducing the fixed cost of hiring NMS immigrants, as mentioned before. However, other contemporaneous factors may have differentially influenced the hiring decisions of small and large firms, such as the inflow of immigrants due to the Syrian crisis or immigrant-biased demand shocks.

We isolate the effects of the policy on firms' immigrant employment using the variation across time and nationalities introduced by the policy within an event-study framework.

Figure 4: Immigrant share for before and after the EU enlargement



Notes: We divide establishments into bins based on employment size and, for each bin, plot the median immigrant share of the wage bill. We compute 95% confidence intervals using 200 bootstrap repetitions. The red and blue lines correspond to the periods 2003-2010 (before the EU enlargement) and 2011-2018 (after the EU enlargement), respectively. To compute this fact we use the SIEED database (see Section 2 for details).

We begin with equation 1, where we estimate the overall effect of the policy on the hiring of immigrants from new member states.

$$\frac{Emp_{o,j,t}}{Emp_{j,2010}} = \sum_{\tau \neq 2010} \beta_\tau \times \mathbb{1}(o = NMS) \times \mathbb{1}(t = \tau) + FE_{o,j} + FE_{j,t} + \epsilon_{o,j,t} \quad (1)$$

where $Emp_{o,j,t}$ is the employment of nationals from group o at firm j in year t, and $Emp_{j,2010}$ is firm j's total employment in 2010. We consider two country groups: NMS members, which is the treated group, and European countries that do not yet belong to the European Union, which are the control group.[13] Immigrants from European countries not joining the EU are a good control group as they might be similar to NMS immigrants in terms of the tasks they perform and other characteristics, but they are not subject to the enlargement policy. $\mathbb{1}(o = NMS)$ is a dummy variable that equals one for the employment of NMS and is zero otherwise, and $\mathbb{1}(t = \tau)$ are year-fixed effects. $FE_{o,j}$ are fixed effects at the country group-firm level that control for pre-existing differences between immigrant groups and firms, such as a tendency of firm j to hire NMS nationals. $FE_{j,t}$ are fixed effects at the firm-year level. They account in a flexible way for the effect

[13]The largest countries in the control group are Serbia, Ukraine, and Bosnia.

of demand and cost shocks faced by the firm that affect its hiring decisions. $\epsilon_{o,j,t}$ is the error term, which we cluster at the firm level. The coefficients β_τ measure the differences in the outcome variables between year t and 2010, our baseline year, for the treated group relative to the control group. For example, a positive $\beta_{\tau>2010}$ indicates that, on average, firms increased the employment of NMS nationals relative to the control group after 2010. Thus, we use our estimates of β_τ to infer if firms hired relatively more NMS nationals after the NMS integration.

Once we establish the effect of the policy on all firms, we estimate equation 2, where we separate the effect for large and small establishments.

$$\frac{Emp_{o,j,t}}{Emp_{j,2010}} = \sum_{\tau \neq 2010} \left(\theta_\tau \times \mathbb{1}(j \in SME) + \beta^L_\tau\right) \times \mathbb{1}(o = NMS) \times \mathbb{1}(t = \tau) + FE_{o,j} + FE_{j,t} + \epsilon_{o,j,t} \tag{2}$$

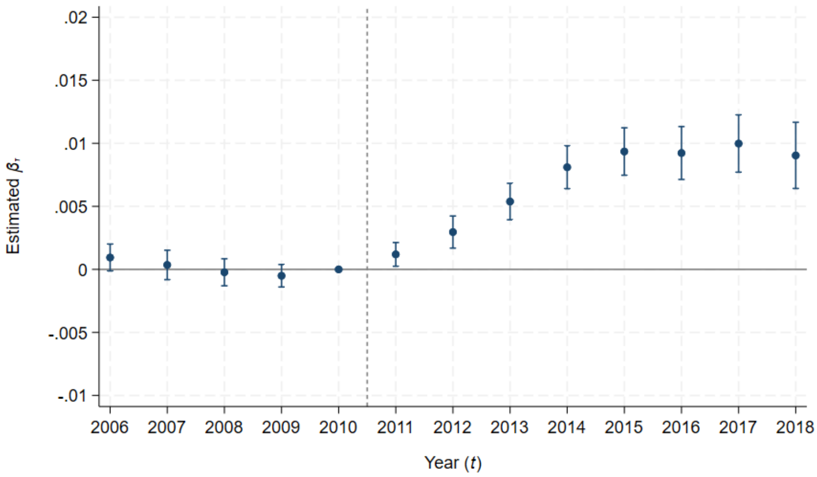
where SME is the group of small and medium firms that, motivated by Figure 4, we define as having fewer than 200 employees in 2010 (e.g. they have a similar size - immigrant intensity gradient in the pre and post periods). The coefficients $\beta^{SME}_\tau \equiv \theta_\tau + \beta^L_\tau$ and β^L_τ decompose the average effect measured by β_τ into that effect at SMEs and large firms. Both regressions restrict the sample to firms that did not hire either treated or control group immigrants in 2005 to transparently show the effect of the policy on the extensive margin. Results are robust to not imposing this restriction as shown in Appendix B.

The identifying assumption in this event-study framework is that, in the absence of the policy change, the expected change in the share of o in firm j's workforce after 2010 would have been the same for the treated and control groups, conditional on the controls. We assess the plausibility of this assumption by formally testing whether β_τ, β^{SME}_τ, and β^L_τ are zero before 2010. Failing to reject this hypothesis would suggest that the hiring trends for NMS nationals and nationals from the control group were parallel before 2010. It would then be plausible that the hiring of these two groups would have evolved at similar rates in the absence of the EU enlargement.

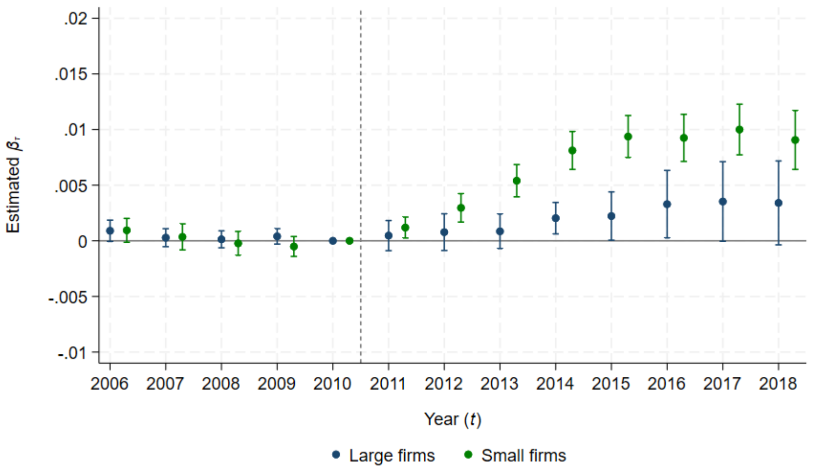
Figure 5a plots the estimated coefficients β_τ, suggesting that firms began to increase their hiring of NMS nationals relative to the control group only after the restrictions on NMS nationals were lifted. Figure 5b shows that β^{SME}_τ tend to be higher than β^L_τ, suggesting that smaller firms increased the hiring of NMS nationals relative to large firms. Moreover, column 1 of Appendix Table B3 shows that this decreasing effect on firm size persists even when the SME group is further disaggregated. We interpret the findings of this section as providing evidence of policy-induced fixed costs to hire immigrants that were in place until 2011, our period of analysis.

Figure 5: Evidence of fixed cost to hire immigrants before 2011

(a) All firms



(b) Firms by size



Notes: Panel a plots the coefficients β_τ from equation 1 while panel b plots the coefficients β_τ^L (for large firms) and $\theta_\tau + \beta_\tau^L$ (for small firms) from equation 2. Large firms are firms with more than 200 employees. The sample is restricted to all firms that did not hire NMS or other European migrants in the year 2005 (the year before our sample begins). We cluster standard errors at the firm level and report 95% confidence intervals.

Robustness exercises: Given that lower-ability workers are more likely to work at lower productivity firms (Card et al., 2013), our estimates could be biased upward if the post-2011 inflow of immigrants had lower abilities compared to those who arrived before 2011. However, our data suggests that, if anything, the new NMS migrants are positively selected in the post-period. For instance, the wages paid to NMS increase by 9.8% between the pre- and post-period while they increase by 8.2% for immigrants in the control group. Similarly, if we look at the average occupation wage (as a measure of the quality of the occupations chosen by each group), NMS workers increase their occupational wages by 2.8% between pre- and post-period while Europeans not in the EU increase by 2.1%.

Appendix Section B.3 shows that the result of smaller firms increasing NMS hiring relative to larger firms is robust to alternative specifications. For clarity, we report the difference-in-difference estimates associated with the event studies analogous to equation 2. Table B3 considers alternative outcome variables such as new hires by nationality, new entrants in the labor market employed by the firm, and the immigrant share by nationality. While we focus on firms that did not employ treated or control group immigrants in 2005, Table B4 shows results are robust to including all firms or focusing on firms with more than 10 employees. Finally, Table B5 shows that results are robust to including an alternative set of fixed effects, such as origin-time fixed effects.

4.3 Additional evidence guiding modeling assumptions

For firms to optimally hire immigrants despite fixed costs, immigrants and natives must differ in the workplace. If they were perfect substitutes, firms would hire only native-born workers. We provide evidence on what makes immigrants and natives different in Appendix B.4, showing that immigrants from different countries have different bundles of characteristics — such as age, gender, and education — and specialize in different occupations than natives. We also provide evidence consistent with this specialization being related to origin-specific comparative advantage. Based on this evidence, our model will treat immigrants and natives, as well as immigrants from different origin countries, as imperfect substitutes in production.

5 The Model

This section studies how firm heterogeneity in immigrant share shapes the economy's adjustment to immigration inflows and the effects on native workers' welfare. To do so, we develop a model informed by the evidence from previous sections. Firms with heterogeneous productivities seek to hire immigrant labor because immigrants are imperfect substitutes for native workers. However, doing so requires two types of fixed costs: an initial cost to begin hiring immigrants and an additional cost for each new country they source immigrants from. This cost structure implies that larger, more productive firms spend a larger share of their wage bill on immigrants (Figure 1), are more likely to hire immigrants (Figure 3a), and more likely to recruit immigrants from more countries (Figure 3b) compared to smaller firms. We then use the model to analytically study the role of firm heterogeneity in immigrant share in the effects of an immigrant labor supply shock. We focus on immigrant *supply* shocks to contribute to the large immigration literature studying the effects of immigrant inflows on the receiving economy. In Section 8, however, we study quantitatively the effects of exogenous immigrant supply shocks as well as the effects of policies that reduce fixed costs to hire immigrants. We focus on the main components of the model and relegate derivations to Appendix C.

Environment: The world comprises two regions, Germany and the rest of the world (RoW) indexed by g and r respectively. The latter being composed of a continuum of countries indexed by o. In Germany, there is a tradable and a non-tradable sector indexed by $k = \{T, NT\}$, each populated by N_k firms indexed by j. Good markets are monopolistically competitive and labor markets are perfectly competitive.

Consumption: Consumers in Germany have Cobb-Douglas preferences for goods from the two sectors and CES preferences over varieties z within a sector k

$$U = (Y_T)^{\alpha}(Y_{NT})^{1-\alpha} \quad , \quad Y_k = \left(\int_{J_k} (y_k(z))^{\frac{\sigma_d - 1}{\sigma_d}} dz\right)^{\frac{\sigma_d}{\sigma_d - 1}} \tag{3}$$

where Y_k stands for the consumption level of sector k, α is the share of expenditure spent on goods from the tradable sector, J_k represents a fixed set of varieties available in k, and $\sigma_d > 1$ is the domestic elasticity of demand. Consumers are either firm owners, whose income are profits, or workers who earn wages. They choose $y_k(z)$ to maximize U subject to their income.

Production: Each firm produces a specific variety. Firms employ only labor inputs, which can be native-born 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 (Peri and Sparber, 2009, 2011). This is consistent with firms combining native and foreign effective units of labor (d_j and

x_j, respectively) in a CES manner as shown in equation 4.

$$y_j = \psi_j \left(\beta_k d_j^{\frac{\epsilon-1}{\epsilon}} + (1-\beta_k) x_j^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}} \tag{4}$$

where β_k is a sector-specific distributional parameter, ϵ is the elasticity of substitution between native and immigrant workers within the firm, and ψ_j is a firm-specific productivity draw. Using CES properties, the unit cost can be written as in equation 5:

$$u_j = \left(\beta_k^{\epsilon} w_{d,k}^{1-\epsilon} + (1-\beta_k)^{\epsilon} W_{x,j}^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}} \tag{5}$$

where $w_{d,k}$ is the wage per effective unit of native labor and $W_{x,j}$ is the firm-specific wage per effective unit of immigrant labor, respectively. The expenditure share in native workers is:

$$s_j = \frac{\beta_k^{\epsilon} w_{d,k}^{1-\epsilon}}{\beta_k^{\epsilon} w_{d,k}^{1-\epsilon} + (1-\beta_k)^{\epsilon} W_{x,j}^{1-\epsilon}} = \frac{\beta_k^{\epsilon} w_{d,k}^{1-\epsilon}}{u_j^{1-\epsilon}} \tag{6}$$

If the wage per effective unit of immigrant labor, $W_{x,j}$, was the same across firms in k, the unit cost of production would also be the same. In that case, all firms in k, regardless of their productivity or size, would have the same immigrant and native 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 based on our evidence on why firms hire different shares of immigrants.

Environment to Recruit Immigrants: To theorize on the firm choice of its immigrant share that accommodates our facts and remains tractable in general equilibrium, we follow Blaum et al. (2018) and Blaum (2024), who develop a theory of how firms choose their intermediate input share. Motivated by the evidence in subsection B.4, we assume that the immigrant labor input, x_j, is a composite of labor from different origin countries as in equation 7:[14]

$$x_j = \left(\int_{\Sigma_j} \delta_o x_{j,o}^{\frac{\kappa-1}{\kappa}} d_o \right)^{\frac{\kappa}{\kappa-1}} \tag{7}$$

where δ_o is the importance of source-country o in the production function, $\kappa > 1$ is the elasticity of substitution between origin countries and Σ_j is the hiring strategy of the firm given by the countries o where the firm hires immigrants from. Given that immigrants from different origins are imperfect substitutes, every additional origin country the firm hires immigrants from will have a positive impact on productivity and lower the firm j's

[14] Evidence from the literature also suggests that immigrants from different countries may serve as different inputs in production due to differences in comparative advantage (Hanson and Liu, 2023).

effective immigrant unit cost $W_{x,j}$.

Following the evidence presented in Section 4, 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.[15] For example, if the firm hires immigrants from two origins, it spends $w_{d,k} \times (f_{imm} + 2 \times f_j)$ 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 spending resources to understand foreign education credentials and labor experience necessary to screen workers.

We make two additional assumptions to maintain tractability in general equilibrium. First, we assume that foreign countries are perfectly ranked in terms of importance in the production function 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 reduces the dimensionality of the sourcing problem 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 $\bar{\delta}$. These assumptions allow us to get a closed-form expression for the wage index of immigrants as in equation 8:

$$W_{x,j} = \; w_{x,k} \, \bar{z} \, n_j^{-\iota} \tag{8}$$

where $w_{x,k}$ is equilibrium wage per effective unit immigrants in Germany.[16] The parameters $\bar{z} > 0$ and $\iota > 0$ are determined by $\bar{\delta}$, ξ, and κ and can be interpreted as the average productivity of immigrants and the elasticity of the immigrant unit cost to expanding the mass of sourcing countries. 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.

Distributional assumptions of ψ_j and f_j: We assume that productivity ψ_j and hiring cost f_j are jointly drawn from a multivariate sector-specific lognormal distribution with mean $[\mu_\psi, \mu_f]$, dispersion $[\sigma_\psi, \sigma_f]$, and covariance $\sigma_{\psi,f}$.

Pricing Decision: Given CES preferences, the optimal price p_j is a constant markup over the marginal cost:

$$p_j = \frac{\sigma_d}{\sigma_d - 1} \frac{u_j}{\psi_j} \tag{9}$$

[15] The model without heterogeneity in f_j already captures the qualitative facts of interest, but we allow for firm-level heterogeneity to better match the correlation between firm size and immigrant share.

[16] In equilibrium, immigrants earn the same wage per efficient unit regardless of origin. This equilibrium result enables the closed-form solution in equation 8, which allows us to keep tractability in general equilibrium while letting efficient wages for both immigrants and natives be determined endogenously.

Optimal native share: An advantage of this setup is that we can write the unit cost u_j, price p_j, and the mass of countries n_j as a function of the key object s_j as follows:

$$p_j = \frac{\sigma_d}{\sigma_d - 1} \frac{1}{\psi_j} \underbrace{\beta_k^{\frac{\epsilon}{1-\epsilon}} \; w_{d,k} \; s_j^{\frac{1}{\epsilon-1}}}_{u_j} \tag{10}$$

$$s_j = \frac{\beta_k^{\epsilon} w_{d,k}^{1-\epsilon}}{\beta_k^{\epsilon} w_{d,k}^{1-\epsilon} + (1-\beta_k)^{\epsilon} w_{x,k}^{1-\epsilon} \; \bar{z}^{1-\epsilon} \; n_j^{\iota(\epsilon-1)}} \longrightarrow n(s_j) = \bar{\chi}_k \left(\frac{1}{s_j} - 1\right)^{\frac{1}{\iota(\epsilon-1)}} \tag{11}$$

where $\bar{\chi}_k \equiv \left((\frac{1-\beta_k}{\beta_k})^{\epsilon} \; \bar{z}^{1-\epsilon} \right)^{\frac{1}{\iota(\epsilon-1)}} (\frac{w_{x,k}}{w_{d,k}})^{-\iota}$.

Firms maximize their profits by choosing the optimal native share s_j:

$$\max_{s_j} \Pi_j = \underbrace{\left(p_j(s_j) - \frac{u_j(s_j)}{\psi_j} \right) y_j}_{\text{variable profits}} - \underbrace{n_j(s_j) f_j w_{d,k} - w_{d,k} f_{imm,k} \mathbb{1}(n_j(s_j) > 0)}_{\text{Sourcing cost}} \tag{12}$$

How do firms choose their optimal native share? They face a trade-off between the drop in the marginal cost of production induced by the 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 to pay f_j more times than small firms. Thus, larger firms hire immigrants from more countries than small firms, and they become more immigrant-intensive.

An important takeaway of the role of s_j in understanding the effects of immigration is the following. 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 native share. In other words, the native share acts as a firm exposure to a common immigration shock and becomes the key empirical object to learn about how much each firm benefits from immigration.

Export Decision: German firms in the tradable sector can export their goods by paying a fixed cost f_x, as in Melitz (2003). The firm chooses to export if the variable profits from export sales are larger than f_x. Under the assumption that consumers in RoW have CES preferences over tradable varieties with elasticity of demand σ_x, the optimal export price p_j^x is again a constant markup over total marginal cost, which now includes an iceberg cost $\tau > 1$:

$$p_j^x = \frac{\sigma_x}{\sigma_x - 1} \frac{u_j \tau}{\psi_j} \tag{13}$$

Finally, conditional on its export decision, the firm chooses s_j by solving a problem analogous to 12.

Rest of the world: Given our focus on the German economy, we simplify the modeling of the RoW. We assume it has a single tradable sector, firms are equally productive, and use only native labor to produce with a constant return to scale production function $y_j^r = \bar{\psi}^r d_j^r$. Foreign firms incur iceberg trade costs τ when exporting to Germany but face neither these costs when exporting within the RoW nor a fixed cost to start exporting.

Workers: Each country o has an exogenous mass of workers born in o N_o. Each worker i from o draws a sector k, location ℓ specific ability $(\eta_{i,\ell,k}^o)$ from the following Fréchet distribution:

$$F(\eta) = exp\left(-\sum_k A_{o,k,\ell}(\eta)^{-\nu}\right) \tag{14}$$

where $\nu > 1$ is the shape parameter and $A_{o,k,l}$ is the scale parameter, which we assume is the same across origins in RoW, e.g., $A_{o,k,\ell} = A_{x,k,\ell}$ for $o \in$ RoW. The scale parameters can be interpreted as the comparative advantage of nationals from RoW and Germans in industry k in ℓ.

Labor supply to sector k in Germany: Workers from o choose the industry k and country ℓ that yield the highest real wage net of iceberg migration costs $\phi_{o,k,\ell}$ with $\phi_{\ell,k,\ell} = 1$. We assume that there is free mobility across countries within RoW and that migration costs to move to ℓ outside RoW are the same, e.g., $\phi_{o,k,\ell} = \phi_{x,k,\ell}$ for $o \in$ RoW. Due to data limitations, we also assume the cost of migration out of Germany is infinity, such that German workers are immobile across countries.[17]

Following the properties of the Fréchet distribution, the fraction of natives and immigrants from country o who choose industry k in Germany ($\ell = g$) is:

$$\pi_{g,k,g} = \frac{A_{g,k,g}\left(w_{d,k}\right)^{\nu}}{\sum_k A_{g,k,g}\left(w_{d,k}\right)^{\nu}} \quad , \quad \pi_{x,k,g} = \frac{A_{x,k,g}\left(\frac{w_{x,k}}{P_g}\right)^{\nu}\phi_{x,k,g}^{-\nu}}{\sum_k A_{x,k,g}\left(\frac{w_{x,k}}{P_g}\right)^{\nu}\phi_{x,k,g}^{-\nu} + A_{x,k,r}\left(\frac{w_r}{P_r}\right)^{\nu}} \tag{15}$$

where w_r and P_r are the wage per efficient units of labor and price index in RoW. Similar expressions apply for the share of workers from o choosing $\ell \neq g$ (see Appendix C). The share $\pi_{x,k,g}$ shows that reducing costs to migrate to Germany increases the supply of immigrants into the country.[18]

[17] This may not be an strong assumption as the emigration rate of Germans in 2010 is approximately 3.5%, according to the IAB brain-drain dataset.

