Effects of Immigrants on Non-host Regions Evidence from the Syrian Refugees in Turkey

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Most recent draft here.

Abstract

This paper investigates how immigration-induced wage shocks can propagate beyond the regions receiving immigrants through the production network. Using the Syrian refugee crisis in Turkey as a quasi-experiment and the near universe of domestic firm-to-firm transaction data from VAT records, I show that the immigration shock propagates both forward and backward along the supply chain. Firms in non-host regions who directly or indirectly buy from host regions demand more labor. Firms who sell to host regions weakly increase their sales. Estimates imply an elasticity of substitution between labor and intermediate goods of 0.76 and an elasticity of substitution of nearly 1 between intermediates. Counterfactual analyses show that the spillover effects on non-host regions are economically meaningful when the host regions are central nodes of the domestic trade network. For example, a 1% increase in labor supply in Istanbul decreases real wages in Istanbul by 0.56% and increases real wages in the average non-host city by 0.38%.

Keywords: Immigration, production network, trade spillovers

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1 Introduction

The last decade has seen a quadrupling of refugees globally, from 11 million in 2012 to 46 million today.[1] During this period, Turkey has received 3.6 million Syrian refugees, which has increased the labor supply of several Turkish provinces by up to 82%. Such a large increase in labor supply in host regions is likely to change prices of goods, which can induce general equilibrium effects throughout the economy. Therefore, the labor market consequences of this massive labor supply shock for the Turkish economy depend on the magnitude of these general equilibrium effects.

There are three key economic mechanisms by which an immigration shock propagates through the supply network to impact labor demand. First, immigrants reduce the wages and therefore the prices charged by firms in the host region. This reduction in prices propagates forward to firms who directly or indirectly buy from the host region. Whether these "upstream exposed" firms increase or decrease their labor demand is governed by the substitutability between labor and intermediate goods. Immigrants' effects also propagate backwards in two distinct ways, which I label as "downstream exposure" effects. If intermediate goods are gross substitutes, then firms whose production costs fall more sharply gain market share. Consequently, they demand more from their suppliers, who observe an increase in sales. Furthermore, when intermediates are more substitutable with other intermediates than with labor, immigrant-intensive firms increase their demand for intermediates, which creates a positive demand spillover for their suppliers. Together, these three economic forces shape the labor market effects of immigrants across the economy.

In this paper, I present theoretical analysis formalizing these three forces, empirical evidence testing for their existence, and counterfactual exercises that quantitatively examine the impact of immigration on real wages and welfare across regions.

My model captures these mechanisms through two key features. First, firms combine local labor with intermediate inputs using CES production technology, where intermediate inputs themselves are CES aggregates of goods from firms across all regions. Second, firms set prices using exogenous markups, which ensures that changes in production costs, whether from labor or intermediate inputs, are passed through to prices. The general equilibrium effects of immigration on labor demand across regions are governed by two key parameters: the elasticity of substitution between labor and intermediates, and the elasticity of substitution across different intermediates. Combined with the structure of the input-output network, these elasticities are sufficient to determine how immigration-induced wage changes in host regions affect labor demand throughout the economy.

[1] Author's calculations using data from UNHCR. Appendix Figure C.2 provides more details.

I estimate these two elasticities by analyzing how Syrian immigration affects manufacturing firms in non-host regions of Turkey. My analysis draws on comprehensive administrative data: VAT records capturing the near universe of firm-to-firm transactions, matched employer-employee records, and firm balance sheet data. These data allow us to calculate model-defined trade exposures for all formal firms in Turkey. To address endogeneity concerns, I construct a shift-share instrument that exploits variation in immigration intensity across regions and years. The shift component captures the aggregate number of Syrian refugees in Turkey in a given year, while the share component reflects the relative travel distance from the Syrian border. The regional immigration shock translates into firm-level trade exposures through firms' baseline input-output relationships. To strengthen the identification strategy, I apply the Synthetic IV method (Gulek and Vives-i Bastida, 2024) to relax the share-exogeneity assumption typically required in shift-share designs (Goldsmith-Pinkham et al., 2020).

Comparing firms within the same region-industry cells who are differentially exposed to immigration through their trading network yields three key findings that align with my theoretical mechanisms. First, firms who directly or indirectly buy from host regions increase their labor demand: they hire more workers and increase both payroll and the labor share in production costs. This pattern implies that labor and intermediate goods are gross complements, with an estimated elasticity of substitution of 0.76. Second, I find that buyer firms maintain stable spending patterns across their suppliers, implying an elasticity of substitution between intermediates of approximately 1. Third, large firms that sell to host regions show modest increases in sales, consistent with intermediates being more substitutable with each other than with labor, a finding that reinforces the first two empirical results. These results remain similar in a series of robustness checks of the identification strategy.

Having established the existence of trade spillovers empirically, I turn to counterfactual analyses to quantify their total effects. I simulate a 1% increase in labor supply for each of Turkey's 81 provinces separately and calculate the resulting changes in real wages across all regions. For 76 provinces, spillovers are negligible: a 1% increase in local labor supply reduces real wages by approximately 1% in the host region while increasing wages by less than 0.02% in non-host regions. However, immigration to central regions generates substantial spillovers. For instance, a 1% increase in Istanbul's labor supply reduces local real wages by only 0.56% while increasing real wages in the average non-host region by 0.38%, a spillover effect nearly two-thirds the magnitude of the direct effect. While both population size and economic development correlate with spillover magnitude, I find that a region's centrality in the production network is the strongest predictor. Greater centrality flattens the labor demand curve in the host region and shifts it rightward in non-host regions, resulting in smaller wage decreases for natives in host regions and larger wage increases in non-host regions.

I conduct a second counterfactual analysis that holds the absolute number of immigrants fixed across simulations, rather than fixing the immigrant-to-native ratio as in the first exercise. This alternative approach directly addresses a crucial policy question facing governments during refugee crises: how does the spatial allocation of immigrants affect aggregate welfare? My results demonstrate that directing immigrants to economically central regions generates welfare gains that are an order of magnitude larger than placement in non-central regions. When immigrants settle in well-connected regions, their impact on local production costs cascades throughout the economy through trade linkages. The importance of network position extends to skill composition: high-skill immigration generates larger spillovers than low-skill immigration because industries that employ high-skill labor intensively tend to have stronger inter-regional trade connections.

In the final analysis, I quantify the aggregate impact of Syrian immigration to Turkey by simulating a low-skill immigration shock that matches the observed spatial distribution of refugees. Because Syrians predominantly settled in non-central southeastern regions of Turkey, I find that spillover effects have been negligible. The variation in wage effects across regions is almost entirely explained by local immigrant-to-native ratios. While the trade linkages between southeastern host regions and the rest of Turkey are strong enough to estimate the structural parameters with precision, these connections are insufficient to generate economically meaningful spillovers, a finding that underscores the importance of economic centrality in determining the broader impacts of immigration.

This paper contributes to the extensive empirical literature studying the economic effects of immigration (seminal papers include Card (1990, 2001); Borjas (2003); Ottaviano and Peri (2012)).[2] Despite three decades of research, the wage effects of immigration remain debated (Borjas, 2017; Peri and Yasenov, 2019). I advance this literature by demonstrating, both theoretically and empirically, that immigration impacts propagate through supply chains via general equilibrium effects. These spillovers become economically significant when immigrants settle in regions that are central in the domestic trade network. This finding has important implications for identification. Comparing outcomes between host and non-host regions, the standard approach in the immigration literature, may not capture the full effects of immigration. In the Turkish context, such comparisons would have overestimated the wage decline had refugees settled in central nodes. More generally, my model shows that the bias in such research designs can run in either direction, depending on the economy's technological parameters.

[2] See Hanson (2009); Lewis and Peri (2015); Dustmann et al. (2016) for reviews of the literature.

This work also contributes to the literature on refugee crises and their economic impacts (Hunt, 1992; Friedberg, 2001; Borjas and Monras, 2017). Recent studies examining refugee crises of the last decade have found stronger displacement effects on native workers compared to traditional immigration studies.[3] My results explain why: refugee settlement patterns differ fundamentally from those of economic migrants. Refugees tend to concentrate in regions near their point of entry, which are often less economically developed, while voluntary immigrants typically gravitate toward major cities (Albert and Monras, 2022). I show that interregional trade acts as a moderating force by flattening the labor demand curve and limiting real wage declines in host regions. This mechanism helps explain the divergent labor market outcomes observed between refugee crises and voluntary immigration episodes.

A related literature examines the interaction between immigration effects and output tradability (Dustmann and Glitz, 2015) and international trade (Caliendo et al., 2021; Brinatti, 2024). Most notably, Burstein et al. (2020) formalize how industry tradability shapes local labor market responses to immigration. I extend their framework by demonstrating that production networks play a crucial role in these adjustments. My analysis shows that beyond industry tradability, the upstream and downstream linkages between industries have first-order effects on local labor market outcomes.

This work also contributes to the growing literature on shock propagation through production networks. Theoretical work by Acemoglu et al. (2012, 2016b, 2017) and Baqaee and Farhi (2019) explores how microeconomic shocks can spread through input-output networks to generate aggregate fluctuations.[4] Empirical studies have documented this propagation for various economic shocks, including trade disruptions (Acemoglu et al., 2016a) and natural disasters (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). In the context of immigration, Akgündüz et al. (2024) provide the closest empirical analysis to mine, showing positive spillovers on firms' sales and employment through first-degree trade linkages to regions hosting Syrian refugees in Turkey. I extend their analysis in several important ways: I formalize the mechanisms through which immigrants' effects spillover through the input-output network; I test these mechanisms empirically; I quantify the general equilibrium effects; and I identify the conditions under which such spillovers become economically significant at the aggregate level.

The paper is organized as follows. Section 2 introduces the data and institutional background. Section 3 develops the model and isolates the economic forces by which an immigration induced wage shock to a region can spread through the production network to other

[3]See Gulek (2024) for the Syrian refugee crisis in Turkey and Bahar et al. (2024) for the Venezuelan refugee crisis in Colombia.

[4]See Carvalho (2014); Carvalho and Tahbaz-Salehi (2019) for a review of the literature on production networks.

regions. Section 4 presents the empirical results. Section 5 concludes.

2 Background and Data

2.1 Syrian Refugee Crisis in Turkey

The Syrian Civil War started in March 2011. By 2017, 6 million Syrians had sought refuge outside of Syria, primarily in the neighboring countries Turkey, Lebanon, Jordan, and Iraq. With 3.6 million registered Syrian refugees, Turkey hosts the highest number of refugees in the world. Figure 1a shows how the number of Syrian refugees in Turkey has evolved over time. It remained small until the end of 2012 but increased substantially after. Turkey hosted around 170 thousand refugees by 2012, 500 thousand by 2013, 1.6 million by 2014, 2.5 million by 2015, and around 3.6 million by 2019.

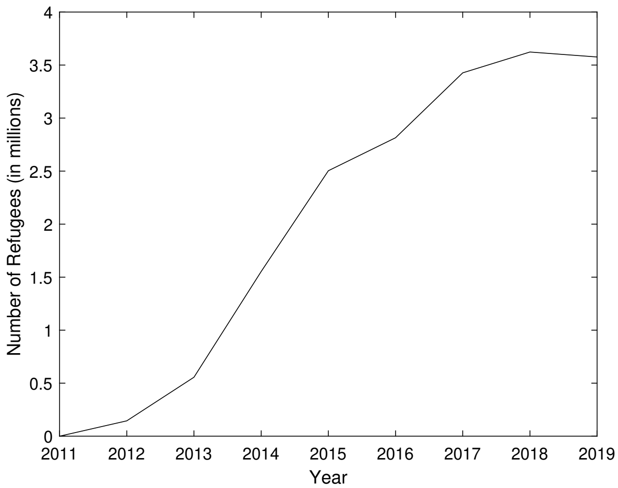
The Turkish government initially tried to host the Syrians in refugee camps in the south-eastern part of the country across the Turkish-Syrian border. However, the camps quickly exceeded capacity as the number of arriving refugees increased. The refugees thus dispersed across Turkey in heterogeneous quantities.[5] Figure 1c shows the distribution of the number of Syrian refugees per 100 natives in Turkey at the province level. Refugees are more densely located in regions closer to the border. Distance to the populous governorates in Syria strongly predicts the number of refugees per native in a given region, which constitutes the backbone of the identification strategy.

Syrian refugees are less educated than Turkish natives. Figure 1b compares the education levels of Syrian refugees in Turkey with those of Turkish natives. For example, 21% of Syrian refugees did not complete primary school, compared to 12% of Turkish natives. Additionally, 83% of Syrian refugees do not have a high school diploma, in contrast to 61% of Turkish natives. Given the potential for educational downgrading (Dustmann et al., 2013) and that most Syrian refugees have only basic proficiency in Turkish (Crescent and Programme, 2019), the influx of Syrian refugees can be interpreted as a low-skill labor supply shock to the Turkish labor markets.

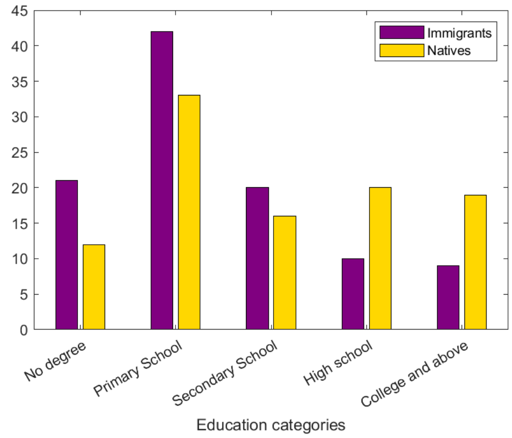
Most Syrians in Turkey do not have formal labor market access, which further limits the types of firms and industries they can work at. As of March 2019, only 31,000 Syrian refugees (1.5% of the working-age Syrians) had work permits. This feature of the immigration shock does not limit the generalizability of the present paper's findings. Gulek (2024) shows that informal and formal labor in Turkey are highly substitutable in production. This implies that the informal immigration shock lowers wages in both the informal and formal sectors.

[5] By 2017, only 8% of the refugees lived inside the camps.

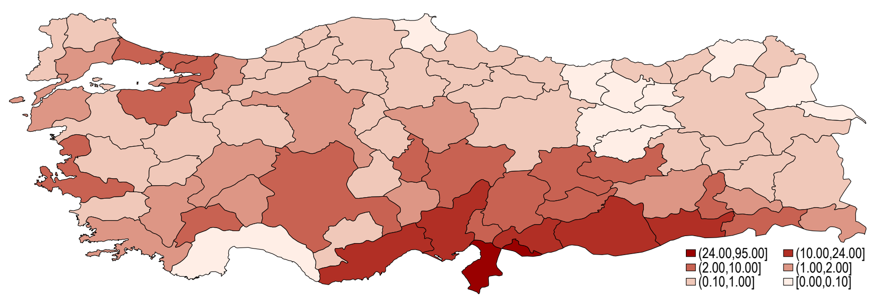
Figure 1: Statistics on the Syrian Refugees in Turkey



(a) Timeseries of the number of Syrian refugees in Turkey



(b) Educational Attainment of Syrians and Natives



(c) Share of Syrian refugees in Turkish population (in%) in 2019

Source: Data on the number of Syrian refugees in a given year and province comoes from Directorate Generale of Migration Management of Turkey. Data on the educational attainment of refugees come from surveys on ESSN recipients. Data on natives' educational attainments come from the household labor force surveys conducted by Turkstat.

2.2 Data

Studying the network spillovers of immigration shocks requires a comprehensive dataset covering who firms trade with, how much they spend for labor and intermediates, and how much they sell. To achieve this, we integrate five datasets covering all formal firms in Turkey between 2006–2019. The Ministry of Industry and Technology maintains these datasets with a unique and homogenous firm identifier, which enables us to merge them.

These datasets are as follows. First, the value-added tax (VAT) data report the value of all domestic firm-to-firm trade that exceeds 5,000 Turkish liras (about \$3,333 in 2010) in a given month. Second, from the income statements, we use the yearly gross sales of each firm. Third, from the firm registry, we extract each firm's province and two-digit industry code according to the Nomenclature Statistique des Activités Économiques dans la Communauté Européenne (NACE), the standard industry classification in the European Union. Fourth, from the customs data, we collect firms' annual exports and imports. Fifth, from the employer-employee data, we collect the average number of workers, total labor costs and average wages per worker per each year.

We complement the network data with labor force surveys conducted by the Turkish statistical institute. Unlike the census data, these surveys collect information on workers' education, which allows us to determine the skill intensity of industries and regions.

Data on the number of refugees in Turkey across years and provinces are acquired from the Directorate General of Migration Management of Turkey (DGMM). DGMM does not share the education and age break-down of refugees at the province level, which prevents the empirical investigation from exploiting that variation.

Appendix Section C provides the details and the summary statistics about the data.

3 Theory

In this section we formalize how a decrease in wages due to immigration in one region can spillover to other regions through the production network, and develop structural equations that directly map to our reduce-form results.

3.1 Setup

The economy consists of N firms indexed by i, R regions indexed by r, where each region is endowed with L_r labor.[6] Each firm operates in one region: r_i denotes the region of firm i. Firms use intermediate goods and local labor in production, and sell their output as both an intermediate good to other producers in all regions and as a final good to local consumers.

[6]Labor is assumed to be homogeneous in the baseline model, which we later relax to become a CES aggregate of labor with different skill levels.

Producers

Firm i chooses labor L_i and intermediate goods $\{x_{i,j}\}_{j=1}^n$ to minimize costs subject to a constant returns nested-CES technology

$$\begin{aligned}
&\min_{\{x_{ij}\}_{j=1}^n, L_i} \sum_{j=1}^n p_j x_{ij} + w_{r_i} L_i \quad \text{subject to} \\
&A_i(\eta_i m_i^{\frac{\sigma_u - 1}{\sigma_i}} + (1-\eta_i) L_i^{\frac{\sigma_u - 1}{\sigma_u}})^{\frac{\sigma_u}{\sigma_u - 1}} \geq y_i \\
&m_i = \left(\sum_{j=1}^n \alpha_{ij} x_{ij}^{\frac{\sigma_l - 1}{\sigma_l}}\right)^{\frac{\sigma_l}{\sigma_l - 1}}
\end{aligned}$$

where A_i is a Hicks-neutral productivity shifter, y_i is total output, p_j is the price of good j, L_i is labor used by firm i, w_r is the wage in region r, m_i is the intermediate good used by the firm, which itself is a CES bundle of goods from different firms. x_{ij} denotes how much firm i uses firm j's goods in production, where firm j can be in any region. We assume common elasticities of substitution in both the upper and lower nests: σ_u denotes the elasticity of substitution between labor and intermediate goods, and σ_l is the elasticity of substitution between different intermediate goods. [7] Constant returns to technology requires $\sum_j \alpha_{i,j} = 1$. Let C_i denote the unit cost of firm i. We assume that firms have constant and exogenous markup μ_i, and therefore set price $p_i = \mu_i C_i$.

Final Demand

All final goods consumption as well as the ownership of firms is local. We assume a representative consumer in each region r, who optimizes her Cobb-Douglas utility subject to budget constraint that equates her spending on final goods with her labor income plus (regional) firm profits.

$$\max_{\{c_{r,i}\}} \Pi_{i\in r} c_{r,i}^{\beta_i} \quad s.t. \quad \sum_{i\in r} p_i x_{0,i} = w_r L_r + \sum_{i \in r} \pi_i$$

where $c_{r,i}$ is how much the representative agent r consumes firm i's goods, and $\sum_{i\in r}\beta_i = 1$.

