No 2025-17 – November 2025

Working Paper

CEPII

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Highlights

- This paper studies how immigrants in intermediate sectors affect downstream export performance.
- We develop a theoretical model in which a sector's exports depend not only on its own immigrant workforce but also on immigrant labor in input-supplying sectors.
- We show that increases in immigrant employment in these sectors raise exports in connected downstream industries.

Abstract

This paper studies how immigrants in intermediate sectors affect downstream export performance. We develop a theoretical model in which a sector's exports depend not only on its own immigrant workforce, but also on immigrant labor in input-supplying sectors. Using a new dataset on U.S. input–output from 2003-2017, we show that increases in immigrant employment in these sectors raise exports in connected downstream industries. This effect operates partly through improved production efficiency that lowers upstream input costs. By linking labor migration to production networks, we identify a new channel through which immigration shapes comparative advantage in international trade.

Keywords

Immigration, Trade, Sectoral Linkages, Intermediate Sectors.

JEL

F22, F16, J61, O31.

Working Paper CEPII

CEPII Working Paper
Contributing to research in international economics

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Editorial Director:
Antoine Bouët

Visual design and production:
Laure Boivin

ISSN 2970-491X

November 2025

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Sectoral Linkages and the Impact of Immigration on Export Performance*

Amandine Aubry†, Anthony Edo‡

1 Introduction

Modern economies operate as intricate production networks, where shocks in one sector ripple through others (Carvalho and Tahbaz-Salehi, 2019). Immigration, meanwhile, reshapes local labor markets and production efficiency (Lewis and Peri, 2015; Dustmann and Schönberg, 2025). Although prior research highlights the importance of sectoral linkages for trade (Caliendo and Parro, 2014; Baqaee and Farhi, 2024), little is known about how immigration interacts with these production networks to affect downstream economic outcomes. This paper investigates this dimension in the context of the migration–export nexus, asking how immigrant employment in input-producing sectors affects the export performance of downstream industries through sectoral linkages.

The relationship between immigration and exports has been studied extensively, motivated by the parallel growth of international trade and cross-border migration. Beginning with the seminal contributions of Gould (1994) and Head and Ries (1998), this literature finds that immigration enhances trade and boosts the export performance of host coun-

*The usual disclaimers apply. We are grateful to Mette Foged, Torsten Jaccard, Sébastien Jean, Gianluca Santoni, André Sesboüé and Camilo Umana-Dajud for their insightful comments. We thank the participants at the XII meeting on international economics, the 14th Annual Conference on Immigration in OECD Countries, the international trade seminar at the Jaume I university, the CoLab lunch workshop at the University of Copenhagen, the CREM-CREST-SMART's workshop.

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tries.[1] Most studies emphasize migration networks as the central transmission mechanism, whereby immigrants lower bilateral trade costs by facilitating information flows. A second channel operates through productivity gains induced by immigration, which reduce production costs and improve export competitiveness (Mitaritonna et al., 2017; Ottaviano et al., 2018; Mahajan, 2024).

The present paper contributes to the literature by introducing a new mechanism through which immigration can enhance export performance. Productivity gains from immigration are not confined to the sectors that employ immigrant labor but can propagate throughout downstream industries via input-output (I-O) linkages. Specifically, immigrants in upstream sectors can help reduce input costs, thereby improving the export performance of downstream sectors. To formalize this idea, we develop a theoretical framework that characterizes how productivity effects from immigrant labor propagate through the production network. This framework also incorporates the standard network mechanism whereby immigrants reduce bilateral trade costs, allowing us to analyze multiple channels of the migration–trade relationship within a unified model. Specifically, our theoretical framework extends the model of Caliendo and Parro (2014) by incorporating immigration as a factor that affects bilateral trade costs, following Aubry and Rapoport (2019), and production costs, consistent with empirical evidence from Mitaritonna et al. (2017); Ottaviano et al. (2018); Mahajan (2024). To model how immigrant labor generates productivity gains and how they diffuse across sectors, we build on the knowledge diffusion framework of Cai et al. (2022). This approach allows us to formalize three distinct channels through which immigration affects exports within a unified framework: (i) a network channel, where immigrants reduce bilateral trade costs with their country of origin; (ii) a productivity channel, where immigration raises productivity in the sector they work; and (iii) a sectoral spillover channel, where immigration in upstream (i.e. input-providing) sectors enhances productivity, thereby lowering input costs for downstream sectors. To our knowledge, no existing study has jointly modeled the network and productivity channels, or incorporated sectoral linkages in analyzing the immigration–trade relationship.

Our theoretical model yields a testable empirical specification, which we estimate using I-O data. Specifically, we construct an enriched I-O matrix by combining the 2002 Detailed Benchmark I-O Accounts with data from the American Community Survey (ACS) and the U.S. Census. These data allow us to map detailed economic characteristics for each sector within the production network and to measure immigrant penetration in both upstream and downstream industries. We then exploit sectoral variations from 2003 to 2017 to estimate the impact of immigration in intermediate sectors on the export performance of final

[1] See, e.g., Peri and Requena-Silvente (2010); Felbermayr and Toubal (2012); Andrews et al. (2017); Parsons and Vézina (2018); Aubry and Rapoport (2019); Bailey et al. (2021); Cardoso and Ramanarayanan (2022); Orefice et al. (2025). See also Genc et al. (2012) for a meta-analysis, and Hatzigeorgiou and Lodefalk (2021) for a review of the literature.

manufacturing sectors.

To ensure that our estimates are not biased by the non-random allocation of immigrants across sectors, we construct shift-share instruments based on the historical distribution of immigrants by country of origin across sectors (Altonji and Card, 1991; Card, 2001). Specifically, we use the 1980 U.S. Census to construct a predicted distribution of immigrants across sectors for the period under study. Our instrumental variable (IV) strategy relies on the fact that the current penetration of immigrants in sectors is partly determined by the presence of previous migrants in these sectors (Patel and Vella, 2013), while the 1980 distribution should be uncorrelated with contemporaneous sectoral shocks. We validate this approach through a series of pre-trend tests.

Our empirical results show that a rise in the immigrant workforce in intermediate sectors improves the export performance of downstream sectors, consistent with the sectoral spillover mechanism. The IV estimates indicate that a 1 % increase in immigrant employment in the two main intermediate sectors of a given final sector raises its exports by approximately 1.2 %. In line with the theoretical predictions, we find evidence that immigrant labor facilitates the adoption of improved production processes in intermediate sectors, lowering input costs for downstream exporters.

We also find that a larger immigrant workforce in a given sector enhances its own export performance. This finding is consistent with Mitaritonna et al. (2017); Ottaviano et al. (2018) who show that immigration boosts regional export performance. By contrast, our cross-sectoral estimates do not show robust evidence of network effects. An increase in the number of immigrants from a given origin country employed in a given sector is not systematically associated with higher exports from that sector to that country.

In sum, our findings highlight a new dimension of the migration–export nexus: immigrants in upstream sectors can enhance the export competitiveness of downstream industries by improving efficiency and reducing production costs. Our paper thus bridges the literature on immigration, trade, and production networks, providing a framework for understanding how immigration shocks affect the economy through sectoral linkages.

The remainder of the paper is structured as follows. Section 2 describes the data and provides preliminary evidence on the correlation between immigrant penetration in key input sectors and the export performance of downstream industries. Section 3 provides a theoretical framework that rationalizes this positive correlation. Section 4 outlines the empirical specification and identification strategy. Section 5 presents the main empirical results, while Section 6 explores a key mechanism that explains our main empirical finding. Finally, Section 7 concludes.

2 Data and Descriptive Evidence

This section describes the data and methodology used to construct the main variables, and presents stylized facts on sectoral linkages and immigration. To analyze how immigrants in intermediate sectors affect the export performance of final sectors, we construct a dataset linking an I-O matrix to trade and economic variables. Specifically, we compile sector-level data on trade, employment, innovation, and prices from multiple sources, standardizing all variables according to the 2002 North American Industry Classification System (NAICS).

2.1 Data

Data on Exports. Export data are taken from Schott (2008) and reported at the 6-digit NAICS level. We aggregate them to the 4-digit level by summing export values across corresponding 6-digit sectors. To ensure comparability, we map the 2007 and 2012 NAICS revisions back to the 2002 classification using official crosswalks. We restrict the analysis to the manufacturing sector due to its "tradable nature". Manufacturing accounted for 92 % of U.S. exports over the 2003–2017 period.[2] Export values are deflated to 2015 U.S. dollars using the World Bank GDP deflator (World Bank, 2020).

Data on Sectoral Linkages. Sectoral linkages are measured using the 2002 Detailed Benchmark I-O Accounts from the Bureau of Economic Analysis (BEA). This matrix reports the value of each commodity purchased by sectors as input for production. Following Acemoglu et al. (2016), we use the I-O matrix that predates the analysis period to avoid potential endogeneity with respect to subsequent migration flows and economic outcomes. Thus, BEA I-O industries are mapped to 2002 NAICS codes using BEA's crosswalks, with imputation based on Economic Census sales data when industries span multiple NAICS sectors. The mapping is nontrivial, as some I-O industries span multiple NAICS sectors, requiring imputation of data at the NAICS level. We perform this imputation using sales from the Economic Census published by the U.S. Census Bureau. Appendix B1 provides additional details on the imputation procedure.

The BEA I-O classification and corresponding crosswalk tables were updated in 2007 and 2012, coinciding with revisions to the NAICS classification. To harmonize sectoral definitions over time, we adopt a two-step procedure. First, we align the data coded with I-O classifications to the NAICS system in effect during each subperiod: the 2002 NAICS for 2003–2006, the 2007 NAICS for 2007–2011, and the 2012 NAICS for 2012–2017.

[2] The tradability of non-manufacturing industries has changed over time. However, manufacturing still represented the vast majority of total U.S. exports in 2018 (89 %).

Second, we map the 2007 and 2012 classifications back to the 2002 NAICS using official crosswalks, ensuring consistency across the entire time series.

Data on Employment. We measure immigrant employment using the ACS, which provides individual-level information on birth country, labor force status and sector of activity. We restrict the sample to individuals aged 16–64 in the workforce, and define immigrants as foreign-born workers. To align ACS industry codes with the 2002 NAICS system, we apply BEA crosswalks. Since some census industries map to multiple NAICS sectors, we allocate workers across NAICS sectors using relative employment shares from the BLS (seeAppendix B2 for details). To harmonize sectoral definitions over time, we follow the same methodology described above.

Our main variable of interest is the size of the immigrant workforce in the "intermediate industry" of manufacturing sectors. Specifically, we define the "intermediate industry" as the two largest input-supplying sectors in 2002 (regardless of whether they belong to manufacturing) linked to a given exporting manufacturing sector, and then take the log number of foreign-born workers in these two input sectors to construct our main immigration variable.[3] We use the two largest input sectors for two main reasons. First, the number of input-supplying sectors varies substantially across manufacturing industries (ranging from 75 to 137). Including all suppliers would make the analysis sensitive not only to changes in immigrant employment but also to differences in sectoral coverage, which could confound the results. By consistently selecting the two largest suppliers, we avoid compositional variation and maintain comparability across industries. Second, focusing on the top two input-supplying sectors captures the uneven distribution of input value across suppliers for a given manufacturing sector. In this regard, Figure 1 shows the distribution of intermediate suppliers for a representative manufacturing (exporting) sector, ranked by the value of inputs purchased by that sector. The largest supplier alone (top 1 %) accounts for nearly 29 % of the total input value, and the two largest input sectors together account for slightly more than 40 % of the total. Finally, we show that our results remain robust when the immigrant workforce is measured in the top three input sectors of a given final sector, which together represent roughly half of the total input value across all input sectors.

