The Effects of Immigration on Regions that Don't Receive Immigrants

Ahmet Gulek and Tishara Garg*

October 18, 2024

Abstract

This paper investigates how immigration-induced wage shocks can propagate beyond the regions receiving immigrants through the production network. Theoretically, we characterize the impact of immigration on real wages in host and non-host regions as a function of the shape of the production network and two elasticities of substitution: one between labor and intermediate goods, and another between different intermediate goods. Using the Syrian refugee crisis in Turkey as a quasi-experiment, along with the near universe of domestic firm to firm transaction data from VAT records, we show that the immigration shock propagates both forward and backward along the supply chain. Firms in non-host regions who directly or indirectly buy from host regions increase their labor share in production. Moreover, firms who sell to host regions weakly increase their sales. Our estimates imply an elasticity of substitution between labor and intermediate goods of 0.76, and an elasticity of substitution of near 1 between intermediate goods. Finally, we quantify the general equilibrium effects of immigration through counterfactuals. We find that the spillover effects on non-host regions are economically meaningful when the host regions are central nodes of the domestic trade network. For example, a 1% increase in labor supply in Istanbul decreases real wages in Istanbul by 0.56% and increase real wages in average non-host city by 0.38%.

Keywords: Immigration, production network, trade spillovers

*Gulek: PhD student in Economics, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, USA (e-mail: agulek@mit.edu). I am grateful to Daron Acemoglu, Josh Angrist, David Autor, Amy Finkelstein, Adam Solomon, Edward Wiles, Emma Wiles, participants in the MIT Labor/PF Seminar, Labor Lunch and Trade Lunch. I acknowledge support from the George and Obie Shultz Fund at MIT.

1 Introduction

How do the labor market impacts of immigration differ across regions that receive and do not receive immigrants? Although there is an extensive literature documenting the effect of immigrants on natives' labor market outcomes and prices in host regions, we know little about how these effects spillover to other non-host regions and the implications of such spillovers.[1] A large increase in labor supply in host regions is likely to change prices of goods, which can induce general equilibrium effects throughout the economy. For example, Turkey has received 3.6 million Syrian refugees between 2012–2019, which has increased the population of several provinces by up to 80%. The labor market consequences of this massive labor supply shock for the Turkish economy depend on the magnitude of these general equilibrium effects.

We study three key economic mechanisms by which an immigration shock propagates through the supply network to impact labor demand. First, immigrants reduce the wages and therefore the prices charged by firms in the host region. This reduction in prices propagates forward along the supply chain to firms who directly or indirectly buy from the host region. Whether these "upstream exposed" firms increase or decrease their labor demand is governed by the substitutability between labor and intermediate goods. The second and third forces capture backwards propagation, which we label "downstream exposure" effects. If intermediate goods are gross substitutes, then firms whose production costs fall more sharply (i.e., those who are upstream exposed) gain market share through *business stealing*. Consequently, they demand more from their suppliers, who observe an increase in sales. Furthermore, when intermediate goods are more substitutable with other intermediates than with labor, *capital deepening* occurs in the host region: firms increase their demand for intermediate goods, which creates a positive demand spillover for its suppliers. Together, these three economic forces shape the labor market effects of immigrants across the economy.

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

Our model has three main ingredients. First, firms use a CES aggregate of local labor and an intermediate good in production, which itself is a CES aggregate of goods from other firms in all regions. Second, firms vary in their tastes for intermediate goods from others, generating an input-output network. Third, firms charge prices based on an exogenously given markup. Therefore, they pass along reductions in production costs, via change in prices of labor and goods, to their prices. In this framework, we characterize the impact of

[1]See Hanson (2009); Lewis and Peri (2015); Dustmann et al. (2017) for reviews of the literature.

immigration on real wages in host and non-host regions as a function of the shape of the production network and two elasticities of substitution: one between labor and intermediate goods, and another between different intermediate goods. Therefore, estimating these two elasticities, together with the knowledge of baseline input-output network, is sufficient to calculate the general equilibrium effects of immigration on labor demand in all regions.

We estimate these two elasticities by studying the effects of Syrian immigrants on firms in non-host regions in Turkey. Using the near universe of firm-to-firm transactions from VAT records, we calculate the model-defined upstream and downstream exposures to immigration for all formal firms in Turkey. We instrument for the regional immigration treatment with a shift-share IV, where the shift is the aggregate number of Syrian refugees in Turkey in a given year, and the share is the relative travel distance from the Syrian border. Specifically, the instrument captures quasi-random variation in immigration intensity across regions and years. This regional immigration shock then turns into firm-level upstream and downstream exposure treatments through firms' input-output matrices at baseline. We further relax the share-exogeneity assumption embedded in our design (Goldsmith-Pinkham et al., 2020) by applying Synthetic IV (Gulek and Vives-i Bastida, 2024).[2]

By comparing firms in the same region-industry cells who are differentially exposed to immigrants through their baseline trading partners, we obtain three findings. First, firms who directly or indirectly buy from host regions increase their spending on labor as a share in their production costs. This implies that labor and intermediate goods are gross complements, with an estimated elasticity of substitution of 0.76. Second, firms who sell to upstream exposed firms do not see a change in their sales. This shows that business stealing is not an empirically relevant effect, which implies an elasticity of substitution between intermediate goods of 1. Third, firms who sell to the host regions observe a positive, yet noisy increase in their sales. This illustrates capital deepening effects and implies that intermediate goods are more substitutable between each other than with labor, which is consistent with our first two findings. These results remain similar in a series of robustness checks of the identification strategy.

Our empirical results demonstrate the existence of trade spillovers of immigration. To quantify the magnitude of these spillovers and numerically investigate the heterogeneity across host regions and skill intensity of immigrants, we conduct counterfactual analyses. In one counterfactual exercise, we treat each of the 81 provinces of Turkey separately with a 1% increase in labor supply, and calculate the real wage change in host and the average non-host region. We find that the spillover effects of an immigration shock on real wages are mostly

[2]Note that the actual shares are functions of both firm-level input-output matrices and regional shares of the shift-share IV.

negligible except when the host region is a central node of the domestic trade network. For example, in 76 out of 81 potential host regions, becuase of the absence of spillovers, the real wages decrease by around 1% in the host region and increase by less than less than 0.02% in non-host regions. In contrast, a 1% increase in labor supply in Istanbul decreases real wages in Istanbul by 0.56% and spills over to increase the real wage in the average non-host region by 0.38%.[3]

This result has important implications for empirical evidence on the effects of immigration on labor markets and why different studies often find opposing results (Dustmann et al., 2016). The standard way of studying the effects of immigrants on labor markets has been a spatial difference in difference design (DiD), in which regions that receive immigrants are compared to others before and after the shock (Altonji and Card, 1991; Card, 2009). Identification in this design requires the stable unit value treatment assumption (SUTVA), which states that the potential outcomes of the control region are independent of the treatment status of the treated region. This result shows that SUTVA fails to hold when the host region is a central node in the trade network. Immigrant arrival to major cities in Turkey such as Istanbul and Ankara changes the labor demand throughout Turkey non-negligibly. In such settings, comparing the host region to non-host regions results in a biased estimate of the effect of immigrants on the host regions.[4]

In our second counterfactual, we answer a policy question. Suppose 100,000 refugees arrive in Turkey today and policymakers can choose where to locate these refugees. Does it matter in terms of welfare where refugees are located? To answer this question, we treat each region in Turkey separately with 100,000 immigrants and compare the total welfare gains between trials. We find that the arrival of 100,000 immigrants, a 0.12% increase in Turkey's population, would have led to welfare gains ranging from 0.02% to 0.42% depending on which region immigrants are settled in. Welfare gains are minimal when the least central nodes located in the north-east of Turkey (Erzincan-Erzurum-Bayburt) receive the immigrants, and highest when the developed provinces like Ankara, Istanbul, Izmir receive them. This implies that policymakers can improve the welfare gains from immigration by an order of magnitude by locating immigrants at the central nodes of the production network so that more regions benefit from the immigration-induced cost declines.[5]

[3]Note that whereas the magnitude of the effect on non-host regions is a function of both the centrality and the local population (1% increase in labor supply in Istanbul is a larger immigration shock than a 1% increase in any other region), the lesser change in the host region's wages is independent of the population: it is driven solely by the centrality of Istanbul in the domestic production network.

[4]In the Turkish where the southeast regions received the overwhelming majority of Syrian immigrants, spillover effects to non-host regions are minimal. SUTVA holds.

