Endogenous Production Networks and Learning-by-Networking

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Abstract: This paper investigates the endogenous formation of production networks while exploring the role of learning in a network model of production. It also provides the theoretical underpinnings of the mechanisms for how production networks amplify firm-level productivity. After finding strong evidence in favor of firm-level production networks' asymmetry, I build a model that lays a theoretical foundation between productivity and the formation of production networks. This paper also exploits a rich micro-level data set of Turkish firms to understand the model's relation to the data. Empirical evidence reveals the close relationship between expanding a firm's production network and its productivity. Furthermore, the productivity changes in each firm are studied through the sophistication of a network while proposing a learning-by-networking hypothesis with other firms in their production network.

Key Words: Aggregate fluctuations, Firms, Input-Output, Learning-by-Exporting, Networks, Shocks, Productivity, Production

JEL codes: E23, E32, F14, L11.

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1 Introduction

Understanding the formation of supply chains and their economic implications is crucial for international trade and globalization. With the increased integration of the production process within and across borders, dynamics behind a firm's production network became the focus of the research. Yet, the existing literature lacks an explanation for the mechanism behind the formation and sophistication of these linkages for a firm. This study proposes the first attempt to fill this gap by offering theoretical and empirical evidence on the productivity gains while suggesting a "learning-by-networking" hypothesis with other firms in their production network.

This paper aims to present the origins of firm heterogeneity with the investigation of its network. For this reason, this study focus on the dynamic changes in productivities and input-output relationships among Turkish manufacturing firms. The goal is to underline the endogenous formation of production networks with the underlying productivity gains. It consists of three parts to achieving this goal. The first part exhibits the facts about the Turkish production network. In addition, it displays the asymmetries among firms by relying on their position in the supply chain. The second part provides a model of endogenous network formation by building on Antras et al. (2017) and presents the theoretical evidence on how firms' productivity depends on their network. Finally, in its most important contribution, the third part provides empirical evidence on how firms learn by networking by illustrating domestic and international supplier/customer networks changes.

Production networks build upon firm-level buyer-seller relationships. Hence, the empirical investigation in this paper relies upon the tax statements reported by Turkish firms. These statements provide pairs and the value of the transactions to cover each linkage among firms. With this data, the aim is to study these linkages by relying on the network's impacts on the economy.[1]. Findings in this study underline the sparsity of the Turkish production network by also exhibiting superstar firms' existence as linkages across firms that follow power laws.[2] Then, the natural question is the reasons behind this asymmetry and the potential mechanisms that originate from this heterogeneity across firms depending on their network position.

This paper presents a model of endogenous network formation to address these

[1] Carvalho (2014) exploits the lack of balance among suppliers by focusing on the out-degree distribution of the U.S Input-Output Network. Further, arguing that most of those linkages are the underlying mechanism behind the shock transmission even at the sectoral level.

[2] As stated in Gabaix (2011), the diversification argument fails if the firm-size distribution exhibits fat-tails that specify the granularity of the economy. Also, Acemoglu et al. (2012) focuses on how idiosyncratic shocks to sectors lead to aggregate fluctuations in the case of a fat-tailed distribution of input-output linkages with specific tail parameters.

questions, and empirical evidence provides the dynamic recoding of the networks. The model, which builds on Antras et al. (2017)[3], provides an insight into the formation of buyer-seller linkages across firms. It offers evidence of the heterogeneity of the firms in their decisions to source and export. Further, these choices endogenize the production network. In the model, firms' trade-off is based on choosing suppliers that contribute to a firm with their supplier-specific intermediate input efficiency, while adding a new supplier is costly. The decision to export follows a parallel pattern, and firms are heterogeneous in their production network. The first prediction of the model is that firms' productivity is determined according to their position in the value chain. A second prediction is that the sophistication of the supply chain alters firms to become more productive by generating a cost advantage. The third prediction underlines the prerequisite for complex production networks for the exporters.

The empirical part is based on the model's predictions by relying on microdata that incorporates business-to-business transactions, imports, exports, and balance sheet information for Turkish manufacturing firms between the years 2006 to 2017. The analysis tracks a firm's productivity with the corresponding weighted in- and out-degree measures[4] in a given year to examine the firm's network characteristics. It tests the link between productivity gains and the enlargement of the firm's network by offering the "learning-by-networking" hypothesis. Order of the improvements is expected to start with its suppliers, and it will be followed by a growth in firm productivity, enhancing the development of the export network. Empirical evidence is consistent with the theory, and it reveals the differential effects of production networks on firm selection. Unlike the previous studies, this paper establishes the role of learning in an endogenous production model as a mechanism that originates from the sophistication of the supply chain.

The rest of the paper is structured as follows. Section 2 presents the contribution of this paper with the literature that it builds on and the facts about the Turkish production network shown in Section 3. Section 4 introduces the model and discusses endogenous production networks. A brief description of the dataset is provided in section 5. Section 6 analyzes the drives of the learning mechanism by focusing on the network structure. Section 7 concludes the paper.

[3]Antras et al. (2017) develop a sourcing model where productivity is the main criteria for the firms that self-select into importing. In this way, their model characterizes firms' sourcing decisions.

[4]Weighted in and out-degree refers to the firm's edges with its partner and weighted according to the transaction volume.

2 Related Literature

This study contributes to several different strands of the literature. The first is the literature that questions the role of input-output linkages across sectors as a transmission mechanism (Long and Plosser (1983); Horvath (2000); Shea (2002); Gabaix (2011); Acemoglu et al. (2012); Carvalho et al. (2016)). Although these papers emphasize sectoral-level links, an emerging component of this strand demonstrates the role of firm-level production networks on the economy.(Di Giovanni et al. (2014); Barrot and Sauvagnat (2016); Mayer et al. (2016); Tintelnot et al. (2018) ; Di Giovanni et al. (2018); Boehm et al. (2019)). However, these papers assume specified network structures while interpreting their role. In this study, I go one step further to present the mechanism behind the formation of these relationships as an endogenous network model of production.

There is recently emerging literature that investigates the endogenous formation of networks including Carvalho and Voigtländer (2014), Oberfield (2018), Acemoglu and Azar (2020) and Taschereau-Dumouchel (2020). Carvalho and Voigtländer (2014) presents how firms in production networks play a significant role in the diffusion of technology with the presence of a new variety of producers such as semiconductors. Oberfield (2018) establishes a matching model for constructing the links between customers and suppliers where firms can rely on only one intermediate input. Subsequent work by Acemoglu and Azar (2020) demonstrates how the arrival of new products can lead to the evolution of the production network, which can also be an engine of economic growth. Taschereau-Dumouchel (2020) discusses a model of firm entry and exit, which endogenizes the network structure of production. Demir et al. (2021) shows how the formation of networks depends on the quality choices by relying on the Turkish firm-to-firm dataset. Relative to the existing literature, this paper offers an understanding of the complexity of production networks by introducing networking costs. Since not all firms can reach the same suppliers, firms have to pay fixed costs to enjoy pair-specific productivities to form their network. The development of these networks leads to export. Hence, the decisions to build a network as an enlargement of suppliers or exports lead to the production network's endogenous formation.

The model in this paper builds on the framework developed in Antras et al. (2017) which offers a quantifiable multi-country sourcing model to describe the relationships among firms' extensive margins associated with offshoring. Antras et al. (2017) also provides the organization of selection into importing while exhibiting how fixed costs of sourcing varies across firms. Unlike the literature that addresses the exporting decisions[5]

[5] See Eaton and Kortum (2002), Melitz (2003) and Chaney (2008) for the case of export and constant marginal costs.

of a firm, marginal costs are not constant further; these costs are interdependent across other markets. This study concentrates on the endogenous formation of the firms while building on Antras et al. (2017). An important difference in this paper is the introduction of networking costs for firms finding a supplier or deciding to export. Finding a supplier depends on the intermediate input and the networking costs. These costs endogenize the production network. Exporting decision follows Eaton and Kortum (2002) and Antras et al. (2017) to exploit the comparative advantage of a firm. Theoretical evidence in this paper presents the role of production networks on the margin of a firm's productivity and its decision to export.

Another strand of the trade literature emphasizes the origins of productivity premia and first-time exporters. There is a long-running debate in the literature about the interpretation of this fact[6]. The improvement in measured productivity can be due to firms' self-selection into export markets or learning from their counterparties. As proposed by Melitz (2003), self-selection argues that firms are heterogeneous in terms of their productivities. More productive firms that can afford the fixed and iceberg costs of international trade can export, demonstrating a selection for exporting in this setting. As studied in De Loecker (2007), another perspective provides evidence on how productivity gains are attributable to exporting, suggesting a learning-by-exporting mechanism. This study adds this literature by exploiting the role of production networks in trade while introducing a learning-by-networking hypothesis. The theoretical and empirical evidence proposes this alternative hypothesis to illustrate how these gains originate from the firms' production network. This paper also presents how firms recode their production networks by focusing on their network degrees as critical insight. Before exporting, firms improve and enlarge their supply chain, and their productivity is amplified further after exporting. Furthermore, the empirical evidence presents the association between productivity, network degrees, and export.

