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

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Most recent draft here.

Abstract

I study how local immigration shocks impact labor markets and firms across the economy through production networks. Using Turkey's Syrian refugee crisis and firm-to-firm VAT data, I show that firms buying from host regions demand more labor, while those selling to host regions increase sales. Estimates imply an elasticity of substitution between labor and intermediates of 0.79 and across intermediates of 1.06. Spillover magnitudes depend critically on network centrality and immigrants' skills. A 1% labor supply increase in Istanbul decreases local real wages by 0.56% while increasing non-host wages by 0.38%. For non-central regions, identical shocks reduce local wages by 1% with negligible spillovers. Similarly, high-skill immigrants create larger spillovers and, therefore, larger welfare gains than low-skill immigrants because high-skill-intensive industries are more central than low-skill-intensive industries. Network position and immigrants' skills thus determine whether immigration only lowers local wages or also generates economy-wide gains.

JEL Classification: F16, F22, J15, J23, J61

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1 Introduction

The number of refugees globally has quadrupled in the last decade, from 11 million in 2012 to 45 million in 2024. During this period, several countries received massive inflows—Turkey received 3.6 million Syrians, Colombia 2.5 million Venezuelans, and European nations millions from Syria and Ukraine—reshaping their labor markets.[1] How do these immigration shocks affect native workers? Three decades of research following Card (1990) have compared regions receiving immigrants to those that do not, yet the literature still lacks consensus on even the sign of these effects.[2] In this paper, I argue that a critical piece of the puzzle has been overlooked: the impact of immigration on non-host regions through production networks. When immigrants reduce production costs in host regions, these effects propagate to firms throughout the economy via input-output linkages, potentially biasing traditional estimates in either direction and shaping our understanding of the aggregate effects of immigration on labor markets. Using the Syrian refugee crisis in Turkey, I present a tractable theory formalizing these mechanisms, empirical evidence testing their existence, and counterfactual exercises quantifying when network spillovers matter for wages and welfare across the economy.

There are three key economic mechanisms by which a local immigration shock propagates through the supply network to impact labor demand throughout the economy. First, immigrants reduce wages, which in turn lowers the prices charged by firms in the host region. This reduction in prices propagates forward to firms that 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 call "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 increases 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 in both host and non-host regions.

My model captures these mechanisms through two key features. First, firms combine local labor with intermediate inputs using constant elasticity of substitution (CES) production

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

[2] See Borjas (2017); Peri and Yasenov (2019); Clemens and Hunt (2019) for a discussion on the effects of Mariel Boatlift (Card, 1990), Dustmann et al. (2016) for a discussion on methodologies and Jaeger et al. (2018) for a discussion of the "past settlement" instrument.

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 (EoS) between labor and intermediates, and the EoS 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.

The Syrian refugee crisis in Turkey provides a useful setting for estimating these elasticities. Between 2011 and 2019, Turkey received 3.6 million Syrian refugees, generating labor supply shocks of up to 82% in southeastern provinces near the Syrian border. I leverage this massive and spatially concentrated labor supply shock by comparing manufacturing firms in non-host regions that are differentially exposed to immigrants through their trading partners. I merge three administrative datasets—value-added-tax (VAT) records capturing the near-universe of firm-to-firm transactions, matched employer-employee records, and firm balance sheets—to calculate model-defined trade exposures for all formal firms in Turkey. To address endogeneity in refugees' location choices, I construct a shift-share instrument where the shift captures aggregate Syrian refugee inflows and the share reflects each region's travel distance from the Syrian border. This regional instrument translates to firm-level variation through baseline input-output linkages. I apply the Synthetic IV method (Gulek and Vives-i Bastida, 2024) to relax the standard share-exogeneity assumption (Goldsmith-Pinkham et al., 2020), allowing me to compare firms on similar trajectories while exploiting variation induced by the instrument for identification. I focus on firms with at least 50 employees to minimize the bias from informal labor and sales.[3]

The empirical results align with my theoretical mechanisms. First, firms that 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 implies that labor and intermediate goods are gross complements. Second, buyer firms maintain stable spending patterns across their suppliers on average, implying that intermediate good production approximates Cobb-Douglas and, therefore, firms with lower costs cannot gain market share through price competition. Third, firms that sell to host region firms increase their sales, which implies that intermediates are more substitutable with each other than with labor, a finding that reinforces the first two results. My regression specifications have a direct structural interpretation, allowing me to recover the model's elasticities from the estimated

[3]Large firms being more formal than small firms is a common attribute of developing economies (Ulyssea, 2020).

coefficients. Since the empirical model is overidentified, I use GMM to efficiently estimate the two elasticities and find an elasticity of substitution between labor and intermediates of 0.79 and an elasticity across intermediates of 1.06. These estimates remain similar across robustness checks, and over-identification tests fail to reject the model.

Having estimated the key elasticities empirically, I turn to counterfactual analyses to understand for which types of host regions the spillover effects of immigration become economically significant. 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 regions that are central in the input-output network 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, 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? I find that directing immigrants to network-central regions generates welfare gains that are an order of magnitude larger than placement in non-central regions. When immigrants settle in regions with extensive input-output linkages, their reduction of local production costs cascades throughout the economy, creating positive spillovers that can outweigh the negative wage effects on host region natives. The importance of network position extends to skill composition: high-skill immigration generates larger spillovers and, therefore, larger welfare gains than low-skill immigration because industries that employ high-skill labor intensively tend to have stronger inter-regional trade connections.

Finally, 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, aggregate spillovers are negligible. The variation in regional wage effects is almost entirely explained by local immigrant-to-native ratios. While individual firms connected to host regions experience

spillovers, these firm-level effects aggregate to economy-wide impacts only when immigrants settle in central nodes.

This paper contributes to the extensive empirical literature studying the economic effects of immigration.[4] A key methodological debate centers on whether immigration effects spill over beyond host regions. While Card (1990, 2001) assume effects are local and compare host to non-host regions, Borjas (2003) argues that spatial integration causes spillovers through native migration responses. However, empirical evidence shows that immigrants have minimal impact on native migration patterns (Card, 2009; Dustmann et al., 2017), including in the present setting (Gulek, 2024).[5] My main contribution is demonstrating that immigrants impact non-host regions through input-output networks. I formalize the main economic forces by extending the production network framework (Acemoglu et al., 2012; Baqaee and Farhi, 2019), test them empirically using novel methods (Gulek and Vives-i Bastida, 2024), and quantify when general equilibrium effects become economically relevant.

My quantitative findings help resolve existing puzzles in the immigration literature by showing that network centrality of host regions can explain why seemingly similar studies reach opposite conclusions. Consider Dustmann et al. (2017) and Beerli et al. (2021), two papers using identical designs but finding opposite results. Dustmann et al. (2017) study low-skill immigration to German border regions containing "various small but no large cities" and find strong negative effects on natives. In contrast, Beerli et al. (2021) examine high-skill immigration to Swiss border regions, including Basel, a major hub for pharmaceuticals and chemicals, and find positive effects on natives. My framework predicts negligible spillovers from low-skill immigration to small German regions but substantial spillovers from high-skill immigration to network-central Basel. While Beerli et al. (2021) attribute their positive findings to productivity gains from immigration, my framework suggests an additional mechanism: when multiple host regions simultaneously receive immigrants near a central node like Basel, positive inter-host spillovers attenuate negative wage effects within treated regions, potentially turning the average treatment effect positive despite local displacement.[6] This network perspective extends beyond individual cases. Economic migrants typically settle in large, central cities (Albert and Monras, 2022; Mayors of Europe, 2019) where spillovers likely violate SUTVA, while refugees settle near borders (Baez, 2011; Del Carpio and Wagner,

[4]Seminal papers include Card (1990, 2001); Borjas (2003); Ottaviano and Peri (2012). See Hanson (2009); Lewis and Peri (2015); Dustmann et al. (2016) for reviews.

[5]Monras (2020) is a notable exception, which shows that native migration responses in the US are significant. In the Turkish setting, Gulek (2024) shows that changes in in- and out-migration in response to Syrian immigration have been minimal.

[6]For example, suppose four host regions each receive identical shocks that reduce local wages by 1% and increase wages in each of the other three host regions by 0.4%. The total effect in any host region is $-1\% + 3 \times 0.4\% = 0.2\%$: the average treatment effect is positive despite local displacement.

2015)—typically non-central regions where SUTVA holds—which helps explain why studies of forced migration find stronger displacement effects than studies of economic migration.[7]

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: tradable industries absorb immigration shocks through output adjustment rather than price changes, allowing tradable industries to absorb immigrants without native crowd-out and wage decreases. I extend their framework by demonstrating that production networks play a crucial role in these adjustments. My analysis shows that beyond industry tradability, the input-output linkages between industries have first-order effects on local labor markets.

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.[8] 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, documenting positive spillovers on firms' sales and employment through direct trade linkages to regions hosting Syrian refugees in Turkey. Their analysis is reduced-form: they estimate the effect of having a direct supplier or buyer in a host region, without distinguishing the underlying economic mechanisms. I extend their analysis in three ways. First, I formalize the economic mechanisms through which immigration propagates via production networks, distinguishing upstream exposure from two distinct downstream exposure channels. Second, I estimate the key elasticities governing these mechanisms using a Synthetic IV approach that addresses pre-trends in trade exposure: labor and intermediates are gross complements, while intermediate good production approximates Cobb-Douglas. Third, I quantify the total effects of immigration on wages and welfare across all regions, including higher-order indirect linkages, and show when the general equilibrium effects of immigration become economically significant.

[7]For a review of papers on largely economic immigration, see Dustmann et al. (2016). For papers analyzing refugee crises of the last decade and finding large displacement of natives, see Gulek (2024); Bahar et al. (2024).

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

2 Theory

This section formalizes how a decrease in wages due to immigration in one region can spill over to other regions through the production network, and develops structural equations that guide the empirical analysis.

2.1 Setup

The economy consists of N firms indexed by i, R regions indexed by r, where each region is endowed with L_r labor.[9] 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 and intermediate goods $\{x_{ij}\}_{j=1}^n$ to minimize costs subject to a constant returns nested-CES technology:

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

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. I assume common EoS across firms in both the upper and lower nests: σ_u denotes the EoS between labor and intermediates, and σ_l is the EoS between different intermediates.[10] I normalize $\sum_j \alpha_{i,j} = 1$. I assume that firms have constant and exogenous markups denoted by μ. Therefore, firm i sets price $p_i = \mu_i C_i$, where C_i denotes the unit cost.

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

[10] The common EoS 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.

Final Demand

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

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

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

Labor Supply

Labor is inelastically 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 labor supply.

General Equilibrium

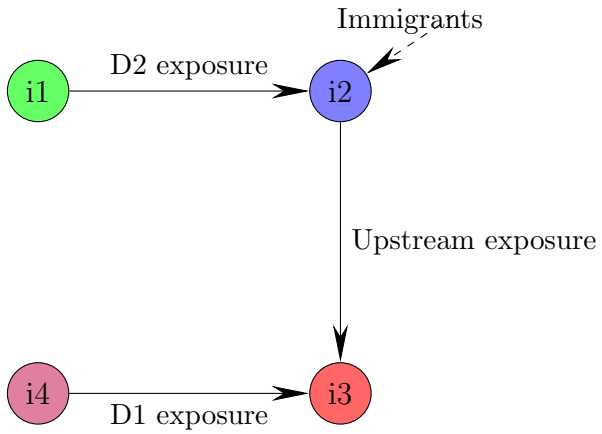
Given exogenous productivities A_i and markups μ_i, equilibrium is a set of prices p_i, wages w_r, intermediate good choices x_{ij}, labor input choices L_i, outputs y_i, and final demands c_{ri} such that each producer minimizes its costs subject to technology constraints and charges the relevant markup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

2.2 Three General Equilibrium Forces

The solution to this model is notation-heavy and, therefore, hard to follow. To facilitate exposition, I describe the three relevant economic forces here. Figure 1 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, a decrease in production costs decreases prices. This creates a chain reaction along the supply chain that propagates both forward and backward.

First, firm i_3 benefits from immigration as the price of the input from firm i_2 decreases. As i_3 faces lower input prices, it can increase or decrease its labor demand depending on the substitutability between intermediates and labor. If labor and intermediates are gross complements, then the reduction in input prices would cause firm i_3 to increase its labor demand. I name this the "upstream exposure effect" of immigration: upstream because, from the recipient i_3's perspective, the shock comes from upstream.

Figure 1: 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.

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 gross substitutes, then as i_2's prices decrease 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 occur: i_3 would increase its demand for i_4's goods, which would increase i_4's demand for labor. I name this the first downstream exposure effect, which I denote $D1$ for the rest of the paper.

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. First, the price of labor decreases compared to its input from i_1. The more substitutable the two inputs are, the less i_2 demands i_1's goods. Second, i_1 incurs a demand shock based on i_3's choice among goods from i_2 and i_4. The more substitutable intermediates are, the more i_3 demands from i_2, which results in i_2 demanding more from i_1. These two forces oppose each other. As I prove later, the net effect on i_1's sales depends on the relative magnitudes of the 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. I name this the second downstream exposure effect, which I denote $D2$ for the rest of the paper. This captures the backward propagation of the immigration shock.

Figure 1 only depicts the first-degree trade exposures: that is, firms being impacted by 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. The same applies to 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, I use the model.

2.3 Input-Output Definitions

To derive the impact of regional labor supply shocks on labor demand across all regions, I establish input-output notation following Baqaee and Farhi (2019).[11] My results are comparative statics describing how the labor payments in any host and non-host region change when a host region receives immigrants. I 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 I present both. All these objects are defined at the initial equilibrium. Without loss of generality, I normalize the nominal GDP to 1. Finally, in my analytical results and counterfactuals, I assume constant markups and technology.[12]

2.3.1 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:

$$b_{ri} = \frac{p_i c_{ri}}{\sum_{j \in r} p_j c_{rj}},$$

where $j \in r$ denotes all firms in region r. Let χ denote the $R \times 1$ vector of regional income shares,

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

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

2.3.2 Input-Output Matrices

To streamline the exposition, I treat labor as a special endowment producer that does not use any input to produce. I 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, I 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

[11] I maintain their notation except where my model's regional labor markets necessitate modifications.

[12] 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).

$(N+R) \times (N+R)$ matrix whose (ij)th element is equal to firm i's expenditure on inputs 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 are 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. I define the share of labor and intermediate good expenditures of firm i as:

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

2.3.3 Leontief Inverse Matrices

I define the revenue-based and cost-based Leontief inverse matrices as:

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

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.

2.3.4 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 the results, I 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, one can formally think of this as a covariance. It answers the question: "Among the suppliers of firm j, do the ones that decrease their prices more also rely more on firm k for intermediate goods?" If the answer is yes, the covariance term is negative.

2.4 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, I 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:

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

Therefore, to understand the impact of immigration on labor payments in all regions, I 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:

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

All proofs are in the Appendix.

Equation 1 captures the forward propagation of cost shocks, which is the upstream exposure effect introduced in Figure 1. Firms' labor share is determined by the trade-off firms face between using labor or intermediate goods in production. Suppose the local wages decrease less than the prices of the suppliers of firm i, so the rightmost parenthesis is positive. 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:*

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

where I is the identity matrix, and $\eta_i = \frac{1}{\lambda_i}\sum_j\sum_r b_{rj}\Psi_{ji}\chi_r\left(\sum_{k\in r}\frac{\pi_k}{\chi_r}d\ln\lambda_k + \frac{\lambda_r}{\chi_r}d\ln\lambda_r\right)$ 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 gross substitutes, $\sigma_l > 1$, 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 who observe larger decreases in costs among the suppliers of firm j are also more dependent on firm i for production. Summing across all firm js 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, intermediate goods are more substitutable with each other than with labor. In this case, if firm j observes larger decreases in local wages than the prices of its intermediate goods, $\left(d\ln w_{r_j} - \sum_{k=1}^{n}\frac{\tilde{\Omega}_{jk}}{\tilde{\Omega}_{j,M}}d\ln p_k\right) < 0$, 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 extent 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. Specifically, immigration changes regional income χ_r through two channels: changes in labor income λ_r from wage and employment effects, and changes in firm profits accruing to local owners. Under the Cobb-Douglas final demand assumption, these income changes translate to product demand proportional to budget shares b_{rj}, and then propagate backward through the supply chain via Ψ.[13]

Given the intuition developed in Propositions 1 and 2, I 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:*

$$d \ln p_i = \sum_{j=1}^{N} \tilde{\Psi}_{ij} \tilde{\Omega}_{j,L} d \ln w_{r_j}. \tag{3}$$

Proposition 3 shows an intuitive result. As firms have constant markups, any change in their production costs is fully represented in their prices. $\tilde{\Psi}_{ij}$ captures how much firm i depends on goods of firm j for production. $\tilde{\Omega}_{j,L} d \ln w_{r_j}$ captures the change in production costs of firm j from the change in local wages. Multiplying the two terms and summing across all firms gives 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 multiplied by the quantity of labor in that region: $\lambda_r = L_r w_r$. Combining this with Propositions 1, 2, 3, I can fully characterize the impact of immigration on this economy.[14]

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

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

[14] Since markups are constant, $d \ln \tilde{\Omega}_{ij} = d \ln \Omega_{ij}$, so I use the cost-based and revenue-based notation interchangeably in what follows.

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

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

Equation 4 presents the economic forces I have described in one system of linear equations. Notice that I observe all the parameters in this equation in the 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 in this model.

2.5 Extensions and Limitations

The model formalizes how immigration shocks propagate through production networks to affect labor demand throughout the economy, but several limitations and extensions warrant discussion.

Labor mobility: The model assumes labor immobility across regions to isolate trade spillovers from migration responses. While native migration can equilibrate regional labor markets (Monras, 2020), this assumption holds empirically in the Turkish context: Syrian immigration induced minimal changes in native migration patterns (Gulek, 2024), which is also documented in Appendix Figure C.2.

Sufficient statistics: Theorem 1 does not yield simple sufficient statistics for predicting spillover magnitudes, limiting intuitive characterization of when general equilibrium effects

deviate substantially from partial equilibrium predictions. I address this numerically through counterfactual analyses in Section 5.

Network formation: The model abstracts from endogenous formation of new trading relationships. Immigration-induced wage reductions could prompt firms to establish new buyer-supplier relationships with host regions. I address this empirically by constructing exposure measures based on connections to region-industry cells rather than individual firms, exploiting the fact that new trade formation predominantly occurs within regions or with firms maintaining existing linkages to host regions (Appendix Section B.1).

Skill heterogeneity: The model includes one skill type and assumes perfect substitutability between natives and immigrants. Both assumptions can be relaxed easily by specifying labor L as a CES aggregate of different worker types. Appendix Section A.4 presents this extension. Intuitively, when labor types are not perfect substitutes, the arrival of one type of labor creates an additional productivity shock from labor complementarity, but the main predictions of the model remain similar.

Labor supply elasticity: The model assumes perfectly inelastic labor supply in each region, abstracting from evidence that immigrants can displace natives. With elastic labor supply $L^S(w) = w^\eta$, $\eta \neq 0$, wage changes in host regions would be attenuated, limiting spillover magnitudes in non-host regions. Under a perfectly elastic labor supply ($\eta \to \infty$), spillovers would vanish completely since wages remain fixed, eliminating the production cost reductions that drive network propagation.

