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

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Abstract
We revisit the old question of how immigration affects the welfare of native workers. As opposed to most of the previous literature, we look at this question through the lens of firms, as they play a crucial role in immigration and are massively heterogeneous even within sectors. We use a novel establishment-level dataset from Germany to document a new dimension of firm heterogeneity: Large firms spend a higher share of their wage bill on immigrants than small firms. We show analytically and quantitatively that ignoring this heterogeneity in immigrant share leads to biased estimates of the welfare gains from immigration. To do so, we set up and estimate a quantitative model where heterogeneous firms choose their immigrant share, and we validate the model using an instrumental variables strategy. We then use the model to quantify the welfare effects of a 20% increase in the number of immigrants in Germany as observed between 2011 and 2017. The welfare of natives increases both through higher wages and profits, and lower prices, with aggregate welfare gains of $4 billion for native workers and $15 billion for firm owners. A new adjustment mechanism that arises under heterogeneity in the immigrant-share is that native workers reallocate across firms, which mitigates the competition effect between immigrants and natives in the labor market. If we ignore the heterogeneity across firms in immigrant share, we would underestimate the welfare gains of native workers by 11%.

*JEL:* F16, F22, J24, J61
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1 Introduction

The rise in immigration flows to countries like Germany, the United Kingdom, and the United States has fueled the ongoing public debate about the consequences of immigration for receiving countries. Firms play a central role in understanding how an economy adjusts to immigration as they tend to select what immigrants come into the country and respond by making production decisions that determine employment and wages. However, the literature on immigration has predominantly focused at the national, regional, or sectorial level due to the lack of firm-level data on immigrant employment, a key missing piece to understanding the role of firms on the economic impact of immigration.

In this paper, we study how the employment decisions of individual firms shape the effects of immigration on native welfare. First, we open the black-box of firm-level employment composition between immigrants and natives and document a new dimension of heterogeneity across firms. Using a novel establishment-level dataset from Germany, we show that large employers are more immigrant-intensive and benefit more from immigration than small employers. We then show analytically and quantitatively that ignoring this heterogeneity leads to biased welfare gains from immigration. We find that the welfare gains from an immigration inflow of 20%, as observed in Germany between 2011-2017, will be underestimated by 11%.

To characterize the relationship between employer size and immigrant intensity, we use a detailed employer-employee matched dataset of social security records in Germany for 2003-2011. We show that establishments in the top wage bill decile spend 5.6% of their wage bill in immigrants, while establishments in the fifth decile spend only 2.9%. This relationship is mainly driven by firms in the tradeable sector, where the immigrant share of the top decile is twice as high than that of the fifth decile. We show evidence suggesting that firms incur fixed hiring costs to start recruiting immigrant labor, and we rule out confounders such as differences in worker skills, production technologies, and local labor markets.

Next, we set up a quantitative model with heterogeneous firms to quantify the general equilibrium adjustment and welfare implications of an influx of immigrants. The model incorporates a tradeable and non-tradeable sector, the decision to export (Melitz, 2003), and crucially, the decision to hire immigrant labor. We follow the literature on importing intermediate inputs (Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015), modeling firms’ decisions to “source” workers, as opposed to intermediate inputs, from different countries. This sourcing decision, which allows firms to endogenously choose their immigrant intensities, is a novel feature of the model relative to the existing quantitative literature on immigration.

To fully capture the rich relationships between size and immigrant intensities across firms observed in the data, the model allows for two sources of firm heterogeneity: innate productivity and the cost of hiring immigrants. To hire immigrants, firms must pay a fixed cost that is common to all firms, so only more productive firms will find it profitable to hire immigrants.
Additionally, firms must pay a firm-specific fixed cost for any additional country they source immigrants from. Thus, conditional on hiring immigrants, more productive firms will source immigrants from more countries and spend a larger share of their wage bill on immigrants. The labor supply side of the model allows workers in Germany and the rest of the world (RoW) to choose the industry and country to work for, based on real wages and their heterogeneous ability draws across options.

We use a simplified version of this model to analytically show that welfare predictions with aggregate data are biased as they ignore the relationship between firm size and immigrant share. To this end, we compare the welfare gains between our model with full heterogeneity and a model without heterogeneity in immigrant intensities. The sign of the bias depends on whether immigration induces reallocation of natives toward native-intensive firms, which increases the specialization of natives and immigrants in producing different varieties, or toward immigrant-intensive firms. By specializing in producing different goods, natives become less substitutable to immigrants in the labor market and the competition induced by immigration is weaker than when natives do not reallocates across firms. Given that this reallocation across firms is absent if firms produce with the same immigrant share, the increase in aggregate demand for natives is larger in the model with heterogeneity and so does the welfare gains from immigration. The magnitude of the bias, on the other hand, depends on the joint distribution between firm size and immigrant share.

There are three parameters critically affecting our results: the elasticity of demand, the elasticity of substitution between immigrants and natives, and the joint distribution between firm-level productivity and firm-level immigrant-hiring costs. We structurally estimate the scale and substitution elasticities using micro-level data. Following Oberfield and Raval (2014), we estimate the elasticity of demand from the average firms’ markups (i.e., the ratio of revenue to total costs). The substitution between immigrants and natives is estimated through an IV approach, as in Ottaviano and Peri (2012), by regressing the firm-level relative wage between immigrants and natives on relative employment, as implied by the firm’s first-order condition with respect to immigrant and native labor. Since the quantities in our model are in effective units of labor, we provide a model-based method to back out the effective units from observed data on labor quantities and wages.

Given the estimates of these two elasticities, we estimate the joint distribution of productivities and costs to match the observed dispersion and correlation between firm-level revenues and immigrant-intensities in the data. The relevant parameters are jointly estimated together with other model parameters through a Simulated Method of Moments approach to match observed micro- and macro-level moments in Germany between 2003 and 2011. We show that the estimated model is capable of replicating the cross-sectional distribution of immigrant intensities across firms, even for important untargeted moments in the distribution.
We validate the model by comparing our model-predicted treatment effects of an increase in immigration across firm sizes with the observed treatment effects estimated independently from the model. To do so, we provide causal reduced-form evidence that larger firms expand their size relative to small firms when there is an increase in the share of immigrants in the local labor market. Specifically, we regress firm outcomes such as revenue on the share of immigrants in the local labor market and its interaction with firm size. To identify the causal effect, we follow Ottaviano and Peri (2012) and instrument the share of immigrants in a labor market with a shift-share instrument that exploits country-of-origin variation in the initial network of immigrants across local labor markets. We find that a 1% increase in the number of immigrants in the local labor market increases revenues for firms in the top decile by 1.21%, while it only increases revenues in the fifth decile by 0.2%. The model does a good job in replicating the observed relative responses to immigration between firms of different sizes.

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

Importantly, we quantify the significance of accounting for the heterogeneity in the immigrant share for our welfare results. To do so, we re-estimate our model for the case where all firms spend the same share of their wage bills on immigrants. Such model is equivalent to a quantitative model estimated without firm-level data on immigrant labor. Overall, the model without heterogeneity understates the change in welfare of natives by 11%, which is mainly driven by an underestimation of both the drop in the price level and the increase in wages caused by immigration. Finally, we look at the role of international trade and show that it is an important channel to quantify the welfare gains from immigration and amplify the size of the bias.

Our main contribution is twofold. First, we present new facts regarding the relationship between firm size and immigration intensity, showing that big firms disproportionately benefit from immigration. Second, we embed immigration into a general equilibrium model with heterogeneous firms and evaluate whether accounting for firm heterogeneity is quantitatively important to calculate the welfare impact of immigration.

In a majority of immigration studies, firms tend to be pushed to the background due to the lack of firm-level data that includes information on immigration. However, several recent papers use novel firm-level data sets to understand the impact of immigration through the lens of the
firm (Arellano-Bover and San, 2020; Card et al., 2020; Dustmann and Glitz, 2015; Kerr et al., 2015; Mahajan, 2020; Mitaritonna et al., 2017; Orefice and Peri, 2020). Previous work in this area has focused their efforts on using a reduced-form approach, which limits the possibility to quantify the aggregate implications of changes in immigration. We contribute to this literature by documenting new facts regarding the relationship between firm size and immigration and by assessing the aggregate consequences of immigration with a general equilibrium model.

To understand our key finding that large firms benefit more from immigration in the context of this literature, it is important to consider the differences in the role of firms in selecting immigrants across countries and time periods. Mitaritonna et al. (2017) focus on France between 1996 and 2005 and find that small and low-productivity firms experience the most gains from immigration. Arellano-Bover and San (2020) focus on Israel after the collapse of the Soviet Union and find that immigrants initially select into small firms. In these two cases, the immigration environment was dominated by supply shocks where firms had a small role in selecting and facilitating immigration. In countries like Germany (particularly before 2011) or the United States (particularly for their high-skill visa programs), immigrants need a guaranteed employment offer in order to migrate. Hence, firms incur large recruitment costs to select and sponsor immigrants. In this paper, we argue these high recruiting costs partially explain why large firms are more immigrant-intensive than small firms. Consistent with our results, Mahajan (2020) finds that high-productivity American firms are the ones who benefit the most from immigration. Differences in the migration policy environment across countries and time periods can help reconcile both results.

Several other papers use general equilibrium models to understand the impact of immigration (Caliendo et al., 2018; Desmet et al., 2018; di Giovanni et al., 2015; Khanna and Morales, 2018; Morales, 2019). Closely related to our paper is Burstein et al. (2020), who highlight the importance of distinguishing between the tradeable and non-tradeable sectors to understand how an economy responds to immigration. They argue that occupations that produce tradeable goods can crowd in natives in response to immigration since the demand for such occupations is more elastic due to the possibility of trade. Our key addition to this literature is to consider the firm as a fundamental channel through which production and labor adjust to immigration. A related literature looks at the relationship between exports and immigration (Bonadio, 2020; Cardoso and Ramanarayanan, 2019; Gould, 1994; Hiller, 2013). We contribute to this literature by providing a micro foundation on why firms that hire immigrants are more likely to export and provide new results regarding sectorial reallocation and firm growth due to immigration.

Finally, our paper is related to the literature on importing intermediate inputs (Antràs et al., 2017; Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015). We follow the methodological contributions in the literature but consider the “importing” of workers as an endogenous decision of the firm. We adapt the models of sourcing to the context of immigration and show that labor sourcing is a quantitatively relevant decision margin for heterogeneous firms.
2 Data

We use a novel, 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 representative sample of establishments over the period 2003-2011. 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 regarding citizenship, occupation, education, and daily wage. On the establishment side, the dataset contains information on industry, location, and total employment. The LIAB dataset has a companion survey in which panel establishments get asked every year a number of questions including revenues, investment, material use, recruitment and human resources practices, and several additional characteristics of the establishment. It is important to note that the German administrative data is at the establishment level, and there is no option to link multiple establishments to a single firm. Throughout the paper, we will use establishment and firm interchangeably.

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.

A key variable needed for our analysis is workers’ immigration status at a given establishment. The German social security data records citizenship instead of country of birth as their immigrant indicator. Since we are interested in country of birth, we have to re-code this key variable to make sure we count immigrants properly. The most common re-coding is when observing individuals with a foreign citizenship who become Germans the next period. We assume that as long as you show up as foreign for at least two periods, a worker is an immigrant from their initial citizenship country. A second issue we face is that some workers might join the labor market with a foreign citizenship but they may have grown up in Germany to foreign parents. To avoid that mistake, we consider a worker as native if they show a foreign citizenship but joins the labor force at age 20 or younger and is not a college graduate, or joins the labor force at age 25 or younger and is a college graduate. Finally, the data contains information on country of citizenship which are grouped into ten regions: 1) Germany, 2) France, United Kingdom, Netherlands, Belgium, Austria, Switzerland, Finland, and Sweden, 3) Italy, Spain, Greece, and Portugal, 4) countries that joined the EU after 2004, 5) countries of former Yugoslavia not in

\[1\]While LIAB is not directly a representative sample of the population, we apply survey weights to get representative aggregates whenever necessary.
the EU, 6) Turkey, 7) all other European countries including Russia, 8) Asia-Pacific, 9) Africa and Middle East, and 10) the Americas.