3 Production Network Facts

This part introduces the characteristics of Turkish production networks that build on buyer and seller linkages across firms. The aim is to assess the implications of these micro relationships by relying on the network theory. The production network consists

[6] For instance, Bernard and Jensen (1999) analyzes the causal relationship between productivity and exporting. They argue that prospective exporters begin to show desirable performance characteristics before shipping abroad. Pavcnik (2002) finds significant evidence of the improvement in plant-level productivity following Chile's trade liberalization while examining Chilean plant-level data. Alvarez and Lopez (2005) offer proof on the premia following the entry. Yeaple (2005) also argues that only firms that are more productive than others can export. Bernard et al. (2019) identify the importance of firm-level networks on productivity.

of both nodes and edges. Edges in this study are established as the intermediate input transactions within firms, and each node corresponds to a firm. These relationships construct a directed and weighted network. Direction displays the transaction to a firm, and the quantity of this exchange weights each linkage.

The goal is to discover the variations among firms by concentrating on firms' weighted degree distributions in the supply chain. Then, calculating both weighted in- and out-degree relies on the number and weights a firm has in the production network. Weighted indegree captures a firm's demand depending on the volume of intermediates, whereas weighted out-degree portrays the intermediate input supplied to other firms.

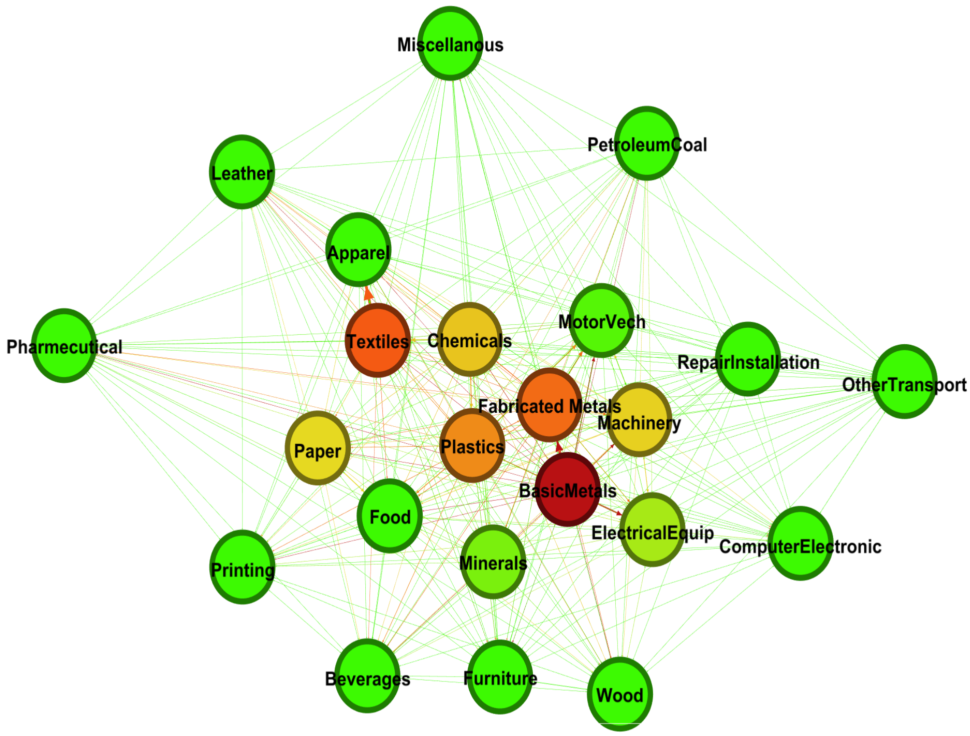


Figure 1: Production Network *Notes:*This figure presents the production network at the two-digit industry level. Manufacturing industries aggregated following the NACE Rev.2. Classification.

Fact 1. *The linkages among manufacturing sectors are heterogeneous for the Turkish production network.*

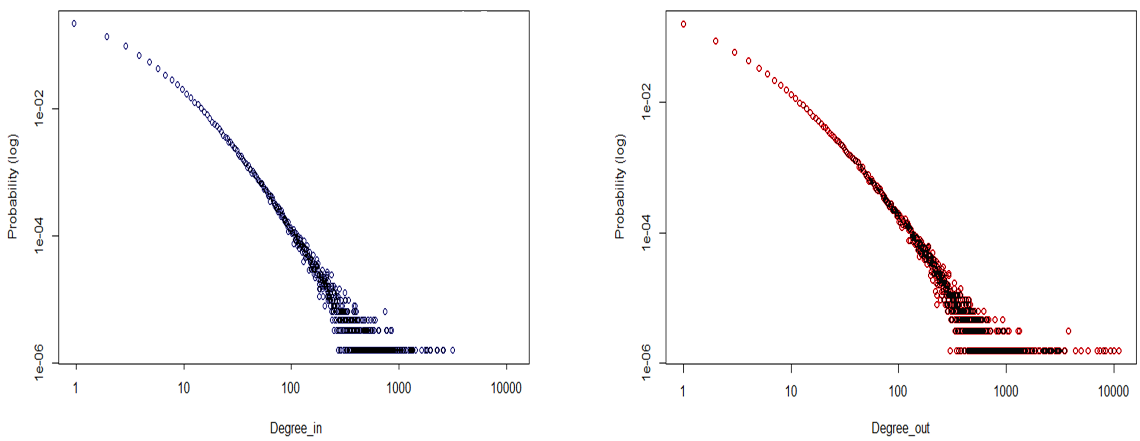
Input-output linkages among two-digit manufacturing sectors present the production network shown in Figure 1. For each industry, colors denote the weighted out-degree of an industry. Hence, colors underline the amount of intermediate input provided by industry to the production network. These colors turn from green to dark red conditional on the sectoral out-degree. Upstream industries that provide intermediate inputs to other sectors tend to have darker colors like the primary metal industry presented in Figure

1. Downstream industries that primarily rely on intermediate inputs, computers, and electronics, are shown in green.

The locations of the network also hint at the transaction intensity among industries. Force Atlas 2 algorithm (see Jacomy et al. (2014)) determines the node locations. Sectors that engage in more transactions of inputs are located closer to each other, including Metal, Chemicals, and Plastics. At the same time, industries that involved fewer intermediates trade than others were pushed away from the center, such as Furniture, Leather, and Beverage industries.

There are several takeaways from the sectoral analysis to motivate the interpretation of this paper. First, the production network illustrates the heterogeneity among the linkages even at the aggregated level. Second, there is a clear distinction between the upstream and downstream industries. Due to their intermediate input transactions, some industries play a dominant role as they interact intensively with others. Third, some sectors are highly reliant on each other, forming clusters. In particular, even the aggregated sectoral level linkages prove the sparsity of the network. The rest of the paper investigates the firm-level production network to understand the formation mechanism of these relationships and the impact of asymmetries in a network.

Fact 2. *Weighted in- and out-degree distributions of the firm network follow a power law.*



(a) Weighted In-Degree

(b) Weighted Out-Degree

Figure 2: Firm-level Weighted Degree Distributions

Figure 2 presents the probability mass function of manufacturing firms' intermediate output supply as a weighted out-degree and input purchase as a weighted in-degree. The distributions of degrees shown in these figures are skewed, revealing the Turkish firm network's asymmetry. The firms located in the right tail of the degree distributions refer to firms with many links, and those found in these fat tails are the superstar firms of the production network. In this type of network structure, if shocks hit those firms in the tails, their impact on the economy will not vanish in the long run.

Shocks to firms with high weighted in- or out-degrees can generate a domino effect through the production network[7]. Based on these graphs, we can argue that the Turkish manufacturing production network is asymmetric at the firm level. These extreme asymmetries in the manufacturing industries are attributable to the firms' presence on the distributions' right tail. As suppliers or purchasers of intermediate inputs, some firms can be "too connected to fail".

In this case, the standard diversification argument does not apply to the production network. Going one step further, there is a need to detect the distribution of both in- and out-degrees of the firm network to comment further. By relying on the Figure 2, the most suitable candidate to fit this data is the power-law distribution (see equation (1)) using the Hill-type MLE estimates of Clauset et al. (2009) with endogenous cutoffs.

Following in the footsteps of Gabaix (2011) and Acemoglu et al. (2012), we examine the tail parameter ζ, which lies at the heart of the analysis corresponding to asymmetries among firms. For the values of ζ larger than 2, the first two moments are well defined, and the shocks wash out consistent with the standard diversification argument. If the tail parameters are smaller than 1, none of the moments of the distributions are defined. Zipf's law applies if the tail parameter is equal to one, $\zeta = 1$, and the decay rate is proportional to $1/ln(N)$. Still, the variance becomes infinite when $\zeta \in (1, 2]$, and standard diversification fails. Hence, firm-level shocks diffuse to the aggregate economy through network links, and production networks play a fundamental role.

$$p_k = ck^{-\zeta} \tag{1}$$

[7]Lucas (1977)'s standard diversification argument states that idiosyncratic shocks die at the rate of $\sqrt{N}$, as N goes to infinity. Notably, this fact does not apply if the production linkages among firms follow fat-tailed distributions. Both Gabaix (2011) and Acemoglu et al. (2012) present results that shows the aggregate volatility of output decays slower with the rate of $\frac{1}{N^{1-1/\zeta}}$ with tail parameter ζ. If the tail parameter ζ lies between 1 and 2, then the decay process in volatility is much slower than the proposed rate of $\sqrt{N}$.

	ζ	xmin	logl	Kstat	Ksp	Obs.
Outdegree	1.51	0.00	229.24	0.04	0.98	5494103
Indegree	1.60	0.00	367.05	0.04	0.99	5494103

Table 1: Power Law Estimation Notes: For the goodness-of-fit test, the estimation relies on The Kolmogorov-Smirnoff (KS), the table of KS values, and test statistics Ksp evaluated for the power-law distribution.