Industry heterogeneity: The model assumes perfect labor mobility across industries within a region, abstracting from differences in immigrants' and natives' industry choices. With limited native mobility, interregional spillovers would depend on the network-centrality of immigrant-employing industries. In the extreme where immigrants work in non-tradable industries and natives are perfectly immobile between tradables and non-tradables, there would be no interregional spillover from the labor supply channel. In the present setting, Syrian refugees work across multiple industries—textiles, construction, agriculture—which limits the relevance of this concern.

Local consumption: I assume local final goods consumption and identical preferences across natives and immigrants. In practice, immigrants consume differently through remittances (Albert and Monras, 2022) and distinct local preferences (Galaasen et al., 2025), but shutting down immigrant demand entirely has virtually no effect on either host or non-host wage changes (Appendix Figure E.4). The model also abstracts from cross-regional final goods trade, which could provide an additional spillover channel.

International trade: I account for firms' imports and exports in measuring their costs and sales, respectively: costs include purchases from all domestic firms, imports, and labor

costs, while sales include total revenue from balance sheet data, which includes exports. However, I do not allow for second-order effects whereby immigration-induced cost reductions in Turkish firms benefit foreign buyers, who in turn increase demand from other Turkish suppliers.

Capital: The model does not explicitly differentiate between materials and capital: both are counted within "intermediate goods" in the model and in the data. The reason is that the VAT data do not include product codes, so I cannot distinguish between purchases of raw materials and capital equipment. In theory, certain types of intermediate goods complement workers (e.g., more textile workers require more cotton) while others substitute for labor (e.g., machines can replace workers). The EoS between intermediates and labor is an aggregate parameter that captures an average across all types of intermediates. In the empirical analysis, I allow this parameter to vary across industries and find limited heterogeneity in the Turkish context.

Constant technology and markups: Immigrants can affect technology adoption (Lewis, 2011), innovation (Bernstein et al., 2022), and markups (Kim et al., 2025), all of which would amplify interregional spillovers. The model can accommodate such changes (Baqaee and Farhi, 2019) given credible estimates of their magnitudes across industries.

2.6 Structural Equations

Having solved the model, I now formalize the economic forces from Figure 1 and derive the structural equations that guide the empirical analysis. I introduce time subscript t and approximate wage changes in region r as $d\ln w_{rt} \approx \frac{\delta_{rt}}{\epsilon^D}$, where δ_{rt} denotes the ratio of immigrants to natives in region r at time t (the immigration shock) and ϵ^D denotes the elasticity of labor demand. Substituting this approximation into equations 1 and 2 yields:

$$
\begin{aligned}
d\ln\tilde{\Omega}_{i,L} =& -\frac{(1-\sigma_u)}{\epsilon^D} \underbrace{\sum_{r=1}^{R}\tilde{\Psi}_{i,r}\delta_{rt}}_{\text{Upstream Exposure (U)}} + \epsilon_{1,it} \\
d\ln\lambda_i =& \frac{(1-\sigma_l)}{\epsilon^D} \underbrace{\sum_{j=1}^{N}\frac{\lambda_j}{\lambda_i\mu_j} Cov_{\tilde{\Omega}^{(j)}}\left(\sum_{r=1}^{R}\tilde{\Psi}_{(r)}\delta_{rt}, \Psi_{(i)}\right)}_{\text{Downstream-1 Exposure (D1)}} \\
&+ \frac{(\sigma_u-\sigma_l)}{\epsilon^D} \underbrace{\sum_{j=1}^{N}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,L}\left(\delta_{r_j,t} - \sum_{k=1}^{n}\frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}} d\ln p_k\right)(\Psi_{ji} - I_{ji})}_{\text{Downstream-2 Exposure (D2)}} + \epsilon_{2,it},
\end{aligned}
\tag{5}
$$

where the error terms ϵ_1 and ϵ_2 capture the direct effects of immigration on host-region wages, spillovers of immigrant demand, and potential model misspecification arising from, for example, the constant markup and CES assumptions. The demand spillovers in the error term do not threaten identification as long as either (1) demand spillovers are uncorrelated with the instrumented trade exposures, or (2) the omitted demand force is small in magnitude. Both conditions are likely satisfied. The first holds because the trade exposure instruments capture variation driven by production cost changes through the pre-shock input-output network, not consumer spending patterns. The second holds because immigrants tend to consume home-country goods through remittances (Albert and Monras, 2022), attenuating local demand effects. Moreover, counterfactual exercises that shut down immigrant demand entirely show negligible effects on both host and non-host wage changes (Appendix Figure E.4).

These equations reveal two key insights. First, the trade-exposure treatments [U, D1, D2] depend only on the pre-shock trade network structure and the spatial distribution of immigration, making them directly computable from the data. Second, the coefficients on these exposure measures identify the structural elasticities: the upstream exposure coefficient recovers σ_u, while the downstream exposure coefficients jointly identify σ_l and confirm the ordering of elasticities. Therefore, the empirical analysis focuses on estimating these reduced-form relationships to recover the key EoS parameters that govern how immigration shocks propagate through the production network.

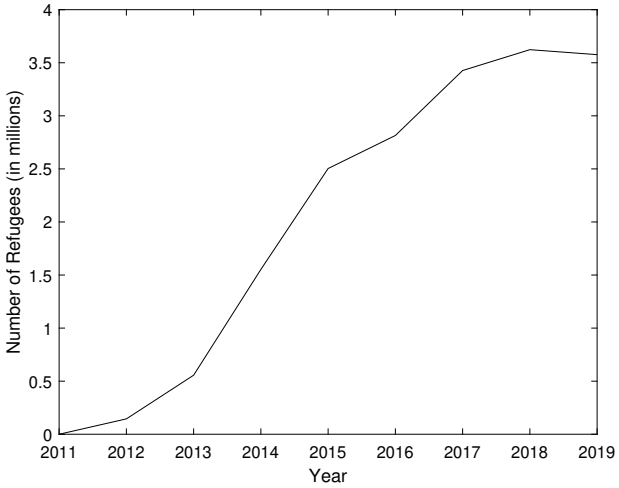
3 Background and Data

3.1 Syrian Refugee Crisis in Turkey

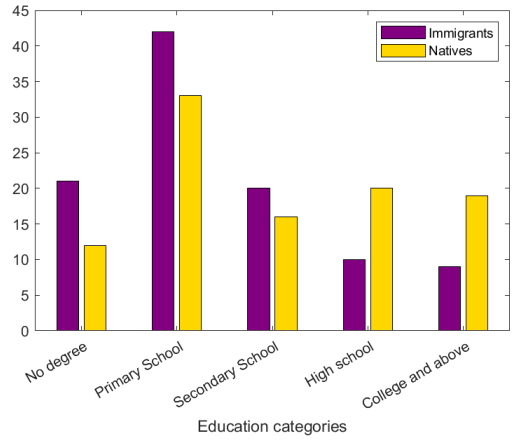
The Syrian Civil War, beginning in March 2011, displaced 6 million Syrians by 2017. Turkey absorbed the largest share—3.6 million registered refugees—dwarfing the numbers in neighboring Lebanon, Jordan, and Iraq combined. Figure 2a documents the rapid escalation: from 170,000 refugees in 2012 to 3.6 million by 2019, with the steepest increases occurring between 2013 and 2015. Figure 2c 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 2b shows that 21% of Syrian refugees lack primary education compared to 12% of natives, and 83% do not have a high school diploma compared to 61% of natives. These educational gaps likely under-

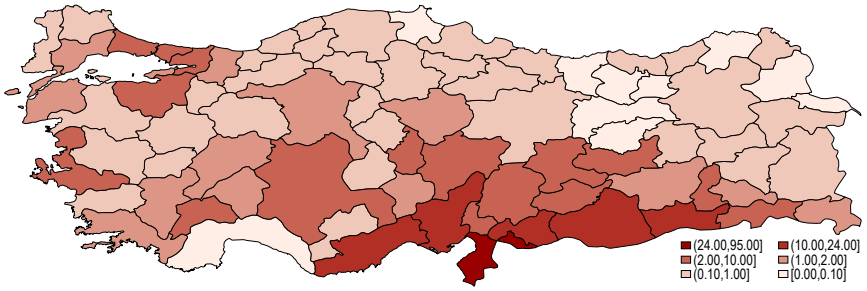
Figure 2: Statistics on the Syrian Refugees in Turkey



(a) Time series of the number of Syrian refugees in Turkey



(b) Educational attainment of Syrians and natives



(c) Number of Syrian refugees per 100 natives in 2019

Source: Data on the number of Syrian refugees in a given year and province comes from the Directorate General 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.

state the effective skill differential. Educational downgrading is common among immigrants (Dustmann et al., 2013), and most Syrians possess only basic Turkish proficiency (Turkish Red Crescent and WFP, 2019), further limiting their access to skilled positions. The Syrian influx therefore constitutes a low-skill labor supply shock to the Turkish labor markets.

Most Syrians in Turkey do not have formal labor market access. As of March 2019, only 31,000 refugees—1.5% of the working-age refugee population—held work permits, constraining the vast majority to the informal sector. However, this does not undermine the generalizability of my findings. Gulek (2024) demonstrates that informal and formal labor are gross substitutes in production, with an elasticity of substitution of around 10; a similar estimate (EoS $\approx$ 11) is later found for Colombia by Bahar et al. (2024). This high substitutability ensures that wage pressures from informal immigration transmit almost fully to

the formal sector.[15]

3.2 Data

Studying the network spillovers of immigration shocks requires a comprehensive dataset covering whom firms trade with, how much they spend on labor and intermediates, and how much they sell. To achieve this, I 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 homogeneous firm identifier, which enables me 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, I use the yearly gross sales of each firm. Third, from the firm registry, I 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, I collect firms' annual exports and imports. Fifth, from the employer-employee data, I collect the average number of workers, total labor costs, and average wages per worker for each year.

The network data are supplemented with labor force surveys conducted by the Turkish statistical institute. Unlike the census data, these surveys collect information on workers' education, which allows me 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 breakdown of refugees at the province level, which prevents the empirical investigation from exploiting that variation.

Lastly, computing the trade exposure variables requires inverting the Leontief inverse matrices for approximately 230,000 firms. While the input-output matrices are sparse, their inverses are dense and memory-intensive. To overcome this constraint, I provided a 512 GB RAM workstation to Turkey's Ministry of Industry and Technology. Appendix Section B.1 documents the matrix construction and treatment variable calculations.

4 Empirical Analysis

This section presents evidence on how immigration-induced trade spillovers affect manufacturing firms in non-host regions. I describe the identification strategy, estimate the causal effect of trade exposures on firms' labor demand and sales, estimate the key EoS parameters,

[15] Appendix Section F.1 discusses how informal workers can be incorporated into the model and reviews the estimation of this elasticity in prior work.

and use these parameters to quantify the total equilibrium effects of immigration across all regions.

4.1 Identification Strategy

There are three threats to identification. First, trade exposures depend on regional immigration intensities (δ_{rt}), which may be endogenous if immigrants select regions with positive labor demand shocks. Second, trade exposures depend on input-output matrices (Ω and $\tilde{\Omega}$), creating potential bias if firms with different trade exposures follow different trajectories. Third, Turkey has a large informal sector: 40% of employment and an unknown share of sales remain unregistered and therefore absent from the census data. This mismeasurement affects both outcome and treatment variables—the latter non-linearly—potentially biasing estimates in either direction.

I address these three challenges through a corresponding three-step approach. I use shift-share instrumental variables (SSIV) to tackle the endogeneity concern, combine this with Synthetic Controls (SC) to address the differential trajectories concern, and focus on large firms that are substantially more formal to mitigate the informality concern. I first introduce the instruments, then explain how I utilize the Synthetic Instrumental Variables (SIV) approach of Gulek and Vives-i Bastida (2024) to combine instrumental variables for immigration patterns with synthetic controls for firm trajectories, before finally explaining why focusing on large firms shields the analysis from bias from informality.

4.1.1 Instruments

My primary shift-share instrument for immigrant location choices combines inverse travel distances between Turkish regions and Syrian governorates (share) with the total Syrian refugee population in Turkey (shift):

$$Z_{r,t} = \underbrace{\sum_{s=1}^{13} \lambda_s \frac{1}{d_{r,s}}}_{\text{Share}} \times \underbrace{\text{Number of Syrians in Turkey in year } t}_{\text{Shift}}, \tag{6}$$

where $d_{r,s}$ measures travel distance between region r and governorate s, and λ_s weights each governorate.[16] Following Aksu et al. (2022), I weight governorates by their population and

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

proximity to Turkey relative to other neighboring countries.

$$\lambda_s = \underbrace{\frac{\frac{1}{d_{s,T}}}{\frac{1}{d_{s,T}} + \frac{1}{d_{s,L}} + \frac{1}{d_{s,J}} + \frac{1}{d_{s,I}}}}_{\text{Relative distance to Turkey}} \times \underbrace{\pi_s}_{\text{Pop. share}}, \tag{7}$$

where $d_{s,c} \quad c \in \{T, L, J, I\}$ is the travel distance from Syrian region s to Turkey, Lebanon, Jordan, and Iraq respectively; and π_s is the population share in 2011, which I 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 the instrument. It 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 I 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 practically no Syrian immigrants in Turkey during those years.[17] After 2011, distance strongly predicts immigrant location in all years. The joint F-statistic for the post-period coefficients is 108, which implies a strong instrument.

A potential threat to the exclusion restriction is that the Syrian civil war disrupted economic activity in border regions through trade disruptions or security concerns. However, Syria was not a major trade partner of any Turkish region, and exports to and imports from Syria did not decrease during the conflict (Gulek, 2024). Moreover, if the war had negatively impacted border regions, upstream-exposed firms—those buying from border regions—would show negative effects as their suppliers became less productive, whereas I find positive upstream effects consistent with immigration-induced cost reductions but not with conflict-related disruptions to border regions.[18]

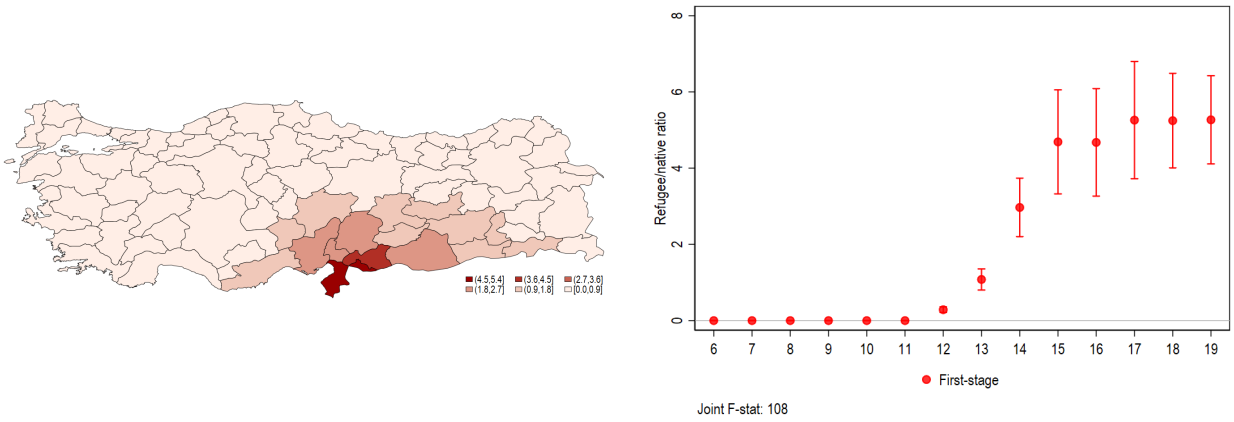
I validate the main instrument with two alternative shares. The first one uses the share of Arabic speakers from the 1965 census. Unlike Card (2001)'s past-settlement instrument, the Arabic-speaking population reflects Ottoman Empire demographics rather than previous Syrian migration. The second alternative instrument uses a dummy indicator for the regions that receive large weights by either the distance or the language instruments.[19] This primarily

[17] Although Syrians started arriving to Turkey in 2011, the initial numbers were minuscule.

[18] Positive demand shocks to border regions (e.g., government investment) are also unlikely to explain the results: Gulek (2024) documents displacement of low-skill natives in host regions, which is consistent with a labor supply shock but inconsistent with a positive demand shock. The combination of local native displacement and positive upstream spillovers to non-host firms is uniquely consistent with an immigration-induced labor supply shock.

[19] This coincides with the host regions shown in Figure B.1.

Figure 3: Distance instrument distribution and first-stage



(a) Distance instrument 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 I weight each region by its population in 2011. Standard errors are clustered at the region level. 95% confidence intervals are plotted.

serves as a sanity check as it is arguably easier to interpret reduced-form effects with a dummy indicator. The respective first-stage estimates can be found in Appendix Figure C.3. While both the language and host dummy instruments predict refugee settlement, they have weaker first stages, which is why I use the distance instrument as the preferred specification.

The 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. Note that $Z_{rt} = Z_r \times$ (total Syrians at time t): the share component Z_r is cross-sectional (based on time-invariant distances), while the shift component introduces time variation. In event-study specifications, I interact the cross-sectional share Z_r with year indicators to assess pre-trends; in IV specifications, I use the full time-varying Z_{rt}.

4.1.2 Synthetic IV Design

The ideal comparison would contrast similar firms that would have followed parallel trajectories absent the immigration shock but happen to be differentially exposed to immigrants through their trading partners. However, as Appendix Section C demonstrates, firms with different trade exposures follow divergent pre-period trajectories even within narrow region-industry or region-industry-size cells. This divergence partly reflects stronger employment growth in southeastern Turkey during 2006–2011 (Gulek, 2024), which likely propagated through production networks to differentially affect firms in non-host regions. These pre-existing differences violate the share-exogeneity assumption underlying standard shift-share

designs (Goldsmith-Pinkham et al., 2020).

To address this challenge, I implement the SIV estimator (Gulek and Vives-i Bastida, 2024), which proceeds in two steps. First, I construct synthetic controls for each firm using pre-period data and generate counterfactual values for outcomes, treatments, and instruments. Second, I apply standard IV estimation to debiased data, defined as the difference between observed and synthetic values.

Formally, let ω_i denote the vector of synthetic control weights for firm i and X represent an $N \times K$ matrix containing outcomes, treatments, and instruments. Using the SC weights, I generate synthetic values $\hat{X}_k = \sum_{j \neq i} \omega_j X_{jk}$ for each variable k. I then subtract these synthetic values from the observed data to obtain *debiased* values: $\tilde{X} = X - \hat{X}$. I then apply two-stage least squares to the debiased data. This procedure effectively partials out unobserved confounders proxied during the matching step. Put differently, pre-trends in the data imply unobserved confounders correlated with the trade exposure instruments; the matching step proxies these confounders using pre-period trajectories, so subtracting the synthetic values removes the confounded component and restores consistency of the IV estimator (Gulek and Vives-i Bastida, 2024).

