

O-Ring Production Networks

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We document strong skill matching in Turkish firms' production networks. Additionally, in the data, export demand shocks from rich countries increase firms' skill intensity and their trade with skill-intensive domestic partners. We explain these patterns using a quantitative model with heterogeneous firms, quality choices, and endogenous networks. A counterfactual economy-wide export demand shock of 5% leads both exporters and nonexporters to upgrade quality, raising the average wage by 1.2%. This effect is nine times the effect in a scenario without interconnected quality choices. We use the model to study the conditions for the success of export promotion policies.

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I. Introduction

The space shuttle *Challenger* exploded because one of its innumerable components, the O-rings, malfunctioned during launch. Using this as a leading example, Kremer (1993) studies production processes in which the value of output dramatically decreases if a single task fails. In his model, just one mistake of an unskilled worker is enough to destroy a product. Thus, firms that produce complex, high-quality products hire skilled workers for all their tasks.

If we extend this rationale beyond firm boundaries, a high-quality, skill-intensive firm will source its inputs from other high-quality firms and sell more to high-quality firms that value its output. In addition, a firm's decision to upgrade quality depends critically on the willingness of its trading partners to also upgrade or on its ability to find new higher-quality partners. This interconnection applies to the quality of products as well as to the quality of a firm's inventory controls, research and development, and internal communications. Improvements in these areas generally allow for a wider product scope and render the firm more flexible to respond to shocks. A firm profits from these improvements if its suppliers also offer scope and flexibility and if its customers value them.

We argue that this interconnection in firms' choices of quality and skills sheds light on why export promotion policies in many developing countries catalyzed widespread improvements in manufacturing firms and increased their skill intensity, and we study the conditions for the success of these policies. Consider a subsidy to the cost of searching for foreign buyers. If the demand for quality is higher abroad, exporters respond by upgrading quality and increasing skill intensity. Since exporters are large and have many domestic connections, it becomes more likely that other firms will match with higher-quality trading partners. Matching with a high-quality supplier decreases the relative cost of producing high-quality goods, and matching with a high-quality buyer increases the demand for high-quality goods. In response, all firms, exporters and nonexporters alike, upgrade their quality and increase their demand for skills, amplifying the original policy shock.

We proceed in several steps. The mechanism above hinges on two conditions: (1) skill-intensive firms use disproportionately more inputs from skill-intensive suppliers, and (2) firms respond to incentives to change

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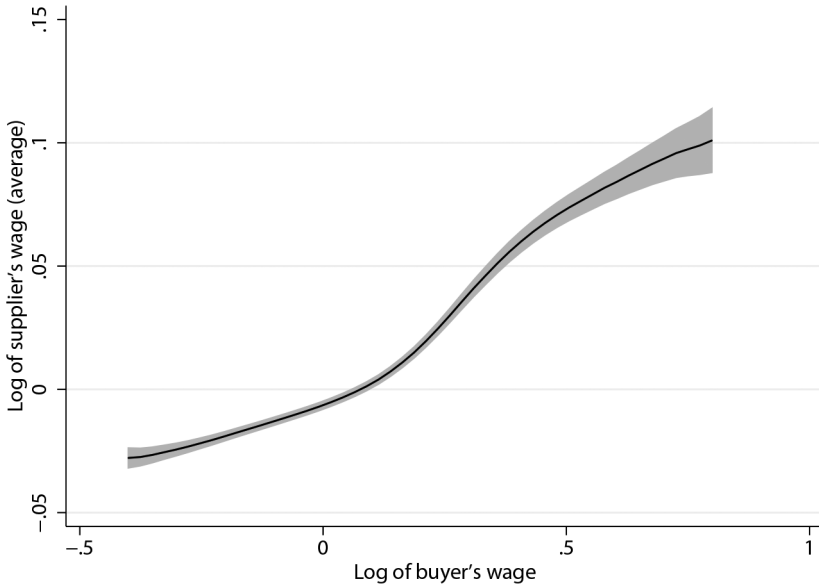


FIG. 1.—Assortative matching on wages. We define the wage as the firm’s wage bill divided by the number of workers. The supplier wage is the average wage across the firm’s manufacturing suppliers, weighted by the firm’s spending on each supplier. Variables in the x - and y -axes are demeaned by four-digit NACE industry and region. The fitted curve is a local polynomial regression with an Epanechnikov kernel. The shaded area shows the 95% confidence intervals. To improve visibility, we trim 1% of the data at each end of the distribution of buyer wages. The regression corresponding to this figure is in column 2 of table 1.

their skill intensity. Section II provides evidence of these conditions using data on Turkish manufacturing firms from 2011 to 2015. Figure 1 illustrates an example of the novel assortative matching facts. It graphs firms’ average wage (adjusted for industry-region) against the average wage of their suppliers.¹ A 10% increase in a firm’s wage is associated with a 2.5% increase in the average wage of its suppliers. A decomposition exercise reveals that 59% of this relationship is due to the extensive margin, that is, high-wage firms matching more with each other. The remaining 41% is due to the intensive margin, that is, high-wage firms spending more on each others’ inputs.

We use shift-share regressions to study firms’ responses to demand shocks from rich countries. We focus on rich countries because the literature provides evidence that these countries demand relatively more high-quality, skill-intensive goods.² Consider a Turkish firm that in 2011 exported a

¹ The figure has only manufacturing firms, which are later used in our structural estimation, but an equally strong pattern holds if we include all sectors. See table 1.

² See Hallak (2006), Brambilla, Lederman, and Porto (2012), Manova and Zhang (2012), Feenstra and Romalis (2014), and Bastos, Silva, and Verhoogen (2018).

particular product category to a rich country, say, Germany. An increase in German imports of that product from countries other than Turkey between 2011 and 2015 is associated with an increase in the Turkish firm's wage and in the average wage of its suppliers and customers. This response arises in part through new employees and network connections and in part because firms facing positive shocks tilt their spending toward their skill-intensive suppliers.

In sections III and IV, we develop a quantitative model. Heterogeneous firms post costly ads to search for other firms.³ More productive firms post more ads and have more customers and suppliers. As in Kremer (1993), firm quality gives rise to complementarities among skilled workers in production—here within and across firms. We assume that high-quality firms are skill intensive, as in Verhoogen (2008), and we allow them to use intensively high-quality inputs, as in Kugler and Verhoogen (2011). When posting ads, firms imperfectly target other firms with similar quality levels. Firms also pay a fixed cost to export, as in Melitz (2003), and we allow the relative demand for quality to be larger abroad.

The procedure to estimate the model is in section V, and its results are in section VI. We apply the method of simulated moments. The moments describe the joint distribution of firm revenue, wages, number of buyers and suppliers, and their wages. In the model, targeted search captures differences in matching across firms with different wages—the extensive margin of assortative matching—while differences in the marginal product of inputs capture the intensive margin. A firm-specific export demand shock in the model increases the firm's quality and skill intensity. The magnitude of the average firm response exactly matches the response implied by the shift-share regressions in the data: a 5% increase in export demand increases the firm's wages by 0.21%.

To understand the general equilibrium effects of export shocks in section VII, we experiment with a counterfactual shock of the same magnitude as this shift-share export shock but applied to all exporters instead of individual firms. The probability that any firm matches with a high-quality firm in the network increases. The ensuing increased demand for higher-quality goods from high-quality buyers accounts for about two-thirds of the counterfactual increase in profit from producing high- relative to low-quality goods. The decrease in the relative cost of producing high-quality goods due to high-quality input suppliers accounts for the remaining one-third. Nonexporting firms not directly impacted by the shock upgrade quality, and their wages increase by 1.0% as they become more skill intensive. The wages of exporters increase by 1.92%, almost an order of magnitude larger than the effect of firm-specific shocks.

³ The network formation is similar to search and matching in labor. See Mortensen (1986) and Rogerson, Shimer, and Wright (2005) for surveys.

These general equilibrium effects are large because exporters are large and skill intensive and have many network connections. In the data and the estimated model, they are fewer than 30% of firms, and yet they account (as buyers or sellers) for more than 90% of firm-to-firm sales.

Section VIII evaluates policies. We study a counterfactual subsidy to the cost of searching for foreign buyers and interpret it as an export promotion that facilitates links to foreign buyers, such as export fairs, allowed under the World Trade Organization rules.⁴ In the model, this subsidy has the same effect on an individual firm as the shift-share shocks to export demand used in the estimation. We pick the size of the subsidy, 9%, to match the increase in exports of the counterfactual export shock above. The policy has a small cost, 0.6% of household income, and similar effects on the sales and skill intensity of exporters and nonexporters.

Additional counterfactual exercises point to critical conditions for export promotion to succeed. Ensuring an elastic supply of skilled labor into manufacturing, possibly through investments in education, is necessary for the widespread adoption of skill-biased quality upgrading. The size of the foreign market relative to the domestic market matters because foreign has a higher relative demand for high-quality goods. So, running a trade surplus, possibly through polemic real exchange rate manipulations, increases quality. Finally, the effect of quality upgrading on output depends on the extent to which there are external scale effects from the agglomeration of skilled workers in manufacturing. Scale effects in the magnitude of the estimates from Diamond (2016) nearly doubles the counterfactual output growth.

Related literature.—Our proposed mechanism is related to the big push literature in its emphasis on complementarities in technology adoption (quality upgrading) and potential large general equilibrium effects of small shocks, for example, Rosenstein-Rodan (1961), Murphy, Shleifer, and Vishny (1989), Matsuyama (2002), and Buera et al. (2021).⁵ While these papers study closed economies, here the foreign market plays a key role because of its higher relative demand for quality.

The network literature has focused on Hicks-neutral shocks, while quality in our model changes the types of material and labor inputs that firms use. We relax Hicks neutrality through log-supermodular shifters. We follow Teulings (1995) and Costinot and Vogel (2010) for labor and Fieler, Eslava, and Xu (2018) for material inputs, and we apply these functions anew to search.⁶ Our novel search-and-matching setup is tractable and yields a closed-form solution in the special case of the model with only

⁴ Rauch (2001) surveys case studies of this type of export promotion policies.

⁵ These features also appear in the literature on infant industry protection, surveyed by Harrison and Rodríguez-Clare (2010).

⁶ The production function in Dingel (2017) aggregates workers with heterogeneous skills in the same manner that our production function aggregates material inputs with

one quality level. We abstract, however, from the following aspects of the network highlighted in the literature: information flows in Chaney (2014), dynamics in Huneeus (2018) and Lim (2018), asymmetries in network centrality in Acemoglu et al. (2012), and market distortions in Jones (2011), Baqaee and Farhi (2019b), Liu (2019), and Bigio and La'O (2020). The model features roundabout production and technologies with constant elasticities of substitution, and each firm has a continuum of suppliers and customers. Some of these theoretical elements and the study of shocks to international trade appear in Dhyne et al. (2018), Eaton, Kortum, and Kramarz (2018), Huneeus (2018), Lim (2018), Bernard, Moxnes, and Saito (2019), Bernard et al. (2022), Demir et al. (2022), and Lenoir, Martin, and Mejean (2023).⁷

The estimated model is consistent with well-established facts in the quality literature. Higher-quality production is intensive in skilled labor, as in Schott (2004), Verhoogen (2008), and Khandelwal (2010), and in higher-quality inputs, as in Kugler and Verhoogen (2011), Manova and Zhang (2012), and Bastos, Silva, and Verhoogen (2018). Bas and Paunov (2021) provide evidence for the complementarity between skilled labor and input quality in increasing output quality, and Fieger, Eslava, and Xu (2018) combine these elements to study, like us, the general equilibrium effects of international trade.⁸ These papers all use data on prices. We complement them with direct information on the extent to which skill-intensive firms trade with each other. These assortative matching patterns are related to Voigtländer (2014), who shows that skill-intensive sectors use intensively inputs from other skill-intensive sectors in the United States.⁹

II. Data and Empirical Facts

A. Data Sources

We combine five datasets covering all formal firms in Turkey from 2011 through 2015. The Ministry of Industry and Technology maintains all the datasets and uses the same firm identifier, allowing us to merge them. Appendix A (apps. A–H are available online) describes the details. We restrict the analysis to the manufacturing sector unless otherwise noted.

heterogeneous qualities. See also Milgrom and Roberts (1990) and Costinot (2009) for early applications of log-supermodular functions to economics and international trade.

⁷ Costinot, Vogel, and Wang (2012) develop an interesting model to study how workers of heterogeneous skills (from different countries) allocate themselves along the sequential stages of the production of a single final good. Our emphasis is on the allocation across different types (or qualities) of final goods.

⁸ In Blaum (2019), a similar complementarity arises between importing and exporting through scale and quality choices.

⁹ Also related, Carvalho and Voigtländer (2014) find that firms are more likely to match with the suppliers of their suppliers. They interpret the finding through information frictions, as in Chaney (2014).

The 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 US\$1,800 in 2015) in a given year. 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 four-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 annual exports and imports by firm, destination country, and four-digit Harmonized System (HS) product code. Fifth, the employer-employee data report the quarterly wage of each worker in each firm, four-digit occupation code according to International Standard Classification of Occupations (ISCO), age, and gender.

In section II.B, we describe assortative matching in the firm-to-firm network. We use the 2015 cross section with 77,418 manufacturing firms. In section II.C, we estimate firm-specific trade shocks in long differences from 2011 to 2015 using annual bilateral trade data from Base pour l'Analyse du Commerce International (BACI), disaggregated by four-digit HS product codes.¹⁰ We use the balanced panel of 33,157 firms to associate these shocks with systematic changes in firm outcomes. In section II.D, we describe other salient features of the data that are not novel but help justify elements of the model.

B. Assortative Matching in the Cross Section

We use a firm's average wage as the main proxy for its skill intensity under the assumption that firms observe skills better than we econometricians and that wages reflect differences in skills. We use other measures of skills for robustness in section II.B.1. We focus on the relationship between a firm and its suppliers here, but mechanically, similar patterns hold between a firm and its customers (see app. B.4.2).

Define wage_f as firm f 's total annual wage bill divided by its number of workers. Define the wage of firm f 's suppliers as

$$\log \text{wage}_f^S = \sum_{\omega \in \Omega_f^S} s_{\omega f} \log \text{wage}_\omega, \quad (1)$$

where Ω_f^S is the set of suppliers to firm f and $s_{\omega f}$ is the share of supplier ω in firm f 's total spending on domestic material inputs.

¹⁰ We aggregate the BACI data from six- to four-digit HS codes because trade flows at the country HS6 product level is excessively volatile. Also, it is less likely for any single country to have significant market power in a given destination at the four-digit product level than at the six-digit level.