Table ref presents the estimated tail parameters are shown in Table 1 for the Turkish production network. From 2006 to 2017, both in- and out-degrees fit power-law distribution[8]. The network structure sustains its asymmetry with very similar tail parameters for the cases of in- and out-degrees. As the tail is concentrated more mass, the production economy is not diversified enough to average out idiosyncratic shocks to firms. This result motivates the fact that determining the linkage formation mechanism across firms is essential to understanding the production economy.

Fact 3. *Average firm-level total factor productivity in the Turkish manufacturing industry is subject to significant fluctuations over time.*

(a) Average TFP

(b) Annual TFP growth

Figure 3: Estimated TFP of the Turkish Manufacturing Firms

Figure 3 presents the annual average and growth of the firm-level TFPs of manufacturing firms over time. As expected, this time-varying measure decreases with the global financial crisis. For this reason, the estimations in this paper take into account these variations by using year-fixed effects. To measure the firm-level

[8]The values of Ksp smaller than 0.5 state that there is no evidence to support that distribution is not power-law.

production functions, I follow Levinsohn and Petrin (2003) and use intermediate inputs as a proxy to control for the unobservables. Estimation follows the correction suggested Ackerberg et al. (2015) to overcome the identification problem that originates with the usage of both labor and intermediate inputs. Thus, the productivity estimates are obtained from estimations with the inclusion of lagged inputs as instrumental variables. Once the production function is measured, total factor productivity corresponds to the difference between the actual and the estimated log output. For robustness, TFP is calculated by following the various approaches and summarized in the Appendix. As described in the correlation matrix, TFP measures obtained using the Levinsohn-Petrin method with the Ackerberg correction correlated with those estimated according to the alternative Olley-Pakes methodology.

Fact 4. *Importers and exporters differ in terms of firm characteristics.*

The literature argues that exporters and importers have different characteristics from firms operating only in the domestic market. Following Bernard and Jensen (1999) and De Loecker (2007), this part of the paper focuses on these differences to assesses the economic importance of international trade. To determine whether firm characteristics do vary across these groups, I run the following OLS regression:

$$y_{i,t,j} = \alpha + \beta\, trade_{i,t,j} + \eta\, l_{i,t,j} + \mu_t + \lambda_j + \epsilon_{i,t,j} \tag{2}$$

where $y_{i,t,j}$ is the characteristics of firm i at year t in industry j; $trade_{i,t,j}$ is the dummy that takes values 0 or 1,indicating the firm exposure to international trade; and $l_{i,t,k}$ is the log of the number of firm employees. The regressions also controlled for different two-digit industry-year fixed effects..

Firm Characteristic	$\beta_{exporter}$	$\beta_{importer}$	β_{both}
Value-added	0.09	0.09	0.10
TFP	0.43	0.41	0.45
Average wage	0.09	0.11	0.16

Table 2: Firm characteristics and premiums associated with international trade. Notes: All regressions include NACE Rev. 2. two-digit industry-year fixed effects. The physical units are deflated according to the 2-digit industry deflators.

A straightforward measure, β of the equation 2, indicates the relative performance of firms that engage in international trade to those that only operate in the domestic market. Firms that import and export have the most distinguished premia for each of these measures. Those firms are more productive and pay higher wages than other firms. But the most crucial distinction relies upon the total factor productivity. Thus, I examine this difference among firms concentrating on their choices for the supply chains.

4 Model

This section presents the theoretical foundation for the formation of endogenous production networks. The model aims to explain network-related productivity gains for a firm. It builds on Antras et al. (2017), which demonstrates the mechanism of selection into importing to understand firms' sourcing decisions. This paper introduces the heterogeneous set of networking strategies and the pattern according to its supplier and customer preferences.

The economy consists of multiple firms with two sectors, manufacturing, and non-manufacturing, as an outside sector. The focus is the manufacturing sector which consists of two types of firms: Upstream and Downstream firms. Downstream firms are heterogeneous in transforming inputs into output, and the market structure of those firms is characterized by monopolistic competition with free entry. Upstream firms deliver intermediate inputs for downstream firms operating in a perfectly competitive market. Therefore, these upstream firms offer their outputs at a marginal cost.

Downstream firms rely on intermediate inputs in the model, which are associated with supplier-specific productivities. Firms decide to form networks with suppliers, which requires the firm to pay networking costs. These costs are not constant, and they vary across suppliers. Hence, building a network depends on the marginal costs that are interdependent among the choices of suppliers.

Households supply labor inelastically, and their preferences are shaped according to the consumption of different goods with a symmetric CES aggregator:

$$U_{mi} = (\int_{w \in \omega_i} q_i(w)^{\frac{(\sigma-1)}{\sigma}} dw)^{\frac{\sigma}{(\sigma-1)}} \tag{3}$$

where w_i defines the available manufacturing goods for the final consumption and $\sigma > 1$ for the elasticity of substitution. Correspondingly, the demand of a variety w follows

$$q_i(w) = E_i P_i^{\sigma-1} p_i(w)^{-\sigma} \tag{4}$$

where P_i is the standard ideal price index, p_i is the price of good w, and aggregate spending is E_i in the industry i. The market demand of firm i has the following form

$$B_i = \frac{1}{\sigma}(\frac{\sigma}{\sigma-1})^{1-\sigma} E_i P_i^{\sigma-1} \tag{5}$$

In this setting, downstream firms produce final goods by relying on intermediate bundles made by the upstream firms. Then the essential part of this model is the development of linkages between upstream firms, which involves downstream firms paying fixed costs to network with other firms in the economy. The choice to finance the networking costs endogenizes the network since buyer and seller linkages are not exogenous in this setting.

Downstream firms follow the definition of Melitz (2003), these firms learn the productivity, φ, after paying the fixed cost of networking, which is in terms of labor. Thus, the productivity distribution is drawn from $g_i(\varphi)$. Besides, intermediate inputs are imperfectly substitutable with each other, and the bundle contains a continuum of firm-specific inputs with the elasticity of substitution ρ.

The downstream firm determines its networking strategy $N_i(\varphi)$ by selecting its suppliers and their associated networking costs. Therefore, this strategy $N_i(\varphi)$ codes the production network of a firm and grants the set of suppliers for a firm i with productivity φ. This strategy is associated with the fixed cost of networking as f_{ij}. As upstream firms offer their outputs at the marginal cost, so the price of an intermediate input supplied from the firm j is

$$p_i(j, \varphi; N_i(\varphi)) = min_{j \in N_i(\varphi)}[n_{ij} a_j(j, \varphi) X_{ij}] \tag{6}$$

where n_{ij} is the cost of networking with the intermediate good producer firm j, $a_j(j, \varphi)$ is the labor requirement of firm j to produce intermediate good and X_{ij} is the amount of intermediate good supplied from firm j to i. Then, the marginal cost encountered by downstream firm i is:

$$c_i(\varphi) = \frac{1}{\varphi}(\int_0^1 p_i(j, \varphi; N_i(\varphi))^{1-\rho} dj)^{\frac{1}{(1-\rho)}} \tag{7}$$

Replacing the prices with the marginal costs from sourcing j:

$$c_i(N_i(\varphi), \varphi) = \frac{1}{\varphi}(\int_0^1 (N_{ij} a_j(j, \varphi) X_{ij})^{1-\rho} dj)^{\frac{1}{(1-\rho)}} \tag{8}$$

Firms operate in this asymmetric market structure while upstream firms provide inputs and downstream firms combine firm-specific intermediate inputs for production. Building on Eaton and Kortum (2002) and Antras et al. (2017) intermediate input efficiencies are firm-specific with $a_j(j, \varphi)$ and upstream firms draw the value of input productivity $a_j(j, \varphi)$ from Fréchet distribution:

$$Pr(a_j(j, \varphi) \geq a) = e^{-T_j a^{\theta}} \tag{9}$$

where T_j is the technology of supplier firm j and θ is the variance of shocks (productivity dispersion parameter). The values of θ represent the variation of comparative advantage across upstream firms as in Eaton and Kortum (2002). Further, these draws are independent across firms and inputs.

4.1 Networking Capability

The main focus of the model is networking capability. Firms form an optimal networking strategy by choosing their suppliers. Firms select the suppliers with the lowest cost by paying a fixed cost. As a result, the probability of downstream firm i buying input from upstream firm j is

$$\alpha_{ij} = \frac{T_j(\frac{n_{ij}}{X_{ij}})^{-\theta}}{\Theta_i(\varphi)} \tag{10}$$

where n_{ij} is the cost of adding a new supplier or customer to the firm's production network, and it is defined as in Eaton and Kortum (2002) and Antras et al. (2017). This term is equal to zero if there is not any network linkage. The networking capability Θ is defined as the sum of all suppliers:

$$\Theta_i(\varphi) = \sum_{k \in N_i(\varepsilon)} T_k(\frac{n_{ik}}{X_{ik}})^{-\theta} \tag{11}$$

The networking capability rises with both technology T_k and the amount supplied as an intermediate good X_{ik}. It declines with the networking fixed cost n_{ik} where k is an upstream firm.