3 Documenting Heterogeneity

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

The relationship between employer size and immigrant intensity is not driven by specific confounders such as industry, labor markets, or immigrant skills. Large employers could be concentrated in industries that are more intensive in skills provided by immigrants. At the same time, immigrants might also concentrate in large cities where immigrant networks are larger, which also happens to be where large employers are located. However, none of these channels seem to explain the observed heterogeneity in immigrant intensities. As shown in the red line in Figure 2, the pattern remains strong after controlling for three-digit industry fixed effects and local labor market fixed effects, indicating that differences in production technologies or geographic destinations of immigrants alone cannot explain the observed relationship between size and immigrant-intensity.

Our relationship of interest is also not driven by immigrant skills. Large firms tend to be more intensive in high-skill labor (Burstein and Vogel, 2017), and if immigration policy in Germany would be skewed toward workers with a specific education, this could drive the relationship between size and immigrant intensity. As shown in Figure 1b, the relationship between size and immigration holds for workers with and without a college education. Additionally, we show that the observed patterns are also not driven by the establishment being foreign owned, or being part of a multiunit firm.

The evidence presented thus far is consistent with the existence of fixed costs to hire immigrants, which act as a barrier for small firms to hire their optimal immigrant labor shares. The immigration literature has well documented that immigrants and natives are imperfect sub-

\[ \text{We use wage bill as our main measure to rank establishments but results are robust to using employment or revenues. We focus on establishments with more than 10 employees, but the relationship between size and immigrant intensity is still positive and strong when including smaller establishments.} \]
Figure 1: Immigrant share in wage bill across establishments

(a) All establishments

(b) By education group

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

Institutes as they perform different tasks in production (Peri and Sparber, 2009, 2011). Hence, all firms would optimally choose to hire immigrants in the absence of hiring costs. In the real world, however, many firms do not hire immigrants, and immigrant intensities across firms are vastly different even when controlling for technology and skill differences.

For the most part, costs to recruit immigrants take the form of fixed costs since they do not depend on the number of immigrants to hire. These costs include legal and human resources staff to comply with immigration law and learn how to screen foreign workers. For example, employers may not be familiar with foreign institutions where the immigrant accumulated work experience or the foreign universities granting their educational degrees. Firms may even need to pay a one-time cost to learn about individual countries and their educational and business institutions. In Germany, particularly before the EU labor market integration in 2011, most immigrants needed a guaranteed employment offer in order to migrate to Germany. Given this context and our data window between 2003 and 2011, it makes sense to focus on the decision of firms to explicitly decide to pay these costs and recruit immigrants.3

Based on this anecdotal evidence, in Appendix A, we show evidence consistent with the presence

3Our framework is well suited to study cases in which firms have an active role in finding and sponsoring immigrants. The US H-1B program and Canada’s point system giving high weights to a guaranteed employment offers, are good examples of cases similar to Germany prior to 2011. After 2011, Germany unified its labor market with the EU, so the active role of firms in recruiting is expected to be somewhat weaker.
of fixed costs to hire immigrants. Importantly, we find that there is a significant mass of small firms that do not hire immigrants, and there is lumpiness in the hiring process. We also find that large firms recruit immigrants from more countries, which is consistent with the learning costs to understand immigrant backgrounds.

As a final fact, we argue it is important to explicitly separate establishments in the tradeable and non-tradeable sectors throughout the analysis. As shown by Burstein et al. (2020), the tradeability of the output produced by immigrants is a key feature to account for, as immigrants are absorbed differently in the labor market when working in tradeable versus non-tradeable occupations. Tradeable sectors face a more elastic demand and can expand output more than non-tradeable sectors in response to an influx of immigrants. As shown in Figure 2, establishments in the tradeable sector are more intensive in immigrants than establishments of similar size in the non-tradeable sector. The tradeable sector presents a stronger positive relationship between size and immigrant intensity than the non-tradeable sector.\footnote{Our preferred definition for the tradeable industry considers manufacturing, professional services and wholesale trade. While immigrants do concentrate in some small establishments in the non-tradeable sector (e.g., restaurants, nail salons, etc.), the representative establishment captured by the median tends to have a low immigrant intensity.}

Figure 2: Tradeable and Non-Tradeable sector.

Note. We divide all establishments with more than 10 employees into total wage bill deciles, with 1 being the smallest establishments and 10 the largest. For each decile, we plot the median immigrant share of the total establishment wage bill. Decile 1 is normalized to 0. We separate establishments in each decile on whether they belong to the tradeable and non-tradeable sectors.

Summing up, the differences in the immigrant share across firm sizes is very strong and can potentially affect our current understanding of the effects of immigration on natives welfare. Most of the current literature has not internalized this fact yet as it relies on aggregate data which can lead to a large bias in the predicted welfare gains. To correctly quantify the welfare gains of immigration and characterize the bias introduced by using aggregate data, we set up
a quantitative model presented in the following section.

4 The Model

Our quantitative model has two main components: the labor demand and the labor supply side. On the labor demand side, heterogeneous firms choose their optimal immigrant share, following the setup proposed by Blaum (2019) for firms choosing their intermediate input shares. Firms also choose whether to export their goods by paying a fixed cost as in Melitz (2003). The labor supply side of the model is based on the combination of Eaton and Kortum (2002) model of comparative advantage with Roy (1951), commonly referred to as EK-Roy models.\(^5\) We focus on the main components of the model and relegate some derivations to Appendix B.

Consumption:

Domestic workers (indexed by \(i\)), supply \(L_d\) effective units of labor inelastically and have Cobb-Douglas preferences for goods from two sectors indexed by \(k\): a tradeable sector \(Y^T\) and non-tradeable sector \(Y^{NT}\) as shown in equation 1:

\[
U_i = (Y^T_i)^\alpha (Y^{NT}_i)^{1-\alpha}
\]  

(1)

Each sector \(k\) is composed by a CES aggregate of varieties (indexed by \(z\)) available in the country as in equation 2:

\[
Y^k_i = \left( \int_{J_z} (y(z)^k)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}
\]  

(2)

where \(J_z\) represents the set of varieties available in the country and \(\sigma > 1\) is the elasticity of demand.

Production:

In each industry \(k\), there is a mass of \(N\) firms indexed by \(j\) that produce a specific variety. Firms employ only labor inputs, which can be native “domestic” workers or immigrants. There is a long tradition in immigration literature to think about immigrants and natives as imperfect substitutes in production, as they have different comparative advantages across tasks and specialize in different occupations (Peri and Sparber, 2009, 2011). We assume that firms combine domestic and foreign effective units of labor \((d_j\) and \(x_j,\) respectively) in a CES manner as shown in equation 3:

\[\text{The so called EK-Roy models have been used to model individual choices such as Lagakos and Waugh (2013) and Lee (2020) for the choice across sectors and Morales (2019) for the choice across countries to migrate, among many other applications.}\]
\[ y_j^k = \psi_j \left( \beta_k d_j^{\frac{1}{1-\epsilon}} + (1 - \beta_k) x_j^{\frac{1}{1-\epsilon}} \right)^{\frac{1}{\epsilon}} \quad (3) \]

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

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

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

\[ s_{d,j} = \frac{\beta_k \epsilon w_d^{1-\epsilon}}{\beta \epsilon w_d^{1-\epsilon} + (1 - \beta) \epsilon W_{x,j}^{1-\epsilon}} = \frac{\beta_k w_d^{1-\epsilon}}{u_j^{1-\epsilon}} \quad (5) \]

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

As discussed in Appendix A, we find multiple features in the data that suggest that firms face fixed costs of hiring immigrants and part of it seems to be region-specific. Larger firms are not only more intensive on immigrants than small firms, but also hire immigrants from more countries. Additionally, there is lumpiness in the observed hiring patterns when firms start hiring immigrants from a given region. Finally, the immigrant share of the firm has a strong correlation with the number of regions that the firm recruits from, and it does not correlate with the actual number of immigrants (after conditioning by the number of countries). These features of the data are consistent with the idea that firms must invest resources into learning how to recruit immigrants from additional origin regions.

**Environment to Recruit Immigrants:**

To theorize on the firm choice of its immigrant share that accommodates those facts and remains tractable in a general equilibrium framework, we follow the intermediate input sourcing literature (Antràs et al., 2017; Blaum, 2019; Blaum et al., 2018; Halpern et al., 2015). We assume that the immigrant input of labor, \( x_j \), is a composite of labor from different countries...
\[ x_j = \left( \int_{\Sigma_j} \delta_o x^{\frac{\kappa - 1}{\kappa}} d_o \right)^{\frac{\kappa}{\kappa - 1}} \]  

(6)

\( \kappa \) is the elasticity of substitution between origin countries, such that every additional origin country the firm hires from will have a positive impact on productivity and lower the effective immigrant unit cost \( W_{x,j} \) faced by firm \( j \). The hiring strategy of the firm, denoted by \( \Sigma_j \), represents those countries the firm hires immigrants from a total of \( O \) origins.

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

We assume that hiring costs \( f_j \) are jointly drawn with the firm-specific productivities \( \psi_j \), from a multivariate sector-specific log normal distribution with mean \([\mu_{\psi,k}, \mu_{f,k}]\), dispersion \([\sigma_{\psi,k}, \sigma_{f,k}]\), and covariance between firm productivity draws and hiring costs of \( \sigma_{\psi,f}^k \).

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

\[ W_{x,j} = w_x \frac{1}{\bar{\delta}^{\frac{1}{\kappa - 1}}} \left( \frac{\xi}{\xi - \kappa} \right) \frac{1}{\left\{ \frac{1}{\kappa - 1} - \frac{\xi}{\xi - \kappa} \right\} n} \]  

(7)

where \( \iota > 0 \) can be interpreted as the elasticity of the immigrant unit cost to expanding the mass of countries the firm hires from. Intuitively, imperfect substitution of immigrants generates productivity gains from hiring immigrants from additional origins. This reduces the

\[^{6}\text{In Appendix B, we show step by step how we use these assumptions to get to equation 7.}\]
wage index of immigrants and the unit cost of production.

Pricing Decision:

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

\[ p_j = \frac{\sigma}{\sigma - 1} u_j \]  

(8)

where \( p_j \) is the price charged in the domestic market.