TABLE 1
ASSORTATIVE MATCHING ON WAGES

	DEPENDENT VARIABLE: $\log \text{wage}_f^S$			
	Manufacturing Firms			All Firms (4)
	(1)	(2)	(3)	
$\log \text{wage}_f$.294 (.013)	.259 (.012)	.188 (.009)	.241 (.013)
$\log \text{employment}_f$.044 (.003)	
R^2	.095	.173	.199	.150
Observations	77,418	77,418	77,418	410,608
Fixed effects		Industry-province	Industry-province	Industry-province

NOTE.— Wage_f is the average value of monthly payments per worker of firm f . The suppliers' average wage $\log \text{wage}_f^S$ is defined in eq. (1). Industry and province refer to four-digit NACE industries and provinces, respectively. Robust standard errors are clustered at the four-digit NACE industry level.

Table 1 reports the results from the regression:

$$\log \text{wage}_f^S = \beta \log \text{wage}_f + \gamma X_f + e_f, \quad (2)$$

where e_f is the residual, scalar β and vector γ are parameters to be estimated, and X_f are control variables that vary across columns. Columns 1–3 contain only the manufacturing subsample. Column 1 has no control variables. Adding fixed effects for each industry-province pair in column 2 decreases the coefficient because firms match more within province and industry, and some industry-province pairs have higher skill shares. Still, the decrease is small, from 0.294 to 0.259, suggesting that most of the systematic variation occurs within industry-province. A 10% increase in the average buyer wage is associated with a 2.5% increase in the average supplier wage.¹¹

Column 3 controls for the buying firm's employment. Since employment and wages are correlated, the coefficient on wages decreases. But it remains large and significant. Column 4 repeats specification (2) with the sample of all firms.¹² The coefficient of 0.241 is similar to 0.259 in specification (2).

1. Decomposition and Nonparametric Patterns

The positive coefficients in table 1 could be driven by high-wage firms having more high-wage suppliers—the extensive margin—or by high-wage firms

¹¹ Table A9 (tables A1–A25 are available online) shows that the positive assortative matching holds not only for mean suppliers' wages but also for all the deciles of the wages of firms' trading partners.

¹² We exclude utilities and public service firms as well as finance and insurance firms that are not in the VAT data.

spending more on their high-wage suppliers given the same matches—the intensive margin.

Define the extensive margin as the unweighted average wage of firm f 's suppliers:

$$EM_f^S = \sum_{\omega \in \Omega_f} \frac{1}{|\Omega_f|} \log \text{wage}_\omega. \quad (3)$$

Define the intensive margin as the difference between $\log \text{wage}_f^S$ in (1) and the extensive margin:

$$\begin{aligned} IM_f^S &= \log \text{wage}_f^S - EM_f^S \\ &= \sum_{\omega \in \Omega_f} \left(s_{\omega f} - \frac{1}{|\Omega_f|} \right) \left(\log \text{wage}_\omega - \sum_{\omega' \in \Omega_f} \frac{1}{|\Omega_f|} \log \text{wage}_{\omega'} \right). \end{aligned} \quad (4)$$

The intensive margin is large if firm f 's spending shares $s_{\omega f}$ are large for its high-wage suppliers ω .

One at a time, we regress $\log \text{wage}_f^S$, EM_f^S , and IM_f^S on the wage of firm f and on industry-province fixed effects. The results are in table 2. The first regression is the same as in column 2 of table 1. By design, the coefficients in columns 2 and 3 add up to column 1 (0.259). Both margins are sizable: the extensive margin accounts for 59% ($=0.152/0.259$) of the partial correlation between firm wage and supplier wage, while the intensive margin accounts for 41% ($=0.107/0.259$).

Figure 2 illustrates assortative matching in the raw data. We split firms into quintiles of wage_f . Figure 2A and 2B describe upstream links. The height of the bars in figure 2A is the supplier quintile's share in the number

TABLE 2
ASSORTATIVE MATCHING ON WAGES: DECOMPOSITION

	Total $\log \text{wage}_f^S$ (1)	Extensive Margin EM_f^S (2)	Intensive Margin IM_f^S (3)
$\log \text{wage}_f$.259 (.012)	.152 (.007)	.107 (.007)
R^2	.173	.150	.089
Observations	77,418	77,418	77,418
Fixed effects	Industry-province	Industry-province	Industry-province

NOTE.—The wage is defined as the average value of monthly payments per worker. The suppliers' average wage $\log \text{wage}_f^S$ is defined in eq. (1). Industry and province refer to four-digit NACE industries and provinces, respectively. Equations (3) and (4) define the extensive (EM_f^S) and intensive (IM_f^S) margins. They capture, respectively, the extent to which firm f matches with high-wage suppliers or tilts its spending toward high-wage suppliers. Robust standard errors are clustered at the four-digit NACE industry level.

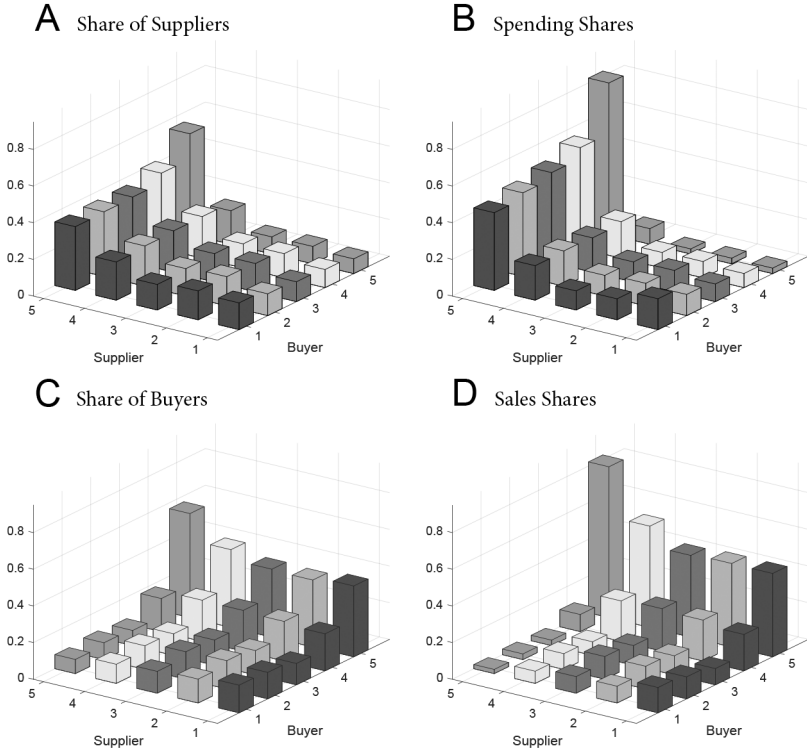


FIG. 2.—Firm-to-firm trade links and values by quintile. The sample includes manufacturing buyers and suppliers. Firms are sorted according to the average value of their monthly payments per worker and grouped into five equal-sized groups. The buyer and supplier quintiles are shown on the x - and y -axes, while the z -axis shows the corresponding shares. *A* and *B* illustrate buyers' upstream connections. In *A*, the z -axis is the share of suppliers that belong to the wage quintiles on the y -axis for each buyer quintile on the x -axis. In *B*, the z -axis is the spending shares. *C* and *D* illustrate suppliers' downstream connections. In *C*, the z -axis is the share of buyers that belong to the wage quintiles on the y -axis for each supplier quintile on the x -axis. In *D*, the z -axis is the sales shares.

of suppliers to firms in each buyer quintile. The height in figure 2*B* is the supplier quintile's share in the spending of firms in each buyer quintile. Thus, by construction, the sum of the bars of the same buyer quintile (same shade of gray) is 1 across supplier quintiles. Suppliers in the highest quintile of wages generally have larger sales and more buyers. But they disproportionately sell to and match with high-wage buyers. In figure 2*A*, the number of suppliers in quintile 5 relative to quintile 1 is 6.8 if the buyer is herself in the highest wage quintile and 2.4 if the buyer is in the lowest wage quintile. This difference is even bigger in figure 2*B* because of the intensive margin. Spending on high-wage suppliers

is 27.4 times larger than on low-wage suppliers for high-wage buyers and 2.5 times for low-wage buyers.

Figure 2C and 2D describe the corresponding patterns for firms' downstream links. They are almost the mirror images of figure 2A and 2B.

2. Robustness of Assortative Matching

We conduct various checks on the robustness of the assortative matching results, detailed in appendix B. To address the concern that wages may contain rents and differences in profit-sharing policies across firms, we use two other measures of skill intensity in appendix B.1.1. First, we decompose the variation in wages into a firm and a worker component, as in Abowd, Kramarz, and Margolis (1999), using the employer-employee data from 2012 to 2015. Following Bombardini, Orefice, and Tito (2019), we take a firm's skill intensity to be the average fixed effect of its workers. Second, we use occupational categories and their classification according to routine/nonroutine analytical/interpersonal skills proposed by Caunedo, Keller, and Shin (2021). When we repeat the regressions in table 2 with these two measures of skill intensity, the coefficients are smaller but still positive and statistically significant. The decrease is not surprising: the first measure eliminates the firm fixed effect, and the second measure eliminates heterogeneity within occupations, which contain most of the heterogeneity in wages (app. B.4.1).

Firm quality and complexity are the source of complementarity in worker skills in Kremer (1993), in the subsequent literature, and in our model.¹³ In appendix B.1.2, we use the number of occupational categories as a proxy for firm complexity, following Tian (2021), and for exporters only, we use the measure of quality in Khandelwal, Schott, and Wei (2013). The network exhibits positive assortative matching in these two measures.

In appendix B.2, we experiment with different specifications and samples. To address the concern that our results are driven by firms matching more within provinces, we conduct three exercises in table A2: we control for firm location at a finer district level; we exclude suppliers in the same province as the firm, and we exclude multiestablishment firms. The positive assortative matching pattern is robust to all three specifications.

In table A3, we add to the baseline table 2 the following firm characteristics as controls: the firm's market share in its four-digit NACE industry, dummy variables for foreign ownership, export status, import status, number of domestic buyers (outdegree), and number of domestic suppliers (indegree). The sorting coefficient is 0.181, very close to the estimate 0.188 in column 3 of table 1, which controls for employment.

¹³ See, e.g., Teulings (1995) and Costinot and Vogel (2010).

Excluding firms with foreign ownership from the sample (table A4) barely changes the results of table 2. Finally, we report the sorting coefficients separately by buyer industry in figure A4 (figs. A1–A8 are available online). The overall sorting coefficient is statistically significant for all industries and ranges from 0.1 (apparel) to 0.4 (motor vehicles). Its decomposition into extensive and intensive margins is stable.

Appendix B.3 evaluates sorting between firms and suppliers along two other dimensions of firm heterogeneity: sales and number of network connections.¹⁴ The overall assortative matching is positive on sales but less pronounced than on wages. Sorting on the number of network links is not robust. In appendix B.3.2, we conduct a horse race between sales and wages to assess their relative importance in sorting. We follow the canonical correlation analysis of Johnson and Wichern (1988).¹⁵ Both wages and sales matter for the positive assortative matching, but wages are about three times more important than sales for downstream linkages and 8.5 times more important for upstream linkages.

C. Trade Shocks

We use shift-share regressions to show that firms respond to firm-specific trade shocks by changing their skill intensity and network connections.¹⁶

Define two shifters associated with country c and product category k :

$$\begin{aligned} Z_{ck}^u &= \Delta \log \text{Imports}_{ck}, \\ Z_{ck}^a &= (\Delta \log \text{Imports}_{ck}) \times \log(\text{GDP per capita}_{c,2010}), \end{aligned} \tag{5}$$

where $\Delta \log \text{Imports}_{ck}$ is the log change between 2011–12 and 2014–15 in the total imports of country c in product category k from all countries other than Turkey, and $\text{GDP per capita}_{c,2010}$ is the income per capita of country c in 2010.

We measure the export shock to firm f as

$$\begin{aligned} \text{ExportShock}_f^u &= \sum_{ck} x_{ckf} Z_{ck}^u, \\ \text{ExportShock}_f^a &= \sum_{ck} x_{ckf} Z_{ck}^a, \end{aligned} \tag{6}$$

¹⁴ Similar patterns for the extensive margin arise in other network data. See Lim (2018) for sales and Lim (2018) and Bernard et al. (2022) for number of network links.

¹⁵ Becker (1973) first introduced canonical correlation analysis to evaluate which individual characteristics are most relevant for matching in marriage.

¹⁶ See Bartik (1991) for an early application of shift-share regressions and Adão, Kolesr, and Morales (2019), Goldsmith-Pinkham, Sorkin, and Swift (2020), and Borusyak, Hull, and Jaravel (2021) for statistical properties in general setups.

where x_{ckf} is the share of firm f 's revenue in 2010 that is exported to country c in product category k . We interpret Z_{ck}^u as a change in the demand for product category k in country c . The underlying assumption is that shocks to imports of product k by country c from countries other than Turkey are uncorrelated with other unobserved shocks to Turkish firms that export k to c in the initial year. Under this assumption and interpretation of Z_{ck}^u , ExportShock_f^u is a standard shift-share shock to the demand for firm f 's exports.

ExportShock_f^a is an adjusted measure that weights more demand shocks originating in rich countries. We hypothesize that these are the shocks that provide incentives for Turkish firms to increase their skill intensity, because rich countries demand relatively more high-quality, skill-intensive goods.

To compare these two measures, we separately use them in the regression

$$\Delta \log \text{wage}_f = \delta \text{ExportShock}_f + \alpha_{sr} + \varepsilon_f,$$

where α_{sr} is industry-province fixed effects.

Columns 1 and 2 of table 3 report the results. The unadjusted ExportShock_f^u has an insignificant effect on firm wages, while the adjusted

TABLE 3
EFFECTS OF EXPORT SHOCK

	$\Delta \log \text{wage}_f$ (1)	$\Delta \log \text{wage}_f$ (2)	$\Delta \log \text{supplier log wages}_f$ (3)	$\Delta \log \text{buyer log wages}_f$ (4)	$\Delta \log \text{domestic sales}_f$ (5)	$\Delta \text{export intensity}_f$ (6)
ExportShock $_f^u$ (unadjusted)	.021 (.033)					
ExportShock $_f^a$ (adjusted)		.042 (.006)	.017 (.009)	.015 (.010)	-.026 (.022)	.0146 (.0023)
Observations	33,157	33,157	33,157	33,157	33,157	33,157
Fixed effects	Industry- province	Industry- province	Industry- province	Industry- province	Industry- province	Industry- province

NOTE.—Wage $_f$ is the average value of monthly payments per worker in firm f . The suppliers' average wage is defined in eq. (1), and the buyers' average wage is defined symmetrically with the weights corresponding to sales shares. The Δ operator denotes changes between 2011–12 and 2014–15. ExportShock_f^u is a weighted average of changes in imports at the country (c) and four-digit HS product (k) level between 2011–12 and 2014–15, where the weights are constructed as the share of firm f 's exports of product k to importer c in its total sales in 2010. ExportShock_f^a adjusts these shocks by weighting them by the GDP per capita of the destinations. See eq. (6). Industry and province refer to four-digit NACE industries and provinces, respectively. Robust standard errors are clustered at the four-digit NACE industry level.