After forming its supplier network, the marginal cost of a firm defined as [9]

$$c_i(\varphi) = \frac{1}{\varphi}(\gamma\Theta_i(\varphi))^{-1/\theta} \tag{12}$$

The marginal cost is defined as a decreasing function of the firm's production network. As firms expand their supplier network, an improvement in the networking capability reduces the marginal cost since adding a new supplier provides an additional draw. However, this entails a fixed networking cost for each supplier. Hence, a firm that can enlarge its network will broaden its productivity gains. Replacement of the networking capability delivers the following profit function for a downstream firm

$$max_{I_{ij}\in\{0,1\}_{j=1}^{N}} \pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma \sum_{j=1}^{N} I_{ij} T_j(\frac{N_{ij}}{X_{ij}})^{-\theta})^{\frac{\sigma-1}{\theta}} B_i - w_i \sum_{j=1}^{N} I_{ij} f_{ij} \tag{13}$$

where I_{ij} is the indicator function that takes a value of one of the firms j is in the supplier network of firm i, and B_i is the residual demand. The profit function suggests that attaching to a new supplier reduces the marginal cost. Yet, a sophisticated network

[9] Derivation of the cost function follows Eaton and Kortum (2002) and Antras et al. (2017) on the derivation of aggregate price index. The assumption follows Antras et al. (2017) $\theta > \rho - 1$.

is any additional linkage accompanied with the fixed cost f_{ij}.

The profit function is non-linear as shown in equation 13, and it is supermodular in networking capability Θ_i, intermediate inputs X_{ij} and productivity φ. Thus, firms can have a higher cost advantage by increasing their upstream suppliers or in-degree network linkages. The profit maximization of firms also depends on the costs of linkage formation cost as N_{ij}.

4.2 Decision to Export

This section expands the model to assess the role of networks on the productivity gains for the firms that engage in international trade. Hence, this section provides an alternative perspective to explain the linkage between productivity and exporting. Similar to Melitz (2003) firms have to pay a fixed cost for exporting, and this decision depends on the networking capability of the firm i. Following Eaton and Kortum (2002) exporting depends on the comparative advantage of the firm, which is determined similarly to the networking capability:

$$\beta_{xi} = \frac{T_i(\tau_{xi} w_i)^{-\theta}}{\Theta_x(\varphi)} \tag{14}$$

where τ_{xi} is the iceberg costs, w_i is the wage in the country i, and β_{xi} is the total of the networking capability of firm i expressed as the terms of probability of finding a customer. As the extension of the previous result, the cost depends on the productivity of its suppliers and network. Similarly, firms can sell their output to foreign markets after a fixed-cost investment as γ. Thus, the export decision depends on the fixed costs and the comparative advantage in productivity. Firm i has the following profit function when its export network is determined endogenously:

$$\begin{aligned} max_{I_{ij}\in\{0,1\}_{j=1}^{N}} \pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma \sum_{j=1}^{N} I_{ij} T_j (\frac{N_{ij}}{X_{ij}})^{-\theta})^{\frac{\sigma-1}{\sigma}} (1 + \sum_{x=1}^{N} \beta_{xi})^{(1+\sigma)} B_i \\ -w_i \sum_{j=1}^{N} [I_{ij} f_{ij} - \gamma_{xi}] \end{aligned} \tag{15}$$

In general equilibrium, consumers spend a constant share in the manufacturing industry. Given the free entry condition for market demand, a unique market demand exists in the industry equilibrium.

Proposition 1. For each values of I_{ij} and $\gamma_{xi} \in (0,1)$, both solution to firm's networking and exporting capability is non-decreasing in φ.

This proposition designates how expanding the firm's suppliers and exporting depends on productivity. Reducing networking costs or fixed costs raises the networking capability by keeping the demand constant. Hence, productive firms can expand their supply chain and also, they can select foreign markets. The sophistication of the supply chain enhances firms to become more productive by generating a cost advantage. In this way, firms learn by networking.

Proposition 2. An increase in networking capability leads to export[10].

This proposition states how firms learn from their production networks and exporting—an increase in firm productivity results in export participation and the requirement of additional suppliers. In addition, variables that improve the networking capability $N_i(\varphi)$, such as reduction of networking costs with other firms or advancement in the technology of the upstream firm, will lead to a rise in γ_{xi}. All in all, these interdependent mechanisms build up learning-by-networking. In other words, productive firms become more effective by expanding their customer and supplier networks.

5 Data

The empirical part combines several Turkish firm-level datasets, including tax statements, balance sheets, and custom transactions from 2006 to 2017. Following the theoretical implications, this paper restricts its attention to manufacturing firms. Thus, firms are identified according to the four-digit NACE Rev. 2. sector codes. Only firms classified as manufacturing industries, according to NACE Rev. 2. are included in the dataset.

The production networks are generated according to the tax statements of each firm in this study. Firms are responsible for reporting each buyer and seller transaction to the Ministry of Finance, and the lower limit for these transactions is 5000 Turkish Liras, approximately 305 Euros. Each of these reports presents a directed link between two firms, and these links are the building blocks of the production networks. To investigate the firm's engagement in international trade, this study relies on the customs declarations for the firm's detailed imports and exports. Custom declarations provide both the country of the partner and the associated volume of the trade.

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[10]Further, reduction in the iceberg costs also leads to participation in export markets. More, it will improve the sourcing of a firm.

Year	Firms (#)	Size	Exporters (%)	Importers (%)
2006	116,575	28.45	15.70	15.30
2007	127,629	28.32	15.52	15.01
2008	133,585	27.59	15.45	14.36
2009	135,768	25.37	15.39	13.29
2010	136,648	26.69	15.69	14.21
2011	140,800	27.88	15.66	14.72
2012	144,983	28.09	15.86	14.39
2013	154,076	27.88	16.19	14.11
2014	161,007	28.11	16.64	13.93
2015	169,049	28.21	16.20	13.63
2016	175,440	27.67	16.18	13.01
2017	182,560	27.49	14.42	11.69

Table 3: Descriptive Statistics *Notes:* The number of firms operating in the manufacturing industry reported in the second column. Average size refers to the mean of the registered full-time employees. Exporters and importers refer to the percentage of exporter and importer firms among all firms in a given year.

The balance sheets, income statements, and the number of registered employees of each firm are included in the estimations to track firm dynamics. The final data is an unbalanced panel covering twelve years, and Table 3 presents the descriptive statistics of this panel. Additionally, all physical units in the corresponding period deflated according to the producer price indices for each two-digit industry[11].

6 Learning-by-Networking

The well-known fact in the literature is that the estimated TFPs tend to rise when firms export, and empirical evidence in the preceding sections support this nexus for the Turkish manufacturing firms. Still, there is a long-running debate regarding the interpretation of this fact, including Selection into exporting[12] and learning-by-exporting[13]. Yet, these studies restrict their attention to only exporting. Even though significant evidence in the literature supports productivity improvement,

[11]Producer price indices collected from the Turkish Statistical Institute for each year and sector pair

[12]Selection into exporting is based on the causality running from productivity to self-selection of firms into international markets as an endogeneous decision of the firm. In this case, firms do not learn by interacting with other firms in their production networks or their competitors in the international markets. This hypothesis argues that these firms are meant to be more productive due to their ability to cover fixed labor costs and iceberg costs to export.

[13]part of the literature offers to learn from trade partners thesis as the premia following the entry of a firm into export markets, including Bernard et al. (1995), Alvarez and Lopez (2005) and De Loecker (2007).

the underlying mechanism is neglected. This part offers an alternative mechanism for this phenomenon as learning-by-networking, suggesting that productivity gains are related to the firm's supply chain, which can be traced through its network.

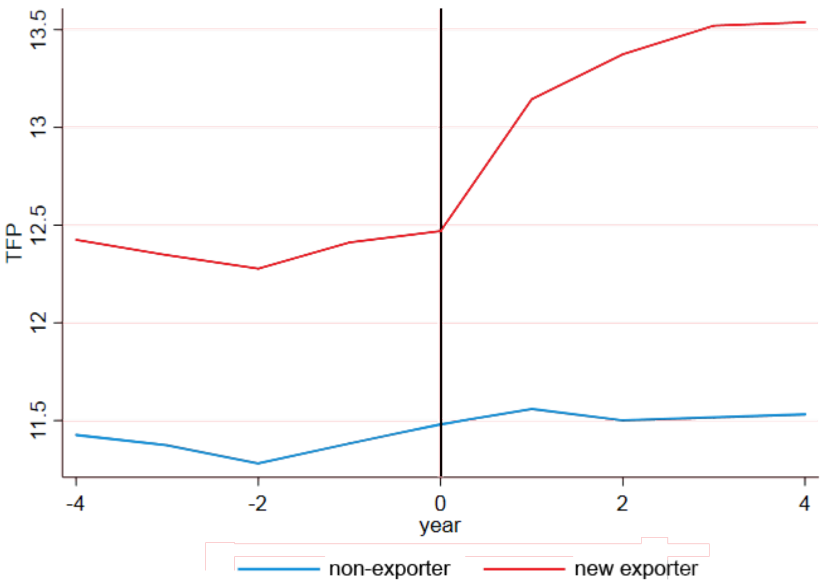


Figure 4: Productivity and Exporting *Notes:* The blue line indicates the average productivity of firms that never export, whereas the red line shows the firms' average productivity level that starts to export at time 0. The y-axis corresponds to firms' productivity levels for both groups.

Going one step further, this part inspects the organization of the firm's network by relying on the firms' weighted in- and out-degree distributions. These distributions track the volume and number of linkages a firm has in its production network. Indegrees build on the supplied intermediate inputs, whereas out-degrees determine the spread of the firm's output. Therefore, the main emphasis in this exercise is the recoding of the firm's networks. Unlike the previous literature, this analysis argues that the mechanism that produces learning is networking with other firms across the supply chain. Thus, the empirical exercise emphasizes the TFP premia and how firms learn by networking and exporting. Principally, these findings suggest that the network sophistication of the firms drives the premium.

