Essays in Production Networks, Productivity and Inflation Connectedness

by

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Essays in Production Networks, Productivity and Inflation Connectedness

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Graduate School of Sciences and Engineering

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To Bekir Nursal Bilgin, amazing father and best friend.

ABSTRACT

Essays in Production Networks, Productivity and Inflation Connectedness

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This thesis consists of three chapters on the firm- and industry-level production networks and their role in firm-level productivity and performance over time, as well as the amplification of inflation shocks across sectors. The first chapter analyzes the interaction between firm heterogeneity, production networks, and productivity. A detailed analysis of 2006-2017 data shows that input-output linkages across Turkish manufacturing firms provide an amplification mechanism for shocks. After finding strong evidence that supports the asymmetry of the firm-level production networks, I build a simple model that captures the interaction between productivity and firm performance in production networks. Empirical results demonstrate the close relationship between the sophistication of a firm's production network, its productivity, and its entry decision to export markets. This study provides evidence on how firms become more productive if they are part of a sophisticated production network while proposing a hypothesis of learning-by-networking with other firms in their production network. It is shown that productivity gains correlated with the firm's position in the supply chain, industry class, and the diversity of its export destinations.

The second chapter applies the Diebold-Yilmaz Connectedness methodology to producer price inflation (1947-2018) and industrial production growth series (1976-2018) for 17 U.S. manufacturing sectors to analyze how supply and demand shocks propagated in the manufacturing industry. The empirical results show that supply (demand) shocks are transmitted downstream (upstream) through the input-output network in the form of price/cost increases (production/input use decreases). Going into further detail, the paper shows that the aggregate and granular input-output network measures Granger-cause the system-wide and

pairwise producer price inflation connectedness measures, respectively. The Granger causality from the input-output network to the inflation connectedness is stronger during periods of major supply-side shocks, such as the global oil and metal price hikes. Similarly, it is shown that the input-output network also Granger cause the industrial production connectedness during times of major aggregate demand shocks, such as the Volcker disinflation of 1981-84 and the Great Recession of 2008.

The third chapter investigates the relationship between input-output networks and the transmission of inflation shocks across manufacturing industries in South Korea, an economy that is more open to external shocks than the United States. Using the dynamic inflation connectedness measures for 1971-2020, we show that production networks are responsible for the amplification of inflation shocks during times of supply shocks, such as the oil price shocks of 1973-74 and 1979-80. On the contrary, production networks are weakly associated with inflation transmission across sectors if the shocks originate from the demand-side such as the East Asian Financial Crisis of 1997.

ÖZETÇE

Doktora Tez Başlığı

Iktisat, Doktora
August 17, 2020

Bu tez, firma ve endüstri düzeyindeki üretim ağları ve bunların firma düzeyinde verimlilik ve zaman içindeki performansındaki rolleri ile enflasyon şoklarının sektörler arası yayılması üzerine üç bölümden oluşmaktadır.

İlk bölüm firma heterojenliği, üretim ağları ve üretkenlik arasındaki etkileşimi analiz etmektedir. 2006-2017 verilerinin ayrıntılı bir analizi, Türk imalat firmaları arasındaki girdi-çıktı bağlantılarının şoklar için bir güçlendirme mekanizması sağladığını göstermektedir. Firma düzeyindeki üretim ağlarının asimetrisini destekleyen güçlü kanıtlar gösterildikten sonra, üretim ağlarında üretkenlik ve firma performansı arasındaki etkileşim basit bir model çerçevesinde incelenmektedir. Ampirik sonuçlar, bir firmanın üretim ağının karmaşıklığı, üretkenliği ve ihracat pazarlarına giriş kararı arasındaki yakın ilişkiyi göstermektedir. Bu çalışma, şirketlerin üretim ağlarındaki diğer firmalarla ağ yoluyla öğrenme hipotezini önerirken, daha sofistike bir üretim ağının parçası olan şirketlerin daha üretken hale geldiklerini göstermektedir. Üretkenlik kazanımlarının, firmanın tedarik zincirindeki konumu, endüstri sınıfı ve ihracat noktalarının çeşitliliği ile olan yakın ilişkisi gösterilmektedir.

İkinci bölüm, imalat sanayinde arz ve talep şoklarının nasıl yayıldığını analiz etmek için 17 ABD imalat sektörü için üretici fiyat enflasyonu (1947-2018) ve endüstriyel üretim büyüme serisine (1976-2018) Diebold-Yılmaz Bağlantılılık metodolojisini uygular. Sonuçlarımız, arz (talep) şoklarının, fiyat / maliyet artışları (üretim / girdi kullanımının azalması) şeklinde girdi-çıktı ağı aracılığıyla aşağı yönde (yukarı yönde) iletildiğini göstermektedir.Granger nedensellik ölçümleri kullanılarak girdi-çıktı ağı ölçümlerinin sektörler arası üretici fiyat enflasyonu bağlantılılığını belirlediği gösterilmektedir.Benzer şekilde, Granger nedensellik ölçümleri kullanılarak girdi-çıktı ağı ölçümlerinin sektörler arası sanayi

üretimi bağlantılılığını belirlediği de gösterilmektedir. Girdi-çıktı ağının enflasyon bağlantılılığı üzerindeki Granger nedenselliği, küresel petrol ve metal fiyat artışları gibi arz yönlü şokların yaşandığı dönemlerde daha güçlüdür. Öte yandan, girdi-çıktı ağlarının endüstriyel üretim bağlantılılığı üzerindeki Granger nedenselliği, 1981-84 Volcker durgunluğu ve 2008-2009'deki büyük durgunluk gibi toplam talep şoklarının yaşandığı zamanlarda gözlenmektedir.

Üçüncü bölüm, dış şoklara ABD'den daha açık bir ekonomi olan Güney Kore'de girdi-çıktı ağları ile enflasyon şoklarının imalat sanayilerine aktarımı arasındaki ilişkiyi incelemektedir. Bu bölümdeki ampirik çalışmanın sonuçları, 1971-2020 için dinamik enflasyon bağlantılılık ölçütlerini kullanarak, üretim ağlarının 1973-74 ve 1979-80 petrol fiyatı şokları gibi arz şokları dönemlerinde enflasyon şoklarının artmasından sorumlu olduğunu ortaya koyar. Ancak şokların 1997 Doğu Asya mali krizinde olduğu gibi talep tarafından kaynaklanması durumunda, üretim ağlarının enflasyon şoklarının sektörler arası yayılması üzerindeki etkisi çok daha sınırlı kalmaktadır.

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PRODUCTION NETWORKS AND LEARNING-BY-NETWORKING

1.1 Introduction

Research on production networks has the potential to improve our knowledge about the nature of aggregate fluctuations that originate from micro shocks. This paper investigates the underlying mechanism of shock propagation while building on firm-to-firm linkages. The productivity changes in each firm studied through the sophistication of a network according to its importance. Moreover, it provides implications for policies that can reduce the losses through shock propagation mechanisms across firms.

This paper focuses on the firm-level production networks and the amplification of shocks through these linkages to provide insights about the micro-origins of aggregate fluctuations in Turkey. The characterization of the production process links productivity and trade in intermediate goods. As part of this effort, I first provide evidence on the diverse response of firms when they face supply and demand shocks. I show that the sophistication of the supplier/customer networks can be an important factor contributing to the firm-level productivity performance. I estimate this association by relying on firm-level data on business-to-business transactions, imports, exports, and balance sheet information for Turkish manufacturing firms between 2006 and 2017.

This paper starts by documenting the empirical sparsity of firm-to-firm linkages and how idiosyncratic shocks to major firms could diffuse through the economy in the presence of asymmetries. According to standard diversification argument of Lucas (1977), as the number of firms goes to infinity, aggregate volatility becomes negligible at the rate of $1/\sqrt{N}$ due to the law of large numbers. However, this reasoning is only valid if the tail parameter of the power-law distribution exceeds 2. Nevertheless, this could be a strong assumption for firm-level linkages.

Importantly, the failure of the standard diversification argument leads to aggregate fluctuations if the economy is not diversified. Thus, this paper focuses on the shock propagation mechanism in a Turkish production network, which is highly asymmetric. As stated in Gabaix (2011), the diversification argument fails if the firm-size distribution exhibits fat-tails that specify the granularity of the economy. Further, Acemoglu et al. (2012a) 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. The literature argues that most of those linkages are the underlying mechanism behind the shock transmission even at the sectoral level, such as Carvalho (2014), which examines the U.S. Input-Output network and its fat-tailed behavior across sectors. It illustrates how skewed is the out-degree distribution of the industry and exploits the asymmetry among suppliers. Bernard et al. (2019) argues that both out-degree distribution, which shows the number of customers per firm, and in-degree distribution, meaning the supplier amount per firm are very skewed. This paper confirms that the Turkish production network is not well-diversified, and so a power-law distribution with fat-tails can capture linkages across firms. Hence, any shock to a firm not absorbed by the network. Further, shocks that hit critical firms may lead to aggregate fluctuations in Turkey's output.

After observing the sparsity of the Turkish production network, this paper builds on a multi-sector economy framework developed by Long and Plosser (1983a) to illustrate the importance of firm linkages. According to the model, shocks that originate from a firm's suppliers and customers can affect the firm's output and productivity. Still, the results are not limited to the domestic supply chain. This analysis also includes firm imports and exports to evaluate the responses to international trade and exchange rate shocks on the Turkish economy.

In its most important contribution, this work provides evidence on how firms learn-by-networking by illustrating the endogenous changes in domestic and international supplier and customer networks with firm performance. As a firm's average productivity and the number of its suppliers/purchasers increase, its productivity is likely to grow. The order of the productivity increase expected to start with the suppliers, and then it is followed by the rise in the firm's productivity, and finally, by the purchasers' productivity. Also, this intuition is valid for the income level of the trade partner. First, the supply network increases, and after that, it is followed by an increase in firm productivity, which, in return, enhances the growth of the export network. Also, this paper demonstrates how exporting decisions increase a firm's productivity. By relying on the Turkish manufacturing firms that are starting to ship abroad, this study examines the causality between productivity and exporting decisions. Unlike previous work, this paper demonstrates that a firm must increase the sophistication of its production network before beginning to export.

One attractive aspect of this paper is its focus on various trade partners. The estimations confirm that the variations generated due to the partner country's characteristics. To demonstrate this, I present the differences between firms that ship to different destinations and those that import from various partners. Interestingly, firms that export to high-income countries tend to increase their productivity significantly. However, more productive firms tend to import from lower-income partners. Therefore, this paper investigates the overall production process of manufacturing firms, focusing on the productivity and quality of the input. The results show that the coefficient of the production function is highly divergent across both sectors and firms. Bearing this in mind, I conclude that these estimations reflect an essential structure of the Turkish manufacturers: productive firms use their geographical and labor cost advantage to export to competitive markets while using imported inputs.

This study contributes to several different strands of the literature. The first is the literature that reviews the role of input-output linkages across sectors as a transmission mechanism (Long and Plosser (1983a); Horvath (1998), Horvath (2000); Shea (2002); Gabaix (2011); Acemoglu et al. (2012a); Carvalho et al. (2016)). Although these papers focus on sectoral-level linkages, an emerging component of this strand declares that firm-level idiosyncratic shocks will diffuse into the economy (Di Giovanni et al. (2014); Carvalho and Voigtländer (2014); Barrot and Sauvagnat (2016); Di Giovanni et al. (2018); Boehm et al. (2019)). Following the evidence on propagation, the estimations in this paper rely on firm-level origins of aggregate fluctuations. Further, Tintelnot et al. (2018) demonstrate that gains from trade depend on domestic firm-to-firm linkages and illustrate the endogenous formation of the links following international trade shocks. Unlike the previous work, this paper provides evidence of the importance of firm competitiveness and productivity by relying on both domestic and international firms' networks.

The focus also includes the direction of shocks. Shea (2002) states that technology and taste shocks have opposite effects. According to those estimations, technology shocks diffuse downstream, whereas taste shocks shift the upstream demand curves. Similarly, Acemoglu et al. (2016a) exploit a pattern for the demand-side and supply-side transmission mechanism. In other words, demand-side shocks, including necessary inputs from China, would deliver to customer industries. Further, there is an inverse propagation for the demand-side shocks to supplier industries. Demir et al. (2018) examines Turkish-firm level data to document that an increase in credit financing for the importers transmitted through the firm's downstream firms as shocks. However, this study restricts its focus to importer firms in Turkey. This work contributes to the literature by testing the direction of shocks with various firm attributes, including the firm's value-added and productivity.

Another strand of the literature evaluates the impact of international trade on productivity. Here the focus of the study is the relationship between engagement in international trade and economic growth. For instance, Bernard and Jensen (1999) analyzes the causal relationship between productivity and exporting. They argue that before shipping abroad, prospective exporters begin to show desirable performance characteristics. Examining Chilean plant-level data, Pavcnik (2002) finds significant evidence of an improvement in plant-level productivity following Chile's trade liberalization. Other studies identify the importance of firm-level networks on productivity, including Bernard et al. (2019). Another trade diagnosis can be destinations as Crinò and Epifani (2012), which focuses on the destinations goods manufactured by Italian manufacturing firms that export. They identify a negative correlation between productivity and sales to low-income countries.

The nature of the production networks of Turkish manufacturing firms is the key to understand the amplification of shocks. Being an upstream or downstream firm directly influences the firm's role in the shock propagation mechanism. This paper demonstrates that production linkages have various implications for the firm's value-added, and productivity. Theory and the empirical results reveal that output is shaped by the supply-side, including the domestic and imported intermediate goods.

Another noteworthy point is the productivity level of the firm that begins to export or import. Interestingly, the results in this paper support the literature that examines learning-by-exporting theories, including De Loecker (2007) and Van Biesebroeck (2005), who find a substantial increase in the productivity of the firms that start to export. Also, Halpern et al. (2015) records that firms that rely on imported inputs generate higher revenue productivity. The empirical evidence supports both positions in the literature.

This study also adds this literature by exploiting the role of production networks in trade while proposing learning-by-networking structure. The findings are in line with studies that demonstrate the link between exporting and total factor productivity. But, the estimations in these studies restrict their analysis to exporting decisions. I build on this literature by proposing that firms learn from their suppliers and customers. Yet the firm's network sophistication is not restricted to the domestic network. I also combine the firm's network expansion in international markets. To compute the relation between production networks and the productivity parameters, I emphasize the diversity of domestic and foreign input-suppliers associated with higher productivity.

The literature also indicates that firms self-select into international markets because of their productivities. Thus, the puzzle is the direction of causality between productivity and new exporters. Introducing trade frictions, Melitz (2003) argues that only firms with higher productivity will export, a decision that attributes to the iceberg costs and the fixed costs incurred by exporting decisions. Consistent with this model, my empirical findings in this paper explicitly show that higher productivity is associated with importing and exporting. Nevertheless, the firm's domestic network linkages, including its output and input, are not related to its productivity. Another way to examine productivity variation is the destination of the firm's exports and origin of its imports. The efficiency of the firm is related to the income level of the partner. As the income level of the trade partner increases, productivity is significantly and positively related to this increase. These results might predict the link between productivity and the quality of the firm's output. Interestingly, the results indicate that higher-income export destinations require higher efficiency by manufacturing firms..

This study shows that Turkish manufacturing firms are heterogeneous in terms of their productivity levels, production network positions, and their roles in international trade. I start by stating the facts about the Turkish production network. Then, the model provides the theoretical facts that underlie the shock mechanism and the pattern of propagation. Firm-level empirical evidence confirms the model's predictions while indicating the heterogeneity originates from the variations in supply-chain. Hence, productivity premia investigated through diversity in firms' input-output networks. Further, this study concludes by providing evidence on the learning-by-networking hypothesis.

1.2 Facts about Turkish Production Network

This section presents the building blocks of this paper, including the general characteristics of Turkish manufacturing firms. I rely on the micro-foundations of network theory to reveal why firm-level shocks in the Turkish manufacturing industry can generate aggregate fluctuations. Then, I shift the focus to the sources of variation in firm-level productivity.

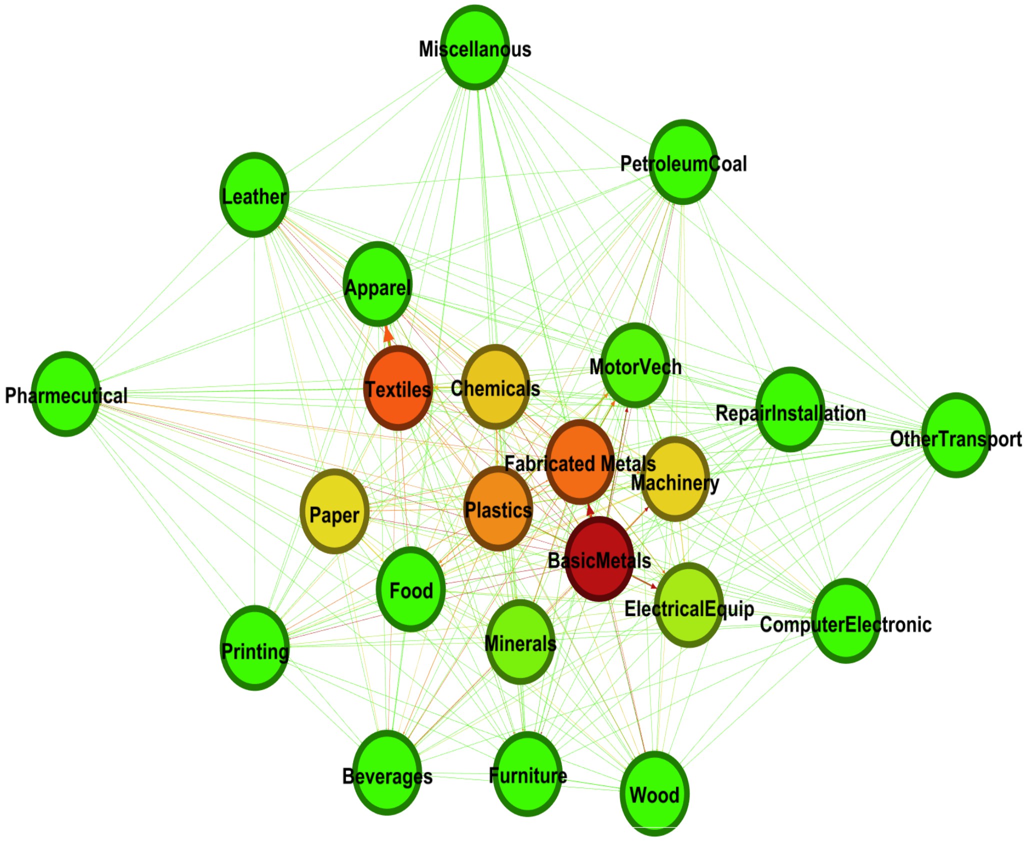


Figure 1.1: Domestic Production Network *Notes:*Turkish Manufacturing Industries aggregated according to 2-digit NACE Rev 2. Classification.

In the remainder of this paper, the adjacency matrix of a network established as the production linkages among manufacturing firms. Vertices represent the sales and purchases of intermediate goods and weighted with the value of the transaction. Correspondingly, each node represents a firm. Since the cost of transactions varies across firms, this paper employs a directed and weighted network structure among firms. The goal is to discover the variations among firms by focusing on the weighted degree distributions of firms in the supply chain. Weighted in- and out-degree distributions capture the demand and supply sides of the production process for each firm.

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

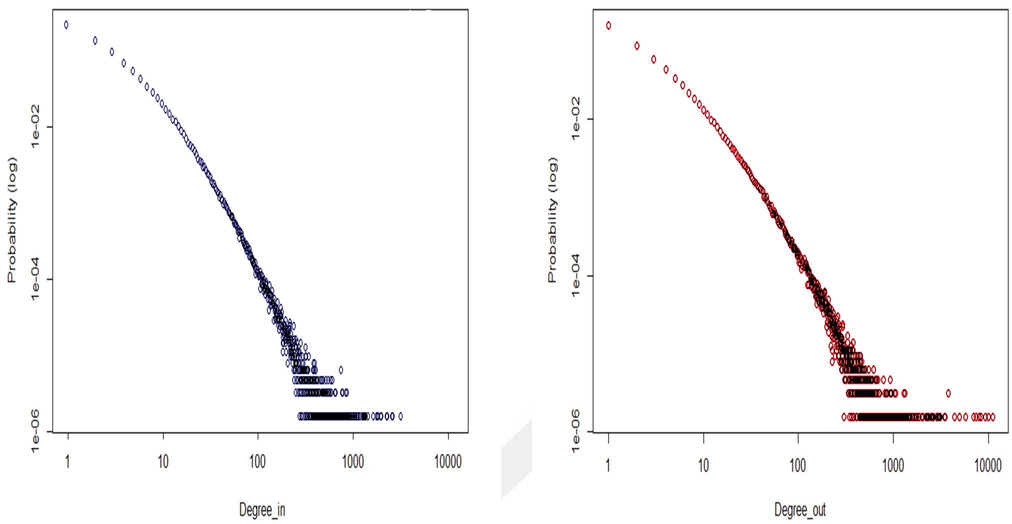
The network shown in Figure 1.1 is constructed from the input-output linkages among the manufacturing sectors. It illustrates the heterogeneity among production linkages at the sectoral level. It attributes to the sectoral level illustration of the weighted links that we observe at the firm-level. In the remainder of this paper, the calculations estimated for the production networks refer to the firm-level.

Location of the nodes determined with The Force Atlas 2 algorithm (see Jacomy et al. (2014a)). Sectors that have higher intermediate input transactions locate closer to each other, others that engage in relatively less trade pushed away from the center. Colors indicate the industry's importance as a supplier to other sectors; they turn from green to dark red depending on the sectoral out-degree. In this way, upstream sectors that have higher weighted out-degrees tend to have red or dark red colors.

Several takeaways from the sectoral network analysis motivate this paper's interpretation of the micro-origins of aggregate fluctuations. First, input-output linkages indicate that trade between sectors is highly heterogeneous. Second, we would expect supply shocks that hit upstream industries, which located close to the center of the network, will transmit to other placed sectors in the periphery through the weighted edges. Third, industries that positioned close to each other due to significant transactions in intermediate inputs. Fourth, even the aggregated sectoral level linkages demonstrate the sparsity of the network. To evaluate the impact of asymmetries in firm performance, the rest of the paper investigates the production network at the firm-level and its corresponding weighted links among firms.

Fact 2. *Both weighted out- and weighted in-degree distributions reveal fat-tails at firm-level.*

Figure 1.2 presents the probability mass function of manufacturing firms' intermediate output supply as a weighted out-degree and intermediate input purchase as a weighted in-degree. The distributions of degrees shown in these figures are incredibly skewed, revealing the asymmetry of the Turkish firm network. The firms located in the right tail of the degree distributions correspond to firms that have a large number of links. Firms found in these fat tails indicate



(a) Weighted In-Degree

(b) Weighted Out-Degree

Figure 1.2: Firm-level Weighted Degree Distributions

that those firms are the significant and superstar firms of the production network. More, if disruptions originate from those firms, their impact on the economy will not vanish in the long run.

Shocks to firms that have high weighted in- or out-degrees may generate domino effect through the production network. Based on these graphs, we can conclude that the Turkish manufacturing production network is highly asymmetric. Extreme asymmetries in the manufacturing industries are attributable to the presence of the firms located on the right tail of the distribution. As suppliers or purchasers of intermediate inputs, they are “too connected to fail.”

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. (2012a) 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 process of decay in volatility is much slower than the proposed rate of $\sqrt{N}$.

Surprisingly, the standard diversification argument does not apply for this supply-chain. Still, just looking at the graphs of in- and out-degrees distribution is not sufficient to conclude. We need to identify the distribution of the firm-level in-and out-degrees using standard tests. As Figures 1.1.a and 1.1.b suggest, it would be best to fit the power-law distribution (see equation (1.1)) to the data 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. (2012a), we check the tail parameter ζ, which lies at the heart of the analysis corresponding to asymmetries among firms. For the values of ζ that are larger than 2, the first two moments well defined, and the shocks wash out at a rate that is consistent with the standard diversification argument. For the tail parameters smaller than 1, none of the moments of the distributions are defined. If the tail parameter is equal to one, $\zeta = 1$, the Zipf's law applies, and the rate of the decay is proportional to $1/ln(N)$. Nevertheless, when $\zeta \in (1, 2]$, the variance becomes infinite, and standard diversification fails. Correspondingly, firm-level shocks diffuse through the aggregate economy.

$$p_k = ck^{-\zeta} \tag{1.1}$$

	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 1.1: 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 1.1 presents the tail parameters of the Turkish production network. From 2006 to 2017, it significantly fits the power-law distribution.[1]. Interestingly, the distribution of the firm-level in and out-degrees associated with power-law distribution. Thus, the network structure sustains its asymmetry with very similar tail parameters. The tail concentrated with more mass, and the economy is not diversified enough to average out the idiosyncratic shocks. This result motivates the fact that shocks propagate through firm-level input-output linkages.

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

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

(a) Average TFP (b) Annual TFP growth

Figure 1.3: TFP of the Turkish Manufacturing Firms

Figure 1.3 presents the annual average and growth of the firm-level TFP 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. For the calculation of the firm-level production functions, I follow Levinsohn and Petrin (2003) and use intermediate inputs as a proxy to control for the unobservables. To overcome the identification problem that originates with the usage of both labor and intermediate inputs, I undertake the correction suggested Ackerberg et al. (2006). In the remainder of this paper, I use the productivity estimates obtained from estimations that have lagged inputs as instrumental variables. Once the production function is estimated, it is possible to get total factor productivity, which is the difference between the actual and the estimated log output. For the robustness, I also obtain the production function estimates using the alternative Olley-Pakes methodology. The correlation matrix in Appendix A shows that the TFP measures obtained using the Levinsohn-Petrin method with the Ackerberg correction highly correlated with those obtained by the alternative Olley-Pakes methodology.