[5]There are various factors that go into governments' decision about where immigrants/refugees should be located. This counterfactual simply highlights a new economic force, considering which can help policymakers

In our third counterfactual, we incorporate skill differences in labor into our model and study the differences in welfare gains between low-skill and high-skill immigration. Specifically, we contrast the impact of treating each region in Turkey with low-skill versus high-skill immigrants. Because high-skill-intensive industries trade more across regions than low-skill-intensive industries, high-skill immigrants create larger spillovers than low-skill immigrants.

Our paper contributes to the extensive empirical literature studying the economic effects of immigration (seminal papers include Card (1990, 2001); Borjas (2003); Ottaviano and Peri (2012)).[6] Despite 30 years of work, whether immigrants lower natives' wages is still debated (Borjas, 2017; Peri and Yasenov, 2019). Our main contribution to this literature is showing, both theoretically and empirically, that the effects of immigrants spread through the supply chain via general equilibrium effects. These spillover effects on the non-host regions are economically significant when the host regions are central nodes in the domestic trade network. In such settings, SUTVA fails to hold: comparing host to non-host regions leads to biased estimates. Moreover, the bias can be both positive and negative, depending on the technology parameters of the economy.

We also contribute to a branch of the immigration literature that focuses on refugee crises (Hunt, 1992; Friedberg, 2001; Borjas and Monras, 2017). Several papers investigated the impact of the refugee crises of the last decade on host countries' labor markets and found larger displacement effects on natives than what is typically found in the literature on immigration.[7] One differentiating factor between refugee crises and economic migration that can explain this discrepancy is that refugees settle in regions closer to the border they arrive from, which are typically not the most economically developed regions, whereas most voluntary immigration in the world occurs toward larger cities. Consequently, trade spillovers violating SUTVA are less of a concern in refugee crises, which may explain why studies of these episodes document larger displacement effects on natives than the rest of the literature.

A related literature investigates how the effects of immigration interact with output tradability (Dustmann and Glitz, 2015) and international trade (Caliendo et al., 2021; Brinatti, 2024). The paper that is closest to ours, Burstein et al. (2020) formalize how industry tradability shapes local labor market adjustments to immigration. We build on their findings by showing how the production network shapes local labor market adjustments to immigration. In addition to industry tradability, who industries, buy from and sell to matter first-order in our analysis.

We also contribute to a growing literature studying the propagation of technology and

improve social welfare. It does not suggest that all immigrants/refugees should be located in major cities.

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

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

factor shocks through the production network. Acemoglu et al. (2012, 2016b, 2017), Baqaee and Farhi (2019) explore the conditions that enable microeconomic shocks to spread through input-output networks, leading to aggregate fluctuations.[8] Empirically, previous work has shown how trade shocks (Acemoglu et al., 2016a) and natural disasters (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021) propagate along the supply chain. The closest empirical work to ours is Akgündüz et al. (2024), who examine the propagation of the Syrian immigration shock through the supply chain in Turkey. They show positive spillovers on firms' sales and employment through first-degree trade linkages in host regions. We extend their analysis by formalizing the mechanisms through which immigration impacts firms in non-host regions, testing these empirically, quantifying general equilibrium effects, and demonstrating when such spillovers are significant at the aggregate level.

The paper is organized as follows. Section 2 introduces the data and institutional background. Section 3 develops the model and isolates the economic forces by which an immigration induced wage shock to a region can spread through the production network to other regions. Section 4 presents the empirical results. Section 6 concludes.

2 Background and Data

2.1 Syrian Refugee Crisis in Turkey

The Syrian Civil War started in March 2011. By 2017, 6 million Syrians had sought shelter outside of Syria, primarily in the neighboring countries Turkey, Lebanon, Jordan, and Iraq. With 3.6 million registered Syrian refugees, Turkey hosts the highest number of refugees in the world. Figure 1a shows how the number of Syrian refugees in Turkey has evolved over time. Their numbers remained small until the end of 2012 but increased substantially after. Turkey hosted around 170 thousand refugees by 2012, 500 thousand by 2013, 1.6 million by 2014, 2.5 million by 2015, and around 3.6 million by 2019.[9]

The Turkish government initially tried to host the Syrians in refugee camps in the south-eastern part of the country across the Turkish-Syrian border. However, these camps quickly exceeded capacity as the number of arriving refugees increased. The refugees thus dispersed across Turkey in heterogeneous quantities.[10] Figure 1c shows the distribution of the number of Syrian refugees per 100 natives in Turkey at the province level.[11] Refugees are more

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

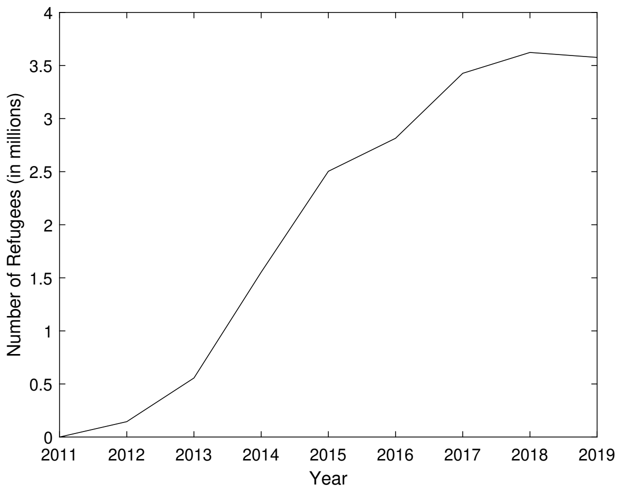
[9]The number of refugees in Turkey across years and provinces are acquired from the Directorate General of Migration Management of Turkey.

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

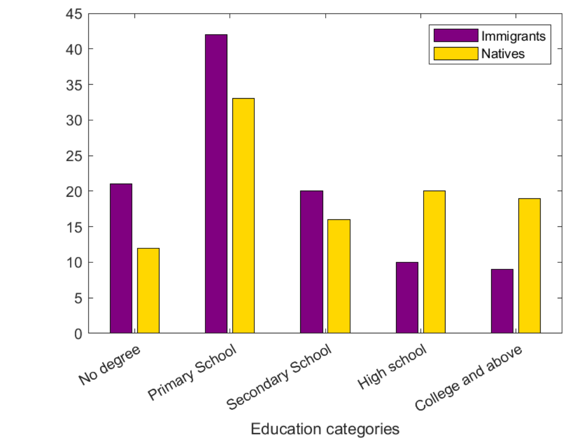
[11]Turkey does not share the education and age break-down of refugees at the province level, which prevents

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.

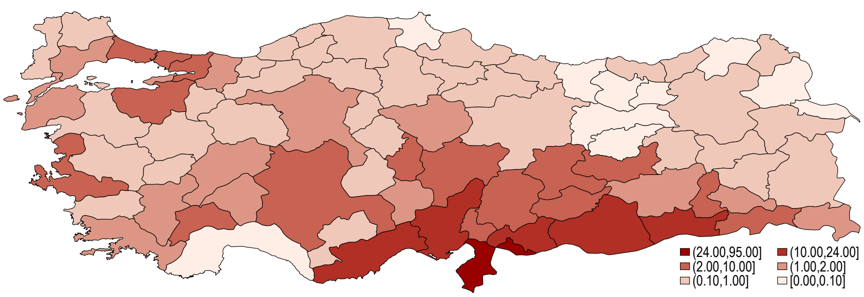
Figure 1: Statistics on the Syrian Refugees in Turkey



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



(b) Educational Attainment of Syrians and Natives



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

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

Syrian refugees are significantly less educated than Turkish natives.[12] Figure 1b compares the education levels of Syrian refugees in Turkey with those of Turkish natives. For example, 21% of Syrian refugees did not complete primary school, compared to 12% of Turkish natives. Additionally, 83% of Syrian refugees do not have a high school diploma, in contrast to 61% of Turkish natives. Given the potential for educational downgrading (Dustmann et al., 2013)

the empirical investigation from exploiting that variation.

[12] This is due to two main factors. Firstly, Syria was less developed than Turkey, resulting in a less educated workforce. Secondly, highly educated Syrians were more likely to seek refuge in Europe.

and the fact that most Syrian refugees have only basic proficiency in Turkish (Crescent and Programme, 2019), the influx of Syrian refugees can be interpreted as a low-skill labor supply shock to the Turkish labor market.

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

The Turkish government initially tried to host the Syrians in refugee camps in the south-eastern part of the country across the Turkish-Syrian border. However, these camps quickly exceeded capacity as the number of arriving refugees increased. The refugees thus dispersed across Turkey in heterogeneous quantities.[13] Figure 1c shows the distribution of the number of Syrian refugees per 100 natives in Turkey at the province level.[14] Refugees are more densely located in regions closer to the border, and with historically more Arabic speakers. These two facts constitute the one of the building blocks of our identification strategy.