Optimal Domestic Share:

An advantage of this setup is that we can write the unit cost \( u_j \), price \( p_j \), and the optimal mass of countries \( n_j \) as a function of the key object \( s_{d,j} \), as in equations 9 and 10. The native share \( s_{d,j} \) can be directly observed in our firm-level data and is the fundamental link between the model and the data.

\[ p_j = \frac{\sigma}{\sigma - 1} \beta_k w_d^{1-\epsilon} s_{d,j}^{1-\epsilon} \]  

(9)

\[ s_{d,j} = \frac{\beta_k w_d^{1-\epsilon}}{\beta_k w_d^{1-\epsilon} + (1 - \beta_k) \epsilon w_x^{1-\epsilon} \bar{z}^{1-\epsilon} n_j^{(\epsilon-1)}} \xrightarrow{n(s_{d,j}) = \bar{\chi} \left( \frac{1}{s_{d,j}} - 1 \right)^{\frac{1}{\epsilon-1}}} \]  

(10)

where \( \bar{\chi} \) is a combination of parameters and wages \( w_d, w_x \). Equation 9 follows from 4 and the consumer’s optimization problem. Equation 10 follows from using equations 4, 5, and 7:

Firms maximize their profits by choosing the optimal native share \( s_{d,j} \). For each firm \( j \), the profit maximization problem becomes as in equation 11.

\[ \max_{s_{d,j}} \Pi_j = (p_j(s_{d,j}) - u_j(s_{d,j})) y_j - n_j(s_{d,j}) f_j w_d - \text{Sourcing cost} \]  

(11)

The main takeaways of the model are as follows: Firms benefit from an immigration inflow because the wage of immigrants drops and so does the unit cost of production. The size of the drop in the unit cost of production is firm-specific, and it depends on the firm’s domestic share. In other words, the domestic share acts as a firm-exposure to a common immigration shock and becomes the key empirical object to learn about how much each firm (and the economy as a whole) benefits from immigration.

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

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

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

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

$$p^x_j = \frac{\sigma_x}{\sigma_x - 1} u_j \tau$$

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

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

**Labor Supply:**

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

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

where $A_{o,k}$ can be interpreted as the comparative advantage of workers from $o$ in industry $k$. Workers within a country are ex-ante identical but ex-post heterogeneous due to different ability draws across sectors, while workers from different countries also differ in that they draw
their abilities from different distributions. Workers choose the industry and country that yield the highest utility as shown in equation 14:

\[
U_{i,d,k}^o = \frac{w_{d,k} \eta_{o,d,k}^o}{P_d} \phi_{o,d,k}^{-1}
\]  

(14)

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

\[
\pi_{o,k,d} = \frac{A_{o,k} \left( \frac{w_{d,k}}{P_d} \right)^\nu \phi_{o,d,k}^{-\nu}}{\sum_{d,k} A_{o,k} \left( \frac{w_{d,k}}{P_d} \right)^\nu \phi_{o,d,k}}
\]  

(15)

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

**Equilibrium and Market Clearing:**

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

4.1 Firm Heterogeneity and Welfare Gains

In this section, we explain why ignoring heterogeneity in \( s_{d,j} \) may lead to biased estimates of the welfare gains of immigration. In doing so, we connect the source of the bias with the lack of information in aggregate data. We focus on a closed economy with one sector, we assume that native workers are homogeneous and that the fixed cost \( f_{imm} \) is zero (but the firm-specific fixed cost \( f_j \) is unrestricted). All derivations are in Appendix C. In this simplified model, the welfare gains of immigration are given by the increase in the real wage or, equivalently, the drop in \( \frac{P}{w_d} \). Equation 16 presents the equilibrium price index (relative to the wage of native

14
The change in the cost of this basket is simply the change in the average unit cost of production which, in turn, is proportional to the average change in the domestic share, as shown in equation 17:

\[
\Delta \log \left( \frac{w_d}{P} \right) = -\frac{\sum \omega_j \Delta \log (s_{d_j})}{\epsilon - 1} = -\frac{\Delta \log (S_{agg})}{\epsilon - 1} \frac{1}{1 + (\sigma - \epsilon) \Gamma(s_{d_j}, \omega_j)} \geq 0
\]  

(17)

where \( \omega_j \) is the market share which measures firm \( j \)'s weight in the consumption basket.

The first component of expression 17 coincides with the welfare prediction of models that ignore heterogeneity in \( s_{d_j} \). This could be our model with \( f_{imm} = f_j = 0 \), the class of heterogeneous and homogeneous models following the Arkolakis et al. (2012) framework, or neoclassical models of immigration with constant elasticity of substitution between immigrants and natives (Card, 2009; Dustmann and Glitz, 2015; Ottaviano and Peri, 2012; Peri and Sparber, 2009), coupled with CES preferences. In this models, immigration reduces the unit cost of production of all firms and, as firms become more competitive, they can afford higher real wages or welfare. In these case, the size of the aggregate influx of immigrants and the elasticity of substitution between natives and immigrants are sufficient statistics to quantify the gains from immigration. However, this prediction is biased if there is heterogeneity in the presence of immigrants across firms and the immigration shock induces a reallocation of natives across firms.

The real wage or welfare gains of natives can be analysed by looking at the response of the aggregate demand for natives, which depends on a within-firm and a across-firm adjustment. Firms substitute natives with immigrants in response to a drop in relative immigrant wage induced by immigration. In addition, firms also increase their scale of production and, in the heterogeneous model, immigrant-intensive firms gain market share from native-intensive firms because their marginal cost of production respond more to the immigrant wage drop. This reallocation mechanism across firms is absent when firms employ the same immigrant share and can induce different welfare predictions.

In the edge case of \( \epsilon = \sigma \), 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.

To understand how real wages adjustment differ in the heterogeneous and in the homogeneous models when \( \epsilon \neq \sigma \), it is helpful to consider how substitutable immigrants and natives are in
the aggregate economy. As shown by Oberfield and Raval (2021), the aggregate elasticity of substitution between immigrants and natives, denoted by $\epsilon^{agg}$, can be written as:

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

if firms employ the same domestic share $\pi = 1$, otherwise $\pi \in (0, 1)$.

When the elasticity of substitution within the firm is stronger than the elasticity of demand ($\epsilon > \sigma$), immigrants crowd-out natives at immigrant-intensive firms who are reallocated towards native-intensive firms. This increase in specialization of natives and immigrant 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 aggregate demand for natives and welfare gains is 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 at 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 compared to the homogeneous world, and the increase in real wage and welfare gains are lower.

Finally, note that the magnitude of the bias depends on the joint distribution of firm size and immigrant share through $\Gamma\{s_{dj}, \omega_j\}$. In Section 7, we quantify the size of the bias using the model estimated to match moments of this joint distribution.

### 5 Estimation

As discussed in Section 4.1, the key parameters of the model are $\epsilon$, $\sigma$, and parameters of the joint distribution of firm’s productivity and fixed costs to hire immigrants. This section explains how we estimate the parameters of the model.

**Elasticity of Demand**

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

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

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

We use data on markups for exporters relative to non-exporters to back out the implied demand elasticity from the RoW. The observed markup for exporters can be expressed as a weighted average between the domestic markup (depending on $\sigma$) and the export markup (depending on $\sigma_x$). Since the average export share for exporters is 0.28, we calibrate $\sigma_x = 3.62$.

Elasticity of Substitution Between Native Workers and Immigrants

In the model, firm $j$’s demand of immigrant labor relative to native labor is given by (19):

$$\ln \left( \frac{w^d_j}{w^x_j} \right) = \ln \left( \frac{\beta^k}{1 - \beta^k} \right) - \frac{1}{\epsilon} \ln \left( \frac{d_j}{x_j} \right)$$

(19)

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

Estimating equation (19) presents a number of challenges. First, effective wages and quantities are not observed directly in the data. Second, estimating equation (19) by OLS would yield biased estimates of $\epsilon$ since unobserved demand shocks at the firm level can affect the relative quantities of immigrants and natives and the wages firms pay to each labor type.

To solve these issues, we proceed sequentially. First, as we explain in Appendix D.2, we use the structure of the model to estimate the immigrant composite $x_j$ based on observed data on labor quantities and wages across origin countries and industries. Second, we propose an instrument to structurally estimate $\epsilon$ from equation (19).

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

Additional Parameters

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

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

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

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

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

<table>
<thead>
<tr>
<th>Moment description</th>
<th>Simulated</th>
<th>Data</th>
<th>Moment description</th>
<th>Simulated</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate $s_d,T$</td>
<td>0.91</td>
<td>0.91</td>
<td>$E(s_d)$</td>
<td>0.93</td>
<td>0.93</td>
</tr>
<tr>
<td>Aggregate $s_d,NT$</td>
<td>0.93</td>
<td>0.93</td>
<td>Share of firms hiring immigrants, $T$</td>
<td>0.57</td>
<td>0.62</td>
</tr>
<tr>
<td>$\Var[\log(\text{rev}_j)</td>
<td>s_d,j,\text{exporter}_j], T$</td>
<td>1.38</td>
<td>1.38</td>
<td>Share of firms hiring immigrants, $NT$</td>
<td>0.63</td>
</tr>
<tr>
<td>$\Var[\log(\text{rev}_j)</td>
<td>s_d,j], NT$</td>
<td>1.23</td>
<td>1.29</td>
<td>GDP per capita Row to Germany</td>
<td>0.32</td>
</tr>
<tr>
<td>$\Var((1-s_d,T)/s_d,T)$</td>
<td>1.36</td>
<td>1.39</td>
<td>Share of firms exporting, $T$</td>
<td>0.34</td>
<td>0.37</td>
</tr>
<tr>
<td>$\Var((1-s_d,NT)/s_d,NT)$</td>
<td>1.48</td>
<td>1.58</td>
<td>$E(\text{Export to Domestic Rev}_j), T$</td>
<td>0.80</td>
<td>0.79</td>
</tr>
<tr>
<td>$E(s_d,T,p_{90}) - E(s_d,T,p_{50})$</td>
<td>0.015</td>
<td>0.021</td>
<td>$E(s_d,NT,p_{90}) - E(s_d,NT,p_{50})$</td>
<td>0.009</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Table 2: Parameter estimates using SMM

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

Model Fit

While the model matches the targeted moments, we want to make sure it also matches non-targeted moments that are relevant to our main mechanisms. As shown in Figure 3, the model does a good job in matching the cross-sectional means and medians of the immigrant share by size decile. The medians are completely untargeted by the estimation routine. The model does a good job in replicating the increasing trend in the tradeable sector and somewhat misses the slight increasing trend in the non-tradeable sector. However, the observed correlation between size and immigrant share in the non-tradeable sector is weak and the model captures the levels reasonably well. The means are also informative of the distribution within decile. These are not completely untargeted since we are matching the mean immigrant share across all establishments in our estimation routine as well as the difference in the means of P90 and P50 for each sector. However, we are not matching the mean by sector nor the relationship between any deciles other than 5 and 9. As shown in Figure 3, the model does a good job matching both means but underestimates the mean for the first deciles in the tradeable sector.
Figure 3: Immigrant share across establishments: model vs data.

(a) Median Tradeable

(b) Mean Tradeable

(c) Median Non-Tradeable

(d) Mean Non-Tradeable

Note. We divide establishments in the model and the data into size deciles, where 1 groups the smallest establishments. We plot the mean and median for each decile and each sector as shown by the data as in Figure 1. For the model, we plot the size distribution predicted by our estimated model.
Model Validation: Heterogeneous Response

Before quantifying the aggregate implications of the model we evaluate whether the data validates the main mechanisms driving its aggregate results. The key prediction from the model is that large firms, which are more immigrant-intensive than small firms, will experience a larger drop in their unit costs and expand more in terms of production and revenues. Such heterogeneity in the response to immigration is expected to be larger in the tradeable sector, where the relationship between size and immigrant intensity is stronger.