Fact 4. *Across manufacturing sectors there is substantial variation in the average TFP during 2007-2016 period.*

Figure 1.4 presents how TFP varies among different manufacturing sectors that classified according to the NACE Rev 2. Least productive sectors involve the

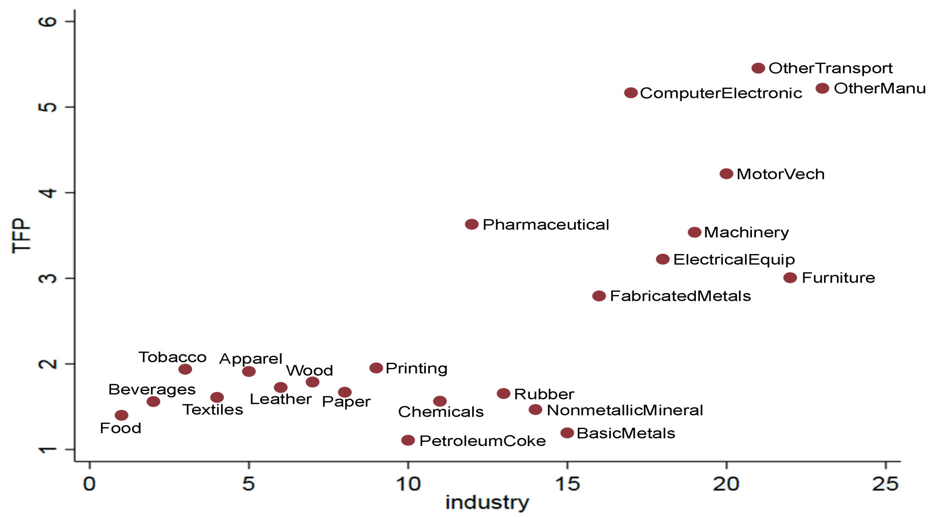


Figure 1.4: Average TFP across manufacturing sectors Turkey

manufacturing of coke and refined petroleum products with the production of primary metals. In contrast, productive manufacturing Turkish sectors dominated with other manufacturers, transport equipment manufacturing, and computer, electronic and optical product manufacturing.

Fact 5. *Importers and exporters differ in terms of firm characteristics.*

Literature argues that characteristics of exporters and importers are differ in terms of firm characteristics from those that operate 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:

$$y_{i,t,j} = \alpha + \beta\, trade_{i,t,j} + \eta\, l_{i,t,j} + \mu_t + \lambda_j + \epsilon_{i,t,j} \tag{1.2}$$

where $y_{i,t,k}$ is the characteristics of firm i at year t in industry k; $trade_{i,t,k}$ is the dummy that takes values 0 or 1, and it indicates whether the firm is only an exporter, only an importer or both importer and exporter; and $l_{i,t,k}$ is the log of the number of firm employees. The regressions controlled for different NACE Rev.2 sectors and years, sequentially.

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

Table 1.2: Firm characteristics and premiums of importing and exporting. Notes: All regressions include industry and time fixed effects. The physical units are deflated according to the 2-digit industry deflators.

A straightforward measure, β of the equation 1.2, estimates the differential between firms that directly import, export, or perform both provided in Table 1.2. This principal interest β indicates the relative performance of the firms according to their engagement in international trade. In each case, groups that participate in international trade display superior performance. The firms, both export and import by themselves, have the highest premia. According to Table 1.2, their value-added per worker is 10% more than firms that do not participate in international trade. Also, they are more profitable, and they tend to pay higher wages than other firms. But the main focus of this exercise is the productivity per worker. I also find that these firms are forty percent more productive than the firms that limit themselves to the domestic market. In the next section, I investigate these variations among the firms.

1.3 Model

Motivated by the facts presented, this section employs a multi-sector economy model (developed by Long and Plosser (1983a), Acemoglu et al. (2012a), and Halpern et al. (2015)) to determine how firm-level shocks diffuse through the production network. The model also allows analyzing the interaction between a firm's performance and the internationalization of its production network through exporting and importing. This part assumes a static modeling framework with N firms to clarify the role of input-output linkages.

The firm i has the following Cobb-Douglas production function,

$$Y_i = A_i {L_i}^{\alpha_i} \prod_{j=1}^{n} X_{ij}^{a_{ij}} \tag{1.3}$$

where Y_i is the output of firm i, A_i is the firm-specific productivity, L_i is the number of labor, and X_{ij} is the amount of intermediate product produced by a representative firm in sector j which used as input by firm i.

The firm can choose to purchase its intermediate inputs from domestic and international markets at prices p_j^H and p_j^F (both in domestic currency), respectively. Firm i can generate a composite intermediate good X_{ij} using the domestic X_{ij}^H and imported X_{ij}^F varieties of good j.

$$X_{ij} = [(\lambda X_{ij}^H)^{\frac{\theta-1}{\theta}} + ((1-\lambda)X_{ij}^F)^{\frac{\theta-1}{\theta}}]^{\frac{\theta}{\theta-1}} \tag{1.4}$$

where θ is the elasticity of substitution parameter. λ, is a distribution parameter between zero and one, which shows the divergence between the imported and domestic varieties required for production.

In the case of firms that export, the definition of the trade frictions introduced into the model relies on Melitz (2003). Firms that export encounter both τ as iceberg costs and f_{ex} as the initial fixed cost to start exporting. To ship one unit to an export market, firms have to pay τ units of iceberg costs per-unit. Further, profits diverge across firms depending on the firm's exporting status since firms pay to hire f_{ex} units of labor.

In this model, the main assumption is that firms that engage in international trade produce more output and gain more profits plus higher productivity. Exports allow firms to increase their production and diversify their activities that enable them to increase profits.

The profit of a firm expressed as,

$$\pi = \begin{cases} \pi_d & \text{if firm } i \text{ does not export } t \\ \pi_d + \pi_e(1-\tau) - f_{ex} & \text{if firm } i \text{ exports to international markets} \end{cases} \tag{1.5}$$

The firm has an option to sell its output as a consumption good to households or as an intermediate good to other firms. In this way, the market-clearing condition for firm i's product is :

$$y_i = c_i + \sum_{j=1}^{n} x_{ij} \tag{1.6}$$

firm's output is the sum of consumption good c_i that sold to the household or x_{ij}

supplied to other firms as intermediate good.

The household utility function is given by

$$u(c_1, c_2, ..c_n, l)) = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} \tag{1.7}$$

The household utility assigns β_i as a weight to the consumption of good c_i. $\gamma(l)$ is a decreasing function of labor, which reflects the disutility derived from work. Households spend all of their income to buy final goods.

The household budget constraint is

$$\sum_{i=1}^{n} p_i c_i = wl \tag{1.8}$$

The classification of the firms relies on their involvement in international trade. In each case, whether they depend on domestic or international linkages, production networks play a significant role in the firm's output. The main interest output depends on the supply-side of production, including all productivity shocks associated with inputs. In equilibrium, firms maximize their profit; all households maximize their utility, commodity, and labor markets clear.

Proposition 1. The change of firm i's output is the linear combination of the productivity shock dz_i with the weighted sum of the changes in its intermediate input supplied from dln_j if the firm operates only in the domestic market.

$$dlny_i = \sum_{j=1}^{n} a_{ij} dlny_j^H + dz_i \tag{1.9}$$

This proposition highlights how shocks propagated through the domestic production network. Note that this expression includes the network effects with the term a_{ij}. Network effects have no significance if and only if firm i does not use any inputs from other firms ($a_{ij} = 0$) Nevertheless, almost all firms rely on intermediate inputs, which are the primary mechanism of circulation in production networks.

The intuition behind the downstream effects is straightforward. The a_{ij} term refers to the intermediate inputs. Still, the expression does not include a term that links the firm's output to customer's demand. In other words, this proposition posits only that supply-side shock propagation matters for the output.

Proposition 2. The change of firm i's output is subject to international supply shocks, measured by $dlny_j^F$ and weighted by λ which the fixed proportion of the imported input in total intermediate input for the firms that import.

$$dlny_i = dz_i + \sum_{j=1}^{n} a_{ij}[\lambda dlny_j^H + (1-\lambda)dlny_j^F] \tag{1.10}$$

According to equation 1.10, the parameter λ reveals the divergence between the same intermediate input from diverse suppliers. Further, the shock propagation mechanism is not limited to the domestic market for importers. Shocks to the production of the firm's international suppliers, $dlny_j^F$, and λ also have an impact on network outcomes. Again, these shocks would diffuse from upstream to downstream firms as determined by the parameter a_{ij}.

Proposition 3. The change of firm i's output is subject to productivity shock $dlnz_i$; intermediate input a_{ij}; the output of its domestic supplier $dlny_j^H$; the iceberg costs from exporting τ; and the export share of the output δ for the firms that export.

$$dlny_i = \frac{dz_i + dln(1-\tau) + \sum_{j=1}^{n} a_{ij} dlny_j^H}{(1-\delta)} \tag{1.11}$$

Intuitively, this proposition captures the fact that exporter firms have a higher output or productivity than firms that sell only to the domestic market. The expression for the output covers the export share and the iceberg costs of transportation. Furthermore, the denominator of this expression guarantees that an exporter firm will have higher output or productivity if the firm can afford the τ and initial fixed cost of f_{ex}. For instance, if the firm chooses not to export $\delta = 0$ and pay zero as iceberg costs $\tau = 0$, then this proposition directly simplifies into Proposition 1.

Proposition 4. The change of firm i's output is subject productivity shock, $dlnz_i$, the weight, λ; intermediate input, a_{ij}; iceberg costs τ; its export share in production, δ; and output of its domestic and international suppliers as $dlny_j^H$ and

$dlny_j^F$ for the firms that import and export.

$$dlny_i = \frac{dz_i + dln(1-\tau) + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H}{(1-\delta)} \tag{1.12}$$

There are several implications of this model. All of the propositions presented above underlines the network effects. This model provides evidence on how firms learn-by-networking by illustrating the endogenous changes in domestic and international supplier and customer networks with firm performance. The supplier firm's productivity and output directly linked to production.

In particular, these network linkages across firms can propagate the shocks that originated in the supplier. Suppose that, as in the model, firm j supplies inputs to firm i, and an adverse shock hits it. The decrease in the supplier firm j's output directly reflected in the firm i's output, and then this shock transmitted to firm i and its customers. These higher-order effects suggest a diffusion mechanism in the aggregate economy. In this way, shocks that originate from the supply-side propagated through downstream.

In this model, the firm heterogeneity originates from the decisions regarding importing or exporting. As stated in Melitz (2003), firms may self-select into export markets because of their ability to undertake more complex production organizations. If the iceberg cost of being involved in export markets, τ, is not equal to zero, then the impact of export premia on output and productivity will be significant, as stated in Propositions 3 and 4.

1.4 Data

The empirical part relies on the combination of several Turkish firm-level datasets between the years 2006 and 2017. This paper restricts its attention to manufacturing firms. To do so, four-digit NACE Rev. 2. sector codes used to identify these firms. Only firms classified as manufacturing industries, according to NACE Rev. 2. included in the dataset.

The production networks identified in this paper created according to the VAT statements of each firm. Firms have to report each transaction to the Ministry of Finance. The lower limit of these transactions is 5000 Turkish Liras, which is approximately 730 U.S. dollars. These reportings are the building blocks of the weighted production links among firms.

The customs declarations are the dataset that covers the different destinations of the firm's international partners, for the firms that directly export or import. Customs report the name of the partner country with which the firm trades. Since estimations for each country would not be efficient, this study forms various groups with similar properties. The appendix provides the details of these groupings.

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Year	**Firms, #**	**Size**	**Direct Exporters**	**Direct 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 1.3: Descriptive Statistics *Notes:* Firms, # is the number of firms each year in the manufacturing industries. The average size is the mean of the number of registered employees. Direct importers or exporters shows the percentage of firms that export or import each year.

The balance sheets, income statements, and number of registered employees of each firm included in the calculations to cover all characteristics. Proceeding parts focus on the estimates of value-added and total factor productivity to distinguish the variations across firms. The final data is an unbalanced panel covering twelve years, and Table 1.3 presents the descriptive statistics. Additionally, all of the firms' physical units in the corresponding period deflated according to the producer price indices for each two-digit industry—these PPI indices collected from the Turkish Statistical Institute.

1.5 Shock Propagation

After classifying the production network by utilizing buyer-seller declarations, this section searches for empirical evidence to find the underlying mechanism of shock propagation. Recall that the model section demonstrates the importance of the input-output linkages and these predictions present the direction of shock propagation. To check for the course of different shocks, I concentrate on diverse patterns of diffusion on firm-level linkages, including the value-added, and TFP variations of the Turkish manufacturing firms. The following specification used to quantify these,

$$dlny_{i,t} = \beta_{Di}\, DomI_{t-1} + \beta_I\, ImpI_{t-1} + \beta_{Dq}\, DomQ_{t-1} + \beta_E\, ExpQ_{t-1} + \zeta_s + \nu_l + \mu_t + \epsilon_i \tag{1.13}$$

According to this designation, input supply $DomI_{t-1}$, refers to the firm's intermediate inputs from the domestic market, whereas imports denoted as $ImpI_{t-1}$. Correspondingly, the output $DomQ_{t-1}$ is the supplied value to the domestic market. $ExpQ_{t-1}$ is the value that the firm directly exports to other markets. ζ_s is the 4-digit industry fixed effects, ν_l is the size fixed effect, and μ_t is the year fixed effect. The coefficients β_{Di}, β_{Ii}, β_{Dq} and β_{Eq} measure the significance for each variable of interest: Value-added and TFP.

1.6 Direct Propagation

Direct propagation refers to the first-order links among firms. This mechanism treats the production network as if it has only direct linkages. In this section, the main interest is whether there is a variation between the different links. Then in a discussion of indirect propagation, examine second-order suppliers and customers in the production network.

1.6.1 Value-Added

In this section, the impact of different network edges on value-added evaluated. Each linkage in the estimations shows are the weights as the volume of transactions rather than dummies. Table 1.4 presents the estimates of production network effects for the real value-added variable of each firm. In this light, Column 5 shows the relevance of the production linkages to the firm's real value-added; these coefficients are in line with the model's predictions. The supply-side inputs including β_{Di} and β_I are significant. More interestingly, linkages that capture the demand-side, such as β_{Dq} and β_E, are insignificant. The results of this exercise are consistent with the theoretical foundations introduced in the Model section. In particular, shocks that originate from the supply-side transferred across the firm network by the forward linkages.

	Value-Added				
β_{Di}	0.88**				0.54**
	(0.08)				(0.11)
β_I		2.08**			1.07+
		(0.25)			(0.43)
β_{Dq}			0.60**		0.17
			(0.03)		(0.09)
β_E				3.26**	0.51
				(0.86)	(0.37)
R^2	0.32	0.28	0.41	0.15	0.49
# of Obs.			—— 1,066,818 ——		

Table 1.4: Propagation of Shocks through Outputs at the Firm-level *Notes:* This table presents estimates calculated by regressing firms' real value-added levels of firms on their domestic input-output linkages with import and export values. All regressions include fixed effects for 4-digit industry code, year, size and firm. The robust standard errors are reported in the parentheses. The stars $**$, $*$, and $+$ indicate significance at the 1% , 5% , and 10% levels, respectively.

The previous estimation treated firm import and export volumes without considering their destinations. Still, there might be variations generated with the trade partners on value-added. The destinations and sources of trade classified into six groups: North America (NA), East Asia (EA), Western Europe (WE), Southern Europe and Balkans (SEB), Middle East and North Africa (MENA), and Others to investigate the differences associated with the partner. The details of the countries and the groups presented in the Appendix.

The significant linkages generated from the supply-side persists even after the decomposition of trade partners, as in Table A.1. Interestingly, there is considerable diversity across distinct trade partners. Imports from North America and MENA countries improve the value-added of the firms. On the contrary, inputs from Southern Europe and the Balkans negatively correlated with the firm's value-added.

1.6.2 Productivity

Due to variations in their capital, labor, sector, and intermediate input decisions, firms are heterogeneous in measured total factor productivity. But what shifts the productivity of manufacturing firms is a black box based on a

Cobb-Douglas production function. This paper purposes learning-by-networking as the change of productivity by considering the complete structure of the productive firms' production networks, including their domestic and international input-output linkages. Interestingly, the superior performance of Turkish manufacturing firms is due to their imports and exports. This explanation is compatible with the hypothesis espoused in the literature that the most productive firms engage in foreign trade.

	Total Factor Productivity				
β_{Di}	0.80				-2.64**
	(1.61)				(1.14)
β_I		3.97**			2.68**
		(1.04)			(0.98)
β_{Dq}			-3.31**		-0.91
			(1.70)		(1.48)
β_E				8.08**	5.18**
				(1.01)	(1.20)
R^2	0.00	0.58	0.01	0.68	0.72
# of Obs.			—— 1,066,818 ——		

Table 1.5: Domestic and International Production Networks and Firm-level Productivity *Notes:* This table presents estimates of the firm-level productivity regressions on domestic and international input-output linkages. All regressions include fixed effects for size, 4-digit industry and year. The robust standard errors are reported in parentheses. $**$, $*$, and $+$ indicate the significance at the 1%, 5% and 10% levels, respectively.

According to Table 1.5, the export and import premia are always positive and significant, despite the sector and size fixed effects. Yet compared to firms that rely on foreign inputs, firms that use domestic inputs are less productive. That said, this paper is the first to establish the significance of international trade based on each firm's production network.

These findings have critical policy-making implications. For Turkish manufacturing firms, involvement in international trade is the only factor associated with higher productivity, as indicated in Table 1.5. Since productivity is a necessary component of growth, eliminating trade barriers, reducing the tariffs for imported intermediate inputs, and using subsidies to promote foreign sales could lead to more productive and competitive manufacturing firms.

1.7 Second-Order Propagation

This section focuses on how firm-level shocks diffuse into the aggregate economy. Therefore, the estimations check whether the second-order degrees reflect indirect propagation through network effects. In particular, the subscript 2 indicates the second-order supplier or customer of firms by including these linkages as $\beta_{Di,2}$, $\beta_{I,2}$, $\beta_{Dq,2}$ and $\beta_{E,2}$ in the regression. For instance, $\beta_{I,2}$ corresponds to the second-order (indirect) importers. Stated differently, $\beta_{I,2}$ is the value purchased by the firm from another direct importer firm, whereas $\beta_{I,1}$ is the amount if and only if the firm itself imports.

	Total Factor Productivity				
$\beta_{Di,1}$	-3.47**				-2.72**
	(1.48)				(1.12)
$\beta_{Di,2}$	0.13**				0.09**
	(0.05)				(0.03)
$\beta_{I,1}$		3.97**			2.69**
		(1.04)			(0.98)
$\beta_{I,2}$		0.01**			0.01**
		(0.00)			(0.00)
$\beta_{Dq,1}$			-3.31**		-0.85
			(1.69)		(1.36)
$\beta_{Dq,2}$			0.09		-0.01
			(0.07)		(0.02)
$\beta_{E,1}$				8.06**	5.14**
				(1.01)	(1.20)
$\beta_{E,2}$				0.16**	0.18**
				(0.05)	(0.04)
R^2	0.01	0.58	0.01	0.69	0.73
# of Obs.			—— 1,066,818 ——		

Table 1.6: Second-order Propagation and Firm-level Productivity *Notes:* This table presents estimates of the firm-level productivity regressions on the first and second-order input-output linkages. All regressions include fixed effects for size, 4-digit industry and year. The robust standard errors are reported in parentheses. $**$, $*$, and + indicate the significance at the 1%, 5% and 10% levels, respectively.

Table 1.6 reports the results for the indirect propagation. Interestingly, the second-order transmission is significant and also consistent with the baseline estimations. Even though the coefficients are smaller than those of the first-order linkages, the shocks persist even in second-order degrees. These results suggest that the firm-level micro shocks would not die out in the networks.

1.8 Productivity and Trade Partners

The impact of international trade on productivity illustrated in the previous part. Therefore, this section concentrates on the role of different trade partners on TFP. Literature finds that gains vary according to the various destinations of exports. De Loecker (2007) demonstrates that productivity gains in Slovenian firms are driven by the firms that export to North America, Western, and Southern Europe. Further, Crinò and Epifani (2012) argues that TFP is negatively associated with sales to low-income destinations for Italian firms. The natural question is whether there is a link between firm-level productivity and the characteristics of the trade partner.

To the best of my knowledge, this is the first study investigating the productivity premia with different trade partners of Turkish firms. Furthermore, the estimations presented in this section add to the literature by also taking import origins into account.

1.8.1 Export Destinations

The following part estimates the premium after the decomposition of the trade partners. Yet, not all of the destinations significantly linked to productivity gains. The firms are more productive if they export to destinations, including North America, Western Europe, and Others, according to Table 1.7. Thus, one can conclude that more productive firms export to higher-income countries, where demand for quality is higher. This section emphasizes a crucial inference: when a firm is not productive, it is not easy to sell or survive in competitive markets, such as Western Europe and North America.

	Total Factor Productivity						
β_{NA}	0.16*						0.11*
	(0.07)						(0.05)
β_{EA}		0.14					-0.02
		(0.11)					(0.08)
β_{WE}			0.11**				0.09**
			(0.02)				(0.02)
β_{SEB}				0.12			0.05
				(0.09)			(0.07)
β_{MENA}					0.03+		0.02
					(0.02)		(0.02)
β_{Oth}						0.13*	0.11**
						(0.06)	(0.04)
R^2	0.06	0.01	0.21	0.04	0.02	0.21	0.31
Obs.				—— 1,066,818 ——			

Table 1.7: Exports Destinations and Productivity *Notes:* This table presents estimates of the firm-level productivity regressions on export partner dummies. All regressions include fixed effects for size, 4-digit industry and year. The robust standard errors are reported in parentheses. $**$, $*$, and $+$ indicate the significance at the 1%, 5% and 10% levels, respectively.

The MENA region deserves special attention. Although Table 1.7 shows it to be significant, that significance is lost when the regressions estimated with the other destinations. This variation first arose when, after the global financial crisis, Turkish exporters switch their export markets following the European Union contraction. Keeping this in mind, the MENA region was the alternative destination for exporters during this turning point.

1.8.2 Import Origins

The previous results, in Section 1.6.2, assess the difference between imported and domestic inputs on the TFP. The following exercise examines whether the origin of the imported intermediates influences on the total factor productivity.

	Total Factor Productivity						
β_{NA}	0.17*						0.06
	(0.05)						(0.05)
β_{EA}		0.16**					0.12**
		(0.04)					(0.02)
β_{WE}			0.09**				0.06*
			(0.03)				(0.03)
β_{SEB}				0.08**			0.08*
				(0.01)			(0.01)
β_{MENA}					0.02**		0.01+
					(0.00)		(0.01)
β_{Oth}						0.05	0.03
						(0.03)	(0.03)
R^2	0.05	0.02	0.05	0.20	0.04	0.10	0.34
Obs.				—— 1,066,818 ——			

Table 1.8: Import Origins and Productivity *Notes:* This table presents estimates of the firm-level productivity regressions on geogaphical import source country dummies. All regressions include fixed effects for size, 4-digit industry and year. The robust standard errors are reported in parentheses. $**$, $*$, and $+$ indicate the significance at the 1%, 5% and 10% levels, respecttively.

Table 1.7 and 1.8 point to the pattern of productive Turkish manufacturers. For imports, most productive firms import from East Asia, including China. Further, the quantitative estimates of significant trade partners dominated by low-income countries. Nevertheless, the pattern is almost the opposite of export destinations, and these estimates yield another puzzle: How do Turkish manufacturing firms that engage in the trade have productivity premia? Almost certainly, this is due to several advantages that Turkey enjoys being part of the Customs Union, its low labor costs, and its geographical location.

In summary, it is clear that the income-level of the trade matters for productivity premia, and there is a variation across each import or export partner, depending on their income level. In contrast to findings in the literature, I find that high-income trade partners correlated with higher TFP for only exports. The pattern is almost the opposite of imports.

1.9 Learning-by-Networking

In this section, I exhibit that firms are more productive if they are part of a sophisticated production network. Put differently; this part reveals that firms learn-by-networking. Previous literature restricts its attention to the exporting decision and the gains after exporting. However, attributing productivity gains to only exporting is not convincing enough to assess growth. I build on this literature by showing that firms learn-by-networking.

There is a long-running debate in the literature on the direction of causality for the premia of exporting. Previous sections demonstrate that exporter firms are more productive than other firms, providing theoretical and empirical evidence. Nevertheless, the underlying direction between efficiency and the exporting is the heart of this literature. First-strand of the literature "self-selection", including Melitz (2003) and Yeaple (2005), argue that only firms that are more productive than others can export. On the contrary, another part of the literature defends the learning thesis after the entry to export markets. Bernard et al. (1995) and Alvarez and Lopez (2005) provide significant evidence on the premia following the entry. Yet, these studies restrict their attention only to exporting. Going one step further, I investigate the firms' network structure that has significantly increased their competitiveness in this part as the literature restricts its attention only to productivity gains. However, understanding the pattern of these gains are substantial. In a critical insight, this section focuses on the change in the firms' networks. In contrast to previous studies, I argue that the mechanism that produces learning is networking across supply-chain. In this section, I focus on the reason behind the efficiency associated with the exporter firms. Interestingly, firms learn both by networking and exporting.

The productivity gains that follow the exporting decision are due to the firm's network position in the supply chain. Hence, increasing out-degree and in-degree of a firm in domestic and international production networks enhances the firm's competitiveness in the global markets. Further, exporting is additionally another determinant that delivers productivity premia. This TFP growth that follows the exporting decision might be due to access to new knowledge, innovation spillovers, or new resources.