Labor Supply

Labor is inelasticly supplied in each region, is immobile across regions and perfectly mobile across firms in a region. This simplifying assumption shuts down spillovers across regions in

[7]The common elasticity of substitution assumption across firms simplifies the exposition but can be relaxed. The empirical analysis relaxes this assumption by estimating heterogeneity across industries and finds limited heterogeneity.

labor supply.[8]

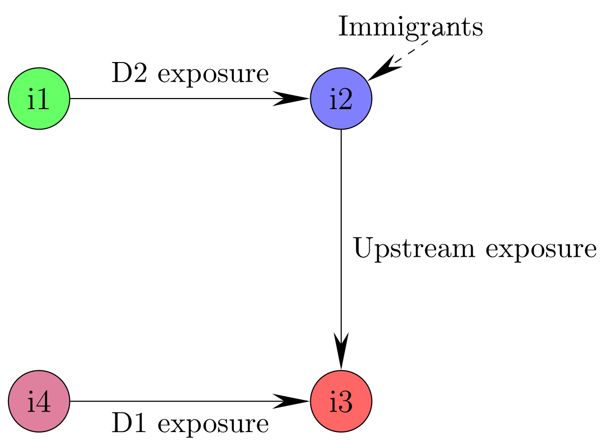
General Equilibrium

Given exogenous productivities A_i and markups μ_i, equilibrium is a set of prices p_i, wages w_r, intermediate good choices $x_{i,j}$, labor input choices l_i, outputs y_i, and final demands $c_{r,i}$ such that each producer minimizes its costs subject to technology constraints and charges the relevant markup on its marginal cost, consumers maximize their utility subject to their budget constraint, and the markets for all goods and labor clear.

3.2 Three General Equilibrium Forces

The solution to this model is notation heavy and therefore hard to follow. To facilitate exposition, we describe the three relevant economic forces here. Figure 2 depicts a simple production network with four firms in four different regions. Firm i_1 sells to i_2, and both i_2 and i_4 sell to i_3. Suppose i_2's region receives immigrants. This increase in labor supply lowers the wages and therefore the production costs of firm i_2. As firms have constant markups, lower production costs results in lower prices. This creates a chain reaction along the supply chain that propagates both forward and backward.

Figure 2: Spillover Effects of Immigration Along the Input-Output Network



Notes: This figure depicts a simple input-output network where firm i_1 sells to i_2, and both i_2 and i_4 sell to i_3. Immigrant arrival to firm i_2 creates a chain reaction that impacts all other firms in this network.

First, firm i_3 benefits from immigration as the price of input from firm i_2 decreases. As i_3 faces lower input prices, it can increase or decrease its local labor demand depending on

[8] Gulek (2024) shows that changes in in- and out-migration in response to Syrian immigration has been minimal in Turkey

the substitutability between intermediates and labor. If labor and intermediates are gross complements, than the reduction in input prices would cause firm i_3 to increase its labor demand. We name this as the "upstream exposure effect" of immigration: upstream because the shock comes from upstream from the recipient i_3's perspective.

Second, the demand for i_4's goods may increase or decrease depending on the substitutability between different intermediate goods. Notice that i_2 and i_4 both supply to i_3. If intermediate goods are largely substitutable, then as i_2's prices go down compared to i_4, i_3 would demand less from i_4. As the product demand for i_4 shrinks, it reduces its labor demand. In contrast, if intermediate goods are gross complements, the opposite would take place: i_3 would increase its demand of i_4's goods, which would increase i_4's demand for local labor.

Notice that the effects on both i_3 and i_4 are parts of the forward propagation channel of the immigration shock. The difference is that, while i_3 is impacted through its suppliers and therefore is upstream-exposed, i_4 is impacted through its customers and hence is downstream-exposed.

Third, the demand for i_1's goods also changes. Notice that i_2 incurs two effects: the price of labor goes down compared to its input from i_1, and it incurs a demand shock based on i_3's choice among goods from i_2 and i_4. The former is governed by the elasticity of substitution between labor and intermediates, and the latter is governed by the elasticity of substitution between intermediates. The effect on $D1$'s sales depends on the relative magnitudes of these two elasticities. If intermediate goods are more substitutable among each other than with labor, then i_2 demands more from i_1, which increases i_1's labor demand. We call this the second downstream exposure effect, which we denote shortly as $D2$ for the rest of the paper. This captures the backward propagation of the immigration shock.

Figure 2 only depicts the first-degree trade exposures: that is, firms being impacted from their immediate customers and suppliers. However, these forces expand beyond the first-degree linkages. Firms that indirectly buy from immigrant-intensive firms are also upstream exposed. Same applies for downstream exposures. Moreover, in more complicated input-output networks, firms can have U, D1, and D2 exposures simultaneously. To understand exactly how much each firm is upstream and downstream exposed to immigrants, we need the model.

3.3 Input-Output definitions

To derive the impact of regional labor supply shocks on labor demand across all regions, we establish input-output notation following Baqaee and Farhi (2019).[9] Our results are comparative statics describing how the labor payments in any host and non-host region change when a host region receives immigrants. We now define accounting objects such as input-output matrices, Leontief inverse matrices, and Domar weights. These quantities have a revenue-based version and a cost-based version, and we present both. All these objects are defined at the initial equilibrium. Without loss of generality, we normalize the nominal GDP to 1. Finally, in our analytical results and counterfactuals, we assume constant markups and technology.[10]

3.3.1 Final Expenditure Shares

Let b denote the $R \times N$ matrix whose (ri)th element is equal to the share of good i in the budget of the final consumer in region r

$$b_{ri} = \frac{p_i c_i}{\sum_{j \in r} p_j c_j}$$

Let χ denote the $R \times 1$ vector of regional income shares

$$\chi_r = \frac{\sum_{j \in r} p_j c_j}{\sum_{r'=1}^{R} \sum_{j \in r'} p_j c_j}$$

where the sum of final expenditures $\sum_{r'=1}^{R} \sum_{j \in r'} p_j c_j$ is nominal GDP

3.3.2 Input-Output Matrices

To streamline the exposition, we treat labor as special endowment producer that does not use any input to produce. We form an $(N + R) \times 1$ vector of producers, where the first N elements correspond to the producers and the last R elements to the labor in each region. For labor, we interchangeably use the notation w_r or p_{N+r} to denote its wage and the notation L_{ir} or $x_{i(N+r)}$ to denote its use by firm i. The revenue-based input-output matrix Ω is the $(N + R) \times (N + R)$ matrix whose (ij)th element is equal to firm i's expenditure on inputs

[9] We maintain their notation except where our model's regional labor markets necessitate modifications.

[10] This decision is driven primarily by the lack of data on prices. Otherwise, the model easily incorporates changes in technology and markups. For more details, see Baqaee and Farhi (2019).

from firm j as a share of its total revenues

$$\Omega_{ij} = \frac{p_j x_{ij}}{p_i y_i}$$

The first N rows and columns of Ω correspond to goods, and the last R rows and columns correspond to labor. Since labor requires no inputs, the last R rows of Ω are zeros.

The cost-based input-output matrix $\tilde{\Omega}$ is the $(N+R) \times (N+R)$ matrix whose (ij)th element is equal to i's expenditure on inputs from j as a share of its total costs

$$\tilde{\Omega}_{ij} = \frac{p_j x_{ij}}{\sum_{k=1}^{N+R} p_k x_{ik}}$$

The revenue-based and cost-based input-output matrices are related by

$$\tilde{\Omega} = diag(\mu)\Omega$$

where μ is the vector of markups, and $diag(\mu)$ is the diagonal matrix with ith diagonal element equal to μ_i.

As labor and intermediate goods appear as the sole two inputs in the upper nest of the CES production function, defining the labor share and intermediate goods share of costs is useful for exposition. We define the share of labor and intermediate good expenditures of firm i as:

$$\tilde{\Omega}_{i,L} = \frac{w_r L_i}{\sum_{k=1}^{N} p_k x_{ik} + w_r L_i} \quad ; \quad \tilde{\Omega}_{i,M} = 1 - \tilde{\Omega}_{i,L}$$

3.3.3 Leontief Inverse Matrices

We define the revenue-based and cost-based Leontief inverse matrices as

$$\Psi = (I - \Omega)^{-1} = I + \Omega + \Omega^2 + \dots, \quad \text{and} \quad \tilde{\Psi} = (I - \tilde{\Omega}) = I + \tilde{\Omega} + \tilde{\Omega}^2 + \dots$$

While the input-output matrices Ω and $\tilde{\Omega}$ capture the direct exposures of one firm to another, the Leontief inverse matrices Ψ and $\tilde{\Psi}$ capture the total exposures, direct and indirect, through the production network.

Note that the revenue-based Leontief inverse matrix Ψ encodes the backward propagation of demand, whereas the cost-based Leontief inverse matrix $\tilde{\Psi}$ encodes the forward propagation of costs.

3.3.4 Domar Weights

The revenue-based Domar weight λ_i of producer i is its sales as a fraction of nominal GDP:

$$\lambda_i \equiv \frac{p_i y_i}{nGDP} = p_i y_i$$

Similarly, the revenue-based Domar weight λ_r for labor in region r is its total labor payments $w_r L_r$.

Before stating our results, we introduce the following input-output covariance operator:

$$Cov_{\tilde{\Omega}^{(j)}}(d\ln p, \Psi_{(k)}) = \sum_i \tilde{\Omega}_{ji} d\ln p_{(i)} \Psi_{ik} - \left(\sum_i \tilde{\Omega}_{ji} d\ln p_i\right)\left(\sum_i \tilde{\Omega}_{ji} \Psi_{ik}\right)$$

where $\tilde{\Omega}^{(j)}$ corresponds to the jth row of $\tilde{\Omega}$, $d\ln p$ is the vector of price changes of all inputs, and $\Psi_{(k)}$ is the kth column of Ψ. Because the rows of $\tilde{\Omega}$ always sum up to 1, we can formally think of this as a covariance. It answers the question: "Among the suppliers of firm j, are the ones who decrease their prices more rely on firm i more or less for intermediate goods?" If the answer is more, the covariance term is negative.

3.4 Effects of a Labor Supply Shock on labor income

To build intuition as to how an immigration shock in a host region can impact the labor payments in any region, we take the change in prices $d\ln p$ and $d\ln w$ as given, and describe how the demand for labor and for goods change in response to these changes in prices. Note that the labor income in region r is the sum of labor payments by all firms in that region.

$$\lambda_r = w_r L_r = \sum_{i\in r} \lambda_i \Omega_{i,L}$$

Hence, the change in labor payments is determined by the change in sales and the change in labor share of sales

$$d\ln\lambda_r = \sum_{i\in r} \frac{\lambda_i \Omega_{iL}}{\lambda_r}(d\ln\lambda_i + d\ln\Omega_{iL})$$

Therefore, to understand the impact of immigration on labor payments in all regions, we need to determine the impact on firms' sales share in GDP and labor share in sales. Propositions 1 and 2 characterize these effects.

Proposition 1. *In response to an immigration-induced wage shock, the following equation* *describes the change in the labor share of production costs*

$$d \ln \tilde{\Omega}_{i,L} = (1 - \sigma_u)(d \ln w_{r_i} - \sum_{j=1}^{n} \frac{\tilde{\Omega}_{ij}}{\tilde{\Omega}_{iM}} d \ln p_j) \tag{1}$$

All proofs are in the Appendix.

Equation 1 captures the forward propagation of cost shocks, which is the upstream exposure effect we introduced in Figure 2. Firms' labor share is determined by the trade-off firms face between hiring labor and using intermediate goods in production. Suppose the local wages go down less than the prices of the suppliers of firm i. If labor and intermediate goods are gross complements, $\sigma_u < 1$, then the firm would increase its labor share in production.

Proposition 2. *In response to an immigration-induced wage shock, the following equation describes the change in the Domar weights / sales share of firms*

$$\begin{aligned} d \ln \lambda_i = & \sum_{j=1}^{n} (1 - \sigma_l) \frac{\lambda_j}{\lambda_i \mu_j} Cov_{\tilde{\Omega}^{(j)}} \left(d \ln p, \Psi_{(i)} \right) \\ & + (\sigma_u - \sigma_l) \sum_{j=1}^{n} \frac{\lambda_j}{\lambda_i} \tilde{\Omega}_{j,l} \left(d \ln w_{r_j} - \sum_{k=1}^{n} \frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}} d \ln p_k \right) (\Psi_{ji} - I_{ji}) \\ & + \eta_i \end{aligned} \tag{2}$$

where I is the identity matrix, and $\eta_i = \frac{1}{\lambda_i} \sum_j \sum_r b_{rj} \Psi_{ji} \chi_r \left(\left(\sum_{i \in r} \frac{\pi_i}{\chi_r} d \ln \lambda_i \right) + \frac{\lambda_r}{\chi_r} d \ln \lambda_r \right)$ captures the demand spillovers of immigrants' demanding locally produced goods.

The first term captures the first downstream exposure effect: demand spillovers from firms substituting across intermediates. The immigration shock propagates forward and lowers costs throughout the supply chain. When different intermediate goods are largely substitutable, $\sigma_l > 1$, those who observe larger decreases in costs gain market share and demand more goods from their suppliers. This is captured by the covariance term, which is negative when those that observe larger decreases in costs among the suppliers of firm j are also more dependent on firm i for production. Summing across all firms in the economy and their suppliers determines the total demand spillover from substitution among intermediates.

The second term captures the second downstream exposure effect: the demand spillovers from firms substituting between intermediate goods and labor. Assume $\sigma_l > \sigma_u$, that is, the different intermediate goods are more substitutable than intermediate goods and labor. In this case, if firm j observes larger decreases in local wages than the prices of its intermediate goods, $\left(d \ln w_{r_j} - \sum_{k=1}^{n} \frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}} d \ln p_k \right) < 0$, then it will spend a larger share of its production costs on intermediate goods. This, in turn, increases the demand for firm i to the extend that firm j relies on firm i's goods, which is captured by Ψ_{ji}. Summing over all such firms determines the total demand spillover from substitution between intermediates and labor.

The third term captures the demand spillovers from changing income shares of the regions due to immigration. Immigrants increase the consumer base in the host regions. Firms that sell goods to these host regions directly or indirectly also observe an increase in their demand.[11]

Given the intuition we developed in Propositions 1 and 2, we now move on to fully characterizing the change in equilibrium prices and quantities with respect to an immigration shock $d \ln L$. Proposition 3 characterizes the change in prices of firm i as a function of changes in wages.

Proposition 3. *In response to an immigration-induced wage shock, the following equation describes the change in prices charged by firms*

$$d \ln p_i = \sum_{j=1}^{n} \tilde{\Psi}_{ij} \tilde{\Omega}_{jL} d \ln w_{r_j} \tag{3}$$

Proposition 3 shows an intuitive result. As firms have constant markups, any change in their production costs are fully represented in their prices. $\tilde{\Psi}_{ij}$ captures how much firm i depends on goods of firm j for production. $\tilde{\Omega}_{jL} d \ln w_{r_j}$ captures the change in production costs of firm j from the change in local wages. Multiplying the two terms and summing across all firm j's give us how much the production cost, and hence the price, of firm i changes in response to changes in wages.

Lastly, note that the share of labor in GDP is simply the wage times the quantity of labor in that region: $\lambda_r = L_r w_r$. Combining this with Propositions 1, 2, 3, we can fully characterize the impact of immigration on this economy.

Theorem 1. *The following linear system fully describes the change in equilibrium prices*

[11] In practice, immigrants and natives can demand different type of goods. Unfortunately, the lack of data on the consumption basket of Syrian immigrants in Turkey prevents us from exploring this dimension in detail without strong assumptions. Hence, in the empirical section we assume that this force enters the error term and is not correlated with our instrument.

and quantities in response to an immigration shock $d\ln L$.

$$\begin{aligned}
d\ln\lambda_r =& \sum_{i\in r}\frac{\lambda_i\Omega_{iL}}{\lambda_r}(d\ln\lambda_i + d\ln\Omega_{iL}) \\
d\ln\Omega_{i,L} =& (1-\sigma_u)(d\ln w_{r_i} - \sum_{j=1}^{n}\frac{\tilde{\Omega}_{ij}}{\tilde{\Omega}_{iM}}d\ln p_j) \\
d\ln\lambda_i =& (1-\sigma_l)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i\mu_j}Cov_{\tilde{\Omega}^{(j)}}\left(d\ln p, \Psi_{(i)}\right) \\
&+ (\sigma_u-\sigma_l)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,L}\left(d\ln w_{r_j} - \sum_{k=1}^{n}\frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}}d\ln p_k\right)(\Psi_{ji} - I_{ji}) \\
&+ \frac{1}{\lambda_i}\sum_j\sum_r b_{rj}\Psi_{ji}\chi_r d\ln\chi_r \\
d\ln\chi_r =& \left(\sum_{i\in r}\frac{\pi_i}{\chi_r}d\ln\lambda_i\right) + \frac{\lambda_r}{\chi_r}d\ln\lambda_r \\
d\ln p_i =& \sum_{j=1}^{n}\tilde{\Psi}_{ij}\tilde{\Omega}_{jL}d\ln w_{r_j} \\
d\ln w_r =& d\ln\lambda_r - d\ln L_r
\end{aligned} \tag{4}$$

Equation 4 presents the economic forces we have described in one system of linear equations. Notice that we observe all the parameters in this equation in our pre-shock data except for the elasticity parameters σ_u and σ_l. Therefore, estimating these two elasticities using the immigration shock is sufficient to quantify the total impact of immigration on all host and non-host regions.

Our model traces how immigration shocks propagate through supply chains to affect firm-level labor demand and sales throughout the economy, but two important limitations warrant discussion.

First, we assume that labor does not move across regions to isolate trade spillovers. While native migration can help equilibrate regional labor markets in practice (Monras, 2020), the Turkish context supports our assumption: Syrian immigration induced no significant changes in native migration patterns (Gulek, 2024), as shown in Appendix Figure D.8.

Second, Theorem 1 does not yield a simple sufficient statistic to predict the magnitudes of spillover, making it difficult to intuitively characterize when general equilibrium effects differ substantially from partial equilibrium predictions. We address this limitation through counterfactual analyses in Section 4.6.

4 Empirical Analysis

This section presents the trade spillover effects of immigration on maunfacturing firms in non-host regions. We first use Propositions 1 and 2 to define the three treatments from trade exposure. The causal effects of these three treatments on firms' labor demand and sales help identify the structural elasticity parameters: the elasticity of substitution between labor and intermediates and the elasticity of substitution between different intermediates. We then use these elasticity parameters to quantify the total effects of immigration on host and non-host regions.

4.1 Treatment Definitions

The model isolates three economic forces that shape immigration's equilibrium effects: forward cost propagation and two types of demand spillovers. We formalize these as upstream exposure (U) and two downstream exposure effects ($D1$ and $D2$). A firm's upstream exposure at time t is defined as:

$$U_{it} = \sum_{r=1}^{R} \tilde{\Psi}_{i,r}\delta_{rt} \tag{5}$$

where δ_{rt} captures Syrian immigration to region r, and $\tilde{\Psi}_{i,r}$ measures firm i's cost exposure to region r. This exposure increases with the firm's direct and indirect purchases from region r and with the labor intensity of its suppliers, as more labor-intensive suppliers experience larger production cost reductions from immigration.

The first downstream exposure measuring substitution between intermediates

$$D1_{it} = \sum_{j=1}^{n} \frac{\lambda_j}{\lambda_i \mu_j} Cov_{\tilde{\Omega}^{(j)}} \left(\sum_{r=1}^{R} \tilde{\Psi}_{(r)}\delta_{rt}, \Psi_{(i)} \right) \tag{6}$$

summarizes how much firm i's customers (measured by the ith column of $\tilde{\Psi}$) observe cost declines from immigration shock δ_{rt} compared to other firms in the economy. This relates to how much firm i's customers gain or lose business depending on whether different intermediate goods are complements or substitutes.

The second downstream immigration shock capturing substitution between labor and intermediates

$$D2_{it} = \sum_{j=1}^{n} \frac{\lambda_j}{\lambda_i} \tilde{\Omega}_{j,l} \left(\delta_{r_j,t} - \sum_{k=1}^{n} \frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,m}} (\sum_{r=1}^{R} \tilde{\Psi}_{k,r}\delta_{rt}) \right) (\Psi_{ji} - I_{ji}) \tag{7}$$

summarizes how much firm i's customers represented by Ψ_{ji} observe *relative* cost declines from their own region's wages, which is measured by $\delta_{r_j,t}$, compared to the immigration shock through their suppliers, which is measured by $\sum_{k=1}^{n} \frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,m}} (\sum_{r=1}^{R} \tilde{\Psi}_{k,r}\delta_{rt})$.

One key empirical challenge lies in computing the treatment variables U_{it}, $D1_{it}$ and $D2_{it}$, which require inverting large matrices. At baseline, our sample includes approximately 230,000 firms trading domestically, resulting in trade matrices with 53 billion elements. While the trade matrices $\tilde{\Omega}$ and Ω are sparse and computationally manageable, their Leontief inverses $\tilde{\Psi}$ and Ψ are not. To overcome this computational constraint, we provided a 512 GB RAM workstation to Turkey's Ministry of Industry and Technology, which houses our primary datasets. Appendix Section A details our matrix construction and treatment variable calculations.