Data on Innovation and Prices. We use two data sources to examine how immigration shocks propagate across sectors. First, we rely on the Business Research and Development and Innovation Survey (BRDIS), conducted by the U.S. Census Bureau from 2008 to 2016. This nationally representative annual survey collects information on firms' research and development activities. We focus on whether firms reported engaging in innovation and the type of innovation undertaken. Data are available for the years 2008-2011 and 2014-2016. As with the calculation of immigrant penetration in the "intermediate industry",

[3] Using the 2002 I-O table, we rank input-supplying sectors by the value of their sales to each manufacturing sector and retain the top two suppliers.

we aggregate responses across the two main input-supplying sectors of each exporting sector to construct an indicator of innovation intensity.

Second, we use output price data over the 2003-2017 period from the Industry Economic Accounts published by the BEA. We apply the same methodology described earlier to match these data to the 2002 NAICS classification via the I-O table. We then compute average log prices for the two main intermediate sectors of each exporting sector using annual chain-type price indexes for gross output (seasonally adjusted). To smooth short-term volatility in output prices, we average prices over three-year intervals. Each year is reassigned to the midpoint of its corresponding window (e.g., 2003–2005 is recoded as 2004, and 2015–2017 as 2016). We then compute the mean log output price for each "intermediate industry" and time interval, using the same aggregation approach as for the immigrant variable. This procedure yields five non-overlapping periods: 2004, 2007, 2010, 2013, and 2016.

2.2 Stylized Facts on Trade, Immigration and Input Sectors

Our final dataset spans 15 years (2003 to 2017) and includes 74 4-digit manufacturing industries and 115 countries of origin. As shown in Table 1, the average export value per sector shows an upward trend, alongside a rising share of foreign-born workers in both manufacturing and intermediate sectors, indicating a growing reliance on immigrant labor, particularly in final sectors.[4]

Understanding these trends, particularly the role of labor and trade in production, requires examining how manufacturing sectors are interconnected. To illustrate these linkages, Figure 2 documents a key stylized fact about the U.S. production network, showing that among the 20 largest suppliers to manufacturing sectors, a small number of hub industries dominate intersectoral linkages. The left panel shows that 10 hubs generate intermediate input sales between $50 billion and $200 billion, while the right panel highlights that 13 of the 20 largest suppliers provide inputs to more than 60 of the 74 manufacturing sectors. Thus, a handful of dominant hubs sustain many manufacturing-exporting industries, while the rest of the network consists of smaller, less connected suppliers.[5] Figure 3 shows substantial variation in employment across input sectors, with little correspondence to their importance in terms of input value. For example, sectors such as "Wholesale Trade", "Truck Transportation" and "Crop Production" account for many immigrant workers, while other key intermediate suppliers, like "Management of Firms," employ

[4] These 115 countries account for 97 % of total export value in the sample.

[5] "Management of Firms" and "Wholesale Trade" emerge as critical suppliers: the former is the leading input provider for 16 manufacturing sectors, while the latter holds that role for 8 of the 74 sectors in our sample.

relatively few. Figure 3 also shows that the sectoral distribution of immigrants tends to mirror that of natives, indicating that sectors with high (or low) employment levels have similar proportions of both groups.

Motivated by the differentiated role of intermediate sectors, we examine the correlation between immigrant employment in the two main input sectors (i.e. our measure of immigration penetration in input industries) and the export performance of the downstream manufacturing sectors they supply over the 2003–2017 (Figure 4). The unit of observation is a sector–year cell. Exports and immigrant supply shocks are measured as residuals from regressions on sector and year fixed effects. Thus, both variables capture deviations from a sector's average, net of common period shocks. Figure 4 reveals a strong positive correlation, suggestive that export growth is higher in sectors linked to intermediate industries experiencing larger increases in immigrant employment (estimated coefficient 0.32, standard error 0.13). This finding suggests that immigration may influence exports through its impact on the production process of exported goods. The remainder of the paper explores this relationship in depth, testing its robustness and providing a framework that explains how immigration shapes trade through production networks.

3 Theoretical Framework

We develop a partial equilibrium model based on the Ricardian trade model of Caliendo and Parro (2014), incorporating sectoral heterogeneity and I-O linkages, while drawing on the endogenous growth model of Cai et al. (2022) to formalize the impact of immigration on total factor productivity (TFP). This model allows us to endogenize three key mechanisms through which foreign-born workers can enhance export performance. First, we formalize the reduction in bilateral trade costs arising from the presence of immigrants in each sector, often referred to as the network effect. Second, we model the effect of immigration on TFP within the sectors where immigrants are employed, capturing the direct productivity gains on export performance (productivity effect). Third, and most importantly, we introduce a propagation channel through which productivity gains in intermediate sectors are transmitted to downstream sectors via in input prices.

We assume that all markets are perfectly competitive. There are N countries and J sectors in each country. We denote countries by *i* and *n* and sectors by *j* and *k*.

3.1 Preferences and Consumer's Decisions

In each country n, there is a measure L_n of representative consumers with income W_n, who maximize the following utility function:

$$u_n = \prod_{j=1}^{J} (C_n^j)^{\alpha_n^j}, \tag{1}$$

where C_n^j is the consumption of a composite good produced in sector j.[6] The preference parameters, α_n^j, measure the share of expenditure on good C_n^j. We assume that $\sum_{j=1}^{J} \alpha_n^j = 1$. Labor supply is exogenous and we assume that each individual consumes her income entirely.[7]

The utility function is maximized subject to the following budget constraint:

$$\sum_{j=1}^{J} P_n^j C_n^j = W_n, \tag{2}$$

where P_n^j defines the price of the composite good C_n^j produced in sector j and consumed in country n. The demand function for the composite good C_n^j derived from the first-order condition of the maximization problem is:

$$C_n^j = \alpha_n^j \frac{W_n}{P_n^j}. \tag{3}$$

3.2 Firm's Decisions

A continuum of intermediate goods $\omega^j \in$ [0,1] are produced in each sector j. The efficiency of production differs across countries and sectors. We denote $z_n^j(\omega^j)$ the efficiency of producing good ω^j in country n. Two types of inputs are used for the production of ω^j; labor, $(l_n^j(\omega^j))$ and intermediate goods from every other sector k, $(m^{j,k}(\omega^j))$. A good ω^j is produced according to the following constant-returns-to-scale technology:

$$y_n^j(\omega^j) = z_n^j(\omega^j) \left[l_n^j(\omega^j)\right]^{\gamma^j} \prod_{k=1}^{J} \left[m_n^{j,k}(\omega^j)\right]^{\gamma^{j,k}}, \tag{4}$$

where $\gamma^j + \sum_{k=1}^{J} \gamma^{j,k}$=1.[8] The parameter $\gamma^{j,k} \geq 0$ is the share of intermediate goods

[6]The subscripts denote the country and the superscripts denote the sector. Whenever there are two subscripts, the leftmost one corresponds to the destination.

[7]See Aubry et al. (2016) for a detailed discussion of this assumption.

[8]Using I-O tables from 2002 and 2012, we follow Caliendo and Parro (2014) in assessing the stability of input shares by computing the correlation of shares over time. We find an average correlation of 0.90 for U.S. manufacturing sectors, consistent with Caliendo and Parro (2014), who report similar results across 26

from sector k used in the production of good ω^j in sector j, and the parameter γ^j is the share of value added.

The cost minimization problem faced by each producer determines her optimal unit cost of production. Since each good ω^j is produced under constant returns to scale and markets are perfectly competitive, the unit cost of producing ω^j is:

$$\frac{c_n^j}{z_n^j(\omega^j)}, \tag{5}$$

where c_n^j denotes the cost of a bundle of inputs and is defined as:

$$c_n^j = (W_n^j)^{\gamma^j} \prod_{k=1}^{J} (p_n^k(\omega^k))^{\gamma^{j,k}} B^j, \tag{6}$$

where W_n^j is a nominal wage index paid in sector j, $p_n^k(\omega^k)$ is the price of a good ω^k produced in sector k in country n and B^j is a constant and equals $\prod_{k=1}^{J}(\gamma^j)^{-\gamma^j}(\gamma^{j,k})^{-\gamma^{j,k}}$.

Equation (6) captures sectoral interdependencies: the cost of the input bundle depends on wages and on the prices of all intermediate goods in the economy. Consequently, a change in the production cost of any sector k, such as a labor shock induced by immigration, indirectly affects all sectors that use its goods as inputs. In this way, Equation (6) formalizes how shocks propagate across sectors through input prices.

Producers in sector j operate under perfect competition and purchase intermediate products ω^k from the lowest-cost supplier. They supply Q_n^j, the total quantity demanded for both final consumption and as an intermediate input in the production of other goods. Q_n^j is an Ethier (1982) aggregator given by:

$$Q_n^j = \left[\int \left(r_n^j(\omega^j)\right)^{\frac{\sigma^j - 1}{\sigma^j}} d\omega^j\right]^{\frac{\sigma^j}{\sigma^j - 1}}, \tag{7}$$

where $\sigma^j > 0$ is the elasticity of substitution across goods within sector j, and $r_n^j(\omega_j)$ is the demand of goods ω^j. The optimal demand of goods ω^j is determined by the cost minimization subject to Equation (7) and is defined as:

$$r_n^j(\omega^j) = \left(\frac{p_n^j(\omega^j)^{-\sigma^j}}{P_n^j}\right)^{1-\sigma^j} Q_n^j, \tag{8}$$

where P_n^j is a price index defined as:

countries.

$$P_n^j = \left(\int p_n^j(\omega^j)^{1-\sigma^j} d\omega^j\right)^{\frac{1}{1-\sigma^j}}, \tag{9}$$

$p_n^j(\omega^j)$ denotes the lowest price of intermediate good ω^j. The market clearing condition implies that:

$$Q_n^j = C_n^j + \sum_{k=1}^{J} \int m_n^{j,k}(\omega^j) d\omega^j. \tag{10}$$

3.3 Technology and Prices

Following Eaton and Kortum (2002) and Caliendo and Parro (2014), we assume that a firm's efficiency in producing good ω^j within sector j in country n is a realization of the random variable $z_n^j(\omega^j)$, drawn from the country–sector-specific distribution $F_n^j(z) = \Pr(z_n^j \leq z)$. Specifically, z_n^j follows a Fréchet distribution characterized by a country–sector-specific location parameter T_n^j and a sector-specific shape parameter θ^j.[9] The parameter T_n^j captures the state of technology in sector j in country n, reflecting absolute advantage: a higher T_n^j indicates greater average productivity and makes high efficiency draws more likely. The shape parameter θ^j governs comparative advantage: smaller values imply greater productivity heterogeneity across goods and thus stronger forces for trade. The cost of purchasing good ω^j from country n in country i is then the realization of the random variable $p_n^j(\omega^j) = \frac{c_n^j}{z_n^j(\omega^j)}$, and the lowest price is the realization of $p_i^j(\omega^j)$=$\min\left(\frac{c_n^j}{z_n^j(\omega^j)}, n = 1, \ldots, N\right)$. Under the assumptions that productivity distributions are independent across goods, sectors, and countries, and that $1+\omega^j$¿σ^j, the distribution of prices can be derived. The exact CES price index of Equation (9) is then given by:

$$P_i^j = D^j \left[\sum_{n=1}^{N} T_n^j (c_i^j)^{-\theta^j}\right]^{-\frac{1}{\theta^j}}, \tag{11}$$

for all sector j and country n, where D^j is a constant.[10]

[9] Kortum (1997) and Eaton and Kortum (1999) show that the Fréchet distribution maps technology with extreme value properties into a corresponding extreme value distribution of prices. Costinot et al. (2011) extends the analysis to more general distributions.

[10] Appendix A1 presents a detailed derivation of the distribution of prices and how to solve for the price index (Equation (11)). The derivation follows Eaton and Kortum (2002) and Caliendo and Parro (2014).