To construct synthetic control weights, I match on pre-2011 demeaned values of log labor share and log sales. Following Sun et al. (2025), I estimate a single set of weights for both outcomes, which improves the signal-to-noise ratio. Appendix Section D confirms that joint estimation outperforms separate weights when predicting unmatched outcomes like payroll and firm size. I restrict donor pools to firms within the same region and two-digit industry, effectively controlling for region-by-industry-by-time fixed effects. Following Abadie and L'hour (2021), I include a penalty term to mitigate overfitting in this disaggregated setting.

This approach compares firms within region-industry cells that *followed similar economic trajectories before the immigration shock* but experienced different exposure to immigrants through their trading networks.

4.1.3 Sample Selection

To address bias from informality, I exploit the well-documented inverse relationship between firm size and informality rates (Ulyssea, 2018, 2020). Appendix Figure B.2b confirms this pattern in Turkey: informality rates decline sharply with firm size, from 60% in firms with fewer than 10 employees to below 5% in firms exceeding 50 employees. The 50-employee threshold marks a particularly sharp discontinuity, as it triggers heightened regulatory scrutiny that plausibly reduces informality in both employment and sales reporting. I therefore restrict the sample to firms with at least 50 formal employees in 2010.[20] While this

[20]The size restriction applies only to the regression sample. The input-output matrices used to construct trade exposure measures are built from the universe of formal firms in 2006–2010, before the immigration

size restriction reduces the number of firms substantially, the resulting sample accounts for 37.5% of all formal workers, 44% of the total wage bill, and 52% of all sales in the balanced panel. Appendix Section D.5 demonstrates robustness to alternative size thresholds.

Two additional restrictions sharpen the identification. First, I exclude firms in regions where the immigrant share exceeds 4% of the native population or where the instrument assigns large weights, ensuring that estimated effects operate through trade linkages rather than the direct impacts of immigration.[21] Appendix Figure B.1 illustrates the excluded regions. Second, since the SIV estimator requires a balanced panel, I restrict the sample to firms with non-missing observations in employment, wage bill, and sales between 2006–2019. I also focus exclusively on manufacturing firms in the empirical analysis.[22]Summary statistics are reported in Appendix Table B.1.

4.2 Estimating Equations

4.2.1 Synthetic IV Design

Given trade exposure treatments U, $D1$, $D2$, and their respective instruments U^z, $D1^z$, and $D2^z$, I define the estimating equations of the structural equation 5 as follows:

$$\begin{aligned} \widetilde{log(LaborShare_{it})} &= \beta_1 \widetilde{U_{it}} + f_i^L + f_t^L + \nu_{it}^L \\ \widetilde{U_{it}} &= \gamma_1 \widetilde{Z_{it}^U} + g_i^L + g_t^L + \omega_{it}^L \end{aligned} \tag{8}$$

$$\begin{aligned} \widetilde{log(Sales_{it})} &= \beta_2 \widetilde{D1_{it}} + \beta_3 \widetilde{D2_{it}} + f_i^S + f_t^S + \nu_{it}^S \\ \widetilde{D1_{it}} &= \gamma_2 \widetilde{Z1_{it}^D} + \gamma_3 \widetilde{Z2_{it}^D} + g_i^S + g_t^S + \omega_{1,it}^S \\ \widetilde{D2_{it}} &= \gamma_4 \widetilde{Z1_{it}^D} + \gamma_5 \widetilde{Z2_{it}^D} + h_i^S + h_t^S + \omega_{2,it}^S \end{aligned} \tag{9}$$

where $\tilde{X}$ refers to the debiased version of the variable X following the SIV algorithm.

Two important considerations guide my specification choices. First, equations 8 and 9 reflect the correct structural relationships for identifying elasticity parameters, which explains the separate treatment of upstream and downstream exposures. Second, the upstream exposure measure U is measured with greater precision than the downstream exposures $D1$ and $D2$ because sales are noisier than costs. Including U in equation 9, while theoretically unnecessary, could capture the causal effects of the noisier downstream measures in a joint

shock. The counterfactual analyses cover the full economy, including services.

[21]While the structural equations apply to all firms, the separation between direct and indirect effects relies on the CES functional form. If this assumption is inexact, direct labor market effects in host regions could leak into the trade exposure coefficients. Excluding directly treated regions prevents this potential bias.

[22]Restricting estimation to manufacturing is standard in the production function literature; see, e.g., Atalay (2017), Oberfield and Raval (2021), and Peter and Ruane (2025).

estimation. Nevertheless, Appendix Section C demonstrates that the main findings remain robust when estimating upstream and downstream effects simultaneously.

4.2.2 GMM Design for Elasticity Estimation

The reduced-form coefficients from equations 8 and 9 map to the structural elasticities through the following relationships:

$$\beta_1 = -\frac{(1-\sigma_u)}{\epsilon^D} \quad ; \quad \beta_2 = \frac{(1-\sigma_l)}{\epsilon^D} \quad ; \quad \beta_3 = -\frac{(\sigma_l - \sigma_u)}{\epsilon^D}, \tag{10}$$

where ϵ^D denotes the wage elasticity of labor demand. Although the system has three reduced-form coefficients and three unknown parameters $\{\sigma_u, \sigma_l, \epsilon^D\}$, all three cannot be identified from these coefficients alone. Note that $\beta_1 + \beta_2 = \beta_3$, so the three structural equations provide only two independent restrictions. With three unknowns and two independent equations, σ_u and σ_l are identified only up to a scale determined by ϵ^D.

I calibrate $\epsilon^D = -1.27$ using the estimate from Gulek (2024), who exploits the same Syrian refugee shock in Turkey to estimate the wage elasticity of labor demand in host regions.[23] Given ϵ^D, the system is overidentified, which provides a specification test: if the model is correctly specified, all three coefficients should yield consistent elasticity estimates.

I estimate σ_u and σ_l via GMM. Define $\hat{\beta} \equiv [\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3]'$ as the vector of reduced-form estimates with covariance matrix $\hat{\Sigma}$, and let $\beta(\sigma)$ denote the theoretical mapping in equation 10. The GMM estimator solves:

$$\min_{\sigma_u, \sigma_l} J \equiv (\hat{\beta} - \beta(\sigma))' \hat{\Sigma}^{-1} (\hat{\beta} - \beta(\sigma)). \tag{11}$$

The minimized objective function provides Hansen's J-statistic for testing overidentifying restrictions. Under the null hypothesis that the model is correctly specified, $J \sim \chi^2(1)$ with one degree of freedom. I reject the model specification if J exceeds 3.84, the 5% critical value.

4.2.3 Event-study Design

The primary advantage of the event-study design is that it allows me to visually and flexibly assess the pattern of outcomes the *debiased* share component of the shift-share instrument captures relative to the beginning of the refugee crisis. The event-study equations of the SIV

[23] Appendix Section F provides further details on the estimation of ϵ^D and presents sensitivity analysis showing that the qualitative conclusions—$\sigma_u < 1$ and $\sigma_l \approx 1$—are robust to alternative values of ϵ^D.

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.

4.3 Empirical Estimates

4.3.1 Effects of Upstream and Downstream Exposures

I begin by estimating the reduced-form effects of upstream exposure on firms' labor demand. Figure 4 plots the results for three outcomes: number of employees (Panel A), total payroll (Panel B), and labor share (Panel C). Panel D shows the effects of downstream exposures on sales.[24] For inference, I cluster standard errors at the firm level, as the identifying variation is in firm-level trade exposures.[25]

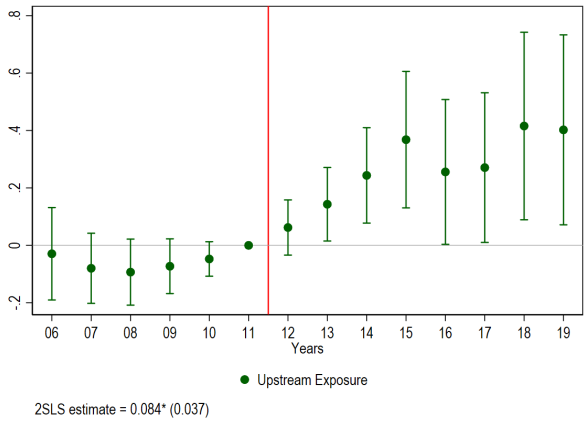
Figure 4a reveals two main patterns. First, there are no statistically or economically significant pre-trends. This is not mechanical since SIV weights are generated to match trends in labor share and sales, not payroll or firm size. The absence of pre-trends in Figure 4a, despite the raw IV design showing pre-trends (as demonstrated in Online Appendix Section D.1), provides evidence in favor of the identification strategy. It shows that an unobserved common factor generates differential trends between more- and less-exposed firms, and that SIV successfully partials out this confounder.

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

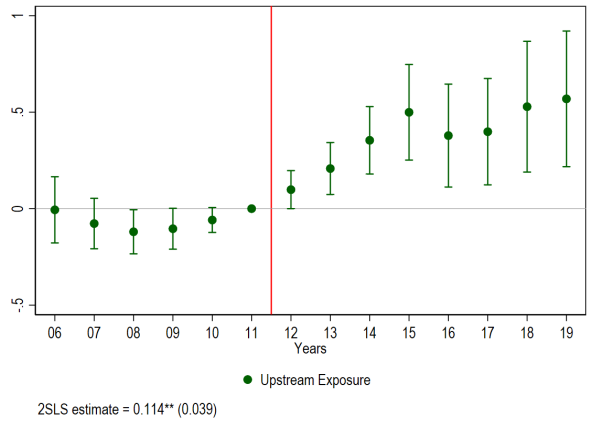
[24] Employment and payroll are not direct outcomes of the structural equations, which identify the EoS parameters through labor share and sales. I report employment and payroll because they are among the primary outcomes of interest in labor economics.

[25] An important feature of SIV is that the synthetic weights are estimated on the pre-period, whereas the treatment effects are estimated on the post-period. This sample-splitting structure reduces the dependence between weight-estimation noise and the post-treatment estimator, so conditional-on-weights inference is more plausible than in plug-in procedures that reuse the same sample twice. In practice, this approximation is most credible when the pre-treatment fit is stable, the synthetic weights are sufficiently dense rather than concentrated on a few donors, and back-testing indicates that the good pre-period fit is not driven by overfitting idiosyncratic noise. See Gulek and Vives-i Bastida (2024) for further details on inference in the SIV framework.

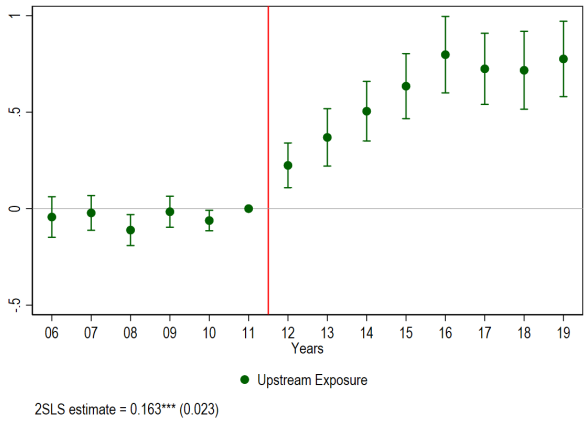
Figure 4: Effects of trade exposures on firms' labor demand and sales



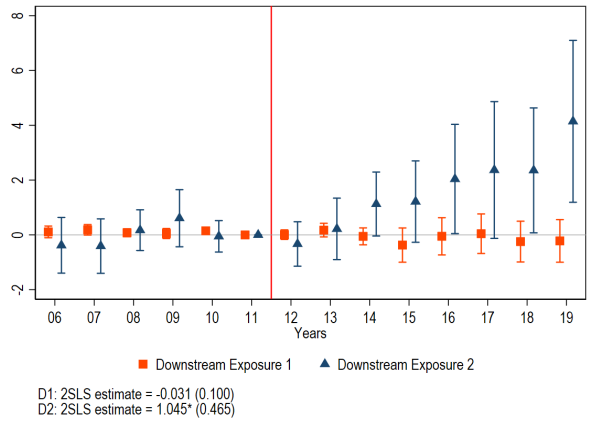
(a) Number of employees



(b) Payroll



(c) Labor share



(d) Sales

Notes: In Panels A, B, and C, 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. In Panel D, the estimates come from the regression equation: $\widetilde{y_{it}} = \sum_{t' \neq 2011} \left(\gamma_{2,t'} \widetilde{D1_i^Z} + \gamma_{3,t'} \widetilde{D2_i^Z} \right) \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$. Both the outcome and the treatment are their debiased versions following the SIV algorithm. The sample is restricted to manufacturing firms with at least 50 employees in 2010. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

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, where each spends half its costs on labor and half on one intermediate good, buys from different suppliers (j_1 and j_2 respectively), and has suppliers that also allocate half their costs to labor. If firm j_1 has one standard deviation higher immigrant exposure through distance than firm j_2, this creates a 0.25 unit difference in upstream exposure between their customers i_1 and i_2. The 0.40 coefficient estimated for 2019 in Panel A thus implies that

firm i_1 increases its size by 10% relative to firm i_2.

Figure 4b presents the effects of upstream exposure on payroll. The effects parallel those for employment: no significant pre-trends and a positive, increasing difference between more- and less-exposed firms. The estimated effects on payroll modestly exceed those on employment, indicating that upstream exposure weakly increases wages, although this wage effect is not statistically significant.

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 since 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 that directly or indirectly buy from host regions increase their labor share relative to similar firms in their region-industry cells. The 2SLS estimate, reported in the figure, is statistically significant (p-value <0.001). This result implies that labor and intermediate goods are gross complements.

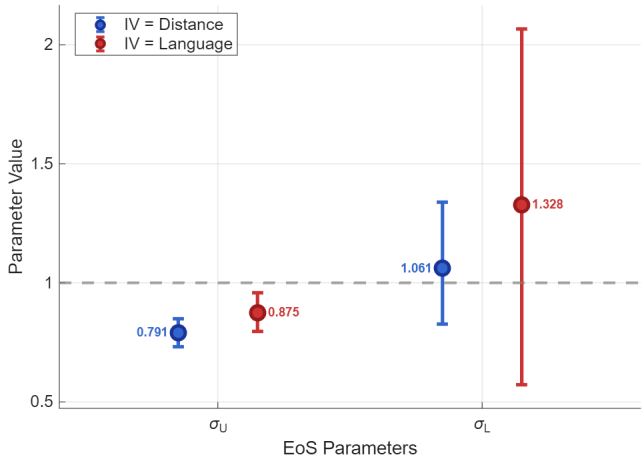
Figure 4d shows the effects of downstream exposure on firms' sales. I observe no significant pre-trend during 2006–2011. In the post-period, while I document precise null effects of $D1$ exposure on sales (p-value: 0.76), $D2$ exposure significantly increases firms' sales (p-value: 0.025). This pattern yields two key insights. First, consider a firm with suppliers from both host and non-host regions. The null $D1$ effect implies that this firm maintains fixed expenditure shares across suppliers and, therefore, does not substitute across them. This pattern is consistent with intermediate good production being Cobb-Douglas, i.e., $\sigma_l = 1$. Second, the positive $D2$ effect implies that firms selling directly or indirectly to host regions increase their sales, which occurs only if intermediate goods are more substitutable with each other than with labor. Together, these mutually consistent estimates provide an intuitive, albeit informal, test of the model.

To estimate the structural elasticity parameters efficiently and provide a formal test of the model, I bootstrap equations 8 and 9 using 1,000 draws with replacement to obtain the covariance matrix of regression parameters $[\beta_1, \beta_2, \beta_3]$. Then, I solve equation 11 to obtain GMM estimates of structural elasticity parameters. Figure 5 shows the results. Using the distance instrument, I estimate an EoS between labor and intermediates of around 0.79 (significantly below 1, implying gross complementarity) and an EoS across intermediates of around 1.06 (not significantly different from 1, consistent with Cobb-Douglas).

These conclusions remain robust when using the language-based instrument. The language instrument predicts slightly larger substitutability for both technologies, but with lower precision because of weaker first-stage results. I cannot statistically distinguish estimates from distance and language instruments. Furthermore, overidentification tests do not

reject the model using either instrument ($J < 3.84$, $p > 0.05$), increasing confidence in the validity of the results.

Figure 5: Elasticity of substitution estimates



This figure shows the 95% confidence intervals of the EoS estimates using two alternative instruments. I draw 1000 bootstrap samples with replacement from the sample of large manufacturing firms. I then estimate the effects of upstream exposure on labor share and downstream exposures on firms' sales. The joint covariance of the regression parameters from different regressions is calculated by using the bootstrapped distribution of the regression coefficients. 95% confidence intervals are displayed. Hansen's J-statistics for the overidentification restriction are 3.13 ($p = 0.077$) for the distance instrument and approximately zero ($p \approx 1$) for the language instrument; the latter reflects the wider confidence intervals of the language-based IV estimates.

To summarize, Figure 4 shows that upstream exposure increases firms' labor demand, $D1$ exposure has a null effect on sales, and $D2$ exposure increases sales. This means that firms buying from host regions increase their labor demand, firms selling to host regions increase their sales, and firms do not substitute across suppliers on average. Using the preferred distance-based instrument, I estimate the elasticity parameters as: $[\hat{\sigma}_u = 0.79, \hat{\sigma}_l = 1.06]$.[26,27]

[26]These estimates depend on the calibrated ϵ^D. To see why, consider the large positive upstream spillover $\hat{\beta}_1 > 0$. Since $\beta_1 = -(1-\sigma_u)/\epsilon^D$, a large $\hat{\beta}_1$ can arise either because σ_u is far below 1 (strong complementarity between labor and intermediates) or because $|\epsilon^D|$ is small (wages responded strongly to the immigration shock, so even modest complementarity generates large spillovers). The qualitative conclusion $\sigma_u < 1$ holds for any $\epsilon^D < 0$ since $\hat{\beta}_1 > 0$ pins the sign, but the magnitude of complementarity scales with $|\epsilon^D|$. Appendix Figure C.5 shows the sensitivity of both estimates to alternative values of ϵ^D.

[27]The estimate $\hat{\sigma}_u = 0.79$ is consistent with the production networks literature, where estimates of the elasticity between value added (or labor) and intermediates range from near-Leontief in short-run quasi-experimental settings (Boehm et al., 2019) to 0.5–0.9 in structural estimation (Atalay, 2017; Baqaee and Farhi, 2019). The estimate $\hat{\sigma}_l = 1.06$ (approximately Cobb-Douglas) is higher than short-run production-side estimates, which cluster near zero (Atalay, 2017; Boehm et al., 2019), but well below long-run estimates of around 2.5 (Peter and Ruane, 2025). This is consistent with the identifying variation capturing medium-run adjustment over several years.

4.3.2 Robustness Checks

I perform extensive robustness checks to ensure that estimated effects represent causal impacts rather than differential trends. I report detailed results in the Appendix and summarize key findings here.

Alternative Instruments

Appendix Figure C.4 replicates the results for labor share and sales using travel distance, language share, a dummy indicator for the host regions, and each share interacted with the skill-intensity of industries. The latter exploits the fact that Syrian immigrants are predominantly lower-skilled than Turkish workers and, therefore, overrepresented in low-skill-intensive industries. All six weighting schemes yield identical conclusions: upstream exposure significantly increases labor demand, $D1$ exposure has a null effect, and $D2$ exposure increases sales. The only caveat is that the language instrument is less precise, so language- or language-skill-based instruments do not yield statistically significant effects on sales. The results for labor share remain robust, since cost-based measures have much lower variance than sales-based measures.