4.2 Identification Strategy

There are two threats to identification. First, the treatment variables depend on regional immigration intensities (δ_{rt}), which may be endogenous if immigrants select into regions with positive labor demand shocks. Second, they depend on input-output matrices (Ω and $\tilde{\Omega}$), which could bias estimates if firms with different trade exposures follow different trajectories.

Addressing these challenges requires both quasi-random variation in immigrant settlement patterns and comparing firms on similar economic trajectories but with different trade exposure through their partners. We achieve this through a Synthetic Instrumental Variables (SIV) approach (Gulek and Vives-i Bastida, 2024), which combines instrumental variables for immigration patterns with synthetic controls for firm trajectories. Below, we first introduce our instrument.

We construct a shift-share instrument for immigrant location choices, combining inverse travel distances between Turkish regions and Syrian governorates (share) with the total Syrian refugee population in Turkey (shift):

$$Z_{r,t} = \underbrace{\sum_{s=1}^{13} \lambda_s \frac{1}{d_{r,s}}}_{\text{Share}} \times \underbrace{\text{Number of Syrians in Turkey in year } t}_{\text{Shift}} \tag{8}$$

where dr, s measures travel distance between region r and governorate s, and λ_s weights each governorate.[12] Following Aksu et al. (2022), we weight governorates by their population and proximity to Turkey relative to other neighboring countries. Previous work shows that

[12]City centers in each region are used to calculate the travel distance. The data is available upon request.

alternative weighting schemes yield similar results (Gulek, 2024).

$$\lambda_s = \underbrace{\frac{\frac{1}{d_{s,T}}}{\frac{1}{d_{s,T}} + \frac{1}{d_{s,L}} + \frac{1}{d_{s,J}} + \frac{1}{d_{s,I}}}}_{\text{Relative distance to Turkey}} \times \underbrace{\pi_s}_{\text{Pop. share}} \tag{9}$$

where $d_{s,c} \quad c \in \{T, L, J, I\}$ is the travel distance between Syrian region s to Turkey, Lebanon, Jordan, and Iraq respectively; and π_s is the population share in 2011, which we calculate using the 2011 census undertaken by the Central Bureau of Statistics of Syria.

Figure 3a shows the cross-sectional distribution of the distance share component of our instrument. The instrument puts higher weights in southeastern Turkey near northwestern Syria, reflecting the higher Syrian population density around Aleppo (northwest of Syria) compared to Al-Hasakah (northeast of Syria) along the Turkish border. Figure 3b shows the first-stage estimates from a nonparametric event-study design where we regress the immigration treatment δ_{rt} on the distance-share Z_r interacted with year indicators. Estimates between 2006–2011 are zero as there are no Syrian immigrants in Turkey during those years. In the post-period 2012–2019, distance strongly predicts immigrant location choice in all years. The joint F-statistic for the post-period coefficients is 108, which implies that we have a strong instrument.

We validate our main instrument with an alternative shift-share measure using the share of Arabic speakers from the 1965 census. Unlike Card (2001)'s past-settlement instrument, our Arabic-speaking population reflects Ottoman Empire demographics rather than previous Syrian migration. While both instruments yield similar results (detailed in the Appendix), we favor the distance-based measure for its stronger first-stage.

Our trade exposure instruments (U^z, $D1^z$, and $D2^z$) are constructed by replacing the regional immigration δ_{rt} with the regional instrument Z_{rt} in the respective exposure measures.

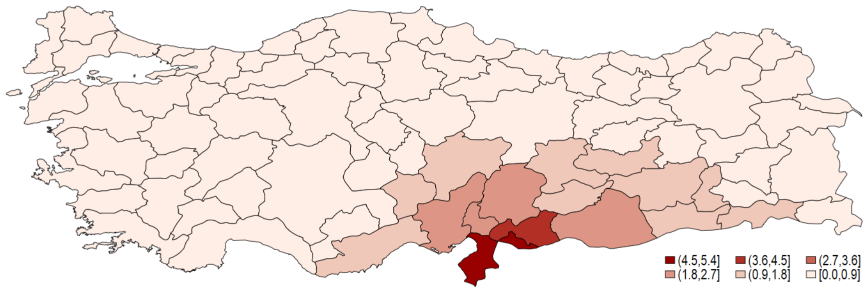
4.3 Estimating Equations

IV Design

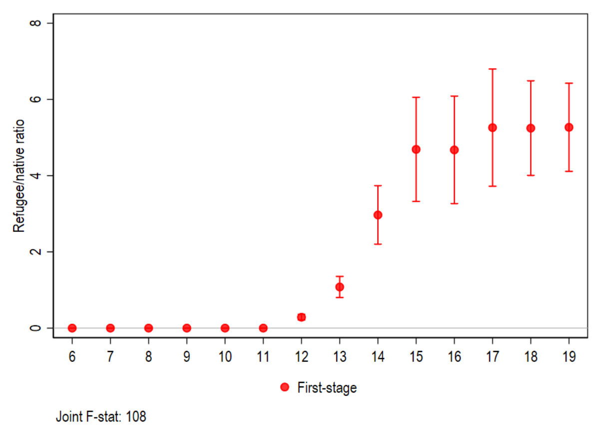
Given trade exposure treatments U, $D1$, $D2$, and their respective instruments U^z, $D1^z$, and $D2^z$, we define the estimating equations following Propositions 1 and 2 as follows. The estimating equation for the labor share is given by:

$$\begin{aligned} log(LaborShare_{isrt}) &= \beta_1 U_{it} + f_i^L + f_{srt}^L + \theta_1 W_{it}^L + \nu_{it}^L \\ U_{it} &= \gamma_1 Z_{it}^U + g_i^L + g_{srt}^L + \vartheta_1 W_{it}^L + \omega_{it}^L \end{aligned} \tag{10}$$

Figure 3: The Distance instrument



(a) Distance IV heatmap



(b) First-stage

Notes: The heatmap shows the cross-sectional distribution of the distance share Z_r, where the measure is normalized to have unit variance and to start from 0 for the least exposed region. The event-study figure shows the estimates from a nonparametric event-study regression of the first-stage: $\delta_{rt} = \sum_{t' \neq 2011} \beta_{t'} \mathbb{1}\{t' = t\} Z_r + \alpha_r + \alpha_t + \epsilon_{rt}$ where we weight each region by its population in 2011. Standard errors are clustered at zero. 95% confidence intervals are plotted.

where $log(LaborShare_{isrt})$ is the natural logarithm of the labor share of firm i in industry s, region r, and at time t, f and g denote the fixed effects in the structural and first-stage equations, respectively, f_i^L and g_i^L denote firm fixed effects, f_{srt}^L and g_{srt}^L denote industry-region-time fixed effects, and ν_{it}^L and ω_{it}^L are the error terms. We include region-industry-time fixed effects to partial out region-industry level shocks such as technology and markup shocks that can be correlated with the treatment.

The estimating equation for firms' sales is given by:

$$\begin{aligned} log(Sales_{isrt}) &= \beta_2 D1_{it} + \beta_3 D2_{it} + f_i^S + f_{srt}^S + \theta_2 W_{it}^S + \nu_{it}^S \\ D1_{isrt} &= \gamma_2 Z1_{it}^D + \gamma_3 Z2_{it}^D + g_i^S + g_{srt}^S + \vartheta_2 W_{it}^S + \omega_{1,it}^S \\ D2_{isrt} &= \gamma_4 Z1_{it}^D + \gamma_5 Z2_{it}^D + h_i^S + h_{srt}^S + \vartheta_3 W_{it}^S + \omega_{2,it}^S \end{aligned} \tag{11}$$

where the terms are defined analogously to equation 10.

The key challenge is the unobserved confounder W_{it}, which captures differential trends between firms with varying trade exposures. The Appendix Section D shows that more exposed firms followed different trajectories than less exposed firms before the immigration shock, likely invalidating the parallel trends assumption.[13] While controlling for W_{it} would address this, we cannot observe it directly. We therefore implement the SIV procedure of Gulek and Vives-i Bastida (2024) to account for these confounding trajectories using synthetic controls.

SIV estimator consists of two steps. In the first step, we find synthetic controls for each unit (firm) in the pre-period and generate counterfactual estimates for the outcome, treatments, and instruments. In the second step, as in the standard IV estimator, we use these counterfactual estimates to compute the first-stage and reduced-form estimates. Appendix Section D discusses the details of the implementation.

We construct synthetic control weights by matching pre-2011 demeaned values of our two target outcomes: log labor share and log sales. Following Sun et al. (2023), we estimate a single set of weights for both outcomes to improve the signal-to-noise ratio. As shown in Appendix Section D, this joint estimation outperforms separate weights when predicting unmatched outcomes like payroll and firm size. To identify effects from within-cell variation, we restrict donor pools to firms in the same region and two-digit industry. We incorporate a penalty term following Abadie and L'hour (2021) to mitigate overfitting concerns in our disaggregated setting.

Essentially, we compare firms in the same region and industry cells that followed similar economic trajectories before the immigration shock, but experienced different exposure to immigrants through their trading network.

Two important considerations guide our specification choices. First, equations 10 and 11 reflect the correct structural relationships for identifying elasticity parameters, which explains our separate treatment of upstream and downstream exposures. Second, the upstream exposure measure U is estimated with greater precision than downstream exposures $D1$ and $D2$. Including U in equation 11, while theoretically unnecessary, could capture the causal effects of the noisier downstream measures in a joint estimation. Nevertheless, Appendix Section D demonstrates that our main findings remain robust when estimating upstream and downstream effects simultaneously.

Our estimating equations 10 and 11 are theoretically linked through the elasticity of

[13] One contributing factor was stronger employment growth in southeastern Turkey during 2006-2011 (Gulek, 2024), which has likely propagated through production networks to firms in non-host regions.

substitution between labor and intermediate goods:

$$\beta_1 = -\frac{(1-\sigma_U)}{\epsilon^D} \quad ; \quad \beta_2 = \frac{(1-\sigma_l)}{\epsilon^D} \quad ; \quad \beta_3 = -\frac{(\sigma_l - \sigma_u)}{\epsilon^D}$$

where ϵ_D represents the wage elasticity of labor demand, calibrated to -1.27 based on Gulek (2024). In the empirical section, we demonstrate that estimates from both equations yield consistent values for these elasticities.

Event-study Design

The primary advantage of the event-study design is that it allows us to visually and flexibly assess the pattern of outcomes the (debiased) share component of the shift-share instruments capture relative to the beginning of the refugee crisis. The event-study equations of the SIV estimator for labor share are defined as:

$$\widetilde{log(y_{it}^L)} = \sum_{t' \neq 2011} \beta_{1,t'} \widetilde{U_i^Z} \mathbb{1}\{t = t'\} + f_i^L + f_t^L + \nu_{it}^L \tag{12}$$

and for sales as:

$$\widetilde{log(y_{it}^S)} = \sum_{t' \neq 2011} \left(\beta_{t'}^{D1} \widetilde{D1_i^Z} + \beta_{t'}^{D2} \widetilde{D2_i^Z} \right) \mathbb{1}\{t = t'\} + f_i^S + f_t^S + \nu_{it}^S \tag{13}$$

where the outcomes and the instrument shares are their *debiased* versions from partialing out the region-industry-time fixed effects and the unobserved confounder.

4.4 Threats of Identification

Evidence from equation 10 likely provides more reliable identification than equation 11 due to two key measurement challenges: data noise and informality. Balance sheet records, which provide our sales data, suffer from significant noise for small firms due to low audit probabilities. This noise affects both our outcome variable, reducing precision, and our downstream exposure measures, leading to attenuation bias.

The informality issue presents a subtler challenge. Studies of informal immigration episodes show increased labor informality in host regions (Gulek, 2024; Bahar et al., 2024). As firms hire more informal workers, their incentives to make informal sales may change. For example, if informal workers are paid largely by informal cash made from informal sales, then the increased demand for informal workers may increase the demand for informal transactions. These transactions would go unrecorded in Balance Sheet and VAT data.

Consequently, this shift toward informality may cause host region firms' transactions with non-host regions to disappear from our data after immigration, biasing our estimates.

We address these measurement challenges through several strategies. To reduce attenuation bias, we construct baseline exposure variables using averaged sales and costs from 2006-2011 rather than single-year data. This averaging mitigates noise in the data-generating process. To address informal sales concerns, we conduct separate analyses for large firms (50+ employees in 2010), exploiting the fact that informality rates decline with firm size in Turkey.[14] Finally, we examine downstream exposure effects on employment in addition to sales because employment is less noisy and less subject to informality shifts in non-host regions.

To ensure that our trade exposure effects do not capture direct immigration impacts, we address potential within-cell correlations between trade exposure and immigration intensity. Such correlations might arise if, for instance, larger firms trade more across regions and employ fewer immigrants. We therefore exclude from our estimation sample firms in regions where the immigrant share exceeds 4% of the native population or where our instrument assigns large weights. Appendix Figure C.1 illustrates the excluded regions.

4.5 Reduced Form and 2SLS estimates

Cost Propagation

We begin by estimating the reduced-form effects of upstream exposure on firms' labor demand. Figure 4 plots the results. The outcome variable is the number of employees in Figure 4a and total payroll in Figure 4b. There are four main takeaways from Figure 4a.

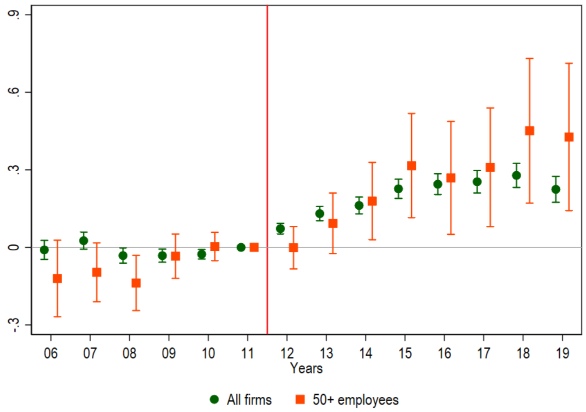
First, we do not see statistically or economically significant pre-trends. This is not mechanical. SIV weights are generated to match the trends in labor share and sales, not payroll or firm size. Therefore, the lack of pre-trends in Figure 4a is strong evidence in favor of our identification strategy. It shows evidence of a common underlying factor that generates differential trends between more/less exposed firms, and that SIV is able to partial out this unobserved confounder.

Second, upstream exposure causes firms to expand employment. Firms in non-host regions who directly or indirectly buy from immigrant-intensive firms in host regions hire more workers. The estimated effects grow over time, paralleling the pattern in our first-stage results, a similarity that strengthens the causal interpretation of our findings.

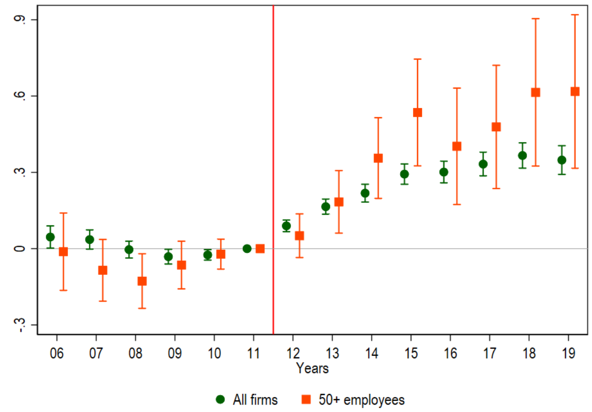
Third, estimates from the sample of only large firms are less precise because of the

[14] 40% of employment is informal in Turkey. This rate goes down to around 5% for firms with more than 50 employees.

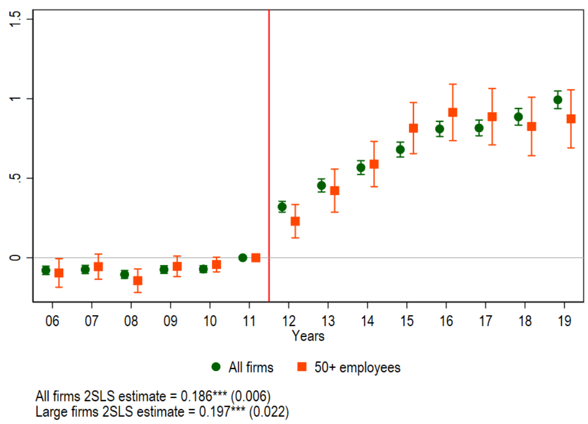
Figure 4: Effect of Upstream Exposure on Firms' Labor Demand



(a) Number of employees



(b) Payroll



(c) Labor share

Notes: The estimates come from the regression equation $\widetilde{y_{it}} = \sum_{t' \neq 2011} \gamma_{1,t'} \widetilde{U_i^Z} \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$, where the outcome variable is the natural logarithm of the number of workers in Panel A, of total payroll in Panel B, and of labor share in Panel C. Both the outcome and the treatment are their debiased versions following the SIV algorithm. In each panel, regression estimates from two separate samples are plotted: one involving firms of all sizes, and one involving only firms with at least 50 employees at baseline. The upstream exposure is given by $U_i^Z = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} Z_r$, where $\tilde{\Psi}$ is the cost-based Leontief inverse matrix, and Z_r is the regional share of the instrument. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

decreased sample size. This is a trade-off between bias and variance. Large firms are less informal and their data is arguably more credible, but there are fewer of them to obtain precise estimates.[15]

Third, estimates using only large firms are less precise due to smaller sample size. This

[15] Among manufacturing firms that survive throughout 2006–2019, only 6.5% have 50+ employees at baseline.

reflects a bias-variance trade-off: while large firms have more reliable data and lower informality, they are too few to generate precise estimates.[16]

Fourth, upstream exposure increases employment by similar magnitudes regardless of firm size. This similarity suggests that small and large firms have similar elasticities of substitution between labor and intermediate goods.

Interpreting coefficients from this reduced-form design requires careful consideration of how general equilibrium exposures propagate. Consider a simple example with two firms, i_1 and i_2. Each:

- Spends half its costs on labor and half on one intermediate good
- Buys from a different supplier (j_1 and j_2 respectively)
- Has suppliers that also use half their costs for labor

Now suppose firm j_1 has two standard deviations higher immigrant exposure through distance than firm j_2. Given the uniform labor share of 1/2, this creates a 1/2 unit difference in upstream exposure between their customers i_1 and i_2. The 0.22 coefficient estimated for 2019 in Figure 4a Panel A thus implies that firm i_1 increases its size by 11

Figure 4b presents the effects of upstream exposure on firm payroll. Prior to the immigration shock, coefficients are close to zero. After the shock, estimates become positive and statistically significant for both small and large firms. The payroll effects modestly exceed the employment effects, indicating that upstream exposure leads to both hiring and weak wage increases, since payroll reflects the product of employment and average wages.

Figure 4c shows the effects of upstream exposure on firms' labor share. The absence of pre-trends during 2006–2011 demonstrates good pre-treatment fit in the training period, a crucial condition for SIV validity, as labor share is included in the matching step. Starting in 2012, upstream-exposed firms show significant increases in labor share: firms in non-host regions who directly or indirectly buy from host regions increase their labor share relative to similar firms in their region-industry cells. Panel C reports 2SLS estimates because they map to the structural elasticity between labor and intermediates. The full manufacturing sample yields a 2SLS estimate of 0.186, implying an elasticity of substitution $\sigma_U = 0.75$ between labor and intermediates. Large firms show nearly identical results, with a 2SLS estimate of 0.197 implying $\sigma_U = 0.76$, confirming that labor and intermediate goods are gross complements.

Labor and intermediate goods are gross complements across all two-digit manufacturing industries. Appendix Figure D.9 presents industry-specific estimates of the elasticity

[16]among manufacturing firms that survive throughout 2006–2019, only 6.5% have 50+ employees at baseline.

of substitution between labor and intermediates. They range from 0.66 to 0.97 across 24 manufacturing industries, with a median of 0.80. These elasticities are not statistically distinguishable from each other, supporting our assumption of homogeneous structural elasticities across industries.