[18] The labor market in Germany is more rigid than other countries (D'Amuri et al., 2010). Such rigidity

Equilibrium and Market Clearing: The equilibrium are prices, efficient wages, and labor allocations such that: workers optimally choose the industry and destination country 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, all markets clear, and trade is balanced. Appendix C includes the main equilibrium conditions.

5.1 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 model with heterogeneous immigrant share ("heterogeneous model") with a model that ignores this heterogeneity but still allows for heterogeneity in innate productivity ("homogeneous model"). The heterogeneous model is a simplified version of our fully quantitative model, where the economy has only one sector and all firms hire some amount of immigrants (e.g., $f_{imm} = 0$). The homogeneous model can be a special case of this heterogeneous model with $f_j = 0$ or any model following the Arkolakis et al. (2012) framework.[19] We first study the role of firm heterogeneity in immigrant share when the economy is in trade autarky and later analyze how the results change when the economy is open to trade. All derivations are included in Appendix D. We denote $\tilde{x} \equiv dlog(x)$.

The native workers' welfare effects of an exogenous change in the number of immigrants, denoted by $\tilde{\mathbb{W}}$, is given by the following change in real wages:

$$\tilde{\mathbb{W}} = - \sum_{j \in J} \frac{\omega_j \tilde{s}_j}{\epsilon - 1} = - \frac{\tilde{S}}{(1-\pi)\,\epsilon + \pi\,\sigma - 1} = - \underbrace{\frac{\tilde{S}}{\epsilon - 1}}_{\substack{\text{Prediction without} \\ \text{heterogeneity in } s_j}} \frac{1}{1 + \frac{\sigma - \epsilon}{\epsilon - 1}\,\pi} \tag{16}$$

$$1 - \pi \equiv \frac{\sum_{j \in J} \omega_j^S \alpha_j}{\sum_{j \in J} \omega_j \alpha_j} \in (0, 1]$$

where S is the native share in the total wage bill in the economy, $\omega_j \equiv \omega(\psi_j, s(\psi_j))$ is the share of firm j in expenditure, $\omega_j^S \equiv \omega^S(\psi_j, s(\psi_j))$ is the share of firm j in native employment and $\alpha_j \equiv \alpha(s(\psi_j))$ is a strictly decreasing function of s_j. The weight π depends on the heterogeneity in immigrant share and its correlation with firm size, and takes the value of zero if firms employ the same immigrant share.

Immigration affects the welfare of native workers through two channels: a labor market

is not explicitly incorporated into our model since we allow natives to move freely across firms.

[19] This includes a model with a CES technology between immigrants and natives, which is the canonical production framework used in the immigration literature, coupled with CES preferences over goods.

competition effect and a price effect. The competition effect depends on how substitutable immigrants and natives are at the workplace, as well as how much firms expand due to the higher availability of immigrant labor. The price effect arises from immigration reducing firms' unit production costs, leading to lower prices for goods and services, which increases the purchasing power of workers' wages.

When firms employ the same immigrant share, the welfare gains on the right-hand side of expression 16 are given by the first component. In these models, the competition effect is characterized by an increase in immigrant shares and a drop in the unit cost of production of the same proportion for all firms. As firms produce at lower cost and charge lower prices, the purchasing power of wages increases. The size of the native-born real wage increase depends on the size of the inflow and the elasticity of substitution between immigrants and natives in the labor market, which is fully determined by ϵ when firms employ the same immigrant share. The more substitutable immigrants and natives are, the lower the productivity gains for firms, and the lower the welfare gains for natives.[20]

The welfare predictions of the homogeneous model may be biased for two reasons: firms experience different proportional reductions in unit costs, as captured by equation 17, and exhibit different elasticity of immigrant-to-native wage bill (or substitution elasticity) in response to relative *market* wages, as captured by equation 18:

$$\tilde{u}_j = (1 - s_j)\,\tilde{W}_{x,j} = (1 - s_j)\,(1 + \zeta(s_j))\,\tilde{w}_x \tag{17}$$

$$\frac{(\tilde{W}_{x,j} + \tilde{x}_j) - (\tilde{w}_d + \tilde{d}_j)}{\tilde{w}_x - \tilde{w}_d} = (\epsilon - 1)\,(1 + \zeta(s_j)) \tag{18}$$

where $1 + \zeta(s_j) \equiv \frac{\tilde{W}_{x,j}}{\tilde{w}_x} = 1 + \frac{\tilde{n}_j}{\tilde{w}_x}$ is the elasticity of firm j's immigrant bundle cost to the immigrant market wage.

To gradually build intuition on how these mechanisms affect the aggregate welfare, consider first a case where the heterogeneity in s_j matters because it leads to heterogeneity in the elasticity of unit production costs to $\tilde{w}_x$ but it does not lead to heterogeneity in the substitution elasticity (e.g., the substitution elasticity is $\epsilon - 1$ for all firms). This occurs, for example, in models where heterogeneity in s_j is due to firm heterogeneity in β, as the drop in immigrant bundle cost is the same across firms (e.g., $\tilde{W}_{x,j} = \tilde{w}_x$). In this case, the elasticity of substitution between immigrants and natives in the labor market, which we will refer to as the *aggregate* elasticity, coincides with the weighted average in the denominator of 16, and π now is proportional to the weighted variance of immigrant

[20] In the limiting case of $\epsilon \to \infty$, the gains are zero because w_d drops in the same proportion as w_x and so does P. If ϵ is finite, real wages increase for natives and decrease for immigrants, e.g., $\tilde{w}_x < \tilde{P} < \tilde{w}_d$

shares, as in Oberfield and Raval (2021).[21] 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. The parameters ϵ and σ pin down the reallocation of natives across firms with different immigrant shares.[22]

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. 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 an 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 the aggregate demand for natives and welfare are larger in the heterogeneous world.

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.

Now, consider the case where the drop in immigrant bundle cost is not the same across firms. Firms with different immigrant shares adjust the number of sourcing countries differently, leading to heterogeneous substitution elasticities. This additional adjustment of the extensive margin makes firms more responsive to the drop in immigrant market wages, inducing a further decline in unit production costs and prices. The associated drop in the price index is stronger when the unit cost reductions are concentrated among the largest firms, as they have a disproportionate weight in consumers' consumption baskets. As a result, there are additional welfare gains when larger firms are more immigrant-intensive than smaller firms.

To sum up, new adjustment mechanisms to immigration arise when firms are heterogeneous in their immigrant shares, which may lead to the welfare predictions of a model

[21] In our case, where the drop in immigrant bundle cost is the same across firms, the aggregate elasticity of substitution is $(1-\pi)\,\epsilon + \pi\,\sigma + \frac{1}{S(1-S)} \sum_j \,\omega_j\,(1-s_j)\,\zeta_j\,\;[(\epsilon-\sigma)s_j - \,(\sigma-1)S]$

[22] Mathematically, $\tilde{d}_j - \tilde{d}_{j'} = \frac{\epsilon-\sigma}{\epsilon-1}\left(\tilde{s}_{dj} - \tilde{s}_{dj'}\right) \approx (\epsilon-\sigma)(s_{j'} - s_j)(\tilde{w}_x - \tilde{w}_d)$.

with homogeneous immigrant shares being biased. Equation 16 shows the sign of the bias depends on the sign of $\epsilon - \sigma$, and its magnitude depends also on the correlation between firm size and immigrant share. Given this insight, we will formally test whether $\epsilon - \sigma > 0$, and calibrate the model to match the observed correlation between immigrant share and firm size. We will also validate the quantitative model based on the insights from equation 17 , which highlights the role of the heterogeneous response of u_j or equivalently sales, and Equation 18, which highlights the role of the heterogeneous response of the immigrant-to-native wage bill ratio $\frac{W_{x,j}x_j}{w_{k,d}d_j}$.

Finally, the results in this section have implications for the relationship between micro and macro elasticities, and their consequences for welfare. Equation 16 shows that the welfare effect of $\tilde{S}$ depends on a weighted average of micro elasticities, where the weights π depend on firms' immigration and market shares. When firm heterogeneity in factor shares does not lead to firm heterogeneity in elasticity of substitution between factors of production, as in Oberfield and Raval (2021), that weighted average coincides with the aggregate elasticity, making the aggregate elasticity sufficient for inferring welfare gains. However, in our fixed-cost model, where factor share heterogeneity also leads to heterogeneous substitution elasticities, the two diverge. As a result, the aggregate elasticity is not informative about welfare effects because it does not fully capture the first-order impact of price changes. Thus, micro elasticities and firms' shares are needed for welfare analysis.[23]

5.1.1 Heterogeneity in immigrant share and the role of international trade

Fundamental theorems of international trade (Rybczynski (1955); Samuelson (1948)) suggest that international trade may play an important role in mitigating the effects of immigration. Building on this theoretical insight, we study whether the gains from immigration are larger or lower when a country is open to trade *due to firm heterogeneity in immigrant shares.*

To do so, we compare the welfare gains from immigration in an economy open to trade and the corresponding one under trade autarky. The welfare gains in an open economy where trade is balanced, $\sigma_d = \sigma_x = \sigma$, and firms must pay a fixed cost to export and iceberg trade costs are given by equation 19:

$$\tilde{\mathbb{W}} = -\lambda \frac{\tilde{S}}{\epsilon(1-\pi) + \pi\sigma - 1} - (1-\lambda)(\tilde{w}_r - \tilde{w}_d) \tag{19}$$

where λ is the aggregate domestic trade share. The welfare effects under trade autarky

[23]Mathematically, $\tilde{\mathbb{W}} = -\frac{\tilde{S}}{\epsilon^{agg}-1}\left(\sum_j \omega_j \frac{1-s_j}{1-\tilde{S}}\zeta_j\right)$ where ϵ^{agg} is the aggregate elasticity.

in equation 16 are an special case of equation 19 where $\lambda = 1$ and $\pi(\{s_j, \omega_j, \omega_j^S\})$ is evaluated in the equilibrium under trade autarky.

The analytical expression reveals two differences in the welfare effects of immigration between an open and a closed economy. First, the second term on the right-hand side vanishes in the closed economy because λ equals one. Intuitively, when workers reallocate from the rest of the world to Germany, labor costs abroad increase relative to native-born wages in Germany ($\tilde{w}_r - \tilde{w}_d > 0$). In an open economy, this reduces the purchasing power of German workers by increasing the price of imported goods, an effect that does not occur under trade autarky. This terms of trade type of effect operates regardless of whether firms have heterogeneous immigrant shares and is present in standard quantitative models of international trade and immigration.

Second, the value of π in the open economy can be larger or smaller than under trade autarky. Consider two firms: firm j, which is relatively productive and exports when the country is open to trade, and firm j', which is relatively unproductive and does not export. An inflow of immigrants leads firm j to expand production relative to firm j', more so when the economy is open to trade. This differential relative expansion implies that π may be higher or lower under trade openness than in autarky, depending on the strength of two countervailing forces. On the one hand, the relative expansion of production increases the relative employment of all inputs by firm j, including native labor. Therefore the relative share of firm j in the hiring of native workers $\omega_j^S/\omega_{j'}^S$ is higher in the open economy, which implies that π is lower. Intuitively, the reallocation of native-born workers toward smaller, native-intensive firms is weaker compared to autarky. On the other hand, the relative expansion in production means that firm j also becomes relatively more profitable than firm j' and is able to afford the fixed cost of hiring immigrants from additional sources. Thus, firm j expands its immigrant share relative to j', more than it would under autarky. This implies that π is higher in the open economy, as the reallocation of natives from j toward j' is stronger compared to the closed economy. Ultimately, whether π is larger or smaller in an open economy depends on the relative magnitude of these two opposing effects.

According to equation 19, the difference between the welfare gains in an economy with homogeneous immigrant share ($\pi = 0$), with and without trade is informative about the first mechanism:

$$\tilde{\mathbb{W}}^{homog,open} - \tilde{\mathbb{W}}^{homog,closed} = -(1-\lambda)\left(\tilde{w}_r - \tilde{w}_d\right)$$

The extra difference between the gains in an open relative to a closed economy when firms employ different immigrant shares is informative about the second mechanism:

$$\begin{aligned}&\left(\tilde{\mathbb{W}}^{heterog,open} - \tilde{\mathbb{W}}^{heterog,closed}\right) - \left(\tilde{\mathbb{W}}^{homog,open} - \tilde{\mathbb{W}}^{homog,closed}\right) = \\ &-\lambda\, \tilde{S} \left(\frac{1}{\epsilon(1-\pi^{open}) + \pi^{open}\sigma - 1} - \frac{1}{\epsilon(1-\pi^{closed}) + \pi^{closed}\sigma - 1}\right)\end{aligned} \tag{20}$$

Motivated by these results, we will use the quantitative model to compute the left-hand side of this expression and thus assess if firm heterogeneity in immigrant share matters for the role of international trade in the gains from immigration.

6 Estimation

We estimate the parameters of the model in two steps. First, we estimate outside the model the elasticity of demand in Germany and the rest of the world (σ_d and σ_x), the elasticity of substitution between immigrants and natives (ϵ), the elasticity of substitution across origin countries (κ), and the elasticity of labor supply (ν). Then, we calibrate the remaining parameters to match relevant aspects of the data, as we discuss in detail shortly.

6.1 Elasticity of Demand

Following Oberfield and Raval (2014), we infer the demand elasticity σ_d from firms' markups, i.e., the ratio of revenue to total costs. According to the model, the following moment condition holds:

$$\mathbb{E}\left(\frac{Revenue_j}{Cost_j}\right) = \frac{\sigma_d}{\sigma_d - 1} \tag{21}$$

where j are firms in the non-tradable sector. To take this moment to the data, we compute the average revenue-to-cost ratio across firms and use equation 21 to infer the value of σ_d.[24] The average markup for firms in the non-tradable sector is 1.54, which implies that $\hat{\sigma}_d = 2.84$.

Based on the analogous model's moment condition for firms in the tradable, we calibrate the demand elasticity from the RoW σ_x, to match the average revenue-to-cost ratio of firms in the tradable sector, given the calibrated value of σ_d and the the average share of exports in their sales.[25] We find that $\hat{\sigma}_x = 5.16$, which implies an average elasticity in the tradable sector of 3.60.

[24] 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.

[25] We use the following condition $\mathbb{E}\left(\frac{Cost_j}{Rev_j}\right) = \frac{Rev_d}{Rev}\frac{Cost_d}{Rev_d} + \frac{Rev_x}{Rev}\frac{Cost_x}{Rev_x} = \frac{Rev_d}{Rev}\frac{\sigma_d - 1}{\sigma_d} + \frac{Rev_x}{Rev}\frac{\sigma_x - 1}{\sigma_x}$

The calibrated values is consistent with previous estimates in the literature, which tend to depend on the granularity of the categories of sectors. For instance, for narrower categories than ours, Broda and Weinstein (2006) found an average elasticity of 4, and for broader categories, estimates tend to be around 0.5 (Comin et al., 2021; Cravino and Sotelo, 2019).[26]

6.2 Elasticity of Substitution Between Natives and Immigrants

We use the first-order conditions with respect to d_j and x_j to obtain equation 22:

$$Log\left(\frac{\text{Wage Bill Immig}_{j,t}}{\text{Wage Bill Natives}_{j,t}}\right) = \frac{\epsilon-1}{\epsilon} Log\left(\frac{d_{j,t}}{x_{j,t}}\right) + Log\left(\frac{\beta_k}{1-\beta_k}\right) \tag{22}$$

where we add a year subidex t to endogenous variables. This equation shows that ϵ regulates the change in firms' labor spending in native workers relative to immigrants to changes in their relative efficient units of labor.

Given that the efficient units of native labor d_j and the CES composite of immigrant labor x_j are not directly observable, we proceed in two steps to take this equation to the data. First, given that the ability draws η are Fréchet distributed we can write the effective units of domestic labor, $d_{j,t} = \gamma_{g,k,t}\ N_{g,j,t}$ where $\gamma_{g,k,t}$ is the average ability of native workers in industry k and $N_{g,j,t}$ is the number of native workers in firm j in year t. Second, we can also write the CES composite of immigrant effective units as $x_{j,t} = \left(\sum_o \zeta_{o,k,t}\left(N_{o,j,t}\right)^{\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{\kappa-1}}$, where $\zeta_{o,k,t} \equiv \delta_o(\gamma_{o,k,t})^{\frac{\kappa-1}{\kappa}}$ and $\gamma_{o,k,t}$ is the average ability of nationals from o in sector k. We follow the approach proposed by in Ottaviano and Peri (2012) to jointly estimate $(\zeta_{o,k,t}, \kappa)$ using within firm variation over time and across nationalities of immigrant employees. Once we obtain these parameters, we compute $\hat{x}_{j,t} \equiv \left(\sum_o \hat{\zeta}_{o,k,t}\left(N_{o,j,t}\right)^{\frac{\hat{\kappa}-1}{\hat{\kappa}}}\right)^{\frac{\hat{\kappa}}{\hat{\kappa}-1}}$ (see Appendix E for details). These two steps allow us to replace the unobservable $d_{j,t}$ and $x_{j,t}$ by functions of observables $N_{d,j,t}$ and $\hat{x}_{j,t}$ respectively, and rewrite 22 as:

$$Log\left(\frac{\text{Wage Bill Immig}_{j,t}}{\text{Wage Bill Natives}_{j,t}}\right) = \frac{\epsilon-1}{\epsilon} Log\left(\frac{\hat{x}_{j,t}}{N_{g,j,t}}\right) - Log\Big(\gamma_{g,k,t}\Big) + Log\left(\frac{1-\beta_k}{\beta_k}\right) + \xi_{j,t} \tag{23}$$

where $\xi_{j,t} \equiv Log(x_{j,t}) - Log(\hat{x}_{j,t})$ is a measurement error term.

There are two concerns to identify $\frac{\epsilon-1}{\epsilon}$ by estimating equation 23 via ordinary least

[26]Rather than using variable costs in the calibration of σ_d, we use total costs, which include fixed costs. As a result, our estimate could be upward biased. Fortunately, the direction of the bias means that it is even more likely that $\sigma < \epsilon$ maintaining the qualitative findings of subsection 6.2.2. Quantitatively, we expect its effect to be small, as the wage bill of occupations related to fixed costs account for approximately 1% on average of our variable costs.

squares approach (OLS). First, the measurement error $\xi_{j,t}$ may correlate with firm, industry, or labor market factors determining hiring decisions. Second, omitted variable bias would arise if unobserved shocks to a firm's demand, technology, or shocks to a firm's labor market induce firms to expand and simultaneously hire more immigrants *relative* to natives.

To address these concerns, we incorporate a rich set of fixed effects, and follow an instrumental variable approach. Specifically, we estimate the equation 24:

$$Log\left(\frac{\text{Wage Bill Immig}_{j,t}}{\text{Wage Bill Natives}_{j,t}}\right) = \beta Log\left(\frac{\hat{x}_{j,t}}{N_{g,j,t}}\right) + FE_j + FE_{m,t} + FE_{k,t} + u_{j,t} \tag{24}$$

where FE_j, $FE_{m,t}$, and $FE_{k,t}$ are firm, commuting zone-year and industry-year fixed effects respectively, $\epsilon = \frac{1}{1-\beta}$, and $u_{j,t}$ is the error term. We use a bootstrap procedure to generate confidence intervals that properly account for the fact that $\hat{x}_{j,t}$ arose from a previous estimation procedure.

We construct our instrument, denoted by $Z_{j,t}$, following the model's definition of $dLog(\frac{x_{j,t}}{N_{g,j,t}})$:[27]

$$Z_{j,t} = \sum_{o \neq g} \left(\frac{\text{Wage Bill Imm}_{o,j,2003}}{\text{Wage Bill Imm}_{j,2003}}\right) \frac{\Xi_{o,t}}{\Xi_{g,t}} \tag{25}$$

where $\Xi_{x,t}$ is the country-wide employment growth of workers from country group x between 2003 and t. This is a shift-share instrument where the shift is given by the growth of immigrants in Germany from nationality o relative to the growth of native workers, and the share is given by the fraction of the immigrant workforce of each firm that is accounted by nationals from o.

6.2.1 Results:

Our OLS estimate for β is 0.88 with a 95% confidence interval (CI) between 0.85 and 0.92. Our 2SLS estimate is 0.87 with CI between 0.78 and 0.97, and the F-stat of the first stage is 78.7. The similarity between the OLS and 2SLS estimate suggests that the stringent set of fixed-effects may account for a large fraction of the endogeneity concerns and that firm-level shocks biased toward immigrant relative to natives may not confound the effect of interest. The 2SLS estimate of ϵ is 7.95 (CI between 4.33 and 29.58). Comparing our estimates with the literature is not straightforward because estimates of the firm-level elasticity are limited due to the scarcity of firm-level data on immigrant employment.[28] Mahajan et al. (2025) estimates imply that the elasticity of substitution

[27] i.e., $dLog\left(\frac{\hat{x}_{j,t}}{N_{d,j,t}}\right) = \sum_{o \neq g}\left(\frac{\text{Wage Bill Imm}_{o,j,t}}{\text{Wage Bill Imm}_{j,t}}\right) dLog\left(\frac{N_{o,t}}{N_{g,t}}\right)$, where $N_{c,t} \equiv \sum_{j} N_{c,j,t}$.