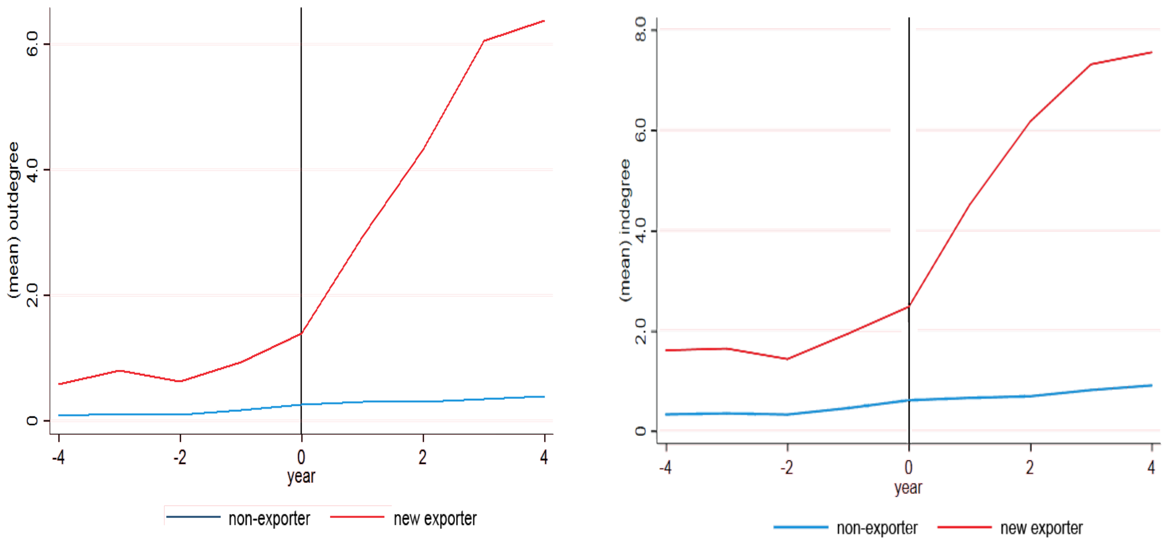
As firms become more productive, they may develop their local supplier and customer networks before their productivity moves over the export threshold. First, they extend their position in the domestic supply chain, which raises their demand for intermediate inputs. Second, their supply to others increases. Enlargement in the out-degree and in-degree of domestic and international production networks raises its competitiveness globally. Third, firms learn by networking due to their recoding in the production network.

For the preliminary analysis, the mean productivity of the firms that have never exported is presented with the blue line. In contrast, the red color exhibits the first-time exporters—the reference year entitled as $t = 0$, which is the time for the first export. In addition, firms that were already exporters at the beginning of the sample dropped. After designating the reference year, other years were distributed accordingly.

Before time zero, the distinction between the two levels is the main criteria to test the self-selection hypothesis. From the $t = -4$ to $t = 0$, first-time exporters exhibit higher productivity levels, suggesting self-selection, yielding almost eight percent premia in TFP. Yet, parallel trends in the two trajectories diverse substantially following the reference year. For the learning-by-hypothesis test, the crucial part relies upon the changes observed following the time $t = 0$. Interestingly, the most valuable observation of the analysis in Figure 4 is the rise in the TFP levels of the first-time exporters. Following the reference year, parallel trends disappear. The red line follows a definite upward trend after period 0, demonstrating proof of the learning mechanism. In contrast, firms that had never exported do not experience any benefits in terms of TFP. Visual inspection of Figure 4 hints at a distinction, but it requires empirical evidence to comment further. For this reason, the following part relies on a differences-in-differences estimation by taking the firms' network into account.

6.1 Network Characteristics and Exporting

Network characteristics are reviewed in this section to check whether the TFP premia is generated with learning-by-networking. To do so, weighted in- and out-degree distributions capture the upstream and downstream linkages. The firm's in-degree distribution refers to its number of suppliers and the corresponding volume of its intermediate input purchases. Similarly, weighted out-degree distribution presents the number of customers weighted by the supplied outputs to other firms. Figure 5 displays the domestic production network characteristics by depending on the business-to-business transactions. As the import and export data is accessible for the firm-country pairs, the weights are converted among countries for the international network features like import and export degrees portrayed in Figure 6.

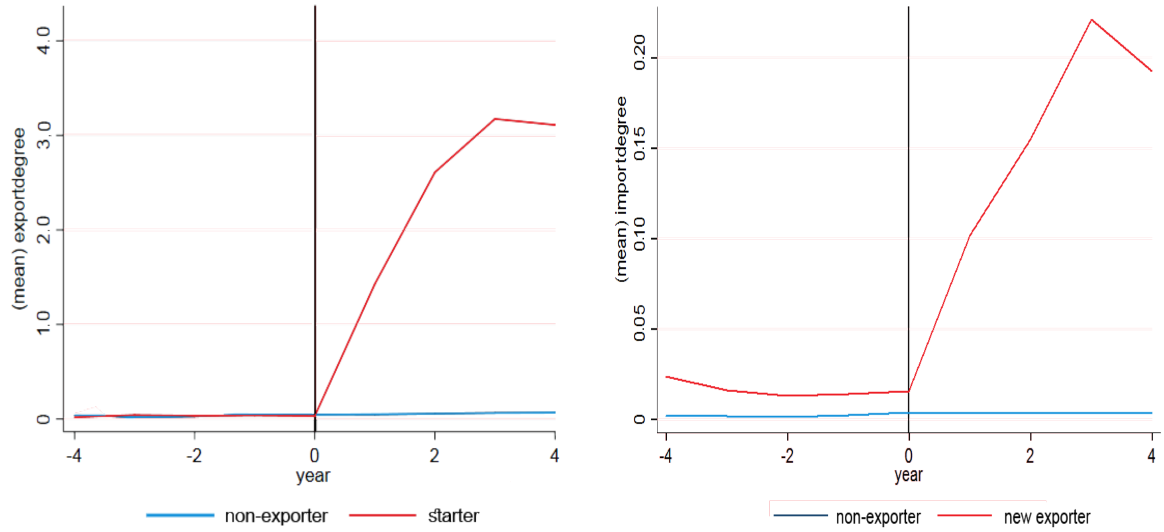


(a) Out-degree (b) In-degree

Figure 5: Domestic Network Characteristics *Notes:* The figure on the left exhibits the means of out-degree distribution of the firms, whereas the graph on the right shows the means of in-degree distribution. The blue line indicates the firms that never export, whereas the red line refers to the first-time exporters. The values correspond to the average of the weighted in- and out-degree distributions. Weighted degree distributions refer to the number of links a firm has and the transaction amount of the links treated as weights.

Figure 5 tracks the weighted out- and in-degrees while illustrating how a firm's network position shifts in the domestic network. Before export, the rank of firms' suppliers/customers starts to diversify. But this diversification deviates further after time zero. According to Figure 5, suppliers of a firm become more complex, which suggests the firms' dependency on more specialized inputs. Firms ' production processes become more sophisticated rather than being a firm with a smaller group of customers or suppliers. The intuition is clear: before exporting, firms prepare themselves by increasing their network complexity as either being customers or suppliers, as revealed in Figure 5. After they start exporting, their specialization in the supply-chain increases substantially, suggesting a learning-by-networking mechanism.

The firm's international network features are presented in Figure 5 which refers to the trade partners that the firm exports or imports. Import-degree exhibits a critical mechanism; the firms that would start to be involved in international trade have higher import-degree than those that never export during the estimation interval. Another point to notice is that export-degree have a positive trend after the entry, as expected. All in all, these network characteristics are always ignored in the literature. Yet, Figures 5 and 6 offers an alternative mechanism for the TFP premia. Investigating networks suggests that the manufacturing firms diversify further in their supply chains and become more productive and specialized.



(a) Export degree

(b) Import degree

Figure 6: International Network Characteristics *Notes:* The figure on the right exhibits the means of the import degree distribution of the firms, whereas the graph on the left shows the means of export degree distribution. The blue line indicates the firms that never export, whereas the red line refers to the first-time exporters. The values correspond to the average of the weighted import and export degree distributions. Import and export degree distributions are estimated according to the number of partner countries with the transaction volume as weights.

6.2 Difference-in-Differences Estimations

Eyeballing analysis of the previous figures illustrates the diversification among two groups after zero. In this section, the empirical specification targets determining the causal effects of exporting. Thus, the following part relies on the differences in differences. The calculation period incorporates the years between 2006 and 2017. The treatment is exporting for the first time, and the treatment group involves firms that export for the first time. Contrarily, the control group contains the firms that only supply to the domestic market.

The aim is to distinguish the impact of treatment by analyzing the shifts in the firm's productivities as estimated TFP and network dynamics by relying on the firm's degree distributions. Yet, the judgment based only on this criterion is misleading without matching the firms with similar properties. Thus, firms matched according to their propensity scores by relying on nearest neighbor matching. The primary purpose of this exercise is to design a control group with similar properties in terms of firm size as the treatment group. An attractive feature of this matching is selecting the control and treated firms with the closest propensity scores[14]. This exercise is crucially important since these marginal gains in productivity may fluctuate across various sizes. Thus, the comparison exposed the productivity differences between control and treated firms with comparable sizes.

		TFP	**Outdegree**	**Indegree**
β_{Exp}		0.19^{***}	0.11^{***}	0.14^{***}
	s.e.	(0.02)	(0.02)	(0.02)
	R^2	0.07	0.03	0.04

Table 4: Productivity and Network Gains from Exporting *Notes:* This table presents the difference-in-difference estimates of TFP, out-degree, and in-degree distribution. Treatment is to export for the first time. Standard errors clustered at the firm-level in each regression, $***$, $**$, and $*$ indicate the significance at the 1%, 5%, and 10% levels, respectively.