The results are robust to several specification checks, particularly regarding two key concerns with synthetic control estimators: under-fitting and over-fitting. Under-fitting occurs when no convex combination of donor units can match treated units, while over-fitting happens when synthetic control weights match noise rather than signal. The absence of pre-trends in a targeted outcome (labor share) demonstrates that more exposed firms are not outliers: we successfully construct synthetic firms with similar trends. Furthermore, the lack of pre-trends in untargeted outcomes (firm size and payroll) provides evidence against over-fitting, as these variables were not used in calculating synthetic control weights.

A potential concern with our empirical design is that distance-based instruments might be problematic if border regions experience different labor demand shocks that propagate through the supply network. Appendix Figure D.7 addresses this by replicating Figure 4 using an alternative shift-share instrument. This instrument maintains the same shift (number of Syrians in Turkey by year) but uses the ratio of Arabic speakers from the 1960 census as the share component. The results remain similar under this alternative specification.

To summarize, upstream exposure increases firms' labor demand, implying that labor and intermediate goods are complements in production with an elasticity of substitution of 0.76. This finding holds similarly for both small and large firms, suggesting that small and large firms in Turkey are similar in production technologies combining labor and intermediates. Quality checks of our SIV estimator demonstrate good pre-treatment fit while showing limited potential for over-fitting bias.

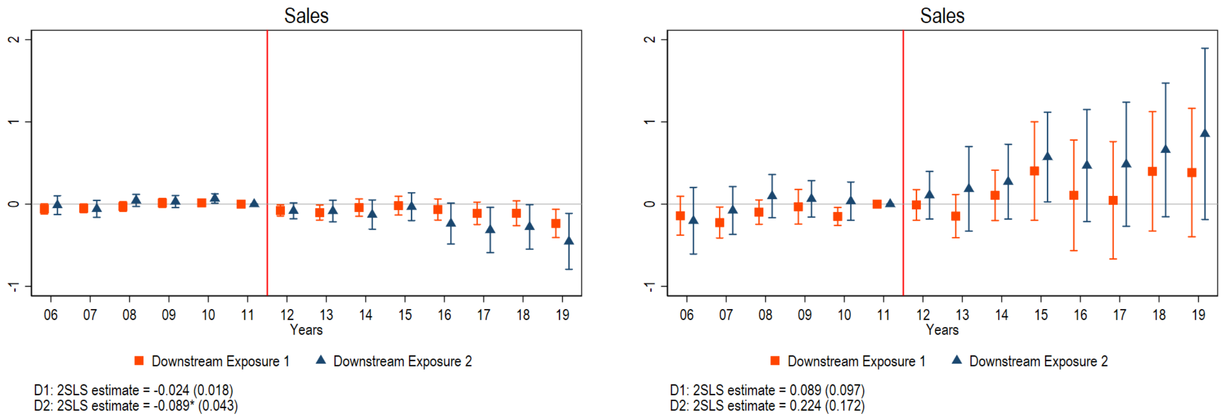
Demand Spillovers

We next examine the reduced-form effects of downstream exposures on firm sales by estimating equation 13. Figure 5 presents these results, with Panel 5a showing effects for all manufacturing firms and Panel 5b focusing on large manufacturing firms.

Comparing the effects of $D1$ and $D2$ exposures between small and large firms reveals two key findings. First, the effects of $D1$ are small in magnitude and statistically indistinguishable from zero. This is true for both small and large firms. A zero effect of $D1$ exposure indicates that firms maintain stable expenditure shares across intermediate goods following the immigration shock, implying an elasticity of substitution $\sigma_L \approx 1$ between intermediates.

Second, comparing the effects of $D2$ between small and large firms shows a dichotomy.

Figure 5: Effect of Downstream Exposures on Firms' Sales



(a) All firms

(b) Large Firms

Notes: The estimates come from the reduced-form regression equation $\widetilde{log(Sales_{it})} = \sum_{t' \neq 2011} \beta_{t'}^{D1} \widetilde{D1_i^Z} \mathbb{1}\{t = t'\} + \beta_{t'}^{D2} \widetilde{D2_i^Z} \mathbb{1}\{t = t'\} + \alpha_i^{Sales} + \alpha_t^{Sales} + \nu_{it}^{Sales}$, where both the outcome and the two treatments are their debiased versions following the SIV algorithm. The downstream exposures are calculated by replacing the immigration treatment δ_{rt} in equations 6 and 7 with the instrument share Z_r. 95% confidence intervals are plotted.

Whereas $D2$ exposure lowers firms' sales on average, it increases the sales of large firms. If true, the former would have been a surprising result and a rejection of the model. A negative $D2$ estimate means that labor and intermediates are more substitutable than different intermediates in production. This is inconsistent with both the effects of upstream exposure in Figure 4 and prior estimates from the literature (Burstein et al., 2020). In contrast, the evidence from large firms is consistent with our earlier results. The 2SLS estimates among large firms imply an elasticity of substitution between labor and intermediate goods of around 0.83, which is similar to the 0.76 we find from upstream exposure effects.

Second, $D2$ exposure effects reveal a stark contrast between firm sizes. While $D2$ exposure reduces average firms' sales, it increases sales for large firms. The negative average effect would be surprising and inconsistent with our model, as it would imply that labor and intermediates are more substitutable than different intermediates in production, contradicting both our upstream exposure findings (Figure 4) and previous literature (Burstein et al., 2020). The evidence from large firms, however, aligns with our earlier results: 2SLS estimates imply an elasticity of substitution between labor and intermediates of 0.83, close to our upstream-based estimate of 0.76.

We perform several robustness checks to verify that the negative $D2$ exposure effect on small firms' sales reflects hidden domestic transactions rather than decreased product demand. Appendix Section D.4 presents these checks. If $D2$ exposure truly reduced product demand, we would expect corresponding decreases in labor demand. However, Appendix Table D.2 shows that $D2$-exposed firms actually increase employment and labor share. This evidence suggests that Figure 5a suffers from negative bias due to small firms underreporting domestic sales. We therefore interpret Figure 5b, based on large firms, as capturing the true effects of $D1$ and $D2$ exposures on sales.

To summarize, we find elasticities of substitution of $\hat{\sigma_u} = 0.76$ between labor and intermediates, and $\hat{\sigma_l} = 1$ between different intermediates. Given the consistency of these estimates across both structural equations -upstream exposure effects on labor share and downstream exposure effects on sales— for large firms, we proceed to counterfactual analysis to quantify immigration's total effects on host and non-host labor markets.

4.6 Counterfactuals

This section uses the model to quantify how immigration affects host and non-host regions through counterfactuals. We examine the economic significance of trade spillovers, their dependence on host region and immigrant characteristics, and their implications for our understanding of immigration's effects on labor market.

Recall that Theorem 1 characterizes the general equilibrium effects of an immigration shock on regional wages and firms' prices as a function of the baseline production network and the structural elasticity parameters. We observe the baseline production network in the data and the previous section estimates the structural elasticity parameters. Therefore, solving the system linear equations given in Theorem 1 gives us the general equilibrium effects on wages and prices. For computational reasons, we assume a representative firm at the region-industry level. We also start with a single labor type in each region as in Section 3, and later introduce skill heterogeneity to discuss the differential effects based on immigrants' skill level.

Theorem 1 characterizes immigration's general equilibrium effects on regional wages and firm prices as a function of the baseline production network and structural elasticity parameters. Having observed the network in our data and estimated the elasticities, we can solve the system of linear equations in Theorem 1 to obtain these general equilibrium effects. For computational feasibility, we use representative firms at the region-industry level. We begin with homogeneous labor within regions as in Section 3, then introduce skill heterogeneity to analyze how effects vary with immigrant skill levels.

An important consideration is that our model expresses wages relative to nominal GDP, while real wages typically reference local prices. Therefore, we define real wage changes as $d\ln w_{real} = d\ln w - b * d\ln p$, where b denotes the $R \times N$ matrix of final expenditure shares and $d \ln p$ is the $N \times 1$ vector of price changes.

Counterfactual 1: Spillover effects of a 1% Labor Supply Shock

In our first counterfactual, we analyze how immigration spillovers vary across potential host regions. We simulate a 1% labor supply increase separately for each of Turkey's 81 provinces and calculate two effects: the real wage change in the host province and the average real wage change across the other 80 provinces. This generates 81 pairs of estimates for host and non-host wage effects.

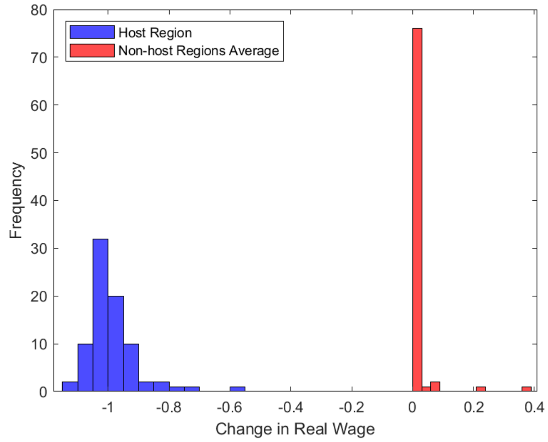
Figure 6a presents the distribution of wage effects, revealing two key patterns. First, a 1% increase in labor supply typically reduces the real wages of the host region by about 1% while leaving the non-host regions largely unaffected. In 71 of 81 simulations, average non-host region real wages change by less than 0.01%, and in 76 cases by less than 0.02%. This pattern emerges because most firms predominantly trade within their own region, so host region price changes rarely generate economically meaningful spillovers to non-host regions.

Second, 5 of 81 provinces generate economically meaningful spillovers (greater than 0.04% change in non-host real wages): Bursa, Kocaeli, Izmir, Ankara, and Istanbul. Istanbul and Ankara produce particularly large spillovers—up to two-thirds the magnitude of direct effects. A 1% labor supply increase in Istanbul reduces local real wages by 0.56% while raising the average non-host region's real wages by 0.38%. Similarly, in Ankara, a 1% shock decreases local real wages by 0.71% and increases average non-host wages by 0.22%. Figure 6b maps these spillover effects across regions. While the largest spillovers come from the most populated cities (Istanbul and Ankara), significant effects also emerge from major agricultural hubs (Manisa and Adana) and resource centers (Zonguldak with its coal deposits).

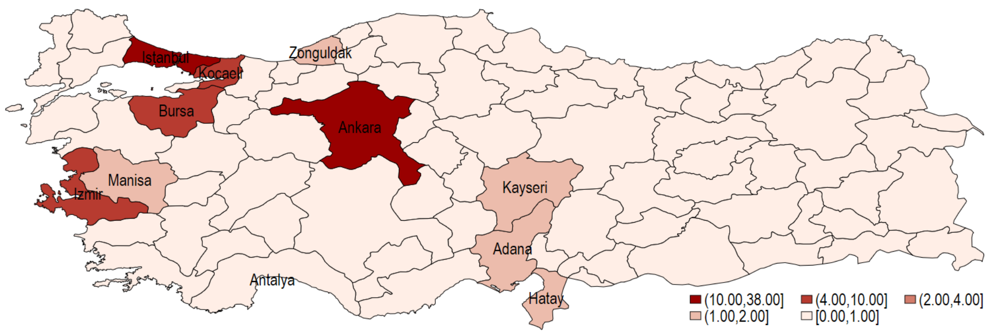
What explains this variation in regional spillovers? Population offers one explanation: a 1% labor force increase in Istanbul represents seven times the absolute immigration shock of a similar percentage increase in Gaziantep, a major host region. However, population alone cannot explain the pattern. Kocaeli, despite its smaller population than major host regions like Gaziantep, Sanliurfa, and Adana, generates larger spillovers than all three combined. Similarly, while Domar weights correlate with spillover magnitude, they don't tell the complete story. Consider Adana and Antalya: despite similar populations and Domar weights, Adana's spillovers are triple those of Antalya. This difference likely stems from their economic structures: Adana's role as an agricultural hub involves extensive inter-regional trade, while Antalya's tourism-focused economy generates mainly local transactions. This suggests that a region's position in the domestic trade network might better predict spillover effects.

We formally investigate this network position hypothesis using Bonacich centrality mea-

Figure 6: Real Wage Changes in Host and Average Non-host Region



(a) Histogram of Host and Average Non-host Region effects



(b) Heatmap of Non-host Region effects

Notes: This figure shows the results from 81 counterfactuals, one for each province in Turkey. Each counterfactual consists of a 1% increase in labor supply in the host province. The "non-host mean" refers to the simple average of real wage changes across the 80 non-host regions. Real wages are calculated by the difference between the change in nominal wages and the change in the regional price index.

sures for both cost-based and sales-based trade matrices: $\widetilde{B} = \tilde{\Psi}'\mathbf{1}$ and $B = \Psi'\mathbf{1}$.[17] These measures capture how much other regions depend on a given region r through costs ($\widetilde{B}_r$) and sales (B_r). To assess which regional characteristics best predict spillover effects, we regress average non-host wage effects on the host region's population, Domar weight, and both centrality measures. Table 1 presents these results. In Column 1, a one standard deviation increase in population (normalized to mean zero and unit variance) corresponds to a 4.6% larger change in non-host real wages. Columns 2-4 show similar univariate regressions for Domar weight and both centrality measures, while Column 5 includes all four predictors simultaneously.

[17] For more on the Bonacich centrality measure, see Bonacich (1987) and Jackson (2008).

Several patterns emerge from these results. While all four variables strongly predict spillover magnitudes (minimum R-squared of 0.88 across 81 observations), centrality measures outperform both population and Domar weights. The sales-based centrality measure proves especially powerful, achieving an R-squared of 0.93. Moreover, sales-based centrality maintains its positive correlation with spillovers even after controlling for population, Domar weight, and cost-based centrality.

Table 1: Provincial Attributes and Spillovers from a 1% increase in Labor Supply

	(1) $\Delta W_{Non-host}$	(2) $\Delta W_{Non-host}$	(3) $\Delta W_{Non-host}$	(4) $\Delta W_{Non-host}$	(5) $\Delta W_{Non-host}$
Population	0.046***				0.0070
	(0.003)				(0.005)
Domar weight		0.046***			-0.079**
		(0.004)			(0.033)
Cost-Based Centrality: $\tilde{\Psi}\mathbf{1}$			0.047***		-0.024
			(0.004)		(0.039)
Sales-Based Centrality: $\Psi\mathbf{1}$				0.047***	0.14**
				(0.004)	(0.064)
N	81	81	81	81	81
R-sq	0.886	0.883	0.918	0.931	0.967

Note: All explanatory variables are standardized to have mean zero and standard deviation of 1. Robust standard errors are used. * 0.1 ** 0.05 *** 0.01

These results shed new light on why studies on the effects of immigration on the labor market often reach conflicting conclusions (Dustmann et al., 2016). The standard spatial difference-in-differences (DiD) approach compares host regions to others (Altonji and Card, 1991; Card, 2001). In his seminal paper, Card (1990) examined the Mariel Boatlift's impact on Miami's labor markets by comparing Miami to Atlanta, Houston, Los Angeles, and Tampa; and found null effects. This DiD approach relies on the stable unit treatment value assumption (SUTVA): immigration to "treated" (host) regions does not affect "control" (non-host) regions. Our results show that SUTVA fails when immigrants arrive at central nodes of the trade network.[18] For example, when Istanbul receives a 1% labor supply increase, "control" region real wages rise by 0.30-0.46% while Istanbul's fall by 0.56%. A DiD

[18]Note that the idea of spatial spillovers of immigration shocks violating SUTVA is not new in the immigration literature. Similar concerns were initially raised by Borjas et al. (1997); Borjas (2003), but the focus was more on natives' ability to move from host to non-host regions in response to immigration.

comparison would therefore substantially overestimate immigration's negative wage impact in Istanbul.

While this potential overestimation does not explain Card's finding that Cuban migrants did not reduce Miami natives' wages and employment, our results suggest two alternative explanations. First, the sign of the bias depends on technology parameters: if labor and intermediates were gross substitutes, or if intermediates were more substitutable, immigration to central nodes could reduce non-host wages, causing DiD to underestimate the impact on the host region. Second, we find that inter-regional trade flattens the host region's labor demand curve. If Miami firms were sufficiently connected to other US regions or countries, Cuban immigration's effects may have diffused across a broad enough area to minimize local wage impacts.

Counterfactual 2: Does where immigrants live matter for welfare?

Several host countries, including Germany, Sweden, Norway, and Finland, actively direct refugees and asylum seekers to specific regions, often to prevent overcrowding. Our analysis of varying spillover effects raises a natural question: could there be meaningful welfare gains from concentrating immigrants in cities that are central to the production network?

To investigate this question, we simulate the arrival of 100,000 immigrants in Turkey's 26 major regions.[19] For each simulation, we calculate the changes in prices across the economy and the aggregate welfare gains. The regional welfare change $d\ln Y_r$ is given by:

$$d\ln Y_r = d\ln \chi_r - \sum_{i\in N_r} b_i d\ln p_i \tag{14}$$

where welfare improves when either the region's share of total GDP (χ_r) increases or the prices of goods in its consumption basket decrease. We aggregate these regional welfare changes into a national measure using population-weighted averages.

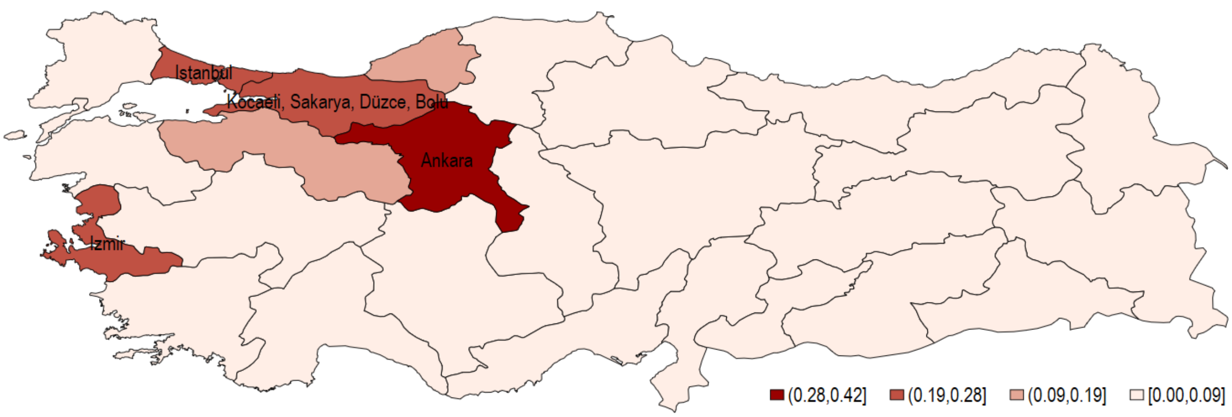
Figure 7 shows the heatmap of the total welfare effects of 100,000 immigrants, a 0.12% increase in total population in Turkey, across different host regions. We see a significant heterogeneity in the total welfare effects of immigration. Whereas immigrants increase total welfare across all 26 trials, it does so little in most regions in Turkey. In 21 out of 26 trials, we document less than 0.09% increase in welfare. In contrast, the welfare effects increase by 0.19-0.42%, up to 21 times larger than the smallest welfare effect of 0.02%, when regions like Izmir, Istanbul, and Ankara receive immigrants. Welfare effects are largest when these

[19]We use the 26 NUTS-2 regions rather than the 81 NUTS-3 regions because the extreme population heterogeneity across provinces (from 120 thousand in Kilis to 14 million in Istanbul) would make equal-sized immigration shocks generate vastly different percentage changes in local populations.

cities receive immigrants because they are central nodes in the trade network based on Eigenvector centrality. Firms in these regions buy from and sell to firms in various other regions. Consequently, more regions benefit from the cost reductions, which results in a larger increase in total welfare.

Figure 7 maps the welfare effects of placing 100,000 immigrants (a 0.12% population increase) across different Turkish regions. While immigration increases welfare in all simulations, the magnitude varies dramatically by location. In 21 of 26 cases, welfare gains are modest: ranging from 0.02% to 0.09%. However, when immigrants settle in Izmir, Istanbul, or Ankara, welfare gains range from 0.19% to 0.42%, up to 21 times larger than the smallest effect. These cities generate larger welfare gains because they are central nodes in the trade network. Their firms' extensive buying and selling relationships across regions allow immigration-induced cost reductions to benefit more regions, which amplifies total welfare gains.