Another perspective is 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 meant to be more productive due to their ability to cover fixed labor costs and iceberg costs to export their output. Thus, self-selection argues that there is not a significant relationship between exporting or networking on productivity. In this section, both of the two phenomena observed in the Turkish manufacturing industry. But the weight of the self-selection is almost negligible when compared to learning-by-networking effects. After all, the network sophistication of the firms mainly drives the premium.

Even though there is significant evidence in the literature supporting the view that firms increase their productivity after they decide to export, the underlying mechanism neglected. Here I argue that the origin of this significant change can be traced through the evolution of the firm's customer and supplier network. That is, it is quite possible that as firms become more productive as they expand their local supplier and customer networks before their productivity moves above the threshold that bars it from exporting. First, they develop their role in domestic supply-chain, which increases their role as both customers. Second, their supply increases. Third, because of their changing role in the production network, firms learn-by-networking.

Figure 1.5 portrays the productivity trajectories of two groups over time. The first group, shown with the red line, represents the firms that start exporting during the sample period. The second group (blue line) comprises firms that have never exported. Here firms that are already exporters at the beginning of the sample are dropped to exploit productivity gains that occur when firms successfully gain access to international markets. Time $t = 0$ denotes the period when a firm starts to export, which previously selling its output only in the domestic market.

The mean productivity of the firms that are never export presented in the blue line. In contrast, the color is different for the new exporters, as indicated in red — the reference year zero when firms decide to enter the international markets. After taking the reference year, other years distributed accordingly. This graph includes the firm's productivity four years before exporting and four years after exporting. The first observation regarding the self-selection hypothesis is the difference before time zero. Even before exporting, including the previous four years, exporters tend to have higher productivity levels. Also though this difference is small, about eight percent, there is a clear distinction between the two groups. Further, on each time interval, firms that started or about to start have significantly higher TFPs than other firms. This considerable difference points out that the two groups display different characteristics. In other words, firms that were operating efficiently than others even before the time $t = 0$. Hence, I can argue that firms can self select themselves due to their differences. However, it is an early conclusion without considering the reaction of firms after they start exporting. Additionally, the two groups obey the parallel trend assumption with the changing slope at time $t = -2$.

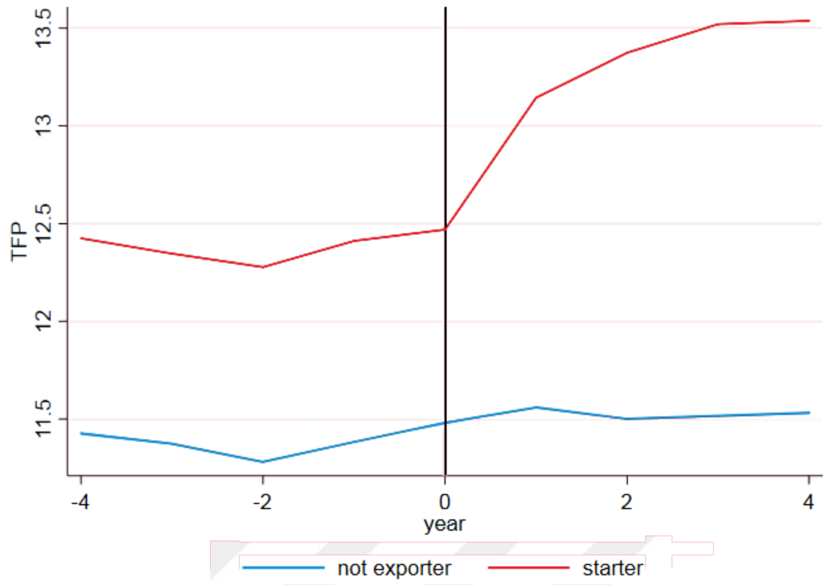


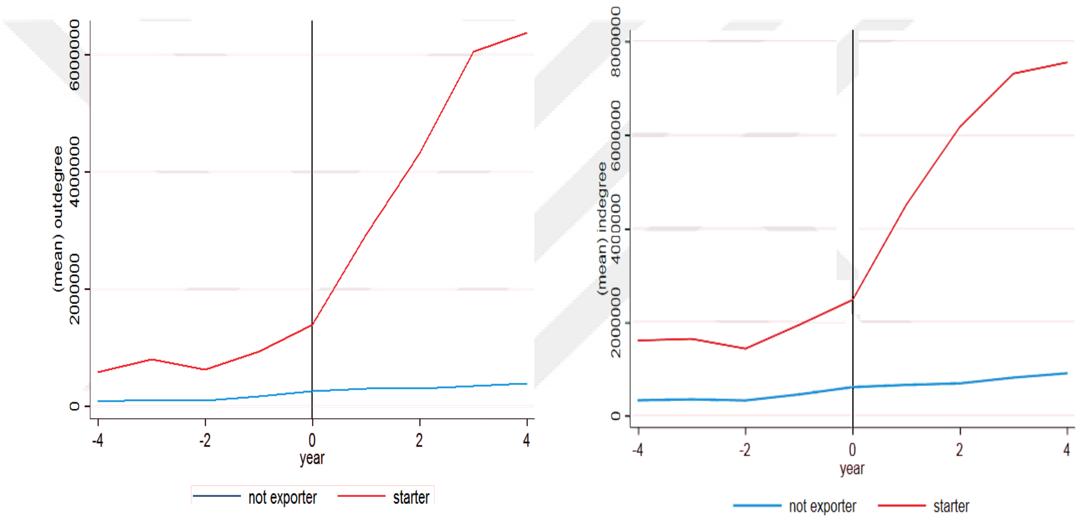
Figure 1.5: Productivity and Exporting

Notes: The blue line indicates the firms that never export, whereas the red line shows the average productivity level of the firms that start exporting at time 0. The y-axis corresponds to the productivity level of firms that never export directly or starts to export for the first time.

For testing the learning-by-hypothesis, the crucial part relies upon the changes observed after time $t = 0$. Interestingly, the most valuable observation of the analysis in Figure 1.5 is the expansion of the TFP levels of the firms that start to export between time $t = -4$ to $t = 4$. After time zero, parallel trends disappear. The red line follows a definite upward trend after period 0, indicating support for the learning-by-exporting hypothesis. In contrast, firms that had never exported experiences no increase in productivity. Visual inspection of Figure 1.5 suggests that there is diversity across firms that begin to export, but does empirical evidence support this conclusion? The following part investigates the significance of TFP differences by relying on a differences-in-differences estimation.

1.9.1 Network Characteristics and Exporting

This section reviews the learning-by-networking, where TFP grows with the expansion of firm networks. Thus, I center on the time-varying upstream and downstream linkages according to their distributions in the network. To incorporate the network sophistication, I rely on network literature where the inputs and outputs of the firm assigned as distributions by depending on the weighted ties among the firms. Building on the volumes of the trade between the firms, four distribution measures are set to a firm: out-degree, in-degree, import, and export degree. Out- and in-degree distributions based on the domestic production network. Out-degree relates to the firm's output, which used as an intermediate input of another manufacturing firm. In contrast, the in-degree assigned as a proxy for the firms' purchases from other firms. As the import and export data available for trading partners, the weights are assigned to different countries cumulatively.



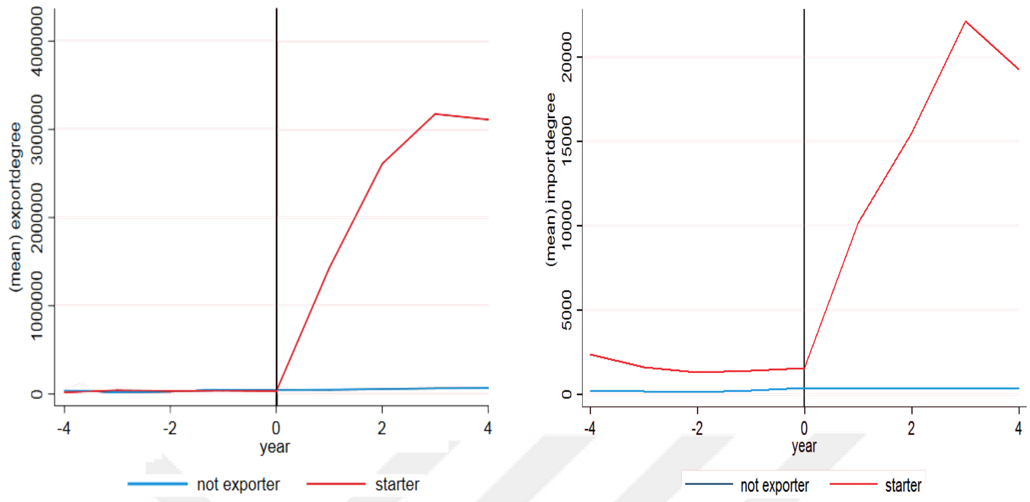
(a) Average TFP

(b) Annual TFP growth

Figure 1.6: Domestic Production Network Characteristics

Notes: The figure on the right presents the time-varying out-degree distribution of the firms, whereas the graph on the left shows the in-degree distribution. The blue line indicates the firms that never export, whereas the red line shows the average degrees of the firms that start exporting at time 0.

Figure 1.6 presents the weighted out- and in-degrees of the firms that start to export. This figure illustrates the firm's network position shifts in the domestic network. Before time zero, the rank of firms as suppliers or customers is different. The inputs and outputs of those firms are already more diversified than the other group. But after time zero, the performance of the two groups changes clearly. After time zero, suppliers become more complex, according to Figure 1.6. These firms depend on more specialized inputs, also out-degree confirms the learning-by-networking. Rather than being a firm that has a smaller group of customers or suppliers, the production process in firms becomes more complicated. The intuition



(a) Export degree (b) Import degree

Figure 1.7: International Production Network Characteristics

Notes: The figure on the right presents the time-varying export degree distribution of the firms, whereas the graph on the left shows the import degree distribution. The blue line indicates the firms that never export, whereas the red line shows the average degrees of the firms that start exporting at time 0.

is clear: before exporting, firms prepare themselves by increasing their network complexity as either customers or suppliers, as shown in Figure 1.6 after they start exporting, their specialization in the supply-chain increases substantially.

The firm's international network characteristics are linked to trade partners that firm exports or imports. Import-degree marks a critical mechanism; the firms that would start to involve in international trade have higher import-degree than the firms that never export during the estimation interval. Another point to notice is that export-degree have a positive trend after the entry. All in all, these network characteristics are always ignored in the literature. But the figures 1.6 and 1.7 exploit the underlying mechanism of productivity gains. As the manufacturing firms become more diversified in their supply-chains, they become more productive and specialized.

1.9.2 Difference-in-Differences Estimations

Eyeballing analysis of Figure 1.5 illustrates the diversity of the firms after time zero. In this section, the empirical specification aims to estimate the causal effects of exporting. Thus, the following part relies on the differences-in-differences between the two groups. The treatment is opening the firm networks to international trade for the first time. The calculation period covers the years between 2006 and 2016. The treatment group consists of firms that do not export at the beginning of the period and chooses to export then. Contrarily, the control group incorporates 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 TFPs, out-degrees, and in-degrees. Yet, judgment based on only this criteria is critical. To match the firms that have similar properties, firms matched according to their propensity scores before the estimation. Thus, I use the nearest neighbor matching. The primary purpose of this exercise is to design a control group whose size is similar to the treatment group. In this way, the algorithm tracks non-exporting firms and export entrants that have comparable properties.

An attractive feature of this matching is the selection of control and treated firms with the closest propensity scores. As noted above, this exercise is crucially important because these marginal gains on productivity may differ across different sizes. Thus, the comparison became the productivity differences between control and treated firms that depend on a similar amount of labor.

		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
β_{Imp}		0.06^{**}	0.04^{**}	0.00^{**}
	s.e.	(0.01)	(0.02)	(0.00)
	R^2	0.03	0.02	0.02

Table 1.9: Productivity and Network Gains from Importing and Exporting

Notes: This table presents the difference-in-difference estimates of TFP, out-degree, and in-degree distribution. Treatment is starting to importing or exporting. Standard errors clustered at the firm-level in each regression, $+$, $**$, and $*$ indicate the significance at the 1%, 5%, and 10% levels, respectively.

Table 1.9 evaluates productivity, out-degree, and in-degree premia by linking the new exporters and importers. The number of controls determines the firms that never import or export, with the comparable size for the treatments. This exercise is suitable for two reasons. First, the results point to the productivity changes associated with learning-by-networking with the exporting or importing decision. As noted in Table 1.9, firms learn as they enter international markets. However, gains from exporting are significantly higher than those for importing. In other words, exporting firms become %19 productive after time= 0. The premia also are significant for new importers, although the increase is only %6. These estimates are consistent with the model suggestions made in Section 3. Thus, the empirical evidence indicates that firms that export enjoy higher productivity than firms that only restrict their sales to the domestic market.

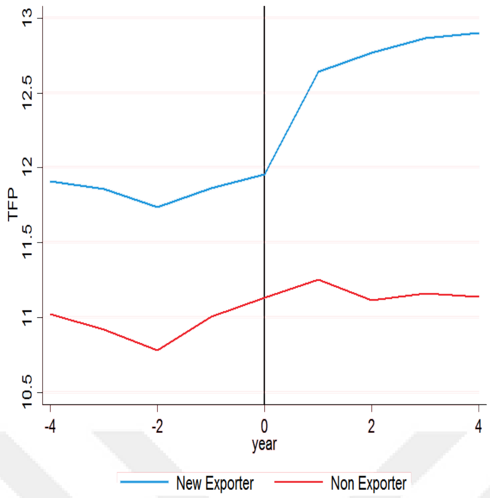
Firms expand their networks as they start to engage in international trade. Different than the literature, these estimations point to how value-chains evolve as the firms enhance their competitiveness. The specialization of their role as supplier/customer increases significantly for the firms in the treatment group. Further, firms with higher degrees generate higher TFPs. These results confirm that there is a link between productivity and the sophistication of all manufacturing firms' networks, but it does not distinguish between sectors. In the next section, I investigate variation in the two-digit manufacturing industries to control for these characteristics.

1.9.3 Productivity and Network Gains at Industry Level

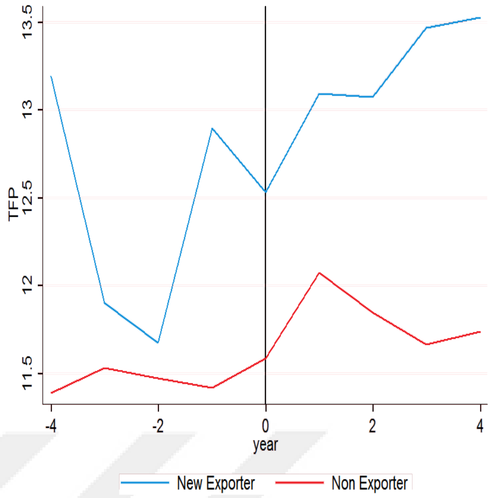
According to the results in the previous part, all Turkish manufacturing firms that start to export for the first time experience a significant and substantial increase in their productivity. Yet, this variation originates from the firms' position in the supply chain. Though limiting these results without considering the industry characteristics could be misleading, since the matching process considers similar sizes for the firms, but sectoral aspects may encounter the consequences.

To investigate the learning-by-networking hypothesis among various manufacturing industries, I run a similar regression for each industry type within NACE 2-digit classified sectors. The matching process detects the nearest neighbor of the firm that has the closest propensity score in the same industry to see the causal impact of shipping internationally.

Figure 1.8 represents the differences between the two industries: Fabricated Metals and Other Manufacturing, which covers the manufacturing of sports goods, toys, and medical instruments. For Fabricated Metals, treatment and control groups exhibit diverse behavior following the treatment, which is beginning to export in this case. This graph designates a critical difference. Though the firms that classified as Other Manufacturing industries, the effect of the treatment is



(a) Fabricated Metals, 25



(b) Other Manufacturing, 32

Figure 1.8: Learning-by-Networking at Industry Level

Notes: The figure on the right shows the firms that are classified as Fabricated Metals according to the NACE 2-digit classification with 25. In contrast, the left graph presents the firms that belong to the Other Manufacturing classification with the code of 32. The blue line indicates the firms that never export, whereas the red line shows the average degrees of the firms that start shipping at time 0.

doubtful since both groups improve their productivity. Besides, these two groups behave very differently before time zero, breaking down the parallel trend assumption.

Table 1.10 presents the difference-in-differences coefficients for each manufacturing industry, after controlling for industry class differences. Surprisingly, not all manufacturing industries learn-by-doing. Only nine sectors experience more sophisticated networks and productivity gains among all 22-manufacturing industry NACE Rev.2. Classes. Further, the evidence is well-matched with Figure 1.8. Fabricated Metals, for instance, significantly benefit from learning from networking. Nevertheless, there is not any noteworthy evidence on Other Manufacturing industries, as expected. Also, the Appendix provides estimates for other sectors that do not experience notable improvements. A remarkable feature of this exercise is how accumulations in productivity and is an essential part of the supply chain are related. Although not all the two-digit manufacturing sectors display the same premiums, the empirical evidence verifies that the two concepts are accompanying.

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 Metals	0.66**	0.84**	0.32**
	(0.19)	(0.23)	(0.11)
Furniture	0.07^{+}	0.09*	0.11
	(0.04)	(0.06)	(0.07)

Table 1.10: 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 clustered at the firm-level in each regression. Standard errors presented in parentheses. $+$, $*$, and $**$ denote the significance of the coefficients at %10, %5 and %1, respectively.

Interestingly, not all manufacturing expands their value-chains or increase their productivity following the exporting decision. This variation might be due to government policies that target different sectors. Back in 2006, The Turkish authorities launched a comprehensive export strategy and action plan named as “TURQUALITY” to promote sustainable export growth in several industries. This program aims to support branding in international markets and encourage their 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 increased their productivity.

1.9.4 Income Level of the Destination

The previous part illustrates the network and productivity gains from exporting to any international market. In this part, I examine the destination characteristics by decomposing their income level. Literature, including De Loecker (2007), argues that firms that only export to high-income destinations learn more from exporting. In this part, I split the export destinations 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 mostly target the low-income countries dropped from the sample due to their small number of observations.

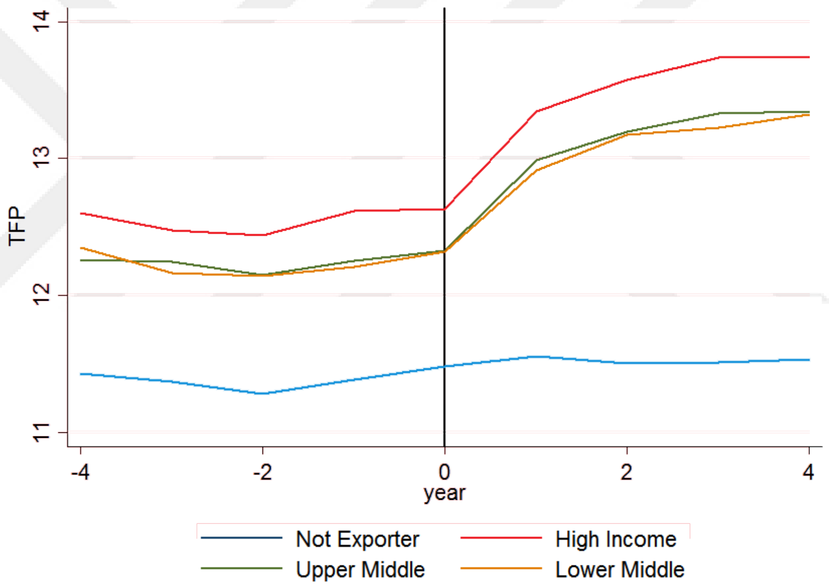


Figure 1.9: Income Level of the Destination

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 upper middle income, and 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 productivity level of the different groups.

To match a firm's destination with the income level, the firms' export destinations broken into World Bank classifications for each reported transaction. Next, the firm's destination category ranked by its highest export volumes for each year. Figure 1.9 illustrates the TFPs of these groups. Unlike the previous findings in the literature, the firms that export to high-income countries for the first time already have higher productivity before zero. Further, this distinction persists until the fourth period. But for the upper-middle and lower-income, the behavior and the trends are roughly identical. Then, by relying on Figure 1.9, self-selection exists. Unlike the previous findings, there is no learning mechanism associated with income-level since the gap between these groups is essentially the same for each estimation period. Hence, the firms that target high-income destinations not necessarily improve their productivities with the exporting. At last, these firms already self-select themselves into higher-income countries even before entering international markets.

1.9.5 Diversification of Exports to Sophistication of Networks

The firms which decide to develop their networks to international markets may choose where and how many markets to export. The diversification of the firm shifting from a single destination target to multiple countries can reach many customers. For the most traditional diversification case, it is a common strategy to encourage positive growth by decreasing the risk. For that reason, the outcomes of creating a more complicated supply network may deviate from targeting only one market. This section covers the gains from the expansion of the export-degree in networks.

Figure 1.10 distinguishes the two cases: TFP differentiation after starting to export to single or multiple destinations. Firms ship to various destinations become more competitive, according to Figure 1.10. Intuitively, learning-by-networking produces notable gains following time zero, whereas firms only restrict themselves to only one destination increase their productivity less than others. The main takeaway is that benefits not only rise by expanding their network role in domestic supply-chain but also with their role in the international input-output network.

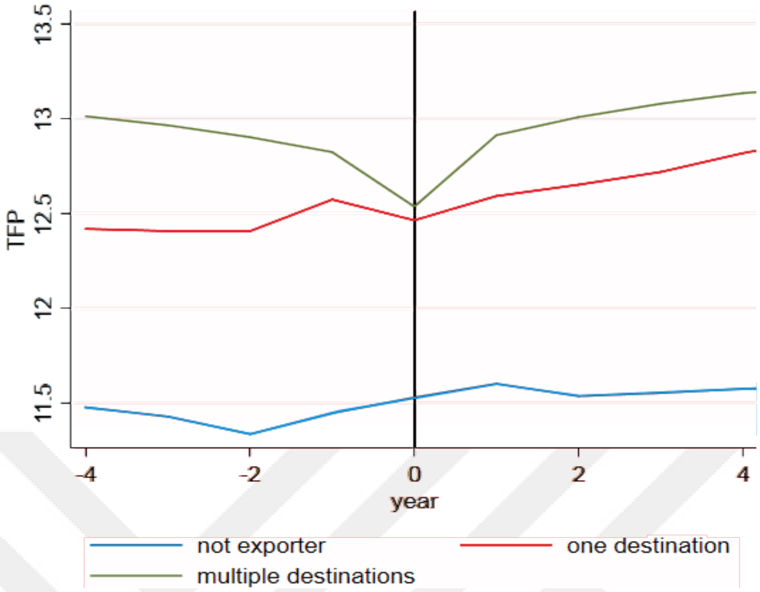


Figure 1.10: Diversification of Exports

Notes: The blue line exhibits the firms that never export; the red line shows the average productivity of the firms that only export to one country, and green line displays the TFP of the firms that ship their output to more than one destination.

1.10 Conclusion

This paper exhibits the importance of firm-level linkages and sophistication of the supply-chains. Building on a model that compromises input-output linkages between firms demonstrates the impact of supplier productivity on the output and TFP. The focus of this paper is the micro-level evidence on shock propagation associated with the firm's balance sheets, transaction, and customs data. In this way, it tracks the underlying factors correlated with firm's performance and growth.

The structure of production network mirrors several aspects of the aggregate economy. Both out- and in-degree distributions are associated with the fat-tails. Therefore, firms located in the tails are "too connected to fail". This asymmetric structure yields a non-diversified economy where even the micro shock-hitting tails may lead to aggregate fluctuations. Therefore, the input-output linkages that construct the production network can operate as a shock transmission mechanism.

On the theoretical side, this paper illustrates how output and productivity growth of firms associated with their production linkages. Thus, this study builds on the multi-sectoral model, where firms rely on intermediates inputs produced by other firms. Trade frictions introduced to understand the role of both domestic and international production networks, which serves as a foundation for the empirical results provided in this paper as a propagation mechanism of shocks.

This paper proposes an alternative hypothesis for productivity premia: learning-by-networking. The critical insight of this study is the change in the sophistication of the firms' networks before exporting. Unlike the previous literature, this paper documents that the underlying mechanism of learning requires a new arrangement of production networks with changing in- and out-degree distributions. The main takeaway of the paper is manufacturing firms learn-by-networking with other firms while expanding their value-chain.

The quantitative section emphasizes the significance of production networks as a transmission mechanism. Gains from trade, reexamined by taking the network structures into account. Productivity gains correlated with the firm's network position in the supply chain, industry class, and the diversity of its export destinations. Yet, the income-level of the export partner is not related to any learning mechanism. All in all, critical evaluation of the alterations in productivity indicates that firms gain from networking.

Chapter 2

CONNECTEDNESS AND THE PROPAGATION OF SHOCKS THROUGH THE INPUT-OUTPUT NETWORK

2.1 Introduction

The fact that microeconomic idiosyncratic shocks can affect the aggregate economy has already attracted attention among macroeconomists. In the earlier and perhaps the more straightforward contribution, Long and Plosser (1983b) show how the propagation of industry-level productivity shocks can generate business cycle movements. Recently, however, studies on real and financial networks have shown that small microeconomic shocks could generate rather large effects on the aggregate economy through the underlying input-output, financial, employment etc. networks (see Acemoglu et al. (2012b), Acemoglu et al. (2016b), Atalay (2017), Baqaee and Farhi (2019)).

Among the contributions to this emerging literature, Acemoglu et al. (2012b) characterize the conditions under which the input-output networks of industries can amplify firm- or industry-level shocks to have significant implications for the aggregate economy. Acemoglu et al. (2016b), on the other hand, empirically show that supply-side shocks (including productivity shocks) are transmitted from upstream (intermediate goods-producing) industries to downstream (final goods-producing) industries, while demand-side shocks are likely to be transmitted from downstream industries to upstream industries.