2.2 Data

We integrate five datasets covering all formal firms in Turkey between 2006–2019. The Ministry of Industry and Technology maintains all the datasets and uses the same firm identifier, which enables us to merge them. Our analysis focuses on the manufacturing sector unless otherwise specified.

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

We also rely on labor force surveys conducted by the Turkish statistical institute the calculate natives' employment rates and the skill intensity of 2-digit industries. These surveys

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

[14] Turkey does not share the education and age break-down of refugees at the province level, which prevents the empirical investigation from exploiting that variation.

are representative at NUTS-2 level.

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

3 Theory

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

3.1 Setup

The economy consists of N firms indexed by i, R regions indexed by r, where each region is endowed with L_r labor.[15] 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 $\{x_{i,j}\}_{j=1}^{n}$ to minimize costs subject to a constant returns nested-CES technology

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

where A_i is a Hicks-neutral productivity shifter, y_i is total output, p_j is the price of good j, L_i is labor used by firm i, w_r is the wage in region r, m_i is the intermediate good used by the firm, which itself is a CES bundle of goods from different firms. x_{ij} denotes how much firm i uses firm j's goods in production, where firm j can be in any region. We assume common elasticities of substitution in both the upper and lower nests: σ_u denotes the elasticity of substitution between labor and intermediate goods, and σ_l is the elasticity of substitution

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

between different intermediate goods.[16] Constant returns to technology requires $\sum_j \alpha_{i,j} = 1$. Let C_i denote the unit cost of firm i. We assume that firms have constant and exogenous markup μ_i, and therefore set price $p_i = \mu_i C_i$.

Final Demand

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

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

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

Labor Supply

Labor is inelasticly supplied in each region, is immobile across regions and perfectly mobile across firms in a region. This simplifying assumption shuts down spillovers across regions in labor supply.[17]

General Equilibrium

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

3.2 Input-Output definitions

To understand how a labor supply shock in one region impacts the labor demand in all regions, we introduce some input-output notation and definitions.[18] Our results are comparative statics describing how the labor payments in any host and non-host region change

[16] The common elasticity of substitution assumption across firms can easily be relaxed. However, each different parameter comes with additional data requirements for estimation, and therefore we maintain a common elasticity assumption for empirical reasons.

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

[18] In particular, we follow Baqaee and Farhi (2019)'s notation closely. We deviate from their notation only when our models' regional labor markets, which is not present in their model, requires us to do so.

when a host region receives immigrants. We now define accounting objects such as input-output matrices, Leontief inverse matrices, and Domar weights. These quantities have a revenue-based version and a cost-based version, and we present both. All these objects are defined at the initial equilibrium. Without loss of generality, we normalize the nominal GDP to 1. Finally, in our analytical results and counterfactuals, we assume constant markups and technology.[19]

3.2.1 Final Expenditure Shares

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

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

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

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

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

3.2.2 Input-Output Matrices

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

[19]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).

element is equal to i's expenditure on inputs from j as a share of its total costs

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

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

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

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

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

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

3.2.3 Leontief Inverse Matrices

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

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

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

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

3.2.4 Domar Weights

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

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

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

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

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

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

3.3 Effects of a Labor Supply Shock on labor income

Before characterizing the full set of equilibrium changes in prices and quantities, we first build intuition as to how an immigration shock in a host region can impact the labor payments in any region. To achieve this, we take the change in prices $d\ln p$ and $d\ln w$ as given, and describe how the demand for labor and for goods change in response to these changes in prices.

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

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

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

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

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

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

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

All proofs are in the Appendix.

Equation 1 captures the trade-off firms face between hiring labor and using intermediate goods in production. Suppose the local wages go down less than the prices of the suppliers of firm i. If labor and intermediate goods are gross complements, $\sigma_u < 1$, then the firm would increase its labor share in production.

Note that, absent changes in markups, $d\ln\tilde{\Omega}_{i,L} = d\ln\Omega_{i,L}$. Therefore, equation 1 also describes the change in the labor share of sales.

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

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

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

The first two lines of this equation describe the two demand spillovers from changes in firms' costs, and the third line captures the demand spillover from immigrants demanding locally produced goods.

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

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

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.[20]

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

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

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

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

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

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

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

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

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

Equation 4 presents the economic forces we have described in one system of linear equations. An important observation for the rest of the paper is that, except for the elasticity parameters σ_u and σ_l, we observe all the parameters in this equation in our pre-shock data. 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.

4 Empirics

In this section, we study the trade spillover effects of immigration on firms in non-host regions. We begin by using our analytical results on the effect of immigrants on the labor share in costs and sales given in Propositions 1 and 2 to estimate the structural elasticity parameters: the elasticity of substitution between labor and materials and the elasticity of substitution between different materials. We then use these elasticity parameters and our VAT data to quantify the total effects of immigration on host and non-host regions. This enables us to quantify when the spillover effects of immigration are economically meaningful, and what these spillovers imply about our understanding of the effects of immigration on labor markets.

4.1 Treatment Definitions

Our model highlights three economic forces that help determine the total effects of immigration on host and non-host regions: a forward propagation of costs and demand spillovers from business-stealing and capital-deepening. Here, we define these treatment variables. We refer to the first treatment as an upstream exposure effect and the latter two as downstream exposure effects. We define upstream and downstream from the firm's perspective: firm i is upstream exposed to immigration if firm i purchases from immigrant-intensive firms, and downstream exposed to immigration if it sells to immigrant-intensive firms.

Specifically, The upstream exposure of firm i at time t

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

summarizes how the regional arrival of Syrian immigrants δ_{rt} are transmitted to firm i via the cost-based Leontief inverse matrix $\tilde{\Psi}$. Recall that $\tilde{\Psi}_{i,r}$ is higher when firm i buys more, directly and indirectly, from firms in region r and when these supplier firms are labor-intensive and therefore observe greater decreases in production costs due to immigration.

The first downstream exposure measuring business-stealing motives

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

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

The second downstream immigration shock measuring labor-capital complementarity

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

summarizes how much firm i's customers represented by Ψ_{ji} observe *relative* cost declines from their own region's wages, which is measured by $\delta_{r_j,t}$, compared to the immigration shock through their suppliers, which is measured by $\sum_{k=1}^{n} \frac{\tilde{\Omega}_{j,k}}{\tilde{\Omega}_{j,m}} (\sum_{r=1}^{R} \tilde{\Psi}_{k,r} \delta_{rt})$.[21]

[21] One key empirical challenge is to generate the upstream and downstream treatment variables U_{it}, $D1_{it}$ and $D2_{it}$. This requires taking the inverse of huge matrices. For example, at baseline, we have around 230 thousand unique firms that trade in the domestic market, resulting in the trade matrices holding approximately 53 billion values. Whereas the trade matrices $\tilde{\Omega}$ and Ω are sparse and therefore do not take too much

4.2 Specifications for labor share and sales

Using Propositions 1 and 2, in Appendix A we derive the following specifications for firms' labor share and sales.

$$log(LS_{isrt}) = \beta_U U_{it} + \alpha_i^{LS} + \alpha_{srt}^{LS} + \nu_{it}^{LS} \tag{8}$$

where $log(LS_{isrt})$ is the natural logarithm of the labor share of firm i in industry s, region r, and at time t, U_{it} is the model-defined upstream exposure treatment, α_i is the firm fixed effect, α_{srt}^{LS} is the industry-region-time fixed effect that partials out region-industry level shocks such as technology and markup shocks that can be correlated with the treatment, and ν_{it}^{LS} is the error term.

The treatment effect of upstream exposure U_{it} on labor share is

$$\beta_U = -\frac{(1-\sigma_U)}{\epsilon^D} \tag{9}$$

where ϵ_D is the elasticity of labor demand with respect to wages. We calibrate $\epsilon^D = -1.27$ from Gulek (2024). Therefore, estimating the effect of upstream exposure β_U is equivalent to estimating the elasticity of substitution between labor and intermediate goods σ_U.

The model-driven specification for the effect on sales is given by

$$log(Sales_{isrt}) = \beta_{D,1} D1_{it} + \beta_{D,2} D2_{it} + \alpha_i^{Sales} + \alpha_{srt}^{Sales} + \nu_{it}^{Sales} \tag{10}$$

where $log(Sales_{isrt})$ is the natural logarithm of sales of firm i in industry s, region r, and at time t, $D1$ and $D2$ are the model-defined downstream immigration shocks capturing the demand spillovers from business stealing (BS) and (2) labor-material complementarity (LMC), respectively, the firm fixed effect α_i^{Sales}, industry-region-time fixed effect α_{srt}^{Sales}, and error term ν_{it}^{Sales} are defined analogously.