Figure 7: Heatmap of Total Welfare Effects of Immigration across Host Regions



Notes: This figure shows the results from 26 counterfactuals, one for each NUTS-2 region in Turkey. Each counterfactual consists of an arrival of 100,000 immigrants to the host region. The change in total welfare is calculated by taking a weighted average of the change in regional welfare, where the weights are the share of the population living in that region.

Counterfactual 3: Does the skill composition of immigrants impact spillover effects?

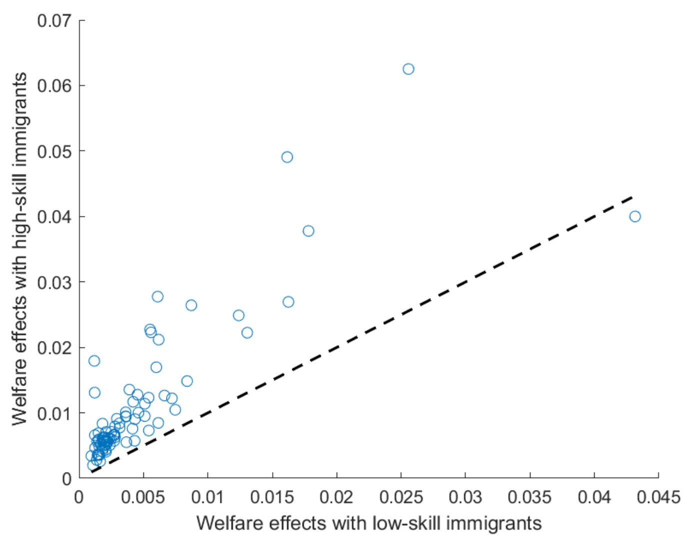
Immigration shocks often involve skill-specific labor supply changes. Syrian immigrants in Turkey, for example, have lower average education levels than natives and work in less skill-intensive industries like Textiles, Construction, and Agriculture (Crescent and Programme, 2019). When low-skill and high-skill labor are imperfect substitutes, immigrants of different skill levels affect production costs in different industries. The magnitude of spillovers may therefore depend on the extent to which these affected industries trade with other regions.

To analyze skill-specific effects, we extend our baseline model to incorporate both low- and high-skill labor, with details provided in Appendix Section B. One important caveat is that we must assume the elasticity of substitution between low- and high-skill workers ($\sigma_S = 1$) because our employer-employee matched data do not show workers' education.

To examine how spillovers vary with immigrant skill levels, we conduct paired counterfactuals for each of Turkey's 81 provinces. For each province, we simulate two scenarios: one with 10,000 low-skill immigrants and another with 10,000 high-skill immigrants, then compare the resulting welfare effects.

Figure 8 compares the welfare effects of low-skill versus high-skill immigration. Each circle represents one of the 26 NUTS-2 regions, with low-skill immigration effects on the x-axis and high-skill effects on the y-axis. The dashed 45-degree line represents equal welfare effects; points above this line indicate regions where high-skill immigration generates larger welfare gains.

Figure 8: Comparison of welfare effects across low-skill and high-skill immigration



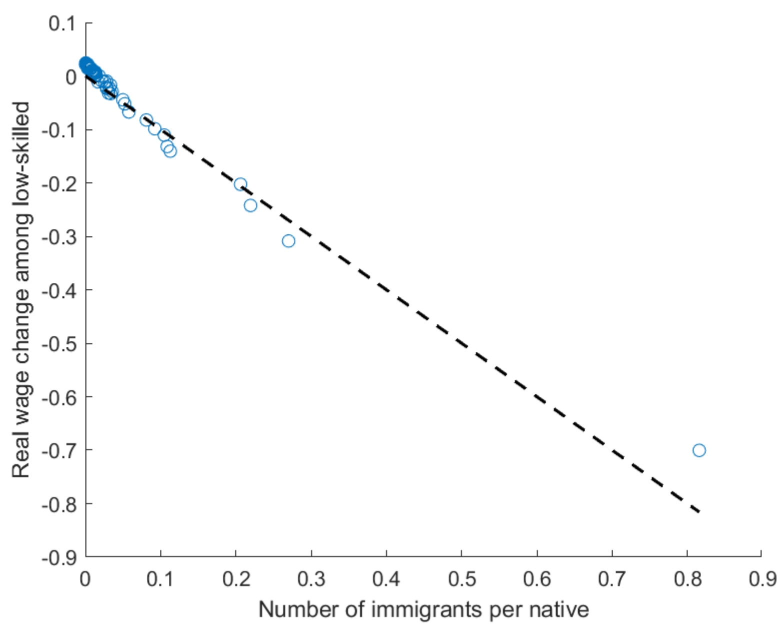
Notes: This figure shows the results from 162 counterfactuals, two for each NUTS-3 region in Turkey. For each region, we calculate the total welfare change when (1) 10,000 low-skill immigrants arrive in the host region and (2) 10,000 high-skill immigrants arrive in the host region. Low-skill is having less than a high school degree, and high-skill is having at least a high school degree.

Figure 8 reveals two key patterns. First, most regions show negligible welfare effects from both low-skill and high-skill immigration. This aligns with our earlier finding that spillover effects—and thus total welfare effects—are minimal when host regions aren't central nodes in the domestic trade network. In these cases, immigrant skill level matters little because cost reductions remain localized within the region. Second, in central regions where welfare gains are substantial, high-skill immigration generates markedly larger benefits. For instance, 10,000 high-skill immigrants in Bursa increase total welfare by 0.064

Model-based factual: Quantifying the general equilibrium effects of the Syrian immigration

Our counterfactuals suggest that immigration spillovers are largest when host regions are central in the trade network and immigrants are high-skilled. Since Syrian immigrants are concentrated in less-developed southeastern regions and have lower skill levels than native Turkish workers, we expect limited general equilibrium effects.

Figure 9: Partial vs General Equilibrum Effects of Syrian Immigration in Turkey



Notes: Provincial distribution of the number of immigrants per native in 2019 is used. The general equilibrium changes in wages and prices are calculated as a solution to the system of linear equations given in the Appendix Section B. Each blue circle denotes a Turkish province. The dashed line is the -45° line.

To test this prediction, we calculate how the low-skilled Syrian immigration affects Turkish natives' real wages and compare these general equilibrium effects with partial equilibrium predictions. Figure 9 plots this comparison across Turkey's 81 provinces, showing changes in low-skill natives' real wages (y-axis) against the 2019 Syrian-to-native ratio (x-axis). The dashed -45° line represents what we would observe with only partial equilibrium effects.

The actual estimates closely track this line: the correlation between wage changes and immigration intensity is -0.99 (R-squared of 0.97), indicating that partial equilibrium effects accurately predict general equilibrium outcomes.

This finding validates prior studies of Syrian immigration's labor market effects in Turkey. Both Gulek (2024) and Gulek and Vives-i Bastida (2024) document displacement of low-skill natives by Syrian immigrants. Their results accurately capture these effects because Syrian immigrants settled in regions non-central to Turkey's trade network, where SUTVA violations are minimal.

5 Conclusion

This paper demonstrates how immigration-induced wage changes propagate through production networks across regions. We find that immigration can generate substantial spillover effects, particularly when immigrants settle in central nodes of the domestic trade network or work in skill-intensive industries. These findings emphasize the crucial role of regional trade structures in shaping immigration's economic impacts.

This network perspective challenges traditional approaches to studying immigration that ignore interregional spillovers and helps explain conflicting results in previous research. By incorporating production networks into immigration analysis, we provide new insights for both research methodology and policy design.

Our findings suggest practical guidance for future research when firm-level network data are unavailable. Immigration to smaller, less developed regions generally produces minimal spillovers, allowing traditional difference-in-differences analyses to capture local effects accurately. This explains why studies of refugee settlement in border regions, such as Syrians in southeastern Turkey (Gulek, 2024) or Venezuelans along the Colombian border (Bahar et al., 2024), yield reliable results. In contrast, economic migration often targets larger, more connected cities. For instance, European hubs like Brussels, Frankfurt, and Munich, which have the highest foreigner-to-native ratios in the EU (Mayors of Europe, 2019), likely generate significant spillovers throughout Europe, potentially biasing traditional empirical approaches.

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A Proofs

Before showing the proofs, we introduce some notation. The trade matrix Ω is of size $(N+R)\times(N+R)$, where the last R rows are zeros. We decompose this matrix as follows.

$$\Omega = \left(\begin{array}{c|c} \Omega^p & \Omega^f \\ \hline 0 & 0 \end{array}\right)$$

where Ω^p denotes the first $N \times N$ portion.

Similarly, the Leontief inverse is defined as

$$\Psi = \left(\begin{array}{c|c} \Psi^p & \Psi^p\Omega^f \\ \hline 0 & I \end{array}\right)$$

where $\Psi^p = (I - \Omega^p)^{-1})$

For ease of notation, we use r only to refer to regions. For example, $\Psi_{i,r}$ refers to ith row and $(N+r)$th column, while $\Psi_{i,j}$ refers to ith row and jth column.

Proof of Proposition 1. The labor share in production of firm i is given by

$$\tilde{\Omega}_{i,L} = \frac{(1-\eta_i)^{\sigma_u} w_r^{1-\sigma_u}}{(1-\eta_i)^{\sigma_u} w_r^{1-\sigma_u} + \eta_i^{\sigma_u} p_{m,i}^{1-\sigma_u}}$$

where $p_{m,i}$ is the price of the CES aggregate intermediate good of firm i. Taking the natural logarithm and differentiating, we get:

$$\begin{aligned} d\ln\tilde{\Omega}_{i,L} &= (1-\sigma_u)d\ln w_r - (1-\sigma_u)\left(\tilde{\Omega}_{i,L}d\ln w_r + \tilde{\Omega}_{i,m}d\ln p_{m,i}\right) \\ &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})d\ln w_r - (1-\sigma_u)\tilde{\Omega}_{i,m}d\ln p_{m,i}. \end{aligned}$$

Using CES attributes, we can write $d\ln p_{m,i}$ as:

$$\frac{1}{1-\sigma_L}\frac{\sum_{j=1}^n \alpha_{ij}^{\sigma_L}(1-\sigma_L)p_j^{-\sigma_L}dp_j}{\sum_{j=1}^n \alpha_{ij}^{\sigma_l}p_j^{1-\sigma_l}}$$

note that

$$\frac{\alpha_{ij}^{\sigma_l}p_j^{-\sigma_l}}{\sum_{k=1}^n \alpha_{ik}^{\sigma_L}p_k^{-\sigma_L}} = \tilde{\Omega}_{i,j}/(1-\tilde{\Omega}_{i,L})$$

Putting this back into the previous equation, we get:

$$
\begin{aligned}
d\ln\tilde{\Omega}_{i,L} &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})d\ln w_r - (1-\sigma_u)\sum_{j=1}^{n}\tilde{\Omega}_{i,j}d\ln p_j \\
&= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})\left(d\ln w_r - \sum_{j=1}^{n}\frac{\tilde{\Omega}_{i,j}}{\tilde{\Omega}_{i,L}}d\ln p_j\right)
\end{aligned}
\tag{15}
$$

■

Proof of Proposition 3. Prices are given by $p_i = \frac{\mu_i C_i(p,w,\overline{y}=1)}{A_i}$. Keeping markups and technology constant, $d\ln p_i = d\ln C_i$.

Using Shephard's Lemma, we can show the change in costs as:

$$
\begin{aligned}
d\ln C_i &= d\ln\left(\sum_{j=1}^{n}p_j x_{ij} + w_{r_i}L_i\right) \\
&= \sum_{j=1}^{n}\tilde{\Omega}_{i,j}d\ln p_j + \tilde{\Omega}_{i,L}d\ln w_{r_i}
\end{aligned}
$$

Writing this in vector form, we get:

$$
\begin{aligned}
dlnp &= \tilde{\Omega}d\ln p + \tilde{\Omega}_{,L}.*d\ln w \\
&= \tilde{\Psi}^p(\tilde{\Omega}_{,L}.*d\ln w)
\end{aligned}
$$

which implies

$$
dlnp_i = \sum_{j=1}^{n}\tilde{\Psi}^p_{i,j}\tilde{\Omega}_{j,L}d\ln w_{r_j}
$$

■

Proof of Proposition 2. From accounting identity

$$
\lambda = b'\Psi \leftrightarrow \lambda_i = \sum_{j=1}^{n}b_j\Psi_{ji} = \sum_{j=1}^{n}b_j\Psi_{ji} = \sum_{j=1}^{n}\overline{b_{r_j}}\chi_{r_j}\Psi_{ji}
$$

$$
d\lambda_i = \sum_j \overline{b_{r_j}}d\chi_{r_j}\Psi_{ji} + \sum_j \overline{b_{r_j}}\chi_{r_j}d\Psi_{ji} \tag{16}
$$

Focusing on the first part of equation 16, we can write χ_{r_j} as:

$$\chi_r = \sum_{i \in r} \pi_i + w_r L_r$$

which gives

$$d \ln \chi_r = \sum_{i \in r} \frac{\pi_i}{\chi_r} d \ln \lambda_i + w_r L_r d \ln L_r + w_r L_r d \ln w_r$$

Focusing on the second part of equation 16 and using matrix calculus, we can show:

$$d\Psi = \Psi d\Omega \Psi$$

so, we need to get $d\Omega$. First, using CES algebra, we can write

$$\tilde{\Omega}_{i,j} = \frac{1}{A_i} \eta_i^{\sigma_u} \alpha_{ij}^{\sigma_l} p_j^{1-\sigma_l} \overline{p_{m,i}}^{\sigma_l - \sigma_u} \overline{p_{y,i}}^{\sigma_u - 1}$$

Taking the natural logarithm and totally differentiating gives:

$$d \ln \tilde{\Omega}_{i,j} = (1 - \sigma_l) d \ln p_j + (\sigma_l - \sigma_u) d \ln \overline{p_{m,i}} + (\sigma_u - 1) d \ln \overline{p_{y,i}}$$

where $\overline{p_{m,i}}$ is the unit price of intermediate goods for firm i and $\overline{p_{y,i}}$ is the unit price of production for firm i. Rewriting these two terms as functions of changes in wages and intermediate good prices gives

$$\begin{aligned} d \ln \Omega_{i,j} =& (1 - \sigma_l) d \ln p_j + (\sigma_u - 1) \tilde{\Omega}_{i,L} d \ln w_r \\ & + (\sigma_l - 1 + (1 - \sigma_u)(1 - \tilde{\Omega}_{i,m})) \frac{1}{\tilde{\Omega}_{i,m}} \sum_{k=1}^{n} \tilde{\Omega}_{i,k} d \ln p_k \end{aligned}$$

Collecting terms, one can show

$$d \ln \tilde{\Omega}_{i,j} = (1 - \sigma_l) \left(d \ln p_j - \sum_{k=1}^{n+R} \tilde{\Omega}_{i,k} d \ln p_k \right) + (\sigma_l - \sigma_u) \tilde{\Omega}_{i,L} \left(\frac{1}{\tilde{\Omega}_{i,m}} (\sum_{k=1}^{n} \tilde{\Omega}_{i,k} d \ln p_k) - d \ln w_{r_i}) \right)$$

Using $d \ln \Omega_{i,j} = d \ln \tilde{\Omega}_{i,j}$ when markups are constant, and using the covariance term, we get:

$$d\Omega_{i,j} = \frac{1 - \sigma_l}{\mu_i} Cov_{\tilde{\Omega}^{(i)}}(d \ln p, I_{(j)}) + \frac{\sigma_l - \sigma_u}{\mu_i} \tilde{\Omega}_{i,j} \tilde{\Omega}_{i,L} \left(\frac{1}{\tilde{\Omega}_{i,m}} (\sum_{k=1}^{n} \tilde{\Omega}_{i,k} d \ln p_k) - d \ln w_{r_i}) \right)$$

From proposition 3, we know

$$d\ln p_i = \sum_{j=1}^{n} \tilde{\Psi}^p_{ij}\tilde{\Omega}_{j,L} d\ln w_{r_j}$$

More succinctly, we can write it as:

$$d\ln p = \sum_{r=1}^{R} \tilde{\Psi}_{(r)} d\ln w_r$$

replacing price changes $d\ln p$ in the equation for $d\Omega_{i,j}$, we get:

$$d\Omega_{i,j} = \frac{1-\sigma_l}{\mu_i} Cov_{\tilde{\Omega}^{(i)}}\left(\sum_g \tilde{\Psi}_{(g)} d\ln w_g, I_{(j)}\right) + \frac{\sigma_l-\sigma_u}{\mu_i}\frac{\tilde{\Omega}_{i,L}}{\tilde{\Omega}_{i,m}}\tilde{\Omega}_{i,j}\left(\sum_{k=1}^{n}\tilde{\Psi}^p_{ik}\tilde{\Omega}_{k,L} d\ln w_{r_k} - d\ln w_{r_i}\right)$$

Using $d\Psi = \Psi d\Omega\Psi$, we get:

$$\begin{aligned} d\Psi_{o,s} =& \sum_{j=1} \frac{\Psi_{o,j}}{\mu_j}(1-\sigma_l) Cov_{\tilde{\Omega}^{(j)}}\left(\sum_g \tilde{\Psi}_{(g)} d\ln w_g, \sum_i I_{(i)}\Psi_{is}\right) \\ &+ \sum_{i=1}^{n} \Psi_{0,i}\frac{\sigma_l-\sigma_u}{\mu_i}\frac{\tilde{\Omega}_{i,L}}{\tilde{\Omega}_{i,m}}\left(\sum_{k=1}^{n}\tilde{\Psi}^p_{ik}\tilde{\Omega}_{kl} d\ln w_{r_k} - d\ln w_{r_i}\right)\sum_{j=1}^{n}\tilde{\Omega}_{i,j}\Psi_{j,s} \end{aligned}$$

Using $d\lambda_i = \sum_j \overline{b_{r_j}} d\chi_r \Psi_{ji} + \sum_j \overline{b_{r_j}}\chi_{r_j} d\Psi_j$ and combining terms, we get:

$$\begin{aligned} d\ln\lambda_i =& (1-\sigma_l)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\frac{1}{\mu_j} Cov_{\tilde{\Omega}^{(j)}}\left(\sum_g \tilde{\Psi}_{(g)} d\ln w_g, \Psi_{(i)}\right) \\ &+ (\sigma_l-\sigma_u)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\frac{\tilde{\Omega}_{j,l}}{\tilde{\Omega}_{j,m}}\left(\sum_{k=1}^{n}\tilde{\Psi}^p_{ik}\tilde{\Omega}_{kl} d\ln w_{r_k} - d\ln w_{r_i}\right)(\Psi_{ji} - I_{ji}) \\ &+ \frac{1}{\lambda_i}\sum_j\sum_r \overline{b_{rj}}\Psi_{ji}\chi_r d\ln\chi_r \end{aligned}$$

where $d\ln\chi$ is given by:

$$d\ln\chi_r = \sum_{i\in r}\frac{\pi_i}{\chi_r} d\ln\lambda_i + w_r L_r d\ln L_r + w_r L_r d\ln w_r$$

This completes the proves of propositions 1, 2 and 3. Theorem 1 is proven directly by these propositions.

■

B Model with skill heterogeneity

B.1 Setup

The economy consists of N firms indexed by i, R regions indexed by r, where each region is endowed with ℓ_r low-skill and h_r high-skill labor. Each firm operates in one region: r_i denotes the region of firm i. Firms use intermediate goods and local labor in production, and sell their output as both an intermediate good to other producers in all regions and as a final good to local consumers.