We begin by estimating a regression as shown in equation 20:

\[
\ln(y_{j,m,k,t}) = \theta_1 S_{mf} + \theta_2 S_{mf} \log(emp_{j,t-1}) + \theta_3 X_{j,t} + \delta_j + \delta_{k,t} + \delta_{m,t} + \epsilon_{j,m,k,t}
\] (20)

where the outcome variable is the value of sales for establishment \( j \) located in labor market \( m \), industry \( k \), in year \( t \). The regressor \( S_{mf} \) is the share of immigrants in \( m \) in year \( t \), \( emp_{j,t-1} \) is establishment size measured by employment, and \( X_{j,t} \) are establishment-level control variables. This model allows for labor markets to be in different linear trends as captured by \( \delta_{m,t} \). It also includes industry-time fixed effects to control for factors affecting all establishments in an industry over time, and an establishment fixed effect to control for unobservable characteristics that are time-invariant. We define the immigrant shock \( S_{mf} \) at the local labor market level as we aim to understand how different establishments adjust within a labor market whenever there is an immigration influx. The key parameter of interest is \( \theta_2 \): If positive, it implies that a rise in the share of immigrants in a labor market promotes faster growth for larger establishments compared to smaller ones operating in the same market. Thus, \( \theta_2 > 0 \) will suggest that larger establishments respond more to immigration than small establishments. Even though the fixed effects and controls included in the empirical specification aim to capture unobservable shocks and establishment heterogeneity, ordinary least squares (OLS) estimates will be upward biased if, for example, productivity shocks at the local labor market level improve establishment outcomes and attract migration inflows into the region. To address these endogeneity concerns, we follow an IV approach inspired by Card (2001) and Ottaviano et al. (2018), and define a shift-share instrument as shown in equation 21:

\[
Z_{m,t} = \sum_o \frac{\text{Wage Bill}_{o,m,2003}}{\text{Wage Bill}_{m,2003}} \frac{1 + \gamma_{o,t}^{GER}}{1 + \gamma_{t}^{GER}}
\] (21)

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

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

$$
\epsilon_{j,m,k,t} \equiv \frac{\frac{\partial y_{j,m,k,t}}{\partial S_{m,t}^f} S_{m,t}^f}{y_{j,m,k,t}} = \left( \theta_1 + \theta_2 \log (\text{emp}_{j,t-1}) \right) \frac{S_{m,t}^f}{y_{j,m,k,t}} \quad (22)
$$

The elasticity of firm $j$’s outcome $y_{j,m,k,t}$ to an immigration shock depends on both its size and the participation of immigrants in the labor market where it operates.

### 6.1 Heterogeneous Response of Revenues to Immigration:

In this section, we present the OLS and two-stage least squares (2SLS) estimates of equation 20 for total revenues as outcome variable to show that larger firms expand more in response to an immigration shock.

Table 3 presents estimates for total revenues for the full sample in columns 1 to 3 and for the tradeable and non-tradeable sectors in columns 4 and 5. The OLS estimate in column 1 shows that, on average, establishments in local labor markets with larger increases in the share of immigrants register larger revenue growth. Column 2 shows that the 2SLS estimate is lower than the OLS estimate consistent with the hypothesis that OLS estimates are upward biased. This 2SLS suggests that immigration into a local labor market has no statistically significant impact on establishments’ revenues. This average effect masks significant heterogeneity, uncovered in column 3. After accounting for the heterogeneous effect across establishment sizes, the average effect is negative and strong. That is, an increase in the share of immigrants in the labor market shrinks firms’ revenues on average and increases the revenue of large establishments relative to small establishments. The implied threshold size of the establishment above which the elasticity is positive is ninety employees. In terms of elasticity of revenues, the average elasticity of revenues to changes in the labor market immigrant share is 0.28 (i.e., a 1% increase in the share of immigrant in a local labor market increases firm’s revenue by 0.28%). Table 4 unfolds the heterogeneity across establishment size in terms of these elasticities: Revenues of an establishment in the first decile of the employment distribution drop by 0.21% whereas those of an establishment in the highest decile increases by 1.21%.

Columns 4 and 5 in Table 3 make it clear that the heterogeneity in size is driven primarily by
establishments in the tradeable sector, where large establishments grow their revenues significantly more than small establishments. Establishments in the non-tradeable sector do not seem to differentially respond to the immigration shock, consistent with the patterns in Figure 2, where establishments in the non-tradeable sector present a low correlation between immigrant share and size.

Table 3: Heterogeneous benefits of immigration shock

<table>
<thead>
<tr>
<th></th>
<th>Log Revenues</th>
<th>Log Revenues</th>
<th>Log Revenues</th>
<th>Log Revenues</th>
<th>Log Revenues</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tradeable</td>
<td>Non-Tradeable</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>5.83***</td>
<td>3.00</td>
<td>-32.17***</td>
<td>-57.43***</td>
<td>7.08</td>
</tr>
<tr>
<td></td>
<td>(1.98)</td>
<td>(3.29)</td>
<td>(11.37)</td>
<td>(17.42)</td>
<td>(0.69)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>7.56***</td>
<td>12.27***</td>
<td>-0.49</td>
<td>-0.49</td>
<td>-0.49</td>
</tr>
<tr>
<td></td>
<td>(2.44)</td>
<td>(3.77)</td>
<td>(0.89)</td>
<td>(0.89)</td>
<td>(0.89)</td>
</tr>
</tbody>
</table>

Average elasticity: 0.28 0.54 0.26

N observations: 3507 3507 3507 1974 1533
N establishments: 949 949 949 532 417
Estimation: OLS 2SLS 2SLS 2SLS 2SLS
1st stage F-stat: 234.1 36.4 27.1 15.77

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

Table 4: Elasticity of revenues to immigration shock by firm size

<table>
<thead>
<tr>
<th>Size deciles</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>All establishments</td>
<td>-0.27</td>
<td>-0.16</td>
<td>-0.07</td>
<td>0.02</td>
<td>0.14</td>
<td>0.20</td>
<td>0.36</td>
<td>0.55</td>
<td>0.79</td>
<td>1.30</td>
</tr>
<tr>
<td>Tradeable</td>
<td>-0.49</td>
<td>-0.30</td>
<td>-0.09</td>
<td>0.07</td>
<td>0.25</td>
<td>0.48</td>
<td>0.71</td>
<td>1.02</td>
<td>1.50</td>
<td>2.25</td>
</tr>
<tr>
<td>Non-Tradeable</td>
<td>0.33</td>
<td>0.27</td>
<td>0.28</td>
<td>0.23</td>
<td>0.25</td>
<td>0.26</td>
<td>0.21</td>
<td>0.29</td>
<td>0.24</td>
<td>0.27</td>
</tr>
</tbody>
</table>

Note. We rank establishments in terms of employment and compute the mean elasticity of revenues to local labor market immigrant share for each decile using equation 22. Sample used is the same as in Table 3.

In Appendix E, we also show that export revenues are more elastic than domestic revenues, as predicted by the model. These estimates imply that by each 1% increase of the labor market immigration share, domestic revenues increase by 0.44% whereas export revenues increases by 1.15%. Since the response of export revenues is stronger than domestic revenues, this channel can explain part of the heterogeneous effects found in Table 3. Large establishments, which are more likely to be exporters, may adjust more to the immigration shock because they are able to expand their export revenues whereas for small firms, expansion is constrained by the size of the domestic market.
Appendix E also shows alternative specifications of equation 20, where we remove the industry-time fixed effects, the local labor market time trends, and the firm controls. Overall, the qualitative implications of our results hold under the additional specifications. We also run a set of specification tests to verify the validity of our instrument following the recent literature on shift-share instruments as suggested by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2021), among others. We find no evidence of pre-trends, and other labor market characteristics drive little variation in the initial shares used to construct the shift-share instrument.

6.1.1 Predicted Treatment Effects: Data vs. Model

As a final step, we assess whether our model can generate counterfactual predictions that match the observed heterogeneous treatment effects across employer sizes estimated in Table 4. This is a key validation of the model as the reduced form estimates in this section have not been targeted at all for the model estimation. First, we compute in our model the revenue elasticities for each firm in each size decile in response to a 1% change in the immigrant share in each labor market (i.e., in each sector), and we calculate the mean by size decile.\(^7\) Second, we take the estimated elasticities by decile from Table 4 and compare them to the estimated elasticities in the model. As shown in Figure 4, the model does a good job in replicating the relative treatment effects from our empirical exercise. The changes in the tradeable sector predicted by the model, replicate the responses in the data almost exactly until decile seven, and predict a more conservative response to immigration for firms in the highest three deciles. For the non-tradeable sector, the model does a good job in replicating the treatment effects in the data across deciles, where establishments of different sizes do not respond differently to the immigration shock.\(^8\)

6.2 Heterogeneous Response of Immigrant-Intensity:

Given that \(\hat{\epsilon} > \hat{\sigma}\), the model also predicts that immigrants will crowd-out natives from immigrant-intensive firms, and natives will reallocate towards native-intensive firms. This prediction implies that immigration will induce larger firms, who are immigrant-intensive, to increase their immigrant share with respect to small firms. Table 5 shows the 2SLS estimates for the firm-level ratio between immigrant and native wage bill, and provides consistent evidence with such prediction. Column 1 suggests that immigration into a local labor market has no statistically significant impact on the immigrant intensity of establishments but this result masks significant heterogeneity across sectors. Column (2) shows that large firms in the trad-

---

\(^7\)Same as in the counterfactual discussed in section 7, we lower migration costs to each sector such that the total number of immigrants in Germany increases by 1%.

\(^8\)The model-generated elasticities include general equilibrium changes in prices and quantities due to immigration, while in the data, we control for aggregate changes through industry-time fixed effects and local labor market trends. Given this discrepancy, we should not expect the levels of the elasticities to necessarily match between model and data. Instead, the key object to compare when judging whether the model can replicate the heterogeneous responses observed in the data is the relative elasticity across size deciles.
Figure 4: Elasticity of revenues to immigration: Model vs data

(a) Tradeable sector

(b) Non-Tradeable sector

Note. For the model, we rank establishments in terms of revenues into 10 deciles, with decile 1 being the establishments with lowest revenues. We compute the elasticity of revenues to a 1% increase in the immigrant share and calculate the mean elasticity for firms in each decile. For the data, we use the sector-specific elasticities by size decile presented in Table 4.

able sector increase their immigrant-intensity relative to small firms. More specifically, firms with more than 40 employees increase their immigrant-intensity, while smaller firms become more native-intensive. In the non-tradeable sector, however, this heterogeneous effect across firm size is absent, as expected based on the relatively flat relationship between firm size and the immigrant-share shown in Figure 2.

Table 5: Effect of Immigrant on Immigrant Intensity

<table>
<thead>
<tr>
<th></th>
<th>Log relative wage bill</th>
<th>Log relative wage bill</th>
<th>Log relative wage bill</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tradeable</td>
<td>Non-Tradeable</td>
<td></td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>-0.62</td>
<td>-2.31*</td>
<td>3.96</td>
</tr>
<tr>
<td></td>
<td>(1.14)</td>
<td>(1.19)</td>
<td>(2.78)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>0.16</td>
<td>0.65**</td>
<td>-0.68</td>
</tr>
<tr>
<td></td>
<td>(0.24)</td>
<td>(0.28)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>Average elasticity</td>
<td>0.04</td>
<td>0.06</td>
<td>0.04</td>
</tr>
<tr>
<td>N observations</td>
<td>3507</td>
<td>1974</td>
<td>1533</td>
</tr>
<tr>
<td>N establishments</td>
<td>949</td>
<td>532</td>
<td>417</td>
</tr>
<tr>
<td>Estimation</td>
<td>2SLS</td>
<td>2SLS</td>
<td>2SLS</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>36.4</td>
<td>27.1</td>
<td>15.77</td>
</tr>
</tbody>
</table>

Note. ** *= $p < 0.01$, ** *= $p < 0.05$, *= $p < 0.1$. The relative wage bill is defined as the wage bill spent on immigrants relative to natives. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employees.
7 Aggregate implications

This section measures the economic and welfare consequences of an inflow of immigrants into Germany. Section 7.1 explains and quantifies the main forces shaping the adjustment to the immigration shock, and section 7.2 quantifies the importance of accounting for heterogeneity when assessing its welfare gains for natives. Finally, section 7.3 discusses the role of trade for our quantitative results.