3.4 Migration, Trade and Production costs

3.4.1 Network Effect

International trade in goods is costly, and we model this using iceberg costs: delivering one unit from country n to i requires producing τ_{in}^{j} units in n. Trade costs vary across countries and sectors, reflecting various underlying barriers. A growing literature highlights information frictions as a key component of trade costs that inhibit and distort trade flows (Allen, 2014; Steinwender, 2018; Bailey et al., 2021). Immigrants in the producing country help reduce such frictions by facilitating contract enforcement and transmitting knowledge of their origin country's language, regulations, market opportunities, and institutions (Chaney, 2016; Parsons and Vézina, 2018). We therefore follow the diaspora networks literature in assuming that trade costs decrease with diaspora size (Munshi, 2003; Beine et al., 2011). As in Felbermayr and Toubal (2012); Aubry and Rapoport (2019), we model bilateral variable trade costs of exports from country n to country i as the product of physical transport costs (η_{in}^{j}) and information costs (inf_{in}^{j}):

$$\tau_{in}^{j} = \eta_{in}^{j} inf_{in}^{j} t_{i}^{\phi_{i,\tau}} t_{n}^{\phi_{n,\tau}} > 1, \tag{12}$$

where t_i and t_n represent multilateral components of trade costs. These factors capture the "potential advantages" of a country relative to all its trading partners, such as the presence of larger airports. The information cost is defined as:

$$inf_{in}^{j} = \frac{e_{in}^{j}}{{M_{ni}^{j}}^{\delta_\tau}}, \tag{13}$$

where e_{in}^{j} captures the extent of information costs and M_{ni}^{j} denotes the stock of migrants from country i working in sector j in country n. We assume that the triangular inequality holds; $\tau_{hn}^{j}\tau_{ih}^{j} \geq \tau_{in}^{j}\ \forall\ n,h,i$.

The relative changes of the bilateral trade cost with respect to migration is then defined as:

$$\frac{d\tau_{in}^{j}}{\tau_{in}^{j}} = -\delta_\tau \frac{dM_{ni}^{j}}{M_{ni}^{j}}. \tag{14}$$

This mechanism is widely recognized in the literature as the main driver of the positive correlation observed between bilateral migration and exports. Specifically, an increase in the stock of migrants from country i residing in country n lowers the variable trade costs for firms in country n exporting to country i. Delivering a unit good ω_j produced in country n to country i costs then:

$$p_{in}^j(\omega^j) = \frac{c_i^j \tau_{in}^j}{z_i^j(\omega^j)} \quad \text{with} \quad \tau_{in}^j > 1 \quad \text{if} \quad n \neq i \quad \text{and} \quad \tau_{in}^j = 1 \quad \text{if} \quad n = i. \tag{15}$$

Since markets are perfectly competitive, $p_{in}^j(\omega^j)$ denotes the price paid by a buyer in country i for good ω^j produced in country n, which is the lowest price available across all countries:

$$p_{in}^j(\omega^j) = min\left(\frac{c_n^j \tau_{in}^j}{z_n^j(\omega^j)}, n = 1, \ldots, N\right), \tag{16}$$

with $\tau_{in}^j > 1$ if $n \neq$ i and $\tau_{i,n}^j$=1 if $n = i$.

3.4.2 Productivity and Spillover Effects Across Sectors

A large body of research shows that immigration fosters productivity growth in host countries through mechanisms such as task specialization (Peri and Sparber, 2009), technology adoption (Lewis, 2013; Ottaviano and Peri, 2012; Lafortune et al., 2019; Sequeira et al., 2019), process innovation (Gray et al., 2020), patenting (Hunt and Gauthier-Loiselle, 2010; Mayda et al., 2022; Moser and San, 2023), or reduced offshoring costs (Ottaviano et al., 2013, 2018). While total factor productivity (TFP) and innovation are often associated with high-skilled immigrants (Docquier et al., 2014), recent evidence indicates that low-skill immigration can also raise productivity by fostering process innovation (Gray et al., 2020) and supporting production and investment (Clemens and Lewis, 2023).

Guided by this evidence, we model immigration as a productivity-enhancing factor without imposing restrictions on migrants' skill levels. Specifically, we endogenize the location parameter T_n^j, which captures the state of technology in sector j of country n, following Cai et al. (2022).[11] We assume that T_n^j is increasing in the stock of migrants employed in that sector:

$$T_n^j = \lambda_n^j (M_n^j)^{\beta_n^j}, \tag{17}$$

where λ_n^j is an exogenous component of innovation efficiency unrelated to migration, M_n^j denotes the stock of immigrants in sector j, and $\beta_n^j \geq 0$ governs the elasticity of technology with respect to migration. Ceteris paribus, sectors employing more migrants attain higher T_n^j and thus higher expected productivity levels. Firms in such sectors are

[11] Cai et al. (2022) interpret T_n^j as reflecting not only the state of technology but also the stock of knowledge in sector j of country n.

more likely to draw higher productivity realizations $z_n^j(\omega^j)$ and to charge lower prices $p_n^j(\omega^j)$ than firms in sectors with fewer migrants.

This mechanism can be formalized as follows. From Equation (5) and the assumption that productivity follows a Fréchet distribution, the expected price is:[12]

$$\mathbb{E}[p_n^j] = c_n^j \, \Gamma\Big(1 + \frac{1}{\theta^j}\Big) \, (T_n^j)^{-1/\theta^j}, \tag{18}$$

where $\Gamma(\cdot)$ denotes the Gamma function. Equation (18) directly links technology to prices. Substituting Equation (17) into Equation (18) gives:

$$\mathbb{E}[p_n^j] = c_n^j \, \Gamma\Big(1 + \frac{1}{\theta^j}\Big) (\lambda_n^j)^{-1/\theta^j} (M_n^j)^{-\beta_n^j/\theta^j}. \tag{19}$$

This formulation of the productivity effect of immigration delivers two main results. First, immigration (M_n^j) raises sectoral productivity by increasing the expected technology level T_n^j, thereby lowering prices:

$$\frac{\partial \mathbb{E}[p_n^j]}{\partial M_n^j} = -\frac{\beta_n^j}{\theta} \, c_n^j \, \Gamma\Big(1 + \tfrac{1}{\theta}\Big) (\lambda_n^j)^{-1/\theta} (M_n^j)^{-\beta_n^j/\theta - 1} < 0. \tag{20}$$

Second, productivity gains transmit to downstream sectors. An increase in immigrants employed in input sector k reduces downstream sector j's marginal costs, improving the competitiveness of its exports. Substituting Equation (17) into Equation (6), and using the simplifying CES assumption that $p_n^k = \mathbb{E}[p_n^k]$, yields

$$c_n^j = (W_n^j)^{\gamma^j} B^j \prod_{k=1}^{J} \Big[c_n^k \, \Gamma\Big(1 + \tfrac{1}{\theta}\Big) (\lambda_n^k)^{-1/\theta} (M_n^k)^{-\beta_n^k/\theta} \Big]^{\gamma^{j,k}}. \tag{21}$$

Taking logs facilitates differentiation and clarifies the effect of immigration in sector k on the marginal cost in sector j:

$$\log c_n^j = \gamma^j \log W_n^j + \log B^j + \sum_{k=1}^{J} \gamma^{j,k} \Big[\log c_n^k + \log \Gamma\Big(1 + \tfrac{1}{\theta}\Big) - \tfrac{1}{\theta} \log \lambda_n^k - \tfrac{\beta_n^k}{\theta} \log M_n^k \Big]. \tag{22}$$

[12] See the derivation in Appendix A2.

Differentiating with respect to sector $\log M_n^k$ yields:

$$\frac{\partial \log c_n^j}{\partial \log M_n^k} = -\frac{\beta_n^k}{\theta}\gamma^{j,k} + \sum_{h=1}^{J} \gamma^{j,h} \frac{\partial \log c_n^h}{\partial \log M_n^k}. \tag{23}$$

Under the usual assumptions that $\beta_n^k > 0$ and the input shares are such that the recursion converges, the total derivative is negative, $\partial \log c_n^j / \partial \log M_n^k < 0$. Hence, increases in immigrant employment in sector k reduce marginal costs throughout the production network.

Since trade flows X_{in}^j increase in T_n^j and decrease in c_n^j (see Section 3.5), it follows that:

$$\frac{\partial X_{in}^j}{\partial M_n^j} > 0, \qquad \frac{\partial X_{in}^j}{\partial M_n^k} > 0.$$

3.5 Trade Flows

Using the properties of the Fréchet distribution, we can derive the expected expenditure of country i in sector j from country n, $\mathbb{E}[X_{in}^j]$, as a function of technologies, prices, and trade costs:[13]

$$\mathbb{E}[X_{in}^j] = \frac{T_n^j (c_n^j \tau_{in}^j)^{-\theta^j}}{\Phi_i^j} X_i^j, \tag{24}$$

where X_i^j is the total expenditure of country i in sector j. Φ_i^j is the multilateral resistance term, capturing the overall competitiveness of all potential exporters to i in sector j.

Log-linearizing Equation (24) and incorporating Equations (12), (13), (17), and (21) gives the following log-linearized gravity Equation:

$$\begin{aligned}
\log(\mathbb{E}[X_{in}^j]) = {} & \log(X_i^j) - \log(\Phi_i^j) + \log(\lambda_n^j) - \theta^j \gamma^j \log(W_n^j) - \theta^j \log(B^j) \\
& - \theta^j \phi_{i,\tau} \log(t_i) - \theta^j \phi_{n,\tau} \log(t_n) - \theta^j \log(\eta_{in}^j) - \theta^j \delta_\tau \log(e_{in}^j) \\
& - \theta^j \sum_k \gamma^{j,k} \left[\log c_n^k + \log \Gamma\left(1 + \frac{1}{\theta^k}\right) - \frac{1}{\theta^k} \log \lambda_n^k \right] \\
& + \underbrace{\theta^j \delta_\tau \log(M_{ni}^j)}_{\text{Network effect}} + \underbrace{\beta_n^j \log(M_n^j)}_{\text{Productivity effect}} + \underbrace{\theta^j \sum_k \gamma^{j,k} \frac{\beta_n^k}{\theta^k} \log(M_n^k)}_{\text{Sectoral spillover effect}}
\end{aligned} \tag{25}$$

[13] See the derivation in Appendix A3.

Equation (25) takes the form of a multi-sector version of a gravity equation.[14] This framework enables to ground the theoretical mechanisms linking migration to bilateral trade flows through its effects not only on trade costs but also on production costs.[15] As we can see, a change in a bilateral trade flow from country n to country i can be decomposed into three components, each influenced by immigrants working in country n:

1. **Network Effect.** An increase in the number of immigrant originating from country i working in country n (M^j_{ni}) reduces the information frictions between the two countries, reducing trade costs and increasing bilateral trade.
2. **Productivity Effect.** An increase in the size of immigrant workers in sector j in country n (M^j_n) boosts the TFP in that sector (increasing the probability of a high efficiency draw), thereby increasing its export level.
3. **Sectoral Spillover Effect.** Exports in final sector j increase when a greater number of migrants are employed in the input sectors supplying intermediate goods to that sector (M^k_n). Specifically, a higher stock of migrants in these input sectors raises efficiency and lowers input prices, thereby reducing production costs in sector j and enhancing its export performance.

4 Empirical methodology

4.1 Baseline Equation

Our empirical specification tests Equation (25), which posits that an increase in the supply of foreign-born workers in an exporting country raises sector-j exports. This effect arises through three complementary channels: lower trade costs (*the network effect*), higher productivity within the exporting sector (*the productivity effect*), and productivity gains in upstream input-supplying sectors (*the sectoral spillover effect*). We estimate the following equation:

$$log(X^j_{it}) = \beta_1 log(1 + M^j_{it}) + \beta_2 log(M^j_t) + \beta_3 log(M^{input,j}_t) + \gamma log(N^j_t) + \theta^j_i + \theta_{it} + \varepsilon^j_{it} \quad (26)$$

[14] Appendix A3 discusses more the similarity with a standard gravity equation.