In particular, the treatment effects of the first and second downstream exposures are given by

$$\beta_{D,1} = \frac{(1-\sigma_l)}{\epsilon^D} \quad ; \quad \beta_{D,2} = -\frac{(\sigma_l - \sigma_u)}{\epsilon^D} \tag{11}$$

which implies that estimating the effect of business stealing $\beta_{D,1}$ and of labor-material complementarity $\beta_{D,2}$ is equivalent to estimating the elasticity of substitution between labor and materials σ_u, and the elasticity of substitution between different types of materials σ_l.

Note that our two estimating equations 8 and 10 are linked: both estimate a version of

memory, the Leontief inverse matrices $\tilde{\Psi}$ and Ψ are not sparse. To make progress, we donated a workstation with 512 GB of RAM to the Ministry of Industry and Technology of Turkey, which hosts the majority of the datasets we use in this study. Appendix Section A provides the details of how we construct these matrices and our treatment variables.

the elasticity of substitution between labor and intermediate goods. In the empirical section, we explicitly show that the estimates of these two equations are consistent.

We omit the downstream treatments, $D1$ and $D2$, in equation 8 and the upstream treatment, U, in equation 10, for two reasons. First, these are the correct structural regression equations for identifying the elasticity parameters. Second, as discussed in the identification section, the upstream treatment U is measured with greater precision than the downstream treatments $D1$ and $D2$. Consequently, even though the upstream treatment U does not structurally belong in equation 10, it could absorb the causal effects of the less precisely measured downstream treatments $D1$ and $D2$ if they were estimated jointly.

4.3 Identification

Immigrants choose where to locate based on local labor market conditions, which implies that our regional immigration treatment δ_{rt} can be correlated with unobserved shocks to labor demand. To address this issue, we rely on a shift-share instrument, where the share is the average inverse travel distance between Turkish regions and Syrian governorates, and the shift is the aggregate number of Syrians in Turkey. Specifically, our main regional instrument is defined as:

$$Z_{r,t} = \underbrace{\sum_{s=1}^{13} \lambda_s \frac{1}{d_{r,s}}}_{\text{Share}} \times \underbrace{\text{Number of Syrians in Turkey in year } t}_{\text{Shift}} \tag{12}$$

where $d_{r,s}$ is the travel distance between Turkish region r and Syrian governorate s, and λ_s is the weight given to Syrian governorate s.[22] Different weights λ have been used in the literature. In practice, weights matter little. We use the weights suggested by Aksu et al. (2022), which takes into account two empirical facts: the number of refugees from a Syrian region s increases with population and proximity to Turkey compared to other bordering countries.

$$\lambda_s = \underbrace{\frac{\frac{1}{d_{s,T}}}{\frac{1}{d_{s,T}} + \frac{1}{d_{s,L}} + \frac{1}{d_{s,J}} + \frac{1}{d_{s,I}}}}_{\text{Relative distance to Turkey}} \times \underbrace{\pi_s}_{\text{Pop. share}} \tag{13}$$

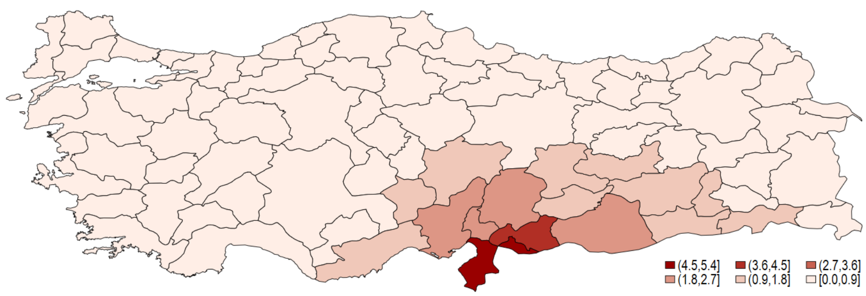
where $d_{s,c} \quad c \in \{T, L, J, I\}$ is the travel distance between Syrian region s to Turkey, Lebanon, Jordan, and Iraq respectively; and π_s is the population share in 2011, which we calculate using the 2011 census undertaken by the Central Bureau of Statistics of Syria.

Figure 2a shows the cross-sectional distribution of the distance share. As expected, the

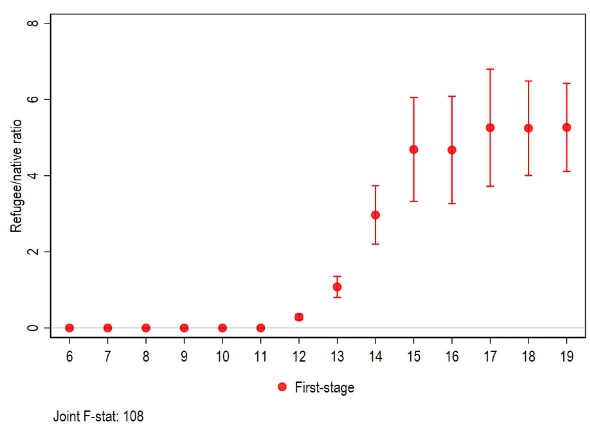
[22] City centers in each region are used to calculate the travel distance. The data is available upon request.

instrument puts more weight on south-east regions of Turkey that are closer to the north-west part of Syria. This is because in 2011, along the Turkish-Syrian border, more Syrians lived in Aleppo (north-west) than Al-Hasakah (north-east). Figure 2b shows the first-stage estimates from a nonparametric event-study design where we regress the immigration treatment δ_{rt} on the distance-share Z_r interacted with year indicators. The estimates between 2006–2011 are zero as there are no immigrants in Turkey during those years. In the post-period 2012–2019, distance strongly predicts immigrant location choice in all years. The joint F-stat for the post-period coefficients is 108, which implies that we have a strong instrument.

Figure 2: The Distance instrument



(a) Distance IV heatmap



(b) First-stage

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

As a robustness check, we also show results in the Appendix using an alternative shift-share instrument, where the share is the ratio of Arabic speakers at the province level in the 1965 census. This is similar to the past-settlement instrument of Card (2001), with the main difference being that Arabic-speaking populations were not generated by the past migration of Syrians in Turkey: they are a result of the multi-ethnic population of the Ottoman Empire. Details of this instrument can be found in the Appendix. Our results are robust to using either instrument. We use distance in the main text as it provides a stronger first-stage.

The instruments for the trade exposures U, $D1$, and $D2$ are obtained simply by replacing the immigration treatment δ_{rt} with the instrument Z_{rt}. We refer to the instrumented versions of trade exposures by adding an upperscript z: U^z is the instrument for the upstream exposure treatment U. $D1^z$ and $D2^z$ are defined analogously.

In shift-share designs similar to ours, identification comes from either the exogeneity of shares (Goldsmith-Pinkham et al., 2020) or shifts (Borusyak et al., 2022). In our case, whereas the timing of the immigration shock is exogenous, the stock of immigrants is not i.i.d. across time. Therefore, identification comes from the exogeneity of shares assumption. In other words, we need our more and less exposed firms based on the distance-share intensity of their trade partners to follow similar trends absent the immigration shock.

However, in our case firms who are upstream and downstream exposed to immigrants do not follow similar trends before the shock, making it unlikely that they would follow similar trends in the post period absent the immigration shock. For example, firms who buy from immigrant-intensive firms (i.e., firms who are upstream exposed) increase their labor share between 2006—2011 compared to other less-exposed firms, resulting in significant pre-trends in reduced-form estimates.[23] Consequently, standard IV regressions using these instruments would result in inconsistent estimates.

To make progress, we employ the Synthetic instrumental variable (SIV) strategy à la Gulek and Vives-i Bastida (2024). SIV uses synthetic controls to account for unmeasured confounding in IV-DiD settings similar to ours, while still using the weights assigned by the instrument for identification.[24] SIV estimator consists of two steps. In the first step, we find synthetic controls for each unit (firm) in the pre-period and generate counterfactual estimates for the outcome, treatments, and instruments. In the second step, as in the standard IV estimator, we use these counterfactual estimates to compute the first-stage and reduced-form estimates.

In particular, we find the weights by matching on the demeaned values of our two target outcomes: the natural logarithms of labor share and sales between 2006-2011. To rely on the variation in treatment across firms in the same region-industry cell for identification, we restrict the donor pool to firms in the same region-industry cell, where industry is defined at the 2-digit level. We further add a penalty term á la Abadie and L'hour (2021) to lower

[23] Appendix C.1 shows details of these pre-trends.

[24] We discuss the details of the implementation in Appendix Section C.

over-fitting bias when working with disaggregated data.