[28] The elasticity of substitution among workers using a CES aggregator has been estimated in various studies, with notable papers reporting values ranging from 4 to 20 (Burstein et al., 2020; Cortes, 2008;

between college-educated immigrants and natives within firms in the U.S. is 4.3. These firms operate under an immigration system similar to that of our German firms, given the sponsorship-based structure described above. Appendix Section E includes pre-trend tests and diagnostics suggested by the literature on the validity of shift-share instruments (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020).

6.2.2 Test for the sign of $\epsilon - \sigma$:

Section 5.1 shows that the welfare gains predicted by the homogeneous model are downward biased if $\epsilon < \sigma$ and are upward biased if $\epsilon > \sigma$. In this section, we obtain an empirical distribution for the statistic $\widehat{\epsilon - \sigma}$ to test the null hypothesis that $\epsilon - \sigma < 0$.

We use a bootstrap procedure to obtain this empirical distributions that takes into account the correlation between $\hat{\sigma}$ and $\hat{\epsilon}$. Using 5,000 bootstrapped samples, we re-estimate ϵ using equation 23 and σ using equation 21. To calibrate σ under the assumption imposed in Section 5.1, namely $\sigma = \sigma_d = \sigma_x$, we pool firms from both the tradable and non-tradable sectors to compute the average markup. We find that $\widehat{\epsilon - \sigma} < 0$ in only 0.007% of the 5000 cases. That is, the p-value of the null hypotheses that $\epsilon - \sigma < 0$ is 0.007, suggesting that the welfare gains of native workers predicted by the homogeneous model might be downward biased. Figure 6 plots the distributions of $\widehat{\epsilon - \sigma}$.

6.3 Additional Parameters

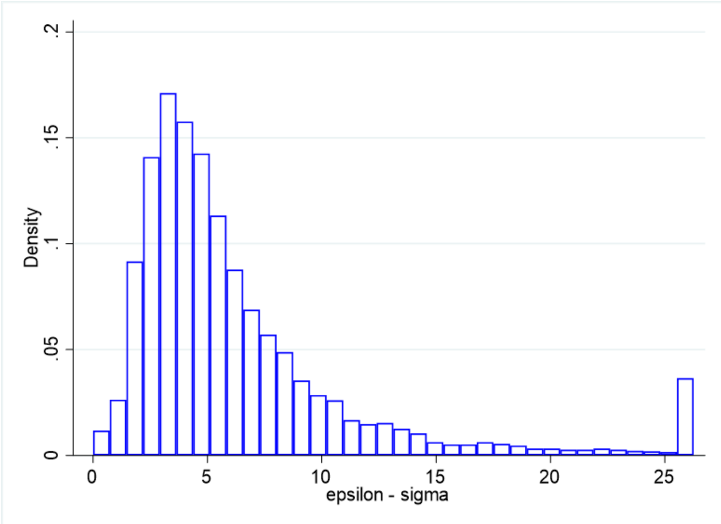
The elasticity of labor supply ν regulates the dispersion of workers' productivity draws. We estimate this parameter using the observed residual variance of wages following the approach used by Hsieh et al. (2019) and Fan (2019) (see Appendix F for details). These residuals are obtained from a regression of log wages on sector-year fixed effects and other covariates. We obtain a range of values between 4.90 and 6.14 and choose as our baseline estimate $\nu = 6.14$, the specification with the most detailed fixed effects.[29] We set 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).

We calibrate the rest of the parameters inside the model 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

Ottaviano and Peri, 2012). While our estimate is within the range of this literature, differences in the level at which production is defined, the nesting order, and the composition of the immigration shock make direct comparisons challenging.

[29]In Appendix H, we show our results are robust for different values of this elasticity, with our baseline estimate yielding the most conservative native workers' welfare gains from immigration.

Figure 6: Distribution of $\widehat{\epsilon - \sigma}$



Notes: The distribution includes the realization of $\hat{\epsilon} - \hat{\sigma}$ from 5,000 bootstrapped samples, were we estimate ϵ using equation 23 and σ using equation 21. The fraction of observations for which $\widehat{\epsilon - \sigma}$is 0.007, rejecting the null hypothesis that $\epsilon - \sigma < 0$ at a 1% confidence. For clearer visualization of the distribution, we replaced negative values with zero and the top 2.5% values with the 97.5th percentile value.

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 ($\mu_{\psi,k} = 1$).

As a second step, we are left with fourteen parameters, which we jointly calibrated 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 variance of the immigrant-to-native wage bill ratio identifies the variability of fixed costs $\sigma_{f,k}$. The difference in the mean of s_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 to identify the mean productivity of RoW $\bar{\psi}^r$.

Table 1 shows the fourteen moments that are targeted in the estimation, their observed values in the data and the ones generated by the model. The model does a good job in approximating their observed values. Table 2 contains the final calibration of the fourteen parameters that minimize the distance between simulated and empirical moments.

Table 1: Simulated vs data moments

Moment description	Simulated	Data	Moment description	Simulated	Data
Aggregate s_T	0.91	0.91	$\mathbb{E}(s_{j,p90}) - \mathbb{E}(s_{j,p50}), NT$	0.008	0.008
Aggregate s_{NT}	0.93	0.93	Share of firms hiring immigrants, T	0.62	0.62
$\mathbb{V}ar(log(rev_j)\|s_j, exporter_j)$, T	1.37	1.38	Share of firms hiring immigrants, NT	0.60	0.61
$\mathbb{V}ar(log(rev_j)\|s_j)$, NT	1.29	1.29	GDP per capita RoW to Germany	0.32	0.32
$\mathbb{V}ar((1-s_j)/s_,), T$	1.31	1.39	Share of firms exporting, T	0.37	0.37
$\mathbb{V}ar((1-s_j)/s_j), NT$	1.43	1.58	$\mathbb{E}$(Export to Domestic Rev$_j$), T	0.76	0.79
$\mathbb{E}(s_{j,p90}) - \mathbb{E}(s_{j,p50}), T$	0.027	0.021	$\mathbb{E}(s_j)$	0.94	0.93

Table 2: Parameter Calibrated to Match Micro- and Macro- Moments

Parameter description	Parameter	Estimate	Parameter description	Parameter	Estimate
Share of natives, T	β_T	0.89	Covariance of ψ and f_j, NT	$\sigma_{\psi,f,NT}$	30.82
Share of natives, NT	β_{NT}	0.88	Fixed cost of immigrants, T	$f_{imm,T}$	2.79E-05
Dispersion in ψ_j, T	$\sigma_{\psi,T}$	1.15	Fixed cost of immigrants, NT	$f_{imm,NT}$	0.0008
Dispersion in ψ_j, NT	$\sigma_{\psi,NT}$	0.37	Productivity in RoW	ψ_x	1.53
Dispersion in f_j, T	$\sigma_{f,T}$	15207	Fixed cost of exporting	f_g	0.003
Dispersion in f_j, NT	$\sigma_{f,NT}$	16385	Iceberg trade cost	τ	1.35
Covariance of ψ and f_j, T	$\sigma_{\psi,f,T}$	-54.03	Elasticity s_j to n	ι	0.002

7 Model Validation: Heterogeneous Response

The model aims to perform counterfactual analysis to understand the effects of exogenous immigrant inflows on native-born welfare given the documented heterogeneity in immigrant share. Before using it, we must verify that the calibrated model properly captures the mechanisms through which this heterogeneity affects welfare. Specifically, this heterogeneity in immigrant shares matters because it leads to heterogeneity in the elasticity of unit production costs or equivalently sales (equation 17) and the elasticity of the immigrant-to-native wage bill (equation 18) to immigrant labor inflows. Therefore, we validate the model by comparing its predicted changes in firms' sales and the immigrant-to-native wage bill ratio due to an exogenous immigrant inflow with those empirically estimated from the data.[30]

In the model, the change in the outcome variables is only due to the exogenous inflow of immigrants. On the contrary, in the data, firms' outcomes are affected by factors other than immigrant inflows. We must isolate the effects of the exogenous immigration inflow from other factors that are absent in our model to obtain the outcome variable from the real data that is comparable with that from the model. To do so, we obtain these data counterparts, we estimate equation 26:

$$y_{j,t} = \theta_1 \; I_{m,t} \; + \theta_2 \; I_{m,t} \; log(emp_{j,2003}) \; + \theta_3 \; X_{j,t} \; + \delta_j \; + \delta_{k,t} \; + \delta_m t \; + u_{j,t} \tag{26}$$

where y is sales and immigrant-to-native wage bill ratio of establishment j in year t. Sub-indices m and k denote the labor market, defined by commuting zones, and 2-digit industries respectively. $I_{m,t}$ is the share of immigrants in the total wage bill, and $emp_{j,2003}$ captures the initial establishment size. $X_{j,t}$ is j's initial cost-to-revenue ratio interacted with year dummies, to compare firms with similar mark-ups, and initial employment size interacted with a time trend, which increases the precision of our estimates. In terms of fixed effects, this specification allows for labor markets to be in different linear trends as captured by $\delta_m t$, for factors affecting all establishments in an industry over time captured by $\delta_{k,t}$, and for time-invariant establishment unobservable characteristics δ_j that may confound the effects of immigration. $u_{j,t}$ is the error term that we cluster at the industry level and labor market level, motivated by our theoretical model and the empirical literature documenting sorting of immigrants into labor markets (Altonji and Card, 1991) and sectors (Hanson and Liu, 2023).[31] The parameter θ_1 measures the overall effect of an immigration inflow on firms operating in that labor market and θ_2, our coefficient of interest, captures whether firms of different sizes have differential responses to this inflow. If positive, it implies that a rise in the share of immigrants in a labor market promotes faster growth in y for larger establishments compared to smaller ones. Given that we control for the standalone variables $I_{m,t}$ and $emp_{j,03}$ (absorbed by the firm fixed effect), θ_2 is identified by comparing the differential growth of two firms i and i' in a labor market with a relatively large inflow of immigrants with the differential growth of two firms j and j' with same sizes located in a market with a low inflow of

[30]We cannot compare the model's predicted $\tilde{w}_{d,k}$ to the data because efficient wages are not observable and, even if using earnings, reduced-form coefficients do not identify level changes due to the commonly known "missing intercept problem" (see Section 7.2).

[31]This two-way clustering leads to wider standard errors than clustering at the level of variation of the main regressor and instrument (e.g., firm-level), which is common practice in the literature.

immigrants.[32]

Even though the fixed effects and controls included in the empirical specification aim to capture unobservable shocks and establishment heterogeneity, 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), with the following shift-share instrument:

$$Z_{m,t} = \sum_{o \neq g} \frac{\text{Wage Bill}_{o,m,2003}}{\text{Wage Bill}_{m,2003}} \frac{\Xi_{o,t}}{\Xi_t} \tag{27}$$

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 in the labor market 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 conditional on our controls. The interaction term is instrumented by this labor market instrument interacted with the initial size of the firm, $Z_{m,t} \ \ log(emp_{j,2003})$.

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

$$\epsilon^y_{j,t} \equiv \Big(\theta_1 \ + \theta_2 \ log(emp_{j,2003})\Big) I_{m,t} \tag{28}$$

when y is the log of sales, $\epsilon^y_{j,t}$ equals and elasticity of y and when y is the wage bill ratio, it equals the semi-elasticity.[33]

7.1 Estimated Immigration Effects by Firm Size

We present the estimates of equation 26 using 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.

[32]e.g., $(\Delta y_i - \Delta y_{i'})$ - $(\Delta y_j - \Delta y_{j'})$ where i and i' are in market m, j and j' are in market m', and the difference in size between i and i' is the same than between j and j'.

[33]Specifically, it equals $\frac{\partial y_{j,t}}{\partial I_{m,t}} \frac{I_{m,t}}{y_{j,t}}$ and $\frac{\partial y_{j,t}}{\partial I_{m,t}} I_{m,t}$, respectively.

Table 3 presents 2SLS estimates for revenues (columns 1-3) and the immigrant-to-native wage bill ratio (columns 4-6). We present the results for the full sample as well as for the tradable and non-tradable sectors separately. Appendix Table G2 reports the first stages estimation results, showing that the instruments are strong. Column 1 shows that an increase in the share of immigrants in the labor market increases the revenue of large establishments relative to small establishments.[34] Columns 2 and 3 show that this heterogeneous effect by firm size is driven primarily by establishments in the tradable sector. Establishments in the non-tradable sector do not seem to differentially respond to the immigration shock. Column 4 suggests that immigration into a local labor market has no differential impact on the immigrant intensity of establishments, but once again, this result masks significant heterogeneity across sectors. Column 5 shows that large firms in the tradable sector increase their immigrant intensity relative to small firms, while column 6 shows that this heterogeneous effect across firm size is absent in the non-tradable sector. Section G reports pre-trend tests and shows the robustness of our estimates to alternative sets of controls.

Table 4 presents the average value of $\epsilon^y_{j,t}$ from equation 28 by firm size and sector, which will be used to compare the elasticities implied by our quantitative model. In the tradable sector, a 1% increase in the labor market immigrant share decreases establishments' revenues in the lowest size decile by 0.71% on average, while increasing establishments' revenues in the highest decile by 1.12% on average. The elasticity of revenues in the non-tradable sector, on the other hand, is similar across establishments of different sizes.

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 tradable sector, a 1% increase in the share of immigrants in the labor market would decrease the ratio of an establishment in the lowest decile by 0.17 while increasing the ratio for an establishment in the highest decile by 0.19. The elasticities across deciles in the non-tradable sector seem to be decreasing with size but are not statistically significant.

7.2 Immigration Effects by Firm Size: Data vs. Model

We assess whether our model can generate counterfactual predictions that match the observed heterogeneous response across employer sizes estimated in Table 4. This is a key validation of the model as the reduced form estimates in this section have not been targeted at all during the estimation stage.

[34] Our finding that larger firms benefit more than smaller ones aligns with evidence from other settings where firms actively select immigrants, such as the U.S. firm-sponsoring visa system (Mahajan, 2024). This pattern may not hold in contexts where immigrants were readily available to firms, as in France Mitaritonna et al. (2017) or Israel Arellano-Bover and San (2020).

Table 3: Effects of immigration for firms of different size

	Log of Revenues			Immigrant-Native Wage Bill		
	(1) All	(2) Tradable	(3) Non-tradable	(4) All	(5) Tradable	(6) Non-tradable
θ_1	-15.99**	-29.96***	0.425	-2.15	-6.52**	3.65
	(7.79)	(7.98)	(7.30)	(2.04)	(2.75)	(3.58)
θ_2	4.09**	6.93***	0.018	0.54	1.41***	-0.79
	(1.62)	(1.86)	(1.01)	(0.39)	(0.47)	(0.76)
N observations	5,212	2,923	2,289	5,212	2,923	2,289
1st stage F-stat	20.48	22.49	10.49	20.48	22.49	10.49

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. This table reports the 2SLS estimation results of equation 26. We restrict the sample to years between 2008 and 2011, and establishments with more than 10 employees. Standard errors are two-way clustered at the industry and labor market level.

Table 4: Estimated response to immigration by firm size decile

	Size deciles									
Tradable	1	2	3	4	5	6	7	8	9	10
Revenues	-0.71	-0.47	-0.36	-0.28	-0.21	-0.06	0.11	0.34	0.52	1.12
Relative Immigrant WB	-0.17	-0.12	-0.09	-0.08	-0.07	-0.03	0.00	0.04	0.08	0.19
Non-tradable	1	2	3	4	5	6	7	8	9	10
Revenues	0.03	0.03	0.03	0.02	0.02	0.03	0.03	0.02	0.03	0.03
Relative Immigrant WB	0.12	0.08	0.08	0.05	0.03	0.03	0.01	-0.01	-0.03	-0.07

Notes: We use estimates from Table 3 to compute the $\epsilon^y_{j,t}$ for each observation using equation 28. We divide establishments into deciles based on employment and, for each decile and sector, compute the mean value of $\epsilon^y_{j,t}$.

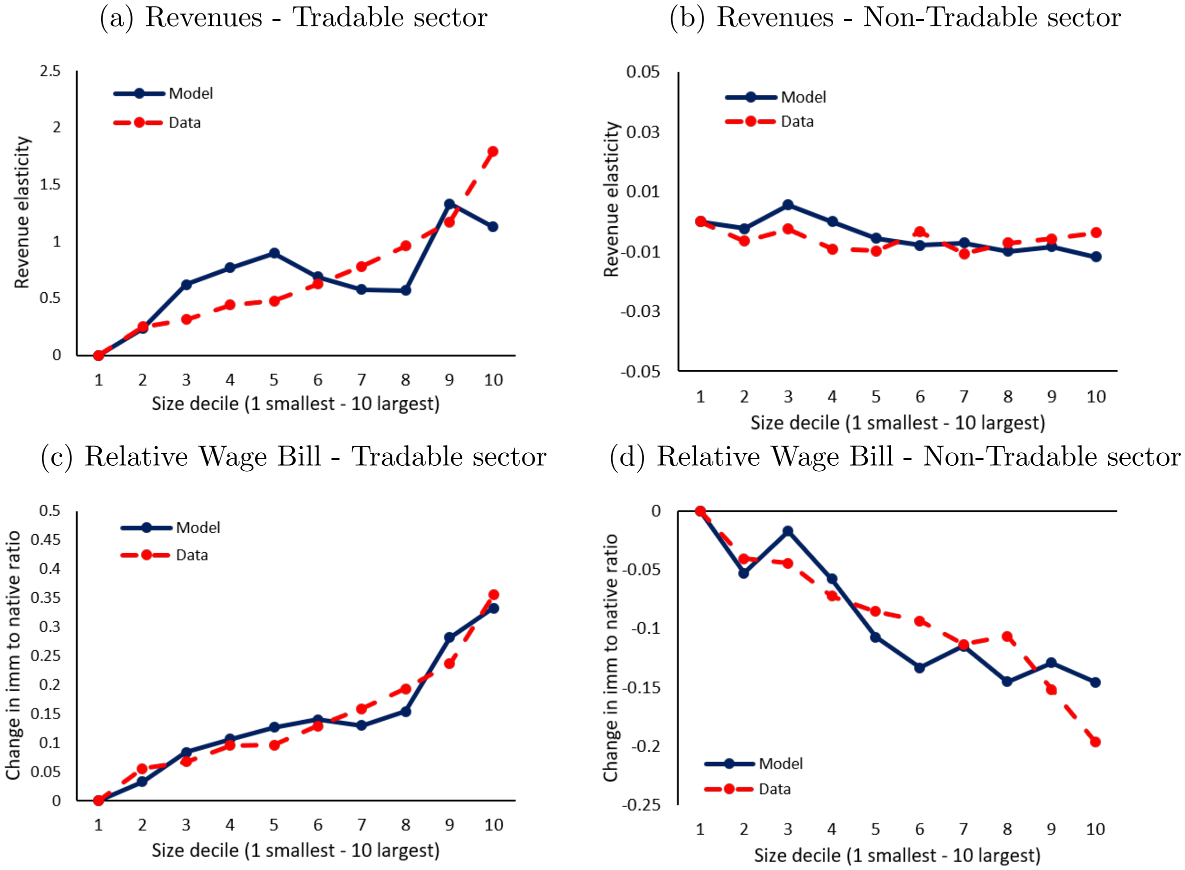
Using the calibrated model, we generate a marginal change (e.g., 1%) in the immigrant share in each sector and compute the change in the two outcome variables of interest: the log of revenues and the wage bill ratio between immigrants and natives.[35] We divide firms into deciles based on their initial size and compute the average response for each decile and sector.

With this model-generated data and the estimates using actual data from Table 4, we construct Figure 7 which treats both datasets in the same way. That is, this figure plots the average effect across all firms in each of the deciles for each sector. While the *levels* of the responses between the data and the model are not directly comparable, the *relative* differences across deciles are. The levels are not comparable because the estimates of the empirical regression identify relative effects, but might not identify the level effect of the shock (this is what the literature refers to as "The Missing Intercept Problem," see Nakamura and Steinsson (2014) and Wolf (2023) for a more in-depth discussion). To explicitly compare the relative differences, we first normalize both the data and the

[35]We lower migration costs such that the total number of immigrants increases by 1% in each sector.

model responses to be zero in the first decile. We then re-scale the model responses to a comparable scale with the data.[36] Figure 7 shows that the changes in the tradable and non-tradable sectors predicted by the model are in line with both the revenue and the relative immigrant-to-native wage bill responses in the data.[37]

Figure 7: Immigration effects by Firm Size: Data vs. Model



(a) Revenues - Tradable sector

(b) Revenues - Non-Tradable sector

(c) Relative Wage Bill - Tradable sector

(d) Relative Wage Bill - Non-Tradable sector

Notes: We rank establishments into size-based deciles, with decile 1 being the smallest. We compute the elasticity of revenues (top panels) and immigrant-to-native wage bill ratio (bottom panels) to a 1% increase in the aggregate immigrant share and calculate the mean elasticity across firms in each decile in each sector. Data values are the same as in Table 4, and model values are generated by reducing migration costs $\psi_{x,k,g}$ to achieve a 1% increase in the aggregate immigrant share in both sectors. We normalize both model and data responses in decile 1 to zero. We then rescale the model responses to be on the same scale as the data, by multiplying them by a constant, which is the average data responses across all deciles relative to the average model responses.