7.1 Quantitative Exercise

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

We define welfare of natives, denoted by $W_g$, as their ex-ante real labor income (see equation 23). Note that, ex-post, the change in welfare of a particular native worker may be different. For example, the welfare change of a worker who does not change the sector due to the immigration shock is the change in the real wage of that sector as follows:

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

(23)

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

Wages also go up as a response to immigration, since immigrants are a complementary input to natives. However, natives also compete with immigrants to some extent, muting the wage.
The welfare gains of firm owners is significantly larger because they do not compete with immigrants in the labor market as native workers do. Their real income from firm profits increase by 1.22% due to the drop in production costs induced by immigration, amounting to a gain of $15 billion.9

Table 6: Effect of immigration on welfare of native workers

<table>
<thead>
<tr>
<th></th>
<th>Real Income</th>
<th>Price Index</th>
<th>Nominal Income</th>
<th>Monetary Gains</th>
</tr>
</thead>
<tbody>
<tr>
<td>Native Workers</td>
<td>0.24%</td>
<td>-0.17%</td>
<td>0.07%</td>
<td>$4B</td>
</tr>
<tr>
<td>Firm Owners</td>
<td>1.22%</td>
<td>-0.17%</td>
<td>1.04%</td>
<td>$15B</td>
</tr>
</tbody>
</table>

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

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

Wages per native worker increase in both sectors. In the tradeable sector, this is due to selection as lower ability natives reallocate to the non-tradeable sector, and those natives who stay in the tradeable sector are, on average, of higher ability. In the non-tradeable sector, there are two counteracting effects. On one hand, lower ability natives get in the sector decreasing average wages. On the other hand, the additional domestic demand created by the new immigrants

9Our findings are somewhat larger than those estimated by Caliendo et al. (2018), who predict immigration after the EU labor market integration increases welfare for the original EU members by just 0.04%. Our larger gains can be explained due to allowing immigrants and natives to be imperfect substitutes, while in Caliendo et al. (2018) they are considered perfect substitutes within skill group. Their estimates also are mainly driven by the UK who opened their goods and labor market simultaneously. They conclude that a phased policy like Germany, where the labor market was opened in a later period, would likely have created higher welfare gains.
increases demand for the sector pushing effective wages up. Overall, the latter effect dominates, and workers in both sector earn higher wages due to immigration.

Table 7: Effect of immigration on employment and wages

<table>
<thead>
<tr>
<th></th>
<th>Labor units</th>
<th>Effective units</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Tradeable</td>
<td>Non-Tradeable</td>
</tr>
<tr>
<td>Total</td>
<td>2.49%</td>
<td>2.09%</td>
</tr>
<tr>
<td>Native</td>
<td>-0.11%</td>
<td>0.23%</td>
</tr>
<tr>
<td>Immigrant</td>
<td>20.01%</td>
<td>20.01%</td>
</tr>
</tbody>
</table>

Wages

<table>
<thead>
<tr>
<th></th>
<th>Natives</th>
<th>Immigrants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.07%</td>
<td>-6.32%</td>
</tr>
<tr>
<td></td>
<td>0.07%</td>
<td>-6.26%</td>
</tr>
<tr>
<td></td>
<td>0.05%</td>
<td>-3.51%</td>
</tr>
<tr>
<td></td>
<td>0.11%</td>
<td>-3.45%</td>
</tr>
</tbody>
</table>

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

The benefit of immigration for firms is also large in the aggregate, but it masks large heterogeneous benefits for firms of different sizes in the tradeable sector. From the top panel of Figure 5, three facts stand out. First, there is a large dispersion in the within-sector price responses and the initial exposure to the immigration shock, which can be a quantitatively important determinant of the aggregate results described before. Second, the cross-sectional differences in the initial exposure \((1 - s_{dj})\) go a long way in explaining differences in price responses (Figure 5a). Third, the exposure to the shock is significantly higher for larger firms (Figure 5b). Thus, the positive relationship between firm size and immigrant intensity, as observed in the data, drives the positive relationship between firm size and price decrease in the model. Larger firms, by virtue of being immigrant-intensive, are more exposed to the decrease in immigrant wage than smaller firms, and their unit cost of production and price decrease more than the unit cost of small firms. Thus, as a result of immigration, larger firms increase their market share. Even though larger firms gain market share to small firms (Figure 5c), they reduce their share in the labor market of natives (Figure 5d). Within each sector, native workers reallocate from large firms (immigrant-intensive) to small firms (native-intensive) because immigrants substitute natives as long as the substitution effect is larger than the scale effect \((\epsilon > \sigma\), see Section 4.1).

7.2 Role of Heterogeneity in Immigrant Share

In this section, we assess the importance of the documented heterogeneity in quantifying the adjustment of the German economy to an immigration inflow. We show that ignoring the heterogeneity in the immigrant share predicts welfare gains that are too small.

We assess the importance of heterogeneity in the immigrant share by comparing the model predictions to the same immigration shock across two models: the heterogeneous model and
Figure 5: Responses to immigration across sectors and firms.

(a) Change in domestic price

(b) Immigrant intensity

(c) Change in market share

(d) Change in native employment share

The x-axis of figure 5a groups firms into deciles in terms of their immigrant intensity \((1 - s_{dj})\) and that of figure 5b, 5c, and 5d in terms of their total revenues. The y-axis in all figures measures the average change in the variable in the counterfactual equilibrium in which immigrant stock increases by 20% relative to the initial equilibrium.
the homogeneous model. The heterogeneous model is the general model presented in section 4, whereas the homogeneous model is a particular case in which the parameters generating the heterogeneity in immigrant share are turned off. Importantly, both models are re-calibrated to match the same aggregate moments and are subject to the same immigration shock (20% increase in the stock of immigrants). In terms of equation 17, it means that in both economies, $d\log(S_{agg})$ is the same. The homogeneous model, however, does not match the observed cross-sectional heterogeneity in the immigrant share; that is, $\text{Var}(s_{dj})$, $\text{Cov}(s_{dj}, \text{rev}_j)$, and the share of firms hiring immigrants. To estimate the homogeneous model, we impose the following restrictions on parameters: $\sigma_{f,T} = \sigma_{f,NT} = \sigma_{\psi,f,T} = \sigma_{\psi,f,NT} = 0$.

As shown in the last row of Table 8, the homogeneous model underestimates the welfare gains by 11% because it predicts a weaker increase in workers’ income and a weaker drop in the price index. As explain in section 4.1, the increase in wage is stronger in the heterogeneous model because native-intensive firms do not lose much market share to immigrant-intensive firms, making the aggregate demand for native labor remain relatively strong after the immigration shock. The stronger drop in prices in the heterogeneous model, specially in the tradeable sector, is explained by the fact that larger firms are immigrant-intensive. Large firms, by virtue of being immigrant-intensive, experience a relatively strong drop in the price of the good they produce and, given that they account for a large share of the consumption basket, their price drops are capable of affecting the price index of the economy.

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

<table>
<thead>
<tr>
<th></th>
<th>Welfare</th>
<th>Nominal</th>
<th>Price</th>
<th>Price Index</th>
<th>Price Index</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Workers</td>
<td>Wage</td>
<td>Index</td>
<td>Tradeable</td>
<td>Non tradeable</td>
</tr>
<tr>
<td>Heterogeneous</td>
<td>0.24%</td>
<td>0.07%</td>
<td>-0.17%</td>
<td>-0.18%</td>
<td>-0.15%</td>
</tr>
<tr>
<td>Homogeneous</td>
<td>0.22%</td>
<td>0.06%</td>
<td>-0.16%</td>
<td>-0.16%</td>
<td>-0.15%</td>
</tr>
<tr>
<td>Homog/Heterog</td>
<td>89%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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

7.3 The Quantitative Role of Trade

Exports and trade have a key role in the quantitative results of increasing immigration and the size of the bias. We compare our baseline model with an alternative model where Germany and the RoW are in autarky, such that trade is not allowed between countries. This model is analogous to a model where the fixed cost of selecting into trade goes to infinity (e.g., $f_x \to \infty$).
As shown in Table 9, if countries cannot engage in international trade, the price decrease induced by immigration is too strong. The model with no trade overstates the decrease in the price index by more than double the decrease predicted by the baseline model. Both trade and migration lower the marginal cost of production and, in turn, the price index. When trade is not allowed, migration becomes more important as a source of reducing the cost for consumers as they cannot adjust their consumption through trade.

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

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

<table>
<thead>
<tr>
<th></th>
<th>Welfare</th>
<th>Nominal Wage</th>
<th>Price Index</th>
<th>Revenues</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.24%</td>
<td>0.07%</td>
<td>-0.17%</td>
<td>1.05%</td>
</tr>
<tr>
<td>No Trade</td>
<td>0.34%</td>
<td>-0.04%</td>
<td>-0.37%</td>
<td>0.98%</td>
</tr>
<tr>
<td>No Trade and homogeneous</td>
<td>0.31%</td>
<td>-0.02%</td>
<td>-0.33%</td>
<td>0.98%</td>
</tr>
</tbody>
</table>

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

8 Conclusion

In this paper, we document a large degree of heterogeneity across employers regarding their immigrant share, where large employers are more intensive in immigrant labor. To understand the general equilibrium implications, we set up and estimate a model of heterogeneous employers...
in the tradeable and non-tradeable sectors who decide how many immigrants to hire. We validate our model using an instrumental variables approach and find that the prediction of the model on how immigration affects firms throughout the firm-size distribution matches the observed treatment effects estimated independently from the model. We use the model to quantify how the economy adjusts to a 20% increase in immigrants, a similar magnitude to the one observed in Germany post-labor market integration with new EU member states between 2011 and 2017. We find that native workers in both sectors experience higher wages and lower prices due to immigration. Total welfare gains amount to $4 billion for native workers and $15 billion for firm owners. Native labor reallocates from the tradeable sector to the non-tradeable sector as the tradeable sector becomes more intensive in immigrants. A model that ignores firm heterogeneity will understate the gains from immigration mainly by understating the decrease in the aggregate price level. Our estimates predict that a model with no heterogeneity in immigrant intensities would underestimate welfare gains by 11%.

References


A Empirical Evidence Motivating Fixed Cost Assumption

This section presents 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 from which it hires immigrants from. Importantly, these facts are not compatible with models in which differences in immigrant-intensity across firms are only due to differences in the production function. In the data, countries of origin are grouped in nine blocks as explained in Section 2.

First, as shown in Figure 1, there is a significant mass of small firms that do not hire any immigrants. If immigrants and natives are imperfect substitutes, as documented intensively in the literature (Peri and Sparber, 2009, 2011) and in Section 5 of this paper, firms would optimally choose to hire a strictly positive level of both native and immigrant workers, which contradicts our first stylized fact. This fact could be rationalized if firms have to pay a fixed cost to hire immigrants. Even if immigrants and natives are complementary inputs, if profits earned by small firms are not enough to afford the fixed cost of hiring immigrants, their choice set is restricted to native workers. Fixed costs thus imply that small firms are more likely to hire only native workers, as shown in Figure 1a.