[15] We follow Ottaviano and Peri (2012) and assume that firms continuously invest in capital in response to immigration. This implies that production costs are influenced by changes in immigration through their effects on total factor productivity and the prices of intermediate goods.

The dependent variable, $log(X_{it}^j)$, is the log of exports from sector j to country i at time t. Our key explanatory variables capture different migration-driven channels.

- M_{it}^j denotes the number of immigrants from country i employed in exporting sector j at time t. To account for the substantial fraction of zero entries (roughly 40 %), we measure the *network effect* as $log(1 + M_{it}^j)$, capturing how immigrant networks reduce bilateral trade costs.

- $log(M_t^j)$ is the log of all immigrants employed in sector j, capturing the *productivity effect* of immigration in that exporting sector.

- The main variable of interest, $log(M_t^{input,j})$, measures the log of immigrant employment in the two main input sectors supplying sector j. This variable captures the *sectoral spillover effect*, i.e., how migration shocks in intermediate sectors affect downstream export performance.

Taking logs of immigrant employment follows directly from the theoretical framework in Section 3, and is consistent with the identification strategy in Clemens and Hunt (2019). Their approach, building on the specification correction in Kronmal (1993), defines immigration shocks in log levels while controlling for native employment. This strategy allows instrumenting only the immigrant variables, without addressing the endogeneity of the native workforce. We also include, $log(N_t^j)$, the log number of native workers in sector j at time t to control for labor market size. A potential concern, however, is bias from scale effects. We thus show that our results are robust to using the log share of immigrants as an alternative regressor of interest in Section 5.2. This measure has also been used in Angrist and Kugler (2003), Card (2001), Cortes (2008), and D'Amuri and Peri (2014). In any case, we rely on a shift-share IV strategy to address endogeneity from unobserved sector-time shocks that may simultaneously affect immigration and exports.

In addition, we include a large set of fixed effects. θ_i^j is a vector of sector-importer fixed effects controlling for any pair specific factor affecting bilateral trade (such as geographic variables like distance, common colonial ties or common language). θ_{it} represents importer-year fixed effects, controlling for any unobserved factors at the importer country-year level that may affect export performance to market i.[16] The use of these fixed effects implies that β_2 and β_3 are identified from changes within sectors over time. The main parameter of interest β_3 identifies the impact of the size of the immigrant workforce in key input sectors on the export performance of the downstream sector they supply.

Finally, the term ε_{it}^j captures zero-mean idiosyncratic shocks. We cluster the standard errors at the sector-importer level to account for the possibility of a within-group correlation of random disturbances. Moreover, we estimate Equation (26) using weighted least-squares, where the weights are the employment shares across manufacturing sectors per

[16] More precisely, θ_i^j captures $log(X_i^j) - log(\Phi_i^j) - log(\eta_{in}^j) - \theta^j \delta_\tau log(e_{in}^j)$, while θ_{it} captures $-\phi_{i,\tau} log(t_i)$.

year. This approach corrects for heteroskedasticity related to differences in labor market size across sectors (Solon et al., 2015).

4.2 Identification and IV Strategy

Our main identification concern is that immigrants may not be randomly allocated across sectors. Instead, they are likely attracted to sectors experiencing favorable labor market conditions, potentially driven by sector-specific demand or productivity shocks. In such cases, a positive unobserved shock in a given sector could simultaneously raise both export performance and immigrant employment, including in upstream sectors. This pattern may generate upward bias in OLS estimates, but the estimates could also be downward biased Autor et al. (2020) show that industries experiencing the fastest productivity and export growth tend to become more concentrated. Greater concentration, in turn, is associated with a declining labor share and potentially reduced labor demand. This dynamic can introduce a negative spurious correlation between immigration and exports, leading to downward bias in OLS estimates of the impact of immigration on sectoral export performance, both within final sectors and across upstream input sectors.

To address the endogeneity of the immigration variables, we rely on the migration literature (Altonji and Card, 1991; Card, 2001) and build shift-share instruments based on the historical distribution of immigrants across sectors in 1980.[17] The sectoral allocation of recently arrived immigrants is shaped by the presence of prior immigrants in that sector. Patel and Vella (2013), for example, provide robust evidence of network effects in the occupational choices of new immigrants. Newcomers tend to follow earlier migrants from their country of origin into similar occupations, as co-ethnic networks reduce job search frictions and improve access to employment opportunities.

We exploit this network-based location choice to isolate supply-driven variation in the allocation of immigrants across sectors. Specifically, we use the 1980 distribution of immigrants from each origin country across sectors to predict the sectoral allocation of subsequent immigration inflows during the 2003–2017 period.[18] This shift-share approach generates plausibly exogenous variation in either the number of bilateral migrants working in a given sector or the total number of immigrants employed in a sector, whether it is the exporting sector or an upstream input-supplying sector. Suppose we aim to impute

[17] Altonji and Card (1991) exploit the tendency of immigrants to settle in cities with historically large immigrant populations, using past immigrant distributions across cities to predict future inflows. Card (2001) refines this approach by constructing an instrument based on the propensity of new immigrants to locate near earlier arrivals from the same country of origin.

[18] We use 12 origin groups: Mexico, rest of Latin America, Canada-Australia-New Zealand, Western Europe, Eastern Europe and Russia, China, India, rest of Asia, Africa, and others (mostly Cuba and West Indies).

the number of immigrants working in the sector *Glass and Glass Product Manufacturing* in 2003. If 20 % of Mexican immigrants were working in that sector in 1980, our strategy allocates 20 % of all Mexican workers in 2003 to the *Glass and Glass Product Manufacturing* sector. We then aggregate the imputed number of immigrants across country groups to obtain the predicted number of immigrants in each sector. Formally, the instrument for the number of immigrants working in a particular sector j at time t can be written as:

$$\hat{M}_t^j = \sum_c \frac{M_c^j\,(1980)}{M_c\,(1980)} \times M_c\,(t)\,, \tag{27}$$

where $M_c^j(1980)/M_c(1980)$ is the share of immigrants from country c working in sector j in 1980, and $M_c(t)$ is the total number of immigrants from country c at time t. Aggregating across origin countries ensures that the predicted distribution captures sectoral variation driven by historical settlement patterns rather than contemporaneous labor market shocks.

This approach can be extended to upstream input sectors supplying sector j:

$$\hat{M}_t^{\text{input},j} = \sum_c \frac{M_c^{\text{input},j}(1980)}{M_c^{\text{input}}(1980)} \times M_c^{\text{input}}(t), \tag{28}$$

and to the bilateral sector-origin-time cell (where i indexes the origin country):

$$\hat{M}_{it}^j = \frac{M_i^j(1980)}{M_i(1980)} \times M_i(t). \tag{29}$$

Table C.1 shows the first-stage of the IV regressions. It indicates a strong positive and significant correlation between the instruments and the corresponding potential endogenous variables, regardless of whether we include the two other instruments or the log of the native workforce as additional regressors. Moreover, we provide the Kleibergen-Paap rk Wald F-statistics or in case of multiple endogenous variables, the IV first-stage F-statistics proposed by Sanderson and Windmeijer (2016) to evaluate the strength of our instruments. Most of the first-stage F-tests of excluded instruments are between 20 and 100, indicating that our instruments have strong predictive power.

The exclusion restriction underlying these instruments assumes that the immigrant shares in 1980 are uncorrelated with the unobserved error component in Equation (26), while affecting the immigration variables. A way to minimize the potential correlation between past immigration and current economic shocks is to use a sufficient time lag to predict the actual number of immigrants (Dustmann et al., 2005; Dustmann and Schönberg, 2025). By predicting current inflows based on immigration patterns that occurred at least 20 years earlier, the use of the 1980 census should make our instruments more likely to satisfy the exclusion restriction imposed by the IV strategy. Although the exclusion restriction imposed by the IV strategy is untestable, Appendix-Table C.2 follows Foged and Peri (2016), Dustmann et al. (2019) and Goldsmith-Pinkham et al. (2020) by checking for pre-trends. More specifically, we examine whether sectoral export changes between 2000 and 2002 are correlated with the predicted immigrant levels over the 2003–2017 period. The top panel of the table reports results using changes in predicted immigrant stocks between 2003 and 2005; the middle and bottom panels use changes between 2006 and 2010 and between 2003 and 2017, respectively. None of the estimated coefficients are statistically significant, indicating no correlation between prior export changes and subsequent predicted immigrant inflows across sectors. These results support the validity of our IV strategy.

5 Empirical Results

5.1 Main Results

Table 2 reports the estimates from Equation (26). Columns 1-4 present the OLS results, while columns 5-8 display the corresponding IV estimates. In column 1, we report the results from estimating the effect of bilateral migration on the value of sectoral exports in manufacturing. The regression includes sector and importer–time fixed effects. The coefficient is positive and statistically significant. It indicates that sectors employing a larger number of immigrants from a given country export more to that country of origin. The IV estimate in column 5 confirms this result, indicating that immigrant networks contribute to shaping bilateral trade. Migrants appear to provide firms with valuable information about demand conditions, regulations, and distribution channels in their country of origin.

The other specifications (columns 2–4 and 6–8) extend the analysis by introducing sector–importer and importer–time fixed effects and by progressively adding immigration variables. In these richer specifications, the coefficients on bilateral migration lose statistical significance. This suggests a more limited role for migrant networks in alleviating information frictions at the sectoral level.[19]

By contrast, the results for immigrant employment in input and final sectors are economically meaningful. Both the OLS and IV estimates for $log(M_t^{\text{input,j}})$ and $log(M_t^{\text{j}})$ are

[19] This finding may appear surprising given the well-documented positive effect of migrant networks on trade. Most existing studies, however, identify these effects from the spatial distribution of migrants across countries or regions. By contrast, our analysis focuses on sectoral trade flows, where the role of networks appears less pronounced.

positive and significant.[20] According to the IV estimates in column 8, a 1 % increase in immigrant employment in the main intermediate input sectors supplying a final sector raises that sector's exports by 1.2 %, while a 1 % increase in immigrant employment within the final sector itself increases exports by 0.8 %. The difference between these two elasticities is not statistically significant (t-statistic = 0.57), suggesting that immigrant presence in key intermediate and final sectors contribute similarly to export performance.

The magnitudes imply sizable export gains over time. Between 2003 and 2017, the average number of immigrants working in manufacturing increased by 3.4 % per year. Based on the elasticity estimate in column 8 of Table 2, this trend implies an annual export growth of approximately 2.7 % (0.8×3.4). Over the same period, immigrant employment in key intermediate sectors rose by 1.7 % per year, translating into a 2.0 % increase in export volumes (1.2×1.7).

Overall, Table 2, shows that immigration enhances export performance not only within exporting sectors but also through sectoral linkages, consistent with our theoretical predictions. This new channel highlights the importance of accounting for input–output relationships when assessing the broader economic effects of migration.

5.2 Sensitivity Analysis

Table 3 presents a series robustness tests to assess the sensitivity of our previous findings. Specifically, it reports the IV estimates of $log(M_t^{\text{input,j}})$ on both the log export value (intensive margin) and the probability that a sector exports (extensive margin).[21] Specifically, Table 3 deal with six alternative specifications.

Specification 1 represents our baseline empirical specification. Specification 2 restricts the sample to sectors with continuous positive exports throughout the entire 2003-2017 period, creating a balanced panel. Specification 3 addresses potential specific origin-country biases by excluding migrants originating from country i when constructing the sectoral immigration variables. Specification 4 tests the robustness of our input measure by calculating $\log(M_t^{\text{input,j}})$ using the three main input sectors, rather than the two largest suppliers. Specification 5 uses the log share of immigrant workers in the input and final sectors.[22] Specification 6 assesses the role played by the inclusion of the log employment

[20]The magnitude of the IV estimates consistently exceeds that of the OLS estimates, suggesting that the latter may be downward biased. As discussed earlier, this bias could stem from a decline in the labor share associated with the concentration of economic activity among a few firms within sectors.