ExportShock $_j^a$ has a positive and significant effect. As anticipated, an increase in the demand for a firm's exports increases the firm's skill intensity only if the demand originates in rich countries.¹⁷ The F -statistic (not in the table) is 0.40 in column 1 and 43.6 in column 2, indicating that only the adjusted export shock is informative about changes in wages.

The mean of ExportShock $_j^a$ is 0.12. To understand the magnitude of the coefficient 0.042 in column 2, consider two firms. They both export a quarter of their sales (the mean export intensity among exporters in the data). One firm exports to a country at the 90th percentile of the per capita GDP distribution (US\$41,300, France), and the other firm exports to a country at the 10th percentile (US\$766, Benin). For the average change in imports over the sample period, $Z_{ck}^a = 5\%$, the implied ExportShock $_j^a$ for the two firms is 13.3% ($= 0.25 \times 0.05 \times \log(41,300)$) and 8.3%, respectively, and the estimated wage increase is 0.56% ($= 0.042 \times 0.133$) and 0.35%.

Given these results, we henceforth use the adjusted export shock in all exercises. In columns 3 and 4, we replace the dependent variable with the log changes in the weighted average of suppliers' and buyers' wages. Consistent with the increase in the firm's own wage, the export shock is associated with an increase in both suppliers' and buyers' wages, though the coefficient is not statistically significant for the latter.

In column 5, we replace the dependent variable with domestic sales. The insignificant coefficient is reassuring, since we assume that ExportShock $_j^a$ is uncorrelated with domestic shocks to firm f . It is also reassuring that the shock is not spurious but associated with an increase in export intensity (export sales divided by total sales) in column 6.¹⁸

1. Mechanisms

The increase in the wages of workers, suppliers, and customers in table 3 arises at least in part through new workers and network connections. Recall that the export shock is constructed from changes between 2011–12 and 2014–15. Take the workers that firm f added between 2013 and 2015. Using matched employer-employee data, we regress the log difference between these new workers' wages in 2011–12 (before they entered the firm) and firm f 's average wage in 2011–12 (before the shock) on ExportShock $_j^a$. The results are in column 1 of table 4. Columns 2 and 3 repeat the exercise for the firm's new suppliers and new customers. The

¹⁷ A related finding is in De Loecker (2007). For Slovenian firms, the productivity gains from exporting are larger when the firm exports to high-income destinations than to low-income destinations.

¹⁸ Consistent with col. 5, the export shock is not associated with changes in employment or number of network links upstream or downstream in table A13.

TABLE 4
EFFECTS OF EXPORT SHOCK ON COMPOSITION OF INPUTS

	LOG OF		
	Average Wage of New Workers Relative to All Workers at $t = 0$	Average Wage Paid by New Suppliers Relative to All Suppliers At $t = 0$	Average Wage Paid by New Buyers Relative to All Buyers at $t = 0$
ExportShock _{<i>t</i>}	.0189 (.010)	.0241 (.007)	.0303 (.009)
R^2	.0531	.0439	.0434
Observations	33,157	33,157	33,157
Fixed effects	Industry-province	Industry-province	Industry-province

NOTE.—The wage is defined as the average value of monthly payments per worker. ExportShock_{*t*} is a weighted average of changes in imports at the country (c) and four-digit HS product (k) level between 2011–12 and 2014–15, where the weights are constructed as the share of firm f 's exports of product k to importer c in its total sales in 2010. ExportShock_{*t*} adjusts these shocks by weighting them by the GDP per capita of the destinations. See eq. (6). Time $t = 0$ represents the period before the export shock, 2011–12. Industry and province refer to four-digit NACE industries and provinces, respectively. Robust standard errors are clustered at the four-digit NACE industry level.

coefficients in all columns are positive. They are statistically significant at the 10% level for column 1 and at the 1% level for columns 2 and 3.¹⁹

We evaluate two other mechanisms in appendix C.3.2. First, we check and find evidence that a typical firm responds to a positive export shock by tilting its spending toward its high-wage suppliers among the set of continuing suppliers. We find no evidence of the corresponding tilting in sales to high-wage buyers. Second, we check whether firms respond to the shocks of their initial suppliers and buyers. These indirect effects are positive and diminish with network distance. They are also much smaller than the firm's own shock and imprecisely estimated.²⁰ In sum, the increase in the wages of workers, buyers, and suppliers in columns 2–4 of table 3 arises through new connections and through the tilting of spending on material inputs toward continuing high-wage suppliers.

The association of skill intensity to quality, made in the literature and the model below, also appears in table A12. We regress the change in the export quality measure of Khandelwal, Schott, and Wei (2013)

¹⁹ We use the unweighted average from equation (3) because we cannot measure the weights s_{cjt} that the firm would have placed on new suppliers in the initial year or the equivalent weights of new customers on initial sales. In table A15, we obtain similar results when we compare the wages of new connections relative to those of workers, suppliers, and customers that left the firm between 2010 and 2015. Table A14 associates the export shock with the share of newly hired workers after the shock, who received higher monthly wages than the firm's average worker before the shock. Thus, table 4 is not driven by a few outliers among new connections.

²⁰ We find that the suppliers' responses to the firm's export shock is larger than the customers' responses. This finding is consistent with the importance of backward linkages to multinationals in Smarzynska Javorcik (2004) and Alfaro-Urea, Manelici, and Vasquez (2022).

on the export shock and obtain a positive and statistically significant coefficient.²¹

2. Identification and Robustness Checks

Recent papers discuss shift-share regressions similar to ours. Borusyak, Hull, and Jaravel (2021) and Goldsmith-Pinkham, Sorkin, and Swift (2020) propose methods to study, respectively, which shifts or shares matter most for consistency. Following the recommendation in Borusyak, Hull, and Jaravel (2021), we check three key conditions in appendix C. First, shifts are numerous. To calculate shifts Z_{ck}^a , we use 208 distinct destination countries c and 1,242 four-digit HS codes k , generating 153,186 country-product pairs. Second, the shifts are dispersed within industries. The average Herfindahl-Hirschman index of shares x_{ck} within industry is 5×10^{-5} , and the largest value of country-product average share, $x_{ck} = \sum_f (1/N) x_{ckf}$, is 0.003. The standard deviation of Z_{ck}^a is 3.26 across all firms and industries and 3.24 across firms within industries. Third, the shifts are relevant. We obtain a coefficient close to zero when we substitute ExportShock_z^a with a placebo $\text{ExportShock}_f^{\text{random}}$ generated from randomly drawn shifts Z_{ck}^a .

Table A11 presents additional checks. Putting the ExportShock_f^a and ExportShock_f^b in the same regression does not change the coefficients relative to columns 1 and 2 of table 3. The baseline results in column 2 of table 3 are robust to controlling for the total export share of the firm to address the concern in Borusyak, Hull, and Jaravel (2021) that shares x_{ck} do not add up to 1. They are also robust to controlling for the export shares x_{ck} weighted by destination income per capita. This exercise addresses the concern in Adão, Kolesr, and Morales (2019) that observations with similar shares have correlated residuals. In column 5, we substitute the ExportShock_f^a with the interaction between ExportShock_f^b and the weighted destination income per capita. The interaction has a positive and statistically significant coefficient, consistent with the baseline, but the F -statistic is much smaller. In column 6, the results are also robust to including nonexporting firms in the sample. Last, we construct an export shock that weights destination by their total GDP instead of GDP per capita. Relative to the baseline, the coefficient and the F -statistic decrease, suggesting that this shock is less informative about changes in wages.

²¹ In col. 1 of table A12, we regress the measure of skill intensity proposed by Bombardini, Orefice, and Tito (2019) on the export shock. Because the measure is identified through workers that switch firms, the positive coefficient confirms that new workers have higher wages than exiting workers.

D. Other Features of the Data

Two other features of the data are salient. First, sales is the most important indicator of the number of suppliers and customers of a firm. Table 5 reports the endogenous elasticity of the number of customers and suppliers with respect to sales. Firm sales explain about one-third of the variation in the number of buyers and 60% of the variation in the number of suppliers (R^2 in cols. 1 and 4). Columns 2 and 5 add industry fixed effects, and columns 3 and 6 also add wages. The coefficients on wages are insignificant and do not change the coefficients on sales or the R^2 .

To illustrate the role of size, take the example of exporting firms. Although only 28% of firms are exporters, the share of manufacturing firm-to-firm trade with at least one exporter is 78% in number of links and 91% in value.

Second, larger firms are typically skill intensive, but the relationship is far from perfect. The correlation between sales and wages (in logs and demeaned from industry and regional averages) is 0.47. The rank correlation is 0.44.

To summarize, cross-sectional data in section II.B reveal that skill-intensive firms buy and sell relatively more inputs from other skill-intensive firms. This clustering of skilled workers in production chains would be rigid if it arose exogenously, say, from a common social network of skilled workers and entrepreneurs. But panel data in section II.C reveal its endogeneity. In response to export demand shocks, firms hire skilled workers and switch toward skill intensive suppliers and buyers. The quantitative analysis of the general equilibrium effects of exporting, which we pursue below, also captures exporters' large sales, number of network connections, and skill intensity.

TABLE 5
FIRM SALES AND NETWORK CONNECTIONS

	NUMBER OF CUSTOMERS			NUMBER OF SUPPLIERS		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales _{<i>f</i>}	.440 (.016)	.462 (.013)	.459 (.013)	.577 (.011)	.593 (.009)	.590 (.009)
Wage _{<i>f</i>}			.278 (.211)			.208 (.175)
R^2	.328	.472	.472	.609	.645	.645
Observations	77,418	77,418	77,418	77,418	77,418	77,418
Fixed effects		Industry	Industry		Industry	Industry

NOTE.—Wage is defined as the average value of monthly payments per worker. All variables are in logarithms. Industry refers to four-digit NACE industries. Robust standard errors are clustered at the industry level.

III. The Closed Economy Model

To highlight the novel features of the model, we first present the closed economy case. We design the basic elements of the model to capture the data facts above.

There are two sectors: services and manufacturing. There is an exogenous set of manufacturing firms Ω with heterogeneous productivity. These firms produce differentiated goods that serve as inputs into manufacturing itself and into services. They post ads to find suppliers and customers and thus form the firm-to-firm network. As in Lim (2018), each firm is matched with a continuum of suppliers and customers and charges the monopolistic competition markup. More productive firms endogenously post more ads and have more customers and suppliers (as in table 5).

Manufacturing firms are also heterogeneous in their quality q . All tasks performed in a firm of quality q are indexed by q . The marginal product of higher-quality inputs may be higher in the production of higher-quality output, and firms imperfectly direct their ads toward other firms with similar quality levels. With these elements, the latent variable quality governs the intensive and extensive margins of assortative matching in the network (in table 2 for the data). In the estimated model, wage per worker is increasing in firm quality. Directed search increases the probability that high-quality, high-wage firms find each other (the extensive margin). Given matches, differences in the marginal product of inputs lead high-quality firms to spend more on their high-quality input suppliers (the intensive margin).

Firms choose their quality from a line segment $Q \subset \mathbb{R}_+$. A shock that prods a firm to upgrade its quality increases the quality of its tasks and changes its network links and relative spending on high-wage input suppliers (as in tables 3 and 4).²²

The service sector has constant returns to scale and is perfectly competitive. Firms aggregate manufacturing goods into a homogeneous service good that serves as an input in manufacturing and as household consumption. This sector allows us to match the aggregate input-output matrix of Turkey, where service firms, mostly wholesalers and retailers, account for almost half of domestic sales and material purchases of manufacturing firms.

The manufacturing sector is in section III.A. We set up the firm's problem in section III.A.1 and aggregate firm choices to form the network in section III.A.2. The service sector is in section III.B, and the equilibrium is in section III.C. Section III.D presents key properties of the model.

²² We present the model as static. But sequential choices of quality and ads would yield the same equilibrium as long as there is no new information between these choices.

Parametric assumptions in the estimation ensure functions are continuous and differentiable.

A. Manufacturing

1. The Firm's Problem

The revenue of a firm with quality q , price p , and a mass v of ads to find customers (v stands for visibility) is

$$p^{1-\sigma} v D(q), \quad (7)$$

where $\sigma > 1$ is the elasticity of substitution between manufacturing varieties and $D(q)$ is an endogenous demand shifter.

The cost of a bundle of inputs to produce quality q when the firm posts a measure m of ads to find manufacturing suppliers is²³

$$C(m, q) = w(q)^{1-\alpha_m-\alpha_s} P_s^{\alpha_s} [m^{1/(1-\sigma)} c(q)]^{\alpha_m}, \quad (8)$$

where $(\alpha_m, \alpha_s) \gg 0$ are Cobb-Douglas weights with $(\alpha_m + \alpha_s) \in (0, 1)$, P_s is the price of the service good, $w(q)$ is the wage rate per efficiency unit of task q , and $c(q)$ is the cost of a bundle of manufacturing inputs when the firm posts a measure 1 of ads to find suppliers. The marginal cost of the firm is $C(m, q)/z$, where z is its productivity.

The costs of posting v ads to find customers and m ads to find suppliers are, respectively,

$$\begin{aligned} w(q) f_v \frac{v^{\beta_v}}{\beta_v}, \\ w(q) f_m \frac{m^{\beta_m}}{\beta_m}, \end{aligned} \quad (9)$$

where f_m, f_v, β_m , and β_v are positive parameters with $\beta_m > \alpha_m$ and $\beta_v > \beta_m/(\beta_m - \alpha_m)$. Parameters f_v and f_m govern the level of costs, and parameters β_v and β_m govern the curvature.

From (7), the firm charges markup $\sigma/(\sigma - 1)$ over marginal cost. Given q and z , she chooses v and m to maximize profit:

$$\max_{v, m} \frac{v m^{\alpha_m}}{\sigma} \left[\frac{\sigma}{\sigma - 1} \frac{C(1, q)}{z} \right]^{1-\sigma} D(q) - w(q) f_v \frac{v^{\beta_v}}{\beta_v} - w(q) f_m \frac{m^{\beta_m}}{\beta_m}. \quad (10)$$

²³ We assume a Cobb-Douglas function because the shares of manufacturing inputs and of service inputs over total variable costs (labor plus material inputs) do not vary systematically with firm size. See fig. A6.