Analyzing the contribution of sectoral shocks to business cycle fluctuations, Atalay (2017) concludes that product complementarity across industries is the channel through which industry-specific shocks are magnified to account for at least half of the aggregate output volatility.

As part of their main findings, Acemoglu et al. (2016b) further emphasize that supply-side shocks create powerful downstream propagation while a similar upstream propagation is not observed in the case of demand-side shocks. This is so because the product price increases in upstream industries imply higher costs of production and cascade effects in the final good-producing industries. Demand-side shocks, on the other hand, have minor or no effects on the prices of final goods and the resulting propagation of shocks to upstream firms would be very weak. Despite this emphasis on the propagation of supply shocks taking place through the price effects, Acemoglu et al. (2016b) instead only focus on the propagation of shocks across industries through output levels only.

In this paper we take up from where Acemoglu et al. (2016b) left off. In particular, we focus on supply shocks being transmitted downstream through input price changes while at the same time focus on demand shocks being transmitted upstream through increased demand for inputs. Using the simple general equilibrium model of Acemoglu et al. (2012b), we show that the input-output linkages across industries form the underlying network through which the supply shocks are transmitted downstream wjhile demand shocks transmitted upstream. In particular, price increases in an upstream industry will lead to an increase in the production costs of the downstream industries that use the products of the upstream industry as intermediate input. The firms in the downstream industry will eventually have to reflect this cost increase in their product prices.

One of the contributions of this paper is the use of the Diebold-Yilmaz connectedness index (DYCI) methodology to analyze how supply (producer price inflation) and demand (industrial production change) shocks are transmitted across industries. With this methodology, we measure the extent of the change in sectoral producer price inflation and industrial production changes due to shocks originated in other industries. Rather than the inherently symmetric (hence non-directional) measures, such as correlation, the DYCI framework is used because it allows for asymmetries in the pairwise linkages across sectors. While the system-wide connectedness measures are quite useful in gauging how much of inflation/output shocks are transmitted across sectors, the pairwise directional connectedness measures are used to distinguish between sectors that on average transmit inflation/output shocks to others from the ones that on average receive inflation/output shocks from others.

Both static and dynamic connectedness measures are obtained. Static connectedness measures over the full sample identify the industries that generate inflation connectedness to others over a 70-year period from February 1947 to June 2018. Basic metals and chemical products, the leading upstream industries, turn out to be the most important generators of inflation connectedness to others in the full sample. We then obtain dynamic connectedness measures for rolling sample windows to study the variation in system-wide and directional inflation connectedness over a 70-year period. System-wide connectedness measures clearly show that inflation connectedness fluctuates significantly over time, with jumps as well as gradual increases during some important international market developments, such as the first and second oil price shocks of 1973-1974 and 1979-1980, and metal commodities price increases in the late 1980s, mid-1990s and from 2003 through 2011.

Focusing on the dynamic inflation connectedness, the price index for metals and minerals turns out to have a more important impact on the system-wide inflation connectedness than the price of oil. Furthermore, taking the impact of the metals and minerals commodity price index into account, it is not possible to reject the hypothesis that the system-wide connectedness index of the underlying input-output network Granger-causes the system-wide inflation connectedness measure. Moving from the aggregate to the granular, the variation in pairwise input-output network linkages accounts for up to 58 percent of the variation in the pairwise directional inflation connectedness across industries. The relationship between the inflation connectedness and input-output network declined significantly during the Great Recession (2008) and Volcker disinflation (1981-1984), which were effectively aggregate demand shocks affecting the downstream industries first.

Over the last decade, a growing body of research has studied various aspects of inflation spillovers across countries and industries. Among these, Wang and Wen (2007) show that cross-country inflation correlations are significantly larger than output growth correlations. Mumtaz and Surico (2009) and Monacelli and Sala (2009a) use factor models to analyze the transmission of inflation shocks across countries. Ciccarelli and Mojon (2010a) documents that inflation in industrialized countries shares a common global factor that accounts for close to seventy percent of the variation in inflation.

More recently, Auer et al. (2017) goes one step further and decompose producer price inflation series into global, sectoral and country factors. They show that sectoral shocks are the main reason behind the synchronization of producer price inflation across countries. Several other papers, including Di Giovanni and Levchenko (2010a), Auer and Saure (2013a), and Antoun de Almeida (2016a) also pointed out to the role of input-output linkages in driving inflation synchronization across countries.

Our paper differs from the above-mentioned contributions to the literature. While some of these studies restrict their analysis to the correlation of inflation, the current paper uses the DYCI framework to take into account the covariance of the error terms from the VAR model. By using Diebold-Yilmaz connectedness framework, the current paper concentrates on directional bilateral linkages across sectors rather than the nondirectional correlation measure studied in the literature. This paper differs from the above cited research on real netwrorks, in taht it not only considers how demand and supply shocks spread across the input-output network, it differentiates between upstream and downstream propagation of shocks in th product and prices spheres.

The remainder of the paper is structured as follows. After a brief literature review in the next section, section 2.2 outlines the general equilibrium model of inflation transmission through input-output linkages. Section 2.3 provides information about the DYCI methodology and the data used in the paper. Sections 2.4 and 2.5 present the static and dynamic analysis of inflation connectedness across the three-digit U.S. manufacturing industries. The relationship between the annual input-output and inflation networks at the aggregate and granular levels are presented in section 2.6. Section 2.8 concludes the paper.

2.2 A Model of Perfect Competition

The multi-sector static competitive economy model of Acemoglu et al. (2016b) takes into account the input-output structure of the manufacturing industry to analyze how input and/or output shocks are transmitted across industries. They show that the demand shocks to the downstream industries are transmitted to the upstream industries through the change in demand for intermediate inputs.

The multisector static competitive economy model of Acemoglu et al. (2016b) is flexible enough to be used in the analysis of supply shocks to the upstream industries that increase the cost of production are transmitted do downstream industries through higher cost of products supplied to these industries as intermediate inputs.

Each sector has the following Cobb-Douglas production function, where labor and intermediate inputs are used to produce the output of industry i:

$$y_i = e^{z_i} l_i^{\alpha_i} \prod_{j=1}^{n} x_{ij}^{a_{ij}} \tag{2.1}$$

where y_i is the output of industry i, l_i is the level of employment, and z_i is the sector-specific productivity. x_{ij} is the amount of industry j's product used as intermediate input in the production of industry i's output. For each sector, we assume $\alpha_i > 0$,

$a_{ij} \geq 0$ and $\alpha_i + \sum_{i=1}^{n} \alpha_{ij} = 1$.

Market clearing condition for industry i dictates the equality of the industry i's output and the final consumption and intermediate input demand for the output of industry i:

$$y_i = c_i + \sum_{j=1}^{n} x_{ij} \tag{2.2}$$

where c_i is the final consumption of the product of industry i. As equation (2.2) shows the product each industry is either consumed as a final good or used as an intermediate input by other industries.

The representative household is endowed with one unit of labor and has the following utility function defined over the labor and the consumption of goods from industries 1 to n:

$$u(c_1, c_2, ..c_n, l)) = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} \tag{2.3}$$

where $\gamma(l)$ is a decreasing function of labor and β_i is the weight assigned to good i in the household's preferences.

We can write the household's budget constraint as

$$\sum_{i=1}^{n} p_i c_i = wl \tag{2.4}$$

where p_i is the producer price of output of industry i.

The competitive equilibrium of this economy of n industries with price levels $(p_1, p_2, ..., p_n)$, wage rate w, consumption bundle $(c_1, c_2, ..., c_n)$ is obtained when the representative household chooses consumption of each good and labor to maximize her utility, representative firm in each industry chooses employment, intermediate inputs and output to maximize profits, and the markets for labor and goods 1 to n clear. In this competitive equilibrium, we can then show that the following proposition holds.

Proposition 1. The producer price of industry i will increase in response to an increase in the price of intermediate input produced by industry j as well as the adverse productivity shocks in industry i (namely, $dz_i < 0$):

$$dlnp_i = \sum_{j=1}^{n} a_{ij} dlnp_j - dz_i \tag{2.5}$$

Both the adverse productivity shock and the input price increase causes the average cost of production cost to increase, which in turn leads to an increase in the price that industry i firms sell their products.

Intuitively, equation 2.5 captures the fact that the impact of the price change dp_j in industry j can possibly have an impact on the producer price of industry i depending on the intensity with which industry i uses good j as an intermediate input in its production, namely a_{ij}.

It also implies that price shocks propagate from upstream industries to downstream industries. As emphasized by Acemoglu et al. (2016b), supply-side shocks propagate from input-supplier industries to customer industries through higher intermediate input prices. When there are changes in producer prices, there are no upstream effects but only downstream effects owing to the coefficient (a_{ij}).

2.3 Methodology and Data

This section provides a summary of the DYCI methodology and brief information on the data set used. The DYCI framework was initially developed by Diebold and Yilmaz (2009, 2012) to study spillovers of financial shocks/crises across countries. Later, Diebold and Yilmaz (2014) showed that the DYCI methodology was closely linked to the modern network theory. In that perspective, the pairwise directional connectedness measures correspond to the directed, weighted edges of a network, while the system-wide connectedness index corresponds to its mean degree.

2.3.1 DYCI Framework

The connectedness index is built upon the variance decomposition matrix associated with an N -variable vector autoregression. The total connectedness index is the ratio of the sum of off-diagonal elements of the forecast error variance-covariance matrix to the sum of all elements of the same matrix.

We obtain variance decompositions from an N-variable VAR(p) model, $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. Covariance stationarity of VAR(p) ensures that it has a moving average representation of the form: $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the coefficient matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for $i < 0$.

In the VAR framework introduced above, *own variance shares* are the fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1, 2, .., N$, and *cross variance shares* are the fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_j, for $i, j = 1, 2, .., N$, $i \neq j$. DYCI framework uses only the *cross variance shares* in calculation pairwise directional, total directional and system-wide connectedness measures.

Identification of shocks is one of the critical steps in the impulse response and variance decomposition analyses. It might become quite difficult to adopt a satisfactory identification scheme when the number of variables N is relatively high. Standard decomposition approaches such as Cholesky factorization are not robust to the ordering of the variables. This is a serious limitation if one would like to obtain not only the system-wide but also directional connectedness measures. For that reason, we follow Diebold and Yilmaz (2014) and use the generalized approach of Koop et al. (1996a) and Pesaran and Shin (1998b) that produces variance decompositions invariant to ordering. Unlike the Cholesky factorization which orthogonalizes shocks, the generalized approach allows for correlated shocks taking the correlation into account.

Having chosen the generalized identification method for the variance decompositions, we can now introduce the connectedness measures. We start with the highly-granular pairwise directional connectedness measures, and proceed with the total directional connectedness measures obtained through the first degree of aggregation for the source variable ("total connectedness to others") or the target variable ("total connectedness from others"). Then we move to the highly-aggregative system-wide connectedness index through the aggregation for both the source and target variables.

The contribution of a one-standard deviation shock in variable j to the H-step-ahead generalized forecast error variance of variable i, $\theta_{ij}^g(H)$, is

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, ..., \tag{2.6}$$

where σ_{jj} is the standard deviation of the disturbance of the j^{th} equation, Σ is the covariance matrix of the disturbance vector ε, and e_i is the selection vector with one as the i^{th} element and zeros otherwise. θ_{ij} is nothing but the *cross variance share* of variable j in the H-step-ahead forecast error of variable i.

By construction, in the generalized VAR framework forecast error variance shares do not necessarily add to 1; hence, in general, $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Taking this into account, we normalize each entry of the generalized variance decomposition matrix (2.6) by the row sum to obtain pairwise directional connectedness from variable j to variable i. Furthermore, in order to introduce a more informative notation, we define pairwise directional connectedness from variable j to variable i as:

$$C_{i\leftarrow j}^{H} = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{2.7}$$

Now, by construction $\sum_{j=1}^{N} C_{i\leftarrow j}^{H} = 1$ and $\sum_{i,j=1}^{N} C_{i\leftarrow j}^{H} = N$.

Once the pairwise directional connectedness measure, $C_{i\leftarrow j}^{H}$, is obtained, total directional connectedness measures can be obtained by means of aggregation for each variable i. Total directional connectedness from all other variables j to variable i is

$$C_{i\leftarrow \bullet}^{H} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} C_{i\leftarrow j}^{H}}{\sum_{i,j=1}^{N} C_{i\leftarrow j}^{H}} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} C_{i\leftarrow j}^{H}}{N}. \tag{2.8}$$

Similarly, total directional connectedness from variable i to all other variables j is

$$C_{\bullet\leftarrow i}^{H} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} C_{j\leftarrow i}^{H}}{\sum_{i,j=1}^{N} C_{j\leftarrow i}^{H}} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} C_{j\leftarrow i}^{H}}{N}. \tag{2.9}$$

Once the shocks transmitted and received by variable i are calculated, the difference between the two will result in a measure of the net total directional connectedness transmitted from variable i to all other variables as

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow \bullet}^{H} \tag{2.10}$$

The net total directional connectedness index, equation 2.10, provides information about how much shocks to a variable contributes in net terms to the variation in other variables.

Finally, by summing all non-diagonal entries of the normalized variance decomposition matrix (namely, the normalized *cross variance shares*) we obtain the system-wide connectedness index:

$$C^H = \frac{\sum_{\substack{i,j=1 \\ j \neq i}}^{N} C^H_{i \leftarrow j}}{\sum_{i,j=1}^{N} C^H_{i \leftarrow j}} = \frac{\sum_{\substack{i,j=1 \\ j \neq i}}^{N} C^H_{i \leftarrow j}}{N}. \tag{2.11}$$

2.3.2 Data

In our empirical analysis of the inflation connectedness we use producer price data from the Bureau of Labor Statistics (BLS) for the three-digit U.S. manufacturing industries, that are included in the U.S. input-output tables. Producer price inflation data used at the monthly frequency covers a period longer than 72 years, from February 1947 to July 2019.

We calculate the input-output measures directly from the input-output tables, which report the intermediate product flow within and across sectors and published annually by the Bureau of Economic Analysis (BEA).[1] The annual availability of the input-output tables allows for regular updating of the input-output network information every year. Annual data on other control variables, such as the sectoral employment, output, exports, and imports, are obtained from the BEA as well.

2.4 Static Analysis

We start the analysis of inflation connectedness across industries with the static framework. Connectedness measures are obtained from the estimation of a VAR model of monthly producer price inflation series over the period from February 1947 to July 2019. After the inflation connectedness measures we calculate the average annual input-output network over the 1947-2017 period. Then we analyze it along with the inflation connectedness network to understand the possible relationship between the inflation and input-output connectedness over the full sample. Table 2.1 reports the static inflation connectedness table (a 17x17 matrix), which is obtained from the estimation of a VAR model of order two and a forecast horizon of 12 months.[2]

[1] Even though, the U.S. input-output tables cover 19 manufacturing industries, we include 17 of these industries in our empirical analysis because the producer price data for the remaining two industries started later in the sample.

[2] The sensitivity of the empirical results to the order of the VAR model, forecast horizon and the rolling window size are presented in Appendix B.1.

Table 2.1: Inflation Connectedness Table (1947-2019)

	321	327	331	332	333	335	3361	337	339	311	313	315	322	323	324	325	326	**From**
321 - Wood	83.2	0.5	1.8	2.1	0.2	0.2	1.9	0.5	0.4	0.5	3.7	1.7	1.0	0.4	0.1	0.3	1.4	16.8
327 - Minerals	0.3	51.3	3.3	2.6	7.9	3.3	0.0	8.2	3.3	1.1	0.6	2.6	3.4	3.2	1.2	5.3	2.5	48.7
331 - Basic Metal	0.6	2.9	66.3	2.1	2.6	3.4	0.0	1.2	0.5	1.2	0.8	1.3	3.0	2.5	2.0	8.5	1.0	33.7
332 - Fabricated Metals	2.1	1.9	2.6	69.0	2.4	1.5	0.0	4.7	4.0	0.5	0.9	1.6	1.5	0.4	0.3	1.6	5.1	31.0
333 - Machinery	0.2	6.1	4.5	4.1	34.1	16.0	0.6	5.3	2.2	1.1	0.5	3.3	3.7	4.3	1.3	4.5	8.1	65.9
335 - Electrical Equip.	0.1	3.6	4.6	3.0	23.0	42.5	0.2	3.4	2.5	0.7	0.3	2.8	2.4	1.9	0.5	3.0	5.5	57.5
3361 - Motor Veh.	2.2	0.2	0.2	0.2	2.1	0.7	91.4	0.5	0.3	0.1	0.1	0.1	0.2	0.8	0.5	0.2	0.3	8.6
337 - Furniture	0.3	6.9	3.0	5.5	12.6	6.4	0.2	34.9	3.7	1.6	0.7	5.1	3.0	2.7	1.2	4.2	7.8	65.1
339 - Miscellanous	0.1	3.4	0.9	5.6	3.8	3.5	0.3	7.1	69.5	0.4	0.2	0.6	0.9	0.4	0.3	1.4	1.4	30.5
311 - Food & Bev.	0.2	1.1	1.2	0.4	1.0	0.4	0.0	1.4	0.3	83.9	0.8	1.6	1.5	1.8	0.2	3.9	0.4	16.1
313 - Textiles	1.8	0.7	1.3	0.9	0.3	0.2	0.1	0.6	0.2	1.1	87.0	1.6	1.3	0.5	0.1	1.7	0.8	13.0
315 - Apparels	2.3	1.5	2.0	4.9	3.8	3.5	0.1	2.1	1.0	3.3	5.3	53.3	2.4	0.4	0.4	4.6	9.0	46.7
322 - Paper	0.5	3.6	5.8	2.9	3.7	2.7	0.0	2.2	0.8	1.7	1.2	5.1	41.4	17.6	0.7	5.4	4.6	58.6
323 - Printing	0.1	3.3	5.2	1.5	4.1	2.0	0.3	1.8	0.3	1.5	0.5	1.4	20.0	50.3	1.1	3.7	2.7	49.7
324 - Petroleum & Coal	0.0	1.5	2.0	0.4	0.9	0.5	0.3	1.1	0.1	0.3	0.1	0.5	0.7	1.4	88.6	1.0	0.5	11.4
325 - Chemicals	0.1	3.8	10.2	2.1	4.3	2.5	0.1	2.3	0.9	3.1	1.1	3.8	4.3	3.6	1.1	52.4	4.3	47.6
326 - Plastics	0.9	1.7	2.8	5.3	3.8	3.3	0.0	2.0	0.9	1.2	1.1	5.2	3.5	2.5	0.5	7.1	58.1	41.9
To Others	11.8	42.8	51.3	43.7	76.6	50.3	4.2	44.3	21.4	19.5	17.9	38.3	52.9	44.3	11.5	56.4	55.4	
Net To Others	-4.9	-5.9	17.6	12.7	10.8	-7.2	-4.3	-20.8	-9.0	3.4	4.9	-8.4	-5.7	-5.3	0.1	8.8	13.5	**37.8**

The ij^{th} entry of this matrix represents the pairwise connectedness $C_{i\leftarrow j}$, i.e., the percent of the 12-month-ahead forecast error variance of producer price inflation in industry i due to producer price changes in industry j. 'From Others' column reports the row sums excluding the diagonal elements, which is the total directional connectedness from other industries to industry i. 'To Others' row reports column sums excluding the diagonal elements, which is the total directional connectedness from industry i to others. The last row is the 'net connectedness to others,' the difference between 'to connectedness' and 'from connectedness'. The bottom-right element is the system-wide connectedness measure, which is the sum of all entries of the matrix excluding the diagonal elements, divided by the number of industries.

The off-diagonal ij^{th} entry of the connectedness table is the pairwise connectedness measure, which shows the proportion of 12-month-ahead forecast error variance of industry i's inflation due to inflation shocks in industry j. The diagonal ii^{th} entries are the own connectedness measures. In addition to the 17x17 matrix of pairwise connectedness measures, the last column of Table 2.1 reports the total 'from connectedness' of each industry i, which is equal to the sum of all off-diagonal elements of the i^{th} row. The last two rows of Table 2.1 respectively report the total 'to connectedness' and 'net connectedness' of each industry i, which are equal to the sum of all off-diagonal elements of the i^{th} column and the difference between the 'to' and 'from' connectedness for each industry i.

Among the total directional connectedness measures, 'to connectedness' row indicates each industry's contribution to the inflation forecast error variance of other industries. In our framework, sectors that have higher 'to connectedness' measures act as major transmitters of inflation shocks to others. With values of 87.2, 72.2 and 67.8, respectively, machinery, chemical products and basic metals are the top three industries that generated the highest inflation connectedness to other industries. They are followed by and nonmetallic mineral products (57.1), fabricated metal products (53.3), electrical equipment (49.1), furniture (48.1), paper (44.2), apparel (42.4), printing (40.3), plastics (27.3) and miscellaneous (20.9).

Industries with higher 'from connectedness' are the receivers of inflation shocks that originated in other sectors. With 'from connectedness' values of 65.7, 63.2 and 62.1, plastics, furniture and machinery industries are the industries that receive the largest inflation shocks from other industries. They are followed by electrical equipment (58.9), paper (55.7), non-metallic minerals (55.5), chemicals (50.4) and printing (50.4). Even though, their 'to' and 'from' inflation connectedness measures are the highest among the 17 sectors, the 'to connectedness' of chemicals and basic metals sectors are much higher than their corresponding 'from connectedness' measures, with the implication that these two industries have highest net connectedness' measures, 51.3 and 28.1, respectively. Machinery (-38.9), plastics (-22.4), and electrical equipment (-13.6) industries have negative 'net connectedness', indicating that they are in net terms receivers of inflation shocks from other sectors, especially from chemicals and basic metals.

Table 2.2: Input-Output Network Table (1947-2017)

	321	327	331	332	333	335	3361	337	339	311	313	315	322	323	324	325	326	**From Others**
321 - Wood	19.9	1.1	1.1	3.2	0.8	0.7	0.7	0.6	0.4	0.1	0.5	0.0	0.7	0.1	0.9	2.0	0.7	13.5
327 - Mineral	0.5	11.1	0.9	1.5	0.4	0.2	0.3	0.0	0.2	0.1	0.3	0.0	2.4	0.1	1.1	3.4	0.8	12.1
331 - Basic Metal	0.2	0.7	26.2	2.3	0.9	0.7	0.3	0.0	0.1	0.0	0.0	0.0	0.3	0.0	1.0	1.2	0.2	8.1
332 - Fabricated Metals	0.3	0.6	24.5	9.1	1.5	0.6	0.5	0.0	0.1	0.1	0.0	0.0	0.8	0.1	0.5	1.8	0.8	32.4
333 - Machinery	0.2	0.5	10.0	6.6	7.0	3.4	2.8	0.1	0.4	0.0	0.1	0.0	0.5	0.0	0.6	0.8	1.7	27.7
335 - Electrical Equip.	0.3	1.5	13.8	5.0	1.3	6.5	0.9	0.0	0.3	0.1	0.1	0.0	1.1	0.1	0.7	2.3	1.9	29.6
3361 - Motor Veh.	0.3	1.1	9.1	6.2	2.3	0.9	28.1	0.0	0.2	0.0	0.9	0.2	0.4	0.1	0.3	0.9	3.0	25.9
337 - Furniture	9.7	1.2	5.4	5.7	0.2	0.1	0.3	2.4	0.2	0.4	5.6	0.2	1.6	0.0	0.4	2.0	4.4	37.5
339 - Miscellanous	1.5	0.8	7.6	3.2	0.6	0.7	0.3	0.2	6.9	0.4	2.9	0.3	2.6	0.1	0.6	3.5	3.3	28.6
311 - Food & Bev.	0.1	0.9	0.2	2.5	0.2	0.1	0.1	0.0	0.0	17.6	0.1	0.0	2.5	0.3	0.4	0.7	1.3	9.5
313 - Textiles	0.1	0.3	0.1	0.4	0.4	0.1	0.1	0.0	0.3	0.2	25.4	0.8	0.9	0.0	0.4	15.0	0.8	19.9
315 - Apparels	0.2	0.1	0.1	0.5	0.1	0.0	0.0	0.0	1.7	3.0	21.9	14.7	0.9	0.3	0.3	3.1	1.1	33.4
322 - Paper	2.5	0.1	0.4	1.4	0.6	0.1	0.2	0.0	0.1	0.6	1.0	0.0	25.1	0.1	1.6	5.0	1.5	15.2
323 - Printing	0.0	0.0	0.3	0.6	1.6	0.1	0.1	0.0	0.4	0.3	0.6	0.8	17.3	6.2	1.1	3.5	1.0	27.7
324 - Petroleum & Coal	0.0	0.2	0.9	0.5	0.1	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.2	0.0	5.1	1.3	0.1	3.6
325 - Chemicals	0.1	0.5	0.9	1.6	0.6	0.1	0.1	0.0	0.3	1.3	2.1	0.2	1.7	0.2	1.9	21.7	1.5	13.1
326 - Plastics	0.3	0.7	0.6	1.8	0.5	0.2	0.1	0.1	0.1	0.1	3.5	0.0	1.9	0.1	0.5	19.2	4.9	29.7
To Others	16.2	10.3	75.9	43.1	12.0	8.1	6.9	1.0	4.7	6.9	39.8	2.8	35.7	1.6	12.4	65.9	24.2	
Net To Others	2.7	-1.8	67.8	10.7	-15.7	-21.5	-19.0	-36.5	-23.9	-2.6	19.9	-30.6	20.5	-26.1	8.8	52.8	-5.5	**21.6**

This table illustrates the normalized flows of the sales and purchases of domestic industry output and imports. The ij^{th} entry of this matrix reports the intermediate good purchase of industry j from industry i (domestic industry plus imports). To be compatible with the connectedness table, we construct from, to and net measures of flows. The “To Others” row reports the amount supplied by each industry to other industries, while the “From” column reports the total amount of domestic and imported inputs purchased by each industry from other industries. The difference between the “To” row and the “From” column is reported the “Net to Others” row.