[21]For the extensive margin, we estimate a linear probability model.

[22]We employ the same instruments as in specification 1. This IV strategy is analogous to instrumenting with the log share of predicted immigrant workers by fixing the denominator at its 2003 value. Fixing the denominator at the start of the period follows Edo and Özgüzel (2023); Orefice and Peri (2024); Mahajan (2024) and mitigates potential bias arising from endogenous employment growth within sectors over the

size control.

Overall, the results are robust. Across all specifications, an increase in immigrant employment in the input sectors of a final sector raises that sector's export performance, consistent with our theoretical predictions. At the extensive margin, however, we find no significant effect. The probability that a sector exports is unaffected by changes in immigrant labor in its input sectors. This suggests that the mechanism linking immigrant labor to export performance operates mostly by expanding exports in sectors already engaged in international trade, rather than by facilitating the entry of new sectors into export markets.

6 The Role of Innovation in Mediating Sectoral Spillovers

This section examines how immigration in intermediate sectors affects the export performance of downstream industries. Section 3 outlines a mechanism through which this sectoral effect operates: immigration raises productivity in intermediate sectors and lowers the prices of the inputs they supply. Lower input costs reduce production costs in final goods sectors, thereby enhancing competitiveness and boosting exports. This section focuses on innovation as a transmission channel and shows that immigration fosters process innovation in intermediate sectors. Consistent with the theoretical framework, we also provide evidence that a migration shock in intermediate sectors reduces input prices.

Empirical Strategy. To estimate the impact of immigration on innovation and output prices, we estimate the following econometric equation:

$$y_t^{input,j} \quad = \quad \alpha log(m_t^{input,j}) + \rho log(N_t^{input,j}) + \theta_j + \theta_t + \eta_t^{input,j} \, , \tag{30}$$

where the dependent variable $y_t^{input,j}$ denotes the outcome in the "intermediate industry" (i.e., the two largest input-supplying sectors) of exporting sector j at time t. The key explanatory variable, $\log(m_t^{\text{input},j})$, is the logarithm of the immigrant employment share in the two main input-supplying sectors of exporting sector j at time t. This definition of the immigration variable is identical to that in row 5 of Table 3. Specifically, it follows Angrist and Kugler (2003), Card (2001), Cortes (2008), and D'Amuri and Peri (2014), who use the logarithm of immigrant shares to study immigration's effects on wages, employment, and prices.[23] As in Equation (26), we control for the size of the labor market by including

2003–2017 period.

[23] In unreported results, we find that our findings are robust to using the log of the number of immigrant workers in a sector as an alternative explanatory variable.

the logarithm of native employment, $log(N_t^{input,j})$. To address endogeneity, we instrument $log(m_t^{input,j})$ with the logarithm of the predicted number of immigrants divided by initial sectoral employment (i.e., employment in the first year of our sample).

The sector fixed effects θ_j absorb all time-invariant characteristics that may influence both the outcome variable and the immigrant penetration across sectors. The time fixed effects θ_t capture common shocks specific to the year. The error term is denoted $\eta_t^{input,j}$. The coefficient α is therefore identified from within-sector variation over time. To address serial correlation, we cluster the standard errors at the sectoral level. Since the number of clusters is relatively small (fewer than 100), we apply the wild cluster bootstrap method of Cameron et al. (2008) and report the corresponding p-values.

Impact on Innovation. We begin by examining how immigration shapes innovation outcomes. Using sector-level data for the United States over 2008–2016, we distinguish between product and process innovation. Product innovation is measured as the logarithm of the number of companies that introduced new or significantly improved goods or services. Process innovation is defined as the logarithm of the number of firms introducing new or significantly improved production method. As emphasized by Gray et al. (2020, p. 7), process innovation typically reflects changes in the production process aimed at raising efficiency.

Columns 1-2 in Table 4 show the OLS estimates. Immigration is positively and significantly associated with process innovation, but negatively and insignificantly related to product innovation. This asymmetry mirrors the evidence in Gray et al. (2020) who show that the inflow of low-skill labor into the United Kingdom following the 2004 EU enlargement stimulated process innovation but not product innovation. Columns 3-6 further show that immigration in intermediate sectors raises the share of process innovation within total innovation, whether measured directly (columns 3-4) or as the difference between the two types of innovation (columns 5-6). Both OLS and IV estimates confirm that a higher immigrant share in intermediate sectors increases the relative amount of process innovation in that sector while the effect on support activities is weaker and only marginally significant.

Table 5 provides further results. Process innovation is broken down into specific categories: new manufacturing or production methods, new logistics and distribution, and new support activities. The results, reported in columns 1-3, indicate that immigration is mostly positively associated with improvements in production and distribution methods, which enhance sectoral efficiency. The IV estimates in columns 4–5 suggest that the negative association with product innovation is driven mainly by a decline in the introduction of new services.[24]

In light of our theoretical model in Section 3.4.2, our empirical findings thus suggest

[24] The negative effect on new services may reflect the limited role of migrants in service innovations that must closely match local customer demands and are rooted in localized markets (Tidd and Bessant, 2018).

that, by promoting innovation, immigration should reduce production costs and raise productivity through an increase in the location parameter, T_n^j.

Impact on Prices. Building on the evidence that immigration fosters new production and distribution methods in intermediate sectors, we expect these changes to reduce production costs. Consequently, output prices in intermediate sectors should decline (as formalized in Section 3.4.2). Table 6 presents the results of estimating Equation (30), using the logarithm of output prices in intermediate sectors as the dependent variable over the 2004–2016 period. Specifically, columns 1–2 rely on five smoothed 3-year intervals (2004, 2007, 2010, 2013, 2016), while columns 3–4 restrict the sample to the first and last periods (2004 and 2016) to capture longer-run changes.

The OLS and IV estimates indicate a negative impact of immigration on output prices. The IV results suggest that a 1 % increase in the immigrant share within intermediate sectors reduces output prices by approximately 0.6 % to 1 %. This evidence is consistent with our earlier findings that immigration fosters process innovation and efficiency gains, thereby lowering output prices.

Taken together, our results indicate that an immigration-induced increase in labor supply within intermediate sectors boosts innovation in that sector, raising average productivity, and reduces production costs. Our price estimates support this interpretation, showing that a migration shock in intermediate sectors tends to lower prices in that sector. By spilling over to downstream industries, these reductions in input costs help explain the pro-trade effect of immigration in input sectors, as documented in Section 5.1.

7 Conclusion

This paper identifies a new channel through which immigration enhances export performance. Beyond reducing bilateral trade costs (network effect) and raising productivity in exporting sectors (productivity effect), we show that immigration in input-supplying sectors increases exports in downstream industries (sectoral spillover effect). By leveraging intersectoral input–output linkages, the paper provides new insights into the trade effects of immigration.

We formalize these three channels in a multi-sector Ricardian trade model and test the model's predictions using U.S. data for 2003–2017. We enrich the input–output matrix with immigration and export data, allowing us to trace the propagation of labor shocks across sectors. Our empirical results indicate that immigration shocks in intermediate sectors significantly raise exports in downstream industries. We also examine the mechanism underlying this effect and find that a larger immigrant workforce in intermediate sectors fosters the adoption of new production and distribution methods, which in turn lowers input prices. These findings underscore the role of immigrants in input-supplying sectors in improving the competitiveness of downstream industries through reductions in production costs.

Overall, our results emphasize the importance of sectoral linkages in the migration–trade nexus. The export-enhancing effects of immigration are broader and more multifaceted than previously documented. Beyond the context of trade, the findings illustrate how labor market shocks in upstream sectors propagate through production networks, offering new perspectives on globalization, productivity, and structural change.

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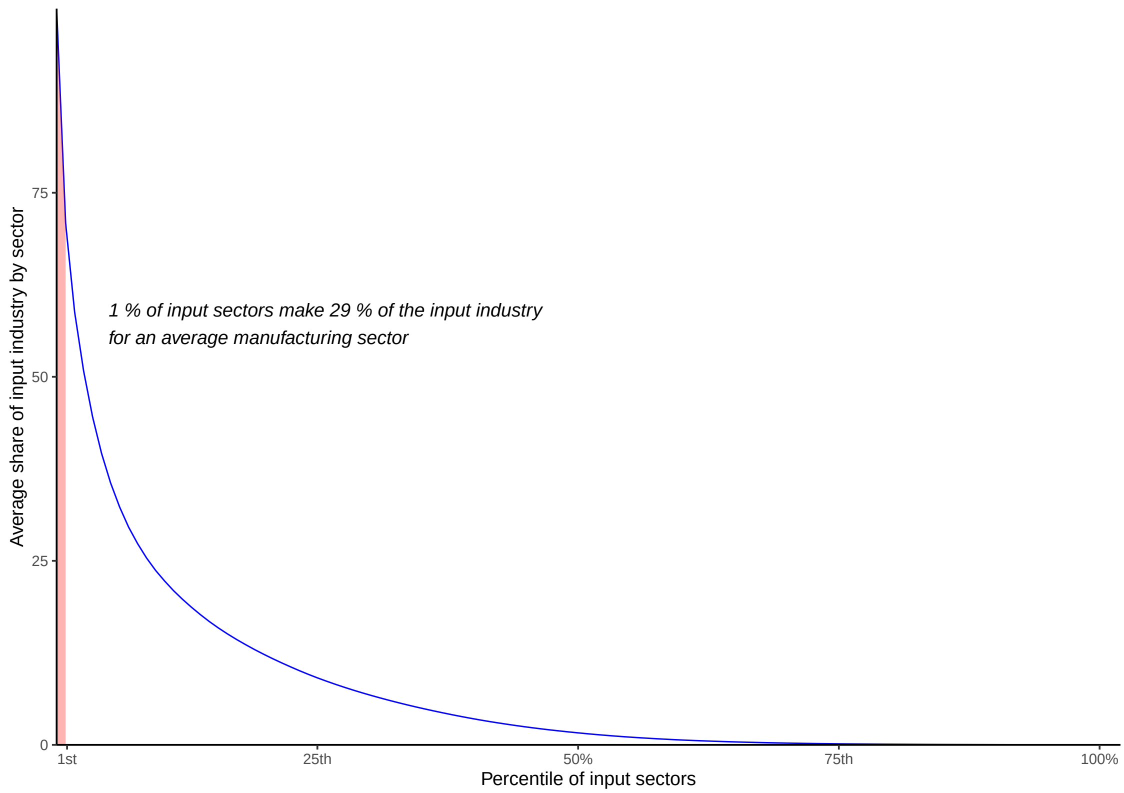
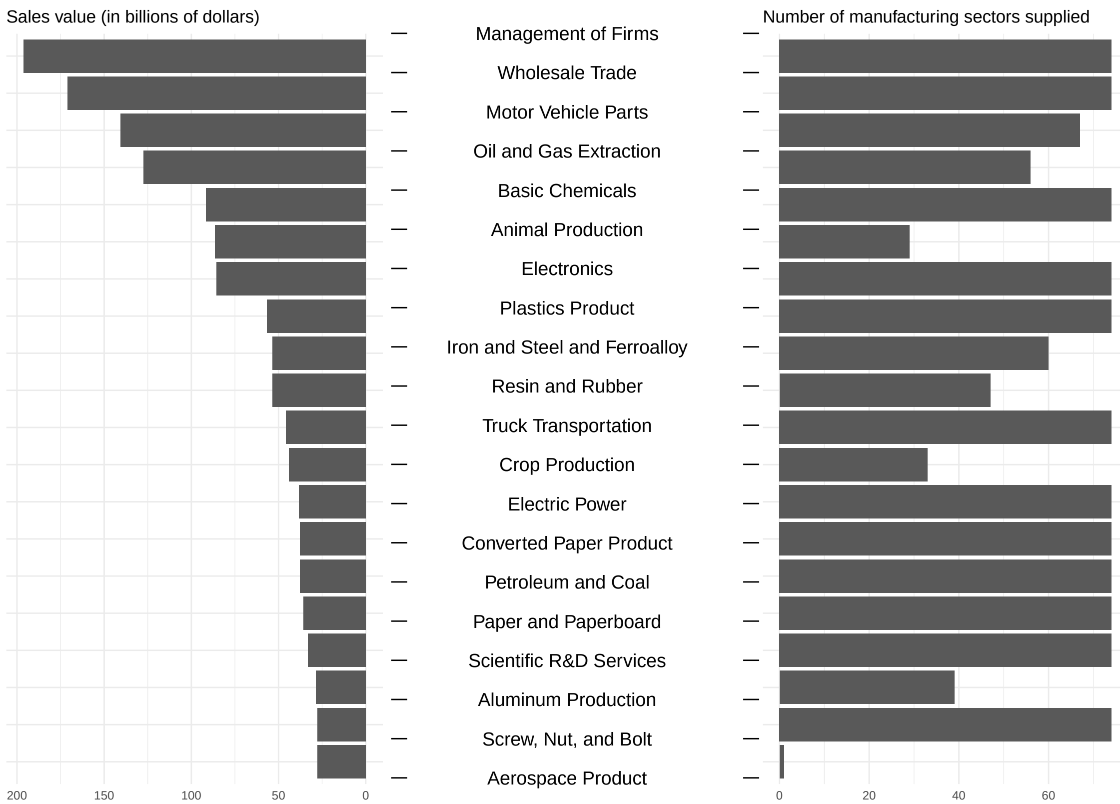
Figures