If we rearrange the first-order conditions, the firm's revenue x , mass of ads to find customers v and to find suppliers m , and price p are functions of productivity z and quality q :

$$\begin{aligned} x(z, q) &= \Pi(q)z^{\gamma(\sigma-1)}, \\ v(z, q) &= \left(\frac{x(z, q)}{\sigma f_v w(q)} \right)^{1/\beta_v}, \\ m(z, q) &= \left(\frac{\alpha_m x(z, q)}{\sigma f_m w(q)} \right)^{1/\beta_m}, \\ p(z, q) &= \frac{\sigma}{\sigma-1} \frac{C(m(z, q), q)}{z}, \end{aligned} \tag{11}$$

where

$$\begin{aligned} \Pi(q) &= [\sigma w(q)]^{1-\gamma} \left[D(q) \left(\frac{\sigma}{\sigma-1} C(1, q) \right)^{1-\sigma} \left(\frac{f_m}{\alpha_m} \right)^{-\alpha_m/\beta_m} f_v^{-1/\beta_v} \right]^\gamma, \\ \gamma &= \frac{\beta_v \beta_m}{\beta_v(\beta_m - \alpha_m) - \beta_m} > 1. \end{aligned} \tag{12}$$

A firm is characterized by a vector $\omega = (\omega_0, \omega_1) \in \mathbb{R}^2$ that determines its productivity for each quality level:

$$z(q, \omega) = \exp\{\omega_0 + \omega_1 \log(q) + \bar{\omega}_2 [\log(q)]^2\}, \tag{13}$$

where $\bar{\omega}_2$ is a parameter common to all firms. Parameter ω_0 captures the firm's absolute advantage in production, and ω_1 captures her comparative advantage in producing higher quality. These two dimensions of heterogeneity capture the joint distribution of sales and wages. Since profit (10) is a share $1/(\gamma\sigma)$ of revenue, firm ω chooses q to maximize revenue:

$$q(\omega) = \arg \max_{q \in Q} \{x(z(q, \omega), q)\} = \arg \max_{q \in Q} \{z(q, \omega)^{\gamma(\sigma-1)} \Pi(q)\}. \tag{14}$$

If wage $w(q)$ is continuous in q , then function $\Pi(q)$ (below) is continuous in q , and (14) is the maximization of a continuous function in a compact set Q . Firms' quality choices are interconnected through the endogenous terms in $\Pi(q)$: $D(q)$, $C(1, q)$, and $w(q)$. Manufacturing firm-to-firm trade determines the cost of manufacturing inputs $c(q)$ and the component of demand $D(q)$ that comes from other firms.

2. Manufacturing Firm-to-Firm Trade

Production function.—The quantity produced by firm ω producing quality q is

$$z(q, \omega) l^{1-\alpha_m-\alpha_s} y_s^{\alpha_s} Y(q)^{\alpha_m},$$

where l is efficiency units of labor, y_s is units of the service good, and $Y(q)$ is an aggregate of manufacturing inputs. This production function yields input costs in (8). Following Fieler, Eslava, and Xu (2018), we assume

$$Y(q) = \left[\int_{\omega' \in \Omega} y(\omega')^{(\sigma-1)/\sigma} \phi_y(q, q(\omega'))^{1/\sigma} d\omega' \right]^{\sigma/(\sigma-1)}, \quad (15)$$

where $y(\omega)$ is the quantity of input ω and function $\phi_y(q, q')$ governs the productivity of an input of quality q' in the production of output of quality q . The firm's relative demand for any two inputs 1 and 2 with prices $p(1)$ and $p(2)$ and qualities $q(1) > q(2)$,

$$\frac{y(1)}{y(2)} = \left(\frac{p(1)}{p(2)} \right)^{-\sigma} \frac{\phi_y(q, q(1))}{\phi_y(q, q(2))}, \quad (16)$$

is strictly increasing in the producing firm's quality q if ϕ_y is log-supermodular.

We parameterize

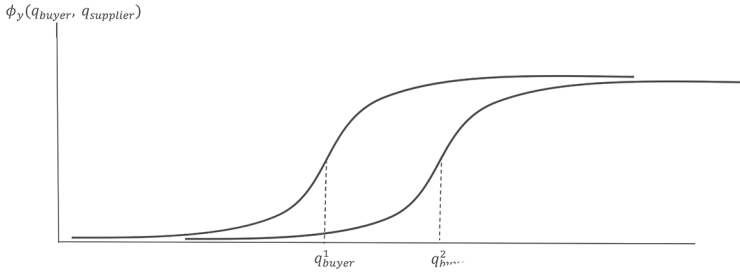
$$\phi_y(q, q') = \frac{\exp(q' - \nu_y q)}{1 + \exp(q' - \nu_y q)}. \quad (17)$$

It is increasing in input quality, and if $\nu_y > 0$, it is log-supermodular and decreasing in output quality. Figure 3A illustrates ϕ_y as a function of supplier quality for two buying firms. One can see how, given the same prices and matches, the higher-quality buyer 2 spends relatively more on high-quality input suppliers than buyer 1.²⁴

Directed search.—Buyers can see only sales ads that target their own quality level. The ads posted by a seller with quality q' are distributed across buyer qualities $q \in Q$ according to function $\phi_v(q, q')$. We parameterize $\phi_v(q, q')$ as the density of a normal distribution with variance parameter ν_v and mean q' , the quality of the seller posting the ads. Figure 3B illustrates the distribution of ads across buyers for two suppliers. Clearly, the ads posted by the higher-quality supplier 2 disproportionately target higher-quality buyers. Here, the direction of ads is exogenous for simplicity. In appendix F.1, we modify the model to allow firms to choose

²⁴ A special case of ϕ , makes stark the complementarity between the quality of input suppliers and buyers. Suppose that ϕ , in fig. 3A is a step function. The marginal product of all inputs with quality $q' < q$ is zero, and the marginal product of all inputs with quality $q' \geq q$ is 1. Suppose also that a major buyer (the only buyer, for illustrative purposes) has quality q . Its input suppliers would not choose $q' < q$, otherwise their sales would be zero. Similarly, they would not choose $q' > q$ if producing higher quality is costly. So, all suppliers would choose the same quality as the buyer.

A **Intensive margin of assortative matching:** The marginal product of input supplier is $\phi_y(q_{\text{buyer}}, q_{\text{supplier}})^{1/\sigma}$ and spending given prices is proportional to $\phi_y(q_{\text{buyer}}, q_{\text{supplier}})$. The figure plots $\phi_y(q_{\text{buyer}}, q_{\text{supplier}})$ for two buyers with output qualities q_{buyer}^1 and q_{buyer}^2 .



B **Extensive margin of assortative matching:** The distribution of ads posted by two sellers with output qualities q_{supplier}^1 and q_{supplier}^2 are targeted at buyers according to function $\phi_v(q_{\text{buyer}}, q_{\text{supplier}})$.

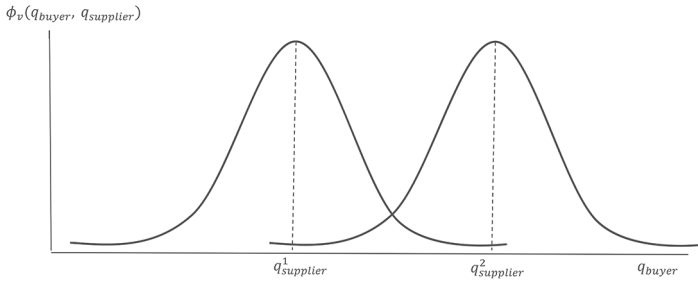


FIG. 3.—Assortative matching on quality in model.

the direction of their search (the mean of ϕ_v), and we obtain similar estimation and counterfactual results.

Aggregation.—Firm choices in (14) give rise to the measure

$$J(z, q) = |\{\omega \in \Omega : z(q(\omega), \omega) \leq z \text{ and } q(\omega) \leq q\}|. \quad (18)$$

Assume that J has a density denoted with $j(z, q)$. Directed search implies that there is a continuum of matching submarkets, one for each buyer quality. In the submarket of buyers with quality $q \in Q$, the measures of ads posted by buyers and sellers are, respectively,

$$M(q) = \int_z m(z, q)j(z, q)dz, \quad (19)$$

$$V(q) = \int_Q \phi_v(q, q')\bar{V}(q')dq', \quad (20)$$

where $\bar{V}(q)$ is the measure of ads posted by sellers of quality q :

$$\bar{V}(q) = \int_z v(z, q)j(z, q)dz.$$

A standard matching function determines the measure of matches with buyers of quality q .²⁵

$$\tilde{M}(q) = V(q) \left[1 - \exp\left(-\frac{\kappa M(q)}{V(q)}\right) \right], \quad (21)$$

where parameter $\kappa > 0$ captures efficiency in the matching market. The success rate of ads is $\theta_v(q) = \tilde{M}(q)/V(q)$ for sellers and $\theta_m(q) = \tilde{M}(q)/M(q)$ for buyers.

When we use (20), for each ad posted by a buyer of quality q , the probability of finding a supplier with productivity quality (z', q') is

$$\frac{\theta_m(q)}{V(q)} \phi_v(q, q') v(z', q') j(z', q'). \quad (22)$$

We combine this expression with the price index associated with (15). Then, a bundle of manufacturing inputs used by a firm of quality q and $m = 1$ costs

$$c(q) = \left[\frac{\theta_m(q)}{V(q)} \int_Q \phi_y(q, q') \phi_v(q, q') P(q')^{1-\sigma} dq' \right]^{1/(1-\sigma)}, \quad (23)$$

where

$$P(q) = \left[\int_z p(z, q)^{1-\sigma} v(z, q) j(z, q) dz \right]^{1/(1-\sigma)} \quad (24)$$

takes into account the greater visibility of firms that post more sales ads $v(z, q)$.

We now turn to demand. A firm with quality q posts price p and a measure v of sales ads. From (19), the measure of buyers with (z', q') matched to the firm is

$$v\theta_v(q')\phi_v(q', q) \frac{m(z', q')j(z', q')}{M(q')},$$

where $\phi_v(q', q)$ is the density of the firm's ads that are directed to quality q' and $\theta_v(q')$ is the success rate of these ads. Conditional on the match, the firm's sales to a buyer with (z', q') are

$$\phi_y(q', q) \left(\frac{p}{c(q')} \right)^{1-\sigma} \frac{\alpha_m(\sigma - 1)}{\sigma} \frac{x(z', q')}{m(z', q')}.$$

²⁵ See Petrongolo and Pissarides (2001) for a survey on matching functions and their properties.

When we multiply these last two expressions and sum over buyers (z' , q'), the sales of the firm to other manufacturing firms are²⁶

$$p^{1-\sigma} v D_m(q),$$

where

$$D_m(q) = \frac{\alpha_m(\sigma - 1)}{\sigma} \int_Q \frac{\theta_v(q')}{M(q')} \phi_y(q', q) \phi_v(q', q) c(q')^{\sigma-1} X(q') dq', \quad (25)$$

$$X(q) = \int_Z x(z, q) j(z, q) dz.$$

B. Service Sector and Final Demand

An exogenous set of service firms aggregate manufacturing inputs into a homogeneous good sold in a perfectly competitive market. Their production function is given by $Y(0)$ in (15). Each firm is endowed with a fixed measure \bar{m} of manufacturing suppliers. The probability that any of these suppliers has productivity quality (z , q) is

$$\frac{v(z, q) j(z, q)}{V_T},$$

where

$$V_T = \int_Q \bar{V}(q) dq.$$

Then, the price index of the service good is

$$P_s = \left[\frac{\bar{m}}{V_T} \int_Q \phi_y(0, q) P(q)^{1-\sigma} dq \right]^{1/(1-\sigma)}. \quad (26)$$

Total sales to the service sector by a manufacturing firm with price p , quality q , posting v ads in the home country to find customers are

²⁶ We may also derive $D_m(q)$ from buyer connections. When we use (23), the share of spending on materials by buyers of quality q' allocated to a supplier with price p , quality q , and v ads is

$$\theta_m(q') \frac{\phi_y(q', q) \phi_v(q', q) v p^{1-\sigma}}{V(q) c(q')^{1-\sigma}}.$$

Multiplying by domestic spending on materials $[\alpha_m(\sigma - 1)/\sigma] X(q')$ and integrating over buyers q' , demand is

$$v p^{1-\sigma} \frac{\alpha_m(\sigma - 1)}{\sigma} \int_Q \frac{\theta_m(q')}{V(q')} \phi_y(q', q) \phi_v(q', q) c(q')^{\sigma-1} X(q') dq',$$

which is the expression above since $\theta_m(q)/V(q) = \theta_v(q)/M(q)$.

$$\frac{v}{V_T} \left(\frac{p}{P_s} \right)^{1-\sigma} \bar{m} \phi_y(0, q) X_s,$$

where X_s is the total absorption of services. When we substitute (26), these sales are

$$p^{1-\sigma} v D_s(q), \tag{27}$$

where $D_s(q) = \phi_y(0, q) \left[\int_Q \phi_y(0, q') P(q')^{1-\sigma} dq' \right]^{-1} X_s$.

They do not depend on \bar{m} .

Take total manufacturing absorption to be the numeraire. Households consume only the service good. Then, service absorption X_s is the share of service plus labor inputs plus profits in manufacturing:

$$X_s = 1 - \frac{(\sigma-1)}{\sigma} \alpha_m.$$

C. *Equilibrium*

The demand shifter faced by manufacturing firms in (7) is the sum of demand from manufacturing (25) and from services (27):

$$D(q) = D_m(q) + D_s(q). \tag{28}$$

We take the supply of efficiency units of labor to produce task q as an exogenous function $L(q, w)$, where w is the whole wage schedule $w(q)$ for all $q \in Q$. Labor markets clear if for all q ,

$$L(q, w) = \frac{1}{w(q)\sigma} \left[(1 - \alpha_m - \alpha_s)(\sigma - 1) + 1 - \frac{1}{\gamma} \right] X(q), \tag{29}$$

where the constant is the labor share in manufacturing production in (10).

Denote with Θ a set of firm outcomes, specifying for each $\omega \in \Omega$ its quality, productivity, sales, measures of upstream and downstream ads, and price. Aggregate outcomes are functions of Θ and of equilibrium wages $w(q)$. Measure $J(z, q)$ is in (18). The success rates of ads are $\theta_m(q) = \bar{M}(q)/M(q)$ and $\theta_v(q) = \bar{M}(q)/V(q)$, where $M(q)$, $V(q)$ and $\bar{M}(q)$ are in (19)–(21). Costs $C(m, q)$ and $c(q)$ are in (8) and (23), demand $D(q)$ is in (28), and sales $X(q)$ are in (25). Firms maximize profits in (10) given wages $w(q)$ and other firms' actions summarized in $C(1, q)$ and $D(q)$.

An *equilibrium* is a set of wages w and of firm outcomes Θ such that functions $D(q)$ and $C(1, q)$ exist and that the following conditions hold:

1. The labor market clears (29).

2. Firms maximize profits. Firm ω chooses $q(\omega)$ in (14) and has productivity $z^*(\omega) = z(q(\omega), \omega)$ at the optimal. Its sales, measure of ads, and prices are $x(z^*(\omega), q(\omega))$, $m(z^*(\omega), q(\omega))$, $v(z^*(\omega), q(\omega))$, and $p(z^*(\omega), q(\omega))$ in (11).

D. Properties of the Model

The model has two novel features: the use of log-supermodular functions to capture assortative matching and the search-and-matching setup of network formation. We explain these features in sections III.D.1 and III.D.2, respectively.

1. Assortative Matching

In the estimation below, we assume that the wage per worker is increasing in firm quality. Then, assortative matching in wage per worker in the network arises through buyers' and sellers' quality levels.