We estimate a common set of weights for both the labor share and sales to minimize the noise-to-signal ratio. Sun et al. (2023) show that estimating a common weight instead of separate weights for separate outcomes leads to lower bias bounds. Moreover, in the Appendix, we show that estimating a common weight for labor share and sales creates a better fit for unmatched outcomes of interest, such as total payroll and firm size, than estimating separate weights.

4.4 Threats of Identification

There are a few threats to identification that are worth discussing. First, equation 8 is "better identified" than equation 10 due to two separate but equally important issues: noise and informality in the sales data of small firms. Our sales information λ comes from balance sheet records. Due to the low audit probability of small firms, balance sheet sales are highly noisy, especially for small firms. This causes multiple problems in estimation. Noise in the outcome variable decreases precision. More importantly, noise in sales enters the numerator and denumerator of $D1$ and $D2$ treatments in two separate places: while calculating relative sales between firms i and j, $\frac{\lambda_j}{\lambda_i}$, and while calculating firm j's dependence to firm i as a customer Ψ_{ji}. These create separate *division biases* (Card, 1991; Angrist, 1991), which can cause both positive or negative bias in estimation. In contrast, the upstream exposure treatment uses information on costs, which is substantially better measured than sales and, therefore, does not suffer from a similar bias.

The second problem is related to informal sales. Gulek (2024) shows that Syrian immigration in Turkey increases the demand for informal labor. As informal labor is often paid by unregistered cash, especially for small firms, the increase in demand for informal labor in host regions can change the incentives for firms to report their sales to host regions. This can cause bias in both the the business-stealing and labor-material complementarity effects.

We address these problems in two ways. First, we define our baseline exposure variables by averaging sales and costs between 2006—-2011 instead of relying on data from any particular year. Averaging across years lowers the noise embedded in the data-generating process and, hence, should lower the bias from noise. Second, we show evidence separately for large firms as informality rates decrease with firm size. In particular, we show evidence separately for firms with more than 1 or 50 employees at baseline, and claim causal estimates only when our estimates are consistent across both. If/when estimates are different across small and large firms, we highlight them and discuss their implications.

4.5 Reduced Form and 2SLS estimates

Cost Propagation

We begin by estimating the reduced-form effects of upstream exposure on the labor share of firms using SIV. In particular, we estimate the following equation

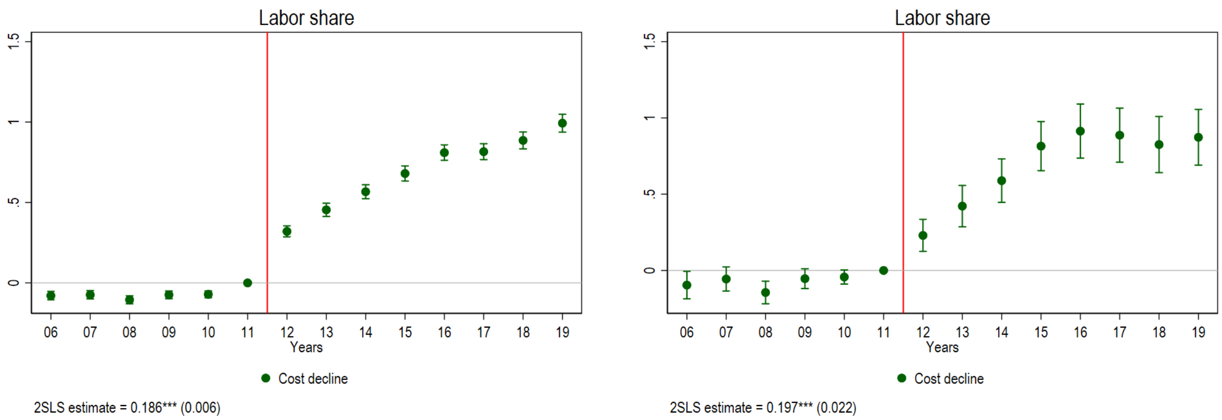
$$\widetilde{log(LS_{it})} = \sum_{t' \neq 2011} \beta^U_{t'} \widetilde{U^Z_i} \mathbb{1}\{t = t'\} + \alpha^{LS}_i + \alpha^{LS}_t + \nu^{LS}_{it} \tag{14}$$

where $\widetilde{log(LS_{it})}$ is the debiased labor share, and $\widetilde{U^Z_i}$ is the debiased unit-fixed upstream exposure to immigration, which we calculate by replacing the immigration treatment δ_{rt} in equation 5 with the share part Z_r of the shift-share instrument Z_{rt}. Equation 14 is an event-study design where the unit exposure is a continuous variable U^Z_i instead of the standard dummy variable. We estimate equation 14 using OLS separately for all firms and firms with at least 50 employees at baseline. Standard errors are clustered at the firm level.

Figures 3a and 3b show the results for firms with more than 1 and 50 employees at baseline, respectively. Looking at figure 3a, we do not find significant pre-trends in the data between 2006–2011. This shows good pre-treatment fit in the training period, which is an important condition for SIV to function well. Second, starting from 2012, we document a significant increase in the labor share of upstream exposed firms. Firms in the non-host regions who directly or indirectly buy from the host regions increase their labor share compared to other similar firms in the same region-industry cells. Moreover, this increase in labor share increases over time, similar to the first-stage shown in Figure 2b, which improves our confidence that the estimated effects are causal effects, not differential trends. The 2SLS estimate, which is reported in the bottom left of the figure, is 0.186. This implies that labor and intermediate goods are gross complements, with an elasticity of substitution of $\sigma_U = 0.75$.

As we alluded to earlier, there are two significant concerns for identification: informality of small firms impacting measurement of both the outcome and the treatment, and over-fitting. Here, we discuss the robustness of both. First, Figure 3b repeats the same analysis on large firms with 50+ employees at baseline. We find similar results: there are no economically meaningful pre-trends between 2006–2011, which shows good pre-treatment fit. The trajectory of the reduced-form is similar to the trajectory of the first-stage. The 2SLS estimate is 0.197, which implies an elasticity of substitution of $\sigma_U = 0.76$, which is highly similar to what we find in Figure 3a. The fact that we find similar evidence across small and large firms implies that informality is not a concern for the estimation of upstream exposure

Figure 3: Effect of Upstream Exposure on Buyers



(a) All firms

(b) Large Firms

Notes: The estimates come from the reduced-form regression equation $\widetilde{log(LS_{it})} = \sum_{t' \neq 2011} \beta^U_{t'} \widetilde{U^Z_i} \mathbb{1}\{t = t'\} + \alpha^{LS}_i + \alpha^{LS}_t + \nu^{LS}_{it}$, where both the outcome and the treatment are their debiased versions following the SIV algorithm. The upstream exposure is given by $U^Z_i = \sum_{r=1}^{R} \tilde{\Psi}_{i,r} Z_r$, where $\tilde{\Psi}$ is the cost-based Leontief inverse matrix, and Z_r is the regional share of the instrument. 95% confidence intervals are plotted.

effects.

The second concern is the possibility that SIV estimates are not consistent: this can happen due to (1) bad pre-treatment fit, i.e., there are many firms for whom we cannot find a convex combination of other firms that follow similar trajectories in labor share and sales, and (2) over-fitting, i.e., that SIV matches on the noise instead of the signal in the data. The lack of economically meaningful pre-trends implies good pre-treatment fit. However, we can further improve the pre-treatment fit by matching only on the trend in labor share instead of matching on labor share and sales. Appendix figure C.3 shows these results. Our results remain very similar: we estimate an elasticity of substitution between intermediate goods and labor σ_U of around 0.76 for all firms and 0.73 for large firms.

Another way to test for over-fitting is to check whether the SIV estimator performs similarly for outcomes that it is not trained on. Recall that in the matching step, we generate synthetic firms based on the trends in labor share and sales. Using the same weights, we also analyze the effect of upstream exposure on firms' payroll and number of employees, two outcomes that are linked to firms' performance but are not explicitly targeted in the matching process. Figure C.4 shows the results. We find that firms that buy from host regions increase their payroll and size. Most importantly, we do not find economically meaningful pre-trends. This is not mechanical. It shows strong evidence of a common underlying factor generating differential trends between more/less exposed firms. The fact that SIV eliminates the differential trends in non-targeted outcomes is a strong indicator that our estimator does not suffer from over-fitting.

Lastly, we also repeat this exercise using our alternative instrument. Results are shown in Appendix Figure C.5. We find very similar reduced-form and 2SLS estimates.

To sum up, we find that upstream exposure increases firms' labor share in costs, which implies that labor and intermediate goods are complements in production, with an elasticity of substitution of around 0.76. Our results are similar across small and large firms, eliminating concerns related to informality. Quality checks of the SIV estimator show good pre-treatment fit and limited room for over-fitting.