8 Aggregate implications

Having validated our calibrated model, we proceed to use it to study several counterfactuals. Section 8.1 quantifies the economic and welfare effects of an inflow of immigrants into

[36]To do so, we multiply them by the average response in the data across deciles relative to the average response in the model.

[37]A model with no heterogeneity in immigrant shares would predict a flat response across deciles. While this might be a reasonable approximation for the revenues in the non-tradable sector, it would not match the patterns observed in the other plots.

Germany. Section 8.2 quantifies the importance of accounting for firm heterogeneity for these welfare effects. Section 8.3 studies whether the gains from immigration are larger or lower when a country is open to trade due to firm heterogeneity in migrant shares. Finally, Section 8.4 evaluates the aggregate effects of alternative policies that reduce the fixed costs of hiring for specific firms.

8.1 Aggregate adjustment to an exogenous inflow of immigrants

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%.[38] To do so, we reduce the migration cost from the RoW to Germany, $\phi_{x,k,g}$, such that it increases the total stock of immigrants by 20% in each sector.

We compute the welfare of native-born workers as their real labor income:

$$\mathbb{W} = \frac{\sum_{k}(L_{g,k}w_{d,k})/N_g}{P_g} \tag{29}$$

where $L_{g,k}$ is the number of efficient units of native labor in sector k. Table 5 shows that the welfare of native workers would increase by 0.1%, representing \$1.5 billion for the aggregate economy.[39] These gains are fully explained by the drop in the cost of the consumption basket: while nominal wages decrease by 0.06%, prices decrease by 0.16%. Wages decrease in response to immigration because the expansion in production does not fully offset the substitution effect between natives and immigrants, leading to an inward shift in aggregate native labor demand. The positive welfare effects alongside negative wage effects highlight the importance of accounting for changes in the price index when evaluating the impact of immigration, which tends to be absent in empirical work.[40] The welfare gains of firm owners are significantly larger than those of native workers because they experience the same price decreases but do not compete with immigrants in the labor market. Total income, which includes labor income and profits, increases by 1.21% or \$16.8 billion.

[38] This counterfactual does not aim to evaluate specific post-2011 migration events, such as the EU enlargement or the Syrian refugee crisis.

[39] These effects are relatively large. For reference, estimates of the U.S. welfare gains from China's rise in world trade using quantitative general equilibrium trade models are of a similar order of magnitude: Hsieh and Ossa (2016) and Caliendo et al. (2019) estimates are 0.03% and 0.2%, respectively.

[40] A challenge of this literature is estimating the real wage effects of immigration because data availability limits price index computation.

Table 5: Effect of immigration on welfare

	Real Income	Price Index	Nominal Income	Monetary Gains
Native Workers	0.10%	-0.16%	-0.06%	\$1.5B
Firm Owners	1.23%	-0.16%	1.07%	\$15.3B
Total	1.21%	-0.16%	1.05%	\$16.8B

Notes: We compute the changes on endogenous variables of going from the observed equilibrium to an equilibrium where the number of immigrants is 20% higher. The wage in the RoW, w_r, is the numeraire. 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.

Table 6 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. The rise in immigrant intensity and production is associated with increased demand for natives in the non-tradable sector *relative* to the tradable sector, leading to a reallocation of native-born workers from the tradable to the non-tradable sector.

Figure 8 shows the reallocation of natives across firms, which illustrates the intuition laid out in Section 5.1. Firms in the top size decile of the tradable sector, being the most immigrant-intensive, absorb a large share of incoming immigrants, leading to the reallocation of many native workers to other firms (30,000 approximately in total). Given their size, large firms in the non-tradable sector absorb a significant portion of these native workers. This reallocation between firms explains most of the cross-sector reallocation of native workers. Natives also reallocate within sectors toward less immigrant-intensive firms. As previously noted, some small firms in the non-tradable sector with high immigrant shares also displace natives in response to immigration (deciles 3–6), but given their low market shares, the overall effect of this reallocation is limited.

Wages per native worker decline in both sectors, partly because wages per effective unit of native labor fall as the substitution effects of immigration outweigh the scale effect. In the non-tradable sector, the wage drop is also driven by a selection effect: as lower-ability natives move from the tradable to the non-tradable sector, the average ability of workers in the non-tradable sector falls, while it rises in the tradable sector.

These findings contrast with Rybczynski (1955)'s theorem, which predicts that immigration does not affect native-born workers' wages and welfare. This discrepancy arise because this theorem relies on assumptions, including free trade and fixed prices, which ensure that factor prices and factor shares remain unchanged. Under these conditions, an

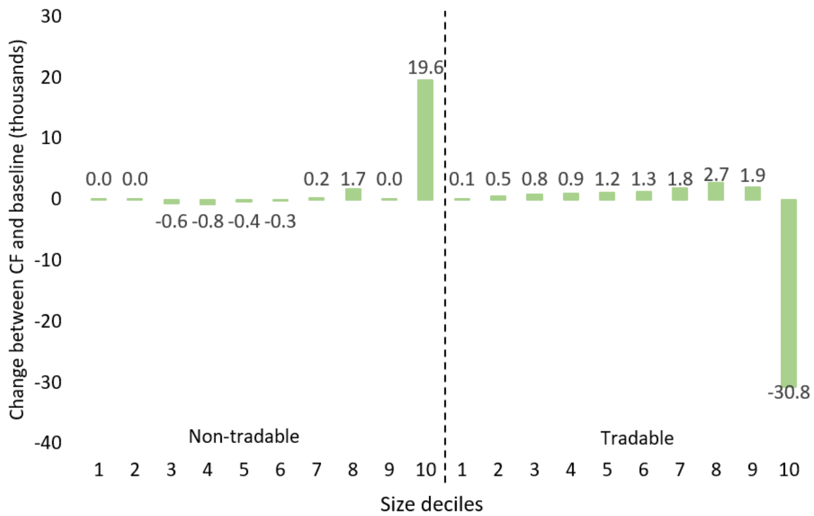
Table 6: Effect of immigration on employment and wages

	Labor units		Effective units	
Employment	Tradable	Non-Tradable	Tradable	Non-Tradable
Total	3.94%	3.29%	6.10%	5.31%
Native	-0.09%	0.20%	-0.08%	0.17%
Immigrant	20.00%	20.00%	16.49%	16.49%
Wages				
Natives	-0.06%	-0.06%	-0.07%	-0.03%
Immigrants	-3.00%	-2.95%	-2.63%	-2.10%

Notes: We compute the changes on endogenous variables of going from the observed equilibrium to an equilibrium where the number of immigrants is 20% higher. The wage in the RoW, w_r, is the numeraire.

economy accommodates the cross-country reallocation of workers by adjusting sectoral trade flows and production: output and net exports expand in the immigrant-intensive sector in the receiving economy while they contract in the native-intensive sector. Since factor shares are fixed, this adjustment occurs only if native workers reallocate from the native-intensive to the immigrant-intensive sector.

Figure 8: Reallocation of natives across sectors and firms.



Notes: The x-axis shows the distribution of firms in the non-tradable (left) and tradable (right) sectors in terms of deciles of revenues. The bars plot the absolute change in thousands of workers employed in each decile between the baseline and the counterfactual scenario of 20% increase in the number of immigrants in each sector.

8.2 The Role of Immigrant Share Heterogeneity on Welfare

In this section, we quantify the importance of the documented heterogeneity in the native workers' welfare effects of immigration. As suggested by the analytical results in Section

5.1, one way to do so is by comparing the effects of an exogenous increase in labor supply $\tilde{S}$ across two models: the *heterogeneous model*, our baseline model, and the *homogeneous model*, which does not have within-industry firm heterogeneity in immigrant shares.[41] In terms of primitives, the homogeneous model differs from the heterogeneous model in that fixed costs to hire immigrants are zero ($f_j = f_{imm,k} = 0$), while the innate firms productivities ψ_j and parameters other than $\sigma_{f,T}, \sigma_{f,NT}, \sigma_{\psi,f,T}$ and $\sigma_{\psi,f,NT}$ remains the same. Thus, the comparison across these models is informative about the role of within-industry firm heterogeneity in immigrant share in the welfare effects of a given immigrant shock $\tilde{S}$. Table 7 shows the effects of the inflow considered in the previous subsection for both the heterogeneous and homogeneous models. The homogeneous model underestimates the welfare gains by 54% (0.05pp) because it predicts a stronger drop in native-born workers' income and a weaker drop in the price index.[42] This result aligns with the two mechanisms highlighted in Section 5.1. On one hand, immigration increases the specialization of immigrants and natives in producing different varieties, which weakens the competition faced by natives in the labor market and reduces the downward pressure on their wages. On the other hand, the stronger drop in prices in the heterogeneous model follows from the additional decline in unit production costs and by being concentrated among larger firms, which have a greater weight in consumers' consumption baskets.[43]

Table 7: Welfare effects with and without firm heterogeneity in the immigrant share

	Open to Trade			Trade Autarky		
	Welfare Workers	Nominal Wage	Price Index	Welfare Workers	Nominal Wage	Price Index
Heterogeneous s_j	**0.10%**	-0.06%	-0.16%	**0.12%**	0.01%	-0.11%
Homogeneous within-sector s_j	**0.05%**	-0.07%	-0.12%	**0.06%**	-0.03%	-0.09%
Homogeneous/Heterogeneous	**54%**					

Notes: 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 and the homogeneous model does not have within-industry firm heterogeneity in immigrant shares.Columns 1-3 compare the effect for an economy open to trade. Columns 4-6 show the effects for a closed economy.

These results highlight the importance of accounting for the substantial heterogeneity in immigrant-native hiring decisions across firms within industries. Immigration triggers a reallocation of native workers across firms, with quantitatively significant aggregate implications.[44]

[41] Alternatively, one could compare the effects of the same change in the model primitives (e.g., drop in migration costs). This comparison yields an almost identical quantitative conclusion as in Table 7.

[42] The homogeneous model's welfare effects aligns with Caliendo et al. (2021), who finds that EU labor market integration raised original members' welfare by 0.04% using a model without firm heterogeneity.

[43] The main price differences between the two models lie mainly in how the tradable sector adjusts.

[44] An alternative exercise would be to assess the value of having firm-level data on immigrant employment available. In this case, we would re-calibrate the homogeneous model to match the same moments as the heterogeneous model. This homogeneous model underestimates the gains by 11%.

8.3 The Quantitative Role of Trade

Motivated by the discussion in section 5.1, this section studies quantitatively whether the gains from immigration are larger or lower when a country is open to trade *due to firm heterogeneity in immigrant shares.* We do so by quantifying the double-difference stated in equation 20 using our fully-fledged quantitative model. We need to know $\tilde{\mathbb{W}}^{heterog,open}$, $\tilde{\mathbb{W}}^{heterog,open}$, $\tilde{\mathbb{W}}^{homog,open}$ and $\tilde{\mathbb{W}}^{homog,closed}$. Given that we already computed the $\tilde{\mathbb{W}}^{heterog,open}$ and $\tilde{\mathbb{W}}^{homog,open}$, we only need to compute the welfare effects in the economy under autarky. To compute $\tilde{\mathbb{W}}^{heterog,closed}$, we proceed in two steps. First, starting from the baseline equilibrium with heterogeneous firms and trade openness, we eliminate international trade by raising iceberg trade costs high enough. This resulting new equilibrium serves as the initial equilibrium in this economy under trade autarky. Second, we induce the same $\tilde{S}$ as before and compute the real wage change for native-born workers, $\tilde{\mathbb{W}}^{heterog,closed}$. To compute $\tilde{\mathbb{W}}^{homog,closed}$, we follow the same two-step procedure, but now the starting point is the equilibrium with homogeneous firms and trade openness.

We find that international trade dampens the gains from immigration, with the vast majority of this dampening effect explained by the differential importance of firm heterogeneity. In particular, we find that the welfare gains in an economy with heterogeneous migrant shares under trade autarky is 0.123%, which is 27% (0.026pp) larger than the 0.10% gains in the baseline economy (e.g., $\tilde{\mathbb{W}}^{heterog,closed}/\tilde{\mathbb{W}}^{heterog,open} = 1.27$). The welfare gains with homogeneity in immigrant shares are $\tilde{\mathbb{W}}^{homog,open}$ and $\tilde{\mathbb{W}}^{homog,closed}$ are 0.052% and 0.056% respectively, suggesting that terms-of-trade effects dampen the gains from immigration by 0.004 pp (15% of the total dampening effects), while differences in firm heterogeneity further reduce these gains by 0.022 pp (85% of the total dampening effects).

These findings indicate that, given current levels of international trade, firm heterogeneity in migrant shares plays a key role in dampening the gains from immigration. Ignoring this heterogeneity may significantly underestimate the role of international trade in mitigating the gains from immigration.

8.4 Comparing policies that affect firm heterogeneity

Beyond policies that affect migration costs or the number of immigrants in the country, as studied in prior literature and in our previous sections, we can also study policies that alter the hiring costs of immigrants for specific firms.

In Section 4, we mentioned that the German government implemented policies to reduce the frictions faced by small and medium enterprises (SMEs) for recruiting immigrants. These policies motivate our first counterfactual analysis, referred to as "Policy 1". We divide firms into two groups based on whether their productivity ψ_j is above or below the median. The policy lowers the immigrant recruitment cost f_j for below-median productivity firms to the 10th percentile of the f_j distribution. We compare it with three alternative policies to shed light on how policies that alter the distribution of firms' immigrant intensities can affect aggregate outcomes. An alternative policy reduces frictions by the same total amount but for firms in the top half of the productivity distribution ("Policy 2"). This policy aligns with efforts to facilitate hiring by large firms, such as the U.S. L-1 visa program, which allows multinational companies to transfer employees across subsidiaries and streamline applications for multiple workers in the same role. While Policies 1 and 2 are not sector-specific, they primarily affect non-tradable firms because they face higher frictions for hiring immigrants. This motivates two additional policies: reducing frictions in the tradable sector by the same total amount, either for firms below the sector's median productivity ("Policy 3") or for those above it ("Policy 4").[45]

We begin by studying Policy 1's effect on aggregate outcomes (Column 1 of Table 8). Appendix Figure H2a plots the reallocation of immigrants and native workers across sectors and productivity deciles. The policy substantially raises immigrant employment in below-median productivity firms within the non-tradable sector, while the increase in the tradable sector is modest. This difference across sectors arises for two main reasons. First, non-tradable firms face higher initial costs f_j than firms in the tradable sector, so reducing these costs to the 10th percentile represents a larger relative shock. Second, low-productivity firms in the tradable sector hold a much smaller market share within their industry.[46] As a result, even with lower fixed costs, unproductive firms in the tradable sector remain at a steep disadvantage relative to their domestic competitors and see modest expansion in hiring or production. The increase in immigrant hiring by small firms in the non-tradable sector crowds out native coworkers, who relocate to higher productivity firms in both sectors. Regarding the aggregate effects of the policy, real earnings for native workers increase but only slightly due to countervailing effects. On one hand, immigrant employment increases, which pushes prices down for all consumers by 0.15%. On the other hand, the influx of immigrants reduces native-born wages due to higher labor market competition in the non-tradable sector. Natives mitigate such losses by moving to the tradable sector, but overall earnings decrease by 0.11%. While native-born workers' earnings decline, firm owners' income rises due to higher profits, leading to a net total income increase of 0.32% for Germans.

We now turn to the analysis of alternative policies, highlighting how aggregate outcomes

[45] We also study the effects of removing the cost to start hiring immigrants $f_{imm,k}$ (see Appendix H.1).

[46] For reference, while the top decile of tradable firms accounts for 90% of production in that sector, the top decile in the non-tradable sector produces only 30%.

differ relative to Policy 1. Lowering f_j for firms at the top of the productivity distribution (Policy 2) primarily increases immigrant employment by top-productivity firms in the non-tradable (see Appendix Figure H2b). The aggregate effects more than double those of Policy 1 because of two reasons. First, the total inflow of immigrants is more than double that under Policy 1 because the affected firms are larger and their production and immigrant labor demand is more elastic to drops in immigrant hiring costs. Second, larger firms account for a larger share of the consumption basket of consumers, so a drop in the price of their goods induces a stronger drop in the price index of consumers. Lowering fixed costs for firms in the tradable sector below the median productivity (Policy 3) has no better effects on the aggregate economy than Policy 1. This policy is not effective because, as mentioned before, a drop in hiring costs is not enough for the below-median productivity firms to overcome productivity differences within the sector and expand (see Appendix Figure H2c for details of labor adjustment). Finally, lowering fixed costs for high-productivity firms in the tradable sector (Policy 4) yields better outcomes for native workers and overall welfare. Large tradable firms face more elastic demand, and can expand production without significantly lowering prices. This implies that when high-productivity firms in the tradable sector increase immigrant employment (see Appendix Figure H2d), they do not reduce the prices of other factors as much as firms in the non-tradable sector would.

Table 8: Aggregate effects of alternative immigration policies

	Policy 1	Policy 2	Policy 3	Policy 4
Total income	0.32%	0.83%	0.02%	1.95%
Earnings Natives	-0.11%	-0.24%	0.00%	0.03%
Price Index	-0.15%	-0.31%	-0.01%	-0.08%
Real Earnings Natives	0.04%	0.07%	0.00%	0.11%
Real Wages per efficiency units				
Natives - T	0.09%	0.18%	0.00%	-0.02%
Natives - NT	-0.08%	-0.17%	0.01%	0.40%
Immigrants - T	0.14%	0.62%	0.07%	4.26%
Immigrants - NT	2.52%	5.06%	0.01%	0.38%
Employment				
Natives - T	0.32%	0.65%	-0.01%	-0.80%
Natives - NT	-0.72%	-1.46%	0.03%	1.80%
Immigrants - T	0.84%	3.81%	0.43%	29.02%
Immigrants - NT	16.50%	35.28%	0.04%	2.18%
Immigrants	4.36%	10.42%	0.26%	17.56%

Notes: The table shows the change in endogenous variables of four counterfactual reductions in f_j. Policy 1 reduces f_j to the firms with productivity ψ below the median of the economy. This fixed cost is lowered to the 10th percentile of the distribution. The three alternative policies reduce fixed costs by the same total amount but for firms in the top half of the productivity distribution (Policy 2), for the bottom half of firms in the tradable sector (Policy 3), and for the top half of firms in the tradable sector (Policy 4).

Overall, our findings suggest that policies that target highly productive firms in tradable sectors might have the best outcomes for both labor and total income. Also note than this policy increases the number of immigrants by 17.56%, a smaller inflow than in our baseline counterfactual, yet it leads to a larger rise in welfare. Thus, firm-targeted immigration policies that reduce fixed cost to hire immigrants is a rich policy tool capable of achieving better aggregate outcomes than policies focused solely on inflow size.

9 Conclusion

This paper documents significant heterogeneity in immigrant share across employers, with larger firms being more immigrant-intensive than smaller firms due to fixed costs of hiring immigrants. Based on these facts, we set up a model to study the welfare implication of firm heterogeneity in immigrant shares for the welfare effects of immigration. We show analytically that the sign of the bias depends on whether the elasticity of substitution between immigrants and natives within the firm is larger or smaller than the elasticity of demand. The magnitude of the bias depends on these elasticities and also on the joint distribution between firm size and immigrant share.

We calibrate the model to match our novel evidence and use it to study the effects of a 20% increase in the number of immigrants. We find that the welfare gains of native-born workers and firm owners are 0.10% and 1.23%, respectively. In monetary terms, these gains amount to $1.5 billion for native workers and $15.3 billion for firm owners. A model without within-industry heterogeneity in immigrant shares predicts the welfare gains for native workers would be approximately 50% lower. This means that immigration induces a reallocation of resources across firms with quantitatively important aggregate implications. We also find that firm heterogeneity in immigrant share is important for the role of international trade in mitigating the welfare gains from immigration. We use our model to study alternative policies that reduce the hiring frictions for specific firms. Finally, we find that policies that reduce frictions for large firms in the tradable sector have larger aggregate effects for natives. Our results also imply that this type of firm-targeted immigration policy can achieve better aggregate outcomes than policies focused solely on inflow size.

References

Altonji, J. G. and D. Card (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, Trade, and the Labor Market*, pp. 201–234. University of Chicago Press.

Amior, M. and J. Stuhler (2024). Immigration, Monopsony and the Distribution of Firm Pay. *Working paper*.

Arellano-Bover, J. and S. San (2020). The Role of Firms in the Assimilation of Immigrants. *Working Paper*.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012). New Trade Models, Same Old Gains? *American Economic Review 102*(1), 94–130.

Beerli, A., J. Ruffner, M. Siegenthaler, and G. Peri (2021). The Abolition of Immigration Restrictions and the Performance of Firms and Workers: Evidence from Switzerland. *American Economic Review 111*(3), 976–1012.

Blaum, J. (2024). Global Firms in Large Devaluations. *The Quarterly Journal of Economics 139*, 2427–2474.