Chemicals and basic metals industries are effectively the upstream industries that mainly supply intermediate inputs to downstream sectors. It turns out that they are transmitting inflation shocks to other industries as well as to each other. While pairwise inflation connectedness from chemicals to basic metals amounts to 13.2 percent, the connectedness from basic metals to chemicals amounts to 15 percent. Actually, the basic metals industry's net pairwise connectedness with 14 of the other 16 industries is positive, indicating that it is the generator of inflation connectedness to the whole manufacturing industry. While chemicals is the industry that receives the highest inflation connectedness from the basic metals industry (15.0), it is the plastics that receives the highest inflation connectedness from the chemicals industry (16.4).

Next, we focus on the input-output network table to see whether the inflation connectedness across industries has anything to do with the underlying input-output network. Table 2.2 reports the edge weights for the input-output network over the 1960-2016 period. Its entries are the average of the entries of the annual domestic input-output tables from 1960 through 2016. Hence, each entry ij of the static input-output table denotes the output normalized intermediate product flow from industry j to industry i. Both output and intermediate products are measured in constant prices.

The diagonal elements in Table 2.2 provides a measure of the use of products as intermediate inputs within the same industry, whereas the off-diagonal elements measure the use of products as intermediate inputs by other industries. We need to note that unlike the inflation connectedness table the sum of each row in the input-output table does not add to 100.[3]

With the highest 'to connectedness' (75.9 and 65.9, respectively) and 'net connectedness' (67.8 and 52.8) measures, basic metals and chemicals industries appear to be the two top upstream industries, followed by fabricated metals (43.1 and 10.7), textiles (39.8 and 19.9), paper (35.7 and 20.5), petroleum, wood (16.2 and 2.7) and coal (12.4 and 8.8). All other industries have negative net input-output network connectedness measures. Among these, furniture (-36.5), apparels (-30.6), printing (-26.1), other industries (-23.9), electrical equipment (-21.5), motor vehicles (-19.0), and machinery (-15.7) are the downstream industries that depend on intermediate inputs from other industries.

[3] We also prepared row-sum-normalized input-output network table whose rows add up to 100 and plot the resulting static network and the dynamic system-wide connectedness index. Neither the static network graph nor the dynamic system-wide I-O connectedness index was affected by normalization.

Tables 2.1 and 2.2 can be analyzed in further detail. Many of the entries in both tables are quite close to zero, indicating very low pairwise connectedness across some of the industries. Yet, some entries are quite large. As can be guessed these entries are located in the columns of the upstream industries and in the rows of their immediate downstream industries. In the case of basic metals, it has the stronger input-output links to fabricated metals (24.5), electrical equipment (13.8), machinery (10.0), motor vehicles (9.1), other industries (7.6) and furniture (5.4). Yet, the pairwise inflation connectedness of the basic metals industry is spread more evenly across industries. One can interpret this as in addition to input-output network links there must be other forces at work that influence the pairwise inflation connectedness measures. However, we don't want to reach a conclusion at the moment because so far we are analyzing the static networks which represent an average of 63 years of data.

Even though displaying the estimated static inflation connectedness measures along with the average input-output matrix in a tabular setting is quite informative, displaying them graphically is even more revealing. Next, the two networks are presented graphically following the network graphing convention used in Demirer et al. (2018a).

The open-source Gephi software (`https://gephi.github.io/`) is used for network visualization. Node locations are determined by the ForceAtlas2 algorithm of Jacomy et al. (2014b) as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting forces exactly balance; nodes repel each other like similar poles of two magnets, while edges between two nodes attract their nodes, like springs. The attracting force of an edge is proportional to the average pairwise directional connectedness between the two nodes, which also determines the thickness of the edge.[4] Finally, the edge color is the same as the color of the node that generates net positive directional connectedness to its pair.

Figure 2.1: Color Spectrum of the Networks

Inflation connectedness and input-output network graphs created with the

[4] In the inflation connectedness network, the edge thickness represent the average pairwise 'to' and 'from' inflation connectedness between two nodes. In the case of the input-output network, the edge thickness between two nodes represents the average product flow between the two industries relative to their respective levels of production.

conventions listed above are presented in Figures 2.2 and 2.3, respectively.

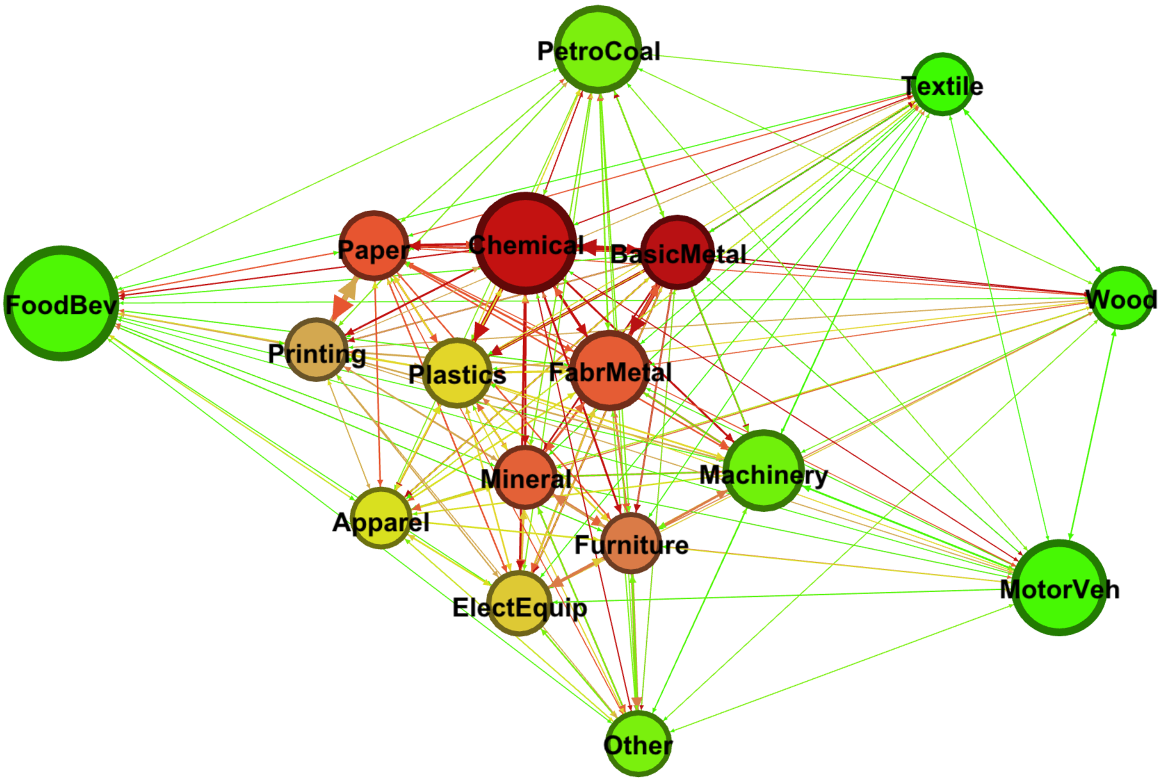


Figure 2.2: Inflation Connectedness Network (1960–2016)

Node labels are short acronyms of the industry names listed in Appendix Table B.1. Node size indicates the average gross industry output throughout 1960-2016.[5] The node color indicates total directional inflation connectedness to others, ranging from bright green (lowest) to luminous vivid yellow, whiskey sour, bright red and dark red (highest). The node color spectrum is presented in Figure 2.1.

We have three major takeaways from Figures 2.2 and 2.3. First, in Figure 2.2 red/orange/brown colored nodes which represent the inflation connectedness generating industries tend to locate in the center of the networks with higher connectedness to others.

Similarly, in Figure 2.3 the upstream industries represented by red, orange and, to some extent, brown colored nodes also tend to locate close to the center of the

[5] While the node size represents the average gross output of the industry, they are not directly proportional. Huge gross output differences between the largest and smallest industries in our sample make a directly-proportional representation of the output in the node size impossible.

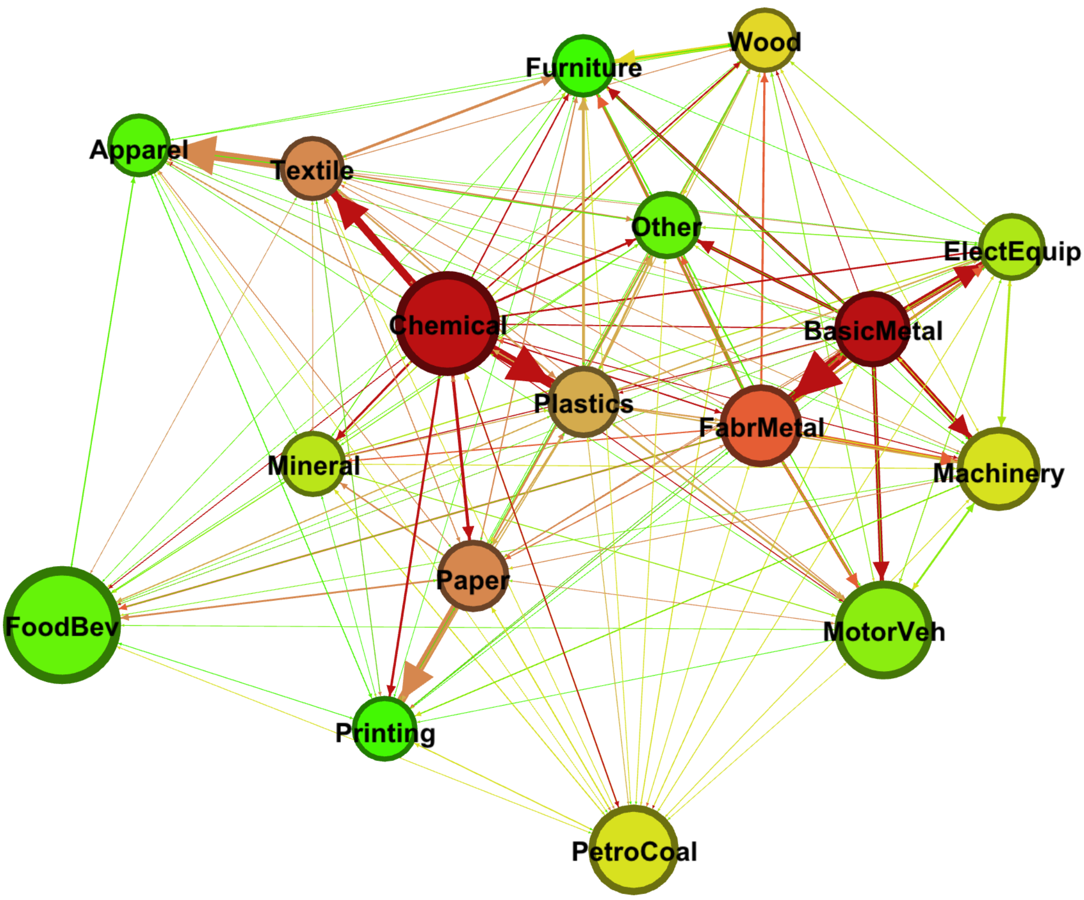


Figure 2.3: Input-Output Network, Domestic Inputs plus Imports (1960–2016)

network, but now we can identify two major clusters formed around the top two upstream industries. Paper, textiles, plastics, minerals, others and furniture that are the main users of chemical products as inputs are located close to the chemicals industry. Fabricated metals, machinery, motor vehicles, electrical equipment and other industrues are located around the basic metals industry again with sizeable input use from that industry.

Second, having a closer look at Figure 2.2, we can discern that basic metals generate positive net inflation connectedness to chemicals. The pairwise inflation connectedness of the two industries with each other is more than implied by their underlying input-output network. They also form a similar cluster structure of their downstream industries. Yet, it is more difficult to separately observe the two groups.

Finally, bright green nodes (with the exception of 'others' industry) representing the inflation-shock receiving and downstream industries are, in general, located in the periphery of their respective networks.

The largest node in the input-output network represents the food and beverages industry, which accounts for the largest gross output among the industries considered. However, the node for the food and beverages industry is located in the periphery of the input-output and inflation connectedness networks. Being a downstream industry it is on the receiving end of the inflation shocks transmitted by other industries. On the other hand, with its low gross output the basic metals industry is located in the middle of a cluster of industries in both networks because it is one of the top two upstream industries in the U.S. manufacturing sector.

2.5 Dynamic Analysis

Static inflation and input-output network graphs we presented in the previous section are quite informative. Yet, it is not realistic to expect the inflation connectedness stay unchanged over a period of two decades. One needs to take into account the possible effects of domestic and global shocks on inflation connectedness over time. For that reason, this section focuses on the dynamic (time-varying) analysis of inflation connectedness. It starts with the dynamic behavior of the system-wide inflation connectedness followed by the dynamic analysis of the total 'net connectedness' of 17 manufacturing industries.

2.5.1 System-wide Connectedness

One of the strengths of the Diebold-Yilmaz connectedness index framework has been its flexibility of implementation over rolling sample windows to obtain dynamic connectedness measures. For each sample window, we compute the system-wide connectedness index along with the total and pairwise directional connectedness measures from the VAR model estimates and the resulting variance decompositions.

We present the system-wide connectedness index in Figure 2.4 along with the World Bank commodity price index for metals and minerals and the price of oil (West Texas Intermediate oil, U.S. $ per barrel). The system-wide connectedness index is based on the Lasso estimation of a second-order VAR model over 60-month rolling sample windows with a forecast horizon of 12 months. For each rolling sample window, the system-wide connectedness index measures the total inflation shock transmission across industries for that particular sample period. Inflation shock transmission fluctuates substantially over time. Furthermore, it increases significantly during periods of major supply-side inflationary shocks, such as the oil and metal/minerals price hikes.

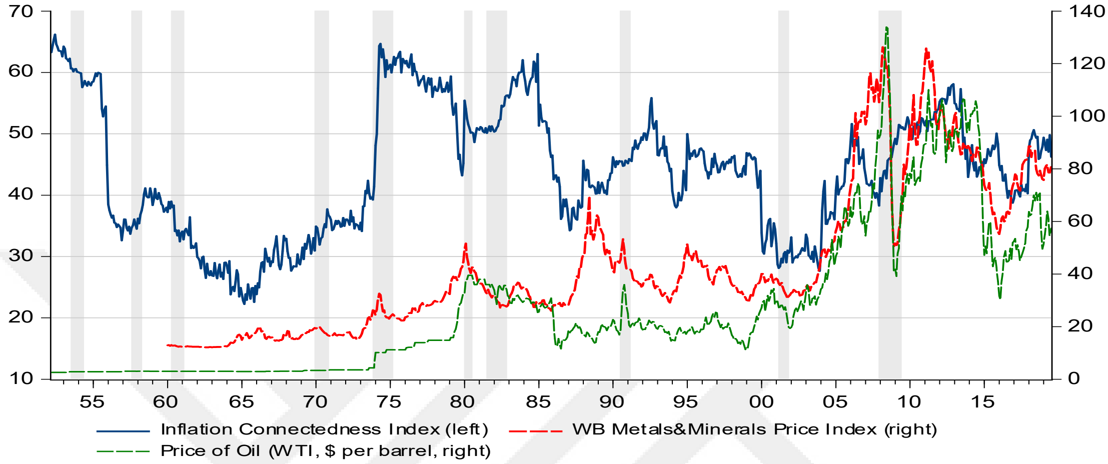


Figure 2.4: System-wide Connectedness and World Bank Metal & Minerals Price Index Notes: Bars indicate U.S. recessions. Connectedness Index based on LASSO estimates of VAR(2) model, rolling window length of 60 months and forecast horizon of 12 months

We analyze the behavior of the connectedness index over time along with the consumer and producer price inflation series and the world metal and oil prices.

1947 and 1950-51 were years of exceptionally high inflation. From the invasion of South Korea in June 1950 to the imposition of general price and wage controls in January 1951 the U.S. monthly wholesale inflation rate reached on average to 2% per month. As noted by Ginsburg (1952) (p. 517) the prices of 28 sensitive agricultural and industrial commodities increased by more than 6% per month over this period.[6] As a result, the producer price inflation connectedness across manufacturing industries was at the highest level to begin with. Once the general price and wage controls were implemented the inflation rates declined substantially. As the observations for 1947 are dropped out of the sample window, the connectedness index gradually declined from 65 to around 60 over a three-year period. This rather gradual decline was followed by a 30-point large drop followed by a 25-point drop as the data for 1950-51 are dropped out of the rolling sample windows.

After the largest drop, the index first moved slightly up towards the end of the

[6] According to Figure 1 of Radetzki (2006), global metal price index increased by 45% from 1948 to 1952.

1950s, a period during which the PPI inflation increased to around 5% per annum. Then the connectedness index moved from 40 in 1960 to all the way down 23 in 1965, its lowest level over the 72-year long period of our analysis. Consistent with the behavior of the inex, the producer price inflation was mostly below 1% per annum over this period. As the the metal commodity prices increased by 40% in 1965 and 1966 (see Figure 2.4 and Figure 1 of Radetzki (2006)). During this period inflation connectedness moved up by 7 percentage points. From 1968 through 1973, the metals and minerals price index continued its upward swing, while the system-wide inflation connectedness index increased by another 7 percentage points over this period.

The following two major hikes in the system-wide connectedness index were due to two oil price shocks. Since we are studying the manufacturing industries and oil is an essential input for the manufacturing production, oil price shocks had a significant impact on production costs in major U.S. industries as anticipated. The connectedness index increased by close to 30 percentage points in a matter of a year, thanks to the sudden increase in oil prices following the OPEC's oil embargo decision in October 1973. Over this period, the spot price of crude oil ((WTI) tripled, from $3.56 per barrel in August 1973 to $10.1 in January 1974 and further to $11.2 in October 1974. Even before the oil price hikes started, the global price index for metals & minerals commodities started to increase in December 1972, doubling by April 1974. Obviously, the increase in the global metals and minerals prices might have also contributed to the increase in the connectedness index at the end of 1973 through the end of 1974.

In 1979 as a result of the islamic revolution in Iran, one of the world's major oil exporters, the spot price of WTI oil went up from $14.9 in January 1979 to $26.5 in September 1979. Following the outbreak of the hostage crisis in early November (where 52 American diplomats were taken hostage in Tehran) the spot price of oil continued to climb as high as $39.5 per barrel in May 1980. In the meantime, the global metal and mineral commodity prices (as measured by the World Bank index) started to increase from 29.1 in May 1978 reaching 51.6 in February 1980.

As can be expected, second oil price shock also had an impact on the system-wide inflation connectedness index. The increase in the connectedness index in 1979, however, was smaller (less than 10 percentage points) and lasted shorter than the one experienced following the first oil price shock. It was perhaps so because the impact of the second round of increases in oil (and metal and mineral commodity) prices in 1978 through 1980 was much less than the one in the first round of increases in 1973-1974. More importantly, the manufacturing industry was better prepared to the second round of price hikes after being caught off-guard by the unexpected price hikes of 1973-74.

As we have already noted above, it was not just the global oil price shocks that affected the system-wide inflation connectedness across industries over time. Global metals and minerals prices also affect the system-wide inflation connectedness. The system-wide inflation connectedness index started to increase gradually in the second-half of 1982, towards the end of the 1981-1982 recession, along with a 30% increase in the global metals and minerals commodity price index.

1987 was a year during which the World Bank commodity price index for metals and minerals increased from 28 in January to 47 in December. Metals and minerals price index continued to increase in 1988 to reach 62 in December (see Figure 2.4). Reflecting the impact of the 121% increase in metals and minerals price index over this period, the system-wide connectedness index recorded a significant jump, from 30 to 45, in 1987 and 1988 (see Figure 2.4).

After a correction that lasted for five years, metals and minerals experienced another round of price increases in 1994: the price index increased continuously in 1994, from 31 in January to reach a local peak of 51 in January 1995 (see Figure 2.4). This time around, the connectedness index increased from 30 at the end of 1993 to 41 in early 1995.

More importantly, following China's integration to the global economy in the early 2000s, the World Bank metals and minerals commodity price index experienced quite a long-lasting super cycle of price hikes starting from around 34 at the end of 2002 to reach 69 by the end of 2005 and 116 by May 2007. During this period, the system-wide connectedness index increased from 23 to 38 (see Figure 2.4).

After another brief correction during the Great Recession of 2008, the metals and minerals commodity price index stayed above 100 until 2012. During this period inflation connectedness continued its upward gradual move albeit at an increased pace reaching around 50 by the end of 2012. It started moving down in 2013 along with the decline in the metals and minerals commodity price index. Recently, the metals and minerals commodity price index started to increase since 2016. Yet, until recently the system-wide connectedness index has not moved up. However, as we will discuss below in section 2.5.3, the uptick in the index since January 2018 could also be due to the U.S. President Donald Trump's decision to impose additional tariffs on imports in different sectors including the primary metals.

So far we have focused on the upward moves in the connectedness index over time. However, as we have noted above the index does also go through significant drops as we roll the sample window over time. Most of these drops in the index, however, result from the use of rolling sample windows framework to undertake the dynamic connectedness analysis. For example, the index starts fluctuating between 60-79% as we roll the window forward from 1952 through 1955. However, as we roll the window forward the inflation data for 1950 drop out of the sample window and the index drops down quickly from 65% to 53%, to 43% and 35% as we roll the windows eight months forward. This is an expected result because 1950 was an exceptional year when the annual producer price inflation jumped to 14.7%. Similarly, the index recorded a substantial drop in 1978, as the data for late 1973 and early 1974 are dropped out of the sample window. Similar drops are observed in 1985, 1993 and 1999 that followed the upward jumps in the index with a five-year delay.

2.5.2 Net Directional Connectedness

After the dynamic analysis of the system-wide connectedness measures, we now shift the focus to the behavior of the total net directional connectedness measures over time. Figures 2.5 and 2.6 present the net directional inflation connectedness measures for 17 manufacturing industries. Rather than analyzing each graph in some detail, the focus of the section will be more on general trends, as well as those industries whose net inflation connectedness dynamics revealed some distinguishing characteristics.

We first focus on the dynamic net inflation connectedness of the two main upstream industries, namely, basic (primary) metals (see Figure 2.5) and chemical products (see Figure 2.6). Both industries have positive 'net connectedness' in general. Primary metals industry had high 'net connectedness' in the second half of the 1950s (in the 20-30% range), following the first oil price shocks of 1974-1975 (reaching as high as 80%), briefly in 1985, and following China's ever-increasing demand for metals from 2003 to 2014 (in the 25-70% range). As can be expected, the 'net connectedness' of the primary metals increased significantly during all the metal and mineral price increase episodes (see Figure 2.4) except for the 1987 episode. Primary metals industry's net inflation connectedness was negative for a short period in the late 1980s and early 1990s (around -30%).

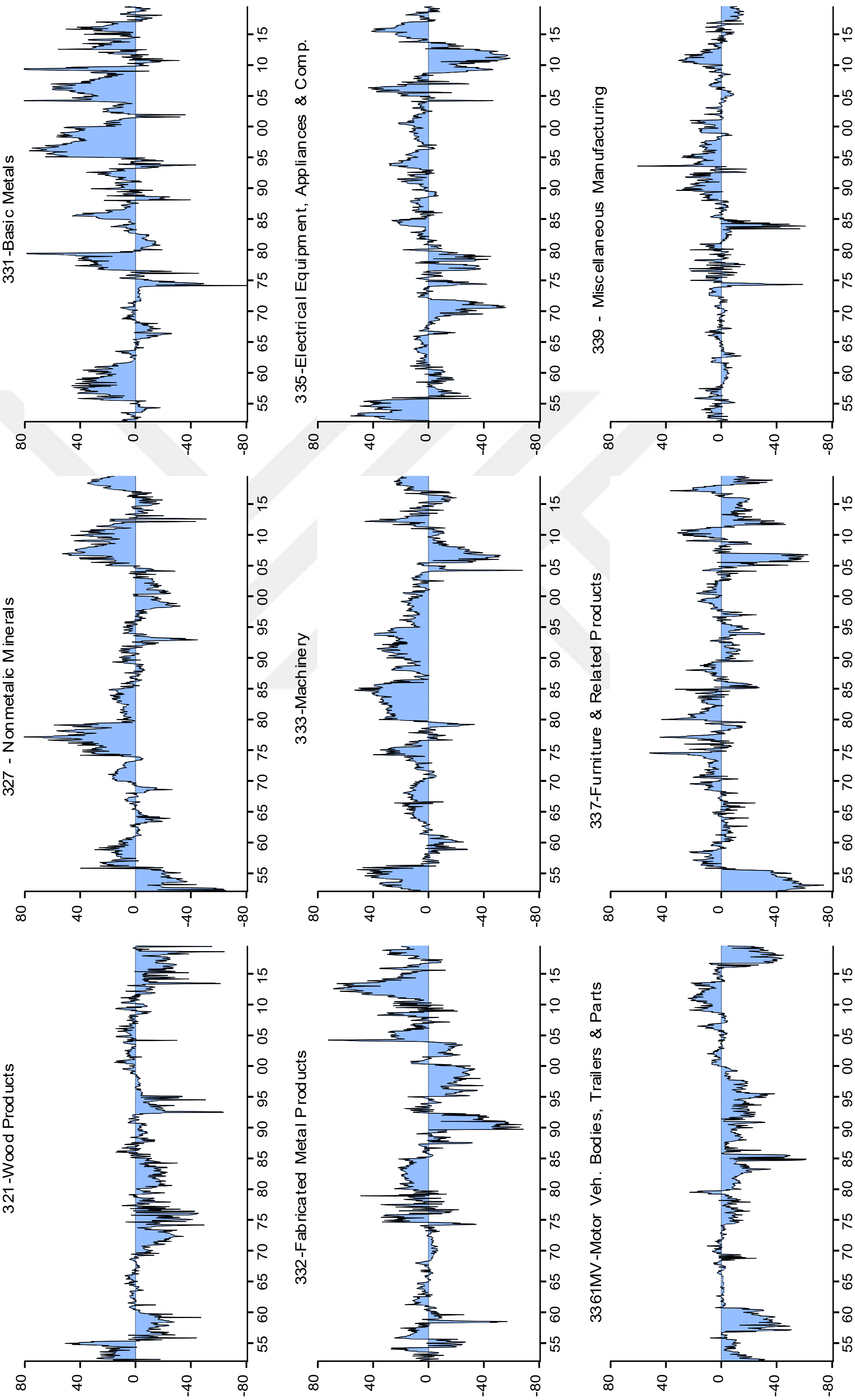


Figure 2.5: Net Directional Inflation Connectedness – U.S. Manufacturing Industries (1)

The net inflation connectedness of the chemical products industry (Figure 2.6) was very low until the first oil price shock of 1974-75, after which it increased all the way up to 70% before dropping back to around 20% for the rest of the 1970s. It fluctuated between 30 and 40 % from the second oil price shock of 1979-1980 until 1985. After having low positive and negative values for a decade, the ‘net connectedness’ of the chemicals industry jumped to more than 40% in the 1995-2000 period. It again started to increase gradually from around 10 % in 2002-2003 to reach 40% by 2005. Even though its ‘net connectedness’ dropped significantly during the global financial crisis, since then it picked up to reach 60% by 2014-2015 and stayed in the 20-30% band by the end of our sample period. To summarize, the net inflation connectedness plot for the chemical products industry shows the industry’s increased importance for the inflation connectedness across the U.S. manufacturing industries over time.