Demand Spillovers

We continue by estimating the reduced-form effects of downstream exposures on firms' sales using SIV. In particular, we estimate the following equation

$$\widetilde{log(Sales_{it})} = \sum_{t' \neq 2011} \beta_{t'}^{D1} \widetilde{D1_i^Z} \mathbb{1}\{t = t'\} + \beta_{t'}^{D2} \widetilde{D2_i^Z} \mathbb{1}\{t = t'\} + \alpha_i^{Sales} + \alpha_t^{Sales} + \nu_{it}^{Sales} \quad (15)$$

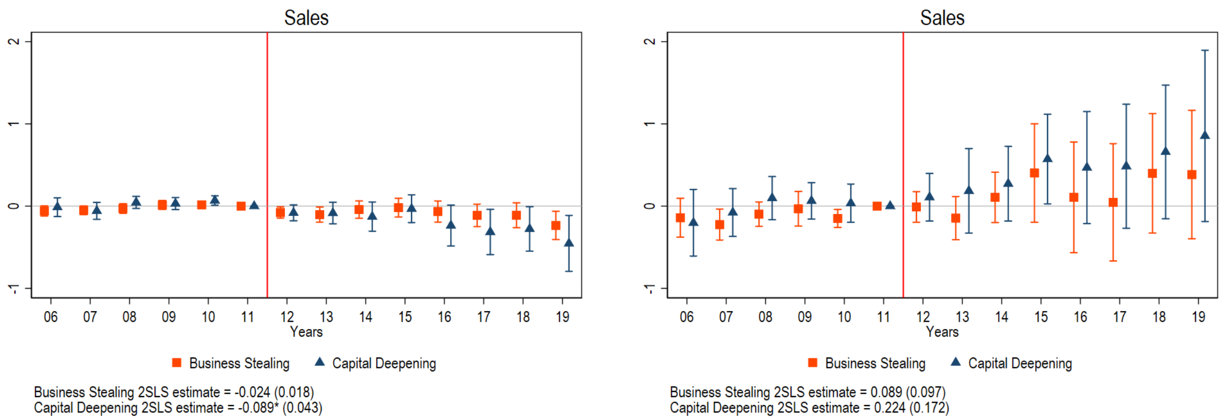
where $\widetilde{log(Sales_{it})}$ is the debiased sales, $\widetilde{D1_i^Z}$ is the debiased unit-fixed downstream exposure capturing business stealing effects, and $\widetilde{D2_i^Z}$ is the debiased unit-fixed downstream exposure capturing capital-deepening effects. Unit-fixed exposures $D1^Z$ and $D2^Z$ are defined by replacing the immigration treatment δ_{rt} in equations 6 and 7 with the share part Z_r of the shift-share instrument Z_{rt}. We estimate equation 15 using OLS separately for all firms and firms with at least 50 employees at baseline. Standard errors are clustered at the firm level.

Recall that the estimated downstream exposure effects could differ across small and large firms due to both noise and informality. The noise in sales enters both the left-hand and the right-hand sides of the regression in non-linear ways, which can induce bias in both directions, and potential increases in the demand for informal sales can cause negative bias. In fact, Figure 4 proves these concerns. Figures 4a and 4b show the estimated effects for firms with more than 1 and 50 employees at baseline, respectively. We see that the sign of the estimated effects of both business stealing and labor-material complementarity change when we go from small firms to large firms. Whereas small firms' observed sales decrease, large firms' observed sales increase.[25]

There is a clear bias-variance trade-off between the estimates coming from small and large firms. Evidence from large firms is less biased but also less precise. To make progress,

[25]This is consistent with both small firms' hiding their sales due to increased demand for informal trade and the noise in sales creating negative bias.

Figure 4: Effect of Business Stealing and Labor-Material Complementarity on Firms' Sales



(a) All firms

(b) Large Firms

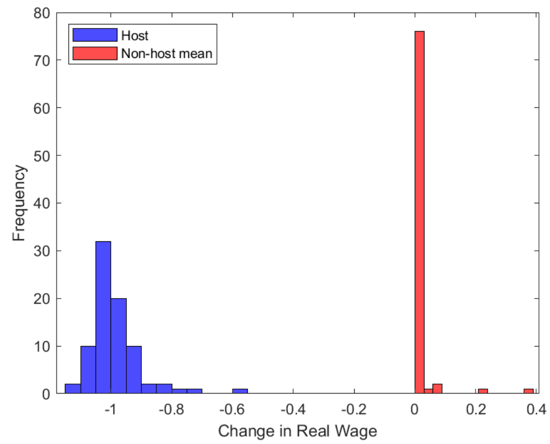
Notes: The estimates come from the reduced-form regression equation $log(\widetilde{Sales_{it}}) = \sum_{t' \neq 2011} \beta_{t'}^{D1} \widetilde{D1_i^Z} \mathbb{1}\{t = t'\} + \beta_{t'}^{D2} \widetilde{D2_i^Z} \mathbb{1}\{t = t'\} + \alpha_i^{Sales} + \alpha_t^{Sales} + \nu_{it}^{Sales}$, where both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

we look at what inference we can get that is consistent across small and large firms. Notice that the business stealing effect is approximately one-third / one-fourth of the magnitude of the capital-deepening effect. From equation 11, this implies that $|(1 - \sigma_l)| < |\sigma_l - \sigma_u|$. In fact, we cannot statistically distinguish $1 - \sigma_l$ from 0, implying that $\sigma_l \approx 1$. This means that the lower nest in our production function, the CES between different intermediate goods, is not distinguishable from Cobb-Douglass.

It is worth testing whether the evidence of downstream exposure effects is inconsistent with the evidence from the upstream exposure effects. The estimates of downstream exposure effects from large firms imply an elasticity of substitution between labor and intermediate goods of around 0.83, which is similar to the 0.75 we find from upstream exposure effects. This implies that the data does not reject the theory: among large firms for which we have more credible data, our estimates are consistent across different specifications.

To sum up, we estimate the elasticities of substitution between labor and intermediate goods as $\hat{\sigma_u} = 0.76$, and between different intermediate goods as $\hat{\sigma_l} = 1$. Given that the evidence across the structural equations, upstream exposure effect on labor share and downstream exposure effects on sales, are consistent (i.e., the data does not reject the model), we move on to our counterfactual estimates to quantify the total effects of immigration on host and non-host labor markets.

Figure 5: Histogram of real wage changes in host and average non-host region



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.

5 Counterfactuals

This section uses the model to quantify the effects of immigration on the host and non-host regions through counterfactuals. We investigate the economic significance of the trade spillovers of immigration, how these spillovers depend on host regions' and immigrants' characteristics, and what these spillovers imply about our understanding of the effects of immigration on labor markets.

5.1 Counterfactual 1: Do immigrants impact non-host regions in economically meaningful amounts?

In our first counterfactual, we investigate whether immigrants can impact the labor markets in non-host regions in economically meaningful amounts. To answer this question, for each of the 81 provinces in Turkey, we shock the economy with a 1% increase in labor supply in that region, and calculate the change in real wages in the host region and the average non-host region. The latter is an average of real changes in the other 80 provinces. This gives us 81 different estimates for the real wage effects in the host and non-host regions. Figure 5 shows the histogram of these wage effects. Note that since we assume inelastic labor supply, in an economy where firms only traded within region, a 1% increase in labor supply would have decreased real wages in the host region by 1% and not change the real wages in the non-host regions.

There are two key observations from Figure 5. First, in most counterfactuals, the real wage in the host region decreases by around 1%, and the real wage in the non-host regions does not change on average. In 76 out of 81 host region selections, the real wage in the average non-host region changes by less than 0.02%. This is because, in most regions, firms trade overwhelmingly within the region. Consequently, real wage changes in the host region do not lead to economically meaningful price changes in the non-host regions. Put differently, the spillover effects of an immigration shock on real wages are mostly negligible.

How are these results consistent with our earlier findings that firms in non-host regions who buy directly or indirectly from host regions increase their demand for labor? The answer is that only a relatively small number of firms in non-host regions are upstream exposed in meaningful amounts to the immigration shock to the south-east regions. While our identification strategy enables us to isolate the effect on these firms, the aggregate effect on the non-host regions remains negligible.

Second, there are two clear outliers in the real wage impacts on non-host regions. These belong to Istanbul and Ankara, Turkey's two largest and most developed cities. A 1% increase in labor supply in Istanbul decreases the real wages in Istanbul by 0.56% and increases the real wages in the average non-host region by 0.38%. Similarly, a 1% shock in Ankara decreases real wage in Ankara by 71% and increases the real wage in the average non-host region by 22%.