Producers

Firm i chooses labor ℓ_i, h_i, and intermediate goods $\{x_{i,j}\}_{j=1}^{n}$ to minimize costs subject to a constant returns nested-CES technology

$$\min_{\{x_{ij}\}_{j=1}^{n}, L_i} \sum_{j=1}^{n} p_j x_{ij} + w_{r_i,\ell}\ell_i + w_{r_i,h}h_i \quad \text{subject to}$$

$$A_i(\eta_i m_i^{\frac{\sigma_u - 1}{\sigma_i}} + (1-\eta_i)L_i^{\frac{\sigma_u-1}{\sigma_u}})^{\frac{\sigma_u}{\sigma_u-1}} \geq y_i$$

$$m_i = \left(\sum_{j=1}^{n} \alpha_{ij} x_{ij}^{\frac{\sigma_m - 1}{\sigma_m}}\right)^{\frac{\sigma_m}{\sigma_m-1}}$$

$$L_i = \left(\alpha_{i\ell}\ell_i^{\frac{\sigma_L-1}{\sigma_L}} + (1-\alpha_{i\ell}h_i^{\frac{\sigma_L-1}{\sigma_L}}\right)^{\frac{\sigma_L}{\sigma_L-1}}$$

where A_i is a Hicks-neutral productivity shifter, y_i is total output, p_j is the price of good j, ℓ_i and h_i are the low-skill and high-skill labor used by firm i, $w_{r,l}$ and $w_{r,h}$ are the low-skill and high-skill wages in region r, m_i is the intermediate good used by the firm, which itself is a CES bundle of goods from different firms. x_{ij} denotes how much firm i uses firm j's goods in production, where firm j can be in any region. We assume common elasticities of substitution within nests: σ_u denotes the elasticity of substitution between labor and intermediate goods, unlike the text, σ_m is the elasticity of substitution between different intermediate goods, and $\sigma_L$is the elasticity of substitution across labor. Constant returns to technology requires $\sum_j \alpha_{i,j} = 1$. Let C_i denote the unit cost of firm i. We assume that firms have constant and exogenous markup μ_i, and therefore set price $p_i = \mu_i C_i$.

Final Demand

All final goods consumption as well as the ownership of firms is local. We assume a representative consumer in each region r, who optimizes her Cobb-Douglas utility subject to budget constraint that equates her spending on final goods with her labor income plus (regional) firm profits.

$$\max_{\{c_{r,i}\}} \Pi_{i\in r} c_{r,i}^{\beta_i} \quad s.t. \quad \sum_{i\in r} p_i x_{0,i} = w_{r,l} l_r + w_{r,h} h_r + \sum_{i\in r} \pi_i$$

where $c_{r,i}$ is how much the representative agent r consumes firm i's goods, and $\sum_{i\in r} \beta_i = 1$.

Labor Supply

Both types of labor are inelasticly supplied in each region, are immobile across regions and perfectly mobile across firms in a region.

General Equilibrium

Given exogenous productivities A_i and markups μ_i, equilibrium is a set of prices p_i, low-skill wages $w_{r,l}$ and high-skill wages $w_{r,h}$, intermediate good choices $x_{i,j}$, labor input choices l_i, outputs y_i, and final demands $c_{r,i}$, such that each producer minimizes its costs subject to technology constraints and charges the relevant markup on its marginal cost; consumers maximize their utility subject to their budget constraint, and the markets for all goods and labor clear.

B.2 Input-Output definitions

We use the same notation as in the baseline model. The only difference worth noting is that the trade matrix Ω is of dimension $(N + 2R) \times (N + 2R)$, where the first N columns and rows belong to firms, rows $N+1$ to $N+R$ belong to low-skill labor, and $N+R+1$ to $N+2R$ belong to high-skill labor.

Effects of a Labor Supply Shock on labor income

Note that the labor income in region r is the sum of labor payments by all firms in that region.

$$\lambda_r = l_r w_{rl} + h_r w_{rh} = \sum_{i\in r} \lambda_i \Omega_{i,L}$$

which gives

$$d\ln\lambda_r = \frac{1}{\lambda_r}\left(\ell_r w_{rl}(d\ln l_r + d\ln w_{rl}) + h_r w_{rh}(d\ln h_r + d\ln w_{rh})\right)$$
$$d\ln\lambda_r = s^w_{LS}(d\ln\ell_r + d\ln w_{rl}) + s^w_{hs}(d\ln h_r + d\ln w_{rh})$$

where s denotes shares of low-skill and high-skill labor expenses.

Proposition 4 characterizes the change in labor share as a function of changes in wages and prices

Proposition 4. *In response to an immigration-induced wage shock, the following equation describes the change in the labor share of production costs*

$$d\ln\tilde{\Omega}_{i,L} = (1-\sigma_u)\left(\frac{1-\tilde{\Omega}_{i,L}}{\tilde{\Omega}_{i,L}}(\tilde{\Omega}_{il}d\ln w_{rl} + \tilde{\Omega}_{ih}d\ln w_{rh}) - \sum_{j=1}^{n}\tilde{\Omega}_{ij}d\ln p_j\right) \tag{17}$$

Proof follows the same steps as in the baseline model.

Let $\overline{w_j} = \frac{1}{\tilde{\Omega}_{j,L}}\left(\tilde{\Omega}_{j,l}d\ln w_{r_j,l} + \tilde{\Omega}_{j,h}d\ln w_{r_j,h}\right)$ is the change in the average wage for firm j. This allows us to write the change in firms' sales using the notation from the baseline model.

Proposition 5. *In response to an immigration-induced wage shock, the following equation describes the change in the Domar weights / sales share of firms*

$$\begin{aligned} d\ln\lambda_i = &\sum_{j=1}^{n}(1-\sigma_M)\frac{\lambda_j}{\lambda_i\mu_j}Cov_{\tilde{\Omega}^{(j)}}\left(d\ln p, \Psi_{(i)}\right) \\ &+ (\sigma_U - \sigma_M)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,l}\left(d\ln\overline{w_{r_j}} - \sum_{k=1}^{n}\frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}}d\ln p_k\right)(\Psi_{ji} - I_{ji}) \\ &+ \frac{1}{\lambda_i}\sum_j\sum_r\overline{b_{rj}}\Psi_{ji}\chi_r d\ln chi_r \end{aligned} \tag{18}$$

where I is the identity matrix, and $d\ln\chi_r = \left(\sum_{i\in r}\frac{\pi_i}{\chi_r}d\ln\lambda_i\right) + \frac{\lambda_r}{\chi_r}d\ln\lambda_r$ is the change in regional income.

Proof follows the same steps as in the baseline model.

The following characterizes the change in prices.

Proposition 6. *In response to an immigration-induced wage shock, the following equation describes the change in prices charged by firms*

$$d\ln p_i = \sum_{j=1}^{n}\tilde{\Psi}^p_{i,j}(\tilde{\Omega}_{j,l}w_{r_j,l} + \tilde{\Omega}_{jh}w_{r_j,h}) = \sum_{f=1}^{F}\tilde{\Psi}_{i,f}d\ln w_f \tag{19}$$

where f denotes factors, which are the low and high-skill labor in regions.

Proof follows the same steps as in the baseline model.

With these propositions at hand, we can fully characterize the effect of an immigration shock on wages and prices.

Theorem 2. *The following linear system fully describes the change in equilibrium prices and quantities in response to an immigration shock consisting of $d\ln l_r$ change in low-skill labor and $d\ln h_r$ change in high-skill labor.*

$$
\begin{aligned}
d\ln w_f =& d\ln\lambda_f - d\ln L_f \\
d\ln p_i =& \sum_{f=1}^{F}\tilde{\Psi}_{i,f} d\ln w_f \\
d\ln\lambda_i =& \sum_{j=1}^{n}(1-\sigma_M)\frac{\lambda_j}{\lambda_i\mu_j}Cov_{\tilde{\Omega}^{(j)}}\left(d\ln p, \Psi_{(i)}\right) \\
&+(\sigma_U-\sigma_M)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,l}\left(d\ln\overline{w_{r_j}}-\sum_{k=1}^{n}\frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}}d\ln p_k\right)(\Psi_{ji}-I_{ji}) \\
&+\frac{1}{\lambda_i}\sum_j\sum_r\overline{b_{rj}}\Psi_{ji}\chi_r d\ln\chi_r \\
d\ln\chi_r =& \left(\sum_{i\in r}\frac{\pi_i}{\chi_r}d\ln\lambda_i\right)+\frac{\lambda_r}{\chi_r}d\ln\lambda_r \\
d\ln\lambda_r =& s^w_{LS}d\ln\lambda_{rl}+s^w_{hs}d\ln\lambda_{rh} \\
d\ln\lambda_f =& \sum_{i=1}^{n}\frac{\lambda_i\Omega_{if}}{\lambda_f}d\ln\lambda_i+\sum_{i=1}^{n}\frac{\lambda_i\Omega_{if}}{\lambda_f}d\ln\Omega_{if} \\
d\ln\tilde{\Omega}_{il} =& d\ln\tilde{\Omega}_{iL}+(1-\sigma_L)\left[d\ln w_{r_i,l}-\frac{1}{\tilde{\Omega}_{iL}}\left(\tilde{\Omega}_{il}d\ln w_{r_i,l}+\tilde{\Omega}_{ih}d\ln w_{r_i,h}\right)\right] \\
d\ln\tilde{\Omega}_{ih} =& d\ln\tilde{\Omega}_{iL}+(1-\sigma_L)\left[d\ln w_{r_i,h}-\frac{1}{\tilde{\Omega}_{iL}}\left(\tilde{\Omega}_{il}d\ln w_{r_i,l}+\tilde{\Omega}_{ih}d\ln w_{r_i,h}\right)\right] \\
d\ln\tilde{\Omega}_{iL} =& (1-\sigma_u)\left[\frac{1-\tilde{\Omega}_{iL}}{\tilde{\Omega}_{iL}}(\tilde{\Omega}_{il}d\ln w_{rl}+\tilde{\Omega}_{ih}d\ln w_{rh})-\sum_{j=1}^{n}\tilde{\Omega}_{ij}d\ln p_j\right]
\end{aligned}
\tag{20}
$$

Proof follows the same steps as for the baseline model.

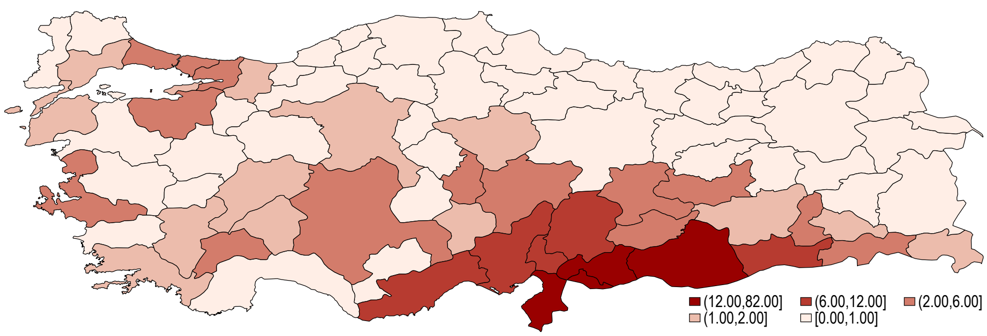
C Data Appendix

Table C.1: Summary Statistics

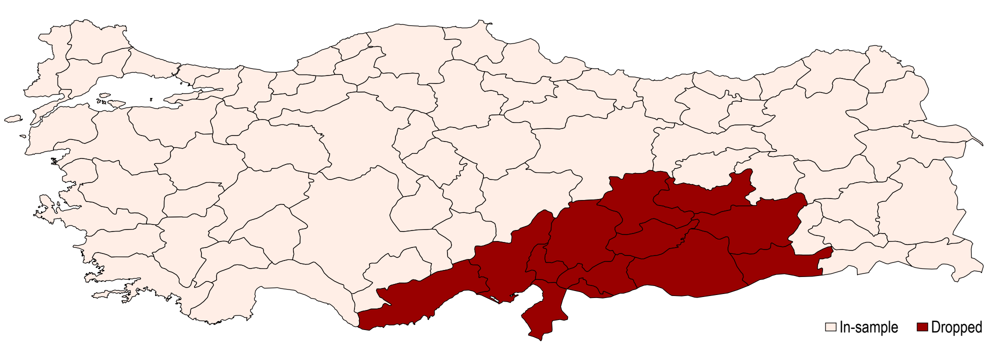
Number of employees	Wage Bill (in million)	Sales (in million)	Exporter	Labor Share
Panel A: All sizes				
33.11	0.52	7.4	0.27	0.31
(172.49)	(4.84)	(164)	(0.44)	(0.32)
Panel B: More than 50 employees in 2010				
217.74	4.00	68	0.71	0.16
(495.77)	(14.51)	(419)	(0.45)	(0.15)

Note: Data is resticted to Manufacturing firms in non-exposed regions that exist throughout 2006–2019. There are 19505 such firms in the sample. 1112 of these firms have more than 50 employees in 2010.

Figure C.1: Omitted Regions



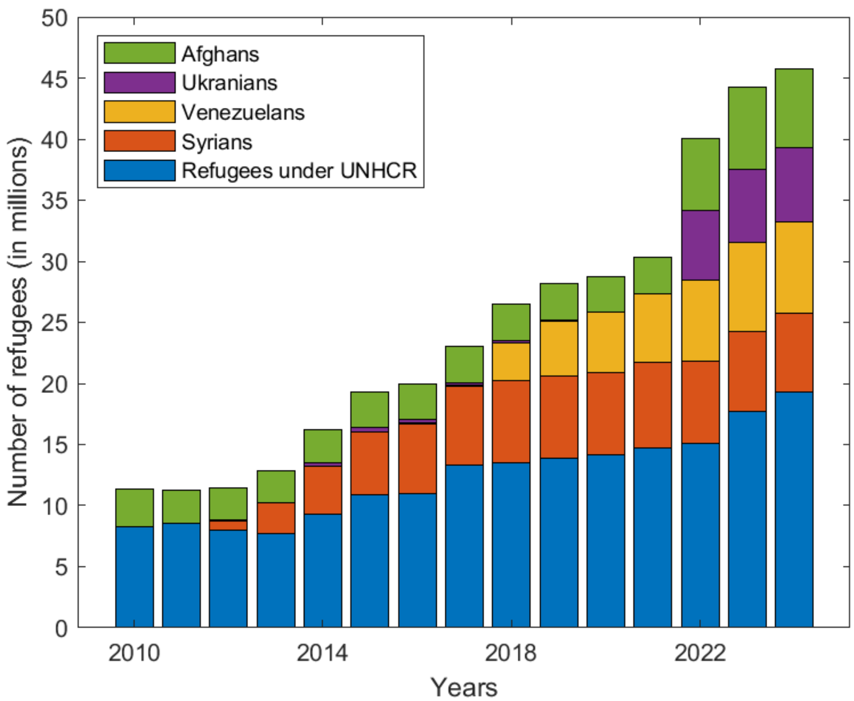
(a) Number of refugees per 100 natives in 2019



(b) Regions omitted from the main analysis

Notes: Panel A uses data acquired from Directorate Generale of Migration Management of Turkey.

Figure C.2: The Evolution of the Number of Refugees Globally



Source: Author's calculations using UNHCR data. This dataset is publicly available from https://www.unhcr.org/refugee-statistics

D Supporting Evidence

D.1 Comparisons between IV and SIV

The main text emphasizes that more and less exposed firms in the same region-industry cells were on different economic trajectories before the immigration shock. This section provides evidence for these claims.

Specifically, we define the event-study equations of the IV estimator for labor share as:

$$log(y^L_{isrt}) = \sum_{t' \neq 2010} \beta_{1,t'} U^Z_i \mathbb{1}\{t = t'\} + f^L_i + f^L_{srt} + W^L_{it} + \nu^L_{it} \tag{21}$$

And for sales as:

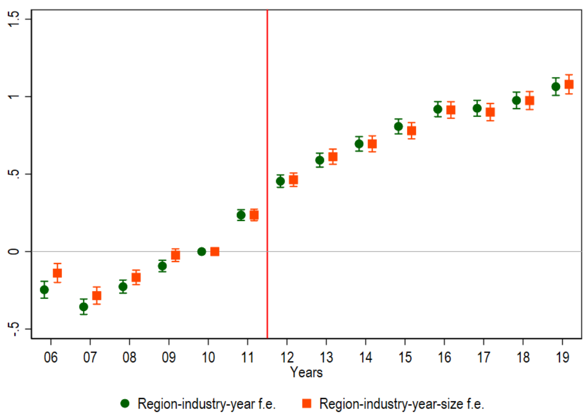
$$log(y^S_{isrt}) = \sum_{t' \neq 2010} \left(\beta^{D1}_{t'} D1^Z_i + \beta^{D2}_{t'} D2^Z_i\right) \mathbb{1}\{t = t'\} + f^S_i + f^S_{srt} + W^S_{it} + \nu^S_{it} \tag{22}$$

Here, f_{srt} denotes industry-region-time fixed effects that partial out industry-region level shocks. In our robustness checks, we further group firms into quartiles based on their baseline sizes and control for industry-region-size-time fixed effects. This specification allows us to compare firms within the same region-industry cell that have similar numbers of employees at baseline.

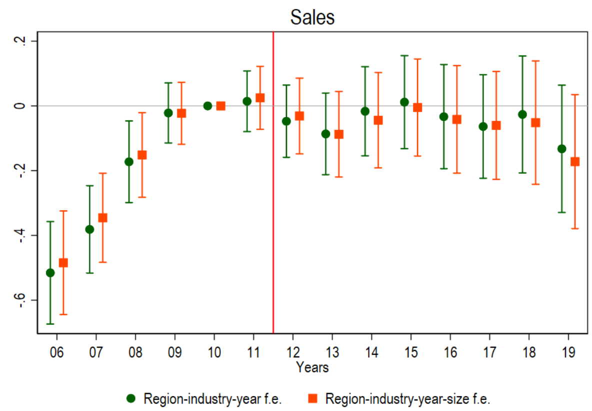
Figure D.3 shows the results. Panel A shows the upstream exposure effects on labor share, while Panels B and C show the downstream exposure effects on sales. In Panel A, more upstream-exposed firms followed a differential trend from 2007 to 2011 compared to less-exposed firms. The differential increase in labor share from 2007 to 2011 matches the magnitude of increase from 2011 to 2016. This pattern persists even when controlling for region-industry-size-time fixed effects. Similarly, Panel B reveals significant pre-trends in the reduced-form analysis with baseline IV, where D1-exposed firms' sales grew differentially between 2006–2011 compared to less-exposed firms. These persistent differential trends motivate our use of Synthetic IV in the main text.

Notice that Panel C shows no pre-trends: more and less D2-exposed firms follow parallel trajectories before the immigration shock. However, this finding alone neither supports nor opposes the use of SIV. To establish causality, we require exogenous variation in all three treatment variables. Since pre-trends appear in two of the three cases, we cannot rely on IV for credible causal inference. This methodological challenge motivates our use of SIV.

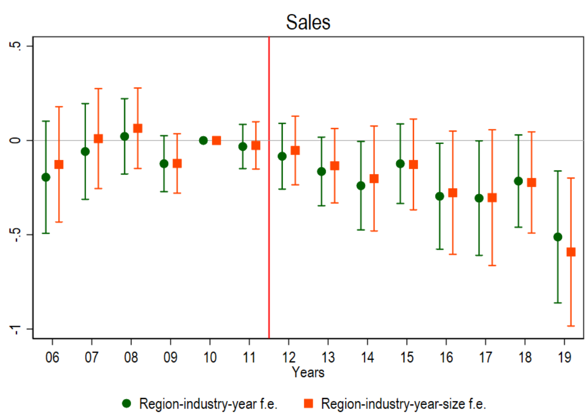
Figure D.3: IV-based Reduced-form Estimates of Upstream and Downstream Exposures on Firms' Labor Demand



(a) Upstream exposure



(b) Downstream exposure 1



(c) Downstream exposure 2

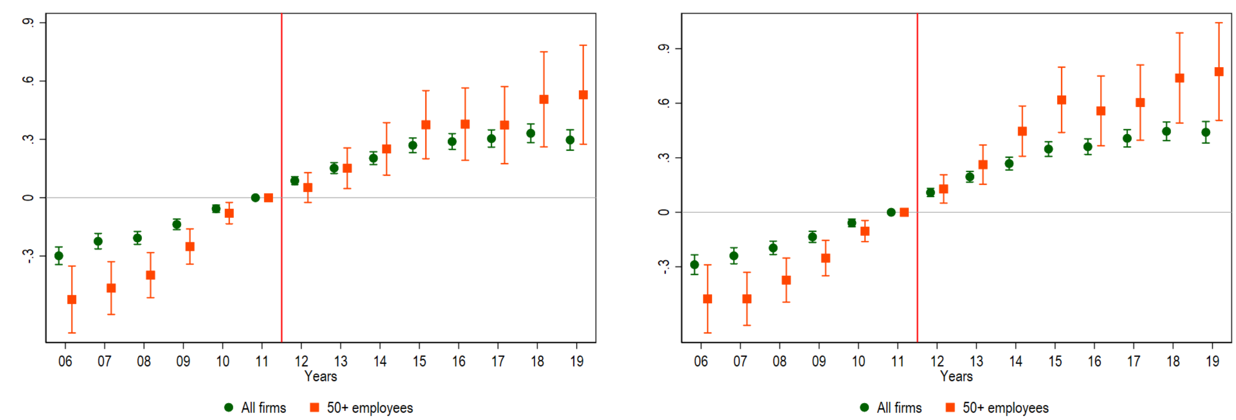
Notes: The estimates in Panel A come from the regression equation $log(y^L_{isrt}) = \sum_{t' \neq 2011} \beta_{1,t'} U^Z_i \mathbb{1}\{t = t'\} + f^L_i + f^L_{srt} + W^L_{it} + \nu^L_{it}$, where the outcome variable is the natural logarithm of the labor share. The estimates in Panels B and C come from the regression $log(y^S_{isrt}) = \sum_{t' \neq 2011} \left(\beta^{D1}_{t'} D1^Z_i + \beta^{D2}_{t'} D2^Z_i\right) \mathbb{1}\{t = t'\} + f^S_i + f^S_{srt} + W^S_{it} + \nu^S_{it}$, where the outcome variable is the natural logarithm of sales. W_{it} denote the region-industry-size-time fixed effects, where size is the quartiles of the number of employees at baseline. Estimates with and without W are plotted. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

D.2 Matching on labor share and sales separately

The main text argues that while applying Synthetic IV (SIV), calculating the Synthetic Control (SC) weights by matching on the trends in labor share and sales jointly, and therefore having only one set of SC weights for all outcomes in the study, performs better than calculating weights separately for each outcome. The latter strategy suffers from overfitting. Here, we provide evidence for these claims.