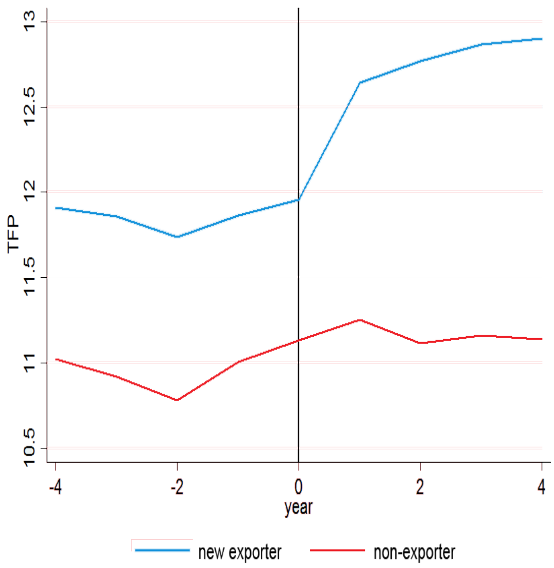
In order to assess the differential effect of exporting on TFP and production network, Table 4 reports the diff-in-diff coefficients for the first-time exporters and suppliers. There are several takeaways from this exercise. Assuming that the domestic and first-time exporters have parallel trends until the reference year by relying on the Figure 4, there are notable disparities among the treatment and control groups. As firms start to export, they raise their calculated productivity by 19%, intensify their supplier network by 14% and expand their customer network by eleven percent. The evidence suggests that productivity improvements are linked to learning-by-networking. As noted in Table 4, firms learn as they start interacting with other markets.

The empirical evidence supports the model predictions. Based on these coefficients, the firms' learning mechanism is also linked to their production network as firms enjoy higher productivities while recoding their networks. The most important contribution of this study is the validation of supply-chain expansion. Unlike the literature, these estimations point to an evolution in the value chains as the firms enhance their competitiveness. The specialization of their role as supplier/customer amplified in the treatment group. Moreover, firms that have higher degrees are associated with higher TFPs. These results designate a relationship between productivity and the sophistication of all manufacturing firms' networks, but it does not distinguish among sectors. The following section explores the variation in the two-digit manufacturing industries to control for these features.

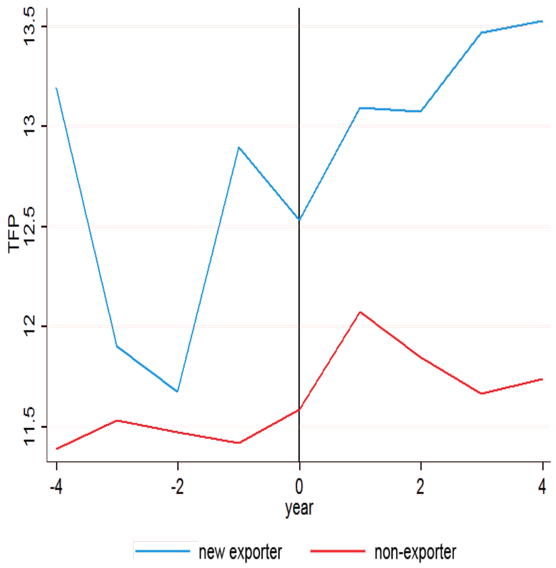
[14]See Appendix for the details on matching.

6.3 Productivity and Network Gains at Industry Level

According to the previous section, all Turkish manufacturing firms that start to export for the first time experience a significant increase in productivity. Yet, this variation originates from the firms' position in the supply chain. Though limiting these results without considering the industry characteristics could be misleading, the matching process controls the firm size, but sectoral properties may affect the outcomes.



(a) Fabricated Metals, 25



(b) Other Manufacturing, 32

Figure 7: Learning-by-Networking at Industry Level *Notes:* The figure on the left shows the firms classified as Fabricated Metals according to the NACE 2-digit classification with NACE Rev.2. as 25. In contrast, the right graph presents the firms belonging to the Other Manufacturing classification with the NACE Rev.2. 32. The blue line indicates the firms that operate only in the domestic market, whereas the red line shows the average estimated TFP of firms that start shipping at time 0.

The same regression was employed for each industry type within NACE 2-digit classified sectors to investigate the learning-by-networking hypothesis among different manufacturing industries. The matching process[15] detects the firm's nearest neighbor with the closest propensity score in the same industry to understand the causal impact.

Figure 7 portrays the difference between two industries: Fabricated Metals and Other Manufacturing, which covers the manufacturing of sports goods, toys, and medical instruments. For firms classified as Fabricated Metal industries, treatment and control groups exhibit different performances following the treatment. Thus, this graph designates a principal difference. While the firms are classified as Other Manufacturing,

[15]See Appendix for the matching details at two-digit industry level.

the treatment's effect is doubtful since both groups improve their productivity. Besides, these two groups follow different trajectories before time zero, breaking down the parallel trend assumption.

Industry	**TFP**	**Outdegree**	**Indegree**
Food	1.70***	1.94***	2.05***
	(0.49)	(0.51)	(0.55)
Textiles	1.11***	1.19***	1.23***
	(0.34)	(0.40)	(0.30)
Apparel	0.86***	0.65**	1.05***
	(0.32)	(0.33)	(0.39)
Wood	0.98**	1.24**	0.78***
	(0.42)	(0.51)	(0.26)
Printing	0.45***	0.24	0.37*
	(0.20)	(0.16)	(0.19)
Pharmaceuticals	0.49	0.50***	0.52***
	(1.94)	(0.17)	(0.16)
Plastics	0.59***	0.50***	0.52***
	(0.20)	(0.17)	(0.16)
Fabricated	0.66***	0.84***	0.32***
Metals	(0.19)	(0.23)	(0.11)
Furniture	0.07*	0.09*	0.11
	(0.04)	(0.06)	(0.07)

Table 5: Productivity and Network Gains at Industry Level *Notes:* This table presents the difference-in-difference estimates of TFP, out-degree, and in-degree distribution at the industry level. Treatment is starting to export—the standard errors clustered at the firm level in each regression. Standard errors are presented in parentheses. $*$, $*$, and $***$ denote the significance of the coefficients at %10, %5 and %1, respectively.

Table 5 presents the difference-in-differences coefficients for each manufacturing industry after controlling for the industry classification. Surprisingly, not all manufacturing industries learn by doing. Only nine sectors experience sophisticated networks and productivity gains within twenty-two manufacturing industries. Further, the evidence is well-matched with Figure 7. Fabricated Metals, for instance, enjoy learning from networking based on empirical evidence.

Nevertheless, as expected, there is no substantial evidence on learning for the firms classified as Other Manufacturing industries. Also, the Appendix provides estimates for other sectors that do not experience notable improvements. A remarkable feature of this exercise is to illustrate how productivity and supply chains are related. Although not all the two-digit manufacturing sectors display the same premiums, the empirical evidence verifies that the two concepts are accompanying. It is important to note that not all manufacturing expands their value-chains or increases their productivity following the exporting decision[16].

6.4 Income Level of the Destination

The earlier section illustrates the network and productivity gains from exporting to international markets. This part explores the destination premium by decomposing according to their income level since literature, including De Loecker (2007), claims that firms that only export to high-income destinations learn more from exporting. With that in mind, the export destinations are split into three categories: lower-middle-income, upper-middle-income, and high-income, following the recent World Bank's country classifications for 2019-2020. The firms that only target the low-income countries dropped from the sample due to their low number of observations.

Firms' export partners are broken into World Bank classifications for each reported transaction to match a firm's destination with the income level. Then, the firm's destination category is derived according to the most significant volumes for each year. Figure 8 demonstrates the TFPs of these groups. Unlike the literature findings, the firms that export to high-income countries already have superior productivity granting a selection mechanism. Further, this distinction persists until the end of the estimation period.

Nevertheless, for the upper-middle and lower-income, the behavior and the trends are approximately identical. Then, based on Figure 8, self-selection exists for the firms that trade with higher-income countries. Unlike the previous findings, there is no learning mechanism related to income level as the gap among these groups is identical for each estimation period. Hence, the firms that trade with high-income destinations do not necessarily improve their productivity by exporting; further, they self-select themselves into higher-income countries before the reference year.

[16]This variation might be due to government policies that target different sectors. In 2006, The Turkish authorities launched a comprehensive export strategy and action plan named "TURQUALITY" to promote sustainable export growth in several industries. This program aims to support branding in international markets and encourage exports. These industries include Food, Textile, Apparel, Machinery, Chemicals, Plastics, Furniture, and Motor Vehicles. Remarkably, most of the targeted industries in this program experience more sophisticated production networks and increase their productivity.