It is not surprising that the effects on non-host regions are largest when Istanbul and Ankara receive immigrants. Based on eigenvector centrality, these are the two central nodes in the regional trade network. Our evidence suggests that regions that take a more central position in the domestic trade network play a more important role in determining the treatment effect of immigrants on regions that do not receive immigrants.

These results have important implications for the accumulated empirical evidence on the effects of immigration on labor markets and why different studies often find opposing results (Dustmann et al., 2016). The standard way of studying the effects of immigrants on labor markets has been a spatial difference in difference design (DiD), in which regions that receive immigrants are compared to others before and after the shock (Altonji and Card, 1991; Card, 2001). Famously, Card (1990) studied the labor market effects of the Mariel Boatlift on Miami's labor markets by comparing Miami to Atlanta, Houston, Los Angeles and Tampa-St. Petersburg, and found mostly null effects.[26] Identification in this type of DiD analysis relies on the stable unit treatment value assumption (SUTVA), which requires that the labor markets in the "control" (non-host) regions are not impacted by the arrival of immigrants to "treated" (host) regions. Our results show that, when immigrants

[26]Mariel Boatlift increased Miami's labor supply by 7%.

arrive at the central nodes of the trade network, SUTVA fails to hold.[27] For instance, when Istanbul receives a 1% increase in labor supply, the real wages in otherwise "control" regions increase between 0.30-0.46%, while the real wage in Istanbul goes down by 0.56%. Comparing Istanbul to other regions in Turkey, as is done in DiD analyses, would cause us to massively overestimate the negative impact of immigrants on wages in Istanbul. If the technology parameters were different, for example, if labor and intermediate goods were gross substitutes or if business-stealing motives were more substantial, then immigrant arrival to Istanbul could have also lowered the real wages in the non-host regions, causing the DiD analysis to under-estimate the impact of immigrants on the host region.

5.2 Counterfactual 2: What is the optimal location for immigrants regarding total welfare?

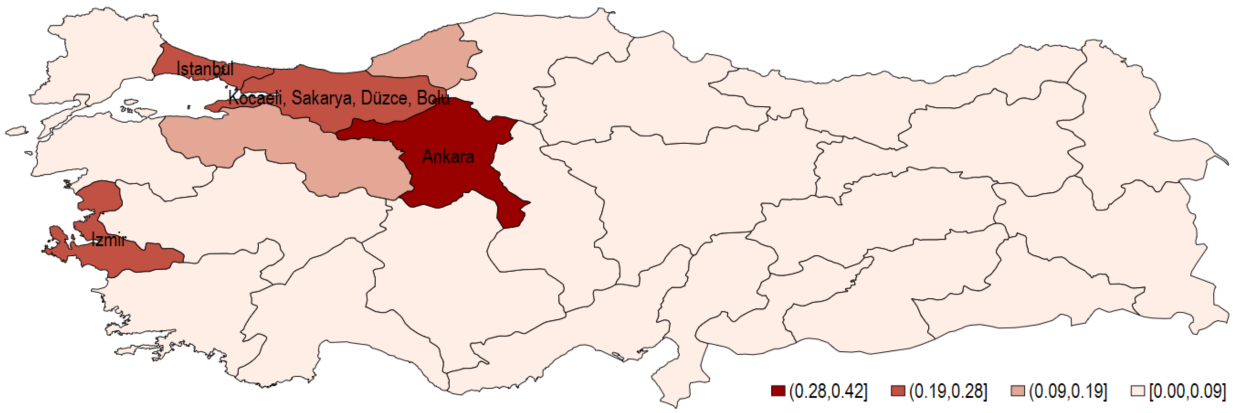
Given that spillover effects of immigration to non-host regions vary substantially based on which region receives immigrants, a natural question is whether these differences in spillover effects matter for welfare. Suppose Turkey receives 100,000 immigrants and can decide where immigrants will be located. Does the location of immigrants impact the total welfare effects of immigration in economically meaningful amounts?

One challenge in answering this question is that, due to the massive heterogeneity in populations across provinces in Turkey (120 thousand in Kilis to 14 million in Istanbul), an immigration shock of the same size creates too large of a difference in the percentage change in local populations. To generate comparable increases in percentage terms, we run our analyses in this subsection at the 26 NUTS-2 level instead of the 81 NUTS-3 (province) level. We run 26 counterfactuals, one for each NUTS-2 region in Turkey, in which we create a percentage labor shock $d \ln L$ equivalent to the arrival of 100,000 immigrants and calculate the change in total welfare.

Figure 6 shows the heatmap of the total welfare effects of 100,000 immigrants, a 0.12% increase in total population in Turkey, across different host regions. We see a significant heterogeneity in the total welfare effects of immigration. Whereas immigrants increase total welfare across all 26 trials, it does so little in most regions in Turkey. In 21 out of 26 trials, we document less than 0.09% increase in welfare. In contrast, the welfare effects increase by 0.19-0.42%, up to 21 times larger than the smallest welfare effect of 0.02%, when regions like Izmir, Istanbul, and Ankara receive immigrants. Welfare effects are largest when these cities receive immigrants because they are central nodes in the trade network based on

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

Figure 6: Heatmap of Total Welfare Effects of Immigration across Host Regions



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

Eigenvector centrality. Firms in these regions buy from and sell to firms in various other regions. Consequently, more regions benefit from the cost reductions, which results in a larger increase in total welfare.

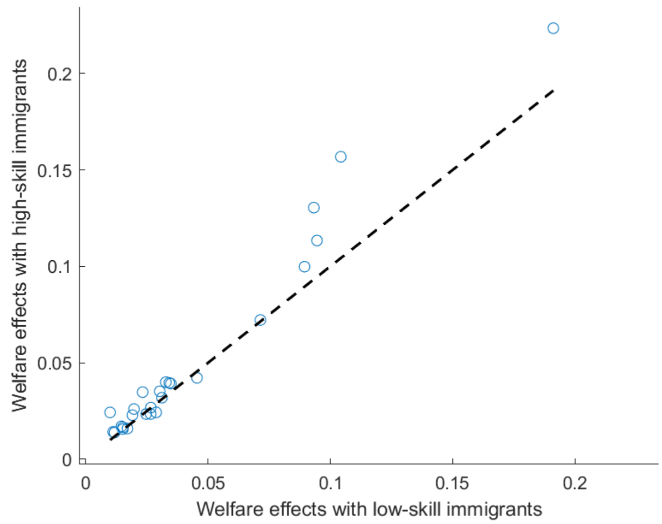
The main takeaway from this counterfactual is that the welfare implications of immigration depend largely on which regions receive immigrants. In the present setting, a social planner that wants to maximize the total welfare in the economy would prefer immigrants settle in the central nodes of the trade network, which are the economically developed provinces like Izmir, Istanbul, and Ankara.[28]

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

Up until this point in the paper, we have abstracted away from the skill heterogeneity of workers by assuming only one type of labor in a region. However, in practice, immigrants and natives can differ in skill levels. For example, Syrian immigrants are less educated than the Turkish native labor force and work in less skill-intensive industries such as Textile, Construction, and Agriculture (Crescent and Programme, 2019). If low-skill and high-skill labor are not perfect substitutes, then low-skill and high-skill immigrants lower production costs in different types of industries. Depending on how much these industries vary in their

[28]We also document sizeable welfare effects when the NUTS-2 region consisting of Kocaeli, Sakarya, Duzce, and Bolu receives immigrants. This is located right between Turkey's two most important domestic trade nodes, and therefore, they trade heavily with these two regions.

Figure 7: Comparison of welfare effects across low-skill and high-skill immigration



Notes: This figure shows the results from 52 counterfactuals, two for each NUTS-2 region in Turkey. For each region, we calculate the total welfare change when (1) 100,000 low-skill immigrants arrive in the host region and (2) 100,000 high-skill immigrants arrive in the host region. Low-skill is having less than a high school degree, and high-skill is having at least a high school degree.

trade relations with other regions, the spillover effects of immigration can also vary by the skill content of immigrants.

To quantify how much the spillover effects of immigration change based on the skill intensity of immigrants, we first extend our model to incorporate skill heterogeneity. Details are provided in Appendix Section A. Then, we run 26 counterfactuals, once for each NUTS-2 region in Turkey, in which we treat the host region with first 100,000 low-skill and then 100,000 high-skill immigrants and compare the welfare effects between the two trials.

Figure 7 plots the welfare effects of low-skill and high-skill immigration. Each small circle represents one of the 26 NUTS-2 regions. The x-axis corresponds to the welfare effects of low-skill immigration, the y-axis corresponds to the welfare effects of high-skill immigration, and the dashed line is the 45-degree line. Points above the dashed line are the regions where high-skill immigration leads to higher welfare gains in the overall economy.