Industry Heterogeneity

While the model allows firm-level heterogeneity, I assume constant elasticity of substitution parameters for computational reasons, yielding average estimates across industries. To relax this assumption, I estimate the elasticity parameters separately for each two-digit manufacturing industry, apply Empirical Bayes shrinkage to improve the stability of estimates from small samples, and plot results in Figure C.1. Overall, across different specifications, labor and intermediates are gross complements in most industries. Although intermediate goods are neither gross complements nor gross substitutes in most industries, they are gross substitutes in some (such as textiles and basic metals) and gross complements in others (such as chemicals). Details of industry-level estimation appear in the Appendix Section C.2.

SIV Validation

The absence of pre-trends in untargeted outcomes (firm size and payroll) provides evidence against over-fitting, since these variables were not used in calculating synthetic control weights. I perform several additional checks in the Appendix. First, comparing IV and SIV event-study estimates (Figure D.1) confirms that standard IV exhibits significant pre-trends that SIV removes, demonstrating the necessity of the approach. Second, matching on labor share or sales separately worsens pre-trends in the unmatched outcome (Figure D.2), demonstrating the necessity of joint matching; results nevertheless remain robust to separate matching for matched outcomes (Figure D.3). Third, results are robust to alternative

training windows of 2006–2009 and 2006–2010 (Figure D.4).

Firm Size Sensitivity

The remaining researcher choice not yet tested is the firm-size restriction. I focus on large firms to address potential concerns regarding informality in both labor costs and sales. The 50-employee threshold was chosen as a legal threshold above which companies face additional liabilities and reporting requirements, making their data more credible. Figure D.5 shows estimates of the effects of trade exposures on labor share and sales across firms of different sizes. While upstream exposure effects on labor share are similar across firm sizes, downstream exposure effects on sales (specifically, $D2$ exposure effects) are sensitive to the 50+ threshold, above which firms' reporting practices become significantly more trustworthy. Above the 50+ threshold, results are consistent across firms with 60+, 70+, 80+, 90+, or 100+ employees. Online Appendix Section D explains how small firm informality can bias $D2$ exposure effects.

Comprehensive Robustness Table

Appendix Table D.1 presents comprehensive robustness checks estimating upstream and downstream exposure effects on each outcome, separately and jointly, for both all manufacturing firms and firms with 50+ employees. Overall, my main results remain robust.

5 Counterfactuals

This section uses the model to quantify how immigration affects host and non-host regions through counterfactuals. I examine the economic significance of trade spillovers, their dependence on host region and immigrant characteristics, and their implications for both policymakers and researchers.

Theorem 1 characterizes immigration's general equilibrium effects on regional wages and firm prices as the solution of a system of linear equations that depend on the baseline production network and structural elasticity parameters. Having observed the network in the data and estimated the elasticities, I can solve this system to obtain the general equilibrium effects. While the empirical analysis operates at the firm level and focuses on manufacturing, the counterfactuals use representative firms at the region-by-two-digit-industry level across all sectors of the economy for computational feasibility. I begin with homogeneous labor within regions as in Section 2, then introduce skill heterogeneity to analyze how the effects vary with immigrant skill levels.

An important consideration is that the model expresses wages relative to nominal GDP, while real wages typically reference local prices. Therefore, I 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.

5.1 Spillover Effects of a 1% Labor Supply Shock

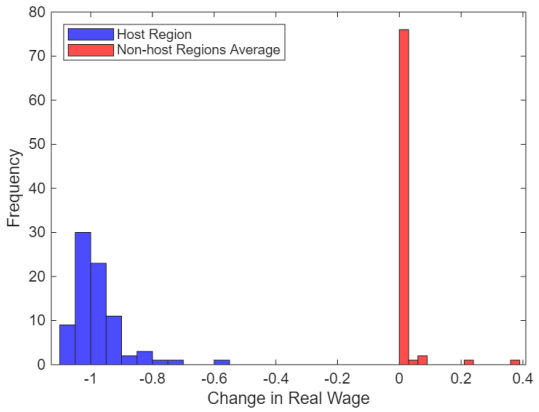
In the first counterfactual, I analyze how immigration spillovers vary across potential host regions. I simulate a 1% increase in labor supply separately for each of Turkey's 81 provinces and calculate two effects: the real wage change in the host province and the average real wage change in the other 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 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.

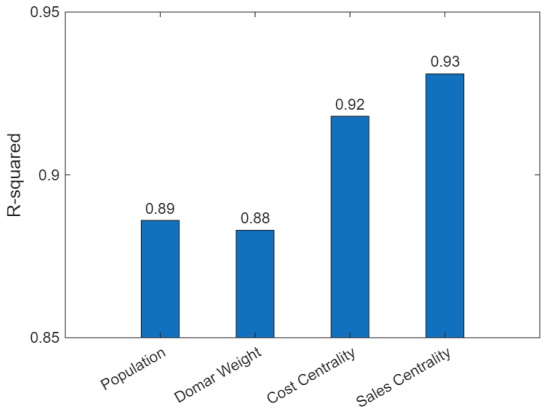
Second, 5 of 81 provinces generate economically meaningful spillovers (greater than 0.04% change in non-host real wages): Bursa, Kocaeli, Izmir, Ankara, and Istanbul. Istanbul and Ankara produce particularly large spillovers, up to two-thirds the magnitude of direct effects. A 1% labor supply increase 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 6c 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 three times 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.

Figure 6: Real wage changes in host and average non-host region



(a) Histogram of host and non-host region effects



(b) R-squared from bivariate regressions



(c) 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. The heatmap legend is in basis points (hundredths of a percent).

I examine this network position hypothesis using Bonacich centrality measures for both cost-based and sales-based trade matrices: $\widetilde{B} = \tilde{\Psi}'\mathbf{1}$ and $B = \Psi'\mathbf{1}$.[28] These measures capture how much other regions depend on region r through cost linkages ($\widetilde{B}_r$) and sales linkages (B_r). To assess which regional characteristics best predict spillover effects, I regress average non-host wage effects on the host region's population, Domar weight, and both centrality measures. Figure 6b presents the R-squared from these bivariate regressions. Sales-based centrality provides the strongest explanatory power (R-squared of 0.93 across 81 observations), indicating that a region's position in the production network determines spillover magnitude. Population shares, an easily observable statistic for regions worldwide, also predict spillovers well (R-squared of 0.89). This establishes a general empirical rule:

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

immigration to large cities generates substantial spillovers to non-host regions.[29]

Implications for Spatial Designs

Given that immigration to central cities generates sizable spillovers affecting labor demand in other regions, what implications does this have for spatial difference-in-differences designs commonly used in immigration research? To answer this question, I conduct one million simulations where I randomly assign 10 of 81 regions to receive a 1% immigration shock and calculate the average treatment effect on the treated (ATT) and control (ATC) regions. Under SUTVA, ATC would be zero, and therefore comparing the treated to control regions would provide a consistent estimate of ATT.

Appendix Figure E.2 presents the relationship between ATT and ATC under the estimated elasticity parameters ($\sigma_u = 0.79$, $\sigma_l = 1.06$). Three patterns emerge. First, the ATT on real wages varies substantially across simulations, ranging from -1.04% to -0.15%. This wide dispersion occurs because the composition of treated regions matters: when multiple central regions receive immigrants simultaneously, their positive spillovers on each other attenuate the direct negative effects. For example, a 1% immigration shock to Istanbul alone reduces local real wages by 0.56% while increasing Ankara's real wages by 0.35%. The same shock to Ankara reduces local real wages by 0.71% while raising Istanbul's real wages by 0.20%. When both receive immigrants simultaneously, their real wages decrease by only 0.36%—substantially less than the -0.64% average of their separate effects. Moreover, ATT can turn positive if accumulated spillovers are large enough: a 3% immigration shock to Istanbul and Ankara fully offsets the negative effects of a 1% shock to the four least central cities, yielding positive average real wage effects in host regions.

Second, ATC estimates are systematically positive, violating the stable unit treatment value assumption. When treated regions are predominantly central cities, control regions experience real wage increases up to 0.82%, making them inappropriate counterfactuals for estimating treatment effects.

Third, the relationship between ATT and ATC depends critically on production technology and the outcome variable. Figure E.2 Panels C and D show results for nominal wages—wages unadjusted for local price changes—a standard outcome in empirical studies. When labor and intermediates are gross substitutes ($\sigma_u = 10$, $\sigma_l = 1$), spillovers reverse direction: immigration to central cities reduces nominal wages in control regions through substitution toward intermediate inputs.

These simulations demonstrate that spatial difference-in-differences designs can yield mis-

[29] Appendix Section E shows that these spillover patterns are robust to alternative values of the elasticity of substitution parameters, which suggests that spillovers can be of first-order importance in various economies with different technology parameters.

leading inferences when host regions are central nodes. Under my estimated parameters, two distinct biases operate simultaneously. First, inter-host spillovers attenuate negative wage effects within treated regions, making the ATT less negative than partial equilibrium would predict, or even positive if enough central regions receive large shocks. Second, positive spillovers to control regions bias the DID estimate downward—toward finding more negative effects—since the control group no longer represents a valid counterfactual. Under different production technologies, spillover directions can reverse: Panels C and D show that when labor and intermediates are gross substitutes, immigration to central cities reduces nominal wages in control regions, biasing DID estimates upward. The bias direction and magnitude depend on both network structure and technological parameters—neither of which is typically known to researchers ex ante.

Consider two well-published papers using identical spatial difference-in-differences designs to exploit policy-induced immigration to border regions: Dustmann et al. (2017) study Czech immigration to Germany, while Beerli et al. (2021) examine EU immigration to Switzerland. Despite methodological similarity, Dustmann et al. (2017) find strong negative effects on native employment and wages, whereas Beerli et al. (2021) find positive effects. My results suggest an explanation beyond standard factors like labor market tightness or skill complementarity. The German host regions contain "various small but no large cities" (Dustmann et al., 2017, p.13), whereas the Swiss host regions include Basel, a major hub for pharmaceuticals, chemicals, and intermediate manufacturing. My framework predicts negligible spillovers in the former case but substantial positive spillovers in the latter. When multiple Swiss host regions simultaneously receive immigrants near a central node like Basel, immigration-induced cost reductions propagate through domestic trade linkages to other host regions, attenuating negative wage effects within treated regions and potentially turning the average treatment effect positive despite local displacement. This inter-host spillover mechanism can reconcile the conflicting findings across these otherwise comparable studies.

My numerical results also offer a possible explanation as to why different papers disagree on the effects of the Mariel Boatlift on Miami's labor market. In the 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. These results are later challenged by Borjas (2017), who find large negative effects on low-skill natives' wages. This challenge itself is later challenged by Peri and Yasenov (2019), who use synthetic controls to address pre-trends and replicate Card's main findings. Clemens and Hunt (2019) show that contradictory findings on the effects of the Mariel Boatlift can be explained by a large difference in the pre- and post-Boatlift racial composition in certain very small subsamples of workers in the Current Population Survey.

My framework offers two complementary explanations for these patterns. First, if Miami maintains sufficient trade connections to the broader US economy, immigration-induced cost reductions would propagate through production networks, flattening Miami's labor demand curve. This mechanism, analogous to Istanbul's experience in my Turkish analysis, could generate genuinely small local wage effects despite substantial immigration inflows. The absence of detectable wage differences between Miami and comparison cities would then reflect economic reality rather than measurement error.

Second, even if wages in Miami decreased, network spillovers could simultaneously reduce labor demand in control regions, masking Miami's true treatment effects. This can happen if firms in the control regions directly or indirectly buy from firms in Miami, and labor and intermediates are gross substitutes for the main industries in these regions. Alternatively, even if labor and intermediates are gross complements, control regions might lose market share if the cost reductions in Miami and Miami's customers steal business from firms in these control regions, again depressing control region labor demand.

These mechanisms can reconcile the contradiction between standard labor demand theory and empirical findings. Labor demand can slope downward in Miami, as Borjas (2003) argues, yet generate no detectable differences between treatment and control regions, as Card (1990); Peri and Yasenov (2019) observe. Unfortunately, the lack of comprehensive firm-level input-output data for the US prevents direct testing of these network-based explanations. Nonetheless, my results demonstrate that production network spillovers can fundamentally alter the interpretation of spatial variation designs in immigration research.

5.2 Does Where Immigrants Live Matter for Welfare?

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

To investigate this question, I simulate the arrival of 10,000 immigrants in each of Turkey's 81 provinces. For each simulation, I calculate the changes in prices across the economy and the aggregate welfare gains. The regional welfare change $d \ln Y_r$ is given by:

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

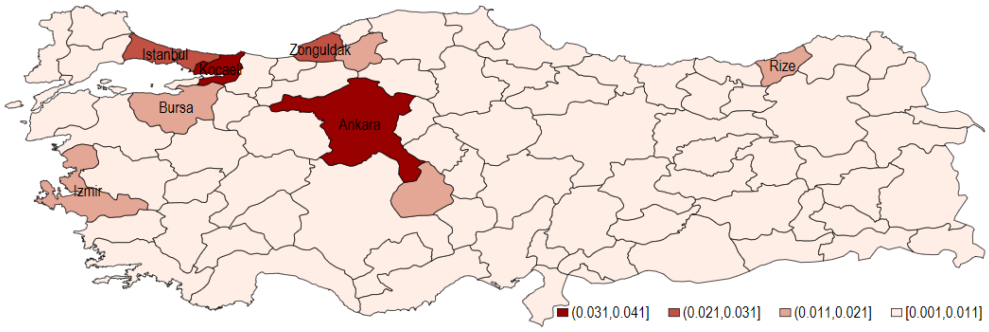
where welfare improves when either the region's share of total GDP (χ_r) increases or the prices of goods in its consumption basket decrease. I aggregate these regional welfare changes

into a national measure using population-weighted averages.

Figure 7 maps the welfare effects of placing 10,000 immigrants (a 0.012% population increase for Turkey) across different provinces. While immigration increases welfare in all simulations, the magnitude varies dramatically by location. In most provinces, welfare gains are modest: less than 0.004%. However, when immigrants settle in Izmir, Zonguldak, Istanbul, Kocaeli, or Ankara, welfare gains range from 0.02% to 0.04%, more than ten times larger than typical effects. These provinces 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, amplifying total welfare gains.

Notably, immigration to Kocaeli provides 50% larger welfare gains than the same number of immigrants going to Istanbul, despite Istanbul being more central. This occurs because Kocaeli's population is one-ninth of Istanbul's, so the same immigration shock lowers production costs in Kocaeli by a larger percentage, generating larger welfare gains in other cities. This highlights an important consideration: while the smallest, least-connected cities are suboptimal host locations from a welfare perspective, the largest cities are not necessarily optimal either. The optimal allocation depends on the precise structure of the production network.

Figure 7: Heatmap of total welfare effects of immigration across host regions



Notes: This figure shows the results from 81 counterfactuals, one for each province of Turkey. Each counterfactual consists of an arrival of 10,000 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.

These results should not be interpreted as advocating that all immigrants be directed to central network nodes, as I abstract from congestion externalities, housing supply elasticity, and local public goods provision. Rather, the key insight is that production network centrality amplifies immigration's economic benefits—a previously unrecognized first-order effect that should complement existing criteria (job availability, population balance) in spatial allocation decisions, particularly when there are multiple feasible destinations.

5.3 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 (Turkish Red Crescent and WFP, 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, I extend the baseline model to incorporate both low- and high-skill labor, with details provided in the Appendix Section A.4. One important caveat is that I must assume the EoS between low- and high-skilled workers ($\sigma_S = 1$) because the employer-employee matched data do not show the education of the workers.

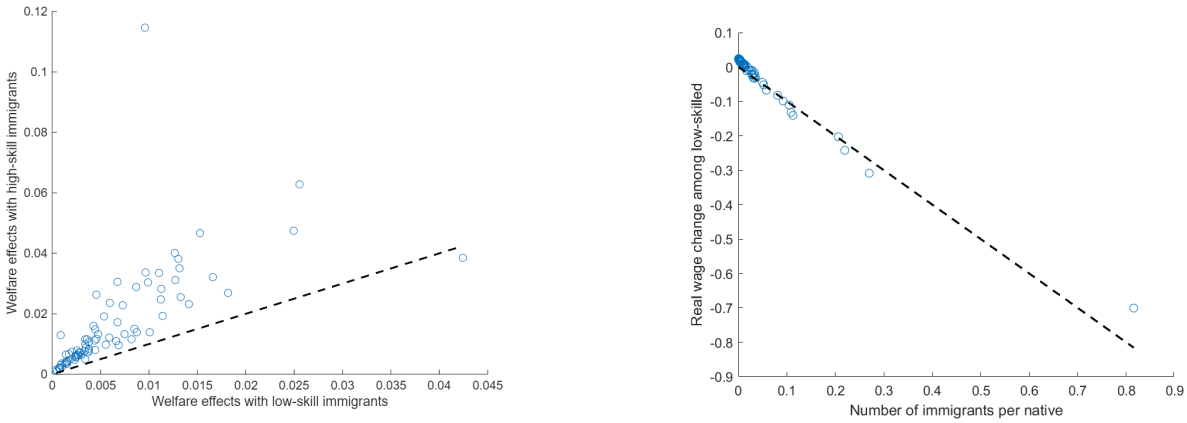
To examine how spillovers vary with immigrant skill levels, I conduct paired counterfactuals for each of Turkey's 81 provinces. For each province, I simulate two scenarios: one with 10,000 low-skill immigrants and another with 10,000 high-skill immigrants, and then compare the resulting welfare effects.

Figure 8a compares the welfare effects of low-skill versus high-skill immigration. Each circle represents one of the 81 NUTS-3 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 8a reveals two key patterns. First, most regions generate negligible welfare effects from immigration regardless of skill composition. These minimal effects reflect the limited spillover capacity of non-central regions: when host regions lack strong inter-regional trade connections, cost reductions fail to propagate through the production network, which constrains the welfare gains.

Second, central regions exhibit stark skill-based differentials in welfare generation. For example, a 10,000-immigrant shock in Bursa increases total welfare by 0.064% when immigrants are highly skilled versus 0.026% when low-skilled, a 2.5-fold difference. This differential stems directly from the structure of Turkey's production network: high-skill-intensive industries maintain stronger inter-regional trade linkages than their low-skill counterparts. Consequently, wage reductions in high-skill-intensive sectors propagate more extensively through the economy, amplifying the aggregate welfare impact of high-skill immigration to central nodes.

Figure 8: Skill composition and general equilibrium effects of immigration



(a) Low-skill vs. high-skill welfare effects

(b) Partial vs. general equilibrium effects

Notes: Panel (a) shows the results from 162 counterfactuals, two for each NUTS-3 region in Turkey. For each region, I calculate the total welfare change when 10,000 low-skill immigrants (x-axis) and 10,000 high-skill immigrants (y-axis) 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. The dashed line is the 45-degree line. Panel (b) shows the partial vs. general equilibrium effects of Syrian immigration using the provincial distribution of the number of immigrants per native in 2019. The general equilibrium changes in wages and prices are calculated as a solution to the system of linear equations given in Appendix Section A.4. Each circle denotes a Turkish province. The dashed line is the $-45°$ line.