Second, larger firms source immigrants from more countries. Figure 6 shows a positive relationship between firm size, measured by the decile of employment, and the median and mean of the number of countries the firm sources immigrants from. Table 10 shows the OLS estimate of a regression of the number of source countries on firm size in the previous year after controlling for sector-year fixed effects. The estimate is positive and statistically significant at a 1% confidence level.
Figure 6: Number of origin regions by establishment size

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

Table 10: Firm size and number of different origin of immigrants: OLS estimate

<table>
<thead>
<tr>
<th>log(employment)_{t-1}</th>
<th>Coef.</th>
<th>Std. error</th>
<th>p-value</th>
<th>95% conf. interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.88***</td>
<td>0.064</td>
<td>0.000</td>
<td>[1.753 , 2.01]</td>
</tr>
</tbody>
</table>

Note: Number of observations and establishments are 8123 and 1419, respectively. Firm size is measured by its employment level (in logs).

Third, firms that increase the number of sourcing countries tend to do it by adding one additional country. Each row in Table 11 shows the number of countries that an establishment sourced immigrants from in period $t - 1$ ($N_{c_{t-1}}$), each column shows that number for period $t$ ($N_{c_t}$), 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 countries that source immigrants from are more likely to go from $N_{c_{t-1}}$ to $N_{c_{t-1}} + 1$ 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 source as firms would optimally start sourcing from all countries after paying that cost. This fact could arise, however, if firms were supposed to pay a cost for every additional country they source immigrants from.

Fourth, the year that the firm adds an additional country, it starts hiring a large number of employees from that country. This *jump* in the number of employees hired from the additional country is consistent with firms paying a *fixed* cost for any additional sourcing country. If this were not the case and the cost were variable, firms would tend to start hiring small quantities of those immigrants. Table 12 shows that the average number of employees from the new source in the year the source was added is 4% of the total employment of the firm, and there is a significant mass of firms (25%) that increase the share of new-country immigrants by 3% or more.
Fifth, firms hiring immigrants from more countries tend to be more immigrant-intensive. This is exactly what the model predicts in equation 10. The following table groups firms by the number of countries they source immigrants from and shows that the average immigrant share in wage bill increases with the number of sourcing countries.

Table 13: Firm size and number of different origin of immigrants

<table>
<thead>
<tr>
<th>Immigrant share</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.103</td>
<td>0.118</td>
<td>0.124</td>
<td>0.126</td>
<td>0.125</td>
<td>0.138</td>
<td>0.142</td>
<td>0.152</td>
<td>0.150</td>
</tr>
</tbody>
</table>

Note: employment in 2008.

Sixth, Figure 7 shows that establishments with higher immigrant share in the wage bill recruit immigrants from more regions. In addition, table 14 shows that, even after controlling for number of immigrants hired, the between domestic share and number of countries is significantly strong.
Figure 7: Number of origin regions by immigrant share

Note: 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.

Table 14: Immigrant share, number of immigrants and number of countries: OLS estimate

<table>
<thead>
<tr>
<th>Immigrant share ( it )</th>
<th>Coef.</th>
<th>Std. error</th>
<th>p-value</th>
<th>95% conf. interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N_{countries} it )</td>
<td>0.017</td>
<td>0.0003</td>
<td>0.00</td>
<td>[0.0166 , 0.0178]</td>
</tr>
<tr>
<td>( N_{immigrants} it )</td>
<td>-6( e^{-0.6} )</td>
<td>8( e^{-0.6} )</td>
<td>0.46</td>
<td>[(-2e^{-0.4} , 1e^{-0.4})]</td>
</tr>
</tbody>
</table>

Note: Number of observations 59,439. The regression includes labor market-time and industry-time fixed effects.

To conclude, we interpret these stylized facts as evidence in favor of an environment in which large firms are more immigrant-intensive than small firms because firms have to afford fixed costs whenever they want to hire immigrants from different origins. Larger firms could be more immigrant-intensive than small firms due to differences in production functions. However, only differences in production functions across firms would not be able to rationalize the facts shown in this section.

B Model Derivations

B.1 Sourcing Decision Details

In this section, we describe step by step how we get to the immigrant wage index expression in equation 7. Following equation 6, we know the price index for foreign labor is as in equation 24:
To match the observed empirical patterns, we need firms to optimally choose different shares of domestic workers. \( \delta_o \) is a Pareto random variable common for all firms in which each source country has a specific productivity. The distribution and density of \( \delta_o \) are as in equation 25:

\[
F(\delta) = 1 - \left( \frac{\tilde{\delta}}{\delta} \right)^\xi \quad \text{and} \quad g(\delta) = \xi \tilde{\delta}^\xi \delta^{-\xi - 1}
\]  

(25)

Since the firm needs to pay a fixed cost \( f_j \) for each additional country they hire from, they will just hire from countries with a \( \delta > \delta_j^* \), for a given \( \delta_j^* \). The mass of countries that the firm hires from is then

\[
n_j = F(\delta > \delta_j^*) = \tilde{\delta}^\xi (\delta_j^*)^{-\xi}.
\]

With this result, we can calculate the price index of foreign labor as in equation 26:

\[
W_{x,j} = \left( \int_{\delta_j^*}^{\infty} \delta_o^\kappa w_x^{1-\kappa} \delta^{\xi - \xi - 1} d\delta \right)^{\frac{1}{1-\kappa}} = \left( \frac{\xi \tilde{\delta}^\xi}{\kappa - \xi} (\delta_j^*)^{-\xi} \right)^{\frac{1}{1-\kappa}} \text{ if } \xi - \kappa > 0
\]  

(26)

Since the mass of countries the firm sources from is \( n_j = \tilde{\delta}^\xi (\delta_j^*)^{-\xi} \), we can now compute the foreign price index as in equation 27:

\[
W_{x,j} = w_x \frac{\frac{1}{\delta_j^{(\kappa-1)/\xi}}} {\kappa - 1 \left\{ \frac{\xi}{\xi - \kappa} \right\}} \left( \frac{\xi}{\xi - \kappa} \right)^{\frac{1}{1-\kappa}} \quad \text{ if } \xi - \kappa > 0
\]  

(27)

### B.2 Equilibrium Equations

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

1) Consumer budget constraint. In a given country, natives and immigrants have identical preferences. The total expenditure in Germany (\( Y_g \)) and RoW (\( Y_x \)) are shown in equation 28:
\[ Y_g = \sum_k (w_{g,k}L_{g,k} + w_{g,x,k}L_{g,x,k} + \Pi_{g,k}) \quad Y_x = w_xL_x + \Pi_x \]  

(28)

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

2) Trade balance: total income from exports in Germany is equal to the total import expenditure as in equation 29:

\[ \sum_j 1 (\text{exporter}_g = 1) p_{j,g,x}^T y_{j,x,g}^T = \sum_j 1 (\text{exporter}_x = 1) p_{j,g,x} y_{j,g,x} \]  

(29)

3) Total labor market clearing. In each industry, the expenditure of labor by industry \(k\) equals the number of effective units supplied by the labor market times the effective wage paid by that industry. The market clearing conditions 30-32 require that demand for effective units of native and immigrant labor equals supply in each industry and country:

\[ \sum_k \sum_j d_{j,k} = \sum_k A_{g,k}^{1/2} (\pi_{g,k})^{u-1} {\Gamma} N_g \]  

(30)

\[ \sum_k \sum_j \sum_o x_{j,o,k} = \left( A_{x,k}^{1/2} (\pi_{x,g,k})^{u-1} {\Gamma} \right) N_x \]  

(31)

\[ \sum_j d_{j,x} = \left( A_{x,k}^{1/2} (\pi_{x,x,k})^{u-1} {\Gamma} \right) N_x \]  

(32)

C Welfare Response to Immigration

We focus on a closed economy with one sector, we choose the wage of natives as the numeraire, and assume that the fixed cost \(f_{imm}\) is zero (but the firm-specific fixed cost \(f_j\) is unrestricted). We present the proof in four steps.

Step 1: Express \(d\log(s_{dj})\) as proportional to \(d\log(s_{d1})\).

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

\[ \Pi_j = A \psi_j^{\sigma - 1} s_{dj}^{\chi} - B f_j (s_{dj}^{\sigma - 1} - 1)^{\theta + 1} + \psi_j^{\sigma - 2} s_{dj}^{-\chi + 1 + \theta} = f_j C (1 - s_{dj})^\theta \]

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

The first order condition for firm \( j \) and firm 1 implies that:

\[
(\chi + 1 + \theta + \frac{\theta}{1 - s_{dj}}) \, d\log(s_{dj}) = (\chi + 1 + \theta + \frac{\theta}{1 - s_{d1}}) \, d\log(s_{d1})
\]

or

\[
d\log(s_{dj}) = \frac{\alpha_j}{\alpha_1} \, d\log(s_{d1}) \quad \text{with} \quad \alpha_j = \frac{1}{\chi + 1 + \theta + \theta(1 - s_{dj})^{-1}} > 0 \quad (33)
\]

**Step 2:** Express \( d\log(s_{dj}) \) as proportional to \( d\log(S_{d}^{agg}) \).

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

\[
S_{d}^{agg} = \frac{\sum_j WB_{dj}}{\sum_j WB_j} = \frac{\sum_j WB_j \cdot s_{dj}}{\sum_j WB_j} = \sum_j \omega_j s_{dj}
\]

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

The change in the aggregate domestic share is then given by

\[
d\log(S_{d}^{agg}) = \sum_j \frac{\omega_j s_{dj}}{\sum_j \omega_j s_{dj}} \left( d\log(\omega_j) + d\log(s_{dj}) \right) \quad (34)
\]

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

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

\[
WB_j = \frac{\sigma - 1}{\sigma} r_j = \frac{D}{\psi_j} s_{dj} \chi \quad \rightarrow \quad d\log(WB_j) = d\log(D) - \chi d\log(s_{dj})
\]

\[
\omega_j = \frac{WB_j}{\sum_l WB_l} \quad \rightarrow \quad d\log(\omega_j) = d\log(WB_j) - \sum_l \omega_l d\log(WB_l)
\]

where \( D \) is a general equilibrium variable common to all firms.

The expression of \( d\log(\omega_j) \) as a function of \( d\log(s_{dj}) \) follows from combining these last two expressions:

\[
d\log(\omega_j) = -\chi \left( d\log(s_{dj}) - \sum_l \omega_l d\log(s_{dl}) \right) \quad (35)
\]
This expression, together with 33 and 34, implies that the change in aggregate share can be expressed as a function of the change in \( s_{d1} \):

\[
\begin{align*}
d\log(S_{d}^{agg}) & = \sum_j \omega_j^S (-\chi(d\log(s_{dj}) - \sum_l \omega_l d\log(S_{dl})) + d\log(s_{dj})) \\
d\log(S_{d}^{agg}) & = \sum_j \omega_j^S (-\chi(\alpha_j - \sum_l \omega_l \alpha_l) + \alpha_j) d\log(s_{dj})
\end{align*}
\] (36)

In a more compact way, it reads as:

\[
d\log(S_{d}^{agg}) = \sum_j \omega_j^S (-\chi(\alpha_j - \bar{\alpha}) + \alpha_j) d\log(s_{d1})
\] (37)

with \( \bar{\alpha} \equiv \sum_l \omega_l \alpha_l \).\(^{10}\)

Expressions 38 and 33 let us express individual changes in domestic share as a function of the aggregate change:

\[
d\log(s_{dj}) = \frac{\alpha_j}{\beta} d\log(S_{d}^{agg}) \quad \text{with} \quad \beta = \sum_l \beta_l
\] (38)

**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 domestic share:

\[
d\log(P) = \sum_j \omega_j^{rev} d\log(p_j) = \frac{\sum_j \omega_j d\log(s_{dj})}{\epsilon - 1}
\] (39)

where we used the fact that \( \omega_j = \frac{p_j^{1-\sigma}}{P^{1-\sigma}} \).

We can express the change in the price index as a function of the change of the aggregate share and an additional factor by plugging equation 38 into equation 39.