There are two takeaways from this figure. First, both low-skill and high-skill immigration create negligible welfare effects for most of our trials. This is consistent with our earlier results, which showed that the spillover effects of immigration, which are inherently linked to the total welfare effects, are negligible when the host regions are not the most developed regions of Turkey. In these cases, it does not matter whether the immigrant is low- or high-skilled: the cost reductions from immigration are contained within the region, resulting in negligible welfare effects. In contrast, in cases where the welfare gains are high or, equivalently, the host region is a central node in the trade network, high-skill immigration leads to sizable gains in welfare. For example, an arrival of 100,000 low-skill immigrants increases total welfare in Turkey by 0.10%, as opposed to an arrival of 100,000 high-skill immigrants, which increases total welfare by 0.16%.

6 Conclusion

This paper presents a comprehensive analysis of how immigration-induced wage shocks propagate through regional economies via production networks. The theoretical model and empirical evidence together show that immigration can have significant spillover effects on labor demand, particularly when immigrants settle in central nodes of a domestic trade network and/or when immigrants work in skill-intensive industries. This highlights the importance of considering regional trade structures when evaluating the economic effects of immigration.

Our findings challenge traditional approaches to studying immigration's impact, which often ignore interregional spillovers, and offer new insights into why previous studies may have produced conflicting results. Overall, this paper contributes to the broader literature on immigration and labor markets by demonstrating the importance of incorporating production networks into the analysis, offering policy-relevant insights into the management of large immigration episodes.

References

Abadie, Alberto and Jérémy L'hour, "A penalized synthetic control estimator for disaggregated data," *Journal of the American Statistical Association*, 2021, *116* (536), 1817–1834.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "Microeconomic origins of macroeconomic tail risks," *American Economic Review*, 2017, *107* (1), 54–108.

_, David Autor, David Dorn, Gordon H Hanson, and Brendan Price, "Import competition and the great US employment sag of the 2000s," *Journal of Labor Economics*, 2016, *34* (S1), S141–S198.

_, Ufuk Akcigit, and William Kerr, "Networks and the macroeconomy: An empirical exploration," *Nber macroeconomics annual*, 2016, *30* (1), 273–335.

_, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The network origins of aggregate fluctuations," *Econometrica*, 2012, *80* (5), 1977–2016.

Akgündüz, Yusuf, Abdurrahman Aydemir, Seyit Cilasun, and Murat G Kïrdar, "Propagation of Immigration Shocks through Firm-to-Firm Trade Networks," IZA Discussion Paper, IZA 2024.

Aksu, Ege, Refik Erzan, and Murat Güray Kırdar, "The impact of mass migration of Syrians on the Turkish labor market," *Labour Economics*, 2022, p. 102183.

Altonji, Joseph G and David Card, "The effects of immigration on the labor market outcomes of less-skilled natives," in "Immigration, trade, and the labor market," University of Chicago Press, 1991, pp. 201–234.

Angrist, Joshua D, "Grouped-data estimation and testing in simple labor-supply models," *Journal of Econometrics*, 1991, *47* (2-3), 243–266.

Bahar, Dany, Isabel di Tella, and Ahmet Gulek, "Formal Effects of Informal Labor Supply and Work Permits: Evidence from the Venezuelan Refugees in Colombia," 2024. Available at: https://shorturl.at/JwuGW.

Baqaee, David Rezza and Emmanuel Farhi, "The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem," *Econometrica*, 2019, *87* (4), 1155–1203.

Barrot, Jean-Noël and Julien Sauvagnat, "Input specificity and the propagation of idiosyncratic shocks in production networks," *The Quarterly Journal of Economics*, 2016, *131* (3), 1543–1592.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar, "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake," *Review of Economics and Statistics*, 2019, *101* (1), 60–75.

Borjas, George J, "The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market," *The Quarterly Journal of Economics*, 2003, *118* (4), 1335–1374.

_ , "The wage impact of the Marielitos: A reappraisal," *ILR Review*, 2017, *70* (5), 1077–1110.

_ **and Joan Monras**, "The labour market consequences of refugee supply shocks," *Economic Policy*, 2017, *32* (91), 361–413.

_ **, Richard B Freeman, Lawrence F Katz, John DiNardo, and John M Abowd**, "How much do immigration and trade affect labor market outcomes?," *Brookings papers on economic activity*, 1997, *1997* (1), 1–90.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel, "Quasi-experimental shift-share research designs," *The Review of Economic Studies*, 2022, *89* (1), 181–213.

Brinatti, Agostina, "Third-Country Effects of US Immigration Policy," *Available at SSRN 4892498*, 2024.

Burstein, Ariel, Gordon Hanson, Lin Tian, and Jonathan Vogel, "Tradability and the Labor-Market Impact of Immigration: Theory and Evidence From the United States," *Econometrica*, 2020, *88* (3), 1071–1112.

Caliendo, Lorenzo, Luca David Opromolla, Fernando Parro, and Alessandro Sforza, "Goods and factor market integration: A quantitative assessment of the EU enlargement," *Journal of Political Economy*, 2021, *129* (12), 3491–3545.

Card, David, "The impact of the Mariel boatlift on the Miami labor market," *ILR Review*, 1990, *43* (2), 245–257.

_ , "Intertemporal labor supply: An assessment," 1991. NBER Working Paper, 3602.

_ , "Immigrant inflows, native outflows, and the local labor market impacts of higher immigration," *Journal of Labor Economics*, 2001, *19* (1), 22–64.

_ , "Immigration and inequality," *American Economic Review*, 2009, *99* (2), 1–21.

Carvalho, Vasco M, "From micro to macro via production networks," *Journal of Economic Perspectives*, 2014, *28* (4), 23–48.

_ **and Alireza Tahbaz-Salehi**, "Production networks: A primer," *Annual Review of Economics*, 2019, *11* (1), 635–663.

_ **, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi**, "Supply chain disruptions: Evidence from the great east japan earthquake," *The Quarterly Journal of Economics*, 2021, *136* (2), 1255–1321.

Crescent, Turkish Red and World Food Programme, "Refugees In Turkey: Livelihoods Survey Findings," 2019.

Dustmann, Christian and Albrecht Glitz, "How do industries and firms respond to changes in local labor supply?," *Journal of Labor Economics*, 2015, *33* (3), 711–750.

_ **, Tommaso Frattini, and Ian P Preston**, "The effect of immigration along the distribution of wages," *Review of Economic Studies*, 2013, *80* (1), 145–173.

_ **, Uta Schönberg, and Jan Stuhler**, "The impact of immigration: Why do studies reach such different results?," *Journal of Economic Perspectives*, 2016, *30* (4), 31–56.

_ **,** _ **, and** _ , "Labor supply shocks, native wages, and the adjustment of local employment," *The Quarterly Journal of Economics*, 2017, *132* (1), 435–483.

Friedberg, Rachel M, "The impact of mass migration on the Israeli labor market," *The Quarterly Journal of Economics*, 2001, *116* (4), 1373–1408.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift, "Bartik instruments: What, when, why, and how," *American Economic Review*, 2020, *110* (8), 2586–2624.

Gulek, Ahmet, "Formal Effects of Informal Labor: Evidence from the Syrian Refugees in Turkey," 2024. Available at SSRN: https://ssrn.com/abstract=4264865.

_ **and Jaume Vives i Bastida**, "Synthetic IV estimation in panels," 2024. Available at: https://economics.mit.edu/sites/default/files/inline-files/Synthetic_Wald%20%283%29.pdf.

Hanson, Gordon H, "The economic consequences of the international migration of labor," *Annu. Rev. Econ.*, 2009, *1* (1), 179–208.

Hunt, Jennifer, "The impact of the 1962 repatriates from Algeria on the French labor market," *ILR Review*, 1992, *45* (3), 556–572.

Lewis, Ethan and Giovanni Peri, "Immigration and the Economy of Cities and Regions," in "Handbook of regional and urban economics," Vol. 5, Elsevier, 2015, pp. 625–685.

Ottaviano, Gianmarco IP and Giovanni Peri, "Rethinking the effect of immigration on wages," *Journal of the European Economic Association*, 2012, *10* (1), 152–197.

Peri, Giovanni and Vasil Yasenov, "The labor market effects of a refugee wave synthetic control method meets the mariel boatlift," *Journal of Human Resources*, 2019, *54* (2), 267–309.

Sun, Liyang, Eli Ben-Michael, and Avi Feller, "Using multiple outcomes to improve the synthetic control method," *arXiv preprint arXiv:2311.16260*, 2023.