Fabricated metal products industry (332), which is a recipient of inflation shocks from the primary metals industry is also a generator of inflation connectedness to other industries. As the fabricated metal products industry provides intermediate inputs to machinery, electrical equipment, and motor vehicles industries, it generates inflation connectedness towards these sectors. Its net inflation connectedness reached as high as 20% in the second half of the 1950s, in early 1990s and in 2010s (see Figure 2.5). On the negative side, its ‘net connectedness’ dropped as low as -30% due to the increases in the metal and mineral prices in the late 1960s and after the oil price shocks of 1974-1975 and 1979-80. Even though we do not present the graphs here, the pairwise connectedness measures show that negative ‘net connectedness’ of the fabricated metal

products industry during both episodes followed from the increase in the pairwise inflation connectedness from the primary metals industry to the fabricated metal products industry.

Following the first oil price shock of 1974-1975, nonmetallic mineral products (327) and petroleum and coal products (324) industries generated substantial (30-40%) net inflation connectedness to other industries (see Figures 2.5 and 2.6). Since the first oil price shock, however, petroleum and coal products industry generated quite low net inflation connectedness to other industries. Nonmetallic mineral products industry, on the other hand, had around 30% ‘net connectedness’ in the second half of the 2000s, followed by a negative ‘net connectedness’ period in the aftermath of the global financial crisis. While the petroleum and coal products industry has become less important for the price dynamics of the major manufacturing industries, two key upstream sectors, namely primary metals and chemical products industries have become more influential in generating inflation connectedness to others.

Several industries, such as the electrical equipment and appliances (335), paper products (322), and plastics and rubber products (326) had high (at or above 40%) net inflation connectedness at the beginning of the sample period (from 1952 to 1956). As the sample windows are rolled and the inflation observations pertaining to the high inflation year of 1950 are dropped out of the sample windows, the net inflation connectedness of these industries drops as well.

Afterward, the electrical equipment and appliances industry had negligible positive 'net connectedness' measures, along with two episodes of high (in absolute value) negative connectedness before and after the first oil price shock. Following this period, its 'net connectedness' dropped to -30% in the second half of the 1950s. Given that both fabricated metals and basic metals generated high net inflation connectedness over this period, the electrical equipment industry is one of the downstream industries receiving the inflation shocks. Other downstream industries that had negative net inflation connectedness in the early 1950s are the machinery (333), motor vehicles (3361MV) and furniture and related products (337) industries.

Plastics and rubber products also had high (in absolute value) negative connectedness in the second half of the 1970s and the first half of the 1980s, as well as from 2005 to the end of the sample in 2017. These negative 'net connectedness' are due to the high pairwise inflation connectedness from the chemical products industry to the plastics and rubber products.

Majority of the remaining 17 U.S. manufacturing industries have had low positive or negative net inflation connectedness to others for the most part of the 1947-2017 period. To take an example, apparel and leather products (315AL) industry had high net inflation connectedness (reaching as high as 60%) following the first oil price shock, but its net inflation connectedness is low (lower than 20%) before and after this episode.

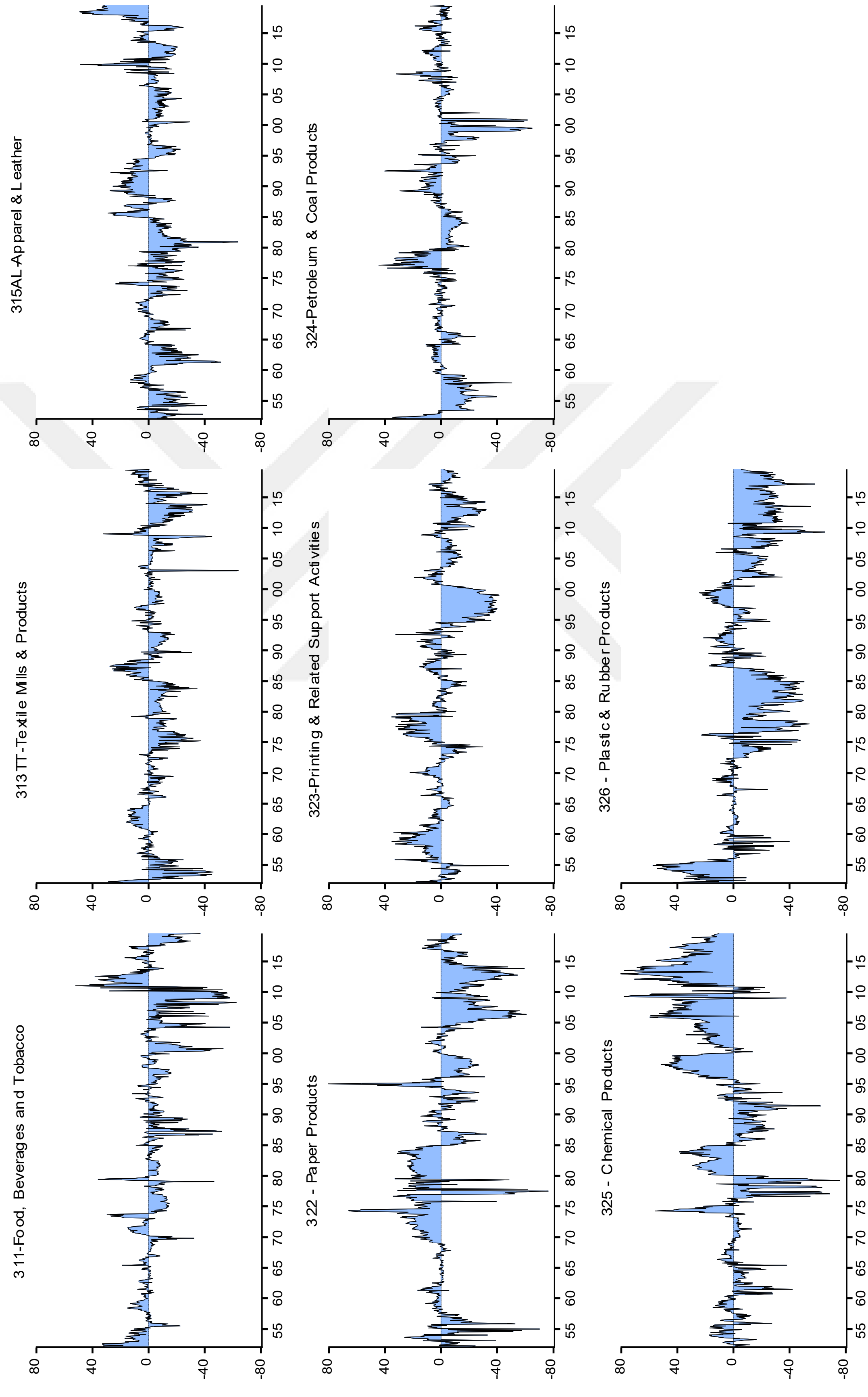


Figure 2.6: Net Directional Inflation Connectedness – U.S. Manufacturing Industries (2)

Two industries, paper products (322) and printing (323) had relatively sizeable positive net inflation connectedness until the mid-1990s. To be more specific, paper products industry's net connectedness reached close to 40% in the first half of the 1950s, as well as during the period between the two oil price shocks. The industry had relatively high (around 30%) net connectedness from 1980 to 1985, followed by a net connectedness of around 20% in 1987 through 1992 and a spike in net connectedness in 1995. In the case of the printing industry, the net connectedness was relatively high after the oil price shocks of 1975 (exceeding 40%), followed by a more modest net connectedness of around 15-20% in the 1980s.

In the mid-1990s net connectedness of both industries moved to the negative territory. The shift has been a result of the increased reliance of paper products industry to chemicals with developments in the production technology as well as the increased prices in the chemicals industry and its increased role as the transmitter of inflation shocks to other industries. This is exactly the period during which the chemical products industry had a net inflation connectedness of around 40%. Looking at the pairwise connectedness measures we can see that most of the inflation shocks in the chemical products were transmitted to the paper products and printing industries.

2.5.3 Trump Tariffs & Inflation Connectedness: A Preliminary Analysis

Recently, the U.S. President Donald Trump decided to impose tariffs on U.S. imports from China and other major trade partners of the U.S. The first of Trump tariffs was imposed on January 22, 2018 in the form of 20% tariffs on washing machine imports and 30% tariff on solar panel imports. This was followed by an even more significant step announced on March 8, that imposed 25% and 10% tariffs on steel and aluminum imports, respectively. More recently, on July 6 and August 23 Trump administration imposed tariffs on $34 and $16 billion worth of imports from China, respectively..

At the moment, it is quite early to evaluate the impact of Trump tariffs on inflation connectedness across U.S. manufacturing industries. Yet, the system-wide connectedness index has recorded 5.5 percentage points increase from January to June 2018. The 5.5 pp increase in connectedness is not as significant an increase as we observed in previous episodes discussed above. Furthermore, one can argue that the 5.5 pp increase in the system-wide inflation connectedness could be due to the increase in metals and minerals commodity price index in 2016 and 2017, followed by a slight decline in 2018.

However, analyzing the directional connectedness measures of all 17 manufacturing industries, one can observe four industries recording substantial increases in their ‘to connectedness’ measures over the first half of 2018. Comparing their average ‘to connectedness’ measures, it is observed that four industries recorded the most significant increase in their ‘to connectedness’ from the last quarter of 2017 to the second quarter of 2018. These are machinery (with a 20 p (which corresponds to 129%) increase), fabricated metals (with a 24.7 pp (93%) increase), basic metals (with a 29 pp (64%) increase) and petroleum and coal products (with a 33.8 pp (52%) increase).

Even though it is too soon to reach a final verdict on this issue, it is worth pointing out that three of the four industries (except for the petroleum and coal) are the ones targeted by Trump’s new tariff policy. Therefore, it’s worth the effort to keep an eye on the possible impact of Trump tariffs on inflation connectedness across U.S. manufacturing industries in the near future.

2.6 Input-Output & Inflation Connectedness Nexus

After analyzing the dynamic behavior of the system-wide and net directional connectedness measures at some detail, we are now ready to analyze the relationship between the inflation connectedness and the underlying input-output networks. Towards that end, we first focus on system-wide connectedness measures followed by the analysis at the granular level, using pairwise connectedness measures for both networks.

2.6.1 System-wide Connectedness

In Figure 2.7 we present the annual average system-wide connectedness index for inflation along with the system-wide connectedness of the input-output network. Similar to the inflation connectedness index, the input-output connectedness index is the sum of all off-diagonal elements of the U.S. domestic input-output matrix.[7]

The system-wide connectedness index for the input-output network varies much less (between 17 and 25%) compared to the inflation connectedness index (between 25 and 65%). Such a result is quite expected: While input-output network connectedness is a reflection of the technological relationship which does not

[7] As the data on input-output tables are available only on an annual basis we converted the inflation connectedness measures from monthly to yearly frequency by taking averages for each year. Furthermore, as the data for input-output tables are availabe only until 2016, the joint annual analysis of the two connectedness measures covers the period until 2016.

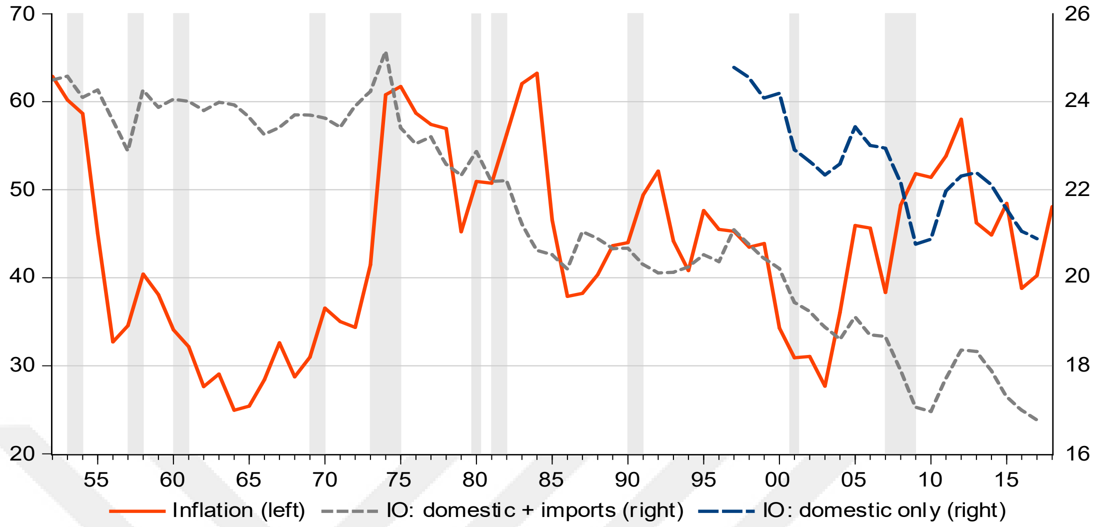


Figure 2.7: System-wide Inflation vs Input-Output Connectedness Three-digit NAICS industries; Based on VAR(2) model, rolling window length of 60 months and forecast horizon of 12 months

change substantially in a year or two, inflation connectedness can vary substantially depending on the size of the inflation shocks, as well as the underlying input-output networks and the domestic market conditions that propagate those shocks across sectors.

The two connectedness indices behave quite differently before the 1960s. We have already explained above that the inflation connectedness index was high to begin with, and declined with the removal of the data pertaining to the high inflation year of 1950 from the rolling sample windows. The two indices started to move closely especially in the 1970s. After going through an upward move in the early 1970s both indices started to follow a downward long-run trend which lasted until the mid-2000s.

The behavior of the two indices slightly deviate from each other in the mid-2000s to early 2010s; while the input-output connectedness (including both domestic and imported inputs) declined from 24% in 2003 to 21% in 2008, the inflation connectedness increased from 35% to almost 50% over the same period. After this divergent behavior, the two indices continued to follow a similar downward path starting in 2011 until the end of the sample in 2016.

Conducting an eye-balling analysis of the behavior of the input-output network connectedness (ION) and the inflation connectedness (IC) series is quite revealing about the possibility of a close long-run relationship between the two indices. In order to have a more conclusive evidence, we need to move one step further and test whether there is any statistically causal relationship between the two series.

Towards that end, we undertake a simple Granger causality test. We separately regress each of the system-wide ION and IC indices on its own lag as well as the lagged values of the other index and test whether the coefficient on the other lagged values of the other index is statistically significantly different from zero. We repeat the Granger causality test for time lags up to five years. The results are presented in Table 2.3.[8]

Table 2.3: Granger Causality: System-wide Inflation (InfC) vs I-O Network Connectedness (IoC); (Annual, 1960-2018)

	Dependent Variable: InfC (1960-2018)					**Dependent Variable: IoC (1960-2017)**				
Lag	**InfC**	**IoC**	P_m	$\bar{R}^2$	**GCT p-val**	**InfC**	**IoC**	P_m	$\bar{R}^2$	**GCT p-val**
1	0.743**	0.732*	0.18**	0.799	0.021	-0.0002	0.903**	-0.02	0.962	0.98
	(0.06)	(0.31)	(0.06)			(0.013)	(0.07)	(0.012)		
2	0.508**	1.090*	0.27**	0.570	0.013	0.018	0.717**	-0.06**	0.928	0.34
	(0.09)	(0.42)	(0.08)			(0.018)	(0.09)	(0.016)		
3	0.347**	1.141*	0.28**	0.385	0.023	0.026	0.569**	-0.08**	0.903	0.205
	(0.10)	(0.49)	(0.09)			(0.02)	(0.10)	(0.017)		
4	0.159+	1.345**	0.32**	0.258	0.007	0.015	0.545**	-0.09**	0.882	0.505
	(0.09)	(0.48)	(0.09)			(0.022)	(0.11)	(0.02)		
5	0.072	1.07*	0.26**	0.123	0.015	-0.003	0.654**	-0.06**	0.872	0.890
	(0.10)	(0.42)	(0.09)			(0.024)	(0.12)	(0.02)		
6	0.130	0.427	0.10	0.011	0.334	-0.015	0.752**	-0.05*	0.864	0.565
	(0.11)	(0.44)	(0.09)			(0.026)	(0.13)	(0.02)		

Notes: All variables in logs. As the World Bank Metals and Minerals Commodity Price Index starts in 1960, regressions are based on observations over the 1960-2018 period; As Input-Output data are available up to 2017, t statistics in parentheses; $^+$: $p < 0.10$, *: $p < 0.05$, **: $p < 0.01$.

In the IoC equation, the coefficient estimates of the one- to five-year lagged InfC variables are not statistically different from zero. All explanatory power in the equation is obtained from the lagged values of the ION variable. In the IC equation, on the other hand, the coefficient estimates of the two- to five-year lags of ION variable are statistically significant. The explanatory power in the IC

[8] As the dynamic behavior of the system-wide inflation connectedness index is found to be closely related to the World Bank Metals and Minerals Commodity Price Index, we have undertaken the Granger causality tests by including this index as an exogenous variable in both ION and IC equations.

equation diminishes quite quickly as the coefficient estimates of the lagged IC variable becomes statistically insignificant at four- and five-lags. The hypothesis of insignificant lagged ION coefficients is rejected at the 6% level or below. Together, these Granger casuality test results indicate that the system-wide connectedness of the input-output network Granger-causes the system-wide inflation connectedness. As such the test results support the Acemoglu et al. (2016b) model's prediction that the stronger the system-wide connectedness of the input-output network the stronger would be the system-wide inflation connectedness across industries .

2.6.2 Pairwise Connectedness

Having found strong statistical evidence for Granger causality at the aggregate level, we are now ready to test for Granger causality using granular pairwise connectedness measures for the inflation and input-output networks over time. First, we run regressions for the full sample and report the results in Table 2.4. In the pairwise connectedness regression, the dependent variable is the pairwise inflation connectedness from industry j to industry i, while the input-output network edge from industry j to industry i (which is defined as the value of the intermediate inputs from the source industry j used by the target industry i relative to the total output of the target industry i) as the key explanatory variable. In addition, we use the GDP share of source industry j relative to the GDP share of the target industry i as a control variable. We estimate this equation with and without year, source industry and target industry fixed effects.

For each specification, the coefficient of the pairwise input-output network measure is positive and significant. For the 1952-2016 estimation period, 39%of the fluctuations in the pairwise inflation connectedness can be explained by the fluctuations in pairwise input-output linkages and the GDP share of the source industry relative to that of the target industry. When we take the source and target industry fixed effects along with year fixed effects, the explanatory power of the cross-section regression increases to 44%. Apparently, industries that are dependent on each other's intermediate products tend to spread price changes through cascade effects.

After showing the close relationship between the pairwise connectedness measures for the input-output and inflation network in the full sample, we repeat the same cross-section regressions for every year. As there are 289 pairwise measures of connectedness for every rolling sample window, we undertake cross-section regressions for every year and plot the behavior of the resulting the

Table 2.4: Pairwise Inflation and Input-Output Connectedness (1953-2018)

Dependent Variable: Pairwise Inflation Connectedness (t)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Pairwise IoC (t-1)	0.083**	–	0.087**	0.083**	0.085**	0.074**
	(0.011)		(0.011)	(0.011)	(0.011)	(0.011)
S/T GDP Share (t-1)	–	0.052*	0.093**	0.072**	0.077**	0.030
		(0.023)	(0.024)	(0.024)	(0.023)	(0.053)
Pairwise InfC (t-1)	–	–	–	0.068**	0.061**	0.047**
				(0.010)	(0.010)	(0.010)
F statistic	61.9	4.8	35.9	35.5	11.5	24.3
Adjusted R^2	0.006	0.000	0.007	0.017	0.044	0.128
Number of Obs.	17,952	17,952	17,952	17,697	17,697	17,697
Year FE	N	N	N	N	Y	Y
Source Industry FE	N	N	N	N	N	Y
Target Industry FE	N	N	N	N	N	Y

Notes: Standard errors in parentheses. + $p < 0.1$; * $p < 0.05$; ** $p < 0.01$

coefficient estimate of the input-output network connectedness in Figure 2.9.

2.7 Granger Causality

In this section, we go ahead and analyze the relationship between the input-output network and inflation connectedness Using the pairwise inflation connectedness measures estimated in the rolling-windows analysis along with the input-output measures used to test whether

Figure 2.8 plots the time-varying explanatory power of pairwise domestic input-output network entries (domestic input-output matrix entries) on inflation connectedness for every year from 1952 to 2016. In the earlier part of the sample, the goodness of fit fluctuates between 0.30 and 0.45. It first starts in the 0.30-0.35 range, but as soon as the data for 1947 are dropped out of the rolling window sample the goodness of fit increases to reach 0.45. It does not stay at this level for a long time and fluctuates in the 0.32-0.41 band until the mid-1980s. It increases following the first and second oil price shocks but decreases during and immediately after the Volcker Recession of 1981-82, which was an aggregate demand shock. However, as we consider windows from 1985 onwards the goodness of fit increases steadily from 0.32 in 1985 to 0.58 by 2007. This is exactly the period during which both the system-wide inflation and input-output network connectedness measures follow a downward trend in Figure 2.7. It is no surprise that this period coincides with the so-called Great Moderation, a term used to describe the significant decline in the volatility of business cycle fluctuations. As the pairwise connectedness of the input-output network declined over time, so did the pairwise inflation connectedness across industries. The increasing goodness of fit from the mid-1980s onwards clearly reflects this fact. Again consistent with the impact of the global financial crisis (an aggregate demand shock) on inflation connectedness, R^2 declines from 0.58 in 2007 to less than 0.41 in 2011.

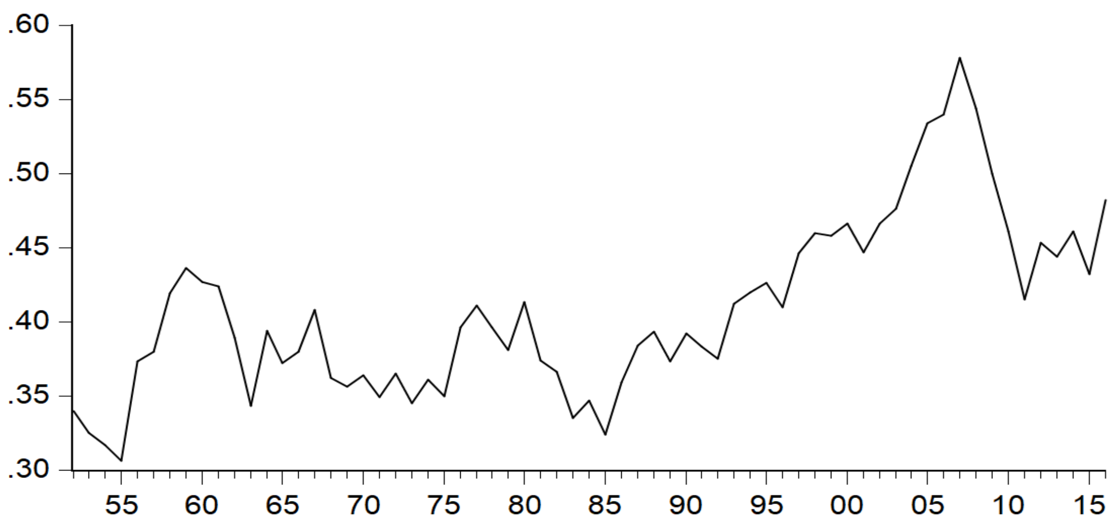


Figure 2.8: Dynamic Pairwise Connectedness Regression Fit. R^2 values obtained from the secondary regression; domestic input-output coefficients are used as explanatory variables

Figure 2.9 plots the beta coefficient from the cross section regression of pairwise inflation connectedness measures on domestic input-output network connectedness measures. Dashed lines indicate the % 95 confidence interval for the estimated beta coefficient.