First, we demonstrate the evidence when matching only on labor share. Figure D.4 displays the effects of upstream exposure on the number of employees in Panel A and on payroll in Panel B. We observe economically and statistically significant pre-trends in the estimates for both firm size and payroll. Within the same region-industry cell, firms that follow similar trends in labor share but differ in their upstream exposure to immigrants exhibit divergent trajectories before the immigration shock. This pattern holds consistent across both small and large firms.

Figure D.4: Pre-trends in Upstream Exposure Design when SC weights match only on Labor Share

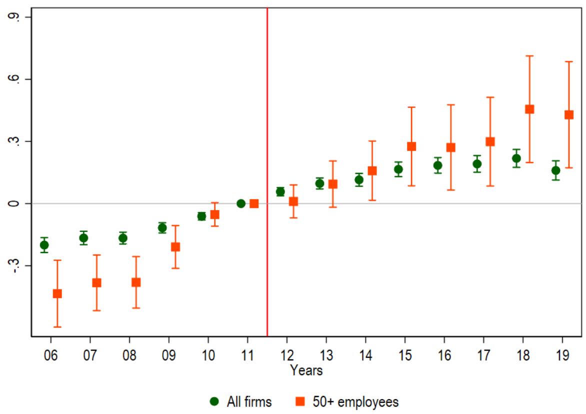


(a) Number of employees (b) Payroll

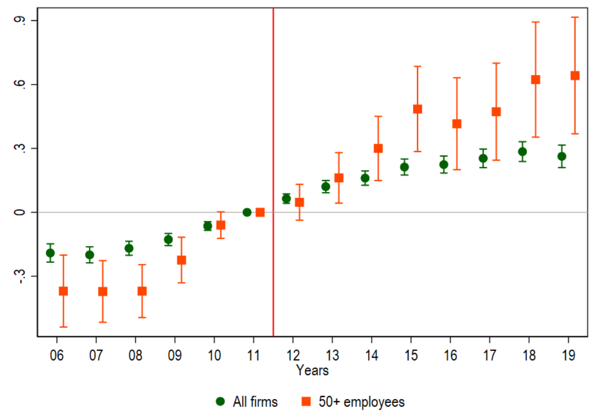
Notes: The estimates come from the regression equation $\widetilde{y_{it}} = \sum_{t'\neq 2011} \gamma_{1,t'} \widetilde{U_i^Z} \mathbb{1}\{t=t'\} + f_i + f_t + \nu_{it}$, where the outcome variable is the natural logarithm of the number of workers in Panel A, of total payroll in Panel B, and of labor share in Panel C. Both the outcome and the treatment are their debiased versions following the SIV algorithm. Unlike the main text, SC weights are calculated by mathing only on the trend in labor shares. In each panel, regression estimates from two separate samples are plotted: one involving firms of all sizes, and one involving only firms with at least 50 employees at baseline. The upstream exposure is given by $U_i^Z = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} Z_r$, where $\tilde{\Psi}$ is the cost-based Leontief inverse matrix, and Z_r is the regional share of the instrument. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

Second, we examine the evidence when matching only on sales trends. Figure D.5 displays the effects of upstream exposure on the number of employees in Panel A and on payroll in Panel B. Similar to our findings with labor share matching, we observe economically and statistically significant pre-trends in both firm size and payroll estimates. Within the same region-industry cell, firms that exhibit similar sales trends but differ in their upstream exposure to immigrants display divergent trajectories. This pattern persists across both small and large firms, reinforcing our concerns about matching on a single variable.

Figure D.5: Pre-trends in Upstream Exposure Design when SC weights match only on Sales



(a) Number of employees



(b) Payroll

Notes: The estimates come from the regression equation $\widetilde{y_{it}} = \sum_{t' \neq 2011} \gamma_{1,t'} \widetilde{U_i^Z} \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$, where the outcome variable is the natural logarithm of the number of workers in Panel A, of total payroll in Panel B, and of labor share in Panel C. Both the outcome and the treatment are their debiased versions following the SIV algorithm. Unlike the main text, SC weights are calculated by mathing only on the trend in sales. In each panel, regression estimates from two separate samples are plotted: one involving firms of all sizes, and one involving only firms with at least 50 employees at baseline. The upstream exposure is given by $U_i^Z = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} Z_r$, where $\tilde{\Psi}$ is the cost-based Leontief inverse matrix, and Z_r is the regional share of the instrument. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

D.3 Language Instrumental Variable

Immigrants choose where to locate based on local labor market conditions, which implies that our regional immigration treatment δ_{rt} may correlate with unobserved shocks to labor demand. To address this issue, in the main text we rely on a distance-based shift-share design. A core part of the identification strategy depends on distance shares creating exogenous variation in immigrant settlement patterns.

We demonstrate that our main results hold even when using an alternative instrument for immigrants' location choice. This alternative relies on a shift-share instrument, where the share is the ratio of Arabic speakers at the province level in the 1965 census, and the shift is the aggregate number of Syrians in Turkey. This approach parallels the past-settlement instrument of Card (2001), with one key distinction: the Arabic-speaking populations were not generated by previous Syrian migration to Turkey but instead reflect the multi-ethnic composition of the Ottoman Empire. As with past-settlement approaches, linguistic similarity strongly predicts immigrant location choices within Turkey.

$$Z_{r,t} = \underbrace{\text{Ratio of Arabic speakers in 1965}}_{\text{Share}} \times \underbrace{\text{Total number of Syrians in Turkey}}_{\text{Shift}} \tag{23}$$

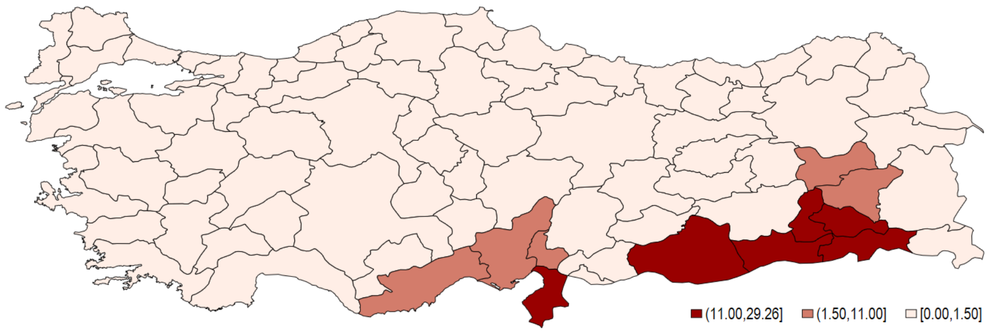
Appendix Figure D.6a displays the cross-sectional distribution of Arabic speakers in 1965 Turkey, while Figure D.6b presents the first-stage estimates in an event-study design. The instrument yields a first-stage F-statistic of approximately 10, considerably weaker than the distance instrument's F-statistic of approximately 100.

Two factors explain the language instrument's reduced power. First, Kilis and Gaziantep, two major host cities near the border, had relatively few Arabic speakers according to the 1965 census. Only 0.17% of natives spoke Arabic. Second, the easternmost provinces along the southern border; Batman, Siirt, and Sirnak, receive high weights in the instrument despite attracting few immigrants in practice. The distance instrument, by contrast, better explains the observed settlement patterns: immigrants predominantly settled in Kilis and Gaziantep rather than Batman, Siirt, and Sirnak due to their proximity to populous Syrian regions.

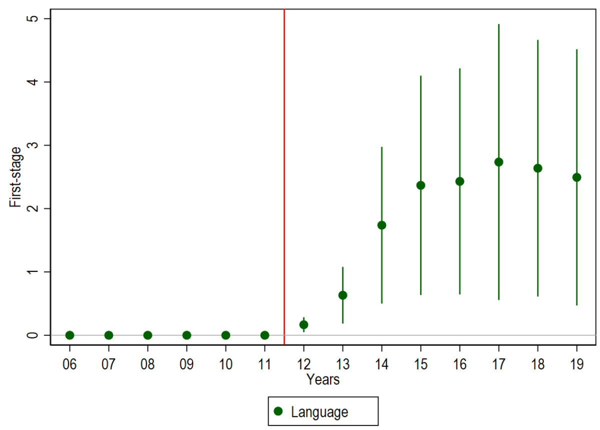
Given the regional language instrument, we define the firm-level upstream and downstream exposure instruments as described in the main text, simply replacing distance-based shares with language-based shares.

Using these language-based instruments, we estimate the reduced-form of the SIV design. Figure D.7 shows the estimated effects of upstream exposure on firms' size, payroll, and labor share. The results largely align with our main sample of all manufacturing firms, showing

Figure D.6: Language Instruments



(a) Language Exposure



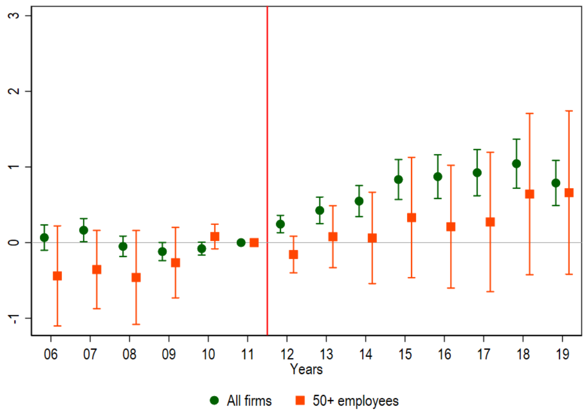
(b) First-stage

Notes: Panel A shows the number of native Arabic speakers per 1000 habitants in the 1965 census. Panel B shows the first-stage estimates from equation: $\delta_{rt} = \sum_{t' \neq 2011} \beta_{t'} \mathbb{1}\{t' = t\} Z_r + \alpha_r + \alpha_t + \epsilon_{rt}$. Standard errors are clustered at zero. 95% confidence intervals are plotted.

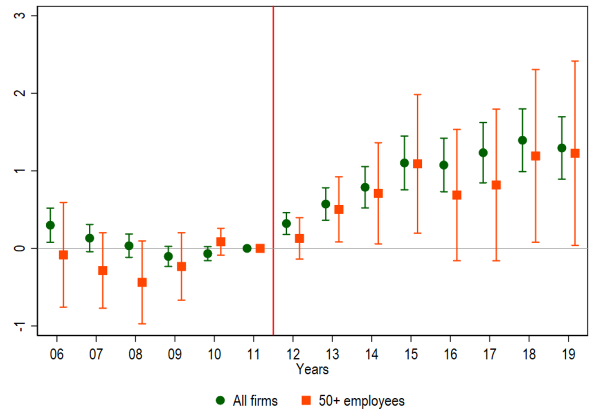
no pre-trends between 2006 and 2011 and positive increases in firms' labor demand in the post-immigration period.

One notable difference from our main results appears in the large-firm subsample: the effect of upstream exposure on employment, while positive, cannot be statistically distinguished from zero. This imprecision stems from the language instrument's weaker first-stage compared to the distance instrument. The lower strength of the instrument naturally yields less precise estimates.

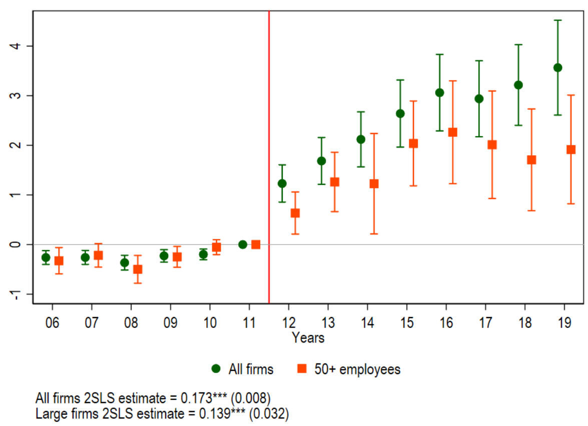
Figure D.7: Effect of Upstream Exposure on Firms' Labor Demand (Language IV)



(a) Number of employees



(b) Payroll



(c) Labor share

Notes: The estimates come from the regression equation $\widetilde{y_{it}} = \sum_{t' \neq 2011} \gamma_{1,t'} \widetilde{U_i^Z} \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$, where the outcome variable is the natural logarithm of the number of workers in Panel A, of total payroll in Panel B, and of labor share in Panel C. Both the outcome and the treatment are their debiased versions following the SIV algorithm. The instruments are based on the Language IV instead of the Distance IV. In each panel, regression estimates from two separate samples are plotted: one involving firms of all sizes, and one involving only firms with at least 50 employees at baseline. The upstream exposure is given by $U_i^Z = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} Z_r$, where $\tilde{\Psi}$ is the cost-based Leontief inverse matrix, and Z_r is the regional share of the instrument. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

D.4 Additional Effects of Upstream and Downstream Trade Exposures

In the main text, we show that downstream exposure appears to decrease sales among small firms. We argue that this is not a true causal effect: downstream exposure reduces reported sales rather than actual sales. To support this claim, we demonstrate that downstream exposure does not decrease firms' labor demand. The idea is that, if a treatment lowers actual sales, treated firms should also lower their labor demand.

We estimate the effects of exposures U, $D1$, and $D2$ on firms' labor demand and sales through three approaches: separately for each exposure and jointly for all exposures. Specifically, for each of our four main outcomes—–firm size, payroll, labor share, and sales—–we conduct three estimations: one for upstream exposure alone, one for downstream exposures alone, and one for all exposures jointly. Table D.2 presents the SIV estimates using the distance instrument, with Panel A showing results for all firms and Panel B focusing on large firms.

The first two rows show the effects of Upstream exposure on firms' labor demand and sales. Consistent with the evidence presented in the main text, we see that upstream exposure increases firms' size, payroll, and labor share. This holds true with and without controlling for downstream exposures. However, notice that in column 10, upstream exposure is negatively correlated with small firms' sales. This is again related to our main argument as to why sales data from small firms can be misleading. We argue that increased labor informality in the host regions also leads to informality in transactions, which causes small firms' reported sales to go down. Notice that this negative correlation does not hold for large firms, which have a positive correlation between sales and upstream-exposure.

Looking at the effects of D1 exposure on all firms shown in rows 3–4, we see that D1-exposure is positively correlated with increases in firm size and payroll, but this correlation disappears after controlling for upstream exposure. The easiest explanation is that Upstream and D1-exposures are positively correlated. Since upstream exposure has a causal effect on labor demand as shown in the model, D1-exposure gets credit for this effect when we do not control for upstream exposure.

Effects of D2 exposure are reported in rows 5–6. Starting from the end, we see that D2 exposure lowers the reported sales of small firms. Column 11 repeats the results reported in the main text, and column 12 shows that this is robust to controlling for upstream exposure. If the sales effect were true, we would also $D2$ exposure to lower labor demand. However, columns 2–9 show that $D2$ exposure does not lower labor demand. If anything, it is positively correlated with firms' labor share. This pattern suggests that $D2$ exposure is not actually decreasing product demand for these firms. Rather, domestic transactions are disappearing from the data, manifesting as decreased sales while formal employment remains stable

Panel B reports the results for large firms. Our main results remain robust. Upstream exposure increases firms' size, payroll, and labor share. It should be noted that controlling for D1 and D2 exposures, as is done in columns 3 and 6, mildly lowers the coefficient estimates of upstream exposure, and mildly increases the standard errors. The consequence is that the statistical significance of these effects do disappear. The effects on labor share, however, remains statistically significant despite controlling for downstream exposures.

Overall, our main results remain robust to estimating upstream and downstream exposures jointly. One caveat of our analysis is that, we do not formalize our argument that informal labor leads to informal transactions for small firms here. We leave it for future work, as integrating informality in sales (both to the final consumer and to other firms) and informality in labor into the production network framework is a significant challenge.

Table D.2: Effects of Trade Exposures on Firms in Non-Host Regions

	Number of employees			Payroll			Labor Share			Sales		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All sizes												
U	0.056***		0.051***	0.077***		0.074***	0.186***		0.204***	-0.013*		-0.012
	(0.006)		(0.007)	(0.006)		(0.007)	(0.006)		(0.007)	(0.007)		(0.009)
D1		0.101***	0.024		0.128***	0.017		0.221***	-0.087***		-0.025	-0.008
		(0.015)	(0.018)		(0.016)	(0.020)		(0.015)	(0.017)		(0.018)	(0.023)
D2		0.021	0.010		0.025	0.009		0.140***	0.095***		-0.089**	-0.087**
		(0.028)	(0.027)		(0.029)	(0.029)		(0.029)	(0.027)		(0.043)	(0.043)
Panel B: 50+ employees												
U	0.084**		0.067	0.114***		0.082	0.163***		0.195***	0.012		-0.022
	(0.037)		(0.048)	(0.039)		(0.052)	(0.023)		(0.031)	(0.038)		(0.051)
D1		0.147	0.045		0.219*	0.093		0.202***	-0.096		0.063	0.096
		(0.109)	(0.148)		(0.120)	(0.164)		(0.061)	(0.072)		(0.100)	(0.137)
D2		0.229	0.211		0.141	0.119		0.006	-0.046		0.182	0.188
		(0.156)	(0.158)		(0.162)	(0.167)		(0.140)	(0.141)		(0.155)	(0.155)

Notes: Sample is restricted to manufacturing firms that report positive sales throughout 2006–2019. Panel A shows the SIV estimates for firms from all sizes. Panel B shows the results for firms with 50+ employees in 2010.There are 19155 firms in Panel A and 1224 firms in Panel B. U denotes the upstream exposure on firms who directly or indirectly buy from the host regions. D1 is the downstream exposure effect capturing cross-price elasticity between different intermediate goods. D2 is the downstream exposure on firms who directly or indirectly sell to the host region firms. Standard errors are clustered at the firm level.

D.5 OLS estimates

In the main text, we argue that SIV addresses two distinct issues: the potential endogeneity from immigrants choosing where to locate, and the differential trends across firms that are more or less trade-dependent. Here, we show that immigrants' location choice is not highly correlated with unobserved labor market shocks, resulting in only small differences between IV and OLS estimates.

Table D.3 replicates the analyses reported in Table D.2, replacing 2SLS with OLS after the debiasing step of the SIV algorithm. The results remain broadly similar: while OLS and 2SLS estimates differ quantitatively, their qualitative implications hold constant. Specifically, we continue to find that labor and intermediate goods are gross complements, while different intermediate goods are neither substitutes nor complements.

It is worth noting that these small quantitative biases align with our prior expectation that immigrants positively select into regions experiencing positive labor demand shocks. The OLS estimates exceed the IV estimates. However, these differences are not large enough to meaningfully affect our qualitative conclusions.