For a firm with quality q , the measure of its suppliers that have quality q_1 relative to quality q_2 is (integrating [22] over z')

$$\frac{\phi_v(q, q_1) \bar{V}(q_1)}{\phi_v(q, q_2) \bar{V}(q_2)}. \tag{30}$$

The firm's average spending per supplier of quality q_1 relative to spending per supplier of quality q_2 is (using [16] and [24])

$$\frac{\phi_y(q, q_1) \left(\frac{P(q_1)}{P(q_2)}\right)^{1-\sigma} \bar{V}(q_2)}{\phi_y(q, q_2) \bar{V}(q_1)}. \tag{31}$$

When we multiply these expressions, the ratio of the firm's total spending on the two qualities is

$$\frac{\phi_v(q, q_1) \phi_y(q, q_1) \left(\frac{P(q_1)}{P(q_2)}\right)^{1-\sigma}}{\phi_v(q, q_2) \phi_y(q, q_2)}. \tag{32}$$

These expressions summarize the extensive margin (30), intensive margin (31), and total (32) assortative matching in the network. Since the terms $\bar{V}(q)$ and $P(q)$ are common to all buyers, functions ϕ_y and ϕ_v alone govern assortative matching. By definition, a function ϕ is log-supermodular if $\phi(q, q_1)/\phi(q, q_2)$ is increasing in q whenever $q_1 > q_2$ or, equivalently, if $\partial^2 \log(\phi(q, q'))/\partial q \partial q' > 0$. Function $\phi_v(q, q')$ governs the distribution of sales ads posted by suppliers with quality q' across buyers of quality q . We parameterize ϕ_v as the density of a normal random variable with variance ν_v . Its derivative $\partial^2 \log(\phi_v(q, q'))/\partial q \partial q' = 1/\nu_v > 0$. Then, high-quality firms have relatively more high-quality suppliers in (30). Function $\phi_y(q, q')$

governs the marginal product of an input of quality q' in the production of output quality q . It is log-supermodular if $\nu_y > 0$ in (17). Then, high-quality firms spend relatively more on their high-quality suppliers in (31).

2. Search and Matching

A special case of the model highlights its search and matching setup.²⁷ Assume that there is only one quality and $\beta_v = \beta_m \equiv \beta$. Set $\phi_v = \phi_y = 1$ without loss of generality. Let the wage be the numeraire, and drop the quality arguments from functions. We refer to a firm by its productivity z instead of ω . The mass of firms N and the distribution of z are exogenous. Appendix D.2 has the complete closed-form solution to this special case and analyzes its efficiency properties.²⁸

With $\beta_v = \beta_m$, the ratio of ads to find suppliers and customers in (11) is $m(z)/v(z) = (\alpha_m f_v / f_m)^{1/\beta}$, independent of firm productivity. Then, the success rates of ads θ_m and θ_v are functions of parameters. The number of customers and the number of suppliers of firm z are both equal to

$$\theta_v \left(\frac{x(z)}{\sigma f_v} \right)^{1/\beta} = \theta_m \left(\frac{\alpha_m x(z)}{\sigma f_m} \right)^{1/\beta}.$$

They increase log-linearly with firm sales, as in table 5.

All firms are equally more likely to match with more productive firms, and there is no assortative matching in the network.²⁹ The probability that a firm with productivity z is the buyer or the seller in a match is

$$\frac{m(z)}{M} = \frac{v(z)}{V} = \frac{z^{\gamma(\sigma-1)/\beta}}{N\mathbb{E}(z^{\gamma(\sigma-1)/\beta})}.$$

The market share of a firm with productivity z in total manufacturing sales is

²⁷ This special case relates to the setup of Miyauchi (2019), who incorporates matching frictions in firm-to-firm trade in a version of the multilocation multisector Melitz (2003) model. Arkolakis, Huneus, and Miyauchi (2021) embed this search-and-matching setup in a spatial model.

²⁸ There are two externalities for each ad in the decentralized equilibrium. A positive externality is that ads increase the total mass of matches \bar{M} . A negative externality is that ads decrease the probability of matching for firms in the same side of the market (sellers for v ads and buyers for m ads). The negative externality is greater than the positive externality. So the planner posts fewer ads than the market. There is no inefficiency from the allocation of ads across firms. The allocation of labor is also efficient: markups are constant in manufacturing, and the service sector employs no labor.

²⁹ Huneus (2018), Lim (2018), and Bernard, Moxnes, and Saito (2019) generate an increasing relation between a firm's sales and number of network connections by imposing a fixed cost for firms to trade. Their setting generates strong negative assortative matching because only more productive firms pay a fixed cost to trade with less productive firms.

$$x(z) = \frac{z^{\gamma(\sigma-1)}}{N\mathbb{E}(z^{\gamma(\sigma-1)})}.$$

The expression is the same as Melitz (2003) except for the added parameter $\gamma > 1$. The effect of productivity on sales is larger because more productive firms post more ads to find suppliers and customers. Thus, the model needs a smaller dispersion in fundamental productivity z to generate the same distribution of sales as Melitz (2003).

IV. Open Economy

We extend the model to a small open economy setting. The prices of foreign varieties and foreign demand for domestic goods are exogenous. Manufacturing firms may export by paying a fixed cost and posting ads abroad. Service firms use domestic and foreign manufacturing varieties as inputs. We focus here on only the differences from the closed economy case and present the full model in appendix D.3.³⁰

The manufacturing firm ω observes its productivity $z(q, \omega)$ and chooses $q \in Q$. Afterward, it draws a random fixed export cost f_e units of the service good. She decides her export status and posts ads to search for domestic suppliers, for domestic customers, and, if exporting, for foreign customers. We introduce randomness in the fixed cost of exporting because firms in the data with similar size and wages have different export statuses. The timing simplifies aggregation in the estimation.

The revenue from foreign sales of an exporter with quality q , price p , and v sales ads to find foreign customers is

$$p^{1-\sigma} v e^\sigma D_F(q), \quad (33)$$

where $D_F(q)$ is an exogenous demand function and e is the real exchange rate (or foreign wages). The cost of posting v ads in foreign is the same as the domestic cost in (9), $w(q)f_v v^{\beta_v} / \beta_v$. Assuming the same curvature β_v is important to maintain the log-linearity in the firm's problem. Assuming the same cost parameter f_v simplifies notation only, since we do not observe foreign trading partners.

By backward induction, we start with the problem of the firm after it has chosen its quality and export status. A firm with quality q , productivity z , and export status $E \in \{0, 1\}$ chooses a mass of ads to find suppliers m , a

³⁰ Appendix F.2 extends the model to allow manufacturing firms to directly import some manufacturing inputs. The appendix also estimates this extension and repeats the counterfactual of sec. VII. The results are similar. We do not use this extension as the baseline because app. C.4 does not find evidence that shift-share import shocks systematically influence firms' skill intensity or network connections. This result may be specific to Turkey, where relatively few manufacturing firms import inputs directly (not through distributors). Imports account for only 4% of spending on material inputs by a typical manufacturing firm compared with a 10% share of exports in its total sales.

mass of ads to find customers v , and the share $r_v \in [0, 1]$ of the sales ads that are posted domestically:

$$\begin{aligned} \max_{m, v, r_v} \frac{vm^{\alpha_m}}{\sigma} \left[\frac{\sigma}{\sigma-1} \frac{C(1, q)}{z} \right]^{1-\sigma} & [r_v D_H(q) + (1-r_v) E e^\sigma D_F(q)] \\ & - w(q) f_m \frac{m^{\beta_m}}{\beta_m} - w(q) f_v [r_v^\beta + (1-r_v)^\beta] \frac{v^{\beta_v}}{\beta_v}, \end{aligned} \quad (34)$$

where $C(1, q)$ is the input cost in (8) and $D_H(q)$ is the domestic demand shifter, denoted with $D(q)$ in the closed economy. When we take the first-order conditions, the optimal share of ads r_v is a function of quality q and export status E :

$$\frac{1-r_v(q, E)}{r_v(q, E)} = \left(\frac{E e^\sigma D_F(q)}{D_H(q)} \right)^{1/(\beta_v-1)}. \quad (35)$$

Given the optimal r_v , problem (34) differs from the closed economy case (10) only in the level of demand and of the cost of posting v sales ads. The relationships between sales and ads and prices remain unchanged (eqq. [11]). When we substitute the new demand and cost of v ads into (12), total sales are

$$x(z, q, E) = \Pi(q, E) z^{\gamma(\sigma-1)}, \quad (36)$$

where

$$\Pi(q, E) = [\sigma w(q)]^{1-\gamma} \left[D(q, E) \left(\frac{\sigma}{\sigma-1} C(1, q) \right)^{1-\sigma} \left(\frac{f_m}{\alpha_m} \right)^{-\alpha_m/\beta_m} f_v^{-1/\beta_v} \right]^\gamma, \quad (37)$$

$$D(q, E) = [D_H(q)^{\beta_v/(\beta_v-1)} + E(e^\sigma D_F(q))^{\beta_v/(\beta_v-1)}]^{(\beta_v-1)/\beta_v}. \quad (38)$$

Exporting increases the firm's profit by more than the sum of the profits from operating separately in each market. The firm uses the same input suppliers to produce all its goods, regardless of destination. Then, an exporting firm posts more ads to find suppliers. This lowers its price and increases its incentives to search for customers in both markets. The exponent in the constant elasticity of substitution term $D(q, E)$ and γ captures these magnification effects.³¹

The firm exports if its fixed exporting cost parameter $f_E \leq \bar{f}_E(z, q)$, where

³¹ The interconnection between a firm's decisions on sales, prices, and purchases in the domestic market and its participation in other markets (export or not) does not appear in standard models of exporting à la Melitz (2003) but appears in models of importing, such as Antràs, Fort, and Tintelnot (2017).

$$\bar{f}_E(z, q) = \frac{z^{\gamma(\sigma-1)}}{\gamma\sigma P_s} [\Pi(q, 1) - \Pi(q, 0)]. \quad (39)$$

Denote with Φ the cumulative distribution function of f_E . After observing its productivity $z(q, \omega)$ but before observing f_E , the firm chooses its quality

$$q(\omega) = \arg \max_{q \in Q} \left\{ \frac{z(q, \omega)^{\gamma(\sigma-1)}}{\gamma\sigma} [\Pi(q, 1) \Phi(\bar{f}_E(z(q, \omega), q)) + \Pi(q, 0)[1 - \Phi(\bar{f}_E(z(q, \omega), q))] - P_s \mathbb{E}(f_E | f_E \leq \bar{f}_E(z(q, \omega), q))] \right\}. \quad (40)$$

Appendix D.3 maintains the assumptions on production and network formation from section III. The only difference is that because sales in (36) depend on export status, aggregation in the open economy model is over two measure functions:

$$\begin{aligned} \tilde{J}(z, q, 1) &= J(z, q) \Phi(\bar{f}_E(z, q)), \\ \tilde{J}(z, q, 0) &= J(z, q) [1 - \Phi(\bar{f}_E(z, q))], \end{aligned} \quad (41)$$

where $J(z, q)$ is in (18). The equilibrium is also similarly defined with the exchange rate e as an additional equilibrium variable and a trade equilibrium condition, in which we allow for an exogenous trade imbalance.

V. Estimation and Identification

The key estimation assumption is that the wage per worker ($w(q) \times$ labor endowment per worker) is strictly increasing in q . Using a Roy (1951) model, Teulings (1995) provides a micro foundation for the labor supply $L(q, w)$ and for this estimation assumption.³² Appendix D.1 presents the setup and proves that we can construct a set of labor endowments that exactly matches the distribution of wage per worker across firms in the data.

We calibrate some parameters and estimate others with the method of simulated moments. A closed economy is defined by parameters $\alpha_m, \alpha_s, \sigma, f_m, f_v, \beta_m, \beta_v, \bar{m}, \kappa, \nu_y, \nu_v, \bar{\omega}_2$, the labor supply $L(q, w)$, and the set of firms Ω , itself specified by a mass N and a distribution of productivity parameters (ω_0, ω_1) . In addition, the open economy has the price of the bundle of imported goods P_F , foreign demand $D_F(q)$, and the distribution of the fixed cost of exporting f_E .

³² See Costinot and Vogel (2010) for an application of Teulings (1995) to international trade.

A. *Calibrated Parameters and Normalizations*

We calibrate parameters α_m , α_s , σ , β_v , and β_m . We set $\alpha_m = 0.33$ and $\alpha_s = 0.38$ in (8) to the cost shares of manufacturing and services in the Turkish manufacturing sector. The elasticity of substitution $\sigma = 5$ is from Broda and Weinstein (2006). We set $\beta_m = 1/0.59$ and $\beta_v = 1/0.46$ to match the endogenous elasticity of the number of suppliers and customers with respect to firm sales in table 5 (see v and m in eqq. [11]).³³

We also normalize the mass of firms to $N = 1$ and costs $f_m = f_v = 1$. Since search efforts are not observable, we cannot separately identify the cost of one ad, f_m and f_v , from the matching efficiency κ in (21). Similarly, parameter \bar{m} is not identified because it governs the theoretical price index P_s in (26) but not the observable sales of manufactures to services in (27). We pick \bar{m} so that $P_s = 1$.

We set equilibrium efficiency wages $w(q) = 1$ for all q and real exchange rates $e = 1$. While these variables endogenously respond to counterfactuals, they may be normalized in the estimated equilibrium. We observe the wage per worker in the data, but we can always normalize the endowment of efficiency units of labor per worker so that the efficiency wage $w(q) = 1$. Similarly, we can set e and adjust the foreign demand $D_F(q)$ and price P_F accordingly.

B. *Parameterization*

The distribution of (ω_0, ω_1) is a bivariate normal with mean zero, standard deviation parameters σ_{ω_0} and σ_{ω_1} , and correlation ρ . The distribution of the fixed export costs f_E is lognormal with mean μ_E and standard deviation σ_E . We parameterize

$$D_F(q) = b_1 q^{b_2},$$

where b_1 and b_2 are parameters.

C. *Moments and Identification*

We use 39 moments to estimate the remaining 11 parameters: κ , ν_y , ν_v , $\bar{\omega}_2$, σ_{ω_0} , σ_{ω_1} , ρ , μ_E , σ_E , b_1 , and b_2 . To describe the joint distribution between wages and other firm characteristics, we construct most moments separately by quintile of firm wage per worker:

³³ The number of customers and suppliers in principle also depends on quality through the success rate of ads, $\theta_v(q)$ and $\theta_m(q)$. But in the estimated model, these rates vary little so that the relation between sales and number of customers does not depend on wages, as in table 5.

1. The mean number of suppliers (five moments) and mean number of customers (five moments).
2. The share in total network sales (five moments) and the standard deviation of sales (five moments).
3. The share of firms exporting (five moments) and the average export intensity for exporting firms (five moments).
4. The average log wage of suppliers, unweighted (four moments) and weighted by spending shares (four moments), relative to the first quintile.
5. The shift-share regression coefficient of the wage response to an idiosyncratic export demand shock (one moment).