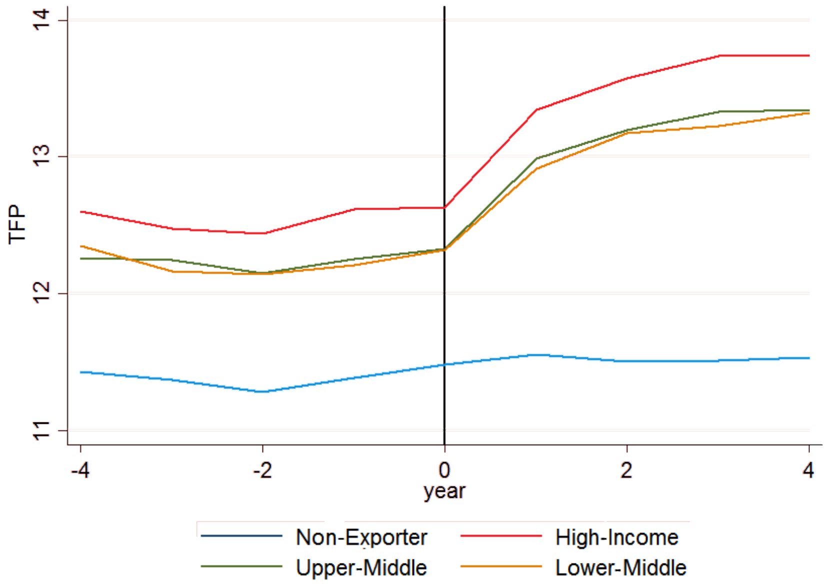


Figure 8: Income Level of the Destination *Notes:* The lines indicate the groupings according to the firm's income level of destination for the exports. The red line presents the firms that export most of their output to high-income, the green line shows the firms that trade primarily with upper-middle-income partners. The yellow line indicates the firms that majorly sell to lower-middle-income countries. Also, the blue line shows the firms that never export. The y-axis corresponds to the estimated productivity level of the different groups.

6.5 Diversification of Exports to Sophistication of Networks

Firms that decide to develop their networks on a global scale may choose how much to diversify. By diversification, the firm that shifts from a single destination target to multiple countries can network with various partners. The most traditional diversification case is a common strategy to encourage positive growth by decreasing the risk. For that reason, the consequences of constructing a more sophisticated supply network may deviate from targeting only one market. This section analyzes the benefits of expanding the export degree in networks.

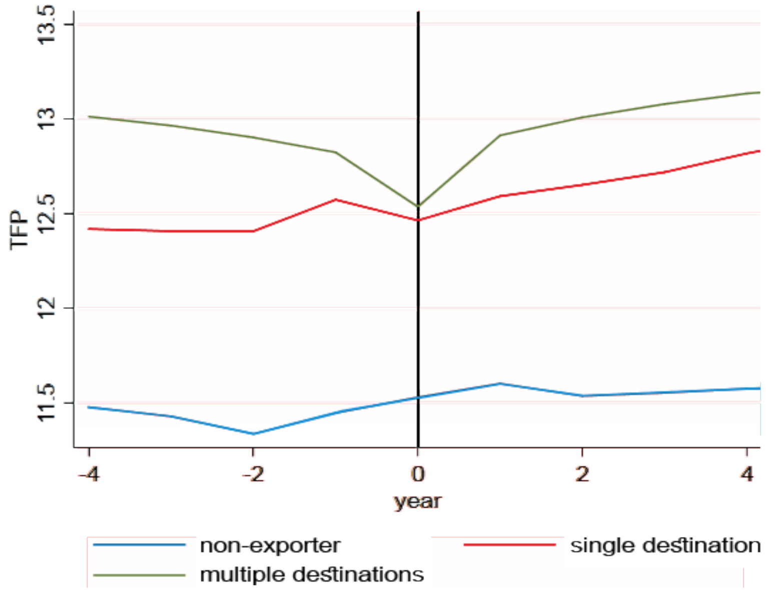


Figure 9: Diversification of Exports *Notes:* The blue line exhibits the firms that never export, the red line shows the average firm productivity for those only export to a single country, and the green line displays the TFP of the firms that trade with more than one destination in a year.

Figure 9 distinguishes the two cases: TFP differences after starting to export to a single destination or multiple destinations. Firms that interact with numerous destinations become more competitive, according to Figure 9. Intuitively, learning-by-networking produces notable gains following zero, whereas learning is limited for the firms only restrict themselves to a single destination. The main takeaway of this exercise is that gains from trade rise with expanding the export network.

7 Conclusion

This paper reveals the importance of a firm's supply-chain network sophistication for productivity. It exhibits the firm's performance and growth network dynamics using the information distilled from a sizeable Turkish manufacturing firm database.

The investigation of the production network structure in this study presents the characteristics of the production. According to the firm-level transactions, distributions of both out- and in- degrees are incredibly skewed, revealing the production network's asymmetry. Hence, firms located in those tails are the superstars of the production network. Further, the sparsity of the production network yields a non-diversified economy. Thus, this study presents the dynamics behind the supply chain heterogeneity across firms and the endogenous formation of network linkages.

After presenting the production network facts, this study focuses on the theoretical foundations of production networks. The model provides the mechanism of learning across a firm's network. Firms are heterogeneous in their networking ability and role in the model's production network. As firms expand their networks, they experience input-specific productivity gains. Further, engaging in international trade recodes the complexity of the firm's production network. In this way, decisions on the selection of suppliers endogenize the production network. Expansion of the production networks generates a cost advantage for a firm and enhances productivity. In addition, exporting requires a new arrangement of the production networks.

This study contributes to the literature by offering an alternative hypothesis for productivity premia as "learning-by-networking". The gains from trade are revisited in this paper to underline the dynamic changes in a firm's role in the production network. Empirical evidence demonstrates how the sophistication of the firms' networks varies with the decision to export. Unlike the previous literature, this paper verifies that the underlying learning mechanism requires a new production network arrangement by demonstrating the variations in weighted degree distributions. Most importantly, this paper contributes to the literature by offering the theoretical model of endogenous network formation with heterogeneous firms. The empirical evidence confirms the model predictions by providing a new mechanism for learning.

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Appendix A. Productivity Calculations

This part implements the robustness of total factor productivity calculations with the different methodologies. TFP_op corresponds to the TFP calculations according to the Olley and Pakes (1996) whereas TFP_levpet is the TFP estimated without ACF Ackerberg et al. (2015) correction. The correlation matrix below shows that the TFP methodology employed in this paper, $TFP\_levpetACF$, is robust to various methodologies.

	$TFP\_levpetACF$	TFP_levpet	TFP_op
$TFP\_levpetACF$	1.00		
TFP_levpet	0.84	1.00	
TFP_op	0.79	0.96	1.00

Table A.1: Correlations across different measures of TFP

Appendix B. Proofs of Propositions

Uniqueness of B_i

The networking of the problem of a firm relies on B_i and exogenous parameters. For this reason, the uniqueness of the market demand among all pairs of different pairs of downstream and upstream firms can be identified with the wages. Since there is a free entry condition, it can be described as f_e

$$w_i f_e = B_i \int_{\varphi_{im(i)}}^{\infty} (\gamma \Theta_i(\varphi) X_{ij})^{\frac{(\sigma-1)}{\theta}} \varphi^{\sigma-1} dG_i(\varphi) - w_i \int_{\varphi_{im(i)}}^{\infty} \sum_{j \in N_i(\varphi)} f_{ij} dG_i(\varphi) \tag{16}$$

where $m(i)$ is the intermediate input supplier of the least productive firm.

$$(\varphi_{im(i)})^{\sigma-1} B_i (\gamma T_{m(i)} (\frac{N_{i(m)}}{X_{ij}})^{-\theta})^{\frac{(\sigma-1)}{\theta}} = w_i f_{im(i)} \tag{17}$$

Taking the derivative of 16 with respect to B_i and replacing by 17 using leads to

$$\int_{\varphi_{im(i)}}^{\infty} \frac{d(\varphi^{\sigma-1}(\gamma\Theta_i(\varphi))^{\frac{(\sigma-1)}{\theta}} B_i - w_i \sum_{j \in N_i(\varphi) f_{ij}}}{dB_i} dG_{i(\varphi)} > 0 \tag{18}$$

As the firm's networking strategy remains constant an increase in market demand will increase the firm i's profits. In this way, the right side of the 16 is monotonically increasing in B_i. Further, as B $\rightarrow \infty$ all firms can source from each upstream firm:

$$B_i(\gamma T_{m(i)}(\frac{N_{i(m)}}{X_{ij}})^{-\theta})^{\frac{(\sigma-1)}{\theta}} - w_i f_{ij} \tag{19}$$

which goes to infinity.

Proof of Proposition 1 Assume there are two firms with productivities φ_1 and φ_2 where $\varphi_1 > v\varphi_2$. Let the networking strategy of the firms defines as $N_1(\varphi_1)$ and $N_2(\varphi_2)$. For firms that have higher productivity φ_1 to select $N_1(\varphi_1)$ over $N_2(\varphi_2)$ requires profits obtained among these two conditions to be

$$\varphi_1^{\sigma-1}(\gamma\Theta_i N_i(\varphi_1)X_{ij})^{\frac{\sigma-1}{\theta}}B_i - w_i \sum_{j\in N_i(\varphi_1)} I_{ij}f_{ij} > \varphi_2^{\sigma-1}(\gamma\Theta_i N_i(\varphi_2)X_{ij})^{\frac{\sigma-1}{\theta}}B_i - w_i \sum_{j\in N_i(\varphi_2)} I_{ij}f_{ij} \tag{20}$$

Further, firms with lower productivity arrange their networking strategy based on the condition

$$\varphi_2^{\sigma-1}(\gamma\Theta_i N_i(\varphi_2)X_{ij})^{\frac{\sigma-1}{\theta}}B_i - w_i \sum_{j\in N_i(\varphi_2)} I_{ij}f_{ij} > \varphi_1^{\sigma-1}(\gamma\Theta_i N_i(\varphi_1)X_{ij})^{\frac{\sigma-1}{\theta}}B_i - w_i \sum_{j\in N_i(\varphi_1)} I_{ij}f_{ij} \tag{21}$$

with these two profit functions,

$$[\varphi_1^{\sigma-1} - \varphi_2^{\sigma-1}][(\Theta_i N_i(\varphi_1))^{\frac{\sigma-1}{\theta}} - \Theta_i N_i(\varphi_2))^{\frac{\sigma-1}{\theta}}]\gamma^{\frac{\sigma-1}{\theta}}B_i > 0 \tag{22}$$

Since the productivity of the first firm is larger than the second firm it will imply that networking strategy of the more productive one should be larger than the other.