The last two expressions and the optimal pricing implies:

\[
d\log(P) = \frac{d\log(S_{d}^{agg})}{\epsilon - 1} \sum_j \omega_j^S \frac{\alpha_j}{\beta} \Gamma(\{s_{dj}, \omega_j\}; \sigma, \epsilon)
\]

This expression shows that the change in the price index can be computed only if firm-level

\(^{10}\)If all firms choose the same immigrant-share, \( d\log(S_{d}^{agg}) = d\log(s_{dj}) \).
data on the market share and immigrant intensity are available.

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

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

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

and can be rewritten as in 40 by adding and subtracting $\sum_j \omega_j^S \bar{\alpha}$:

$$\tilde{\Gamma}(\{s_{dj}, \omega_j\}; \sigma, \epsilon)^{-1} = 1 + \frac{\epsilon - \sigma \sum_j \omega_j^S \alpha_j - \sum_j \omega_j \alpha_j}{\epsilon - 1 \frac{\sum_j \omega_j \alpha_j}{\sum_j \omega_j \alpha_j}}$$ (40)

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

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

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

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

Thus, if $\epsilon > \sigma$, equation 40 shows that $\tilde{\Gamma}(\{s_{dj}, \omega_j\}; \sigma, \epsilon)^{-1}$ is lower than one and viceversa.

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

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

**D Estimation of $\epsilon$**

**D.1 Dataset Description**

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

One limitation of the SIAB dataset is that it does not contain information on every employee at the establishments in the sample. For our purposes we need the migrant and native employment at the establishment level, we group establishments in SIAB into bins by time, geographic district, three-digit industry, and size quartile. We then construct our firm level dataset by considering all employees in the sample working for establishments in a given bin as if they would work for the same “synthetic” firm.

### D.2 Estimation Details

To get an expression for the immigrant composite we start from the supply side of the model. Using the Frechet properties, we can write the number of effective units supplied to firm $j$ in industry $k$ by workers from origin country $o$ as in equation 41:

$$x_{j,o} = A_{o,k}^{\frac{1}{\nu}} \left( \frac{\pi_{o,k,d}}{\gamma_{o,k}} \right)^{\frac{1}{\nu}} N_j^o$$  \hspace{1cm} (41)

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

Using the first order condition of profits from firm $j$ with respect to each $x_{j,o}$ relative to the first order condition with respect to a base origin country $o'$, $x_{j,o'}$, and using equation 41, we can get an expression as in equation 42:

$$\ln \left( \frac{w_o x_{j,o}}{w_{o'} x_{j,o'}} \right) = \ln \left( \frac{\delta_{o,k}}{\delta_{o',k}} \right) + \frac{\kappa - 1}{\kappa} \ln \left( \frac{\gamma_{o,k} N_j^o}{\gamma_{o',k} N_j^{o'}} \right)$$  \hspace{1cm} (42)

Using equation 42 and assigning a value for $\kappa$, we can get to the first estimating equation, 43, which gives us an estimate for the average effective units provided by each migrant worker at firm $j$:

$^{11}$\(\kappa\) stands for the degree of substitution across immigrant origin countries for production. We assume $\kappa = 20$, close to the upper bound of the elasticity of substitution between immigrants and natives estimated by Ottaviano and Peri (2012). We show results are very robust to other values of $\kappa$ between 10 and 30.
\begin{equation}
\text{Ln} \left( \text{Wage bill}_{o,j} \right) - \frac{\hat{\kappa} - 1}{\hat{\kappa}} \text{Ln} (N^o_j) = \text{Ln}(\delta_{o,k}) + \frac{\kappa - 1}{\kappa} \text{Ln}(\gamma_{o,k}) + \text{Ln}(\delta'_{o,k}) - \text{Ln}(\gamma'_{o,k} N^o_j) \tag{43}
\end{equation}

To estimate equation 43, we pool all years between 1995 until 2014 and run a regression at the firm-origin-time level. We include origin-industry-time and firm-time fixed effects, such that we only exploit the cross-sectional variation to estimate the fixed effects. From equation 43, we obtain the fixed effects \( \zeta_{o,k} \) which will allow us to compute the immigrant composite at the firm level using data on the number of immigrants by country, the \( \zeta_{o,k} \) estimates, and the assigned value of \( \kappa \) as shown in equation 44:

\begin{equation}
\hat{x}_j = \left( \sum \delta_{o} \left( \frac{\hat{\kappa} - 1}{\hat{\kappa}} \right) \gamma_{o,k} \right)^{\frac{\hat{\kappa} - 1}{\hat{\kappa}}} \left( \sum \delta_{o} \left( \frac{\hat{\kappa} - 1}{\hat{\kappa}} \right) \gamma_{o,k} \right)^{\frac{\hat{\kappa} - 1}{\hat{\kappa}}} \left( \sum \hat{\zeta}_{o,k} \left( \frac{\hat{\kappa} - 1}{\hat{\kappa}} \right) \right)^{\frac{\hat{\kappa} - 1}{\hat{\kappa}}} \tag{44}
\end{equation}

Once we calculate \( \hat{x}_j \), we can proceed to estimate our key elasticity \( \epsilon \). We can use the firm first order condition with respect to the number of native effective units \( d_j \) and the immigrant composite \( x_j \) to get to estimating equation 45:

\begin{equation}
\text{Ln} \left( \frac{w^d_{j,t} d_{j,t}}{w^x_{j,t} x_{j,t}} \right) = \epsilon \left( \frac{\beta^k}{1 - \beta^k} \right) + \frac{1 - \epsilon}{\epsilon} \text{Ln} \left( \frac{\gamma_{d,k,t} N^d_{j,t}}{\hat{x}_{j,t}} \right) \tag{45}
\end{equation}

With some additional structure, we reach estimating equation 46, as shown in Section 5. We proceed to take logs and re-organize equation (19) into estimating equation 46:

\begin{equation}
\text{Ln} \left( \frac{\text{Wage bill Natives}_{j,t}}{\text{Wage Bill Immig}_{j,t}} \right) = \frac{\epsilon - 1}{\epsilon} \text{Ln} \left( \frac{N^d_{j,t}}{\hat{x}_{j,t}} \right) + \text{Ln} \left( \frac{\beta^k_t}{1 - \beta^k_t} \right) + \text{Ln}(\gamma_{d,k,t}) + \zeta_j + \xi_{j,t} \tag{46}
\end{equation}

We assume the error term can be written as a firm fixed effect \( \zeta_j \) and an unobserved component \( \xi_{j,t} \). We also use the labor supply property that the number of effective units of native workers can be expressed as an interaction between an industry-time constant \( \gamma_{d,k,t} \) and the observed number of German workers at firm \( j \), \( N^d_{j,t} \) as in equation 41. While the model is static, once again we add time subscripts as we pool several years of data to maximize our sample size.

The OLS estimates will not provide a consistent estimate of the elasticity of substitution under the presence of unobservable shocks affecting both the relative labor demand and relative wage. If, for example, firms face productivity shocks that are biased to immigrants, the OLS estimate
will be upward biased. To address endogeneity concerns, we instrument the firm’s relative demand of workers with the following shift-share instrument:

$$Z_{j,m,t}^f = \sum_o \frac{\text{Wage Bill}_{o,m,1995}}{\text{Wage Bill}_{m,1995}} \frac{\text{Employment}_{o,m,t}^{Imm}}{\text{Employment}_{m,t}^{Ger}}$$  \hspace{1cm} (47)

The initial share component of the instrument is the wage bill of immigrants from origin $o$ in market $m$ in year 1995 relative to the total wage bill in market $m$ in 1995.\(^{12}\) We use “kreis” as the market concept ($m$) of this instrument which is the finest geographical area in our dataset. The shift component of the instrument captures the employment level of immigrants from country $o$ relative to Germans in market $m$ in year $t$. This instrument exploits country-of-origin-driven variation in the relative supply of immigrant across markets and “assigns” the increase of immigrants from each origin in that market to firms according to their market-share in 1995.

The validity of the instrument depends on this market share not being correlated with shocks determining the relative wage that firms pay in period $t$. Larger firms tend to have a larger market share and may also tend to pay systematically different average wages to immigrants relative to natives. Even though we control for time-invariant firm heterogeneity, there may be serially correlated time-varying productivity shocks that affect the relative size of firms in 1995 and their hiring decisions in the future. This would bias the 2SLS estimate upward. The time-industry fixed effect will help control for unobserved time-varying shocks. Finally, we cluster standard errors at the firm level to account for the correlation within firm over time.

Table 15 presents the OLS and the 2SLS estimates of 46. The OLS estimate of $\epsilon_{-1}$ is larger than 1 and implies an unreasonable elasticity of substitution between immigrants and natives of -35.1. The 2SLS estimate in column 2 is lower than one and statistically significant. This estimate implies that the elasticity of substitution between immigrants and native workers within the firm is 4.28. As expected, the OLS estimate is upward biased, since the error term includes demand-side shocks that positively affect the wages and employment of immigrants relative to natives. The instrument is strong, as shown by the F-stat in Table 15.

\(^{12}\)While the data is available since 1975, we use 1995 as our base year since administrative data for East Germany only becomes available after 1993.
Table 15: Estimates for $\epsilon$

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>2SLS</th>
<th>First stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimate for $(\epsilon - 1)/\epsilon$</td>
<td>1.029***</td>
<td>0.81***</td>
<td>-0.00025***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.355)</td>
<td>(0.00005)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>458,308</td>
<td>458,308</td>
<td>458,308</td>
</tr>
<tr>
<td>Implied $\epsilon$</td>
<td>-35.1</td>
<td>4.28</td>
<td>1st stage F-stat</td>
</tr>
</tbody>
</table>

$*** = p < 0.01$, $** = p < 0.05$, $* = p < 0.1$. OLS and 2SLS estimates for equation 46. We include industry-time and firm fixed effects. Industry-time FEs are defined according to our tradeable and non-tradeable industries used in the model. Standard errors are clustered at the firm level and bootstrapped with 200 repetitions. Time period used is 1995 to 2014.

E Empirical Results Details

E.1 Heterogeneous Response to Immigration: Additional Results

Table 16 evaluates how the controls added to the regression affect our estimates. Column 2 removes the firm-level controls, column 3 removes the industry-time FEs, and column 4 removes the local labor market trends.

Table 16: Robustness exercises for main specification

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>No firm-level controls</th>
<th>No industry-time FEs</th>
<th>No local labor time trends</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_1$</td>
<td>-32.17***</td>
<td>-37.38**</td>
<td>-52.90***</td>
<td>-25.31**</td>
</tr>
<tr>
<td></td>
<td>(11.37)</td>
<td>(14.40)</td>
<td>(12.79)</td>
<td>(10.99)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>7.56***</td>
<td>8.56***</td>
<td>12.38***</td>
<td>5.93**</td>
</tr>
<tr>
<td></td>
<td>(2.44)</td>
<td>(3.28)</td>
<td>(2.74)</td>
<td>(2.39)</td>
</tr>
<tr>
<td>N observations</td>
<td>3507</td>
<td>3507</td>
<td>3507</td>
<td>3507</td>
</tr>
<tr>
<td>N establishments</td>
<td>949</td>
<td>949</td>
<td>949</td>
<td>949</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>36.4</td>
<td>8.8</td>
<td>33.7</td>
<td>18.2</td>
</tr>
</tbody>
</table>

$*** = p < 0.01$, $** = p < 0.05$, $* = p < 0.1$. Dependent variable in all cases is log revenues. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends, and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employees. Column 1 shows the baseline specification with full controls. Column 2 removes the firm-level controls. Column 3 removes the industry-time fixed effects and controls only for time fixed effects. Column 4 removes the local labor time-trends.