Although all parameters are estimated jointly, some parameters are associated with some moments more closely. The average number of trading partners per firm identifies κ , the efficiency in transforming ads into matches in (21). Total sales and the standard deviation by quintile of wages identify the parameters σ_{ω_0} , σ_{ω_1} , and ρ . Parameter μ_E governs the share of firms exporting, and σ_E governs how this share changes across quintiles of firm wages. If σ_E is large, then the share of firms exporting does not vary much across quintiles because it depends more on firm draws of f_E than on quality choices (wages). Parameter b_1 governs the level of export intensity, while b_2 governs how export intensity changes across quintiles of firm wages. If b_2 is large, $D_F(q)/D_H(q)$ is increasing in q , and export intensity increases with the wage quintile.

The moments on suppliers' wages summarize the total and the extensive margin of assortative matching in the network. As per section III.D, parameter ν , governs the intensive margin, and parameter ν_ν governs the extensive margin.

Finally, the shift-share coefficient in column 2 of table 3 identifies $\bar{\omega}_2$. Consider a shock that increases a single firm's export demand $D_F(q)$ by 5%. If $D_F(q)/D_H(q)$ is increasing in quality as in our estimated model, then the firm increases $q(\omega)$. This increase is associated with an increase in the wage per worker since each quality in the estimated model is associated with an average wage per worker in the data (the ranking is the same). Parameter $\bar{\omega}_2$ governs the concavity of $z(q, \omega)$ in (13). If $\bar{\omega}_2$ is large and negative, then $z(q, \omega)$ is very concave, and the firm does not respond much to the export demand shock. If $\bar{\omega}_2$ is small, the response is large.³⁴

³⁴ In app. E.1, we prove that we can perfectly match the joint distribution of sales and wages with a sufficiently flexible distribution of (ω_0, ω_1) and that $\bar{\omega}_2$ is not identified in the cross section. We also show its identification through idiosyncratic firm-specific shocks, as we interpret the shift-share shocks.

To construct this moment in the model, we sample firms and estimate their response to a firm-specific change in D_F . We take the average of these responses weighted by firms' export probabilities.

D. Model Computation

We solve the equilibrium of the model for each guess of the parameters. We discretize the quality space into a grid of 100 equally spaced choices in $[0, 8]$. Given a guess of σ_{ω_0} , σ_{ω_1} , ρ , we sample 50,000 firms from the bivariate distribution of $\omega = (\omega_0, \omega_1)$ and calculate each firm's productivity at each quality, $z(q, \omega)$ in (13).

The solution algorithm, detailed in appendix E.2, is composed of two blocks. The inner block takes the equilibrium distribution of productivity quality $J(z, q)$ as given. It solves the equilibrium in the matching and product markets given $J(z, q)$ and the optimal export status, search and production decisions for each (z, q) . From this inner block, we obtain the aggregate functions $\Pi(q, 0)$ and $\Pi(q, 1)$ that govern each firm's export cutoff $\bar{f}_E(z, q)$ in (39) and quality choice in (40). The outer block solves the optimal quality choice for each firm ω and updates $J(z, q)$ used in the inner block. We iterate over these two blocks until firms do not change their quality choices.³⁵

VI. Estimation Results

The targeted moments are in table 7.³⁶ The estimated parameters in table 6 are split into three sets. The first set $\{\nu_v, \nu_y, \kappa\}$ governs network formation. Parameter ν_v is the standard deviation of the distribution of ads ϕ_v in figure 3B. The estimated value $\nu_v = 3.09$ implies, for example, that 65% of the ads posted by sellers in the top quintile of quality go to buyers also in the top quintile and 8% go to buyers in the lowest quintile. Parameter $\nu_y = 0.35$ governs complementarity in production, how much more high-quality firms value high-quality inputs (in fig. 3A). Take two suppliers, one in the highest quintile of quality and one in the lowest quintile. The marginal product of the first input is 46% higher than the second input when output is in the top quintile of quality and 10% higher when output is in the bottom quintile.³⁷ Parameter $\kappa = 8.7 \times 10^{-4}$ implies a low probability of finding a trading partner per ad. This is not surprising, given that the number of partners per firm in the data is a tiny fraction of

³⁵ The estimated function $\Pi(q, E)$ is concave in q because all buyers' (service and manufacturing firms') valuation of quality, ϕ , in (15), is concave. Then, the quadratic form of $z(q, \omega)$ in (13), together with $\bar{\omega}_2 < 0$, implies that all firms' problem of choosing quality (14) is concave and that quality choices are bounded even for firms that have a comparative advantage in producing higher quality, $\omega_1 > 0$.

Although we cannot guarantee the uniqueness of the equilibrium, we conduct 500 Monte Carlo simulations, each with random starting choices of firm quality. In all simulations, the algorithm converges to the same equilibrium. We conduct these simulations for the parameter estimates and the baseline counterfactual of sec. VII.

³⁶ In app. E.3, we calculate the 95% confidence interval for the data moments and plot them against the model's predictions.

³⁷ We use the median of each quintile to calculate these numbers.

TABLE 6
PARAMETER ESTIMATES

	Parameter	Estimate	Standard Error
Matching friction	κ	.00087	.00003
Directed search	ν_v	3.09	.06
Complementarity	ν_y	.35	.03
Standard deviation of quality capability	σ_{ω_1}	.116	.001
Standard deviation of efficiency capability	σ_{ω_0}	.110	.000
Correlation	ρ	.137	.002
Efficiency cost of quality	$\bar{\omega}_2$	-.103	.001
Mean of log export cost	μ_E	-3.95	.02
Standard deviation of log export cost	σ_E	1.52	.04
Foreign demand shifter	b_1	93.16	2.49
Foreign demand curvature	b_2	.49	.01

NOTE.—We calculate the standard errors using the bootstrapped variance-covariance matrix of the moments.

all manufacturing firms. The average number of suppliers and customers per quintile of wages ranges from 5.6 to 25.8 in table 7. The model fits these averages well. With only two parameters, ν_v and ν_y , to govern assortative matching, it also fits the increasing relation between buyers' and sellers' wages, weighted and unweighted, reasonably well.

The second set $\{\sigma_{\omega_0}, \sigma_{\omega_1}, \rho, \bar{\omega}_2\}$ determines firm productivity. The firm-specific ω_0 determines a firm's productivity level and ω_1 its comparative advantage in higher quality. Their joint distribution governs the joint distribution of wages and sales. There is a large dispersion of sales across quintiles of wages in table 7. Firms in the highest quintile account for 78% of network sales in the data and in the model.

The third set $\{\mu_E, \sigma_E, b_1, b_2\}$ governs export patterns. The log of the export cost has mean $\mu_E = -3.95$ and standard deviation $\sigma_E = 1.52$. The share of firms exporting is higher among high-wage firms but still about 10% of low-wage firms export in the data and in the model. Parameters $b_1 = 93$ and $b_2 = 0.49$ govern export intensity by wage quintile. Conditional on exporting, export intensity is increasing in firm wages in the data. The model captures this pattern with an estimate of $D_F(q)/D_H(q)$ that is increasing in q .

An increasing ratio $D_F(q)/D_H(q)$ implies that a firm-specific shock that increases $D_F(q)$ leads the firm to upgrade its quality and thereby increase its wage per worker. This prediction is consistent with the shift-share regressions in table 3. In the data, a 5% export shock on average increases the wage per worker by 0.21% for exporting firms, and the estimated model with $\bar{\omega}_2 = -0.103$ exactly matches this response.

Firms that upgrade quality in the model also adjust their network of suppliers and customers. Out of sample, we compare these adjustments with the data. In the data (cols. 3 and 4 of table 3), the 5% export shock is associated with increases of 0.087% and 0.076% in the average wage of

TABLE 7
MODEL FIT: TARGETED MOMENTS

	QUINTILES OF AVERAGE WAGE PER WORKER				
	1	2	3	4	5 (Largest)
Mean number of suppliers:					
Data	5.8	6.7	5.8	11.4	25.8
Model	4.7	4.7	6.0	9.1	29.4
Mean number of customers:					
Data	5.6	7.0	6.7	11.7	25.1
Model	5.4	5.9	7.6	10.9	23.8
Share of total network sales:					
Data	.03	.04	.04	.10	.78
Model	.04	.03	.05	.11	.78
Standard deviation of log sales:					
Data	1.37	1.34	1.37	1.52	1.79
Model	1.20	1.18	1.20	1.24	1.55
Fraction of exporters:					
Data	.08	.18	.16	.34	.57
Model	.11	.13	.18	.29	.60
Export intensity of exporters:					
Data	.24	.21	.23	.23	.26
Model	.18	.21	.22	.23	.25
Unweighted average log wage of suppliers:					
Data	0	.01	.01	.04	.14
Model	0	.02	.04	.07	.12
Weighted average log wage of suppliers:					
Data	0	.02	.02	.07	.23
Model	0	.04	.07	.11	.17
Shift-share coefficient (5% export shock; %):					
Data	.21				
Model	.21				

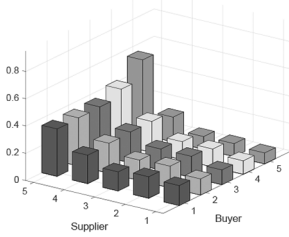
NOTE.—In the last two quintile moments, we normalize the wages in the lowest quintile to zero and match the log difference from the lowest quintile.

the firm's suppliers and buyers, respectively. In the model, these responses are 0.046% for suppliers and 0.053% for buyers. In columns 2 and 3 of table 4, the 5% export shock is associated with a 0.12% increase in the average wage of new suppliers relative to existing suppliers and a 0.15% increase in the wage of new buyers relative to existing buyers. In the model, these increases are 0.032% and 0.036%, respectively, about one-fourth of the data.³⁸

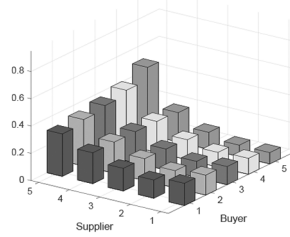
Figure 4 illustrates the predictions of the model for the nonparametric patterns of assortative matching of figure 2. These figures are related

³⁸ In the data, firms drop on average 60% of their suppliers and customers between 2011 and 2015. To capture this large churning, in calculating the model numbers above, we assume that 60% of new suppliers and customers have the same wage as the initial one. In addition, as firms upgrade, they add on average 4.4% of new connections with higher wages.

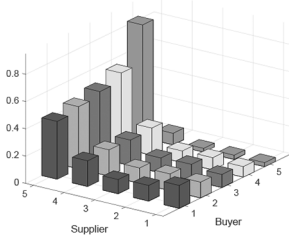
A Share of Suppliers (Data)



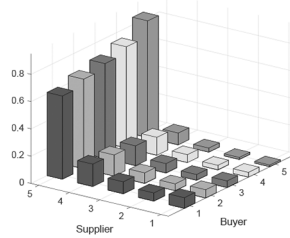
B Model, $R^2 = 0.96$



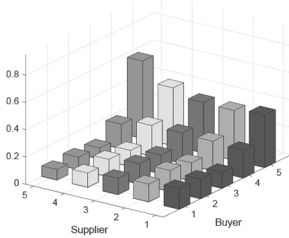
C Spending Shares (Data)



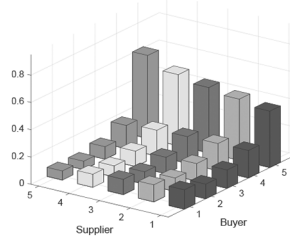
D Model, $R^2 = 0.79$



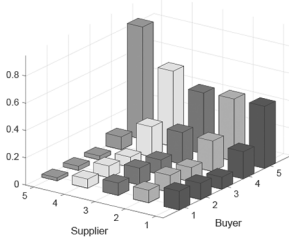
E Share of Buyers (Data)



F Model, $R^2 = 0.89$



G Sales Shares (Data)



H Model, $R^2 = 0.87$

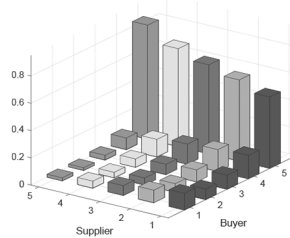


FIG. 4.—Firm-to-firm trade links and values by quintile.

to targeted moments but not directly targeted. The model matches well the extent to which firms with similar wages disproportionately transact with each other, upstream and downstream, on the intensive and extensive margins. The R^2 of the model in the four panels of figure 4 ranges from 0.79% to 0.96%.

In the data and the model, exporters are large, well connected, and skill intensive. Although exporters are only 28% of firms, the share of network connections with at least one exporter is 78% in number of links and 91% in sales. In the model, 26% of firms export. Their shares in the network connections is 80% in number of links and 97% in value.

Overall, in and out of sample, the model matches reasonably well moments from section II on assortative matching of skill intensity in the network, on firms' responses to export shocks, and on the large presence of exporters in the network. These were key conditions for the argument in the introduction that the firm-to-firm network amplifies the effects of export promotion in general equilibrium. We now turn to this mechanism.

VII. Export Shocks in General Equilibrium

In the model, a firm that experiences a 5% increase in export demand upgrades its quality to the extent that its wage increases by 0.21%. This wage response exactly matches the data (last moment of table 7). These shocks have no general equilibrium effects because they are applied separately to individual zero-measure firms. To understand general equilibrium here, we experiment with this same 5% increase in export demand but applied to all exporters.

That is, starting with the equilibrium of the estimated model, we increase export demand $D_f(q)$ by 5% and recalculate the equilibrium. The counterfactual maintains the efficiency wages $w(q) = 1$ for all q , the real exchange rate $e = 1$, and the price of services $P_s = 1$. We allow gross manufacturing output and the trade balance to increase with the shock. We choose this as a baseline because it captures the effect of the shock on manufacturing but shuts down the interaction between manufacturing and the rest of the economy by assuming that (1) labor supply in and out of manufacturing is perfectly elastic ($w(q) = 1$), (2) the export expansion does not lead to a real exchange rate appreciation ($e = 1$), and (3) the price of the inputs that manufacturing firms use from distributors does not change ($P_s = 1$).³⁹ Relaxing each of these assumptions, as we do in section VIII, requires out-of-sample assumptions.

³⁹ The price stays at $P_s = 1$ in a limiting case in which domestic manufacturing is a small share of inputs into services. Other inputs may be imports or other (not modeled) domestic goods or factors.