Blaum, J., C. Lelarge, and M. Peters (2018). The Gains from Inp Trade with Heterogeneous Importers. *American Economic Journal: Macroeconomics 10.*

Bonadio, B. (2023). Migrants, Trade and Market Access. *The Review of Economics and Statistics*.

Borusyak, K., P. Hull, and X. Jaravel (2021). Quasi-Experimental Shift-Share Research Designs. *Review of Economic Studies*.

Brinatti, A., A. Cavallo, J. Cravino, and A. Drenik (2023). The international price of remote work. Technical report, National Bureau of Economic Research.

Brinatti, A. and X. Guo (2024). Third-Country Effects of U.S. Immigration Policy. *Working paper*.

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

Burstein, A., G. Hanson, L. Tian, and J. Vogel (2020). Tradability and the Labor-Market Impact of Immigration: Theory and Evidence from the U.S. *Econometrica 88*(3), 1071–1112.

Burstein, A. and J. Vogel (2017). International Trade, Technology, and the Skill Premium. *Journal of Political Economy 125*(5), 1356–1412.

Busch, C., D. Krueger, A. Ludwig, I. Popova, and Z. Iftikhar (2020). Should germany have built a new wall? macroeconomic lessons from the 2015-18 refugee wave. *Journal of Monetary Economics 113*, 28–55.

Caliendo, L., M. Dvorkin, and F. Parro (2019). Trade and labor market dynamics: General equilibrium analysis of the china trade shock. *Econometrica 87*(3), 741–835.

Caliendo, L., F. Monte, and E. Rossi-Hansberg (2015). The Anatomy of French Production Hierarchies. *Journal of Political Economy 123*(4), 809–852.

Caliendo, L., L. Opromolla, F. Parro, and A. Sforza (2021). Goods and Factor Market Integration: A Quantitative Assessment of the EU Enlargement. *Journal of Political Economy*. Forthcoming.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics 19*(1), 22–64.

Card, D., B. Dostie, J. Li, and D. Parent (2023). Employer Policies and the Immigrant-Native Earnings Gap. *Journal of Econometrics 233*(2), 544–567.

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly journal of economics 128*(3), 967–1015.

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

Cortes, P. (2008). The effect of low-skilled immigration on u.s. prices: Evidence from cpi data. *Journal of Political Economy 116*(3), 381–422.

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

D'Amuri, F., G. Ottaviano, and G. Peri (2010). The Labor Market Impact of Immigration in Western Germany in the 1990s. *European Economic Review 54*, 550–570.

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

di Giovanni, J., A. Levchenko, and F. Ortega (2015, February). A Global View of Cross-Border Migration. *Journal of the European Economic Association 13*(1), 168–202.

Dustmann, C. and A. Glitz (2015, July). How Do Industries and Firms Respond to Changes in Local Labor Supply? *Journal of Labor Economics 33*(3), 711–750.

Egger, D., D. Auer, and J. Kunz (2022). Effects of Migrant Networks on Labor Market Integration, Local Firms and Employees. *Working Paper*.

Fan, J. (2019, July). Internal geography, labor mobility, and the distributional impacts of trade. *American Economic Journal: Macroeconomics 11*(3).

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review 110*(8), 2586–2624.

Gyetvay, S. and S. Keita (2024). Competition, Mobility and Immigration. *Working paper*.

Hanson, G. and C. Liu (2023). Immigration and Occupational Comparative Advantage. *Journal of International Economics 145*(103809), 369–394.

Heining, J., W. Klosterhuber, P. Lehnert, and S. Seth (2016). Linked Employer-Employee Data from the IAB:LIAB Cross-sectional model 2 1993 – 2014 (LIAB QM2 9314). *FDZ-Datenreport, 10/2016 (en), Nuremberg*.

Hiller, S. (2013). Does Immigrant Employment Matter for Export Sales? Evidence from Denmark. *Review of World Economics / Weltwirtschaftliches Archiv 149*(2), 369–394.

Hsieh, C.-T., E. Hurst, C. Jones, and P. Klenow (2019). The Allocation of Talent and U.S. Economic Growth. *Econometrica 87*(5), 1439–74.

Hsieh, C.-T. and R. Ossa (2016). A global view of productivity growth in china. *Journal of international Economics 102*, 209–224.

Kerr, S. P., W. R. Kerr, and W. F. Lincoln (2015). Skilled Immigration and the Employment Structures of U.S. Firms. *Journal of Labor Economics 33*(S1), S147–S186.

Khanna, G. and N. Morales (2025). The IT Boom and Other Unintended Consequences of Chasing the American Dream. *Working Paper*.

Kropp, P. and B. Schwengler (2011). Delineation of Functional Labour Market Regions : a Methodological Approach. *Raumforschung und Raumordnung 69*(1), 45–62.

Lashkari, D., A. Bauer, and J. Boussard (2024). Information technology and returns to scale. *American Economic Review 114*(6), 1769–1815.

Lee, E. (2020). Trade, Inequality, and the Endogenous Sorting of Heterogeneous Workers. *Journal of International Economics 125*.

Mahajan, P. (2024). Immigration and Local Business Dynamics: Evidence from U.S. Firms. *Journal of the European Economic Association 22*(6), 2827–2869.

Mahajan, P., N. Morales, K. Shih, M. Chen, and A. Brinatti (2025). The Impact of Immigration on Firms and Workers: Insights from the H-1B Lottery. *Working paper*.

Mandelman, F., M. Mehra, and H. Shen (2024). Skilled Immigration Frictions as a Barrier for Young Firms. *Working Paper*.

Mehra, M. and H. Shen (2022, November). Skilled Immigration, Firms, and Policy. *Journal of International Economics 139*(103662), S225–S255.

Melitz, M. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*, 1695–1725.

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

Morales, N. (2025). High-skill Migration, Multinational Companies and the Location of Economic Activity. *The Review of Economics and Statistics*.

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

Oberfield, E. and D. Raval (2014). Micro Data and Macro Technology. Technical report, National Bureau of Economic Research.

Oberfield, E. and D. Raval (2021). Micro data and macro technology. *Econometrica 89*(2), 703–732.

OECD (2013). *Recruiting Immigrant Workers: Germany 2013*.

Orefice, G. and G. Peri (2024). Immigration and Firm-Worker Matching. *The Review of Economics and Statistics*.

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

Ottaviano, G. I., G. Peri, and G. C. Wright (2018). Immigration, Trade and Productivity in Services: Evidence from UK Firms. *Journal of International Economics 112*, 88–108.

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

Peri, G. and C. Sparber (2011). Highly-Educated Immigrants and Native Occupational Choice. *Industrial Relations Vol. 50 (3)*, 385–411.

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

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers 3*, 135–146.

Rybczynski, T. (1955). Factor Endowment and Relative Commodity Prices. *Economica 22*(88), 336–341.

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

Satō, K. (1975). *Production functions and aggregation*, Volume 90. North-Holland Publishing Company.

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

A Summary statistics and institutional background

A.1 Summary statistics

In Table A1, 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 A1: 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%

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

A.2 Institutional Background

In this paper, we focus on the period from 2003 to 2011. During that time, the immigration system in Germany had different requirements depending on the origin of the immigrant workers. At the start of the 21st century, Germany's labor immigration system was largely protectionist, prioritizing EU citizens for job vacancies. Employers who sought to hire non-EU workers had to navigate stringent bureaucratic processes, including the "labor market test", which required proving that no German or EU citizen could fill the position.

Citizens of countries who joined the EU before 2004 (Belgium, France, Italy, Luxembourg, the Netherlands, Denmark, Ireland, the United Kingdom, Greece, Portugal, Spain, Austria, Finland, and Sweden) were free to look for a job without requiring employment sponsorship. During this time period, citizens from other countries were required to have an offer of employment and fulfill certain residence requirements (e.g., evidence of means of subsistence during residence) to receive a permit for employment in Germany. Immigrants also need to obtain consent from the Federal Employment Agency to obtain employment. In 2011, Germany opened its labor market to 10 "New Member States" who joined the EU in 2004: Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia. Citizens of these countries were no longer required to obtain employment sponsorship to move and look for work in Germany.

B Empirical Facts - Extensions

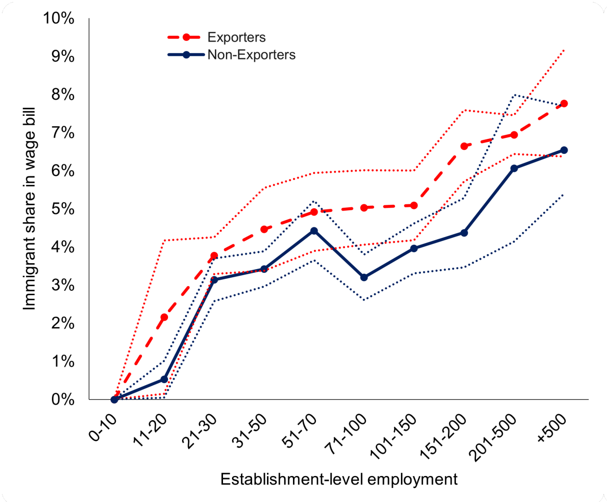
B.1 Additional Facts on Heterogeneity Across Firm Size

We begin by recreating our main fact but splitting the sample of firms between exporters and non-exporters as shown in Figure B1a. We show that while it is true that exporters have a steeper correlation between size and immigrant share, non-exporters also show a positive correlation. In fact, the difference between exporters and non-exporters is not statistically different, which indicates that our fact cannot be solely explained by immigrants and trade. If it were only explained by trade, we would expect this pattern to only be present for exporters. Second, in Figure B1b we plot the same fact, removing industry and labor market fixed effects, effectively comparing firms within the same industry and labor market. Surprisingly, once we remove these fixed effects we find that non-exporters actually have a steeper slope than exporters, as exporters are likely located in regions and industries that are larger immigrant destinations.

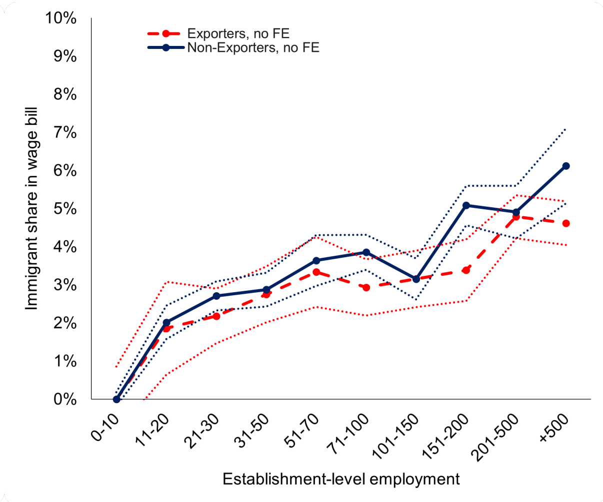
Second, we show that our baseline fact cannot solely be explained by large firms having different skill intensities. Large firms tend to be more intensive in high-skill labor (Burstein and Vogel, 2017), and if immigration policy in Germany were skewed toward workers with a specific education group, this could drive the relationship between size and immigrant intensity. However, as shown in Figure B1c, the relationship between size and immigration holds for workers with and without a college education. Finally, in Figure B1d we also show our fact holds when excluding multinational companies and when looking at firms that are not part of a multi-establishment firm. 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. However, these theories would not rationalize that larger firms also hire workers from more countries, and expand their immigrant share by

Figure B1: Heterogeneity in hiring immigrants across firms - additional facts

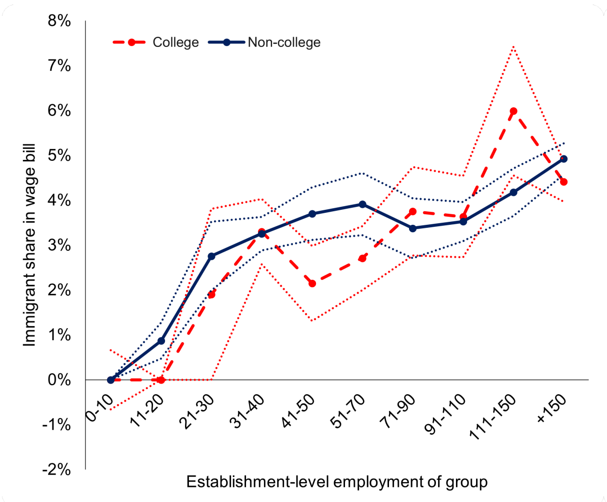
(a) Exporter status



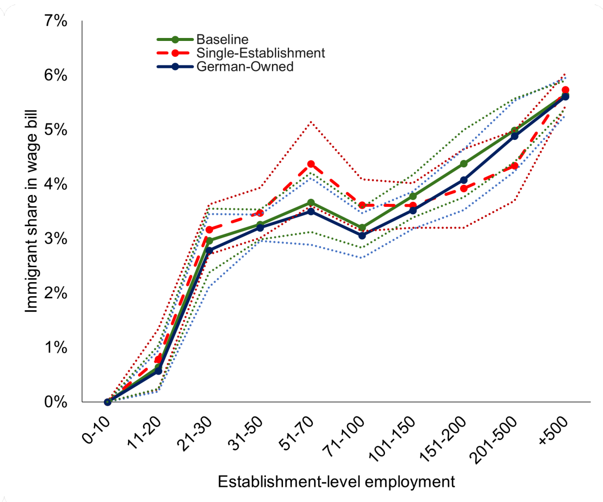
(b) Exporter status, no industry, location



(c) College vs non-college



(d) Multinationals and multi-unit firms



Notes: We divide all establishments into 10 bins according to their reported employment. For each bin, we plot the median immigrant share of the wage bill across firms. In Figure B1a we divide the sample between firms that report positive exports that year and firms that do not. In Figure B1b we do the same split, but first we regress immigrant shares on 3-digit industry and local labor market fixed effects, and plot the residual. We normalize decile 1 to zero for both exporters and non-exporters. Figure B1c classifies establishments into bins according to their non-college (college) employment and plots for each bin the median share of non-college (college) immigrant wage bill as a share of the non-college (college) workforce. Figure B1d shows the main fact when excluding companies that are foreign-owned (blue line) and companies that are part of a multi-establishment firm (red line).

increasing the number of source countries as we discuss in Section 4.

B.2 Descriptive 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 it hires immigrants from. In the data, countries of origin are grouped in nine blocks as explained in Section 2.

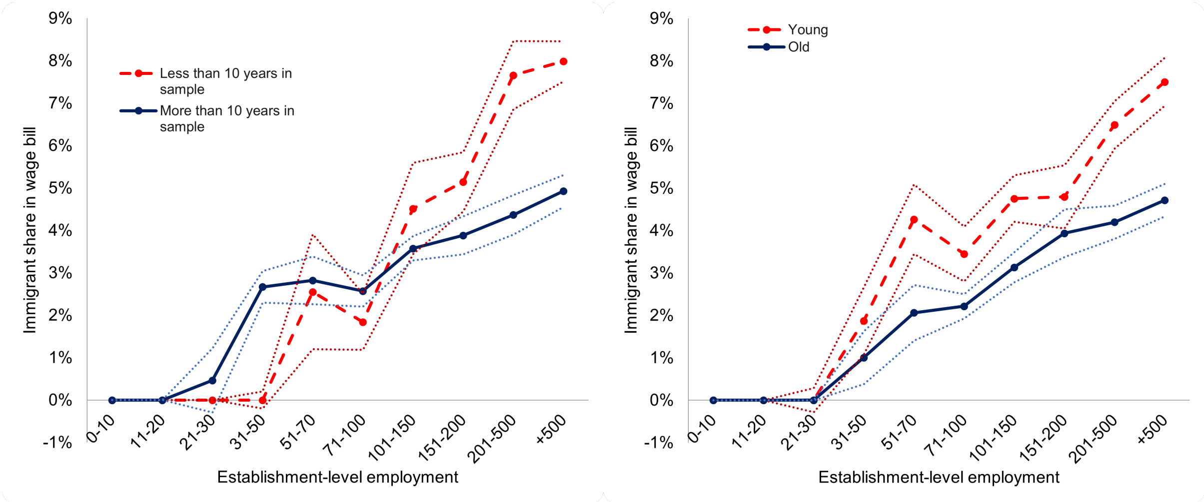
We begin by looking at evidence on the overall cost of hiring immigrants. First, we assess whether the fixed costs to hire immigrants may depend on the time spent in Germany by plotting a figure analogous to the motivating figure for long-term and recent immigrants. We classify workers as long-term or recent immigrants following two common criteria. First, we look at how different our firm heterogeneity looks when comparing immigrants who resided in Germany for over 10 years relative to newer arrivals, inferred from their first appearance in our dataset. We compute the firm-level share of immigrants in a given tenure group as a share of total employees with a similar tenure in our dataset (Figure B2a). Since natives' tenure in the dataset tends to be when they join the labor market while immigrants might have experience before coming to Germany, we look at a second specification where we classify workers into two age groups, whether they are above or below 40 (Figure B2b). This is correlated with time since arrival, as immigrants often arrive in their 20s or early 30s.

Figure B2 shows that the heterogeneity in immigrant share across the firm size distribution is more pronounced among recent immigrants. However, in both cases, the slope for older workers does not flatten completely, indicating that fixed costs associated with hiring immigrants persist relative to hiring natives. This observation is consistent with findings from the existing immigration literature. For example, Peri and Sparber (2009) find that long-term immigrants (over 10 years in the country) perform tasks more similar to natives than recent immigrants, though differences with natives do not fully disappear. Specifically, natives tend to specialize in tasks requiring greater language proficiency compared to long-term immigrants, which German firms have identified as one of the main obstacles to hiring immigrants. There is also persistence in employment, where immigrants might find jobs at big firms when arriving in the country, and then stay at those firms as their career progresses.

As a second step, we test whether the observed dynamics after starting to hire immigrants is consistent with firms paying a fixed cost. Once firms begin to hire migrants, we should observe a jump in hiring for the initial period followed by a drop toward steady-state levels of hiring thereafter. If there was no fixed cost, firms could begin hiring small amounts and expand their hiring over time. We focus on firms that did not hire immigrants and look at their hiring dynamics after the first period in which they begin hiring. To avoid having our results driven by firms that only hire one immigrant and do not hire again, we restrict the sample to firms that hire at least 5 migrants in our period of study. As these sample restrictions are quite stringent, we use the SIEED dataset for this exercise, as we have a larger sample of firms and a longer time-frame which allows us to focus on the small group of firms that begin to hire migrants and continue to do so throughout

Figure B2: Differences in heterogeneity across sub-groups

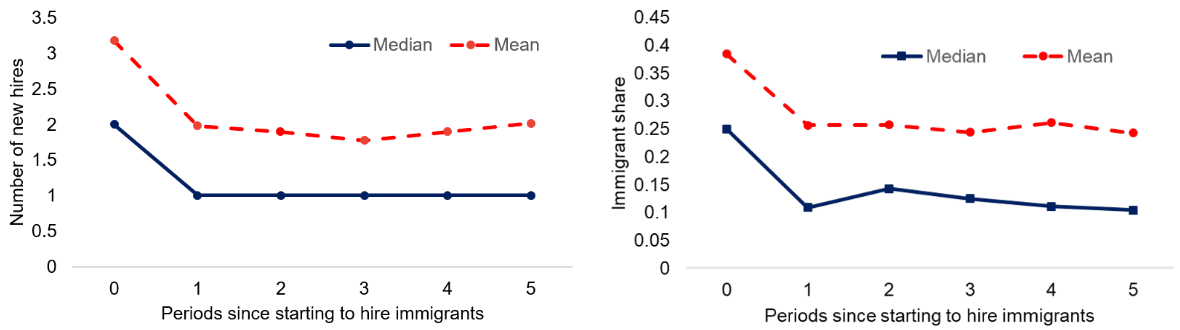
(a) By tenure in the sample (b) By age



Notes: We divide all establishments into 10 bins according to their reported employment. For each bin, we plot the median immigrant share of the wage bill by sub-group across firms. In Figure B2a compute the immigrant share among workers with more (less) than 10 years of tenure in the sample. In Figure B2b, we compute the immigrant share among workers that are above and below 40 years old.

Figure B3: Hiring dynamics after starting to hire immigrants

(a) Number of immigrant new hires (b) Immigrant share among new hires



Notes: We restrict the sample to firms that begin to hire immigrants at some point between 2003 and 2010. We then compute the number of new hires that are immigrants each period and the share among new hires that are immigrants. We restrict the sample to those firms that hire at least 5 immigrants during the period. For this specific analysis, we use the SIEED dataset.

the period.

As shown in Figure B3a, there is a jump in the number of immigrant new hires, where the average firm hires 3.2 new migrants in the first period and then stabilizes at 2 new migrants every period after that. A similar picture is presented in Figure B3b, when looking at the immigrant share of new hires, which jumps to 40% of hires being migrants and then stabilizes at below 30%.