Proof of Proposition 2 The indicator functions of supplier I_{ij} and foreign customer X_{xi} takes values of 0 or 1. The profit function presented as

$$\Pi_i(\varphi, I_{i1}, .., I_{ij}) = \varphi^{\sigma-1}(\gamma\sum_{j=1}^{N} I_{ij}T_j(\frac{N_{ij}}{X_{ij}})^{-\theta})^{\frac{\sigma-1}{\sigma}}(1+\sum_{x=1}^{N}\beta_{xi})^{(1+\sigma)}B_i - w_i\sum I_{ij}f_{ij} - w_i\sum X_{xi}f_{xi} \tag{23}$$

this equation has increasing differences in both I_{ij} and X_{xi}. Further, it also presents increasing differences in X_{xi} and φ. Thus, variables that increase the networking capability $N_i(\varphi)$ such as reduction of networking costs with other firms or increase in the technology of the upstream firm will lead to a rise in X_{xi}. For this reason, firms that increase their supplier network tend to select themselves in foreign markets.

In addition, for the case of complements $(\sigma - 1)/\theta > 1$, if market demand is a constant reduction in iceberg costs results in an increase in exports, as the standard trade model suggests. But depending on this profit function, it will also increase the firm's suppliers. As a result, sourcing will increase following the reduction in iceberg costs of trade since I_{ij} is non-increasing in iceberg costs. Hence, the firms which start to export would increase their production networks. The mechanism behind the exporting and sourcing decisions is to follow more productive firms participating in foreign markets and sophisticating their production network to decrease marginal costs. All in all, productive firms become even more effective by expanding their network.

Appendix C. Industry Classification

NACE Rev 2.	**Industry**
10	Manufacture of food products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture
17	Manufacture of paper and paper products
18	Printing and reproduction of recorded media
19	Manufacture of coke and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of pharmaceutical products
22	Manufacture of rubber and plastic products
23	Manufacture of other non-metallic mineral products
24	Manufacture of basic metals
25	Manufacture of fabricated metal products, except machinery and equipment
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29	Manufacture of motor vehicles, trailers and semi-trailers
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing

Table C.2: Manufacturing Industries classified according to the two-digit NACE Rev 2.

Appendix D. Manufacturing Industries

Industry	**TFP**	**Outdegree**	**Indegree**
Beverages	1.29	1.01	1.05
	(1.79)	(0.53)	(0.50)
Tobacco	17.41	47.18	9.51
	(98.52)	(223.36)	(49.53)
Leather	0.18	0.11	0.19
	(0.17)	(0.09)	(0.13)
Paper	0.80	0.77	0.51
	(0.90)	(0.56)	(0.39)
Petroleum and Coke	1.24	1.13	0.42
	(2.44)	(2.06)	(2.37)
Chemicals	0.12	2.87	3.49
	(0.85)	(5.43)	(4.05)
Mineral	0.40	0.60	0.31
	(0.49)	(0.52)	(0.42)
Primary Metals	-0.90	0.61	0.85
	(1.09)	(1.02)	(0.77)
Computer Electronic	-0.24	0.97	0.19
	(0.84)	(1.45)	(0.82)
Electrical Equipment	0.70	0.79	0.70^{*}
	(0.77)	(0.71)	(0.35)
Machinery	-0.12	0.19	0.14
	(0.19)	(0.18)	(0.12)
Motor Vehicles	0.16	0.31	0.71
	(0.19)	(0.49)	(0.61)
Other Transport	4.33	0.45	1.05
	(6.74)	(0.84)	(3.34)
Miscellaneous	0.86	0.09	0.34
	(1.51)	(0.24)	(0.41)
Repair and Install	0.74	0.12	0.19
	(0.45)	(0.16)	(0.16)

Table D.1: Productivity and Network Gains at Industry Level

Notes: This table presents the difference-in-difference estimates of TFP,out-degree, and in-degree distribution at the industry-level. Treatment is entry to exporting. Standard errors are clustered in firm-level in each regression $+$, $*$ and $**$ denote the significance of the coefficients at %10, %5 and %1. Standard errors are presented in parentheses.

Appendix E. Details on Propensity Score Matching

	# of Controls	# of Treated
β_{exp}	41424	19993

Table D.1: Details on Propensity Score Matching by Size

	# of Controls	# of Treated
Food	6577	1462
Beverages	111	104
Tobacco	1	9
Textiles	2568	1956
Leather	998	604
Apparel	3754	2589
Wood	1468	391
Paper	420	568
Printing	2233	404
Petroleum and Coke	28	54
Chemicals	734	1033
Mineral	2150	1070
Pharmaceutical	27	104
Plastics	6577	1462
Primary Metals	789	696
Fabricated Metals	4978	2931
Computer Electronic	239	99
Electrical Equipment	998	604
Machinery	2823	1521
Motor Vehicles	756	537
Other Transport	177	72
Furniture	2450	1489
Miscellaneous	1892	825
Repair and Install	1594	744

Table D.2: Details on Propensity Score Matching at the two-digit NACE Rev. 2. industry level.

Appendix F. Production Network at 4-digit Level

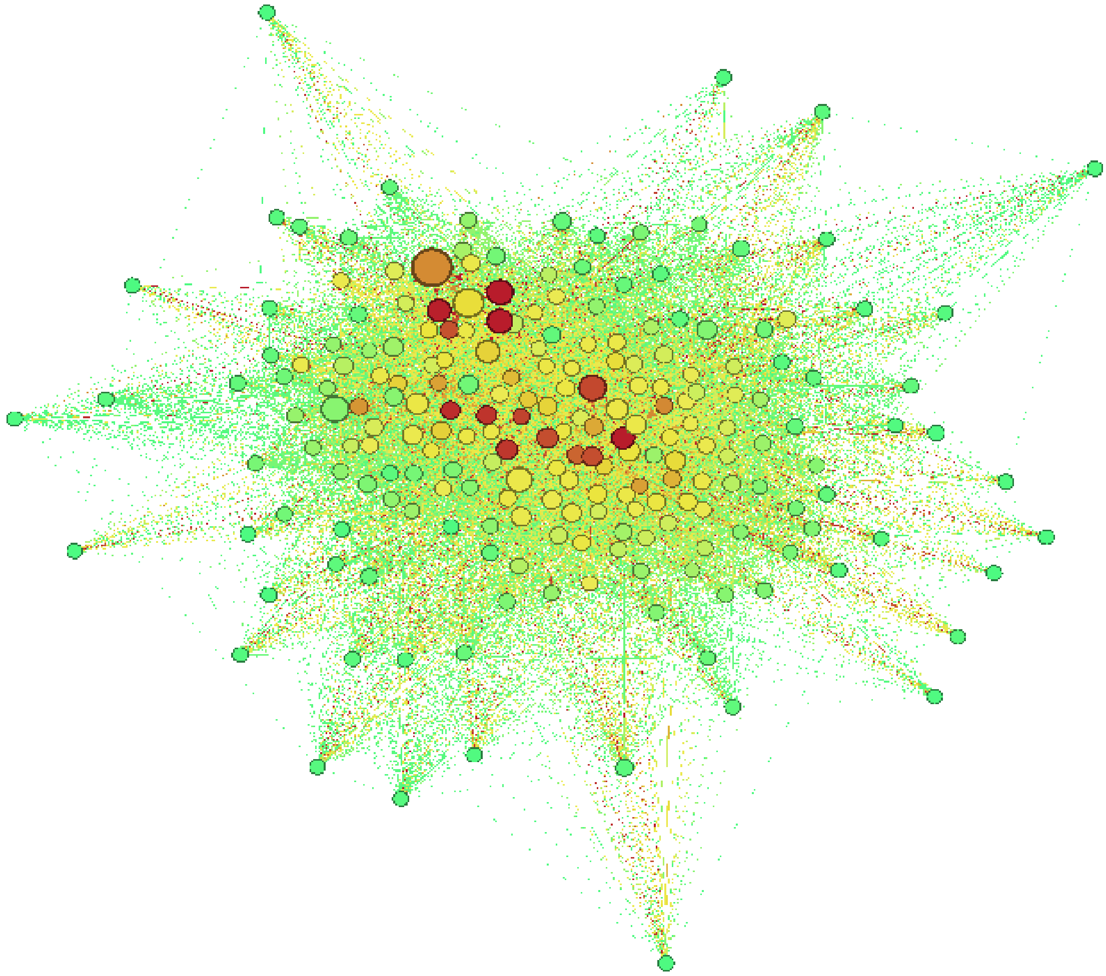

Figure G.1: Domestic Production Network *Notes:* Turkish Manufacturing Industries aggregated according to 4-digit NACE Rev 2. Classification, colors turn from green to dark red depending on the out-degrees of industries. Nodes locations estimated with the ForceAtlas2 algorithm Jacomy et al. (2014). Nodes highly trade with each other located together, and nodes are located in the periphery whether the trade is relatively weak.