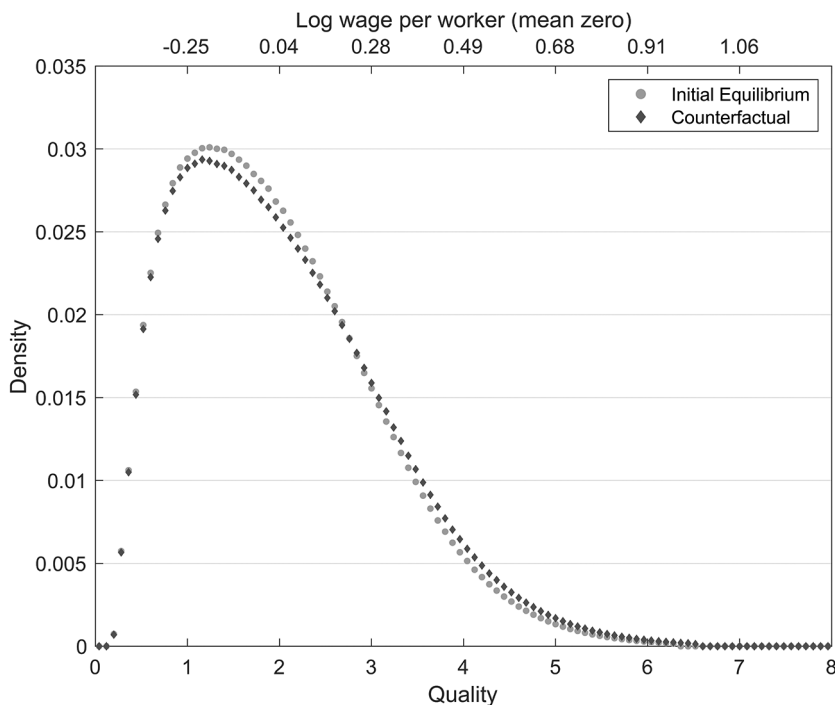


FIG. 5.—Distribution of quality choices.

Figure 5 plots the density of quality choices. The counterfactual first order stochastically dominates the initial equilibrium. To get an order of magnitude of these changes in quality, the top x -axis maps it to average wage per worker.⁴⁰ Table 8 reports the changes in wages, sales, and number of trading partners for exporters and nonexporters by ex ante quintile of the quality distribution. The wage per worker increases in all groups of firms, especially among the ex ante high-quality firms. For example, wages in nonexporting high-quality firms increase by 2.5 log points. Sales generally increase for exporters and decrease for nonexporters, especially low-quality ones. In spite of the positive cross-sectional correlation between sales and wages, the counterfactual simultaneously predicts reductions in sales and increases in wages for nonexporting firms.

These heterogeneous effects arise from how the network propagates the shock from exporting to nonexporting firms. Profit shifter $\Pi(q, 0)$

⁴⁰ The estimated model exactly matches the distribution of average wage per worker across firms in the data. With perfectly elastic labor supply, the mapping of quality to wage per worker is preserved.

TABLE 8
COUNTERFACTUAL CHANGES BY QUINTILE OF QUALITY

	EX ANTE QUINTILES OF QUALITY				
	1	2	3	4	5 (Highest)
A. Export Demand Shock					
log(wage per worker) $\times 10^2$, counterfactual – initial equilibrium:					
Exporters	.31	.52	.92	1.66	2.90
Nonexporters	.23	.48	.89	1.61	2.53
All firms	.24	.48	.90	1.63	2.76
log(sales) $\times 10^2$, counterfactual – initial equilibrium:					
Exporters	-1.25	.50	1.48	3.05	6.58
Nonexporters	-7.69	-7.03	-6.03	-4.25	-1.23
All firms	-6.93	-5.98	-4.58	-2.01	3.60
B. Export Subsidy					
log(wage per worker) $\times 10^2$, counterfactual – initial equilibrium:					
Exporters	.31	.54	.98	1.82	3.21
Nonexporters	.23	.50	.95	1.76	2.78
All firms	.24	.50	.96	1.78	3.04
log(sales) $\times 10^2$, counterfactual – initial equilibrium:					
Exporters	-2.74	-.97	.13	1.92	6.01
Nonexporters	-8.93	-8.25	-7.19	-5.27	-1.94
All firms	-8.21	-7.25	-5.79	-3.07	2.97

summarizes the benefit of upgrading quality for nonexporters. As per equations (8) and (12), $\Pi(q, 0)$ is proportional to a demand component $D(q, 0)^\gamma$ and a cost component $c(q)^{\gamma\alpha_\pi(1-\sigma)}$. Figure 6A plots the counterfactual changes relative to the initial equilibrium of $\Pi(q, 0)$ and each of these components. First, take the demand component $D(q, 0)^\gamma$ on the dashed curve. Exporters upgrade quality and increase their posting of ads. Then, the probability of matching increases for high-quality suppliers that direct their ads toward high-quality market segments. At the intensive margin, conditional on the match, exporters increase their spending on high- relative to low-quality suppliers. Second, take the cost component $c(q)^{\gamma\alpha_\pi(1-\sigma)}$ on the dash-dotted curve. The increased search effort and quality upgrading among exporters decrease the cost of manufacturing inputs for all firms. This decrease accrues disproportionately to high-quality firms whose production is intensive in high-quality inputs (estimated $\nu_y > 0$). The more firms respond to these shifts by upgrading their qualities, the more they augment the effect of the shock. Overall, the profitability for nonexporters increases by 5% in the high-quality segment ($q \approx 5$), and it decreases by about 7% in the low-quality segment ($q \approx 1$). Both $c(q)$ and $D(q, 0)$ significantly contribute to these changes.

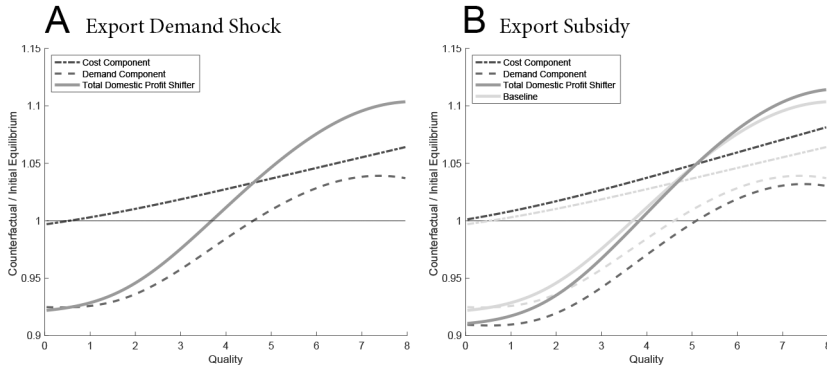


FIG. 6.—Decomposition of changes in domestic profit shifter. The figure displays the counterfactual changes in the domestic profit shifter. This shifter $\Pi(q, 0)$ is proportional to $D(q, 0)^\gamma \cdot c(q)^{\alpha(1-\sigma)^\gamma}$, and we separately plot these demand and cost components. *A* shows results from the baseline counterfactual. *B* shows both results from the export subsidy counterfactual and the baseline counterfactual (light gray) for easier comparison.

The change in the slope of $\Pi(q, 0)$ in figure 6*A* explains why all exporters and nonexporters upgrade quality and their wages increase in table 8. The change in level explains why sales decrease for nonexporters and for exporters in the lowest-quality quintile.

Exporters (not in the figure) experience similar indirect effects. Their profit shifter $\Pi(q, 1)$ is proportional to the same cost component $c(q)^{\gamma\alpha(1-\sigma)}$, and their demand component $D(q, 1)$ is an aggregate of domestic demand $D(q, 0)$ and foreign demand $D_f(q)$ in equation (38). In all, the average wage increases by 1.0% for nonexporters, 1.92% for exporters, and 1.22% for all firms. This increase in exporters’ wages is an order of magnitude larger than the increase of 0.21% induced by the idiosyncratic export demand shocks of the same magnitude.

Mechanisms.—The estimated model matches the extensive and intensive margins of assortative matching in the network and the large number of network connections of exporting firms. We repeat the counterfactual with special cases of the model to illustrate how all these features of the model are all important to generate the large general equilibrium effects of the export shock.⁴¹

Table 9 summarizes the results. High-quality firms do not match more with each other if $\nu_v = \infty$, and they do not use intensively high-quality inputs if $\nu_y = 0$. Both of these cases (cols. 2, 3) substantively decrease counterfactual quality upgrading. Consistent with the cross section (table 2), the extensive margin of assortative matching is more important

⁴¹ Appendix G presents the fit of the model in these special cases. We also repeated the counterfactual imposing a free entry condition (eq. [D.34], available online). The mass of firms increases by 1.1%, and the remaining results do not change much.

TABLE 9
DISSECTING MECHANISMS

Percentage Changes	Baseline	$\nu_v = \infty$	$\nu_y = 0$	$\nu_v = \infty, \nu_y = 0$	Homogeneous Network
	(1)	(2)	(3)	(4)	(5)
Average wage per worker (all)	1.22	.45	.68	.13	.21
Average wage per worker (exporters)	1.92	.58	1.04	.23	.31
Average quality (all)	2.06	.84	1.17	.27	.51

than the intensive margin. In column 4, we set $\nu_v = \infty$ and $\nu_y = 0$. Then, firms quality choices are independent; the shock does not change the shape of $\Pi(q, 0)$, and the average wage response of exporters, 0.23%, is almost equal to the response to the idiosyncratic shift-share shocks of 0.21%.

In column 5, the network is exogenous. All firms are endowed with 10.7 manufacturing customers and suppliers (average links in the estimated model) with identical distributions. There is no extensive margin of assortative matching (as with $\nu_v = \infty$), and exporters have as many links as other firms. The wage changes are nearly half those of column 2, highlighting the importance of the large number of network connections of exporters in the full model.

VIII. Export Promotion Policies

The World Trade Organization prohibits direct subsidies to export sales but encourages export promotion policies that facilitate the links between domestic sellers and foreign buyers. We evaluate this type of policy by studying a counterfactual subsidy to the cost of searching for foreign buyers. In the estimation, we interpreted the shift-share shocks as increases in $D_f(q)$. In the model, this shock has the same effect in terms of quality, sales, and export behavior as a decrease in the cost of searching for foreign buyers.⁴² So to facilitate the comparison, we choose the magnitude of the subsidy ($t = 0.09$ below) to generate the same increase in total exports as the counterfactual of section VII.

From the estimated model, assume that the government decides to pay a share t of this cost. The cost of posting v selling ads in foreign to a firm becomes (see eq. [34])

⁴² In the data, we do not observe firms' foreign buyers, and hence we cannot separately identify shocks to the number of foreign buyers from shocks to sales per foreign buyer. The equivalence in the model appears in equation (H.39) (available online), where the subsidy and $D_f(q)$ enter multiplicatively in the profit shifter $\Pi(q, E)$.

$$(1 - t)w(q)f_v \frac{v^{\beta_v}}{\beta_v}.$$

The government pays for the subsidy with a lump-sum tax on households:

$$T = \frac{t}{\sigma\beta_v(1 - t)} X^*,$$

where X^* is the total exports of home manufactures to foreign.⁴³

We maintain the assumptions $w(q) = 1$, $P_s = 1$, and $e = 1$ for now. Qualitatively, the changes in the domestic profit shifter are similar to the counterfactual export demand shock (compare fig. 6A, 6B). However, domestic demand decreases because of the cost of the subsidy, and the slope of the change in profit shifter increases. As a result, decreases in sales and increases in quality are larger than in the counterfactual export demand shock (compare panels A and B of table 8).

In this counterfactual, a relatively small subsidy, $t = 0.09$, catalyzes widespread quality upgrading and increases in the demand for skilled workers in manufacturing. The total cost of the subsidy is 0.6% of household income, and quality upgrading increases the wages by 1.33% for the average manufacturing firm.

In this baseline, we treat manufacturing as a small share of the economy, with the assumption that labor of all skill levels flows freely into manufacturing ($w(q) = 1$) and that the increase in the manufacturing trade balance has no effect on the wages in foreign relative to home (real exchange rate e and service prices P_s). Table 10 summarizes the results from relaxing these assumptions, and appendix H details the simulation procedures. The policy counterfactual above is in column 1. In all exercises, we set $t = 0.09$.

In column 2, we allow the exchange rate to adjust to balance trade. The increase in sales to foreign is exactly offset by an increase in imports by services and hence a decrease in home sales to services. The real exchange rate e (foreign prices relative to home) decreases by 1.32%, which directly decreases the foreign demand shifter $e^{\sigma}D_F(q)$ in equation (33). Although the change in e is small, it is amplified in the network, leading to much smaller changes in quality. Average wages increase by only 0.21 compared with 1.33 in the baseline.⁴⁴

In column 3, assume that the wages of skilled workers increase in response to the greater counterfactual demand for them from manufacturing firms. In the baseline and the estimated model, $w(q) = 1$ for all q . Here, we assume that the counterfactual $w(q)$ is linear, with $w(0) = 1$ and $w(q^{\max}) = 1.0084$ so that the average counterfactual quality change

⁴³ The subsidy changes the share of home ads $r_v(q, E)$ and shifter $D(q, E)$. See app. H.

⁴⁴ Another related margin of adjustment is the entry and exit of firms. In a previous version of the paper, we show that this margin barely changes the results.

TABLE 10
DIFFERENT SCENARIOS OF EXPORT PROMOTION POLICIES

	Baseline	Balanced Trade	Δ Skill Premium	Agglomeration
	(1)	(2)	(3)	(4)
Percentage changes:				
Average wage per worker (all)	1.33	.21	.17	2.46
Average wage per worker (exporters)	2.11	.35	.15	3.90
Average quality (all)	2.23	.35	.00	4.07
Manufacturing output (X)	5.61	−.60	2.46	9.85
Real exchange rate (e)	0	−1.32	0	0
Efficiency wage at $w(q^{\max})$	0	0	.84	0
Counterfactual levels (%):				
Export/output ^a	26.4	23.9	25.0	28.3
Lump-sum transfer/household income	−.59	−.51	−.54	−.66

^a The export to output ratio in the estimated model is 23.5%.

across firms is zero. This increase in skill premium discourages firms from upgrading to skill-intensive, higher-quality technologies. Only a small change in the wage of high-quality tasks is sufficient to suppress quality upgrading, because positive and negative shocks are similarly amplified through the network.

A recent geography literature points to how the agglomeration of skilled workers increases labor productivity.⁴⁵ In the baseline counterfactual, total employment in the ex ante top quintile of the quality distribution increases by 5.29%. We use the estimates of Diamond (2016) to get a sense of how this increased agglomeration of skilled workers in manufacturing might affect the counterfactual. We infer that the average productivity increases by 0.41% in the top quintile of the quality distribution.⁴⁶

⁴⁵ See, e.g., Diamond (2016), Fajgelbaum and Gaubert (2020), and Giannone (2022).