Table 17 presents the heterogeneous effects of the immigration shock on profits, labor productivity, investment, total employment, and native employment. Profits are measured as revenues net of wage bill and material bill, and labor productivity is measured as the ratio between revenues and employment. The 2SLS estimates in table 17 reassures the previous findings on the heterogeneous effect of immigration. Relative to small establishments, larger establishments
become more profitable (column 1), the pool of employees becomes more productive (column 2), and they hire more workers (columns 4 and 5). Estimates for investment are imprecisely estimated, so we cannot reject a null effect of changes in response to the immigrant share.

Table 17: The impact of immigration on other outcomes

<table>
<thead>
<tr>
<th></th>
<th>Log Profits</th>
<th>Log Employment</th>
<th>Log Revenue per employee</th>
<th>Log Native employment</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \theta_1 )</td>
<td>-135.80</td>
<td>-4.93</td>
<td>-27.23**</td>
<td>-5.35</td>
</tr>
<tr>
<td></td>
<td>(93.26)</td>
<td>(6.44)</td>
<td>(11.35)</td>
<td>(6.17)</td>
</tr>
<tr>
<td>( \theta_2 )</td>
<td>29.436*</td>
<td>1.66</td>
<td>5.89**</td>
<td>1.66</td>
</tr>
<tr>
<td></td>
<td>(15.78)</td>
<td>(1.41)</td>
<td>(2.49)</td>
<td>(1.34)</td>
</tr>
<tr>
<td>Avg elasticity</td>
<td>0.48</td>
<td>0.09</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>N observations</td>
<td>2901</td>
<td>3507</td>
<td>3507</td>
<td>3507</td>
</tr>
<tr>
<td>N establishments</td>
<td>853</td>
<td>949</td>
<td>949</td>
<td>949</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>31.8</td>
<td>36.4</td>
<td>36.4</td>
<td>36.4</td>
</tr>
</tbody>
</table>

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

E.2 Export Revenues vs Domestic Revenues

A second prediction is that the drop in unit costs generated by immigration would expand export revenues more than domestic revenues because an exporter faces a demand curve from the RoW that is more elastic than its domestic demand.

Table 18 presents the estimated results of regression 20 for domestic revenues and export revenues for the sample of exporters. The average response export revenues is stronger than domestic revenues, and in both cases, the heterogeneous effect significantly favors large establishments relative to small establishments. These estimates imply that by each 1% increase of the labor market immigration share, domestic revenues increase by 0.44% whereas export revenues increases by 1.15%. Since the response of export revenues is stronger than domestic revenues, this channel can explain part of the heterogeneous effects found in Table 3. Large establishments, which are more likely to be exporters, may adjust more to the immigration shock because they are able to expand their export revenues whereas for small firms, expansion is constrained by the size of the domestic market.

To summarize our findings, the reduced-form evidence presented in this section shows that larger employers benefit more from an increase in the immigrant share of the local labor market than
Table 18: Revenue regressions by sector and exporter status

<table>
<thead>
<tr>
<th></th>
<th>Log Domestic Revenues</th>
<th>Log Export Revenues</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_1$</td>
<td>-78.64***</td>
<td>-87.69**</td>
</tr>
<tr>
<td></td>
<td>(29.95)</td>
<td>(37.93)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>16.63***</td>
<td>20.55***</td>
</tr>
<tr>
<td></td>
<td>(5.93)</td>
<td>(7.63)</td>
</tr>
<tr>
<td>Avg elasticity</td>
<td>0.44</td>
<td>1.15</td>
</tr>
<tr>
<td>N observations</td>
<td>1650</td>
<td>1650</td>
</tr>
<tr>
<td>N establishments</td>
<td>465</td>
<td>465</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>26.0</td>
<td>25.4</td>
</tr>
</tbody>
</table>

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

small establishments. Establishments’ export revenues are more responsive than its domestic revenues. This evidence is consistent with the mechanisms put forward in the model: given that large firms are more immigrant-intensive than small firms (Figure 1a), large firms face a larger drop in the labor cost of production than small firms when the economy receives a new wave of immigrants. This drop in the cost of production drives large firms to expand their production at the expense of putting downward pressure on the market price of the good they sell. This downward pressure is weaker the more elastic the demand. Given that large firms are likely to export and foreign demand is more elastic, they find it optimal to increase production to all markets and especially to export markets. As a result, an influx of immigrants is mostly absorbed by large firms that find it profitable to expand production.

E.3 Shift-share Instrument Diagnostics

Our instrument falls into the category of shift-share instruments, and as such, we run a series of diagnostics suggested by the literature on the validity of shift-share instruments (Borusyak et al., 2021; Goldsmith-Pinkham et al., 2020). Our setup is not exactly the standard shift-share case because in addition to the shift-share instrument we have an interaction between the instrument and the log size of the establishment. However, we can still use the guidance of these methodological papers to understand the variation driving our instruments.

As a first step, we follow the suggestions in Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2021) and test for pre-trends. The shift-share design implies that the common shock is the main
driver of the observed changes, so we need to make sure there were no pre-existing differences explaining such observed changes. As shown in Table 19, we lag the outcome 5 and 1 years and run our baseline regression. The instrument is still strong, but the second stage coefficients are not significant, and the magnitude of the estimates is close to zero. This corroborates that the observed changes are not driven by pre-existing differences across establishments. Borusyak et al. (2021) also suggest that if the sum of the initial shares does not add up to one within local labor market, we should control for the sum of the exposure shares in our regression. We do so in a non-parametric fashion by including an establishment fixed effect in our regression which would absorb the sum of initial shares at the local labor market level.

Table 19: Pre-trends tests

<table>
<thead>
<tr>
<th></th>
<th>Log Total Revenues $t - 5$</th>
<th>Log Total Revenues $t - 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_1$</td>
<td>2.51</td>
<td>-7.48</td>
</tr>
<tr>
<td></td>
<td>(9.28)</td>
<td>(9.61)</td>
</tr>
<tr>
<td>$\theta_2$</td>
<td>-1.29</td>
<td>2.09</td>
</tr>
<tr>
<td></td>
<td>(1.93)</td>
<td>(1.99)</td>
</tr>
<tr>
<td>N observations</td>
<td>3329</td>
<td>3434</td>
</tr>
<tr>
<td>N establishments</td>
<td>907</td>
<td>937</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>41.16</td>
<td>40.85</td>
</tr>
</tbody>
</table>

$** = p < 0.01, * = p < 0.05, * * = p < 0.1$. We restrict the sample to years between 2008 and 2011. We control for establishment fixed effects, 2-digit industry-time fixed effects, local labor market time trends and lagged firm level controls such as log employment and investment. Standard errors are clustered at the establishment level. Sample is restricted to establishments with more than 30 employees. The first column includes the outcome variable lagged by 5 periods, the second column includes the outcome variable lagged by one period.

As a second step, we focus on the case of testing for exogenous shares, and run a set of diagnostics proposed by Goldsmith-Pinkham et al. (2020). We perform the tests for a simplified version of equation 20, where we do not include the size interaction term nor the industry-time fixed effects and labor market trends. While the regression is different than our main specification, the analysis is still useful to understand what is driving the main shift-share instrument.

In our case, we can write the first stage coefficient on the shift-share instrument as a combination of the estimates of nine separate first stage regressions. Each of these “just identified” regressions uses an instrument that is constructed with the initial share and shock of only one of our nine origin regions. The weights in which each of these nine instruments affects the overall IV are called Rottemberg weights. We proceed to use the code provided by Goldsmith-Pinkham et al. (2020) to calculate such weights and denote them $\alpha$. Each origin region is affected each year by a national level shock we denote by $G$. The just identified coefficients are denoted by $\beta$.

As shown in panel A of Table 20, 89% of the Rottemberg weights are positive, meaning that our
regression is likely not subject to misspecification. In panel B, we show the correlation between the weights, the shocks, and the just-identified coefficients. Panel C shows the top five origin regions in terms of the Rottemberg weights. For the time period between 2003-2011, countries of former Yugoslavia have the largest weight with 0.28. These are followed by Asia-Pacific (0.24), other non-EU countries which include predominantly Russian immigrants (0.17), Africa and Middle East (0.15), and Turkey (0.07). These regions are expected to drive most of the variation in our instrument. It is reassuring however, that no single region accounts for a large majority of the variation in our instrument.

Table 20: Shift-share diagnostics

<table>
<thead>
<tr>
<th>Panel A</th>
<th>Sum</th>
<th>Mean</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha_s \leq 0)</td>
<td>-0.014</td>
<td>-0.014</td>
<td>0.111</td>
</tr>
<tr>
<td>(\alpha_s &gt; 0)</td>
<td>1.014</td>
<td>0.127</td>
<td>0.889</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B</th>
<th>(\alpha_s)</th>
<th>(G)</th>
<th>(\beta_s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha_s)</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>(G)</td>
<td>0.149</td>
<td>1</td>
<td>-</td>
</tr>
<tr>
<td>(\beta_s)</td>
<td>0.013</td>
<td>-0.402</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C</th>
<th>(\alpha)</th>
<th>(G)</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Countries of former Yugoslavia</td>
<td>0.28</td>
<td>0.98</td>
<td>1.54</td>
</tr>
<tr>
<td>Asia-Pacific</td>
<td>0.24</td>
<td>1.11</td>
<td>4.46</td>
</tr>
<tr>
<td>Europe other</td>
<td>0.17</td>
<td>1.23</td>
<td>3.89</td>
</tr>
<tr>
<td>Africa and Middle East</td>
<td>0.15</td>
<td>1.13</td>
<td>3.97</td>
</tr>
<tr>
<td>Turkey</td>
<td>0.07</td>
<td>0.83</td>
<td>1.47</td>
</tr>
</tbody>
</table>

We run the shift-share diagnostics suggested by Goldsmith-Pinkham et al. (2020). Panel A shows the share of Rottemberg weights that are positive and negative. Panel B shows the correlation between the Rottemberg weights, the time-shifter shock \(G\), and the just-identified coefficients \(\beta\). Panel C summarizes \(\alpha\), \(G\), and \(\beta\) for the top 5 origin countries in terms of weights.

Finally, we look into the correlation between the initial shares used in the instrument and other covariates at the local labor market in the initial period. The intuition behind this exercise is that the variation in the initial shares should not be explained by other covariates that can also affect the change in outcomes at the regional level. As shown in Table 21, key characteristics at the regional level only explain 4.4% of the total variation in the shares, indicating that the shares are not significantly driven by other observables.
Table 21: Correlation between initial shares and observables

<table>
<thead>
<tr>
<th>Initial share 03</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg Age</td>
<td>-0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Share Female</td>
<td>-0.0086</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Share College</td>
<td>0.0207</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
</tr>
<tr>
<td>Share Manual Occupation</td>
<td>0.0096</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Share Services Occupation</td>
<td>0.0129</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Share Manufacturing</td>
<td>-0.004</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
</tr>
<tr>
<td>Average Wage</td>
<td>4.60E-07</td>
</tr>
<tr>
<td></td>
<td>(1.08E-07)</td>
</tr>
<tr>
<td>N</td>
<td>936</td>
</tr>
<tr>
<td>R-sq</td>
<td>0.0436</td>
</tr>
</tbody>
</table>

We pool 104 local labor market and 9 origin regions. Regressions include an origin region FE, but results are consistent to not controlling for origin FE or running a separate regression for each origin. As covariates, we include average age, share of women, share of college graduates, share in manual and services occupations, share in manufacturing industry, and average wage. Key statistic for analysis is the R-squared.