One potential concern with OLS and IV results being qualitatively similar is that both OLS and IV are biased the same way. That is, the instrument does not solve the selection problem. This could happen, for example, if by chance the southeast regions in Turkey had received positive technology or other labor demand shocks then other regions. To alleviate these concerns, we also show the results using the Language-based instrument. The results remain qualitatively robust. One caveat is that the language instrument has a weaker first-stage than the distance instrument, so the standard errors increase compared to the OLS and distance-based IV estimates.

Table D.3: Effects of Trade Exposures on Firms in Non-Host Regions (OLS)

	Number of employees			Payroll			Labor Share			Sales		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All sizes												
U	0.056***		0.050***	0.077***		0.073***	0.180***		0.198***	-0.011		-0.009
	(0.005)		(0.007)	(0.006)		(0.007)	(0.006)		(0.007)	(0.007)		(0.009)
D1		0.099***	0.027		0.124***	0.018		0.206***	-0.080***		-0.024	-0.012
		(0.015)	(0.019)		(0.016)	(0.020)		(0.014)	(0.016)		(0.018)	(0.022)
D2		0.034	0.023		0.036*	0.021		0.078***	0.037**		-0.022	-0.020
		(0.022)	(0.021)		(0.022)	(0.022)		(0.020)	(0.018)		(0.027)	(0.027)
Panel B: 50+ employees												
U	0.096***		0.086**	0.130***		0.118***	0.184***		0.227***	0.057*		0.053
	(0.031)		(0.042)	(0.032)		(0.044)	(0.022)		(0.026)	(0.032)		(0.045)
D1		0.157	0.030		0.212*	0.037		0.193***	-0.144**		0.081	0.002
		(0.112)	(0.152)		(0.117)	(0.158)		(0.058)	(0.061)		(0.103)	(0.141)
D2		0.137	0.102		0.153	0.105		-0.031	-0.123		0.195	0.173
		(0.111)	(0.113)		(0.116)	(0.120)		(0.110)	(0.115)		(0.120)	(0.119)

Notes: Sample is restricted to manufacturing firms that report positive sales throughout 2006–2019. Panel A shows the OLS estimates for firms from all sizes. Panel B shows the results for firms with 50+ employees in 2010.There are 19155 firms in Panel A and 1224 firms in Panel B. U denotes the upstream exposure on firms who directly or indirectly buy from the host regions. D1 is the downstream exposure effect capturing cross-price elasticity between different intermediate goods. D2 is the downstream exposure on firms who directly or indirectly sell to the host region firms. Standard errors are clustered at the firm level. Stars indicate the statistical significance levels: * 0.10 ** 0.05 *** 0.01

Table D.4: Effects of Trade Exposures on Firms in Non-Host Regions (Language IV)

	Number of employees			Payroll			Labor Share			Sales		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: All sizes												
U	0.054***		0.040***	0.076***		0.065***	0.173***		0.184***	-0.002		-0.002
	(0.007)		(0.011)	(0.008)		(0.012)	(0.008)		(0.012)	(0.009)		(0.012)
D1		0.121***	0.066*		0.141***	0.053		0.192***	-0.057		0.017	0.020
		(0.028)	(0.038)		(0.030)	(0.041)		(0.026)	(0.038)		(0.025)	(0.032)
D2		-0.029	-0.027		-0.044	-0.042		0.097*	0.104*		-0.273*	-0.274*
		(0.059)	(0.060)		(0.064)	(0.065)		(0.052)	(0.057)		(0.159)	(0.159)
Panel B: 50+ employees												
U	0.022		-0.151	0.047		-0.151	0.094***		0.003	0.024		-0.097
	(0.043)		(0.181)	(0.045)		(0.212)	(0.034)		(0.163)	(0.038)		(0.106)
D1		0.371	0.520		0.474	0.624		0.306	0.303		0.280	0.376
		(0.559)	(0.600)		(0.626)	(0.697)		(0.375)	(0.534)		(0.334)	(0.357)
D2		0.118	0.116		-0.057	-0.059		-0.139	-0.139		-0.014	-0.016
		(0.315)	(0.240)		(0.320)	(0.276)		(0.230)	(0.233)		(0.200)	(0.183)

Notes: Sample is restricted to manufacturing firms that report positive sales throughout 2006–2019. Panel A shows the SIV estimates for firms from all sizes. Panel B shows the results for firms with 50+ employees in 2010.There are 19155 firms in Panel A and 1224 firms in Panel B. U denotes the upstream exposure on firms who directly or indirectly buy from the host regions. D1 is the downstream exposure effect capturing cross-price elasticity between different intermediate goods. D2 is the downstream exposure on firms who directly or indirectly sell to the host region firms. Standard errors are clustered at the firm level. Stars indicate the statistical significance levels: * 0.10 ** 0.05 *** 0.01

D.6 Native Migration Responses

In the main text, we argue that Turkish natives do not move in meaningful numbers in response to the Syrian immigration shock. To demonstrate this, we estimate the following event-study and IV designs at the province level. The event-study design is given by:

$$y_{rt} = \sum_{t' \neq 2010} \beta_{t'} Z_r \mathbb{1}\{t = t'\} + f_r + f_t + \epsilon_{rt} \tag{24}$$

where f_r and f_t are region and time fixed effects. Similarly, the IV design is given by

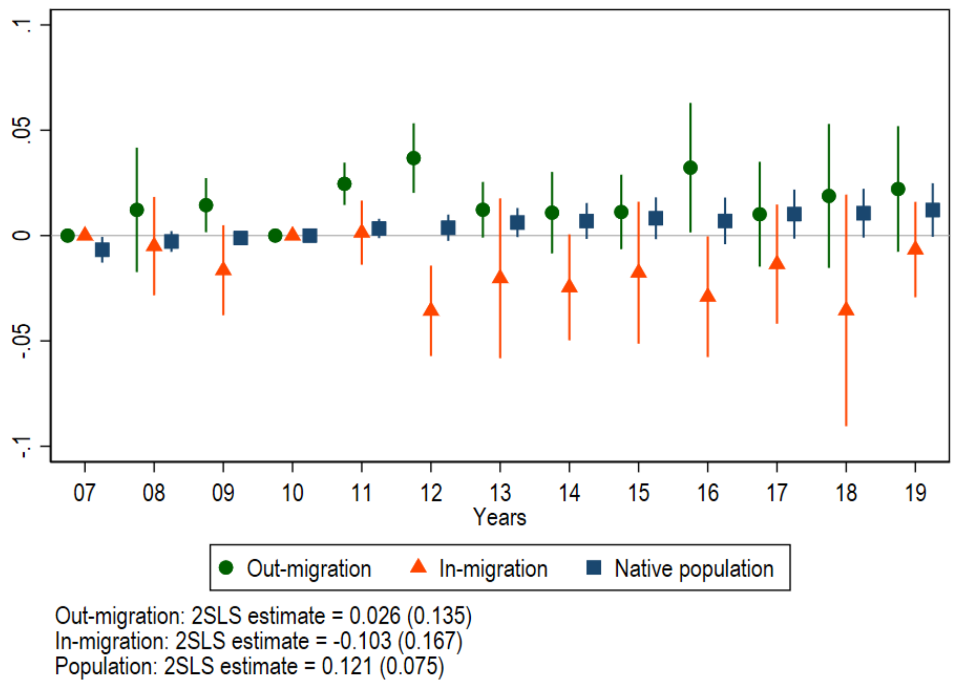
$$\begin{aligned} y_{rt} &= \beta D_{rt} + f_r + f_t + \epsilon_{rt} \\ D_{rt} &= \gamma Z_{rt} \qquad\qquad\qquad\qquad + g_r + g_t + \eta_{rt} \end{aligned}$$

where D is the immigration treatment, Z is the instrument, and f_r, f_t, g_r, g_t are region and time fixed effects. We estimate these equations for three separate outcomes: the natural logarithms of in-migration, out-migration, and population.

Figure D.8 shows the results. We observe a mild decrease in in-migration rates and a mild increase in out-migration rates, primarily during the early years of the Syrian civil war (2011 and 2012), before Syrian immigrants arrived in large numbers. In later years, the estimates are not statistically different from zero, with relatively small magnitudes. For example, a one standard deviation increase in the instrument, which leads to approximately a 9% increase in the immigrant/native ratio by 2018, results in a 4% decrease in in-migration rates. Given that in-migration rates constitute less than 3% of the local population in host regions, even if this effect were statistically significant, a 1% increase in the immigrant/native ratio would decrease the native population by only about 0.01%. Similar calculations apply to the out-migration effects: they are small in magnitude.

The minimal effects on migration rates allow the native population to maintain its upward trajectory in southeastern regions. These regions historically experienced higher population growth due to higher birth rates before the Syrian crisis, and this trend continues despite the arrival of Syrian immigrants. We therefore conclude that native labor movements across regions do not play a significant role in disseminating the immigration shock.

Figure D.8: Native migration responses to Syrian immigration



Notes: Event-study estimates come from the regression $y_{rt} = \sum_{t' \neq 2010} \beta_{t'} Z_r \mathbb{1}\{t = t'\} + f_r + f_t + \epsilon_{rt}$, where Z_r is the regional distance share normalized to have standard deviation of one, f_r and f_t are region and time fixed effects. Three outcome variables are used: natural logarithms of in-migration, out-migration, and naive population. Address-based tracking data starts from 2007. Therefore, estimates for native population start from 2007, and estimates from migration patterns start from 2008. 2010 is normalized because 2011 is the beginning of the Syrian Civil War. Standard errors are clustered at the region level. 95% confidence intervals are plotted.

D.7 Industry Heterogeneity

In the main text, we argue that structural elasticity estimates are common across industries. Here, we provide the empirical evidence. To estimate the elasticity of substitution between labor and intermediate goods in different industries, we estimate equation 10 separately for each two-digit manufacturing industry. This approach yields 24 separate SIV estimates that we use to calculate the structural elasticities.

This industry-specific estimation presents an additional empirical challenge: dividing the data into smaller subgroups reduces the sample size and statistical power for each parameter estimate. Due to pure sampling variation, we might find heterogeneous treatment effects even when the true effect is homogeneous. To address this statistical challenge, we employ Empirical Bayes Shrinkage.

Let β_j be the elasticity of substitution estimate for industry j. Let $\hat{\beta}_j$ be an estimate of β_j. Assume that the identification strategy is correct, hence $\hat{\beta}_j$'s are consistent estimators of unknown β_j's:

$$\hat{\beta}_j | \beta_j \sim N(\beta_j, s_j^2)$$

Let F denote the distribution of industry-specific EoS occupation-specific child penalties. Suppose F is a normal distribution and independent of s_j's. This gives the following hierarchical model:

$$\hat{\beta}_j | \beta_j, s_j \sim N(\beta_j, s_j^2)$$
$$\beta_j | s_j \sim N(\mu_\beta, \sigma_\beta^2)$$

In this normal/normal model, the posterior mean and variance for β_j given $\hat{\beta}_j$ is given by

$$\beta_j^* \equiv E[\beta_j | \hat{\beta}_j] = \left(\frac{\sigma_\beta^2}{\sigma_\beta^2 + s_j^2} \right) \hat{\beta}_j + \left(\frac{s_j^2}{\sigma_\beta^2 + s_j^2} \right) \mu_\beta$$
$$s_j^{2*} \equiv E[s_j^2 | \hat{s}_j^2] = \frac{s_j^2 \sigma_\beta^2}{s_j^2 + \sigma_\beta^2}$$

We use the following estimators for the hyperparameters $\mu_\beta, \sigma_\beta^2$.

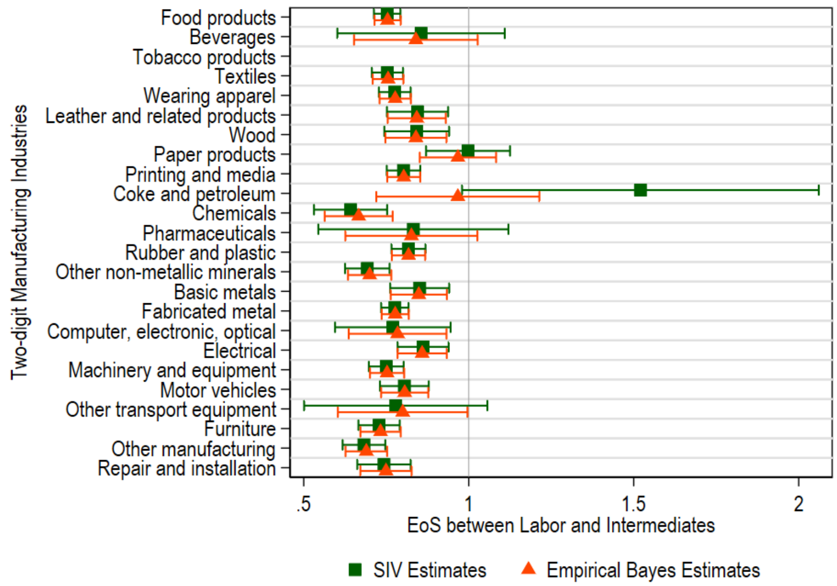
$$\hat{\mu}_\beta = \frac{1}{J} \sum_{j=1}^{J} \hat{\beta}_j$$
$$\hat{\sigma}_\theta^2 = \frac{1}{J} \sum_{j=1}^{J} \left[(\hat{\beta}_j - \hat{\mu}_\beta)^2 - s_j^2 \right]$$

Replacing the unknown parameters by their estimates, we obtain the Empirical Bayes posterior mean and variance:

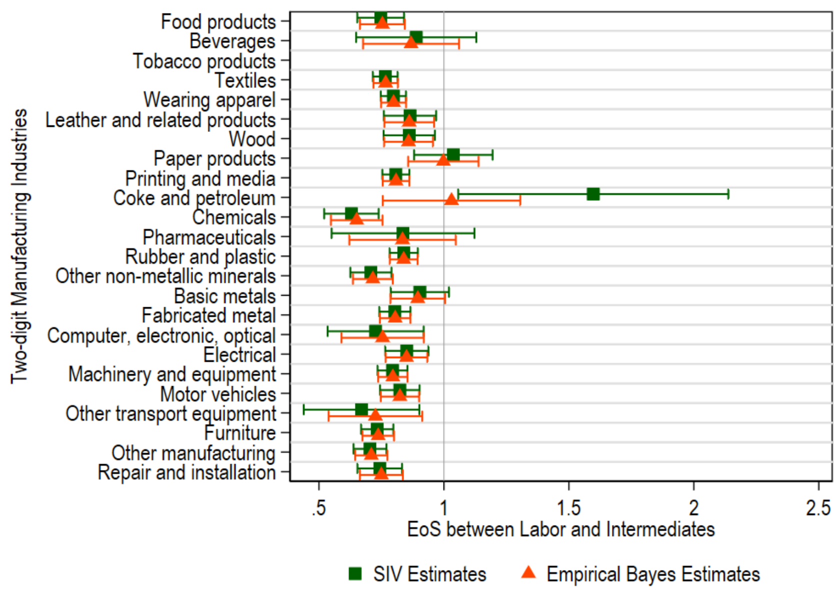
$$\hat{\beta}_j^* = \left(\frac{\hat{\sigma}_\beta^2}{\hat{\sigma}_\beta^2 + s_j^2}\right)\hat{\beta}_j + \left(\frac{s_j^2}{\hat{\sigma}_\beta^2 + s_j^2}\right)\hat{\mu}_\beta$$
$$\hat{s}_j^{2*} = \frac{\hat{s}_j^2 \hat{\sigma}_\beta^2}{\hat{s}_j^2 + \hat{\sigma}_\beta^2}$$

Figure D.9 plots both the SIV and the EB posterior estimates of the structural elasticity of substitution between labor and intermediate goods. Panel A shows the estimates using the distance instrument, and Panel B shows the estimates using the language instrument. The evidence is highly similar across the two measures. Notice that SIV and EB estimates are similar except for Coke and Petroleum. This is because the SIV estimates are precise compared to the observed variation in point estimates across industries. Therefore, EB updating assigns most of the weight to the data and less of the weight to the prior. The EB estimates using the distance instrument ranges from 0.66 Chemicals to 0.97 in Coke and petroleum.

Figure D.9: Heterogeneity of EoS between labor and intermediates across Manufucturing industries



(a) Distance IV



(b) Language IV

Notes: Industry-specific elasticity estimates are acquired by estimating separate regressions for firms in different industries. Elasticity estimates using both SIV estimates and Empirical Bayes estimates are reported. Details of the Empirical Bayes methodology can be found in the Appendix. 95% confidence intervals are plotted.

D.8 Additional Counterfactual Estimates

D.8.1 Comparison between Adana and Antalya

In the main text, we argue that a host region's centrality is the most informative factor in determining the magnitude of trade spillovers from immigration. To strengthen this argument, we compare two cities, Adana and Antalya, that share similar population sizes and Domar weights but differ significantly in their economic connectedness due to their industrial compositions.

Table D.5 presents baseline statistics for these cities. In 2010, Adana had a population of 2.11 million (5th largest in Turkey), while Antalya had 2.04 million (6th largest). Their Domar weights were similar: 2.48% for Adana (7th highest) and 2.70% for Antalya (6th highest).

Despite these similarities, the cities exhibit marked differences in industrial structure: Adana serves as an agricultural hub, whereas Antalya's economy centers on tourism and services. These distinctions manifest in their cost-based and sales-based Bonacich centrality measures, with Adana's measures being 1.7 and 1.4 times larger than Antalya's, respectively. This difference in economic centrality translates directly into spillover effects: the average spillover wage effect from Adana is 2.4 times greater than that from Antalya.

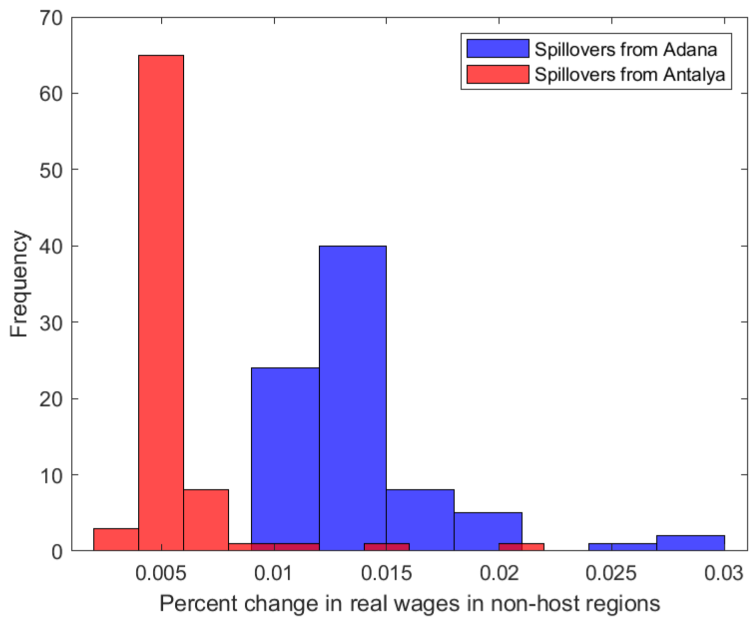
Table D.5: Summary Statistics for Adana and Antalya

	Adana	Antalya
Population (in millions)	2.11	2.04
Domar weight	0.025	0.027
Cost-based centrality: $\tilde{\Psi}1$	10.94	6.54
Sales-based centrality: $\Psi 1$	2.21	1.60
Spillover effect on real wages	1.37%	0.56%

Source: Authors' calculations

A potential concern with the mean spillover difference presented in Table D.5 is that it could be driven by a small number of outliers. To address this issue, Figure D.10 displays the distribution of spillover effects resulting from a 1% immigration shock to each city. The histograms reveal that the spillover distributions for Adana and Antalya barely overlap, with the minimum spillover effect from Adana exceeding the 95th percentile of spillover effects from Antalya. This stark separation in distributions confirms that the difference in spillover effects is systematic rather than driven by outliers.

Figure D.10: Histogram of real wage changes in the non-host regions



Notes: This figure shows the spillover effects from two counterfactuals: a 1% increase in labor supply in Adana and Antalya. Adana and Antalya share similar population sizes and Domar weights but differ significantly in their economic connectedness due to their industrial compositions. Adana is more central as it is an Agricultural hub, while Antalya has a more tourism and services based economy.