5.4 Model-based Factual: Quantifying the General Equilibrium Effects of Syrian Immigration

The 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, one would expect limited general equilibrium effects.

To test this prediction, I calculate how the low-skilled Syrian immigration affects Turkish natives' real wages and compare these general equilibrium effects with partial equilibrium predictions. Figure 8b 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 would be observed 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 the 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.

6 Conclusion

This paper formalizes how immigration-induced wage changes propagate through production networks, isolates the relevant economic forces, tests them empirically using novel methods, and quantifies immigration's total effects on wages and welfare across regions. The results help resolve persistent puzzles in the immigration literature, guide practitioners in identifying potential SUTVA violations in spatial designs, and inform policy decisions regarding immigrant allocation.

The model purposefully abstracts from other channels through which immigrants affect host economies, including technological change (Lewis, 2011), entrepreneurship (Akcigit et al., 2017), consumption patterns (Galaasen et al., 2025), offshoring (Olney and Pozzoli, 2021), markups (Kim et al., 2025), and monopsony power (Naidu et al., 2016). All these forces can propagate through production networks, and investigating them is a natural direction for future work.

My finding that large cities generate substantial spillovers has significant implications for practitioners. Immigration to smaller, less developed regions typically 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 using spatial variation designs. Conversely, economic migration often targets larger, more connected cities. European hubs like Brussels, Frankfurt, and Munich, which maintain the highest foreign-to-native ratios in the EU (Mayors of Europe, 2019), likely generate significant spillovers throughout Europe, potentially biasing traditional empirical approaches that assume spatial independence.

Finally, while my model demonstrates that immigrants can reduce wages in host regions and harm some natives, it also reveals that immigration generates substantial welfare gains when immigrants settle in central regions. The former has dominated academic and policy discourse, while the latter represents a novel finding that can provide important nuance to contemporary immigration debates. This distinction proves particularly relevant today, as anti-immigrant sentiment has intensified globally (Hangartner et al., 2019; Alesina and Tabellini, 2024), making it crucial for policymakers to understand immigration's broader economic benefits alongside its distributional consequences.

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A Model Appendix

A.1 Proofs

Before showing the proofs, I introduce some notation. The trade matrix Ω is of size $(N + R) \times (N + R)$, where the last R rows are zeros. I 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:

$$\Psi = \left(\begin{array}{c|c} \Psi^p & \Psi^p\Omega^f \\ \hline 0 & I \end{array}\right), \tag{15}$$

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

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

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

Putting this back into the previous equation, I get:

$$\begin{aligned} d\ln\tilde{\Omega}_{i,L} &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})d\ln w_r - (1-\sigma_u)\sum_{j=1}^{n}\tilde{\Omega}_{ij}d\ln p_j, \\ &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})\left(d\ln w_r - \sum_{j=1}^{n}\frac{\tilde{\Omega}_{ij}}{\tilde{\Omega}_{i,M}}d\ln p_j\right). \end{aligned} \tag{16}$$

■

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, I can show the change in costs as:

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

Writing this in vector form, I get:

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

which implies

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

■

Proof of Proposition 2. From the accounting identity, I can write

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

Under Cobb-Douglas final demand, within-region budget shares $\overline{b_{r_j}}$ are constant, so $d\overline{b_{r_j}} = 0$ and the product rule yields two terms:

$$d\lambda_i = \sum_j \overline{b_{r_j}}d\chi_{r_j}\Psi_{ji} + \sum_j \overline{b_{r_j}}\chi_{r_j}d\Psi_{ji}. \tag{17}$$

Focusing on the first part of equation 17, I can write χ_{r_j} as:

$$\chi_r = \sum_{k \in r} \pi_k + w_r L_r.$$

Since profits are $\pi_k = \lambda_k(1 - 1/\mu_k)$ and markups are constant, $d \ln \pi_k = d \ln \lambda_k$. Differentiating and dividing by χ_r gives

$$d \ln \chi_r = \sum_{k \in r} \frac{\pi_k}{\chi_r} d \ln \lambda_k + \frac{\lambda_r}{\chi_r} d \ln \lambda_r$$

where $\lambda_r = w_r L_r$ and $d \ln \lambda_r = d \ln w_r + d \ln L_r$.

Focusing on the second part of equation 17 and using matrix calculus, I can show:

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

Hence, I need to calculate $d\Omega$. First, using CES algebra, I can write:

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

Taking the natural logarithm and totally differentiating gives:

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

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:

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

Collecting terms, one can show:

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

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

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

From Proposition 3, I know:

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

More succinctly, I 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 $d\Omega_{ij}$, I get:

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

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

$$\begin{aligned} d\Psi_{os} =& \sum_{j=1}^{n} \frac{\Psi_{oj}}{\mu_j} (1-\sigma_l) Cov_{\tilde{\Omega}^{(j)}} \left(\sum_g \tilde{\Psi}_{(g)} d\ln w_g, \sum_i I_{(i)} \Psi_{is} \right) \\ &+ \sum_{i=1}^{n} \Psi_{oi} \frac{\sigma_l - \sigma_u}{\mu_i} \frac{\tilde{\Omega}_{i,L}}{\tilde{\Omega}_{i,M}} \left(\sum_{k=1}^{n} \tilde{\Psi}_{ik}^{p} \tilde{\Omega}_{k,L} d\ln w_{r_k} - d\ln w_{r_i} \right) \sum_{j=1}^{n} \tilde{\Omega}_{ij} \Psi_{js}. \end{aligned}$$

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

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

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

$$d\ln \chi_r = \sum_{k \in r} \frac{\pi_k}{\chi_r} d\ln \lambda_k + \frac{\lambda_r}{\chi_r} d\ln \lambda_r.$$

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

■

A.2 From Theorem 1 to Structural Equations

I now show how the structural equations in equation 5 follow from Theorem 1. Starting from the labor share equation and substituting $d\ln p_j = \sum_{k=1}^{n} \tilde{\Psi}_{jk}\tilde{\Omega}_{k,L} d\ln w_{r_k}$ from Proposition 3:

$$\begin{aligned} d\ln \Omega_{i,L} &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})\left(d\ln w_{r_i} - \sum_{j=1}^{n} \frac{\tilde{\Omega}_{ij}}{\tilde{\Omega}_{i,M}} \sum_{k=1}^{n} \tilde{\Psi}_{jk}\tilde{\Omega}_{k,L} d\ln w_{r_k}\right) \\ &= (1-\sigma_u)(1-\tilde{\Omega}_{i,L})\left(\frac{1}{\tilde{\Omega}_{i,M}} d\ln w_{r_i} - \frac{1}{\tilde{\Omega}_{i,M}} \sum_{k=1}^{n} \tilde{\Psi}_{ik}\tilde{\Omega}_{k,L} d\ln w_{r_k}\right) \\ &= \underbrace{(1-\sigma_u) d\ln w_{r_i}}_{\text{Direct effect}} \underbrace{-(1-\sigma_u) \sum_{r=1}^{R} \tilde{\Psi}_{i,r} d\ln w_r}_{\text{Upstream exposure}} \end{aligned}$$

where the last step uses $1 - \tilde{\Omega}_{i,L} = \tilde{\Omega}_{i,M}$ and the block structure of the Leontief inverse in equation 15 to write $\sum_{k=1}^{n} \tilde{\Psi}_{ik}\tilde{\Omega}_{k,L} d\ln w_{r_k} = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} d\ln w_r$. The first term captures the direct effect of local wage changes on firm i's labor share. This term is absorbed by the empirical design for two reasons: (1) firms in host regions with large immigrant shares are excluded from the sample, and (2) the SIV estimator compares firms within the same region-industry cells, differencing out common local wage shocks. The upstream exposure in equation 5 is therefore defined as the second term. The downstream exposure measures follow analogously by substituting Proposition 3 into Proposition 2.

A.3 Counterfactuals Without Demand Effects

In the main model, immigrants supply labor and consume goods. It is of general interest to separate the effects of these two actions. To calculate the effects of a scenario in which immigrants supply labor but do not consume goods, I change the system of linear equations in a small way.

$$
\begin{aligned}
d\ln\lambda_r =& \sum_{i\in r}\frac{\lambda_i\Omega_{iL}}{\lambda_r}(d\ln\lambda_i + d\ln\Omega_{i,L}),\\
d\ln\Omega_{i,L} =& (1-\sigma_u)(1-\tilde{\Omega}_{i,L})(d\ln w_{r_i} - \sum_{j=1}^{n}\frac{\tilde{\Omega}_{ij}}{\tilde{\Omega}_{i,M}}d\ln p_j),\\
d\ln\lambda_i =& (1-\sigma_l)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i\mu_j}Cov_{\tilde{\Omega}^{(j)}}\left(d\ln p, \Psi_{(i)}\right),\\
&+(\sigma_u-\sigma_l)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,L}\left(d\ln w_{r_j} - \sum_{k=1}^{n}\frac{\tilde{\Omega}_{jk}}{\tilde{\Omega}_{j,M}}d\ln p_k\right)(\Psi_{ji}-I_{ji}),\\
&+\frac{1}{\lambda_i}\sum_j\sum_r b_{rj}\Psi_{ji}\chi_r d\ln\chi_r,\\
d\ln\chi_r =& \left(\sum_{i\in r}\frac{\pi_i}{\chi_r}d\ln\lambda_i\right) + \frac{\lambda_r}{\chi_r}d\ln w_r,\\
d\ln p_i =& \sum_{j=1}^{n}\tilde{\Psi}_{ij}\tilde{\Omega}_{j,L}d\ln w_{r_j},\\
d\ln w_r =& d\ln\lambda_r - d\ln L_r.
\end{aligned}
\tag{18}
$$

where on line 4, I change the change in regional labor income $d\ln\lambda_r$, which equals the change in wages and labor, into just the change in wages $d\ln w_r$.

A.4 Model with Skill Heterogeneity

A.4.1 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

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

where A_i is a Hicks-neutral productivity shifter, y_i is total output, p_j is the price of good j, ℓ_i 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. I assume common elasticities of substitution within nests: σ_u denotes the elasticity of substitution between labor and intermediate goods, σ_m is the elasticity of substitution between different intermediate goods (denoted σ_l in the baseline model), and σ_S is the elasticity of substitution between low- and high-skill labor. I normalize $\sum_j \alpha_{i,j} = 1$. Let C_i denote the unit cost of firm i. I assume that firms have constant and exogenous markup μ_i, and therefore set price $p_i = \mu_i C_i$.

Note that this specification extends the baseline model by introducing skill heterogeneity through an additional CES nest for labor types. The three-tier structure—with σ_u governing substitution between labor and intermediates, $\sigma_m \equiv \sigma_l$ governing substitution across intermediates, and σ_S governing substitution between skill types—allows the model to capture both skill-biased effects of immigration and their differential propagation through the production network.

Differences from the Baseline Model

Final demand, labor supply, and market clearing conditions are identical to the baseline model, except that the representative consumer's budget constraint now includes both low-skill and high-skill wage income: $w_{r,l}\ell_r + w_{r,h}h_r$. Both types of labor are inelastically supplied and immobile across regions. 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.

The propositions from the baseline model carry through with two modifications. First, the scalar wage change $d\ln w_{r_j}$ is replaced by the employment-weighted average wage change $\overline{w_j} \equiv \frac{1}{\tilde{\Omega}_{j,L}}\left(\tilde{\Omega}_{j,l} d\ln w_{r_j,l} + \tilde{\Omega}_{j,h} d\ln w_{r_j,h}\right)$. Second, the elasticity σ_l is replaced by σ_m. Prices are given by $d\ln p_i = \sum_{f=1}^F \tilde{\Psi}_{i,f} d\ln w_f$, where f indexes factors (low- and high-skill labor across regions). Proofs follow the same steps as in the baseline model.

With these modifications, the following theorem fully characterizes the equilibrium.

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.*

$$
\begin{aligned}
d\ln w_f =& d\ln\lambda_f - d\ln L_f \\
d\ln p_i =& \sum_{f=1}^{F}\tilde{\Psi}_{i,f}d\ln w_f \\
d\ln\lambda_i =& \sum_{j=1}^{n}(1-\sigma_m)\frac{\lambda_j}{\lambda_i\mu_j}Cov_{\tilde{\Omega}^{(j)}}\left(d\ln p,\Psi_{(i)}\right) \\
&+(\sigma_u-\sigma_m)\sum_{j=1}^{n}\frac{\lambda_j}{\lambda_i}\tilde{\Omega}_{j,L}\left(d\ln\overline{w_{r_j}}-\sum_{k=1}^{n}\frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,M}}d\ln p_k\right)(\Psi_{ji}-I_{ji}) \\
&+\frac{1}{\lambda_i}\sum_j\sum_r\overline{b_{rj}}\Psi_{ji}\chi_r d\ln\chi_r \\
d\ln\chi_r =& \left(\sum_{i\in r}\frac{\pi_i}{\chi_r}d\ln\lambda_i\right)+\frac{\lambda_r}{\chi_r}d\ln\lambda_r \\
d\ln\lambda_r =& s^w_{ls}d\ln\lambda_{rl}+s^w_{hs}d\ln\lambda_{rh} \\
d\ln\lambda_f =& \sum_{i=1}^{N}\frac{\lambda_i\Omega_{if}}{\lambda_f}d\ln\lambda_i+\sum_{i=1}^{N}\frac{\lambda_i\Omega_{if}}{\lambda_f}d\ln\Omega_{if} \\
d\ln\tilde{\Omega}_{il} =& d\ln\tilde{\Omega}_{iL}+(1-\sigma_S)\left[d\ln w_{r_i,l}-\frac{1}{\tilde{\Omega}_{iL}}\left(\tilde{\Omega}_{il}d\ln w_{r_i,l}+\tilde{\Omega}_{ih}d\ln w_{r_i,h}\right)\right] \\
d\ln\tilde{\Omega}_{ih} =& d\ln\tilde{\Omega}_{iL}+(1-\sigma_S)\left[d\ln w_{r_i,h}-\frac{1}{\tilde{\Omega}_{iL}}\left(\tilde{\Omega}_{il}d\ln w_{r_i,l}+\tilde{\Omega}_{ih}d\ln w_{r_i,h}\right)\right] \\
d\ln\tilde{\Omega}_{iL} =& (1-\sigma_u)\left[\frac{1-\tilde{\Omega}_{iL}}{\tilde{\Omega}_{iL}}(\tilde{\Omega}_{il}d\ln w_{rl}+\tilde{\Omega}_{ih}d\ln w_{rh})-\sum_{j=1}^{n}\tilde{\Omega}_{ij}d\ln p_j\right]
\end{aligned}
\tag{19}
$$

Proof follows the same steps as for the baseline model.

B Data Appendix

B.1 Calculating Trade Exposures

This section describes the calculation of firm-level and region-industry level trade exposures.

For computational tractability in the counterfactual analyses, I work with representative firms at the region-industry level. I define regions as Turkey's 81 provinces and 86 industries at the two-digit classification level. Given that not every industry operates in each province, I obtain 4185 region-industry cells in total. Computing the trade exposures $[U, D1, D2]$ requires inverting 4185×4185 matrices, which remains computationally feasible at this level of aggregation.

Working with firm-level data introduces several considerations that merit detailed discussion.

B.1.1 Data Cleaning

Trade relationships, transaction volumes, sales, and labor payments exhibit substantial year-to-year variation. To minimize measurement error, I focus on firms that maintain continuous operations and file complete balance sheet statements throughout the pre-period from 2006 to 2010. I further restrict the sample to firms reporting positive labor costs in the tax records, excluding firms without employees. This yields 285,178 firms in the analysis sample, some with observed trading relationships and others without.

I define material costs as total firm purchases recorded in the VAT data, encompassing both domestic purchases and imports. Firms making no intermediate purchases receive a labor share equal to one.

The data reveal 9006 firms (3.2% of the sample) whose total costs (intermediate purchases plus labor costs) exceed reported sales, even when aggregated over the entire 2006–2010 pre-period. This pattern poses challenges for the model's validity. Well-defined Leontief inverse matrices require that each row sum in the trade matrices remains less than or equal to one, a condition violated when costs exceed sales. I address this issue by treating sales information from balance sheets as measured with error relative to the more precisely recorded labor costs and purchases from tax records. Accordingly, I adjust these firms' sales upward to equal their total costs, effectively imposing a markup of one.

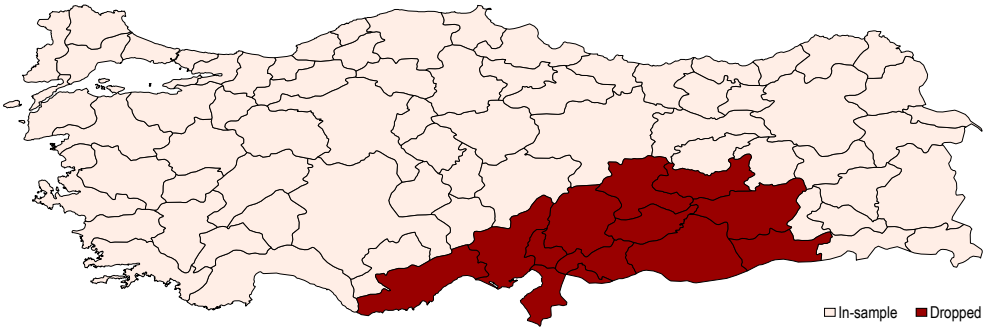
B.1.2 Measuring Upstream Exposure

The upstream exposure effect on labor share follows from the model:

$$U_i = \sum_{k=1}^{n} \tilde{\Psi}_{ik} \tilde{\Omega}_{k,L} \delta_{r_k}$$

Implementing this measure using the full firm-level network would require inverting a $285,000 \times 285,000$ matrix. While the cost-based trade matrix $\tilde{\Omega}$ is sparse, its Leontief inverse $\tilde{\Psi}$ is not. Moreover, the firm-level network approach cannot capture new trading relationships that may form endogenously in response to the immigration shock. Region-industry level trade matrices prove more robust to such endogenous network formation than firm-to-firm matrices. As Appendix Section C.1 demonstrates, most new trading relationships form within rather than across regions. This implies that even when cross-regional relationships do

Figure B.1: Regions omitted from the main analysis



emerge, they occur predominantly between firms that already maintain trading connections with that region.

However, using region-industry level aggregation for the reduced-form analysis reduces statistical power and may compromise identification credibility. Consider comparing textile and finance firms in Istanbul because textile firms typically purchase from southeast regions while finance firms do not. This comparison provides less compelling identification than comparing two textile firms in Istanbul that happen to differ in their exposure to immigrant-receiving regions through their specific trading partners.

To balance these competing considerations, I calculate firm-level trade exposures while exploiting region-industry level variation in trading patterns. Two textile firms in Istanbul exhibit differential upstream exposure if one sources inputs from host regions in the southeast while the other sources from non-host regions. For firms purchasing identical quantities from a particular region-industry cell, I do not distinguish between those buying from labor-intensive versus non-labor-intensive suppliers, as changing trading partners across labor intensity dimensions proves more feasible than changing regional sourcing patterns.