The beta coefficient for the domestic input-output network is statistically significant for all the windows considered. Yet it fluctuates substantially over time, consistent with the fluctuation of the goodness of fit measure, R^2, over time. As the data for 1947 is dropped from the sample window, the beta coefficient increases from around 1.0 to all the way to 2.0. The first oil price shock in 1974 first led to a decline in the beta coefficient, followed by a long-lasting upward trend afterwards. From a value of 1.2 in 1974, it increased steadily to reach 2.4 by 2003.

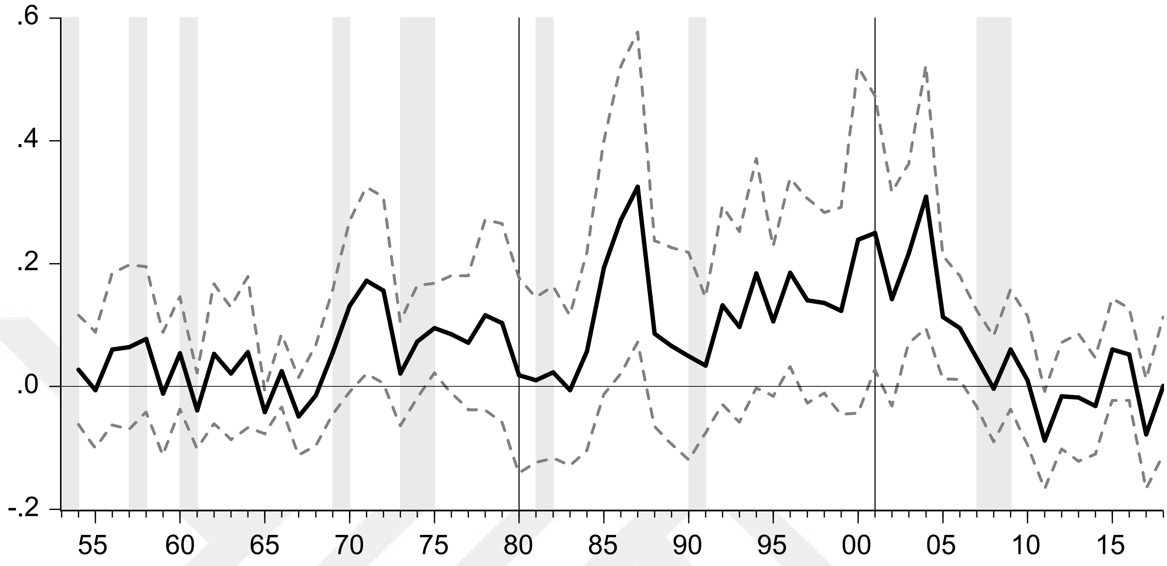


Figure 2.9: Dynamic Pairwise Connectedness Regressions - Domestic IO Coefficients Only. Statistically significant values of β obtained from the secondary regressions; domestic input-output coefficients are used as explanatory variables.

The upward trend of the beta coefficient ended in early 2000s; after reaching a maximum of 2.4 in 2003 it dropped to 2.0 in 2006 and 1.5 in 2012. During the Great Recession, the crisis spread from financial markets to the whole U.S. economy in the form of a substantial decline in the consumption demand by households and investment demand by corporations. The decline in demand put a downward pressure on inflation across sectors generating an increasing inflation connectedness over time. Yet, during this time period, the input-output connectedness did not necessarily follow a similar upward move. As a result, from 2007 to 2012 both the goodness of fit and the coefficient estimate for the pairwise input-output network connectedness declined significantly. After 2012, both parameter estimates edged slightly upwards.

2.8 Conclusion

We analyzed the producer price inflation connectedness across the U.S. manufacturing industries. We first used Acemoglu et al. (2012b)'s simple general equilibrium model to show that under certain conditions supply-side shocks are transmitted from the upstream to downstream industries.

We then applied the Diebold-Yilmaz Connectedness Index methodology to monthly producer price inflation series to estimate the measures of inflation connectedness across 17 three-digit U.S. manufacturing industries over the 1947-2018 period. The static and dynamic analyses of inflation connectedness reveal that supply-side inflation shocks are transmitted from upstream to downstream industries through the underlying input-output network linkages.

In the static inflation connectedness networks, upstream input-supplying industries are located closer to the center of the network with thicker edges and arrows pointing to others, generating pairwise inflation connectedness to others. On the other hand, downstream industries are located further away from the center and are the receivers of inflation shocks from others.

Using the system-wide connectedness measures, we showed that the system-wide connectedness of the underlying input-output network Granger-causes the inflation connectedness across industries over time. Focusing on the pairwise measures, we showed that the input-output network and the inflation connectedness nexus was stronger during periods of major supply-side shocks, such as the global oil and metal price increases, and weaker during the Great Recession of 2008, the most significant aggregate demand shock of the past half century.

Last, but not the least, we use our framework to gauge the impact of the recent Trump tariffs on inflation connectedness across industries. Using data for the first half of 2018, we showed that the U.S. President Donald Trump's decision to impose additional tariffs on imports of primary metals, fabricated metals and machinery from China and other countries led to higher inflation connectedness from these industries to others. However, we need to note that it is too early to reach a final verdict on this issue. For that reason, we will update our data every month to analyze the impact of Trump tariffs on inflation connectedness and report the results in the future drafts of the paper.

Chapter 3

INFLATION IMPLICATIONS OF PRODUCTION NETWORKS IN SOUTH KOREA

3.1 Introduction

How inflation propagates across countries and sectors attracts both researchers' and policy-makers' interest. The mechanism behind inflation transmission has critical implications for the design and macroeconomic policies. In this study, we investigate the impact of production networks by focusing on their role in inflation diffusion. To show how producer prices affect each other through input-output linkages, we built on a multi-sector framework developed Long and Plosser (1983a), Acemoglu et al. (2012a), and Acemoglu et al. (2016a). Guided by these studies, we develop a static multi-sector economy model that provides the inflation transmission mechanism. In this economy, the price of an industry depends on the prices of its input-suppliers. We argue that supply-side shocks in the form of producer price changes of the input-suppliers propagate from upstream to downstream industries.

Following the theoretical framework, we are interested in the empirical evidence to link inflation diffusion to the production networks. Thus, the empirical part focuses on the industry-level inflation spillovers and whether these spillovers associated with the underlying production network as the model suggests. Even though production networks have data as input-output linkages, there is not a direct model to quantify the inflation propagation. To examine the inflation spillovers of each industry, we rely on the Diebold-Yilmaz connectedness framework developed in the Demirer et al. (2018b) by using the producer price indices of each sector. In this way, this paper provides a measure that determines how much of an industry producer price shaped due to shocks originated in other industries. By using this methodology and aggregation of the variance decomposition matrix, it is possible to classify sectors that contribute to others act as inflation transmitters, and while those other industries are the recipient of inflation shocks.

In the empirical analysis, we use the data from South Korean manufacturing industries starting from 1965. We investigate the time-varying inflation connectedness of different Korean manufacturing industries as South Korea transforms its industries from low-tech to high-tech successfully. Going one step further, we exhibit how system-wide inflation shock transmission varies over time by following different industry-based growth policies. Then, this study searches for empirical evidence on the diffusion of producer price changes through production networks. The results indicate that inflation, as a form of supply-side shocks, circulated through production networks across Korean manufacturing industries. On the contrary, the circulation of demand shocks is not due to the production networks. For instance, demand shocks such as East Asian Financial Crisis input-output linkages fail to explain the amplification of inflation shocks as anticipated.

Recent literature often yields a prediction that inflation across countries and sectors are synchronized. By using common factor analysis, Ciccarelli and Mojon (2010b) argue that the inflation series of OECD countries have a common factor that almost accounts for seventy percent of their variance. Further, studies decompose these series into the country, and global factors, including Monacelli and Sala (2009b) find a statistically significant relationship between exposure of inflation to shocks and trade openness at the industry-level. Recently, Auer et al. (2019) decompose inflation into three factors including global, country and sectoral. For most of the countries in their sample, a sectoral factor of inflation is significantly larger than the other factors. Motivated by these studies, inflation transmission and its underlying mechanism attract the researchers' interest. The key question is, how does inflation become strikingly similar over time across countries and sectors

Several papers investigate the input-output linkages for inflation synchronization including Di Giovanni and Levchenko (2010b), Auer and Saure (2013b), Antoun de Almeida (2016b)) and Auer et al. (2019). Di Giovanni and Levchenko (2010b) report countries that trade each other intensively exhibit higher business cycle synchronization. Also, Antoun de Almeida (2016b) adopts their approach to focus on intermediate products role in inflation synchronization. However, these studies restrict their attention to correlations rather than two-sided measures.

Our work is closely related to network shock propagation literature. Input-output linkages across sectors provide a likely explanation for the inflation synchronization starting with Long and Plosser (1983a) multi-sector economy model to explain business cycle movements. Gabaix (2011) argued that idiosyncratic shocks to large firms could generate aggregate fluctuations in the presence of input-output linkages. Acemoglu et al. (2012a) revealed how shocks hitting to critical sectors will not neutralize. Further, these shocks can transform into cascades in the presence of input-output trade. Moreover, shocks originating from natural disasters such as the Japanese earthquake effects, as studied in Carvalho et al. (2016), propagated through firm-level production linkages. In this study, we investigate the inflation diffusion mechanism as the production networks.

This work builds on the Acemoglu et al. (2016a) which investigates the output implications of the demand-side and supply-side shocks. Both theoretically and empirically, Acemoglu et al. (2016a) demonstrated that demand-side shocks such as Chinese imports and changes in government spending would propagate from upstream (input-suppliers) to downstream (customer) industries. On the contrary, supply-side shocks such as TFP growth and patenting shocks amplify from upstream to downstream sectors. In this study, the focus is on the supply-side shocks in the form of PPI changes. We show that inflation shocks diffuse economy from upstream to downstream industries through production networks. Similar to Acemoglu et al. (2016a) results, input-output linkages fail to explain inflation shock propagation in the case of aggregate demand such shock such as the East Asian Financial Crisis.

This study starts by demonstrating the theoretical motivation behind the estimations and suggest a mechanism to link the producer prices of different sectors. Then, we explain the theoretical implications of inflation transmission through input-output linkages. Then, we describe the definitions of bilateral ties originating from producer price changes and production structure. The empirical part continues with both static and dynamic estimation results. Finally, we demonstrate how production networks are responsible for inflation propagation and their time-varying explanatory power.

3.2 Model

In this part, we begin with the theoretical implications of input-output linkages in a dynamic multi-sector economy to demonstrate how inflation shocks propagate through production networks. Our model is closely related to Long and Plosser (1983a), Carvalho (2007), Acemoglu et al. (2012a) and Acemoglu et al. (2016a). Though, these papers emphasize on output implications of the sectors. But we aim to clarify the transmission mechanism of inflation across industries. Our model diverges from these studies by focusing on price levels to define the role of input-output linkages in inflation propagation to emphasis only on the production process. We assume that there is no government.

Each sector has the following Cobb-Douglas production,

$$y_i = {e_i}^{z_i} {l_i}^{\alpha_i} \prod_{j=1}^{n} x_{ij}^{a_{ij}} \tag{3.1}$$

where y_i is the output of industry i, l_i is the labor hired in sector i, x_{ij} is the amount of intermediate product produced by industry j used as input by industry i and z_i is the sector-specific productivity. a_{ij} represents the share of good in the intermediate input use of sector i.

Each industry combines inputs from different industries with the labor,

$$ {\alpha_i}^l + \sum_{i=1}^{n} \alpha_{ij} = 1 \tag{3.2}$$

For each sector, we assume α_i^l >0 and a_{ij} ≥0 . The assumption ensures that each industry would depend on both labor and intermediate inputs from other industries.

The preferences of household defined as follows,

$$u(c_1, c_2, ..c_n, l)) = \gamma(l) \prod_{i=1}^{n} c_i^{\beta_i} \tag{3.3}$$

where $\gamma(l)$ is a decreasing function for labor supply disutility and β_i is the weight of good i in the preferences of the household.

Market clearing condition for industry i

$$y_i = c_i + \sum_{j=1}^{n} x_{ij} \tag{3.4}$$

,

where c_i is the final consumption of industry i. In this way, the output of industries used as an intermediate input for other industries, or it can be consumed as a final good c_i.

The household budget constraint can be written as

$$\sum_{i=1}^{n} p_i c_i = wl \tag{3.5}$$

where p_i is the producer price of output produced by industry i.

The equilibrium of this economy defined with a sequence of prices p_i and consumption bundle c_i, such that goods and labor markets clear, household maximize her utility by combining labor and her consumption with the wage rate w_i and industries maximize their profits.

Productivity shocks and changes in the prices of the input-suppliers shape an industry's output price.

$$dlnp_i = \sum_{j=1}^{n} a_{ij} dlnp_j - dz_i \tag{3.6}$$

Producer price of an industry ,$dlnp_i$, depend on both prices of its input suppliers $dlnp_j$ proportional to their intermediate input usage a_{ij} from industry j and sector-specific productivity shocks dz_i. Correspondingly, this proposition states that the price of an industry i will be affected not only by adverse shocks dz_i but also by the shocks of other sectors that provide inputs to sector i. Productivity shocks aside, shocks in input prices would lead to changes in the cost of the final good.

The propagation of the supply-side shocks depends on the intermediate good trade across industries. The variable a_{ij} captures the fact that diffusion of the PPI changes would transmit from upstream to downstream sectors. Even if there is no productivity shock in industry i (dz_i=0), producer price of the sector will change with the amount that is proportional to intermediate product flow from industry j (a_{ij}). For instance, suppose primary metal (sector j) provides inputs to machinery (sector i). Then, the machinery sector's producer price will be reshaped not only due to its productivity shock but also when there is price change (supply-side shock) in the primary metal sector. There are not any upstream effects just downstream effects according to this proposition. Also, even there are not any downstream effects ($dlnp_j$), the price of industry i would only depend on the productivity changes. Adverse shocks in the form of dz_i would lead to an increase in the producer price of industry i, as expected.

3.3 Empirical Approach

Our primary interest relies upon how producer prices of manufacturing industries affect each other and whether this influence is related to downstream propagation. To study the bilateral impacts of producer prices on each other, we rely on the Diebold-Yilmaz connectedness framework. The pairwise measures of this methodology reveal the amount of future uncertainty in the producer price of sector i due to shocks originated in other industries. In this way, we report inflation connectedness across manufacturing industries. These measures estimated with variance decompositions obtained from vector autoregressions, and this methodology proposed and developed in a series of papers (Diebold and Yilmaz (2009, 2012 and 2014).

Further, by relying on this methodology, we can construct PPI connectedness, and IO networks since Demirer et al. (2018b) showed that connectedness matrix is equivalent to the adjacency matrix in network theory. Accordingly, entries in the adjacency matrix can correspond to the connectedness of producer prices or input-output linkages of sectors. Hence, we can estimate the connectedness and production networks of Korean industries according to their producer prices or intermediate inputs.

The calculation of DY connectedness measures are estimated with the forecast variance decompositions of VAR. We employ the generalized variance decompositions scheme developed by Koop et al. (1996b) and Pesaran and Shin (1998a) to integrate out the effects of ordering in the decomposition. Then, our results become invariant to ordering schemes in a VAR system. We also normalize each row for the interpretation of the shocks. In our estimations, we take lag as one month and adjust the forecast-error horizon as twelve months. We provide the robustness of our results with different variance decomposition methods, lags, and horizons in Appendix B.

3.3.1 Diebold-Yilmaz Framework

Consider the two industries i and j in the Proposition 1, covariance stationary VAR(p) with p lags,

$$x_t = \sum_{i-1}^{p} \phi_i x_{t-1} + \varepsilon_t \tag{3.7}$$

where x_t is the return of the monthly industry producer price return as $x_t = [dlnp_j, dlnp_i]$. Also, $\varepsilon_t \sim (0,\Sigma)$ can be inverted to moving average VMA(∞) process, after it is multiplied with selection matrix. By following relation $A(L).\phi(L)=I_k$ we can obtain moving average coefficients A_i.

$$A_i = \sum_{j=0}^{p} \phi_p A_{i-p} \tag{3.8}$$

Generalized variance decompositions estimated from these coefficients report the contribution of j^{th} variable in h step ahead forecast error variance decomposition of i^{th} variable as

$$\theta_g^{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\epsilon_i^{'} A_h \Sigma \epsilon_j\right)^2}{\sum_{h=0}^{H-1} \left(\epsilon_i^{'} A_h \Sigma A_h^{'} \epsilon_j\right)} \tag{3.9}$$

where σ_{jj} is the standard deviation of ϵ_j and e_i is the selection vector. These selection vectors consist of a diagonal constructed by ones and zeros on the off-diagonal parts. Also, Σ is the covariance matrix for the error vector ϵ_j. To interpret the variance decompositions directly, we normalize each entry by row sums. Otherwise, the row sum of the variance decomposition matrix not necessarily adds up to one. In this way, it is possible to construct comparable measures. Then, this normalization provides a percentage measure of pairwise directional connectedness from industry j to industry i:

$$\theta_{ij}^{\sim g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3.10}$$

where $\sum_{j=1}^{N} \theta_{ij}^{\sim g}(H) =1$ and $\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H) =$ N.

Also, note that this pairwise connectedness from industry i to j and industry j to i are not identical; they indicate different linkages. Total directional connectedness from industry i to all other industries defined as "from the connectedness of industry i". Likewise, the contribution of all industries to industry i's forecast error variance decomposition, except i, as " to the connectedness of industry i ". Total directional "to" connectedness of sector i's producer price change to all other sectors defined as follows,

$$C_{\bullet \leftarrow i} = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ij}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{\sim g}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ij}^{\sim g}(H)}{N} \times 100$$

Total directional "from" connectedness of sector i's producer price change depending on producer prices of all other industries,

$$C_{i \leftarrow \bullet} = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ji}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ji}^{\sim g}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ji}^{\sim g}(H)}{N} \times 100$$

But these measures are industry-specific. To cover the overall shocks in the VAR system, we rely on the connectedness index. It is merely the average of connectedness measures. Hence, this index provides the overall spillover across producer prices of various industries. Therefore, the index reflects the significance of inflation shocks originating in all sectors. In the subsequent section, we use this index to identify the time variation of inflation shocks in the system. Total or system-wide connectedness calculated as:

$$C(H) = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ji}^{\sim g}(H)}{\sum_{i,j=1}^{N} \theta_{ji}^{\sim g}(H)} = \frac{\sum_{j=1, j \neq i}^{N} \theta_{ji}^{\sim g}(H)}{N}$$

3.4 Data

We collect producer prices of two-digit Korean manufacturing industries from the Economics Statistics System (ECOS) provided by the Bank of Korea to estimate the inflation connectedness. The industry classification system that we rely on is KSIC Rev 8. (Korean Standard Statistical Classification). We work with 13 two-digit sectors in this paper. Further, we provide the details of our sample in Appendix B.

The producer price data collected monthly and covers more than fifty years period starting from January 1965 to June 2020. In our connectedness estimation, we work with logarithmic changes rather than price levels. Thus, we focus on the variations of producer prices.

For the production networks, we use Input-Output tables from ECOS. These tables deliver the intermediate product flow between and within sectors. Though, these IO linkages between sectors updated every year or more due to data availability. Unfortunately, we restrict our analysis between the years 1990 and 2017 due to data availability [1].

[1]Due to limited data for the years 1991,1992,1994, and 1998; we assume the previous years' input-output data for those years

3.5 Network Structures of Inflation and Production

In this paper, we are concerned with understanding the diffusion channel of inflation. This chapter introduces how Korean manufacturing industries constructed as networks based on their intermediate inputs or inflation spillovers by using tools from network science. In this way, this section presents the comparable network characteristics of both production and inflation connectedness networks.

The theoretical evidence presented in the model directs our attention to the input-output flow across industries. The proposition proposes the transmission mechanism of inflation as the supply-chains between different sectors. To put it differently, it states that the price of the manufacturing industry will be affected by the shocks originated in its intermediate input suppliers. For this reason, we start by investigating the characteristics of both types of networks. The networks are composed of both nodes and edges. In this study, nodes express the different Korean manufacturing industries, whereas links between these nodes show the weights among each node according to the different datasets. To report comparable results for these various datasets for the same industries, we restrict our analysis between the years of 1990 to 2017.

In each level of disaggregation, inflation across industries display similar trends with each other. We suggest the Diebold-Yilmaz Connectedness framework to weight each link among sectors. This suggestion aims to underline the different bilateral spillovers originating from the changes in producer price inflation of each industry. Thus, the variance-decomposition matrix provides each possible link generated according to the PPI data. Thus, we report the inflation connectedness of industries estimated by using monthly PPI data between the dates January 1990 and December 2017.

Inflation connectedness, estimated with the VAR(1) model by using a 12-month-ahead forecast horizon, is represented in Table 3.1. This table is a 13x13 matrix covering all the possible spillovers among sectors. Each entry of this matrix indicates the forecast error of an industry due to shocks originated in another industry. We estimate these shocks through the vector-autoregressions of the PPI changes. Additionally, "to" row and "from" column are the sum of all diagonal elements of the i^{th} row and i^{th} column, respectively. Thus, "to" measure indicates the amount of the inflation shocks transmitted to other sectors in Table 3.1 by construction. On the contrary, "from" measure shows the inflation shocks received from other industries in Table 3.1.

	1	2	3	4	5	6	7	8	9	10	11	12	13	From
Food and Beverages	17.73	9.53	8.20	4.21	6.09	8.21	2.84	9.07	9.46	5.52	13.39	0.30	5.46	50.45
Textile and Leather	9.60	17.92	9.32	3.21	7.85	7.18	2.78	7.79	10.45	3.14	13.11	0.24	7.43	56.42
Wood and Paper	8.73	9.86	18.96	6.00	9.99	4.99	4.48	7.39	7.18	5.67	10.63	0.17	5.96	56.46
Petroleum and Coal	5.18	4.41	7.76	24.47	14.50	3.78	12.61	10.04	1.24	6.38	4.77	3.99	0.87	35.42
Chemicals	5.88	7.95	9.55	10.74	18.12	3.66	11.69	13.12	1.91	9.29	7.15	0.17	0.78	50.52
Minerals	10.83	9.41	6.18	3.50	4.71	23.51	1.31	9.41	7.68	2.02	11.63	1.06	8.75	41.88
Primary Metals	3.88	4.89	6.18	11.49	14.46	2.40	22.02	12.96	2.17	11.36	5.22	1.85	1.12	45.36
Metal Products	8.69	7.55	6.78	7.19	12.64	6.95	9.95	17.42	3.27	7.81	10.02	0.16	1.57	63.00
Electronic	12.44	13.94	9.07	1.21	2.49	7.86	0.26	4.45	23.71	0.67	15.35	0.02	8.55	42.31
Electrical	7.49	4.41	7.52	6.43	12.89	2.16	12.65	11.20	0.70	25.15	7.54	1.01	0.84	51.61
Machinery	11.97	11.63	8.93	3.19	6.35	7.86	2.80	9.23	10.20	4.83	15.89	0.14	6.98	69.03
Transport	0.37	1.08	0.74	0.30	0.04	3.73	0.14	0.73	0.12	3.56	0.66	87.00	1.53	11.03
Other	8.88	12.14	9.21	0.98	1.24	10.91	0.18	2.63	10.20	0.98	12.88	0.49	29.29	36.67
To	100.53	44.34	31.82	120.99	68.24	20.51	66.37	45.01	20.63	17.59	41.89	7.42	24.81	

Table 3.1: Inflation Connectedness Table

Notes: The ij^{th} entry of this matrix represents the pairwise connectedness $C_{i\leftarrow j}$, i.e., the percent of the 12-month-ahead forecast error variance of industry i due to producer price changes in industry j. From column indicates the row sum excluding the diagonal elements. This column reports the total directional connectedness from all other industries to industry i. To row is calculated by excluding the diagonal elements from column sums, it states the amount of total directional connectedness generated from industry j to others.

	1	2	3	4	5	6	7	8	9	10	11	12	13	From
Food and Beverages	56.74	0.39	8.81	6.05	13.09	2.94	0.13	7.39	1.18	0.25	0.14	0.63	2.25	43.26
Textile and Leather	0.47	61.14	2.24	6.18	22.96	0.12	0.08	1.28	0.92	0.26	0.06	0.20	4.09	38.86
Wood and Paper	0.40	1.51	70.69	6.14	14.36	1.08	0.59	1.69	1.21	0.41	0.12	0.69	1.10	29.31
Petroleum and Coal	0.33	0.75	1.15	53.32	19.50	1.05	1.97	9.86	6.91	1.49	2.48	0.93	0.25	46.68
Chemicals	0.75	1.04	1.72	14.67	70.93	1.26	1.27	3.33	3.00	0.39	0.65	0.44	0.54	29.07
Minerals	0.11	0.80	5.11	17.77	11.03	47.79	4.77	3.66	3.52	1.19	0.47	2.90	0.89	52.21
Primary Metals	0.04	0.17	0.30	4.84	2.84	2.51	85.75	1.10	1.15	0.47	0.38	0.19	0.26	14.25
Metal Products	0.03	0.43	1.83	3.10	7.07	0.75	56.68	22.53	3.83	1.28	0.99	0.48	0.98	77.47
Electronic	0.03	0.31	0.92	2.67	6.28	1.31	25.87	9.95	38.25	10.31	2.05	1.15	0.90	61.75
Electrical	0.02	0.37	1.83	3.03	9.92	6.37	11.47	4.05	3.70	56.74	1.69	0.17	0.63	43.26
Machinery	0.03	0.93	1.94	3.71	14.21	3.65	10.00	9.09	3.17	33.24	17.87	0.95	1.22	82.13
Transport	0.01	0.99	0.54	2.99	9.61	0.93	12.43	5.66	7.48	6.85	1.22	48.83	2.44	51.17
Other	0.11	12.63	21.07	5.80	20.68	2.54	11.29	9.22	1.81	3.36	0.27	0.55	10.66	89.34
To	2.33	20.33	47.46	76.95	151.57	24.50	136.56	66.29	37.88	59.51	10.53	9.29	15.56	

Table 3.2: Production Connectedness Table

Notes: This table illustrates the normalized flows between the sales and purchases of industry output. The ij^{th} entry of this matrix reports the intermediate or final good purchase of industry j from industry i. To be compatible with the connectedness table, we construct from and to measures of flows. To row reports the amount supplied to other industries and from column estimates the amount purchased from different sectors.