Figure 1: Distribution of Input Value Across Intermediate Sectors for the Average Manufacturing Industry



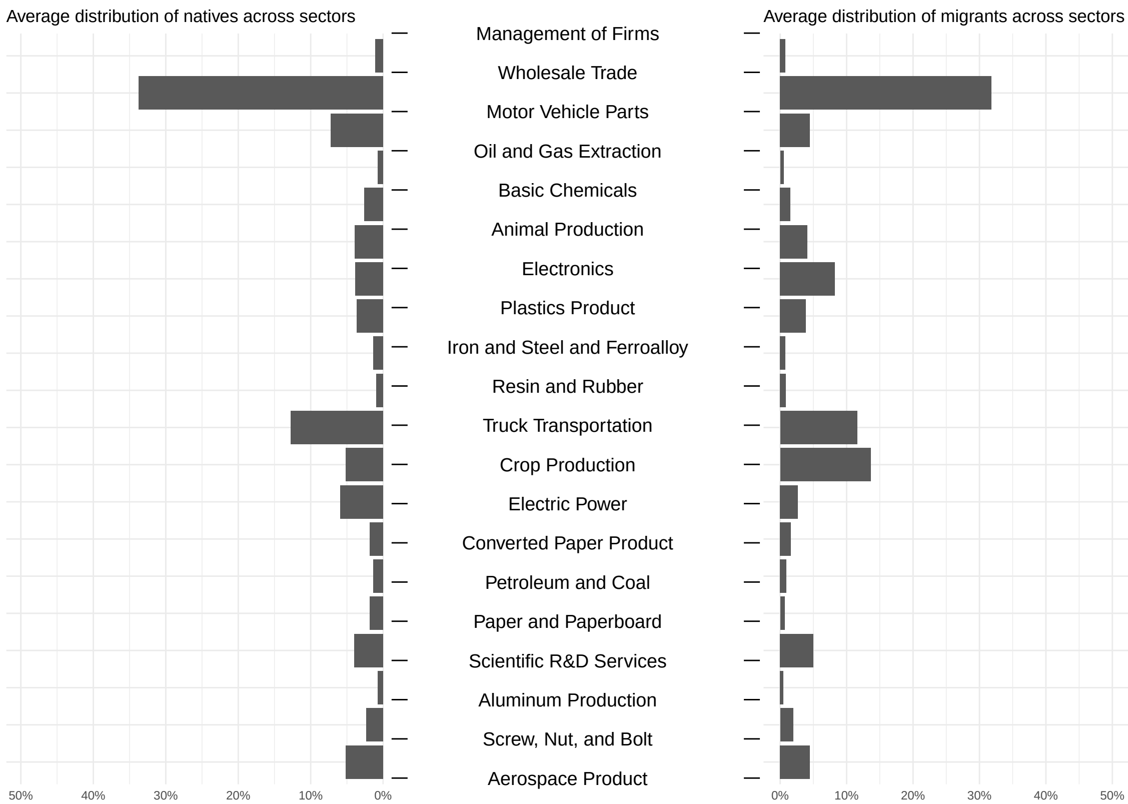
Notes. The graph displays the distribution of intermediate suppliers for a representative manufacturing (exporting) sector, ranked by the value of inputs purchased by that sector, with the largest supplier (top 1 %) accounting for nearly 29 % of the total input value. **Sources.** Bureau of Economic Analysis and authors' computations.

Figure 2: Top 20 Suppliers by Sales Value and Number of Manufacturing Sectors Supplied



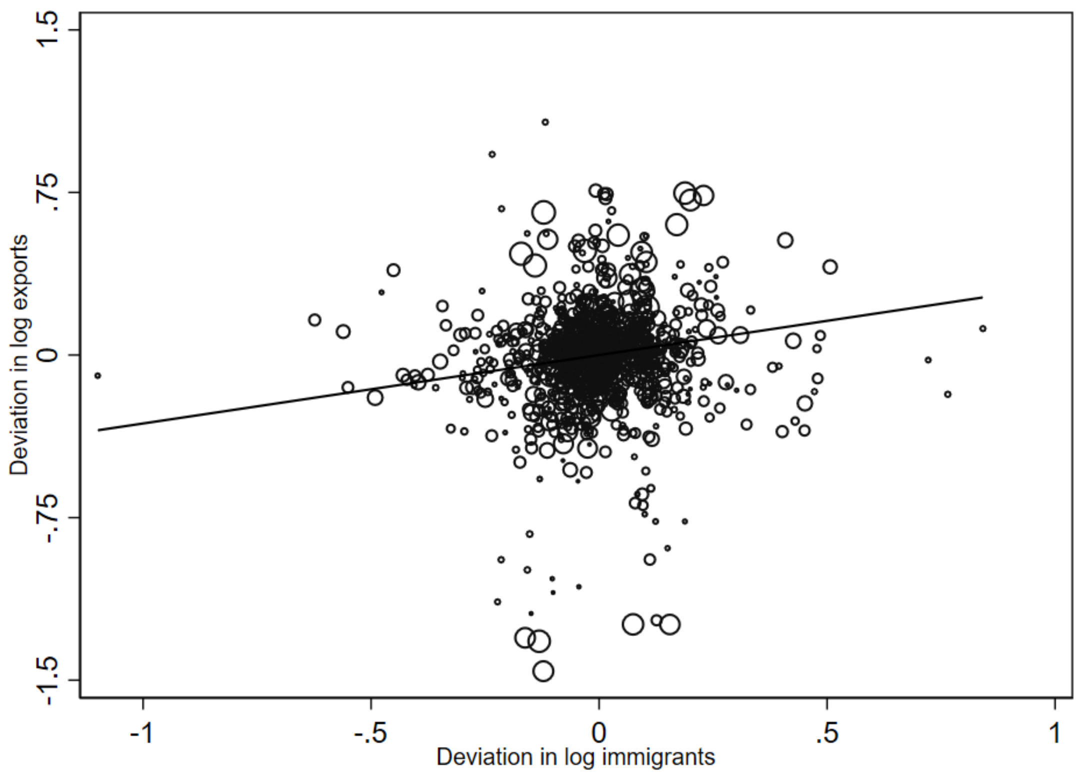
Notes. The graph displays the 20 largest suppliers to manufacturing sectors, ranked by the value of sales to each sector. The left panel shows the total sales value provided by each intermediate sector, while the right panel reports the number of manufacturing sectors supplied by each. **Sources.** Bureau of Economic Analysis and authors' computations.

Figure 3: Distribution of Native and Immigrant Workers in the Top 20 Suppliers



Notes. The graph displays the distribution of workers across the 20 largest suppliers to manufacturing sectors, ranked by sales value. The left panel shows the average distribution of native workers, while the right panel depicts the distribution of immigrant workers across these sectors. **Sources.** Bureau of Economic Analysis and authors' computations.

Figure 4: Relationship Between Final Sector Exports and Immigration in Intermediate Sectors



Notes. The unit of observation in the scatter diagram is a sector-year cell over 2003-2017. The figure plots deviations in the log exports of a final sector j against deviations in the log number of immigrants employed in the two main intermediate sectors, after removing year-specific effects common to all sectors. Deviations are residuals from regressions on sector fixed effects. The regression line is weighted by the number of observations used to compute the dependent variable.
Sources. Bureau of Economic Analysis, IPUMS and authors' computations.

Tables

Table 1: Export Value and Immigration

Year	Export Value	Share of immigrants in final sectors	Share of immigrants in input sectors
2003	962,119	17 %	15 %
2010	1,343,290	18 %	18 %
2017	1,442,655	19 %	18 %

Sources. Schott (2008), IPUMS and authors' computations.

Table 2: Impact on the Intensive Margin of Trade

	OLS estimate				IV estimate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$log\left(1+M_{it}^{j}\right)$	0.044***	0.002	0.002	0.001	0.424***	-0.038	-0.014	-0.027
	(0.005)	(0.002)	(0.002)	(0.002)	(0.083)	(0.108)	(0.107)	(0.105)
$log(M_{t}^{input,j})$	-	-	0.246***	0.251***	-	-	2.089***	1.180**
			(0.043)	(0.043)			(0.517)	(0.573)
$log(M_{t}^{j})$	-	-	-	0.169***	-	-	-	0.800**
				(0.044)				(0.341)
KP F-test	-	-	-	-	159.344	43.704	23.330	14.629
SW F-test M_{it}^{j}	-	-	-	-	-	-	46.656	44.179
SW F-test $M_{t}^{input,j}$	-	-	-	-	-	-	154.783	96.172
SW F-test M_{t}^{j}	-	-	-	-	-	-	-	94.136
θ^{j}	X	-	-	-	X	-	-	-
θ_{i}^{j}	-	X	X	X	-	X	X	X
θ_{it}	X	X	X	X	X	X	X	X
Cluster	7,421	7,421	7,421	7,421	7,421	7,421	7,421	7,421
Observations	104,369	104,369	104,369	104,369	104,369	104,369	104,369	104,369

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sector-importer level. Regressions are run at the sector-importer level over the 2003-2017 period. The dependent variable is the log of exports from a given sector to a given country in a given year. Our shift-share instruments are computed using the 1980 census. Regressions are weighted by the employment share across manufacturing sectors. We report the Kleibergen-Paap (KP) and the Sanderson-Windmeijer (SW) F-tests of excluded instruments for each endogenous regressor. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Estimated Impact on the Intensive and Extensive Margins of Trade