Formally, I calculate upstream exposure as:

$$U_{it} = \sum_{j=1}^{J} \tilde{\Psi}_{ij} \times \tilde{\Omega}_{j,L} \times \delta_{jt}, \tag{20}$$

where $\tilde{\Psi}_{NJ}$ represents the firm-by-region-industry trade matrix whose ijth element captures firm i's cost dependence on region-industry j, $\tilde{\Omega}_{j,L}$ denotes the labor share of region-industry j, and δ_{jt} measures the region-industry-time level immigration shock.

This approach offers several advantages. First, the $\tilde{\Psi}_{NJ}$ matrix requires substantially less computational resources than $\tilde{\Psi}_{NN}$. Second, while upstream exposure retains firm-level variation, it primarily exploits region-industry level differences in trading relationships.

Having defined upstream exposure using region-industry level trading partners, the downstream exposures follow naturally. Both $D1$ and $D2$ depend on how firms' prices and costs respond to the shock, captured by $d\ln p$. I calculate $d\ln p$ using the region-industry level framework and then construct the downstream exposure measures accordingly.

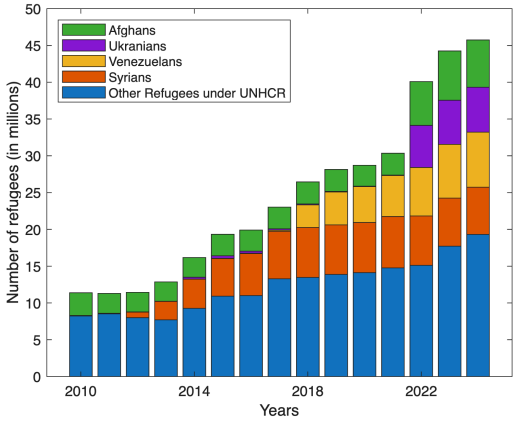
B.2 Summary Statistics

Table B.1: Summary Statistics

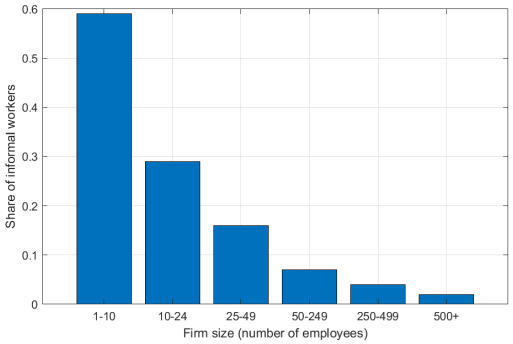
Number of employees	Wage Bill (in million)	Sales (in million)	Exporter	Labor Share
Panel A: All sizes				
33.11	0.52	7.4	0.27	0.31
(172.49)	(4.84)	(164)	(0.44)	(0.32)
Panel B: More than 50 employees in 2010				
217.74	4.00	68	0.71	0.16
(495.77)	(14.51)	(419)	(0.45)	(0.15)

Note: Data is restricted 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. Standard deviations are in parentheses.

Figure B.2: Global refugee trends and informality by firm size



(a) The Evolution of the Number of Refugees Globally



(b) The Ratio of Informal Workers Across Firm Size

Panel (a): Author's calculations using UNHCR data, publicly available from https://www.unhcr.org/refugee-statistics. Panel (b): Author's calculations using HLFS. Informality is defined as the ratio of workers who self-declare that their employer does not pay for social security, which is legally mandated for all formal workers in Turkey.

C Supporting Evidence

C.1 New Trade Formation

The model assumes constant trade networks. While firms can adjust trade volumes with existing partners, the model does not incorporate endogenous network formation. This simplification is unlikely to affect my results because regional connections matter more than specific firm identities: firms predominantly form new supplier relationships within regions where they already have trade partners. I provide both descriptive and regression evidence for this claim.

Descriptive Evidence

Turkey's trade network exhibits strong regional persistence. Of the 6.4 million buyer-seller connections in 2010, 4.0 million (62%) were new since 2008. These new connections display two striking patterns. First, 53% occurred within regions, reflecting the dominance of local trade. Second, among cross-regional connections, 59% involved buyers who already had suppliers in the destination region. Thus, even when firms expand beyond their home region, they overwhelmingly choose regions where they maintain existing relationships.

Regression Analysis

To control for firm characteristics and regional factors, I estimate how pre-existing regional connections predict future network formation. Using all firms in non-host regions, I identify whether each firm had a supplier from a host region in 2010. I then track whether these firms established new supplier relationships by 2019, distinguishing between new connections in host regions (primary outcome) and non-host regions (placebo outcome). I estimate:

$$y_{irj} = \beta D_i + \theta W_{irj} + \epsilon_{irj}, \tag{21}$$

where D indicates having a pre-existing supplier in a host region in 2010, and W includes cubic polynomials of supplier count and region-by-industry fixed effects. This specification compares firms within the same region-industry cell, which isolates the predictive power of existing regional connections.

Table C.1 presents the results. Panel A shows that firms with pre-existing host-region suppliers are 22–40 percentage points more likely to form new relationships in host regions, with larger effects for manufacturing firms. These estimates remain stable across specifications and are statistically significant at the 5% level throughout.

Panel B provides a placebo test using new connections in non-host regions as the outcome. If pre-existing connections merely proxied for firms' general propensity to form new relationships, we would observe similar positive coefficients. Instead, all estimates are small, negative, and statistically insignificant, confirming that the effect is specific to host regions.

The evidence demonstrates that regional connections, rather than specific firm relationships, drive network expansion. Firms with existing ties to host regions are substantially more likely to form additional connections there, validating my focus on region-industry-level rather than firm-level exposure measures.

Table C.1: The Effects of Having an Existing Regional Supplier on New Trade Formation

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: New supplier in host region						
Pre-existing regional supplier	0.279***	0.214***	0.224***	0.376*	0.387*	0.398*
	(0.052)	(0.048)	(0.047)	(0.187)	(0.185)	(0.179)
Panel B: New supplier in non-host region						
Pre-existing regional supplier	-0.029	-0.062	-0.021	-0.046	-0.042	-0.033
	(0.042)	(0.041)	(0.042)	(0.132)	(0.128)	(0.133)
Sample	All	All	All	Man	Man	Man
N	97484	97487	96747	20172	20172	19944
Controls						
Cubic of number of suppliers	N	Y	Y	N	Y	Y
Region-by-industry F.E.	N	N	Y	N	N	Y

Notes: In Panel A, the outcome is an indicator of whether the firm established a new supplier relationship in 2019 with a firm from a host region, where "new" is defined as a relationship that did not exist in 2008-2009. In Panel B, the outcome is an indicator of whether the firm established a new supplier relationship with a firm in a non-host region in 2019. The treatment variable is an indicator for the buyer firm having at least one supplier in host regions in 2010. The sample includes all firms in columns 1–3 and is restricted to manufacturing firms in columns 4–6. Robust standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

C.2 Industry Heterogeneity in Structural Parameters

I estimate equations 8 and 9 separately for each two-digit manufacturing industry and apply Empirical Bayes shrinkage to stabilize estimates from small samples. Figure C.1 presents the results. Panel A shows σ_u estimates using large firms: labor and intermediates are gross complements across all industries, with elasticities clustering around the aggregate estimate of 0.79. Panel B shows σ_l estimates: while most industries have elasticities near 1, some heterogeneity exists (e.g., textiles and basic metals above 1, chemicals below 1). Panel C estimates σ_u using all manufacturing firms, exploiting the similar upstream exposure effects across firm sizes; confidence intervals narrow and cross-industry variation decreases, supporting the common elasticity assumption.

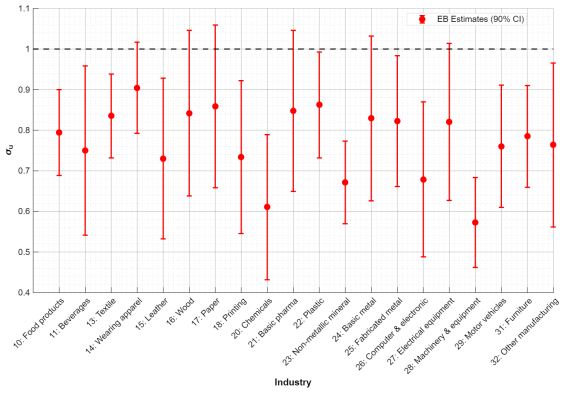
C.3 Native Migration Responses

This section examines whether native population movements respond to Syrian immigration, a potential violation of my identification strategy. I estimate both event-study and IV specifications at the province level to test for native migration responses.

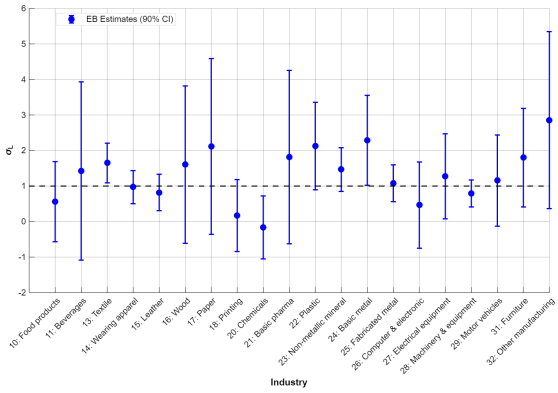
The event study specification is as follows:

$$y_{rt} = \sum_{t' \neq 2010} \beta_{t'} Z_r \mathbb{1}\{t = t'\} + f_r + f_t + \epsilon_{rt}. \tag{22}$$

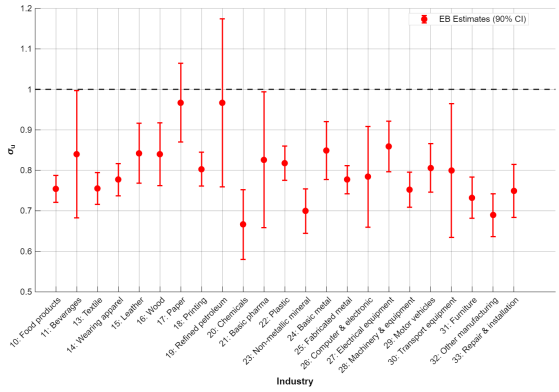
Figure C.1: Heterogeneity of EoS estimates across Manufacturing industries



(a) EoS between labor and intermediates



(b) EoS between intermediates



(c) EoS between labor and intermediates (all manufacturing firms)

Notes: Panels A and B report estimates from the same identification strategy as in the main text, which restricts the sample to manufacturing firms with 50+ employees in 2010, and estimates EoS parameters using GMM. Panel C reports estimates from an alternative design, which uses the sample from all manufacturing firms, and calculates EoS between labor and intermediates using the mapping in equation 10. Elasticity estimates using Empirical Bayes are reported. 90% confidence intervals are plotted.

The IV specification is as follows:

$$y_{rt} = \beta D_{rt} + f_r + f_t + \epsilon_{rt},$$
$$D_{rt} = \gamma Z_{rt} + g_r + g_t + \eta_{rt},$$

where y_{rt} represents the natural logarithm of in-migration, out-migration, or population; D_{rt} is the immigration treatment; Z_{rt} is the distance instrument; and f_r, f_t are region and time fixed effects.

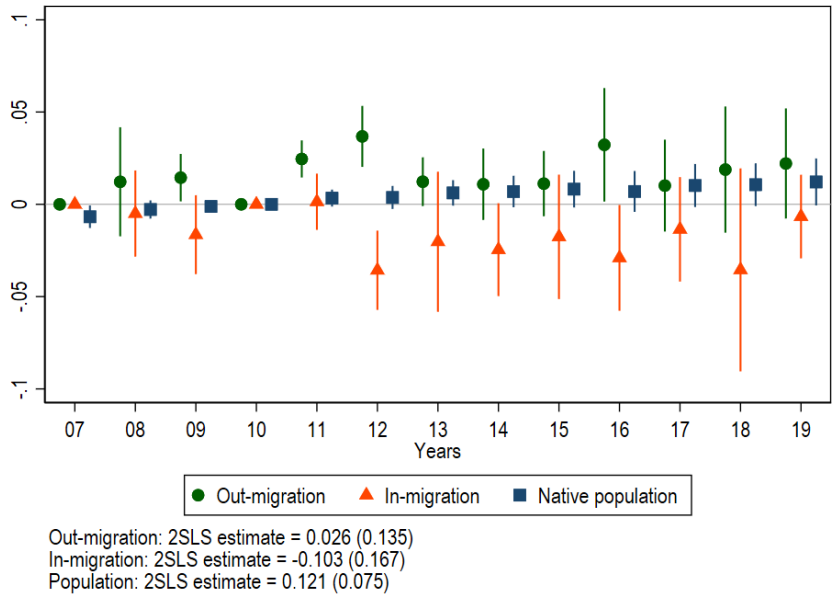
Figure C.2 presents the results. The event-study estimates reveal modest migration responses concentrated in 2011–2012, before large-scale Syrian arrivals. In-migration rates decline slightly while out-migration rates increase marginally during these early years. By 2013 and beyond, when the Syrian presence becomes substantial, native migration responses

are statistically indistinguishable from zero.

The economic magnitudes confirm that native migration cannot explain my results. A one standard deviation increase in the instrument, which corresponds to a 9% increase in the immigrant/native ratio by 2018, reduces in-migration by only 4%. Since annual in-migration constitutes less than 3% of local population in host regions, this translates to a negligible 0.01% population change per percentage point of immigration. Out-migration effects are similarly minimal.

These negligible migration responses allow southeastern regions to maintain their historical population growth trajectories. Despite hosting millions of Syrian refugees, these regions continue experiencing higher native population growth driven by persistently higher birth rates. Native labor mobility therefore plays no meaningful role in equilibrating regional labor markets following the immigration shock.

Figure C.2: Native migration responses to Syrian immigration



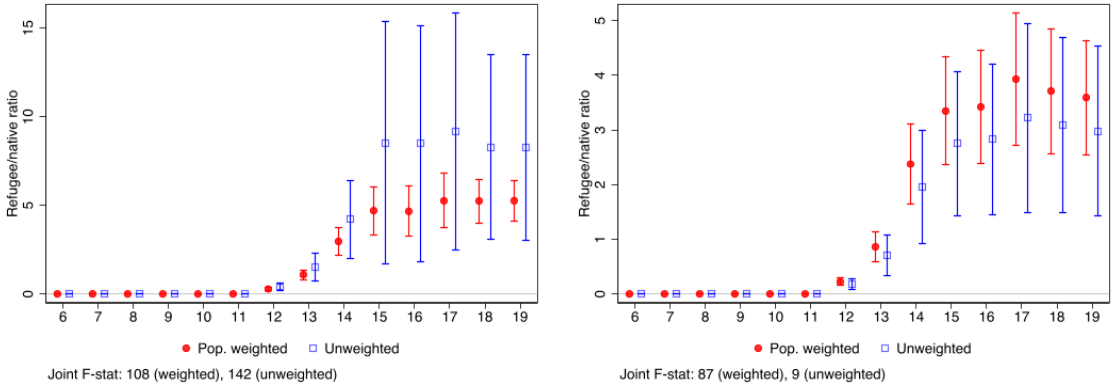
Notes: Event-study estimates from $y_{rt} = \sum_{t' \neq 2010} \beta_{t'} Z_r \mathbb{1}\{t = t'\} + f_r + f_t + \epsilon_{rt}$, where Z_r is the normalized distance share (standard deviation = 1) and f_r, f_t are region and time fixed effects. Outcomes are natural logarithms of in-migration, out-migration, and native population. Address-based tracking data begins in 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.

C.4 Alternative Instruments

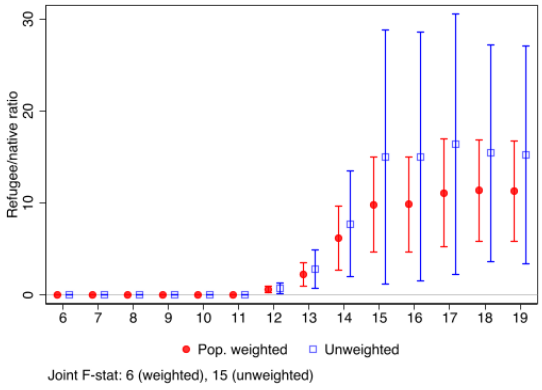
C.5 Sensitivity of Structural Elasticities to (calibrated) Labor Demand Elasticity

Since the structural elasticities depend on the calibrated ϵ^D, specifically $\sigma_u = 1 + \hat{\beta}_1 \epsilon^D$ and $\sigma_l = 1 - \hat{\beta}_2 \epsilon^D$, it is important to assess sensitivity to this calibration. Figure C.5 shows

Figure C.3: First-stage estimates across different instruments



(a) Distance IV **(b)** Language IV

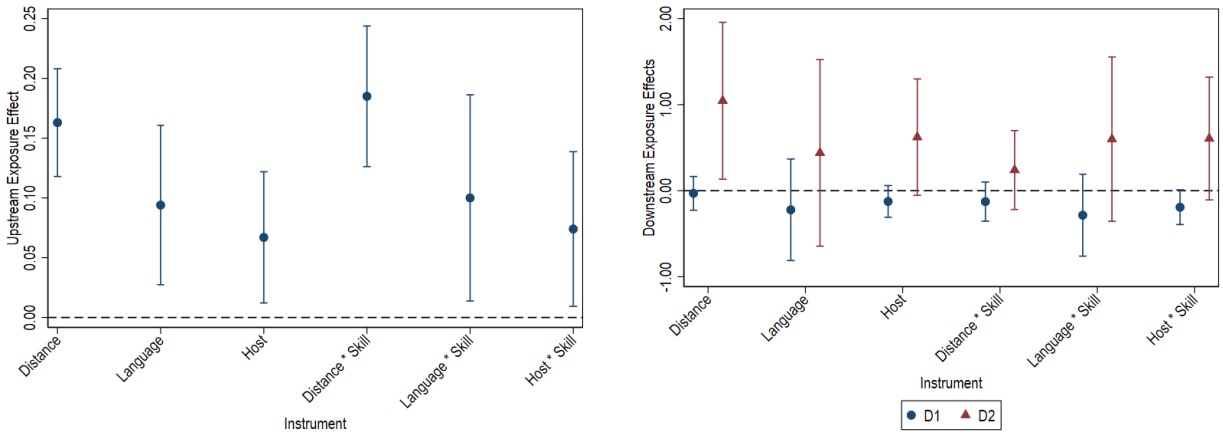


(c) Host Dummy

Notes: Each panel shows first-stage estimates from a nonparametric event-study regression: $\delta_{rt} = \sum_{t' \neq 2011} \beta_{t'} \mathbb{1}\{t' = t\} Z_r + \alpha_r + \alpha_t + \epsilon_{rt}$, where δ_{rt} is the refugee-to-native ratio and Z_r is the instrument share. Distance and language instruments are standardized to unit standard deviation; the host instrument is a dummy for the omitted regions. Red circles show population-weighted estimates, which give more weight to larger regions where more firms operate; blue squares show unweighted estimates, which treat all regions equally. Standard errors are clustered at the region level. 95% confidence intervals are plotted. Joint F-statistics test whether all post-2011 coefficients are jointly zero. The distance instrument has the strongest first stage in both specifications (F=108 weighted, F=142 unweighted), while the language instrument is strong when weighted (F=87) but weaker unweighted (F=9).

the implied 95% confidence intervals under alternative values of $\epsilon^D \in \{-2, -1.27, -1, -0.5\}$, using the distance-based instrument. The qualitative conclusions are robust: since $\hat{\beta}_1 > 0$ (estimated precisely) and $\hat{\beta}_2 \approx 0$, $\sigma_u < 1$ and $\sigma_l \approx 1$ hold for any $\epsilon^D < 0$, regardless of its magnitude.