Third, we show that firms that increase the number of sourcing countries tend to do so by adding a single additional origin, as opposed to multiple origins at the same time. Each row in Table B1 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 B1: Number of immigrant origin countries

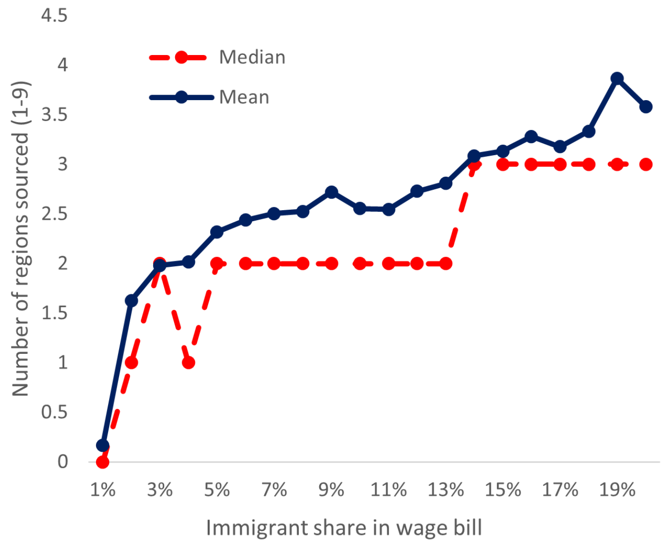
Nc_{t-1}	Nc_t									
	0	1	2	3	4	5	6	7	8	9
0	5,108	368	41	*	*	*	*	*	*	*
1		2,014	319	64	*	*	*	*	*	*
2			1,160	259	47	*	*	*	*	*
3				766	179	40	*	*	*	*
4					512	144	33	*	*	*
5						125	372	106	26	*
6							332	107	26	*
7								310	88	*
8									436	70
9										406

Notes: 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.

Finally, firms hiring immigrants from more countries tend to be more immigrant-intensive. This is exactly what the model predicts in equation 11 and is corroborated by Figure B4, where we group firms by the percentage of their payroll spent on immigrants. Figure B4 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 with the number of sources countries, Table B2 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

Figure B4: Number of origin regions by immigrant share



Notes: We group establishments 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.

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 B2: 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

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. 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.

In practice, these fixed costs can be paid either at the firm-level or the establishment-level. However, we do not observe which establishments belong to the same firm in our data. It is reassuring that, as shown in Figure B1d, our main fact is almost identical when looking at single-establishment firms. While fixed costs such as setting up a legal department and HR protocols might be incurred at the firm level, recruitment related costs such as learning how to search and screen for suitable candidate are plausible to take place at the establishment level.

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.3 Event Study Analysis - Extensions

Table B3: Alternative outcomes and size breakdowns

	$\text{Employment}_{o,j,t}$	$\text{New Hires}_{o,j,t}$	$\text{New entrants}_{o,j,t}$	$\text{Immigrant share}_{o,j,t}$
	Relative to bottom 3 groups			
$\theta_t \mathbb{1}(o \in NMS)$	0.00627***	0.00301***	0.00161***	0.0317***
	(0.0005)	(0.0003)	(0.0002)	(0.004)
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 4)$	-0.00456***	-0.00193***	-0.00135***	-0.0451
	(0.001)	(0.0005)	(0.0003)	(0.028)
	Relative to the largest group			
$\theta_t \mathbb{1}(o \in NMS)$	0.00467***	0.00198***	0.00136***	0.0424
	(0.00106)	(0.000524)	(0.000270)	(0.0275)
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 1)$	0.00505***	0.00206***	0.00136***	0.0393
	(0.001)	(0.0005)	(0.0003)	(0.028)
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 2)$	0.00275*	0.00135**	0.00144***	0.0489*
	(0.0011)	(0.0005)	(0.0003)	(0.028)
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 3)$	0.00154	0.000346	0.000466	0.0683**
	(0.00149)	(0.000690)	(0.000298)	(0.0335)
N	723824	723824	723824	123920

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$, SE are clustered at firm level. In column 1 the outcome is the firm-level employment of workers from o relative to the firm total employment in 2010. Column 2 shows new hires from o relative to employment in 2010. Column 3 uses the outcome of new entrants to the labor market from origin o relative to firm employment in 2010. Column 5 plots the share of nationality o among all immigrants employed by the firm. The top panel includes the interaction between the treated nationality and the largest size bin (+200 employees) while the bottom panel includes the interactions between the treated nationality and each of the three bottom groups (1-29, 30-99, 100-199 employees respectively). All specifications include origin-firm and firm-time fixed effects. We restrict the sample to firms that did not hired from treated and control nationalities in 2005.

Table B4: Robustness to alternative samples

	$\text{Employment}_{o,j,t}$	$\text{Employment}_{o,j,t}$	$\text{Employment}_{o,j,t}$
$\theta_t \mathbb{1}(o \in NMS)$	0.00741***	0.00627***	0.00607***
	(0.0006)	(0.0005)	(0.0006)
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 4)$	-0.00304**	-0.00456***	-0.0017
	(0.0014)	(0.001)	(0.0014)
Sample	Full sample	Not hiring in 2005	More than 10 employees
N	769128	723824	171412

Notes: $* * *p < 0.01, * * p < 0.05, *p < 0.1$, SE are clustered at firm level. Column 1 presents the results for the full sample of firms, column 2 (our baseline) presents the results for firms that did not hired from treated and control nationalities in 2005, column 3 restricts to firms that have more than 10 employees in 2010. All specifications include origin-firm and firm-time fixed effects. The outcome is the employment of nationality o by firm j relative to its total 2010 employment.

Table B5: Robustness to alternative fixed effects

	$\text{Employment}_{o,j,t}$	$\text{Employment}_{o,j,t}$	$\text{Employment}_{o,j,t}$	$\text{Employment}_{o,j,t}$
$\theta_t \mathbb{1}(o \in NMS)$	0.00627***	0.00632***	0.00627***	-
	(0.0005)	(0.0005)	(0.0005)	
$\theta_t \times \mathbb{1}(j \in g = 4)$	-	0.0000323	-0.00342***	-
		(0.0011)	(0.0007)	
$\theta_t \mathbb{1}(o \in \text{NMS}) \times \mathbb{1}(j \in g = 4)$	-0.00456***	-0.00460***	-0.00456***	-0.00502***
	(0.001)	(0.001)	(0.001)	(0.001)
Origin-firm	x	x	x	x
Firm-time	x			x
Origin-time				x
Industry-time market-time		x		
Time			x	
N	723824	720272	723824	723824

Notes: $***p < 0.01, **p < 0.05, *p < 0.1$, SE are clustered at firm level. We restrict the sample to firms that did not hired from treated and control nationalities in 2005. The outcome is the employment of nationality o by firm j relative to its total 2010 employment.

B.4 Differences between immigrants and natives at the firm

This section provides evidence of the dimensions along which immigrants and natives are different. We begin by using raw data to document that immigrants from different countries tend to specialize in different tasks or occupations than natives and have different "bundles of demographics", such as age, gender, and education. We then show that demographic characteristics and unobservable region-specific characteristics may explain productivity differentials (or comparative advantages) consistent with the observed occupational sorting.

Inspired by the literature started by Roy (1951), we measure sorting into occupations as the share of immigrants from a given country choosing occupation *occ* relative to that share for German workers. This measure is shown in panel A of Table B6. Panel B shows the average age, the share of workers that are females, and the share of workers that have earned a college degree for the same group of countries, relative to Germans.

Table B6 highlights substantial heterogeneity in occupational sorting and demographics across workers from different nationalities. The average German worker is 39 years old, has a 13% probability of holding a college degree, is 41% likely to be female, and is predominantly employed in skilled commercial and administrative occupations. In contrast, sorting patterns among immigrants vary significantly. Turkish workers, for instance, are 13 percentage points less likely to have a college degree, are on average three years younger than Germans, and are concentrated in unskilled manual and service jobs. Immigrants from high-income European countries (France, UK, Netherlands, Belgium, Austria, Switzerland, Finland, Sweden) exhibit the opposite pattern, being 11 percentage points more likely to hold a college degree, three years older than Germans on average,

Table B6: Relative occupational sorting and demographics for immigrants and natives

	All Immigrants	High Income Europe	EU Middle Income	New EU	Turkey	Former Yugoslavia	Europe non EU	Asia	Africa & Middle East	Americas
Panel A										
Agriculture	0.68	0.50	0.58	2.33	0.42	0.60	0.67	0.60	0.54	0.53
Unskilled Manual	1.64	1.09	1.76	1.20	2.02	1.82	1.39	1.54	1.47	0.89
Skilled Manual	0.77	0.58	1.00	0.62	0.93	1.00	0.75	0.46	0.42	0.44
Technicians	0.40	1.09	0.44	0.46	0.24	0.36	0.41	0.40	0.31	0.52
Engineers	0.66	1.78	0.50	0.77	0.23	0.24	0.72	1.44	0.69	1.76
Unskilled Services	1.98	1.02	1.87	1.66	2.18	2.12	1.92	1.79	2.67	1.56
Skilled Services	0.80	1.51	0.65	1.25	0.48	0.67	0.90	0.94	0.78	1.90
Semi-Professions	0.39	0.67	0.29	0.80	0.20	0.32	0.53	0.45	0.36	0.79
Professions	0.93	1.59	0.56	2.11	0.21	0.24	1.32	2.36	0.95	1.99
Unskilled Commercial and Admin	0.84	0.87	0.87	0.88	0.82	0.80	0.96	0.72	0.81	0.87
Skilled Commercial and Admin	0.39	0.84	0.42	0.49	0.26	0.31	0.49	0.39	0.28	0.61
Managers	0.50	1.78	0.39	0.64	0.17	0.19	0.51	0.85	0.32	1.69
Panel B										
Share college	0.77	1.79	0.44	1.42	0.22	0.21	1.02	1.67	0.79	1.88
Share female	0.85	0.80	0.82	1.25	0.70	0.88	1.09	0.97	0.71	0.97
Age	0.97	1.07	1.00	0.99	0.92	1.03	0.95	0.94	0.95	1.00

Notes: Panel A plots the relative share of immigrants from a given origin in a given occupation relative to the share of natives in such occupation. Numbers larger than 1 are interpreted as immigrants being overrepresented in such occupations. Blossfeld occupational classification is used. Panel B plots the relative characteristics of immigrants of a given origin relative to natives. Data for 2003 to 2011.

and concentrated in managerial, engineering, and professional occupations (e.g., doctors, dentists, professors). Middle-income EU immigrants (Portugal, Italy, Spain, Ireland) are overrepresented in unskilled manual and service occupations. Immigrants from new EU 2004 countries are predominantly employed in agricultural and professional occupations, while those from Africa, the Middle East, and Yugoslavia concentrate in unskilled service and manual jobs. Immigrants from Asia tend to be engineers.

To examine occupational differences across nationalities and the determinants of sorting, we follow standard approaches in the immigration literature by distinguishing occupations based on their intensity in manual and communication tasks. Following closely Peri and Sparber (2009) and Peri and Sparber (2011), we assign the manual relative to language task contents to workers based on their occupation, allowing us to quantify the task supply of different nationalities.[47] We then analyze the correlation between the relative task content supplied by workers and their country of origin by estimating equation 30 for worker i from country group o in year t:

$$\left(\frac{M}{L}\right)_{occ(it),t} = FE_{o(i)} + FE_{f(it),t} + \epsilon_{it} \tag{30}$$

where the outcome variable is the ratio of manual to communication task content of worker i's occupation in year t. $FE_{o(i)}$ are country of origin dummies, which are the explanatory variables of interest, and $FE_{f(it),t}$ are employer-year fixed effect, which control for firm-

[47]The US Department of Labor's O*NET abilities survey quantifies the importance of 52 distinct employee abilities, which we refer to as "tasks", for each occupation. Peri and Sparber (2009) group these abilities into categories to construct indices for manual and communication tasks. We map these occupations to German categories using a crosswalk and compute the ratio for each occupation-year.

level shocks and allow us to compare workers within the workplace. We also estimate a version of this regression with an immigrant dummy FE_{imm} rather than $FE_{o(i)}$.

The first column of Table B7 shows that, compared to natives, immigrants are more likely to work in occupations with higher relative manual requirements.[48] On average, the index differs by 0.455, equivalent to 20% of the index for the average occupation. The second column breaks the immigrant group into groups of origin countries. Workers from Turkey are the most specialized in manual-intensive occupations, while workers from high-income European countries specialize in communication-intensive occupations, and workers from the Americas have a similar specialization to Germans. Immigrants from the remaining nationalities tend to specialize in manual-intensive occupations relative to Germans with different degrees of intensity. The third column controls for worker's education, gender, and age. The difference in the estimates between columns 2 and 3 suggests that differences in observable characteristics of workers from different origins explain part of the observed sorting into occupations. For instance, not controlling for worker characteristics more than doubles the specialization for high-income European workers ($-0.156/-0.06 = 2.6$), and increases the specialization of Turkish workers by 20% ($0.765/0.639 = 1.20$).

Next, we provide evidence that the observed occupational sorting may be explained by comparative advantages across origin countries. If sorting is driven by comparative advantages, immigrants' wages relative to natives should be higher in occupations where they have a relative specialization. To test this hypothesis, we estimate equation 31:

$$Log(wage)_{it} = \sum_{o} \beta_o \, \mathbb{1}(i \in o) \times \left(\frac{M}{L}\right)_{i,t} + \sum_{o} \alpha_o \, \mathbb{1}(i \in o) + \delta \left(\frac{M}{L}\right)_{i,t} + FE_{f(it),t} + \epsilon_{i,t} \quad (31)$$

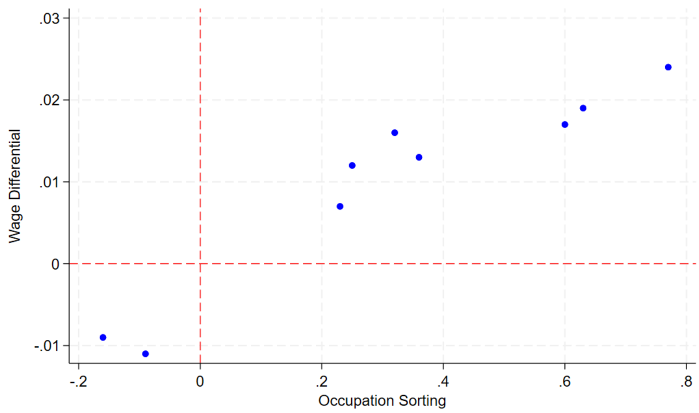
where the omitted category is German nationality. The coefficients of interest are the β's, which capture the wage premium for different immigrant groups relative to Germans in relatively manual-intensive jobs.

The estimates of β are in Columns 4-5 of Table B7. Column 4, which pools all immigrant origins, suggests that there are no significant productivity differences between immigrants and native coworkers along the task distribution. However, this result masks significant heterogeneity in the specialization profiles of workers from different nationalities. Column 5 disaggregates immigrants by nationality and shows that country groups, such as middle-income EU countries, New EU states, Turkey, Yugoslavia, non-EU Europe, Asia, and Africa/Middle East, which tend to sort into manual-intensive tasks, are precisely the

[48]This pattern holds within education groups, which is consistent with the findings of Peri and Sparber (2009) for low-skilled workers and Peri and Sparber (2011) for high-skilled workers.

ones that receive a premium for manual tasks relative to communication tasks. In contrast, country groups that sort into communication-intensive tasks, such as high-income European countries and countries in the Americas, receive a premium for communication tasks relative to manual.[49] In Figure B5 we show the positive relationship between occupational sorting and comparative advantage by plotting the country fixed effects from equation 30 against the wage differentials by country estimated by β_o in equation 30.

Figure B5: Occupational sorting and comparative advantage



Notes: We plot the coefficients for the country fixed effects estimated by equation 30 that capture occupational sorting (horizontal axis) against the β_o coefficients from equation 31 which capture the wage differential when working at a relatively more manual-intensive occupation (vertical axis). We focus on the specification without additional controls.

In summary, workers from different nationalities specialize in different tasks and sort accordingly into different occupations. We provide evidence that productivity differences (or comparative advantage) might be one explanation for this sorting and show what individual characteristics of workers make them useful for specific tasks.

The evidence above is consistent with our modeling assumptions. Specifically, productive sorting into tasks based on comparative advantages is consistent with a CES technology in tasks where efficient labor units from different nationalities are perfect substitutes for a given task and workers from different countries have comparative advantages in specific tasks. As shown by Burstein et al. (2020) and Brinatti et al. (2023), this framework implies the same demand functions as a framework with a CES technology across workers of different nationalities, which is the modeling approach we adopt in this paper. Thus, one interpretation of our CES parameters ϵ and κ is that they capture the elasticity of substitution across nationalities, taking into account that workers of these nationalities have

[49]We also estimate equation 31 replacing the dummies of nationality by demographic characteristics, and find that younger, non-college-educated, and male workers seem to complement better with manual-intensive jobs relative to older, college-educated, and female workers.

a different composition of characteristics such as different occupations and demographics that make them imperfect substitutes.

As a final point, we look at whether immigrants keep the features that make them different as they spend time working in Germany. Long-term and recent immigrants tend to differ in the types of tasks they perform. Peri and Sparber (2009) find that long-term immigrants (those who have been in the country for over 10 years) engage in tasks with a manual-language composition that is closer to natives than to recent immigrants. However, differences with natives do not fully disappear through the life cycle. To understand whether this pattern holds in our setting, we adopt their approach of comparing the relative manual-intensity of occupations as individuals spend more time in Germany. Specifically, we estimate equation 32 separately for each nationality o of immigrants:

$$\left(\frac{M}{L}\right)_{occ(it),t} = \beta_o \, \mathbb{1}(\text{Years in labor market}_i > 10) + X_{i,t} + FE_{f(it),t} + \epsilon_{i,t} \tag{32}$$

where the dummy variable $\mathbb{1}(\text{Years in labor market}_i > 10)$ equals one if worker i has been more than 10 years in the labor market in Germany and zero otherwise. $X_{i,t}$ includes age, education-year fixed effects, and gender-year fixed effects to control for the time-varying factors that may affect the sorting of these workers. $\epsilon_{i,t}$ is the error term, which we cluster at the worker level. The coefficient of interest, β, captures the difference in the manual language intensity of long-term immigrants compared to their compatriots who have been in Germany for less than 10 years.

Table B8 presents the estimates of β for each origin country, showing that long-term immigrants from high-income EU countries and the Americas tend to work in more manual-intensive occupations relative to recent immigrants. These nationalities are precisely those that specialize in linguistic-intensive tasks relative to Germans, suggesting that as immigrants spend more time in the country, the task content of their jobs gets closer to that of their native coworkers. Similarly, immigrants from middle-income EU countries, who specialize in manual-intensive tasks relative to Germans, decrease their manual content over time. The differences between long-term and recent immigrants from other nationalities are not statistically significant at a 5% confidence level.

Table B7: Manual to language occupation sorting and comparative advantage

	$\frac{M}{L}_{o(it),t}$	$\frac{M}{L}_{o(it),t}$	$\frac{M}{L}_{o(it),t}$	$log(\text{wage})_{i,t}$	$log(\text{wage})_{i,t}$
$\mathbb{1}$(Immigrant = 1)	-0.46**			-0.064	
	(0.13)			(0.030)	
$\mathbb{1}$(High-income Europe = 1)		-0.16***	-0.06*		0.117***
		(0.03)	(0.02)		(0.002)
$\mathbb{1}$(Middle-income EU = 1)		0.63***	0.55***		-0.078***
		(0.02)	(0.01)		(0.004)
$\mathbb{1}$(New Member states = 1)		0.23***	0.33***		-0.017*
		(0.03)	(0.03)		(0.006)
$\mathbb{1}$(Turkey = 1)		0.77***	0.64***		-0.137***
		(0.03)	(0.04)		(0.008)
$\mathbb{1}$(Yugoslavia = 1)		0.60***	0.53***		-0.080***
		(0.03)	(0.03)		(0.004)
$\mathbb{1}$(Europe non-EU = 1)		0.32***	0.36***		-0.083***
		(0.03)	(0.03)		(0.004)
$\mathbb{1}$(Asia = 1)		0.25***	0.34***		-0.089***
		(0.03)	(0.03)		(0.007)
$\mathbb{1}$(Africa and Middle East = 1)		0.36***	0.29**		-0.090***
		(0.07)	(0.07)		(0.008)
$\mathbb{1}$(Americas = 1)		-0.09**	0.05		0.023**
		(0.02)	(0.02)		(0.006)
$(M/L)_{o(it),t}$				-0.035***	-0.035***
				(0.001)	(0.001)
$\mathbb{1}$(Immigrant = 1) $\times$ $(M/L)_{o(it),t}$				0.013*	
				(0.005)	
$\mathbb{1}$(High-income Europe = 1) $\times$ $(M/L)_{o(it),t}$					-0.009***
					(0.001)
$\mathbb{1}$(Middle-income EU = 1) $\times$ $(M/L)_{o(it),t}$					0.019***
					(0.001)
$\mathbb{1}$(New Member states = 1) $\times$ $(M/L)_{o(it),t}$					0.007***
					(0.001)
$\mathbb{1}$(Turkey = 1) $\times$ $(M/L)_{o(it),t}$					0.024***
					(0.002)
$\mathbb{1}$(Yugoslavia = 1) $\times$ $(M/L)_{o(it),t}$					0.017***
					(0.001)
$\mathbb{1}$(Europe non-EU = 1) $\times$ $(M/L)_{o(it),t}$					0.016***
					(0.001)
$\mathbb{1}$(Asia = 1) $\times$ $(M/L)_{o(it),t}$					0.012***
					(0.001)
$\mathbb{1}$(Africa and Middle East = 1) $\times$ $(M/L)_{o(it),t}$					0.013***
					(0.002)
$\mathbb{1}$(Americas = 1) $\times$ $(M/L)_{o(it),t}$					-0.011***
					(0.002)
Number of observations	1.26E+07	1.26E+07	1.25E+07	1.25E+07	1.25E+07
R^2	0.52	0.52	0.55	0.67	0.67
Controls for worker demographics	N	N	Y	N	N

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. Columns 1 -3 run an individual level regression where the dependent variable is the ratio of manual to language task content for individual i in time t. The explanatory variables are an immigrant dummy (column 1), origin origin-specific dummies (columns 2 and 3). Column 3 includes controls for age, gender, and education. Columns 4-5, run the regression in equation 31, where the dependent variable is the log wage and the main explanatory variables are country of origin dummies and interactions between country of origin and manual to language intensity.