		Intensive margin			Extensive margin		
Specification		IV	Cluster	Obs.	IV	Cluster	Obs.
1.	Basic estimate	1.180**	7,421	104,369	0.130	7,590	113,850
		(0.573)			(0.086)		
	SW F-test	94.136			103.063		
2.	Balanced panel	1.459***	6,129	91,935	-	-	-
		(0.557)					
	SW F-test	83.319					
3.	Excluding bilateral flows	1.156**	7,421	104,369	0.128	7,590	113,850
		(0.561)			(0.084)		
	SW F-test	95.920			106.176		
4.	Top-3 input sectors	1.391*	7,421	104,369	-0.027	7,590	113,850
		(0.826)			(0.093)		
	SW F-test	195.731			304.053		
5.	Log immigrant shares as	8.404*	7,421	104,369	1.014	7,590	113,850
	alternative regressors	(4.334)			(0.699)		
	SW F-test	28.251			44.228		
6.	No employment control	2.137***	7,421	104,369	0.057	7,590	113,850
		(0.597)			(0.086)		
	SW F-test	131.417			171.198		

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sector-importer level. Regressions are run at the sector-importer level over the 2003-2017 period. To estimate the impact of immigration on the intensive and extensive margins of trade, we respectively use as dependent variable the log of exports from a given sector to a given country in a given year and a binary variable equal to one if the manufacturing sector exports to a given country in a given year. Our shift-share instruments are computed using the 1980 census. Regressions are weighted by the employment share across manufacturing sectors. We report the Sanderson-Windmeijer (SW) F-test of excluded instruments for the immigration variable in key intermediate sectors. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Impact on Innovation in Intermediate Sectors

	Dependent variable					
	Process innovation	Product product	Process innov. relative to product innovation		Intensity of process innovation	
	OLS	OLS	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$log(m_t^{input,j})$	2.470***	-1.243	0.661***	1.003**	3.713***	4.905**
	(0.829)	(0.669)	(0.154)	(0.302)	(0.840)	(1.634)
Wild cluster p-value	0.004	0.147	0.000	0.034	0.000	0.043
Kleibergen-Paap F-test	-	-	-	28.076	-	28.076
Cluster	46	46	46	46	46	46
Observations	322	322	322	322	322	322

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sectoral level. The unit of observation is a sector-year cell over the 2008-2016 period. The dependent variable measures innovation in the "intermediate industry" (i.e., the two largest input-supplying sectors) of a given exporting sector at a given point in time. Our shift-share instrument is computed using the 1980 census. Regressions are weighted by the share of companies introducing an innovation per year. Wild cluster bootstrap p-values are computed using 1,000 bootstrap replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Decomposing the Impact on Innovation in Intermediate Sectors

		Dependent variable				
		Process innovation			Product innovation	
		New production methods	New distribution methods	New support activities	Introducing new goods	Introducing new services
Specification		(1)	(2)	(3)	(4)	(5)
1.	OLS estimate	2.690***	0.262	-4.268**	-1.236	-2.330***
		(0.842)	(0.924)	(1.541)	(0.719)	(0.291)
	Wild cluster p-val.	0.002	0.778	0.028	0.171	0.000
2.	IV estimate	7.302***	5.470***	3.974*	1.574*	-2.177***
		(1.530)	(1.268)	(1.786)	(0.856)	(0.668)
	Wild cluster p-val.	0.000	0.001	0.058	0.070	0.000
	KP F-test	29.958	29.958	29.958	29.958	29.958
Cluster		46	46	46	46	46
Observations		322	322	322	322	322

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sectoral level. The unit of observation is a sector-year cell over the 2008-2016 period. The dependent variable measures innovation in the "intermediate industry" (i.e., the two largest input-supplying sectors) of a given exporting sector at a given point in time. Our shift-share instrument is computed using the 1980 census. Regressions are weighted by the share of companies introducing an innovation per year. We report the Kleibergen-Paap (KP) F-test statistic. Wild cluster bootstrap p-values are computed using 1,000 bootstrap replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Impact on Output Prices in Intermediate Sectors

	Five time periods		Two time periods	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$log(m_t^{input,j})$	-0.106	-0.623**	-0.177	-0.999**
	(0.117)	(0.416)	(0.135)	(0.462)
Wild cluster bootstrap p-value	0.450	0.043	0.084	0.001
Kleibergen-Paap F-test	-	1.873	-	4.823
Cluster	39	39	39	39
Observations	195	195	78	78

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sectoral level. The unit of observation is a sector-time cell. The dependent variable is the log of output prices in the "intermediate industry" (i.e., the two largest input-supplying sectors) of a given exporting sector at a given point in time. While columns 1-2 use five smoothed 3-year intervals (2004, 2007, 2010, 2013, 2016), columns 3-4 restrict the sample to the first and last time periods (2004 and 2016). Our shift-share instrument is computed using the 1980 census. Wild cluster bootstrap p-values are computed using 1,000 bootstrap replications. * significant at 10%; ** significant at 5%; *** significant at 1%.

Sectoral Linkages and the Impact of immigration on Export Performance

Appendix

Appendix A Theoretical Framework

Appendix A1 Price Distribution and CES Price Index

To compute the sectoral price index in Equation (9), we first describe the distribution of firm-level prices. Recall that the efficiency of country n in producing good ω^j in sector j is a random variable z_n^j drawn from a Fréchet distribution:

$$F_n^j(z) = \exp\Big[-T_n^j z^{-\theta^j}\Big], \quad z > 0, \tag{31}$$

where T_n^j is the technology parameter and θ^j governs the dispersion of productivity. The corresponding price of a good sourced from country n is

$$p_{in}^j(\omega^j) = \frac{c_n^j}{z_n^j(\omega^j)}, \tag{32}$$

which has cumulative distribution function (CDF):

$$G_{in}^j(p) = \Pr(p_{in}^j \leq p) = 1 - \exp\Big[-T_n^j (c_n^j)^{-\theta^j} p^{\theta^j}\Big]. \tag{33}$$

Under perfect competition, the observed price in country i is the minimum across all suppliers n:

$$P_n^j = \min_{n=1,\ldots,N} p_{in}^j(\omega^j), \tag{34}$$

with CDF

$$G_n^j(p) = 1 - \prod_{n=1}^{N}\big[1 - G_{in}^j(p)\big] = 1 - \exp\Big[-\Phi_n^j p^{\theta^j}\Big], \tag{35}$$

where

$$\Phi_n^j = \sum_{n=1}^{N} T_n^j (c_n^j)^{-\theta^j} \tag{36}$$

is the multilateral resistance term.
The CES price index for sector j is then

$$\begin{aligned}(P_n^j)^{1-\sigma^j} &= \int_0^1 p_n^j(\omega^j)^{1-\sigma^j} d\omega^j = \int_0^\infty p^{1-\sigma^j} dG_n^j(p) \\ &= \int_0^\infty p^{1-\sigma^j} \theta^j \Phi_n^j p^{\theta^j - 1} \exp[-\Phi_n^j p^{\theta^j}] dp.\end{aligned} \tag{37}$$

Using the change of variable $x = \Phi_n^j p^{\theta^j} \Rightarrow dx = \theta^j \Phi_n^j p^{\theta^j - 1} dp$, the integral becomes

$$(P_n^j)^{1-\sigma^j} = (\Phi_n^j)^{\frac{\sigma^j - 1}{\theta^j}} \int_0^\infty x^{\frac{\sigma^j-1}{\theta^j}} e^{-x} dx = \Gamma\Big(1 + \frac{\sigma^j - 1}{\theta^j}\Big)(\Phi_n^j)^{\frac{\sigma^j-1}{\theta^j}} = A^j (\Phi_n^j)^{\frac{\sigma^j-1}{\theta^j}}, \tag{38}$$

where $\Gamma(\cdot)$ denotes the Gamma function.

Appendix A2 Expected Price and Migration

Using the price distribution in Appendix A1 as a starting point, we derive the expected price and examine the impact of migration on it.

For clarity, set $\tau_n^j = 1$. The probability density function (PDF) for prices from country n is

$$g_{in}^j(p) = T_n^j \theta^j (c_n^j)^{-\theta^j} p^{\theta^j - 1} \exp\Big[- T_n^j (c_n^j)^{-\theta^j} p^{\theta^j} \Big], \quad p > 0. \tag{39}$$

The expected price is

$$\mathbb{E}[p_n^j] = \int_0^\infty p \, g_{in}^j(p) \, dp. \tag{40}$$

Perform the change of variable

$$u = T_n^j (c_n^j)^{-\theta^j} p^{\theta^j} \quad \Rightarrow \quad p = \left(\frac{u (c_n^j)^{\theta^j}}{T_n^j} \right)^{1/\theta^j}, \quad dp = \frac{1}{\theta^j} (T_n^j)^{-1/\theta^j} (c_n^j) u^{\frac{1}{\theta^j} - 1} du, \tag{41}$$

such that

$$\mathbb{E}[p_n^j] = T_n^j \theta^j (c_n^j)^{-\theta^j} \int_0^\infty \left(\frac{u (c_n^j)^{\theta^j}}{T_n^j} \right) e^{-u} \frac{1}{\theta^j} (T_n^j)^{-1/\theta^j} (c_n^j) u^{\frac{1}{\theta^j}-1} du$$
$$= c_n^j (T_n^j)^{-1/\theta^j} \int_0^\infty u^{\frac{1}{\theta^j}} e^{-u} du = c_n^j (T_n^j)^{-1/\theta^j} \Gamma\Big(1 + \frac{1}{\theta^j}\Big). \tag{42}$$

With migration-augmented technology:

$$T_n^j = \lambda_n^j (M_n^j)^{\beta_n^j}, \quad \lambda_n^j > 0, \quad \beta_n^j \geq 0, \tag{43}$$

then

$$\mathbb{E}[p_n^j] = c_n^j \Gamma\Big(1 + \frac{1}{\theta^j}\Big) (\lambda_n^j)^{-1/\theta^j} (M_n^j)^{-\beta_n^j/\theta^j}. \tag{44}$$

The derivative shows the negative effect of migration on expected prices:

$$\frac{\partial \mathbb{E}[p_n^j]}{\partial M_n^j} = -\frac{\beta_n^j}{\theta^j} c_n^j \Gamma\Big(1 + \frac{1}{\theta^j}\Big) (\lambda_n^j)^{-1/\theta^j} (M_n^j)^{-\beta_n^j/\theta^j - 1} < 0. \tag{45}$$

Intuitively the migrant stock M_n^j raises the likelihood of high-efficiency draws in sector j, thereby reducing expected prices. Figure A.1 illustrates this effect.

Appendix A3 Trade flows

Building on the price distribution in Appendix A1, we can derive the expected expenditure of country i on goods from country n.