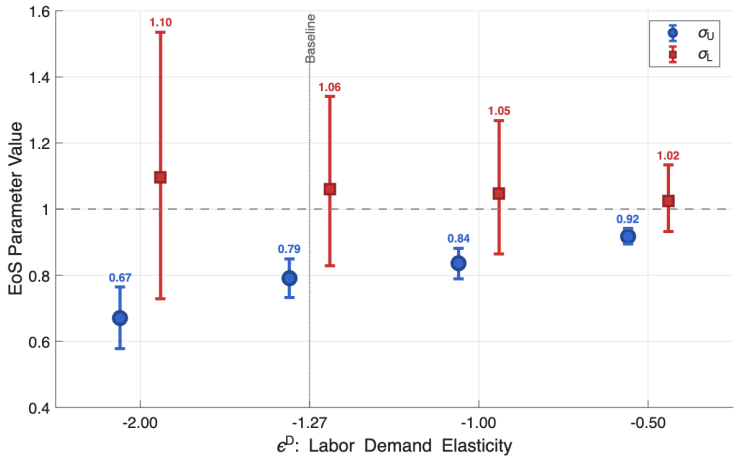
Figure C.4: Effects of trade exposures on labor demand and sales under different instruments



(a) Labor share **(b)** Sales

Notes: This figure shows the SIV estimates of the effects of upstream exposure on labor share and the effects of downstream exposures (D1 and D2) on sales, using different instruments. The regression equations are provided in equations 8 and 9 in the main text. Columns 1–3 use distance, language, and dummy shares in the construction of the shift-share instruments. In columns 4–6, I interact the regional shares with industry-level skill intensity, where skill intensity is measured as the share of workers without high school degrees in each industry. In these specifications, a firm has stronger upstream exposure if it purchases from firms operating in low-skill industries located in immigrant-hosting regions. Downstream exposures are calculated similarly. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

Figure C.5: Sensitivity of EoS estimates to the calibrated labor demand elasticity



Notes: This figure shows the 95% confidence intervals of σ_u and σ_l under alternative values of the calibrated labor demand elasticity ϵ^D, using the distance-based instrument and the sample of manufacturing firms with at least 50 employees. The baseline estimate uses $\epsilon^D = -1.27$ from Gulek (2024). Since $\sigma_u = 1 + \hat{\beta}_1 \epsilon^D$ and $\sigma_l = 1 - \hat{\beta}_2 \epsilon^D$, both estimates scale linearly with ϵ^D: as $|\epsilon^D|$ decreases, the EoS parameters compress toward 1. The dashed horizontal line marks $\sigma = 1$.

D Synthetic IV Robustness Checks

D.1 Comparisons between IV and SIV

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

I define the event-study equations for the IV estimator as follows: for labor share,

$$log(y^L_{isrt}) = \sum_{t' \neq 2011} \beta_{1,t'} U^Z_i \mathbb{1}\{t = t'\} + f^L_i + f^L_{srt} + \nu^L_{it}, \tag{23}$$

and for sales,

$$log(y^S_{isrt}) = \sum_{t' \neq 2011} \left(\beta^{D1}_{t'} D1^Z_i + \beta^{D2}_{t'} D2^Z_i\right) \mathbb{1}\{t = t'\} + f^S_i + f^S_{srt} + \nu^S_{it}. \tag{24}$$

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

Figure D.1 shows the results. In each panel, I plot estimates from the IV design with and without size-region-industry-time fixed effects, together with the baseline SIV estimates using distance-to-border as an instrument. Panels A, B, and C show upstream exposure effects on employment, wage bill, and labor share, respectively, while Panels D and E show downstream exposure effects on sales.

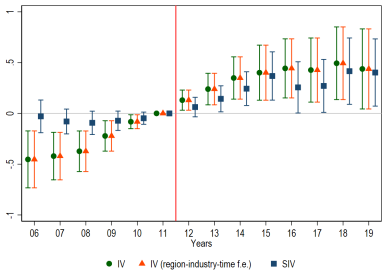
The results reveal that IV is biased in most, if not all, specifications. For example, more upstream-exposed firms followed differential trends from 2006 to 2011 in employment, wage bill, and labor share compared to less-exposed firms. This pattern persists even when controlling for region-industry-size-time fixed effects. Panel D also 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 the use of Synthetic IV in the main text.

Panel E 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, I require exogenous variation in all three treatment variables. Since pre-trends appear in two of the three cases, I cannot rely on IV for credible causal inference. This methodological challenge motivates the use of SIV.

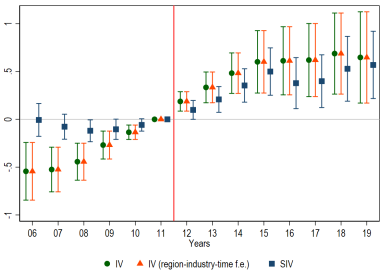
D.2 Robustness to Matching on Different Variables

In the main text, I argue that matching on trends in labor share and sales is crucial to create synthetic firms that follow similar economic trajectories. As evidence, I report that pre-trends disappear also in the unmatched outcomes of employment and payroll. Figure D.2 shows that the trends do not disappear when I match only on labor share or only on sales.

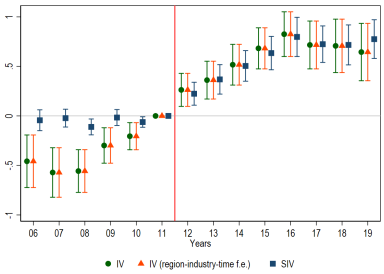
Figure D.1: Effects of trade exposures on firms' labor demand and sales



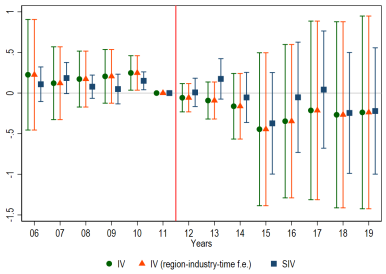
(a) Number of employees



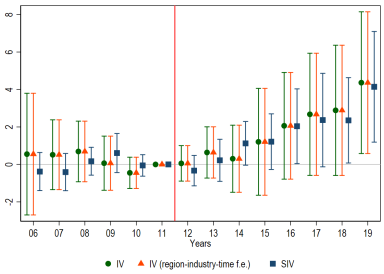
(b) Payroll



(c) Labor share



(d) Sales: Downstream-1



(e) Sales: Downstream-2

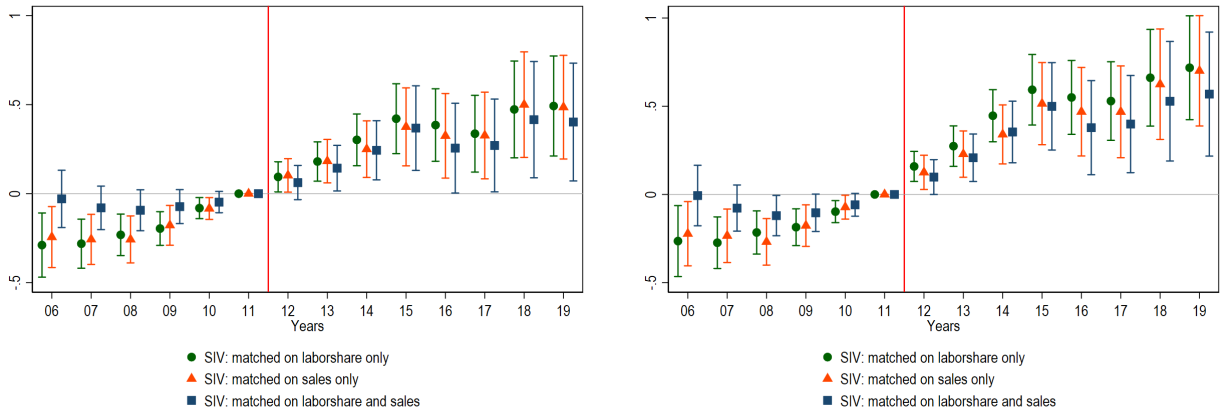
Notes: In Panels A, B, and C, the estimates come from the regression equation $y_{it} = \sum_{t' \neq 2011} \gamma_{1,t'} U_i^Z \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$, where the outcome variable is the natural logarithm of the number of workers in Panel A, of total payroll in Panel B, and of labor share in Panel C. In Panels D and E, the estimates come from the regression equation: $y_{it} = \sum_{t' \neq 2011} \left(\gamma_{2,t'} D1_i^Z + \gamma_{3,t'} D2_i^Z\right) \mathbb{1}\{t = t'\} + f_i + f_t + \nu_{it}$. SIV estimates use the debiased versions of the outcome and exposures, while IV uses the raw versions. SIV matching is based on the demeaned versions of labor share and sales. The instrument is based on the travel distance. Sample is restricted to manufacturing firms with at least 50 employees in 2010. Standard errors are clustered at the firm level. 95% confidence intervals are plotted.

Figure D.2a shows event-study estimates on firms' employment when I match on labor share only, sales only, and when I match on both jointly. Significant pre-trends remain in the pre-period when matching on single variables, which could raise concerns for the empirical design. Notably, the estimated effects in the post-period are similar across all matching types. This occurs because the estimated effects in the post-period are substantially larger than the magnitude of residual differential trends after the matching step. Figure D.2b repeats the analysis for payroll and finds the same results.

D.3 Robustness to Improving Pre-Treatment Fit

Figure D.3a shows the estimated effects when I match to improve pre-treatment fit for each specific outcome. Panel A shows upstream exposure effects on labor share when I match only on labor share (which improves pre-treatment fit) versus the default of matching on labor share and sales. Panels B and C show the estimated effects of D1 and D2 exposures, respectively, on sales when I match on sales only. Improving the pre-treatment fit does not change the results, providing evidence against concerns about under-fitting in the joint matching approach.

Figure D.2: Effects of matching on different variables on unmatched outcomes



(a) Number of employees **(b)** Payroll

Notes: This figure presents event-study estimates using the SIV design, where synthetic control weights are calculated using different matching metrics. Green circles represent estimates from matching on trends in log labor share only, orange triangles show results from matching on trends in log sales only, and blue rectangles display the preferred estimates, which match on trends in both labor share and sales simultaneously.

Figure D.3: Improving training fit: labor share and sales



(a) Labor share **(b)** Sales: D1 exposure **(c)** Sales: D2 exposure

Notes: This figure shows event-study estimates of the effects of upstream exposure on labor share and downstream exposure on sales, comparing the preferred SIV estimator (matching on both labor share and sales) with estimators that match only on trends in the outcome: labor share in Panel A and sales in Panel B. Matching solely on the outcome of interest improves the training fit, but because the baseline fit is already strong, this refinement produces no detectable change in the post-period estimates.

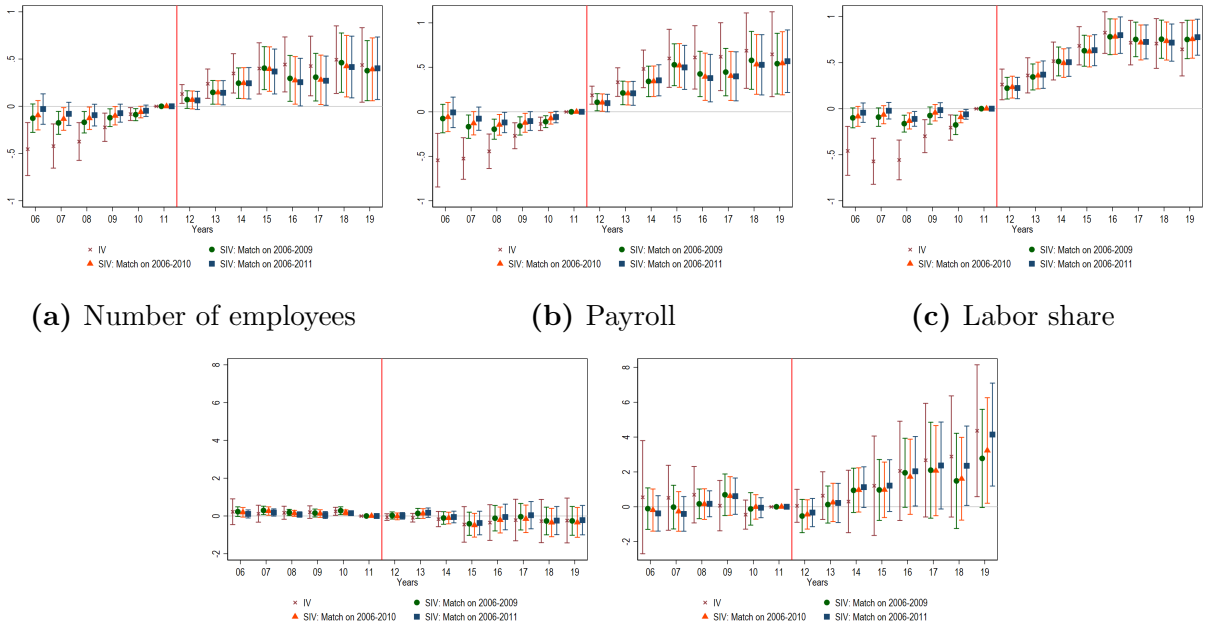
D.4 Robustness to Different Training Periods

To test for overfitting, I perform back-testing by matching on 2006–2009 and 2006–2010 instead of 2006–2011. Figure D.4 shows that SIV finds consistent signals across all variables and training periods.

D.5 2SLS estimates

Table D.1 extends the main analysis to employment and payroll, and compares results across all manufacturing firms and large firms only, using the distance instrument. Results are

Figure D.4: Robustness to different training periods



(a) Number of employees **(b)** Payroll **(c)** Labor share

(d) Sales: D1-exposure **(e)** Sales: D2-exposure

Notes: This figure shows event-study estimates from the SIV design where synthetic control weights are calculated using different training periods. The preferred specification uses the full pre-period (2006–2011) for training. Alternative specifications use truncated training periods of 2006–2009 and 2006–2010. All specifications outperform the reduced-form IV estimates, which are included for comparison.

similar across alternative instruments (language, host-region indicator, and skill-interacted variants).

Employment (Columns 1–3): Upstream exposure increases employment for both large firms and the full sample. The larger sample of all firms yields more precise estimates, but point estimates remain comparable across samples.

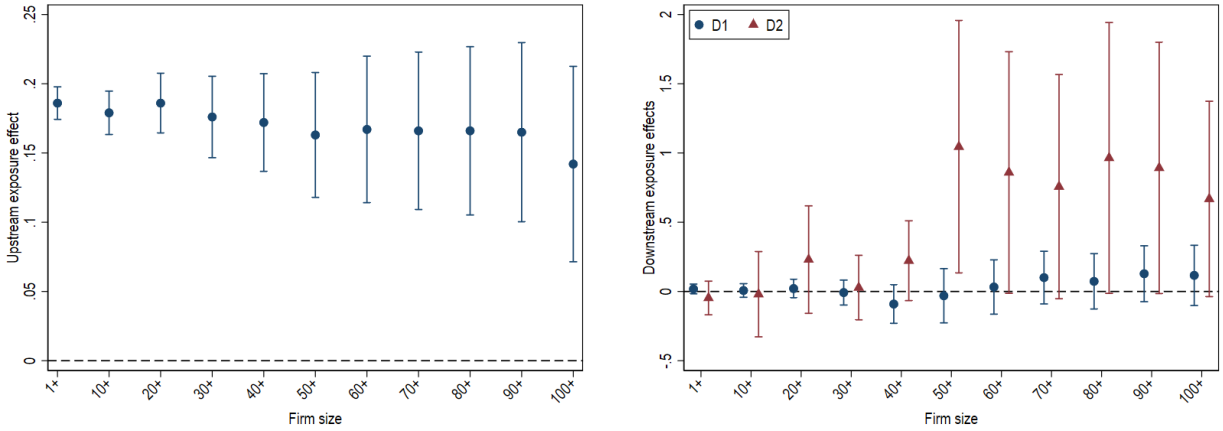
Payroll and Labor Share (Columns 4–9): Results mirror employment effects. Upstream exposure increases labor demand across both samples, with comparable point estimates across specifications, though precision varies when downstream exposures are included as controls.

Sales (Columns 10–12): Here the samples diverge sharply. For large firms, D1 exposure has no effect while D2 exposure significantly increases sales, a pattern robust to controlling for upstream exposure. For all firms, D1 effect remains null but D2 effect becomes negative (though insignificant). This negative D2 effect would violate the model's logic: it implies intermediates substitute more easily with labor than with each other, contradicting the positive upstream exposure and null D1 exposure effects. This pattern suggests that informality biases the sales estimates for small firms.[30] Figure D.5 confirms this: estimated D2 treatment effects jump discontinuously at the 50-employee threshold, precisely where

[30] One potential mechanism is that firms coordinate informality across margins: as firms substitute toward informal labor (Gulek, 2024), they shift some sales and input purchases to informal channels to maintain consistent accounting records, biasing measured D2 effects for small firms.

firms become significantly more formal due to increased government scrutiny.

Figure D.5: Estimated effects of trade exposures across different firm sizes



(a) Upstream Exposure Effects on Labor share **(b)** Downstream Exposure Effects on Sales

Notes: the 95% confidence intervals of SIV estimates, where the training period is 2006–2010, weights are calculated by matching on the trends in labor share and sales, and travel distance is used as an instrument. Each column shows the estimated effects using a different sample of manufacturing firms, where "x+" denotes firms with at least x employees in 2010.