⁴⁶ In Diamond's (2016) model, the inverse demand function for college graduates and noncollege graduates is, respectively,

$$\log w_H = \gamma_H \log L_H - \left(\frac{1}{\sigma}\right) \log L_H,$$

$$\log w_L = \gamma_L \log L_H + \left(\frac{1}{\sigma}\right) \log L_H,$$

where L_H is the supply of college graduates in a location, σ is the elasticity of substitution between skilled and unskilled workers, and γ is the external scale parameter. The productivity of skilled and unskilled workers is $\gamma_H \log L_H$ and $\gamma_L \log L_H$, respectively, which by assumption increases with the supply of skilled workers with elasticities γ_H and γ_L . In table 4 of her paper, Diamond (2016) estimates $\sigma = 1.6$ and $\gamma_H - 1/\sigma = 0.229$ and $\gamma_L + 1/\sigma = 0.697$, which yields $\gamma_H = 0.854$ and $\gamma_L = 0.072$. The share of manufacturing workers in Turkey with a college degree is 0.23. For an order of magnitude, if we take this share in our skill-intensive firms to be 0.25, then together with the 5.29% increase in their labor, the productivity of these firms increases by 0.41%:

$$0.0041 = (1 - \alpha_s - \alpha_m) \times 0.0529 \times (0.25 \times 0.854 + 0.75 \times 0.072).$$

Column 4 gives the results from implementing the export promotion policy together with this productivity increase. Increasing the productivity and output of higher-quality firms increases the incentives for other firms to upgrade quality. The counterfactual average quality change increases from 2.23 in the baseline to 4.07.

Output increases from 5.6% in the baseline to 9.85%. Note that the 5.6% output growth in the baseline counterfactual is larger than Hulten (1978), not because of quality but mostly because the elasticity of substitution is larger than one as in Baqaee and Farhi (2019a) and because there is increasing returns to scale in search and matching, as in Arkolakis, Huneus, and Miyauchi (2021). So, quality upgrading significantly affects manufacturing output in the model only if there are agglomeration effects. The results in column 4 show that these effects may be large.⁴⁷

To summarize, a government subsidy to the cost of searching for foreign buyers of 9% leads to large and widespread increases in the quality of Turkish manufacturing firms. Table 10 highlights critical factors in the effectiveness of these export promotion policies. In column 3, a small rise in the skill premium dampens the incentives for firms to upgrade to skill-intensive qualities. This points to the importance of ensuring an elastic supply of skilled workers into manufacturing, perhaps through education and training. In column 2, the effects of export promotion in quality upgrading are dampened when a real exchange rate appreciation prevents the country from running a trade surplus. A trade surplus is critical because it increases the relative sales in foreign, where the demand for quality is higher. In column 4, output grows when the agglomeration of skilled workers in manufacturing increases firm productivity. These counterfactuals together rationalize the concomitant increases in trade surplus and skill intensity, technological improvements, and output growth in manufacturing commonly observed in fast-growing emerging markets, notably in East Asia.

IX. Conclusion

We document novel facts about firm-to-firm trade using data from Turkey. High-wage firms are more likely to match with each other in the network, and the value of transactions is larger when the trading partners' wages are both high. Over time, a firm-specific export demand shock from a rich country is associated with an increase in the firm's average wage and in the average wage of its suppliers and customers.

We rationalize these findings in a model where firms' choices of quality and skill intensity are interconnected through the production network.

⁴⁷ This exercise is akin to Jones (2011), who emphasizes the roles of complementarity and economies of scale in economic growth.

High-quality production is intensive in skilled labor and in high-quality inputs, and high-quality firms direct their search toward other high-quality firms. Counterfactuals show that even a small export shock leads to large and widespread quality upgrades in manufacturing firms because of the complementarity in their quality choices.

Although we cannot extrapolate beyond Turkey, these findings are broadly consistent with those of Goldberg and Reed (2020), who show that exporting even a small amount of output to developed countries is associated with economic growth in developing countries. The simulation of counterfactual policies in section VIII points to other economic factors that interact with the effects of international trade on manufacturing firms: education, trade imbalances, and agglomeration effects.

Data Availability

Data and code for replicating the tables and figures in this article can be found in Demir et al. (2023) in the Harvard Dataverse, <https://doi.org/10.7910/DVN/GWODZV>.

References

- Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. "High Wage Workers and High Wage Firms." *Econometrica* 67 (2): 251–333.
- Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The Network Origins of Aggregate Fluctuations." *Econometrica* 80 (5): 1977–2016.
- Adão, Rodrigo, Michal Kolesr, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *Q.J.E.* 134 (4): 1949–2010.
- Alfaro-Urea, Alonso, Isabela Manelici, and Jose P. Vasquez. 2022. "The Effects of Joining Multinational Supply Chains: New Evidence from Firm-to-Firm Linkages." *Q.J.E.* 137 (3): 1495–552.
- Antràs, Pol, Teresa C. Fort, and Felix Tintelnot. 2017. "The Margins of Global Sourcing: Theory and Evidence from US Firms." *A.E.R.* 107 (9): 2514–64.
- Arkolakis, Costas, Federico Huneus, and Yuhei Miyachi. 2021. "Spatial Production Networks." Working manuscript, Yale Univ.
- Baqae, David Rezza, and Emmanuel Farhi. 2019a. "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem." *Econometrica* 87 (4): 1155–203.
- . 2019b. "Productivity and Misallocation in General Equilibrium." *Q.J.E.* 135 (1): 105–63.
- Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: WE Upjohn Inst. Employment Res.
- Bas, Maria, and Caroline Paunov. 2021. "Input Quality and Skills Are Complementary and Increase Output Quality: Causal Evidence from Ecuador's Trade Liberalization." *J. Development Econ.* 151:102668.
- Bastos, Paulo, Joana Silva, and Eric Verhoogen. 2018. "Export Destinations and Input Prices." *A.E.R.* 108 (2): 353–92.

- Becker, Gary S. 1973. "A Theory of Marriage: Part I." *J.P.E.* 81 (4): 813–46.
- Bernard, Andrew B., Emmanuel Dhyne, Glenn Magerman, Kalina Manova, and Andreas Moxnes. 2022. "The Origins of Firm Heterogeneity: A Production Network Approach." *J.P.E.* 130 (7): 1765–804.
- Bernard, Andrew B., Andreas Moxnes, and Yukiko U. Saito. 2019. "Production Networks, Geography, and Firm Performance." *J.P.E.* 127 (2): 639–88.
- Bigio, Saki, and Jennifer La'O. 2020. "Distortions in Production Networks." *Q.J.E.* 135 (4): 2187–253.
- Blaum, Joaquin. 2019. "Global Firms in Large Devaluations." Working manuscript, Brown Univ.
- Bombardini, Matilde, Gianluca Orefice, and Maria D. Tito. 2019. "Does Exporting Improve Matching? Evidence from French Employer-Employee Data." *J. Internat. Econ.* 117:229–41.
- Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2021. "Quasi-Experimental Shift-Share Research Designs." *Rev. Econ. Studies* 89 (1): 181–213.
- Brambilla, Irene, Daniel Lederman, and Guido Porto. 2012. "Exports, Export Destinations, and Skills." *A.E.R.* 102 (7): 3406–38.
- Broda, Christian, and David E. Weinstein. 2006. "Globalization and the Gains from Variety." *Q.J.E.* 121 (2): 541–85.
- Buera, Francisco J., Hugo Hopenhayn, Yongseok Shin, and Nicholas Trachter. 2021. "Big Push in Distorted Economies." Working Paper no. 28561, NBER, Cambridge, MA.
- Carvalho, Vasco M., and Nico Voigtländer. 2014. "Input Diffusion and the Evolution of Production Networks." Working Paper no. 20025, NBER, Cambridge, MA.
- Caunedo, Julieta, Elisa Keller, and Yongseok Shin. 2021. "Technology and the Task Content of Jobs across the Development Spectrum." Working Paper no. 28681, NBER, Cambridge, MA.
- Chaney, Thomas. 2014. "The Network Structure of International Trade." *A.E.R.* 104 (11): 3600–3634.
- Costinot, Arnaud. 2009. "An Elementary Theory of Comparative Advantage." *Econometrica* 77 (4): 1165–92.
- Costinot, Arnaud, and Jonathan Vogel. 2010. "Matching and Inequality in the World Economy." *J.P.E.* 118 (4): 747–86.
- Costinot, Arnaud, Jonathan Vogel, and Su Wang. 2012. "An Elementary Theory of Global Supply Chains." *Rev. Econ. Studies* 80 (1): 109–44.
- De Loecker, Jan. 2007. "Do Exports Generate Higher Productivity? Evidence from Slovenia." *J. Internat. Econ.* 73 (1): 69–98.
- Demir, Banu, Ana Cecilia Fieler, Daniel Yi Xu, and Kelly Kaili Yang. 2023. "Replication Data for: 'O-Ring Production Networks.'" Harvard Dataverse, <https://doi.org/10.7910/DVN/GWODZV>.
- Demir, Banu, Beata Javorcik, Tomasz K. Michalski, and Evren Ors. 2022. "Financial Constraints and Propagation of Shocks in Production Networks." *Rev. Econ. and Statis.*, forthcoming.
- Dhyne, Emmanuel, Ayumu Ken Kikkawa, Magne Mogstad, and Felix Tintelnot. 2018. "Trade and Domestic Production Networks." Working Paper no. 25120, NBER, Cambridge, MA.
- Diamond, Rebecca. 2016. "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980–2000." *A.E.R.* 106 (3): 479–524.
- Dingel, Jonathan I. 2017. "The Determinants of Quality Specialization." *Rev. Econ. Studies* 84 (4): 1551–82.

- Eaton, Jonathan, Samuel Kortum, and Francis Kramarz. 2018. "Firm-to-Firm Trade: Imports, Exports, and the Labor Market." NBER Working Paper no. 29685, NBER, Cambridge, MA.
- Fajgelbaum, Pablo D., and Cecile Gaubert. 2020. "Optimal Spatial Policies, Geography, and Sorting." *Q.J.E.* 135 (2): 959–1036.
- Feenstra, Robert C., and John Romalis. 2014. "International Prices and Endogenous Quality." *Q.J.E.* 129 (2): 477–527.
- Fielor, Ana Cecília, Marcela Eslava, and Daniel Yi Xu. 2018. "Trade, Quality Upgrading, and Input Linkages: Theory and Evidence from Colombia." *A.E.R.* 108 (1): 109–46.
- Giannone, Elisa. 2022. "Skilled-Biased Technical Change and Regional Convergence." Working manuscript, Penn State Univ.
- Goldberg, Pinelopi K., and Tristan Reed. 2020. "Income Distribution, International Integration, and Sustained Poverty Reduction." Working Paper no. 27286, NBER, Cambridge, MA.
- Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *A.E.R.* 110 (8): 2586–624.
- Hallak, Juan Carlos. 2006. "Product Quality and the Direction of Trade." *J. Internat. Econ.* 68 (1): 238–65.
- Harrison, Ann, and Andrés Rodríguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In *Handbook of Development Economics*, vol. 5, edited by Dani Rodrik and Mark Rosenzweig, 4039–214. Amsterdam: Elsevier.
- Hulten, Charles R. 1978. "Growth Accounting with Intermediate Inputs." *Rev. Econ. Studies* 45 (3): 511–18.
- Huneus, Federico. 2018. "Production Network Dynamics and the Propagation of Shocks." Working manuscript.
- Johnson, Richard Arnold, and Dean W. Wichern. 1988. *Applied Multivariate Statistical Analysis*, vol. 5. Upper Saddle River, NJ: Pearson.
- Jones, Charles I. 2011. "Intermediate Goods and Weak Links in the Theory of Economic Development." *American Econ. J. Macroeconomics* 3 (2): 1–28.
- Khandelwal, Amit. 2010. "The Long and Short (of) Quality Ladders." *Rev. Econ. Studies* 77 (4): 1450–76.
- Khandelwal, Amit K., Peter K. Schott, and Shang-Jin Wei. 2013. "Trade Liberalization and Embedded Institutional Reform: Evidence from Chinese Exporters." *A.E.R.* 103 (6): 2169–95.
- Kremer, Michael. 1993. "The O-Ring Theory of Economic Development." *Q.J.E.* 108 (3): 551–75.
- Kugler, Maurice, and Eric Verhoogen. 2011. "Prices, Plant Size, and Product Quality." *Rev. Econ. Studies* 79 (1): 307–39.
- Lenoir, Clémence, Julien Martin, and Isabelle Mejean. 2023. "Search Frictions in International Goods Markets." *J. European Econ. Assoc.* 21 (1): 326–66.
- Lim, Kevin. 2018. "Endogenous Production Networks and the Business Cycle." Working manuscript, Univ. Toronto.
- Liu, Ernest. 2019. "Industrial Policies in Production Networks." *Q.J.E.* 134 (4): 1883–948.
- Manova, Kalina, and Zhiwei Zhang. 2012. "Export Prices across Firms and Destinations." *Q.J.E.* 127 (1): 379–436.
- Matsuyama, Kiminori. 2002. "The Rise of Mass Consumption Societies." *J.P.E.* 110 (5): 1035–70.
- Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71 (6): 1695–725.

- Milgrom, Paul, and John Roberts. 1990. "The Economics of Modern Manufacturing: Technology, Strategy, and Organization." *A.E.R.* 80 (3): 511–28.
- Miyauchi, Yuhei. 2019. "Matching and Agglomeration: Theory and Evidence from Japanese Firm-to-Firm Trade." Working manuscript, Boston Univ.
- Mortensen, Dale T. 1986. "Job Search and Labor Market Analysis." In *Handbook of Labor Economics*, vol. 2, edited by Orley C. Ashenfelter and Richard Layard, 849–919. Amsterdam: Elsevier.
- Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny. 1989. "Industrialization and the Big Push." *J.P.E.* 97 (5): 1003–26.
- Petrongolo, Barbara, and Christopher A. Pissarides. 2001. "Looking into the Black Box: A Survey of the Matching Function." *J. Econ. Literature* 39 (2): 390–431.
- Rauch, James E. 2001. "Business and Social Networks in International Trade." *J. Econ. Literature* 39 (4): 1177–203.
- Rogerson, Richard, Robert Shimer, and Randall Wright. 2005. "Search-Theoretic Models of the Labor Market: A Survey." *J. Econ. Literature* 43 (4): 959–88.
- Rosenstein-Rodan, Paul N. 1961. "Notes on the Theory of the 'Big Push.'" In *Economic Development for Latin America*, edited by H. S. Ellis, 57–81. London: Palgrove Macmillan.
- Roy, A. D. 1951. "Some Thoughts on the Distribution of Earnings." *Oxford Econ. Papers* 3 (2): 135–46.
- Schott, Peter K. 2004. "Across-Product versus Within-Product Specialization in International Trade." *Q.J.E.* 119 (2): 647–78.
- Smarzynska Javorcik, Beata. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages." *A.E.R.* 94 (3): 605–27.
- Teulings, Coen N. 1995. "The Wage Distribution in a Model of the Assignment of Skills to Jobs." *J.P.E.* 103 (2): 280–315.
- Tian, Lin. 2021. "Division of Labor and Productivity Advantage of Cities: Theory and Evidence from Brazil." CEPR Discussion Paper no. 16590, Centre Econ. Policy Res., London.
- Verhoogen, Eric A. 2008. "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector." *Q.J.E.* 123 (2): 489–530.
- Voigtländer, Nico. 2014. "Skill Bias Magnified: Intersectoral Linkages and White-Collar Labor Demand in U.S. Manufacturing." *Rev. Econ. and Statis.* 96 (3): 495–513.