Table B8: Manual to language task intensity by time in Germany

	Germany	Europe high income	EU middle income	EU New member states	Turkey
$\mathbb{1}$(Years in Germany $\geq$ 10)	-0.037***	0.136***	-0.082**	0.075	-0.015
	(0.003)	(0.037)	(0.028)	(0.038)	(0.015)
N	1.12E+07	61,838	121,187	53,014	286,643
	Yugoslavia	Europe non-EU	Asia	Africa and Middle East	Americas
$\mathbb{1}$(Years in Germany $\geq$ 10)	-0.095*	-0.017	0.092*	0.013	0.173**
	(0.042)	(0.028)	(0.038)	(0.021)	(0.066)
N	48,649	68,671	43,399	78,331	11,097

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. The outcome of these regressions is the ratio between manual and language task content of individual i's occupation in time t. All regressions include controls for age, education-time fixed effects, and gender-time fixed effects. The explanatory variable is a dummy on whether the individual has been more than 10 years working in Germany. Standard errors clustered at the individual level.

C Model Derivations

C.1 Sourcing Decision Details

In this section, we derive the immigrant wage index expression in equation 8. Following equation 7, we know the price index for foreign labor is as in equation 33:

$$W_{x,j} = \left(\int_{\Sigma_j} \delta_o^{\kappa} w_{x,k}^{1-\kappa} d_o \right)^{\frac{1}{1-\kappa}} \tag{33}$$

where δ_o is a source-country specific importance in the production function assumed to be a Pareto random variable with the following cumulative distribution and density function:

$$F(\delta) = 1 - \left(\frac{\bar{\delta}}{\delta} \right)^{\xi} \quad \text{and} \quad g(\delta) = \xi \bar{\delta}^{\xi} \delta^{-\xi-1} \tag{34}$$

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 35:

$$\begin{aligned} W_{x,j} = \left(w_{x,k}^{1-\kappa} \int_{\delta_j^*}^{\infty} \delta_o^{\kappa} \xi \bar{\delta}^{\xi} \delta^{-\xi-1} d\delta \right)^{\frac{1}{1-\kappa}} &= w_{x,k} \left(\left[\frac{\xi \bar{\delta}^{\xi}}{\kappa - \xi} \delta^{\kappa-\xi} \right]_{\delta_j^*}^{\infty} \right)^{\frac{1}{1-\kappa}} = \\ &= w_{x,k} \left(\frac{\xi \bar{\delta}^{\xi}}{\xi - \kappa} (\delta_j^*)^{-(\xi-\kappa)} \right)^{\frac{1}{1-\kappa}} \quad \text{if } \xi - \kappa > 0 \end{aligned} \tag{35}$$

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 36:

$$W_{x,j} = w_{x,k} \underbrace{\frac{1}{\bar{\delta}^{\frac{\kappa}{\kappa-1}}} \left(\frac{\xi}{\xi-\kappa}\right)^{\frac{1}{1-\kappa}}}_{\bar{Z}} n^{-\underbrace{\frac{1}{\kappa-1}\frac{\xi-\kappa}{\xi}}_{\iota}} \tag{36}$$

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. Formally, the equilibrium conditions are the following:

1) Consumer budget constraint. The total expenditure in Germany (Y_g) and RoW (Y_r) are shown in equation 37:

$$Y_g = \sum_k \left(w_{d,k} L_{d,k} + w_{x,k} L_{x,k} + \Pi_{g,k}\right) \quad Y_r = w_r L_r + \Pi_r \tag{37}$$

where $L_{d,k}$ is the total number of German effective units of labor in sector k, $L_{x,k}$ is the number of effective immigrant units in Germany working in sector k, and $w_{d,k}$, $w_{x,k}$ are the respective effective wages. $\Pi_{g,k}$ are the total profits in sector k in Germany. w_r, L_r, and Π_r 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 38:

$$\sum_{j \in J_T} \mathbb{1}\left(exporter_j = 1\right) p_j^x y_j^x \;=\; \sum_{j \in J_r} \mathbb{1}\left(exporter_j = 1\right) p_j y_j \tag{38}$$

where J_T and J_r is the set of firms in Germany in the tradable sector and in RoW.

3) 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 39-41 require that demand for effective units of native and immigrant labor equals supply in each industry and country:

$$\sum_{j\in J_k}\Big(d_j+n_jf_j+f_{imm}\mathbb{1}(n_j>0)+\mathbb{1}\left(exporter_j=1\right)f_g\Big)=\Gamma\Big(1-\frac{1}{\kappa}\Big)\;A_{g,k,g}^{\frac{1}{\nu}}\left(\pi_{g,k,g}\right)^{\frac{\nu-1}{\nu}}\;N_g \tag{39}$$

$$\sum_{j\in J_k}x_{j,k}=\Gamma\Big(1-\frac{1}{\kappa}\Big)\;A_{x,k,g}^{\frac{1}{\nu}}\left(\pi_{x,k,g}\right)^{\frac{\nu-1}{\nu}}\;N_r \tag{40}$$

$$\sum_{j\in J_r}d_j=\Gamma\Big(1-\frac{1}{\kappa}\Big)\;A_{x,r}^{\frac{1}{\nu}}\;\left(\pi_{x,r}\right)^{\frac{\nu-1}{\nu}}\;N_r \tag{41}$$

where N_r is the total number of workers in RoW and equation 40 uses the fact that $\pi_{o,k,g}=\pi_{x,k,g}$.

D Welfare Response to Immigration

We consider a simplified version of our fully quantitative model, where the economy has only one sector and all firms hire some amount of immigrants (e.g., $f_{imm}=0$). We first study the role of firm heterogeneity in immigrant share when the economy is in trade autarky and later analyze how the results change when the economy is open to trade. We derive the expression for the change in the welfare of natives workers in four steps.

Step 1: Express $\tilde{s}_j$ as proportional to $\tilde{s}_1$. The profit function and the corresponding first order condition with respect to s_j are:

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

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

The first order condition for firm j and firm 1 implies that:[50]

$$(-\chi+1+\frac{\theta}{1-s_j})\;\tilde{s}_j=(-\chi+1+\frac{\theta}{1-s_1})\;\tilde{s}_1$$

or

$$\tilde{s}_j=\frac{\alpha_j}{\alpha_1}\;\tilde{s}_1\quad with\quad \alpha_j=\frac{1}{-\chi+1+\theta(1-s_j)^{-1}} \tag{42}$$

[50]where $\alpha_j>0$ if and only if $\epsilon-\sigma+\iota(1-s_j)$.

Step 2: Express $\tilde{s}_j$ as proportional to $\tilde{S}$.

Let WB_{dj} and WB_j the native and total wage bill of $j \in J_d$. Let S be the associated aggregate native share:

$$S \equiv \frac{\sum_{j \in J} WB_{dj}}{\sum_{j \in J} WB_j} = \sum_{j \in J} \underbrace{\frac{WB_j}{\sum_{j \in J} WB_j}}_{\equiv \omega_j^{wb}} s_j = \sum_{j \in J} \omega_j^{wb} s_j$$

Then the change in the aggregate native share is given by:

$$\tilde{S} = \sum_{j \in J} \underbrace{\frac{\omega_j^{wb} s_j}{\sum_{j \in J} \omega_j^{wb} s_j}}_{\omega_j^S} \left(\tilde{\omega}_j^{wb} + \tilde{s}_j \right) \tag{43}$$

where ω_j^S is the share of firm j in S.[51]

Next, we find an expression for $\tilde{\omega}_j^{wb}$ as a function of $\tilde{s}_j$. To that end, we use firm j's optimal demand for natives and the definition of ω_j^{wb}:

$$\begin{aligned} WB_j &= \frac{\sigma - 1}{\sigma} r_j = \frac{D}{\psi_j} s_j^{-\chi} \quad \rightarrow \quad \tilde{WB}_j = \tilde{D} - \chi \tilde{s}_j \\ \omega_j^{wb} &= \frac{WB_j}{\sum_{l \in J_d} WB_l} \quad \rightarrow \quad \tilde{\omega}_j^{wb} = \tilde{WB}_j - \sum_{l \in J_d} \omega_l^{wb} \tilde{WB}_l \end{aligned}$$

where D is a general equilibrium variable common to all firms.
Combining these last two expressions yield $\tilde{\omega}_j^{wb}$ as a function of $\tilde{s}_j$:

$$\tilde{\omega}_j^{wb} = -\chi \left(\tilde{s}_j - \sum_{l \in J_d} \omega_l^{wb} \, \tilde{s}_l \right) \tag{44}$$

This expression, together with 42 and 43, implies that the change in aggregate share can be expressed as a function of the change in s_1:

$$\begin{aligned} \tilde{S} &= \sum_{j \in J} \omega_j^S \Big(-\chi \Big(\tilde{s}_j - \sum_{l \in J_d} \omega_l^{wb} \, \tilde{s}_l \Big) + \tilde{s}_j \Big) \\ \tilde{S} &= \sum_{j \in J} \omega_j^S \Big(-\chi (\alpha_j - \sum_{l \in J_d} \omega_l^{wb} \alpha_l) + \alpha_j \Big) \frac{\tilde{s}_1}{\alpha_1} \end{aligned} \tag{45}$$

[51] For simplicity we define these shares to exclude the employment related to f_j.

In a more compact way, it reads as:

$$\tilde{S} = \sum_{j \in J} \omega_j^S \underbrace{\Big(- \chi(\alpha_j - \bar{\alpha}) + \alpha_j \Big)}_{\beta_j} \frac{\tilde{s}_1}{\alpha_1} \tag{46}$$

with $\bar{\alpha} \equiv \sum_{l \in J_d} \omega_l^{wb} \alpha_l$.[52]

We can use equations 42 and 46 to express $\tilde{s}_j$ as proportional function of $\tilde{S}$:

$$\tilde{s}_j = \frac{\alpha_j}{\beta} \tilde{S} \quad with \quad \beta = \sum_{l \in J_d} \omega_j^S \beta_l \tag{47}$$

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 is a weighted average of the changes of individual prices which, in turn, are proportional to the change in the native share:

$$\begin{aligned} \tilde{P} &= \sum_{j \in J} \lambda_j \tilde{p}_j \\ &= \sum_{j \in J} \lambda_j \tilde{u}_j \\ &= \sum_{j \in J} \lambda_j \Big(\tilde{w}_d + \frac{\tilde{s}_j}{\epsilon - 1} \Big) \\ &= \tilde{w}_d + \frac{\sum_{j \in J} \lambda_j \tilde{s}_j}{\epsilon - 1} \end{aligned} \tag{48}$$

where λ_j is firm j's share in the expenditure of consumers, which coincides with the market share of the firm denoted by ω_j, $\lambda_j = \frac{p_j^{1-\sigma}}{P^{1-\sigma}} = \frac{p_j q_j}{\int p_j q_j} \equiv \omega_j$. The second equality uses 9, the third equality uses 6, and the fourth equality uses $\sum_{j \in J} \lambda_j = 1$.

[52] If all firms choose the same immigrant-share, $\tilde{S} = \tilde{s}_j$.

Next we solve for the real wage change and substitute $\tilde{s}_j$ using equation 46 to obtain:

$$
\begin{aligned}
\tilde{w}_d - \tilde{P} &= -\frac{\tilde{S}}{\epsilon - 1}\sum_{j\in J}\omega_j \frac{\alpha_j}{\beta} \\
&= -\frac{\tilde{S}}{\epsilon - 1}\left(\frac{\sum\limits_{j\in J}\omega_j^S \beta_j}{\sum\limits_{j\in J}\omega_j\alpha_j}\right)^{-1} \\
&= -\frac{\tilde{S}}{\epsilon - 1}\left(\frac{\sum\limits_{j\in J}\omega_j^S\Big(-\chi(\alpha_j - \bar{\alpha}) + \alpha_j\Big)}{\bar{\alpha}}\right)^{-1} \\
&= -\frac{\tilde{S}}{\epsilon - 1}\left(1 + \frac{\sigma - \epsilon}{\epsilon - 1}\frac{\sum\limits_{j\in J}\omega_j^S\alpha_j - \sum\limits_{j\in J}\omega_j\alpha_j}{\sum\limits_{j\in J}\omega_j\alpha_j}\right)^{-1} \\
&= -\frac{\tilde{S}}{\epsilon - 1}\left(1 + \frac{\epsilon - \sigma}{\epsilon - 1}\pi\right)^{-1}
\end{aligned}
\tag{49}
$$

where $\pi \equiv 1 - \frac{\sum_{j\in J}\omega_j^S\alpha_j}{\sum_{j\in J}\omega_j\alpha_j}$, which equals zero if firms employ the same immigrant share and positive otherwise. The first equality uses that $\lambda_j = \omega_j$, the third and fourth equality use that the firm share in the wage bill coincides the share in shares, $\omega_j^{wb} = \omega_j$.[53]
Next we show that $\pi \in [0, 1)$ which implies the sign of the bias is determined by the sign of $\epsilon - \sigma$.

Step 4: Determine if the bias is larger or smaller than one. There is a tight relationship between ω_j and ω_j^S. Specifically:

$$
\omega_j^S = \omega_j \frac{s_j}{\sum\limits_{j\in J}\omega_j s_j}
$$

This equation 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. Therefore:

$$
1 - \pi = \frac{\sum\limits_{j\in J}\omega_j^S\alpha_j}{\sum\limits_{j\in J}\omega_j\alpha_j} \in (0, 1]
$$

[53] $WB_j = w_d d_j + \sum_c w_x x_{cj} = w_d d_j + w_{jx}x_j = \frac{u_j}{\psi_j}y_j = \left(\frac{\sigma-1}{\sigma}\; p_j\right)y_j = \frac{\sigma-1}{\sigma}\; p_j y_j$

Given that this term is always negative the bias will be higher or lower than one, depending on whether ϵ is larger than σ. If $\epsilon > \sigma$, the last bracket in 49 is lower than one and vice versa.

Economy open to trade:

We now derive the welfare gains in an open economy where trade is balanced, $\sigma = \sigma_x$, and firms must pay a fixed cost to export and iceberg trade costs τ.

The steps of the proof are analogous to the closed economy, but the price index in step 3 now should take into account that imported goods may become more expensive as immigrants reallocated from RoW to Germany. Specifically,

$$\begin{aligned}\tilde{P} &= \sum_{j \in J} \lambda_j \tilde{p}_j \\ &= \sum_{j \in J} \lambda_j \tilde{u}_j \\ &= \sum_{j \in J_d} \lambda_j \left(\tilde{w}_d + \frac{\tilde{s}_j}{\epsilon - 1} \right) + \sum_{j \in J_x} \lambda_j \tilde{w}_r \\ &= \tilde{w}_d + \frac{\sum_{j \in J_d} \lambda_j \tilde{s}_j}{\epsilon - 1} + (1 - \lambda)(\tilde{w}_r - \tilde{w}_d)\end{aligned} \tag{50}$$

where J_d and J_x are the sets of domestic and foreign varieties or firms, respectively; and λ is Germany's domestic trade share $\lambda \equiv \sum_{j \in J_d} \lambda_j = 1 - \sum_{j \in J_x} \lambda_j$.

To relate this expression to those in the closed economy case, it will be helpful to write the expenditure share λ_j in equation 50 in terms of the domestic sales share: $\lambda_j = \lambda \omega_j$

By following analogous steps as in 49, we can rewrite the welfare effects as follows:

$$\begin{aligned}\tilde{w}_d - \tilde{P} &= -\lambda \frac{\tilde{S}}{\epsilon - 1} \left(1 + \frac{\epsilon - \sigma}{\epsilon - 1} \pi \right)^{-1} - (1 - \lambda)(\tilde{w}_r - \tilde{w}_d) \\ &= -\lambda \frac{\tilde{S}}{(1 - \pi)\epsilon + \pi\sigma - 1} - (1 - \lambda)(\tilde{w}_r - \tilde{w}_d)\end{aligned} \tag{51}$$

E Estimation of ϵ

E.1 Estimation of the immigrant composite $x_{j,t}$

We need to estimate the quantity of immigrant labor employed by company j, which is given by the following CES composite:

$$x_{j,t} = \left(\sum_o \delta_{o,k} x_{j,o,t}^{\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{\kappa-1}} = \left(\sum_o \delta_{o,k} (\gamma_{o,k,t} N_{o,j,t})^{\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{\kappa-1}} = \left(\sum_o \zeta_{o,k,t} \left(N_{o,j,t}\right)^{\frac{\kappa-1}{\kappa}}\right)^{\frac{\kappa}{\kappa-1}} \tag{52}$$

where we added year sub-indexes t. $\gamma_{o,k,t} \equiv A_{o,k}^{\frac{1}{\nu}} \left(\pi_{o,k,t}\right)^{-\frac{1}{\nu}} \bar{H}$ is the average ability of nationals from o in sector k in year t and the second equality follows from assuming that $A_{o,k}$ is Fréchet distributed.

To compute $x_{j,t}$ we need to estimate the two unobservable components of the right-hand side: the elasticity of substitution κ and the productivity shifters $\zeta_{o,k,t}$. We do so by following Ottaviano and Peri (2012)'s methodology. First, we use the first-order conditions for $x_{o,j,t}$ relative to $x_{o',j,t}$ to derive the following estimating equation 53:

$$\begin{aligned} dLog\left(\text{Wage Bill}_{o,j,t}\right) = \underbrace{\frac{\kappa-1}{\kappa}}_{\beta} dLog(N_{o,j,t}) + \underbrace{dLog(\delta_{o,k,t}) + \frac{\kappa-1}{\kappa} dLog(\gamma_{o,k,t})}_{\zeta_{o,k,t}\ \text{Origin-Industry-year FE}} \\ \underbrace{- dLog(\delta_{o',k,t}) - \frac{\kappa-1}{\kappa} dLog(\gamma_{o',k,t} N_{j,t}^{o'})}_{\text{Firm-year FE}} \end{aligned} \tag{53}$$

Second, we use the OLS estimates of β and the origin country-industry-year fixed effects to infer κ and $\zeta_{o,k,t}$ respectively. Finally, we compute $\hat{x}_{j,t}$ by plugging these estimates in equation 52.

In practice, we estimate the regression in levels (with the corresponding firm-origin fixed effect) rather than in changes to increase the precision of the estimates, i.e.,

$$Log\left(\text{Wage bill}_{o,j,t}\right) = \beta\ Log(N_{o,j,t})\ +\ FE_{o,j}\ +\ FE_{o,k,t}\ +\ FE_{j,t}\ +\ u_{o,j,t}$$

where $u_{o,j,t}$ is a residual and standard errors are clustered at the origin-firm level. Our estimate of β is 0.95 (CI between 0.93 and 0.97), suggesting a value for $\hat{\kappa} = 20.2$ (CI between 12.6 and 27.6). As mentioned earlier, finding comparable estimates is challenging due to the limited availability of firm-level data on employment by nationality. Keeping this limitation in mind, we find that our estimate is consistent with Busch et al. (2020) who calibrate an aggregate elasticity of substitution between immigrants from different nationality groups (OECD vs. non-OECD) in Germany at 22.6.

These estimates of κ and $\zeta_{o,k,t}$ allow us to estimate $x_{j,t}$. With this estimate at hand, we compute proceed to estimate ϵ as described in Section 6.2.

E.2 Estimation results

Table E1 presents the OLS and 2SLS estimates of β from equation 24 and ϵ.

Table E1: Estimates for ϵ

Method	Parameter	Value	95% Conf. Interval
OLS	$(\epsilon-1)/\epsilon$	0.88^{***}	[0.85 , 0.92]
	Implied ϵ	8.49^{***}	[6.69 - 11.89]
2SLS	Estimate for $(\epsilon-1)/\epsilon$	0.87^{***}	[0.78 , 0.97]
	Implied ϵ	7.95^{***}	[4.33 , 29.58]

Notes: $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. This table reports the OLS and 2SLS estimation output for equation 23. Confidence intervals are bootstrapped with 5,000 repetitions as described in Section 6.2. The number of observations is 4382. The first-stage F stat is 78.74.

E.3 Tests of the identification strategy

Our instrument exploits differential exposure of firms to immigrant arrivals from different countries, where the firm exposure is based on the nationality composition of their workforce. Thus, our setting relies on an identifying assumption in terms of the shares Goldsmith-Pinkham et al. (2020). This section describes the variation underlying our instrument and test the identifying assumption.