Table D.1: Effects of Trade Exposures on Firms in Non-Host Regions (IV: Distance)

	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***	0.186***		0.204***	-0.013*		-0.014
	(0.006)		(0.007)	(0.006)		(0.007)	(0.006)		(0.007)	(0.007)		(0.009)
D1		-0.101***	-0.026		-0.129***	-0.019		-0.221***	0.084***		0.018	-0.003
		(0.015)	(0.018)		(0.016)	(0.020)		(0.015)	(0.017)		(0.018)	(0.023)
D2		0.048	0.038		0.033	0.019		0.108**	0.069*		-0.047	-0.044
		(0.060)	(0.059)		(0.057)	(0.056)		(0.042)	(0.041)		(0.062)	(0.063)
Panel B: 50+ employees												
U	0.084**		0.077	0.114***		0.086	0.163***		0.193***	0.012		-0.017
	(0.037)		(0.050)	(0.039)		(0.054)	(0.023)		(0.031)	(0.038)		(0.053)
D1		-0.128	-0.013		-0.205*	-0.077		-0.217***	0.073		-0.031	-0.056
		(0.107)	(0.147)		(0.120)	(0.167)		(0.058)	(0.070)		(0.100)	(0.140)
D2		0.378	0.354		0.340	0.313		-0.577**	-0.637**		1.045**	1.051**
		(0.361)	(0.361)		(0.380)	(0.380)		(0.292)	(0.283)		(0.465)	(0.466)

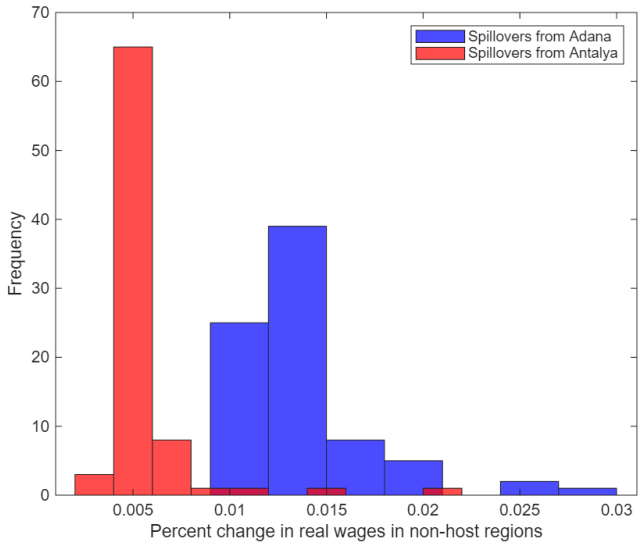
Notes: Sample is restricted to manufacturing firms that report positive sales throughout 2006–2019. Panel A shows SIV estimates for all manufacturing firms; Panel B restricts to firms with 50+ employees in 2010. There are 19,155 firms in Panel A and 1,224 in Panel B. Columns 1–3 report effects on employment, 4–6 on payroll, 7–9 on labor share, and 10–12 on sales. Within each outcome group, the first column estimates upstream exposure only, the second downstream exposures only, and the third includes all three exposures jointly. U denotes upstream exposure on firms that directly or indirectly buy from host regions. D1 captures downstream exposure through cross-price substitution between intermediates. D2 captures downstream exposure on firms that directly or indirectly sell to host region firms. Standard errors are clustered at the firm level.

E Additional Counterfactual Estimates

E.1 Comparison between Adana and Antalya

To illustrate how centrality drives spillover magnitude, I compare Adana and Antalya—two cities with similar populations and Domar weights but different economic structures. Figure E.1 shows the distribution of spillover effects from a 1% immigration shock to each city. The distributions barely overlap: the minimum spillover from Adana exceeds the 95th percentile from Antalya, confirming that the difference is systematic.

Figure E.1: Histogram of real wage changes in the non-host regions: Adana vs. Antalya



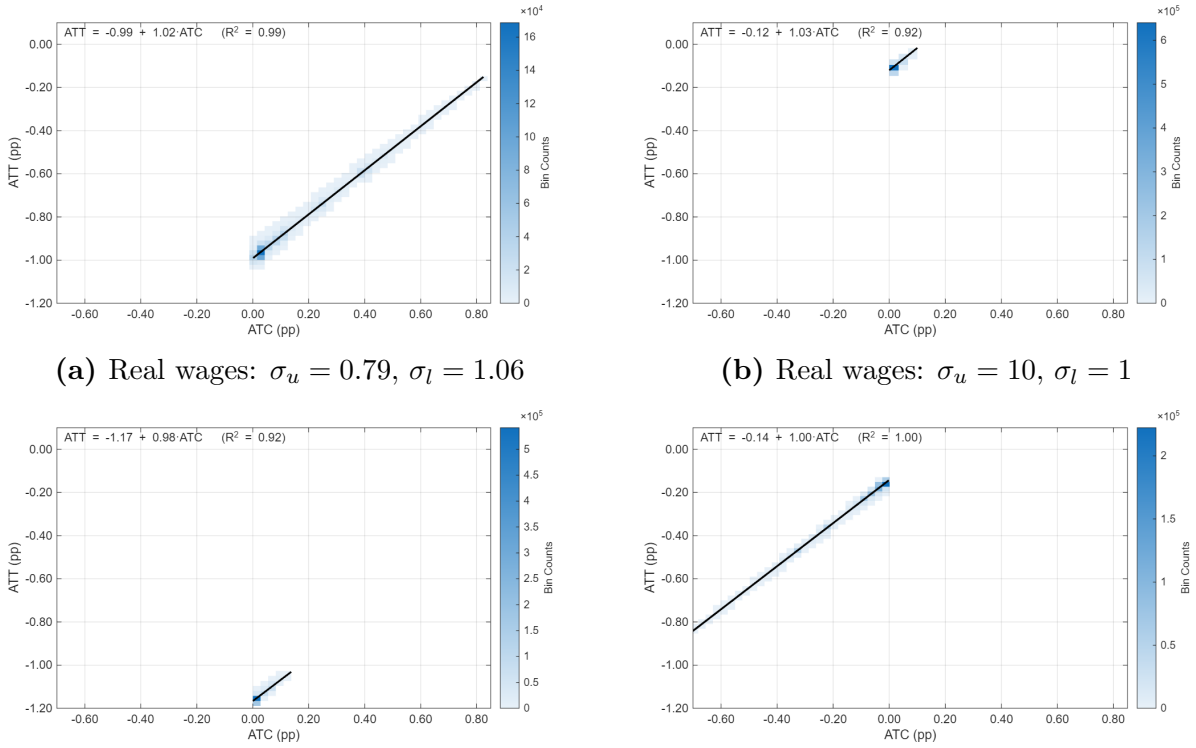
Notes: This figure shows the distribution of spillover effects from a 1% labor supply increase in Adana and Antalya. Despite similar populations (2.11M vs. 2.04M) and Domar weights (2.48% vs. 2.70%), Adana's cost-based Bonacich centrality is 1.7 times Antalya's (10.94 vs. 6.54) and its sales-based centrality is 1.4 times larger (2.21 vs. 1.60), reflecting Adana's role as an agricultural hub with extensive inter-regional trade versus Antalya's tourism-based economy. The mean spillover from Adana (0.014%) is 2.4 times that from Antalya (0.006%).

E.2 SUTVA Violations under Alternative Technology Parameters

E.3 Sensitivity to Elasticity of Substitution Parameters

The counterfactual results depend on the estimated elasticity of substitution between labor and intermediates (σ_u) and across intermediate inputs (σ_l). To assess robustness, I re-run the counterfactual exercises under alternative values of σ_u, holding $\sigma_l = 1$. This exercise is particularly informative because, as shown in Appendix Figure C.5, the main sensitivity of the EoS estimates to the calibrated ϵ^D runs through σ_u: as $|\epsilon^D|$ decreases, σ_u moves toward 1 (Cobb-Douglas), while $\sigma_l \approx 1$ barely changes. The Cobb-Douglas case ($\sigma_u = 1$) therefore represents the relevant edge case for assessing the sensitivity of counterfactual results to the calibrated labor demand elasticity.

Figure E.2: ATT and ATC estimates of real and nominal wages across simulations with different elasticity parameters



(a) Real wages: $\sigma_u = 0.79$, $\sigma_l = 1.06$

(b) Real wages: $\sigma_u = 10$, $\sigma_l = 1$

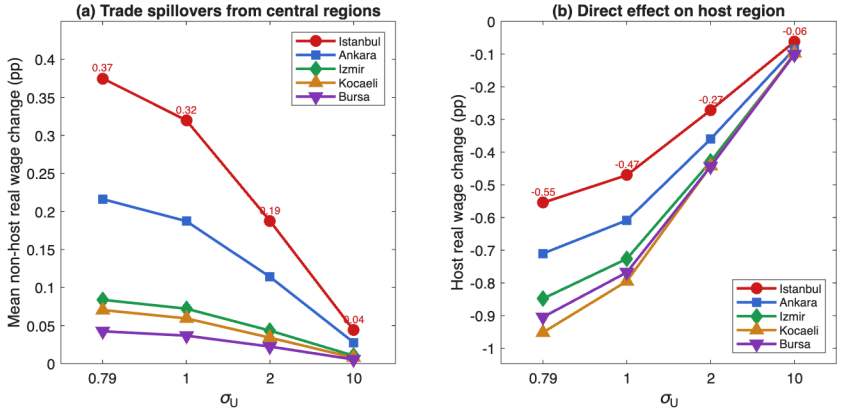
(c) Nominal wages: $\sigma_u = 0.79$, $\sigma_l = 1.06$

(d) Nominal wages: $\sigma_u = 10$, $\sigma_l = 1$

Notes: Each panel shows results from one million simulations under different elasticity parameters. In each simulation, 10 randomly selected regions receive a 1% labor supply increase. Changes in nominal wages and prices are calculated by solving the system of linear equations in Theorem 1. Real wage changes are defined as $d\ln w_{real} = d\ln w - b * d\ln p$, where $d\ln w$ is the vector of nominal wage changes, b is the $R \times N$ matrix of final expenditure shares, and $d\ln p$ is the $N \times 1$ vector of price changes. ATT is the average wage change in treated regions; ATC is the average change in control regions. Each panel displays binscatter plots, the linear fit, and the bivariate regression equation.

Figure E.3 illustrates this sensitivity for the five most central provinces identified in the main text: Istanbul, Ankara, Izmir, Kocaeli, and Bursa. Panel (a) shows the spillover effects (mean non-host real wage change) and panel (b) shows the direct effect on the host region. Moving from the baseline ($\sigma_u = 0.79$, gross complementarity) to Cobb-Douglas ($\sigma_u = 1$), results change modestly: spillovers from Istanbul decrease from 0.37 to 0.32 pp, and the direct effect goes from -0.55 to -0.47 pp. The other four provinces follow a similar pattern. This shows that even if $|\epsilon^D|$ were much smaller than calibrated—pushing σ_u toward Cobb-Douglas—spillovers from central nodes remain economically significant. As σ_u increases further to 2 and 10, i.e., labor and intermediates become gross substitutes, effects attenuate more sharply: host wage declines shrink, and since spillovers depend on the magnitude of the wage reduction in the host region, they shrink proportionally.

Figure E.3: Sensitivity of counterfactual real wage effects to σ_U

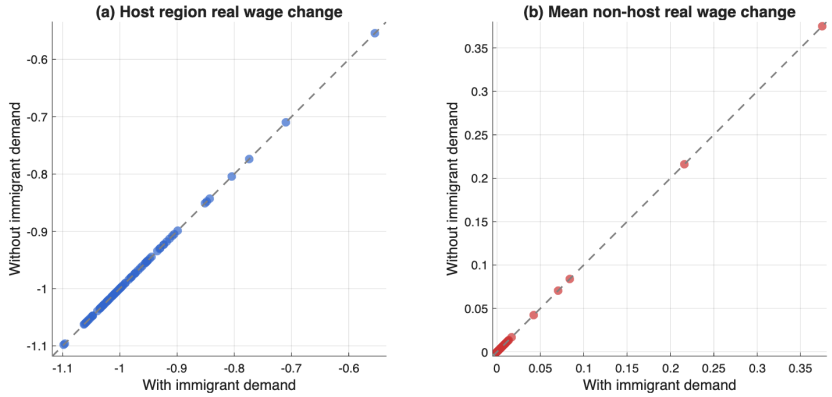


Notes: Each line tracks a province across four parameterizations of σ_u, holding $\sigma_l = 1$. In each counterfactual, the province receives a 1 percentage point labor supply increase. Panel (a) reports the mean real wage change across the 80 non-host provinces; panel (b) reports the real wage change in the host province. The baseline uses estimated parameters ($\sigma_u = 0.79$, $\sigma_l = 1.06$). The five provinces shown—Istanbul (34), Ankara (6), Izmir (35), Kocaeli (41), and Bursa (16)—are the same provinces identified in the main text as generating economically meaningful spillovers.

E.4 Robustness to Immigrant Demand Effects

Figure E.4 compares the results of the 1% labor supply counterfactuals with and without immigrant demand effects. All points lie virtually on the 45-degree line, confirming that immigrant demand has negligible effects on both direct and spillover wage impacts.

Figure E.4: Counterfactual wage effects with and without immigrant demand



Notes: Each point represents one of 81 provincial counterfactuals with a 1% labor supply increase. The horizontal axis shows results from the baseline model where immigrants both supply labor and consume goods. The vertical axis shows results from the model in equation 18 where immigrants supply labor but do not consume goods. The dashed line is the 45-degree line.

F Calibrated Parameters

This section summarizes the partial equilibrium analysis in Gulek (2024), who estimates two key parameters: the elasticity of substitution between informal and formal workers ($\sigma_{i,f} \approx 10$) and the wage elasticity of labor demand ($\epsilon^D = -1.27$). The high substitutability between informal and formal workers justifies the present paper's abstraction from the informal-formal distinction (treating labor as homogeneous), while ϵ^D is calibrated directly in the structural equations. Both parameters come from the same model and estimation. The interested reader is referred to Gulek (2024) for the full analysis; I summarize the main arguments and findings below.

The present paper's counterfactual results validate the partial equilibrium approach used to estimate these parameters. The counterfactuals in Section 5 show that Syrian refugees, who settled predominantly in non-central southeastern regions, generate negligible spillovers to the rest of the economy. This confirms that a partial equilibrium analysis of host regions is appropriate for estimating local labor demand parameters in this setting.

F.1 Empirical Evidence

Gulek (2024) studies the effects of Syrian refugees on natives' labor market outcomes in Turkish host regions, using the same distance-based instrument as the present paper. The treatment is the refugee-to-native ratio at the NUTS-2 region level, and the key outcomes are natives' informal and formal salaried employment rates from the Turkish Household Labor Force Survey (HLFS). Informality is measured through workers' social insurance status: by law, employers must provide social insurance coverage for formal employees, so workers without coverage are classified as informal.[31] The main specification is a 2SLS design with region and year fixed effects, and a linear trend in travel distance to account for the ongoing convergence between the less developed southeastern regions of Turkey and the rest of the Turkish regions.[32]

The paper finds that a 1 pp increase in the refugee/native ratio decreases the informal salaried employment rate of natives by 0.17 pp, the formal salaried employment rate of low-skill natives by 0.13 pp, and does not significantly impact the formal salaried employment rate of high-skill natives. While natives lose informal jobs, total informal employment (refugees plus natives) increases: the economy moves along the downward-sloping informal labor demand curve.

The displacement of natives from *formal* salaried positions is the central finding. Syrian refugees work exclusively in the informal sector, yet natives lose formal jobs. The paper's model shows that whether firms demand more or less formal labor in response to a decrease in informal wages depends on the elasticity of substitution between informal and formal workers: if they are gross complements, firms demand more formal workers (increasing natives' formal employment), and if they are gross substitutes, firms demand fewer (decreasing it). The data show the latter, implying high substitutability.

[31] There is no incentive for workers to misreport their insurance status, as it is not illegal to *work* informally, only to *employ* workers informally.

[32] Gulek and Vives-i Bastida (2024) relax the parametric pre-trend adjustment by using synthetic controls and find similar results.

F.2 Model and Estimation

To quantify the substitutability between informal and formal workers, Gulek (2024) estimates a model of labor demand where firms use informal and formal low-skill labor as the only input.[33] The firm with productivity θ maximizes:

$$\max_{\ell_i,\ell_f} \theta F(\ell_i,\ell_f) - \ell_i^{1+\gamma} w_i - (1+\tau_w) w_f \ell_f, \tag{25}$$

where ℓ_i and ℓ_f denote informal and formal workers, w_i and w_f are the respective wages, τ_w is the payroll tax on formal workers, and $\gamma > 0$ captures the convex expected cost of hiring informal workers, reflecting that larger firms face greater regulatory scrutiny and are more likely to be caught (Ulyssea, 2018, 2020). The production function has a CES form:

$$F(\ell_i,\ell_f) = \left(\eta \ell_i^{\rho} + (1-\eta)\ell_f^{\rho}\right)^{\frac{\alpha}{\rho}},$$

where $\alpha < 1$ governs decreasing returns to scale, ρ determines the elasticity of substitution between informal and formal workers ($\sigma_{i,f} = 1/(1-\rho)$), and η is the share parameter.

The key condition is $\rho > \alpha$: when the elasticity of substitution exceeds the returns to scale parameter, decreasing returns dominate Q-complementarity, and a decrease in informal wages leads firms to substitute formal workers with informal ones.

Some parameters are calibrated directly (α, τ_w, w_i, w_f), while the remaining parameters $\{\gamma, \eta, \rho\}$ and firm productivity types are estimated via Minimum Distance, targeting moments on firm size distribution, informality rates by firm size, and the ratio of informal to formal labor demand elasticities from the IV estimates. Table F.1 reports the estimated parameters. The key estimate is $\rho = 0.89$, which implies an elasticity of substitution between informal and formal workers of $\sigma_{i,f} = 1/(1-0.89) \approx 10$. This high elasticity is consistent with the Turkish context, where informal and formal workers frequently occupy the same positions within the same firms.[34]

F.3 Labor Demand Elasticity

The aggregate wage elasticity of labor demand ϵ^D measures how much wages change in response to an immigration-induced increase in labor supply. Given the estimated model parameters, this elasticity is a weighted average of the informal and formal labor demand responses times the inverse of the informal labor share:

$$\epsilon^D = \frac{s_{li} \cdot \epsilon_{L_i,w_i} + (1-s_{li}) \cdot \epsilon_{L_f,w_i}}{s_{li}},$$

where s_{li} is the share of informal workers among low-skill workers. Using the demand elasticities from Table F.1 ($\epsilon_{L_i,w_i} = -2.50$ and $\epsilon_{L_f,w_i} = 0.64$) and the informality shares from the data, this yields $\epsilon^D = -1.27$.

[33] The null effect on high-skill natives justifies focusing on a single-skill model for estimation, as the high-skill labor market is unaffected by the informal immigration shock.

[34] Bahar et al. (2024) find a similar estimate ($\sigma_{i,f} \approx 11$) for Venezuelan immigration to Colombia, providing independent confirmation in a different country.

Table F.1: Parameter values from Gulek (2024)

Parameter	Description	Source	Value
τ_w	Payroll tax	Statutory values	0.25
w_i	Informal wages	Calibrated	2.95
w_f	Formal wages for the low-skilled	Calibrated	4.44
α	Decreasing returns to scale	Calibrated	0.54
γ	Intensive margin cost of informal labor	Estimated	0.24
η	Informal share parameter	Estimated	0.46
ρ	CES elasticity parameter	Estimated	0.89
$\sigma_{i,f}$	Elasticity of substitution between informal and formal workers	Implied	9.58
ϵ_{L_i,w_i}	Average elasticity of informal labor demand w.r.t. informal wages	Implied	-2.50
ϵ_{L_f,w_i}	Average elasticity of formal labor demand w.r.t. informal wages	Implied	0.64

Note: This table reproduces the estimated parameter values from Gulek (2024). Formal and informal hourly wage estimates are expressed as averages of log hourly earnings. The elasticity of substitution is $\sigma_{i,f} = 1/(1-\rho) \approx 10$. The implied demand elasticities are averages across firms weighted by employment.