Given the Fréchet distribution, the probability that country n is the lowest-cost supplier of sector j for exports to country i is

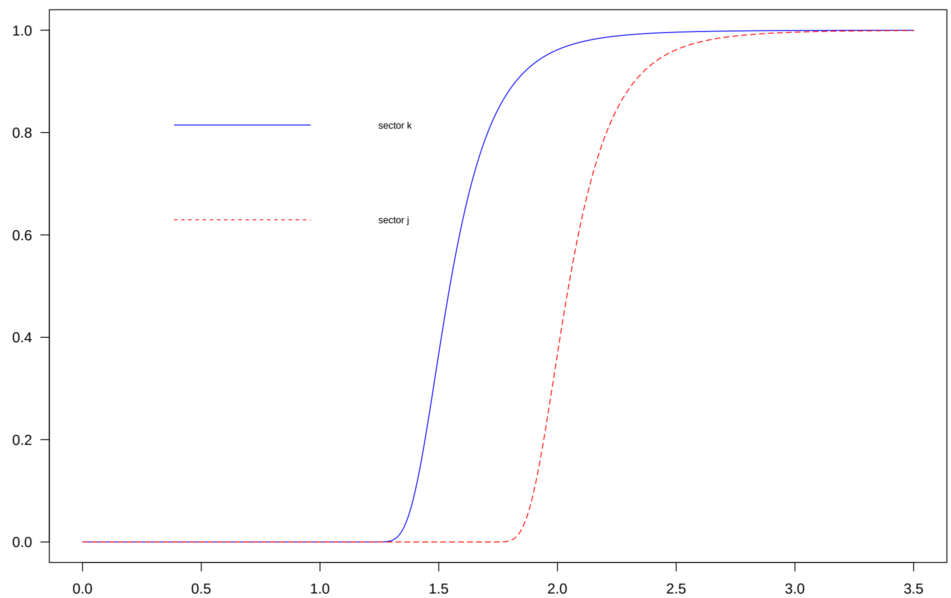
$$\prod_{m \neq n} \Pr(P_{im} \geq p^j) = \prod_{m \neq n} \big(1 - G_{im}^j(p)\big) = \exp\Big[-p^j \sum_{m \neq n} T_m^j (c_m^j \tau_{im}^j)^{-\theta^j} \Big]. \tag{46}$$

Integrating over all prices gives the fraction of sector j goods that country n sells to country i:

$$\pi_{in} = \int_0^\infty \exp\Big[-p^j \sum_{m \neq n} T_m^j (c_m^j \tau_{im}^j)^{-\theta^j} \Big] dG_{in}^j(p) = \frac{T_n^j (c_n^j \tau_{in}^j)^{-\theta^j}}{\Phi_i^j}. \tag{47}$$

Since there is a continuum of intermediate goods, π_{in} is also the share of goods that country n sells to country i in sector j. Equivalently, we can write $\pi_{in} = X_{in}^j / X_i^j$, so that the expenditure from country i on goods from country n is

Figure A.1: Higher Migrant Stocks Are Associated with Greater Sectoral Efficiency



Notes. The figure depicts the cdf of a Fréchet distribution with shape parameter 8. The migrant stock in sector j (M_n^j) is higher than in sector k (M_n^k). Based on the literature on migration and productivity, we assume that it implies that $T_n^j > T_n^k$. In the figure, T_n^j=1 and T_n^k=0,5

$$X_{in}^j = \frac{T_n^j (c_n^j \tau_{in}^j)^{-\theta^j}}{\Phi_i^j} X_i^j. \tag{48}$$

Equation (48) represents a multi-sector extension of the gravity model. Since our primary interest is in assessing how immigration affects bilateral trade flows—through its impact on production costs and informational frictions—this expression forms the focus of our analysis.

Following Eaton and Kortum (2002), let the exporter's total sales in sector j be

$$Q_n^j = \sum_{m=1}^{N} X_{mn}^j = T_n^j (c_n^j)^{-\theta^j} \sum_{m=1}^{N} \frac{(\tau_{mn}^j)^{-\theta^j}}{\Phi_m^j} X_m^j. \tag{49}$$

Solving for $T_n^j(c_n^j)^{-\theta^j}$ and substituting into Equation (48), while incorporating the sectoral price index (38), gives a form closer to the standard gravity equation:

$$X_{in}^j = \frac{\left(\frac{\tau_{in}^j}{p_i^j}\right)^{-\theta^j}}{\sum_m \left(\frac{\tau_{mn}^j}{p_m^j}\right)^{-\theta^j} X_m^j} X_i^j Q_n^j. \tag{50}$$

Appendix B Data

Appendix B1 Input-Output Accounts

The I-O industries are classified according to an I-O nomenclature. We use the concordance between I-O codes and the NAICS classification provided by the BEA. A key challenge is that some I-O industries map to multiple NAICS industries. To address this, we allocate the value of each I-O industry across the corresponding NAICS industries based on the share of each 4-digit NAICS sector within the relevant 2-digit industry, using sales as weights. The data on sales are drawn from the 2002 Economic Census for the 2002 Benchmark I-O Accounts, and the 2012 Economic Census for the 2007 and 2012 Benchmark I-O Accounts.[25]

For example, the I-O code "48A0" corresponds to NAICS industries "487" and "488". We sum the business values of these two NAICS industries and compute each industry's share in the total. In this case, NAICS industry "488" accounts for 97% of the combined business value. Accordingly, 97% of the value of I-O industry "48A0" is assigned to NAICS

[25] These two Economic Censuses are used because the concordance is established between the I-O code and the 2002 NAICS classification only for the 2002 Benchmark I-O Accounts.

industry “488”. When no sales or value-added data are available for the corresponding NAICS industries in the Economic Census, we divide the I-O industry value equally across the relevant NAICS industries. For instance, I-O industry “3372” corresponds to NAICS industries “3371” and “3372”, but the Economic Census lacks sales data for these categories; thus, we split the I-O industry value equally between the two NAICS industries.

Appendix Tables B.1 and B.2 list the I-O industries affected by this issue and the weights assigned to each NAICS industry.

Appendix B2 Mapping Workers from Census Industries to NAICS Sectors

In the ACS, observations are classified by industries according to a U.S. Census nomenclature. We use the crosswalk provided by the BEA to map census industries to 4-digit 2002 NAICS sectors. When a census industry corresponds to multiple NAICS sectors, we allocate the data proportionally based on the employment size of each NAICS sector. Employment data are available annually from the BLS starting in 2002. From 2008 onward, employment is reported under the 2007 NAICS classification. We use the concordance table provided by the BLS to convert industries from the 2007 classification back to the 2002 classification. Three categories (5172 “Wireless telecommunications carriers”, 5311 “Lessors of real estate”, and 7225 “Restaurants and other eating places”) could not be mapped to the 2002 NAICS sectors and were therefore excluded. These categories are of limited relevance given our focus on I-O linkages in manufacturing industries.

Using this methodology, 79.6% of workers are assigned to 4-digit 2002 NAICS sectors, 17.6% to 3-digit subsectors, and 2.25% to 2-digit sectors (mainly sectors 22 “Utilities”, 23 “Construction”, and 42 “Wholesale”). The remaining 0.61% of observations could not be assigned to any NAICS sector.

Our variable of interest is the number of migrants employed in the “intermediate industry”. We define immigrants in the intermediate sector as those working in the two or three main input sectors, reflecting the skewed distribution of employment across input sectors for a given final sector.

Table B.1: I-O industries from 2002 that are included in more than one NAICS classification, the NAICS Industries and the weights assigned to the latter

I-O industries	NAICS industries	Weights
112A	1122	0.25
	1124	0.25
	1125	0.25
	1129	0.25
113A	1131	0.78
	1132	0.22
3372	3371	0.50
	3372	0.50
48A0	487	0.03
	488	0.97
52A0	521	0.05
	5221	0.95
522A	5222	0.88
	5223	0.12
532A	5322	0.81
	5323	10.19
611A	6112	0.50
	6113	0.50
611B	6114	0.25
	6115	0.24
	6116	0.32
	6117	0.19
621A	6211	0.54
	6212	0.18
	6213	0.28
621B	6214	0.70
	6215	0.20
	6219	0.10
6242	6242	0.44
	6243	0.56
711A	7113	0.67
	7114	0.33
713A	7131	0.23
	7132	0.77

Table B.2: I-O industries from 2007-2012 that are included in more than one NAICS classification, the NAICS Industries and the weights assigned to the latter

I-O industries	NAICS industries	Weights
112A	1122	0.25
	1124	0.25
	1125	0.25
	1129	0.25
423A	4232	0.10
	4233	0.16
	4235	0.28
	4237	0.16
	4239	0.30
424A	4241	0.13
	4243	0.14
	4245	0.23
	4246	0.19
	4249	0.31
48A0	487	0.03
	488	0.97
4B00	442	0.25
	443	0.25
	451	0.25
	453	0.25
517A	5175	0.20
	5179	0.80
522A	5222	0.50
	5223	0.50
523A	5231	0.50
	5232	0.50
52A0	521	0.50
	5221	0.50
532A	5322	0.50
	5323	0.50
611A	6112	0.50
	6113	0.50
611B	6114	0.18
	6115	0.25
	6116	0.35
	6117	0.22

623A	6231	0.32
	6233	0.68
623B 6232	0.81	
	0.19	
624A	6242	0.31
	6243	0.69
711A	7113	0.76
	7114	0.24
722A	7223	0.09
	7224	0.04
	7225	0.87
813A	8132	0.79
	8133	0.21
813B	8134	0.20
	8139	0.80

Appendix C Validity of Instruments

Table C.1: First-stage Estimates

	Dependent variable								
	$log\left(1+M_{it}^j\right)$			$log(M_t^{input,j})$			$log(M_t^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$log\left(1+\hat{M}_{it}^j\right)$	0.259***	0.258***	0.266***	-	-0.002	-0.002	-	-0.013**	0.001
	(0.039)	(0.039)	(0.039)		(0.005)	(0.005)		(0.006)	(0.002)
$log(\hat{M}_t^{input,j})$	-	-1.620**	-0.531	1.076***	1.059***	1.116***	-	-1.011***	0.764***
		(0.700)	(0.708)	(0.091)	(0.085)	(0.085)		(0.144)	(0.040)
$log(\hat{M}_t^j)$	-	1.875***	1.903***	-	0.050	0.052	1.252***	1.475***	1.520***
		(0.613)	(0.604)		(0.075)	(0.075)	(0.102)	(0.109)	(0.027)
Employment control	-	-	X	-	-	X	-	-	X

Notes. Standard errors reported in parentheses are heteroscedasticity robust and clustered at the sector-importer level. Regressions are run at the sector-importer level over the 2003-2017 period dealing with 104,369 observations, and include sector-importer and importer-year fixed effects. The dependent variables use the three endogenous immigration variables from our main model. Regressions are weighted by the employment share across manufacturing sectors. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table C.2: Test for Pre-trends

	(1)	(2)	(3)	(4)	(5)
$\triangle^{2003-2005}\, log(1+\hat{M}_i^j)$	-0.009	-	-	-0.010	-0.011
	(0.047)			(0.046)	(0.047)
$\triangle^{2003-2005}\, log(\hat{M}^{input,j})$	-	0.392	-	0.346	0.282
		(0.560)		(0.565)	(0.575)
$\triangle^{2003-2005}\, log(\hat{M}_t^j)$	-	-	0.476	0.419	0.552
			(0.759)	(0.765)	(0.784)
Control for $\triangle^{2003-2005}\, log(N^j)$	-	-	-	-	X
$\triangle^{2006-2010}\, log(1+\hat{M}_i^j)$	-0.012	-	-	-0.015	-0.013
	(0.038)			(0.038)	(0.038)
$\triangle^{2006-2010}\, log(\hat{M}^{input,j})$	-	1.526	-	1.127	0.357
		(1.975)		(1.950)	(2.084)
$\triangle^{2006-2010}\, log(\hat{M}_t^j)$	-	-	1.064	1.005	0.983
			(0.704)	(0.691)	(0.692)
Control for $\triangle^{2006-2010}\, log(N^j)$	-	-	-	-	X
$\triangle^{2003-2017}\, log(1+\hat{M}_i^j)$	-0.008	-	-	-0.010	-0.008
	(0.031)			(0.031)	(0.031)
$\triangle^{2003-2017}\, log(\hat{M}^{input,j})$	-	-0.400	-	-0.665	-0.538
		(0.418)		(0.458)	(0.468)
$\triangle^{2003-2017}\, log(\hat{M}_t^j)$	-	-	0.477	0.823	0.864
			(0.587)	(0.643)	(0.638)
Control for $\triangle^{2003-2017}\, log(N^j)$	-	-	-	-	X

Notes. Standard errors in parentheses are heteroscedasticity robust. Each column of the table reports the estimated results of a single regression. The unit of observation is a sector-importer cell and all regressions have 6,014 observations. The dependent variable is difference in the log of exports from a given sector to a given country between 2000 and 2002. The main regressors of interest are the difference in the predicted immigrant changes between 2003 and 2005 in the top part of the table, between 2006 and 2010 in the middle part, and between 2003 and 2017 in the bottom part. The regressions in column 5 include the difference in log employment over the period considered. ***, **, * denote statistical significance from zero at the 1%, 5%, 10% significance level.