Shift-share Instrument Diagnostics: We describe the variation that the instrument uses by calculating the Rottemberg weights of the Bartik instrument. To do this, we 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 instrument are called Rottemberg weights, which we calculate using the code provided by Goldsmith-Pinkham et al. (2020) and denote as α. Each origin region is affected each year by a national-level shock, which we denote by G. The just-identified coefficients are denoted by β.

As shown in Table E2, panel A, all the Rottemberg weights are positive, meaning that our regression is likely not subject to misspecification and our coefficient is likely to have a local average treatment effect-like interpretation. Panel B shows 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, which indicates they are likely to play an important role in the variation of our instrument. The country with the largest weight is middle-income EU countries (0.175), followed by New EU countries (0.143), other European countries not in EU (0.143), high-income EU countries (0.136), and Turkey (0.125). It is reassuring, that no single region accounts for a large majority of the variation in our instrument.

Table E2: Shift-share diagnostics

Panel A	Sum	Mean	Share
$\alpha_s \leq 0$	-	-	0
$\alpha_s > 0$	0.99	0.11	1
Panel B	α_s	G	β_s
α_s	1	-	-
G	0.066	1	-
β_s	-0.138	0.635	1
Panel C	α	G	β
Europe middle income	0.175	0.879	0.743
New EU members	0.143	1.200	0.772
Europe non EU	0.143	1.202	1.142
Europe high-income	0.136	0.894	0.934
Turkey	0.125	0.952	0.752

Notes: 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 the mean of α, G, and β for the top 5 origin regions in terms of weights

Pre-trend analysis: We assess the plausibility of the identifying assumption with pre-trends tests by estimating the same regressions as in 23 with lagged outcome variables. Failing to reject that an inflow in t had an effect on lagged outcomes would increase the plausibility of the assumption that the common shock caused the change in the changes. Table E3 shows that the effects in the years leading up to the inflow, including up to a five-year lag, are generally insignificant. The only exception is the period immediately preceding the inflow, where the effect is marginally significant (e.g., the lower 95% confidence interval is 0.006) and the point estimate is substantially smaller than the contemporaneous effect (e.g., the contemporaneous effect is approximately 4 times larger).

Table E3: Pre-trend analysis

Lag h	Value	95% Conf. Interval	F stat	N obs
0	0.87	[0.78 , 0.97]	78.74	4382
1	0.22	[0.06 , 0.37]	80.00	3886
2	-0.14	[-0.30 , 0.05]	80.38	3619
3	-0.08	[-0.25 , 0.07]	76.62	3419
4	-0.02	[-0.19 , 0.12]	76.47	3249
5	-0.08	[-0.24 , 0.10]	79.10	3137

Notes: This table reports the 2SLS estimation output for equation 23 for the outcome variable $Ln\left(\frac{\text{Wage Bill Immig}_{j,t-h}}{\text{Wage Bill Natives}_{j,t-h}}\right)$. Confidence intervals are bootstrapped with 5,000 repetitions as described in Section 6.2.

To further assess whether the initial shares used in the instrument correlate with firm covariates that could also affect changes in firm-level outcomes, we perform to additional tests. First, Table E4 shows the importance of key firm characteristics in explaining variation in the initial immigrant share. The firm characteristics that we included are firm size, measured by employment (in logs), the share of exports in sales, the cost-to-sales ratio, the share of college-educated workers, the average immigrant-to-native wage bill ratio, and the average age. This table shows that firm characteristics explain less than 1% of the variation in the shares, indicating minimal influence from these observables.[54]

Table E4: Correlation between firm initial shares and characteristics

	Initial share 03
Log employment	0.0021
	(0.0019)
Share exports in sales	0.0001
	(0.0001)
Cost-to-sales ratio	-0.0012
	(0.01)
Wage bill-to-cost ratio	-3.07
	(4.96)
Share college Workers	-0.0267
	(0.0218)
Avg immigrant-to-native wage ratio	0.0017
	(0.0128)
Avg age	-0.0001
	(0.0002)
N	6,426
R-sq	**0.001**

Notes: $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. We regress the firm's initial share on origin region fixed effects and firm characteristics, including total employment (log), export share, cost-to-sales ratio, wage bill share, share of college workers, immigrant-to-native wage ratio, and average workforce age. The key statistic is the R-squared. Results are consistent when not controlling for origin fixed effects.

Second, we test whether our firm-level shift-share instrument is mean independent of the factors that may affect the changes in the outcome variable (Roth et al., 2023). We re-

[54]We also find minimal explanatory power of these characteristics if we estimate individual regressions for each of the top 5 countries.

estimate the model adding pre-shock firm characteristics interacted with year dummies and present the estimates in Table E5. All of these regressions include the pre-shock firm characteristics included in the baseline specification. Given the stability of the estimates across specifications, it seems plausible that our estimates are not contaminated by the effects associated with the firm characteristics that are affecting firm performance.

Table E5: Robustness of ϵ when controlling for covariates

	(1)	(2)	(3)	(4)	(5)
β	0.873***	0.871***	0.867***	0.866***	0.871***
	(0.056)	(0.057)	(0.056)	(0.056)	(0.057)
N	4382	3326	3473	3473	3056
1st stage F stat	78.97	75.16	78.21	78.28	79.91
Control	Baseline	Export share	Employment	College share	Imm-Nat wage

Notes: $^{***} = p < 0.01, ^{**} = p < 0.05, ^{*} = p < 0.1$. We run equation 23 but controlling for specific covariates at their 2003 level interacted with time fixed effects. We include the covariates export share, total firm employment, college share and the immigrant-to-native wage bill ratio within the firm.

F Estimation of labor supply elasticity ν

We estimate the elasticity of labor supply ν using information on the variability of wages in our sample. A property of the Fréchet distribution is that it governs both, the dispersion in abilities and the elasticity of labor supply. If abilities across sectors and countries are very dispersed, individuals will not respond as much in their choices when wages change. On the other hand, if ability draws across options are very concentrated, worker's choices will be very sensitive to changes in the wage.

To estimate ν, we follow the literature estimating the labor supply elasticity using properties of extreme value distributions and data of the distribution of wages (e.g., Hsieh et al. (2019), Fan (2019), and Lee (2020)). Specifically, the Fréchet distribution assumption implies that the wage distribution for workers from the same nationality that choose the same sector-country pair has a coefficient of variation as in equation 54.

$$\frac{\text{Variance}}{\text{Mean}^2} = \frac{\Gamma\left(1 - \frac{2}{\nu}\right)}{\left(\Gamma\left(1 - \frac{1}{\nu}\right)\right)^2} \tag{54}$$

Following this relationship, we can map the coefficient of variation observed in the data to recover the implied value of ν. Note that the elasticity governs both the sector choice for natives and migrants, and the country choice for migrants. Since we only have data on workers living in Germany, our estimation predominantly captures the elasticity of supply across sectors.[55]

[55] This is desirable since our main exercise changes the total number of immigrants by a given amount.

To estimate ν with our data, we restrict the sample to German individuals between 25 and 65 years of age who work at the establishments in our sample between 2003 and 2011.[56] We run an individual-level regression of log wages on different sets of fixed effects and take the residual of that regression. We try three sets of fixed effects: 1) industry-year fixed effects, 2) industry-year fixed effects, district fixed effects plus age and gender controls, and 3) a fully saturated model that includes age-gender-district-industry-year fixed effects. Implicitly, the residual of that regression is the data counterpart of the ability draws taken by individuals in the model. We then take the exponent of that residual and compute its coefficient of variation. As shown in Table F6, our estimates range from 4.90 to 6.14. We choose as our preferred value $\nu = 6.14$, which is from the specification where we add the most stringent fixed effects. As shown in Table H1, our preferred value of ν also gives the most conservative estimates in terms of welfare.

Table F6: Estimates for ν

	(1)	(2)	(3)
Coefficient of variation	0.104	0.082	0.059
Implied ν	4.90	5.37	6.14
Fixed effects	Industry $\times$ year	Industry $\times$ year, age, gender, district	Fully saturated

Notes: We run a regression of log wages on a set of fixed effects, and take the residual. We then take the exponent and calculate the coefficient of variation. In column 1 we use sector-year fixed effects. In column , we use sector-year FEs, district FEs, age and gender as controls. In column 3, we use a fully-saturated set of fixed effects at the sector-age-gender-district-year level.

G Model Validation: Additional Estimation Results

The following table presents the OLS estimation results of equation 26.

Table G1: OLS estimation results

	Log(revenues)			Immigrant to native wage bill		
	All firms	Tradable sector	Non-Tradable sector	All firms	Tradable sector	Non-Tradable sector
θ_1	-7.838	-11.41*	-2.807	-1.376	-3.771**	0.846
	(5.03)	(6.237)	(5.963)	(0.986)	(1.637)	(1.01)
θ_2	2.844**	3.853**	1.355	0.434**	0.868***	0.0287
	(1.203)	(1.483)	(1.31)	(0.176)	(0.273)	(0.194)
N	5212	2923	2289	5212	2923	2289

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. This table reports the OLS estimation results of equation 26. We restrict the sample to years between 2008 and 2011, and establishments with more than 10 employees. Standard errors are two-way clustered at the industry and labor market level. The outcome variable in the first three columns is log of revenues, and in the second three columns is the immigrant-to-native wage bill ratio.

[56] We focus on Germans as, in the model, they only choose which sector to work on which is the main variation of the estimation. Adding immigrants to the calculations gives practically identical results.

The following table presents the first-stage estimation results of our S2LS estimates of equation 26. This table shows that that our instrument is strong for the three samples,and that the sign of the estimates is as expected.

Table G2: First stage regressions

	Full sample		Tradable sector		Non-Tradable sector	
	$I_{m,t}$	$I_{m,t} \times log(\text{size}_{03})$	$I_{m,t}$	$I_{m,t} \times log(\text{size}_{03})$	$I_{m,t}$	$I_{m,t} \times log(\text{size}_{03})$
$Z_{m,t}$	2.80***	2.16	2.87***	2.31	2.95***	3.01
	(0.54)	(1.71)	(0.61)	(2.39)	(0.61)	(1.58)
$Z_{m,t} \times log(\text{size}_{03})$	0.03	2.43***	0.05	2.63***	-0.06	1.84***
	(0.04)	(0.37)	(0.05)	(0.42)	(0.06)	(0.44)
N	5212		2923		2289	
Kleinberg-Paap F-stat	20.45		22.49		10.50	

Notes: $*** = p < 0.01, ** = p < 0.05, * = p < 0.1$. This table reports the first-stage estimation results corresponding to equation 26. 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.

Next, we follow the suggestions in Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2021) and test for pre-trends in Table G3. These estimates suggest that we can not reject the hypothesis that all coefficients are statistically different from zero at a 5% confidence level.

Finally, Table G4 evaluates the sensitivity of our estimates to different controls. Column 2 removes the firm size-specific trend, column 3 removes the cost to revenue control, column 4 removes the industry-time fixed effects, column 5 removes the local labor market trends, and column 6 includes labor market-year fixed effects.

Table G3: Pre-trends tests

	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$
Log Revenues					
θ_1	-14.41*	1.558	-8.857	-0.667	3.994
	(7.601)	(6.313)	(7.814)	(6.218)	(5.022)
θ_2	3.637*	0.649	1.657	-1.144	-0.227
	(1.865)	(1.138)	(2.073)	(1.116)	(0.961)
Immigrant-to-native wage bill					
θ_1	0.265	-0.504	-0.411	-2.254	-1.414
	(1.978)	(1.856)	(1.577)	(2.891)	(2.364)
θ_2	0.136	0.21	0.228	0.447	0.332
	(0.374)	(0.303)	(0.294)	(0.503)	(0.415)
N	5208	5203	5203	5205	5209

Notes: *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$. Dependent variable is log revenues in the top panel and the ratio of immigrant to native wage bill in the bottom panel. In each column, we take lags of the dependent variable going from one year lag to five year lag. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, log employment of the firm in 2003 interacted with year fixed effects and the wage bill of the firm in 2003 relative to revenues interacted with year fixed effects. Standard errors are clustered at the industry-labor market level. Sample is restricted to establishments with more than 10 employees.

Table G4: Robustness exercises for main specification

	Baseline	No employment control	No cost ratio control	No industry-year fixed effects	No local labor market trend	labor market - year fixed effects
Log Revenues						
θ_1	-15.99**	-17.16**	-17.42**	-28.31***	-8.166	-
	(7.794)	(7.745)	(8.254)	(8.739)	(5.580)	-
θ_2	4.095**	4.371***	4.428**	7.183***	2.349*	4.265**
	(1.616)	(1.587)	(1.695)	(1.886)	(1.326)	(1.657)
Ratio of Immigrant to Native Wage Bill						
θ_1	-2.154	-2.517	-2.584	-2.014	-3.826*	-
	(2.045)	(2.118)	(2.182)	(2.118)	(1.937)	-
θ_2	0.54	0.626	0.636	0.533	0.810*	0.23
	(0.388)	(0.410)	(0.423)	(0.414)	(0.404)	(0.442)
N	5212	5212	5212	5212	5212	5177
1st stage F-stat	20.48	22.68	22.38	22.57	57.76	52.87

Notes: *** $= p < 0.01$, ** $= p < 0.05$, * $= p < 0.1$. Dependent variable is log revenues in the top panel and the ratio of immigrant to native wage bill in the bottom panel. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, log employment of the firm in 2003 interacted with year fixed effects and the wage bill of the firm in 2003 relative to revenues interacted with year fixed effects. Standard errors are clustered at the industry-labor market level. Sample is restricted to establishments with more than 10 employees. Column 1 shows the baseline results. Column 2 removes the firm employment control, column 3 removes the cost to revenue control, column 4 removes the industry-time FEs, column 5 removes the local labor market trends, and column 6 includes labor market - year fixed effects

H Additional Quantitative Results

Table H1: Robustness to alternative values of ν

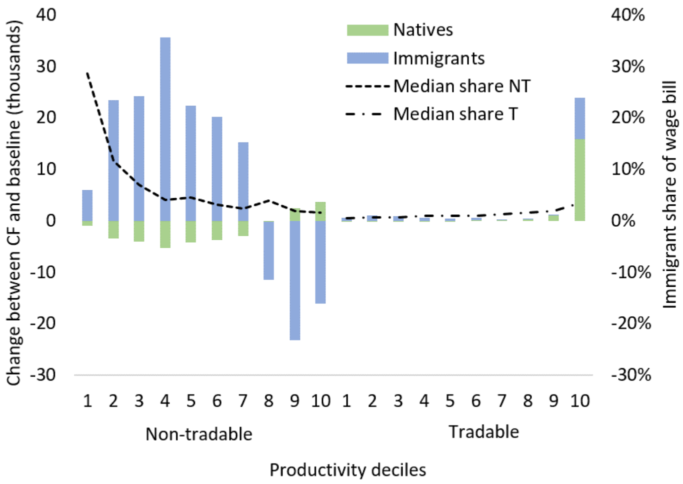
	$\nu = 6.14$	$\nu = 5.37$	$\nu = 4.90$
Real Income			
Native Workers	0.10%	0.14%	0.18%
Firm Owners	1.23%	1.71%	2.08%
Nominal Income			
Native Workers	-0.06%	-0.08%	-0.11%
Firm Owners	1.07%	1.48%	1.79%
Price Index	-0.16%	-0.22%	-0.29%

Notes: We run our counterfactual simulation for different values of ν as estimated in Table F6. Our baseline value of ν is 6.14.

H.1 Eliminating fixed cost of starting to hire immigrants

As a final counterfactual, we look at how the aggregate outcomes change if we remove the initial cost of hiring immigrants $f_{imm,T} = f_{imm,NT} = 0$. This counterfactual is in line with a policy like the restrictions lifted by the EU enlargement for immigrants from all countries. As shown in Figure H1, there is a large increase in the number of immigrants hired by small firms in the non-tradable sector. Natives in these firms experience higher competition and lower wages as shown in Table H2 pushing them to move to large firms in the tradable sector. Smaller firms in the tradable sector do not expand as much, since such firms have a very small market share to begin with, so the lower frictions are not enough to help them take market share from larger productivity firms in the sector. The aggregate real-wage effects of this policy are close to zero, as the reduction in prices is almost identical to the reduction in wages.

Figure H1: Immigrant and Native employment - alternative policies.



Notes: The x-axis shows the distribution of firms in the non-tradable (left) and tradable (right) sectors in terms of deciles of productivity. The bars plot the absolute change in thousands of workers employed in each decile between the counterfactual scenario and the baseline. The dotted lines plot the median immigrant share under the counterfactual scenario. The counterfactual policy is setting the initial cost of hiring immigrants as zero to all firms ($f_{imm,T} = f_{imm,NT} = 0$).

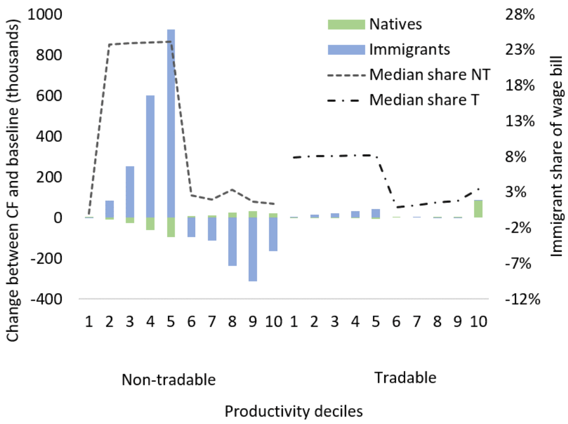
Table H2: Aggregate effects of policy eliminating initial fixed cost of hiring

	Removing cost to begin hiring immigrants
Earnings Natives	-0.02%
Price Index	-0.02%
Real Earnings Natives	0.00%
Real Wages	
Natives - T	0.01%
Natives - NT	-0.02%
Immigrants - T	0.01%
Immigrants - NT	0.27%
Employment	
Natives - T	0.07%
Natives - NT	-0.15%
Immigrants - T	0.08%
Immigrants - NT	1.67%

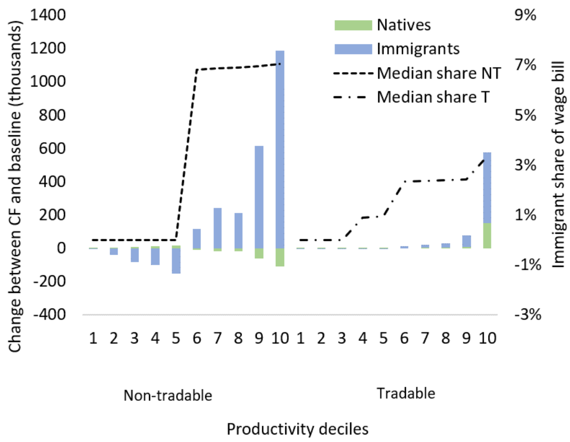
Notes: We compute the changes on the key endogenous variables of going from the observed equilibrium to an equilibrium where we implement the policy of setting the initial fixed cost of hiring immigrants to zero for all firms.

Figure H2: Immigrant and Native employment - alternative policies.

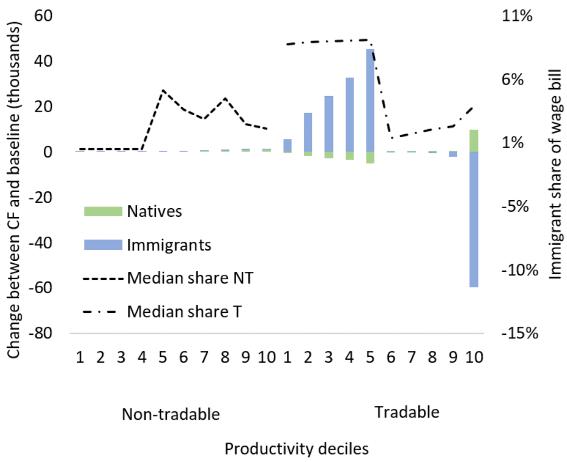
(a) Policy 1



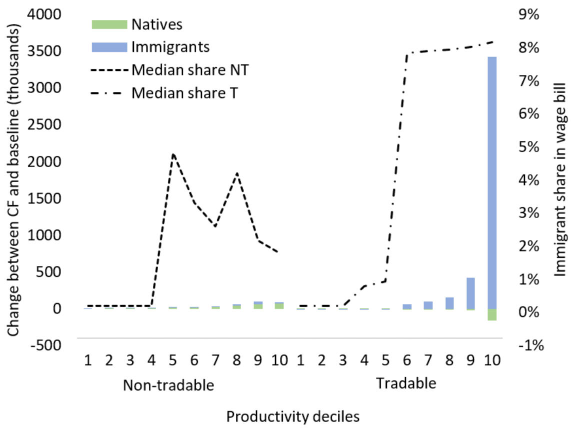
(b) Policy 2



(c) Policy 3



(d) Policy 4



Notes: The x-axis shows the distribution of firms in the non-tradable (left) and tradable (right) sectors in terms of deciles of productivity. The bars plot the absolute change in thousands of workers employed in each decile between the counterfactual scenario and the baseline. The dotted lines plot the median immigrant share under the counterfactual scenario.Each figure four counterfactual reductions in f_j. Policy 1 reduces f_j to the firms with productivity ψ below the median country of the country. This fixed cost is lowered to the 10th percentile of the distribution. The three alternative policies reduce fixed costs by the same total amount but for firms in the top half of the productivity distribution (Policy 2), for the bottom half of firms in the tradable sector (Policy 3), and for the top half of firms in the tradable sector (Policy 4).