Production connectedness presents each input-output linkage among different sectors. The production connectedness measure calculated with the average annual normalized intermediate product trade across industries from 1990 to 2017. Correspondingly, the input supply of industry from another industry presented in the ij^{th} entries in Table 3.2 while diagonal elements in Table 3.2 show the trade among industry's subsectors. To capture the upstreamness measures, we rely on the "to" measure that represents the intermediate input supply of sector to others. Similarly, the "from" column estimates the industry's intermediate input requirements from others.

Surprisingly, this satisfying relationship is still valid for the "from" measures. The industries that depend on the other's input more, such as Machinery and Metal Products forecasts rely on other industries' price changes. These results confirm the model suggestions for the implications of diffusion of inflation through the production networks.

By investigating the pairwise spillovers of inflations, the distinguished connectedness in Table 3.1 accumulated among Petroleum and Coal through Chemicals and Machinery from Metal Products. These pairwise linkages between these industries are relatively more substantial than the other ties. Besides, these industries have the highest value of upstreamness reported in Table 3.2. Therefore, chemicals and Metal industries carry inflation to its downstream industries based on the matrix entries reported in both tables, creating domino effects.

As we noted earlier, connectedness tables of both production and inflation underline the similarities of industries, yet it is not feasible to discuss each linkage. The properties of networks can be applied to industries where production and inflation connectedness relations play a crucial role. Each of these measures corresponds to the adjacency matrix, which is a square matrix by 13x13. Besides, edges of the different vertices correspond to the elements reported in the matrix; we study the features of these networks. To put it differently, each to and from measures across industries corresponds to the bilateral edges between different nodes i.e., manufacturing sectors.

To have further knowledge about these industries, we construct connectedness and production networks by using Gephi, presented in Figures 3.1 and 3.2. Both networks are weighted and directed according to the weights presented in Tables 3.1 and 3.2 according to their pairwise to and from connectedness measures. Also, the edges of production networks design the product flow amount between industries. Further, node colors denote the out-degree distribution of industries, which is the total of weighted out-going edges. For the inflation case, it is the total spillovers generated by industry and output of an industry that provided to other industries as an intermediate input for the production network. Note that node colors shift from bright green to dark red according to increasing weighted out-degree distribution of each node.

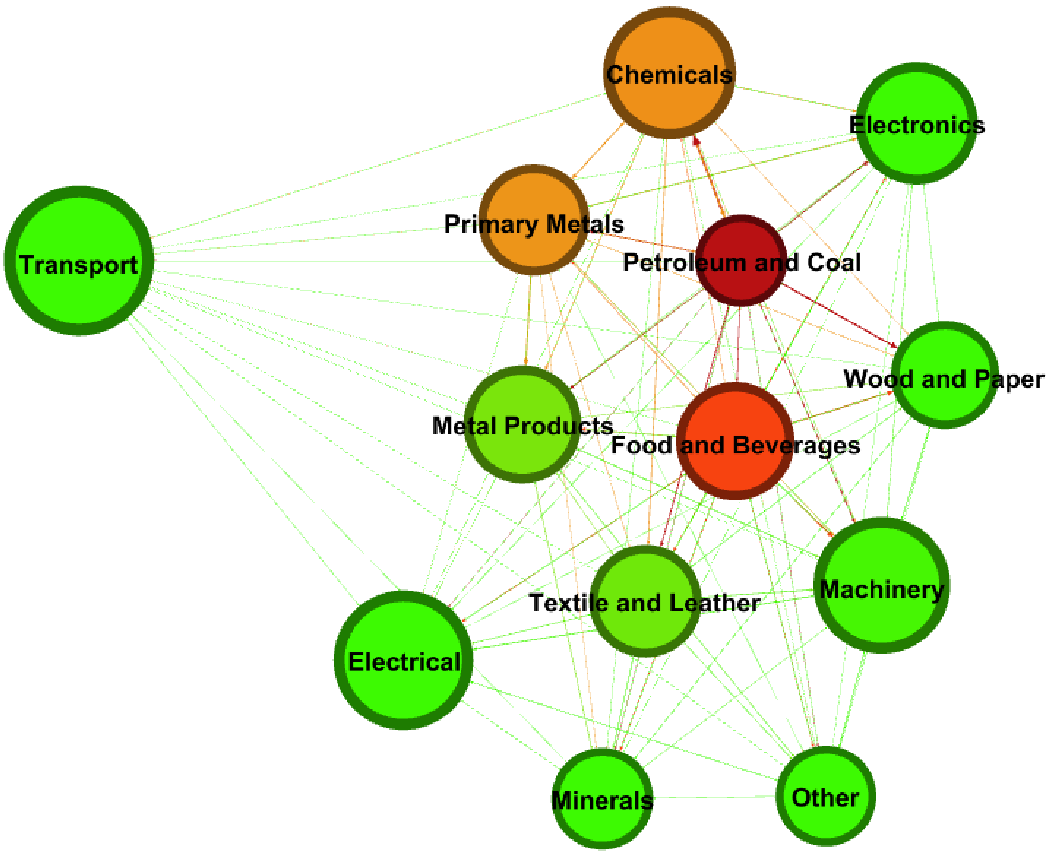


Figure 3.1: Inflation Connectedness Network

Notes: The colors indicate the weighted out-degree distribution of the inflation connectedness of different industries. Size exhibits the number of full-time employees in 2015. Locations are calculated with the The ForceAtlas2 algorithm, Jacomy et al. (2014a)

The ForceAtlas2 algorithm Jacomy et al. (2014a) determines locations of nodes. With this algorithm, nodes are pulled together and pushed further like the electrically charged particles depending on the bilateral links between industries. Firmly linked nodes tend to locate close to each other, whereas the others that have linked weakly pushed away from the center. Finally, node size mirrors the number of total full-time employees in the year 2015 for each industry.

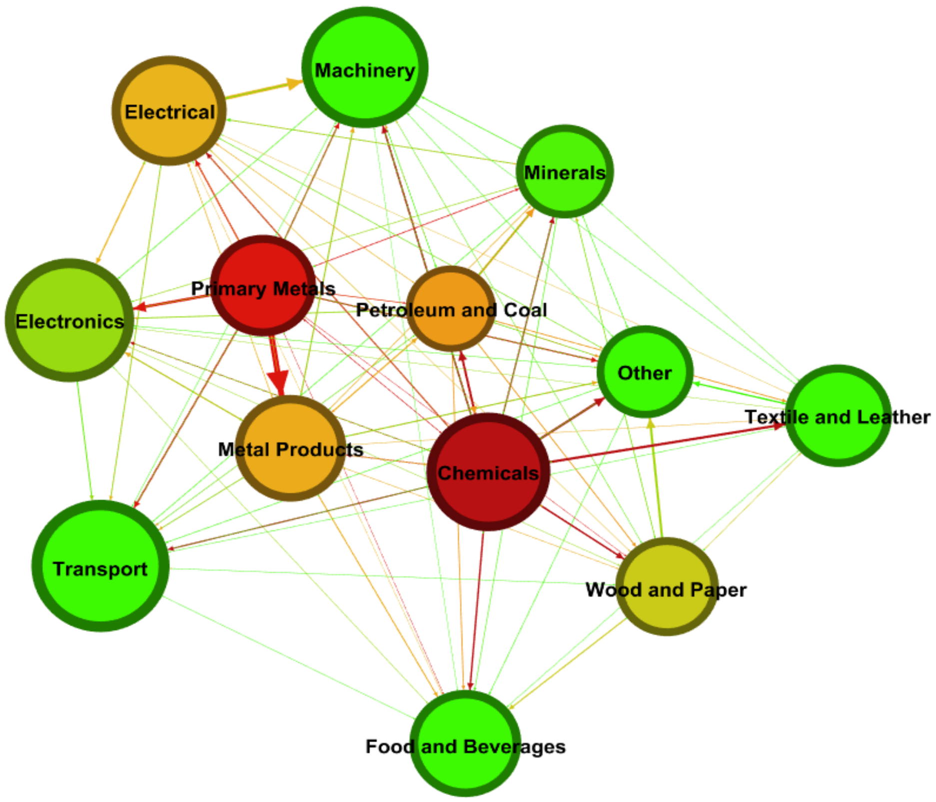


Figure 3.2: Production Network

Notes: The colors indicate the weighted out-degree distribution of the supplies of different industries. Size exhibits the number of full-time employees in 2015. Locations are calculated with The ForceAtlas2 algorithm, Jacomy et al. (2014a)

We present connectedness and production networks of Korean industries. These networks indicate three distinct results. First, nodes that operate as input-suppliers (upstream) tend to locate in the center with higher out-degree distributions. Interestingly, these industries are the inflation transmitters according to connectedness networks such as Primary Metals, Metal Products, Chemicals, Petroleum, and Coal. On the other hand, customer (downstream) sectors are in the periphery with lower out-degree distribution demonstrating less impact on others in both inflation transmission framework and intermediate product supply. These industries include Transport, Electronics, Minerals, and Electrical.

Further, numerous groups show similar clustering tendencies, whether they linked according to their PPI connectedness or cross-sectoral trade flow. In Figures

3.1 and 3.2, there are important chemical and metal product clusters. By construction, we expect these industries to cluster in the production network due to their common intermediate product dependency. Remarkably, these clusters persisted in the connectedness network, which is based on the PPI data. Moreover, primary metals, metal products, and electrical nodes tend to locate closely in two cases.

In this section, we present the resemblances of both PPI connectedness and IO networks. In the remaining part, we search for empirical evidence to link IO to inflation transmission by investigating each pairwise linkage based on inflation transmission and intermediate product trade.

3.6 Time-Varying Connectedness of Inflation

The previous section illustrates the similarities between inflation and production networks. However, inflation dynamics are not stable over time. For this reason, we are interested in the time variation of inflation connectedness. This section presents the changes in the inflation spillovers across time by evaluating the political and economic developments over the fifty years. Transformation of the Korean industries and its increasing role in the global value chains make South Korea an excellent candidate to investigate. The South Korean economic growth defined as a miracle following the devastating effects of the Korean War. By transforming its economy with industry-based growth policies, we investigate how inflation shocks dynamically evolved with connectedness index and the sectoral evolution of these shocks with "to" connectedness measure for each aggregated and disaggregated manufacturing industry.

The estimation period covers the months starting from January 1965 to July 2020. For the VAR designation, we estimate the connectedness index with one lag and forecast horizon of 12 months. The connectedness index presented in Figure 3.6 and the "to" connectedness of each disaggregated industry reported in Figure C.3 and C.4. We start by discussing the connectedness index. By depending on the PPI changes, this index reflects the total spillovers of inflation shocks in the VAR system. This index captures the noteworthy events and turning points in the Korean economy. To estimate the total spillover in the system each month, we construct windows that span sixty months. Then, we roll these windows for each date in the data set.

System-wide connectedness through the estimation period is robust to the different choices of rolling windows, forecast horizon, and lags as presented in the

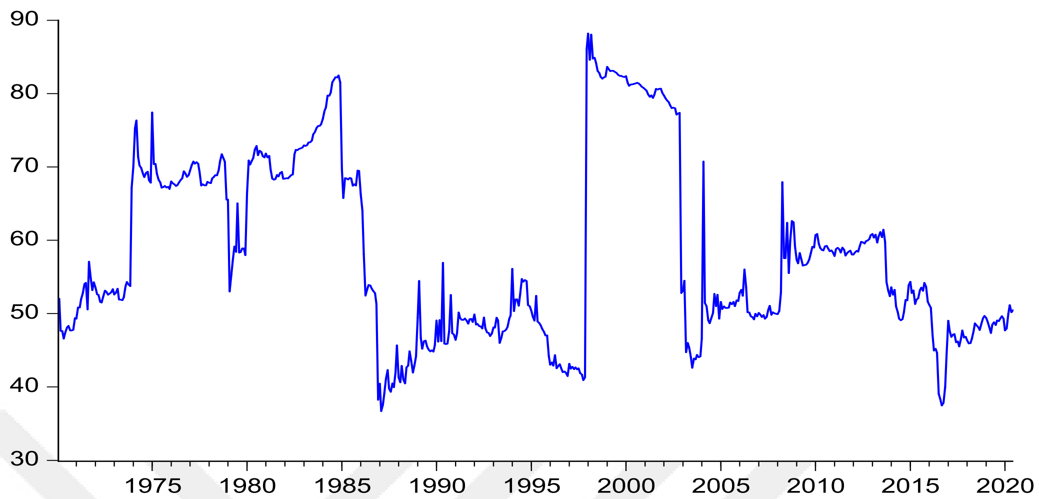


Figure 3.3: Dynamic Connectedness Index

Notes: The blue line shows the connectedness index of disaggregated thirteen manufacturing industries. The red line displays the index that is calculated for the thirty-five disaggregated manufacturing sectors. The rolling window is 60 months, and VAR(1) forecast horizon is twelve months for each run.

Appendix. Having found out the methodology is robust, we focus on the movements of the index. But, inflation transmission was not stable over the estimation period. Interestingly, each index fluctuations are generated after some critical political and economic transformations that affect South Korea.

A first substantial jump in Figure 3.6 observed as an increase of more than twenty percentage points following the OPEC embargo decision in October 1973. Meanwhile, South Korea was an importer of oil and a newly industrialized country; producer prices were reactive to the variation of oil prices. Additionally, 1973 was the year when the direction of Korea's policies shifted from exports of labor-intensive industries such as textile and apparel to heavy chemical industries. Introduction of third and fourth five-year plans aim was to promote industries like petrochemicals, iron, steel, nonferrous metals, shipbuilding, and machinery. Following this period, known as "heavy and chemical industries drive", the connectedness index remained high because the promoted industries were relatively upstream. The index remained high as the industries which operate more like suppliers including Chemicals, Minerals and Primary Metals. With the shift in policies, the origin of the "to" connectedness shifted from Textile and Leather to these industries. At that period, inflation propagated from upstream to downstream sectors, as our model predicted. During this era, "to" connectedness of promoted industries were remarkably higher than their average as reported in Figure C.3 and C.4.

Another surprise targeting these upstream industries was the second oil price shock following the Iranian revolution in 1979. Like its 1973-1974 predecessor, heavy and chemical manufacturing firms were vulnerable to their essential input price changes. By rotating the industry emphasis from light industries to heavy industries, inflation circulation originating from upstream industries raised due to their intermediate product dependency in the production process.

After the mid-'80s, the connectedness index was stable regarding new industry-specific acts. From 1982, the target of the fifth and sixth five-year development plan was to produce high-tech products. The technology-intensive sectors promoted by the government were machinery, electronics, and electrical equipment. As shown in Figure C.3, C.4 and C.5 connectedness of industries including increased by these developments following these policy changes. Except there is an important difference between the previous heavy chemical industry drive period. Considering technology-intensive sectors are downstream (customer) industries, inflation propagation indicated with the connectedness index was relatively lower than the previous period as shown in .

Until the East Asian Financial Crisis, Korea's economy displayed a very impressive growth by transforming its industries from low-tech to high-tech in a short time. As noted in Figure 3.6, the highest connectedness corresponds to the start of this crisis. As the crisis spread from Thailand when national currency Baht devaluated and generating investment panics during the summer of 1997. Panic environment clashed in East Asian countries including Korea with the currency crisis. Hence, many firms controlled by chaebols bankrupt including Korea's largest steel and motor companies such as Hanbo, Kia Motors, and Daewoo. During that period, the system-wide index reached its highest point. It increased more than a hundred percent in two months. Further, the connectedness of almost every industry demonstrated extraordinary hikes in Figure C.3 and C.4. These uncertain years lasted longer than other turning points in the estimation period indicating the highest inflation diffusion in all industries.

Similarly, the global financial crisis was the last event when the index made an unexpected movement in the fall of 2008. The most recent hike corresponds to the U.S. stock and mortgage market collapse. The global economic downturn also affected the Korean economy. Still, its impact is negligible when we compare this crisis to the East Asian crisis according to the overall transmission in the economy. All information considered, the inflation connectedness index is not constant over time and it is highly dependent on the sectoral focus of different government policies and financial crises.

3.6.1 Robustness

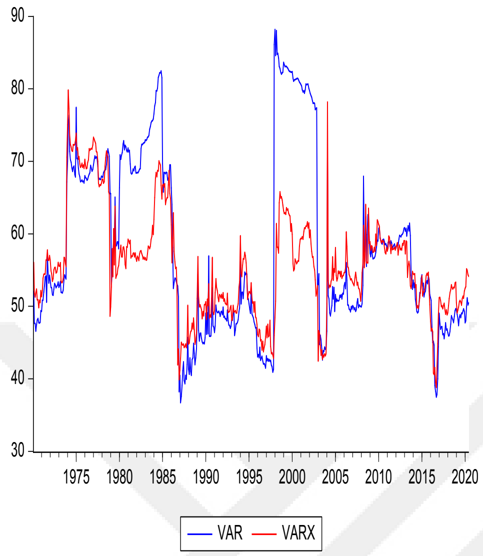
In the earlier section, we argue that jumps in the connectedness index capture the first and second oil price shock. One can claim that these hikes in the index can be due to variations in commodity prices or exchange rates. To check whether these calculations are robust to these measures, connectedness index calculations of these industries repeated with the VARX model by controlling for these commodity prices and exchange rates. In this part, we assume that the system has endogenous variables as the logarithmic return of producer prices and other exogenous variables. Plus, we include the price of West Texas Intermediate (WTI) to cover the oil price, won per dollar as an exchange rate example and gold price as exogenous variables in the following form:

VAR model with exogenous variables

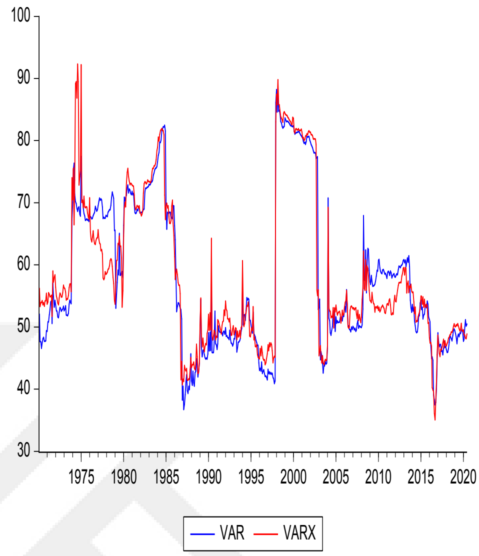
$$Y_t = a_0 + A_1 Y_{t-1} + ... + A_p Y_{t-p} + B_1 X_{t-1} + ... + B_p X_{t-p} + U_t \tag{3.11}$$

X_ts present the exogenous variables in the system and Y_ts are the PPI changes of each 13 industries. Then, we calculate the connectedness index with this VARX model. In Figure 3.4, VARX results presented with the blue line and the VAR index that estimated with only endogenous variables reported with the red line. Further, we include all exogenous variables in the system together in the 3.4.d. The inclusion of different exogenous variables generates various connectedness indices. After controlling for the changes in won per dollar with the VARX model, the index is exhibited in Figure 3.4.a. During the years of East Asian Financial Crises after 1998, won depreciated significantly. With this in mind, we see a gap between the values estimated with VAR and VARX. Controlling for the exchange rate reduces the value of connectedness during these years.

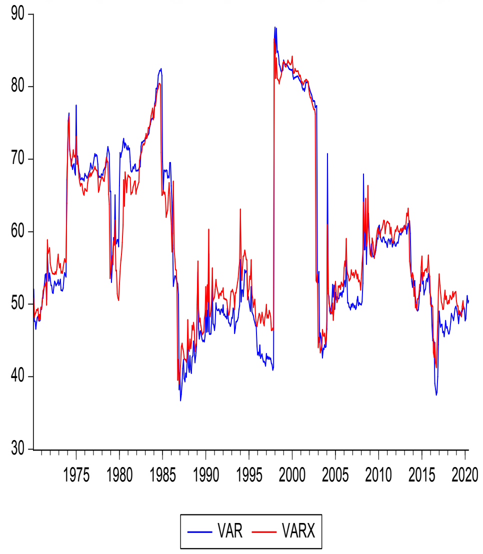
Besides, not only the exchange rate fluctuations are responsible for the movement of the index. Observation of hikes in the connectedness index during the first and



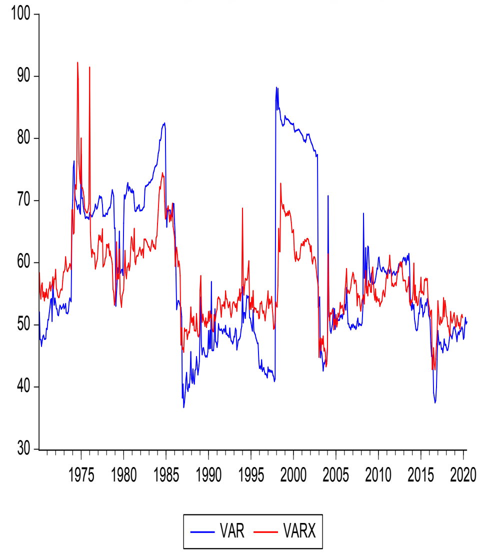
(a) Exogeneous Variable: Exchange Rate



(b) Exogeneous Variable: Oil Price



(c) Annual TFP growth



(d) Inclusion of All Exogenous Variables

Figure 3.4: Connectedness Index from VARX Model Estimation

Notes: Red and Blue lines are respectively the connectedness indices obtained from the VAR and VARX models with the specifications of sixty months of the rolling window, one month as lag and twelve months as forecast horizon.

second oil price makes our index questionable to oil prices. We present the robustness of this index to oil prices in Figure 3.4.b. The main takeaway of this figure is the variation between VAR and VARX is demonstrated following the years of first oil price shock, 1973. Still, this index is robust to oil price shocks during the remaining years in the dataset. To control for the commodity price, we choose gold prices as an exogenous variable and report in Figure 3.4.c. However, there is not almost no distinction between these two models with the inclusion of commodity prices.

Going one step further, Figure 3.4.d demonstrates the index that is calculated with the inclusion of three exogenous variables. In Figure 3.4.d, we observe the largest difference as we expect. But the trends are persisted even with the incorporation of the exchange rate, oil price and commodity price fluctuations to the index. All in all, none of the exogenous variables generate a noticeable difference in the index. Thus, we conclude that the dynamic variation of inflation connectedness is robust. Further, the inflation dynamics across sectors are not easily be attributed to these controls.

3.7 Underlying Mechanism Behind the Inflation Transmission

The resemblance between production and connectedness networks illustrated in the earlier sections. This part searches for empirical evidence that can enlighten the underlying mechanism behind the inflation transmission. Notably, learning the mechanism has critical policy-making implications for central banks and institutions that deal with inflation. With the theoretical motivation in Section 3, these concerns lead to the following designation of regressions to determine the propagation of inflation through production network:

$$C_{j\leftarrow i} = \alpha + \beta_D a_{j\leftarrow i} + \beta_M b_{j\leftarrow i} + \lambda X_i + \gamma_i + \epsilon \tag{3.12}$$

$C_{j\leftarrow i}$ is the dependent variable defined as the connectedness of industry i to j. Since the logarithms of producer prices linked to each other with input-output relations in the presence of Cobb-Douglas production functions, the explanatory variable is the intermediate product flow from industry i to j is $a_{j\leftarrow i}$ as domestic transactions and $b_{j\leftarrow i}$ as the transactions that cover only imports. X_i captures the industry characteristics and used as a control variable, γ_i is the industry fixed effects. Our main interests are β_D and β_M. For this reason, the IO dataset broken into two

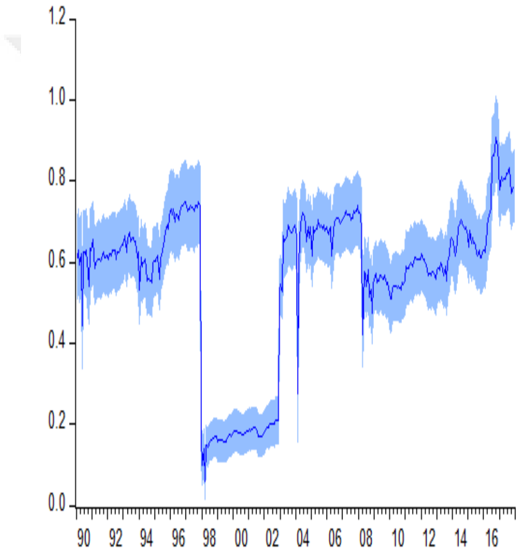
	Inflation Connectedness	*Inflation Connectedness*	*Inflation Connectedness*
Domestic Production Network	0.65***		0.61***
	(0.00)		(0.02)
Imported Inputs		0.24***	0.03*
		(0.03)	(0.01)
R^2	0.56	0.28	0.57
N	3211	3211	3211

Table 3.3: Inflation Propagation *Notes:* This table presents estimates of the industry-level inflation connectedness regressions on both domestic and imported production networks with industry and year fixed effects. The robust standard errors are reported in parentheses. $***$, $**$, and $*$ indicate the significance at the 1%, 5% and 10% levels, respectively.

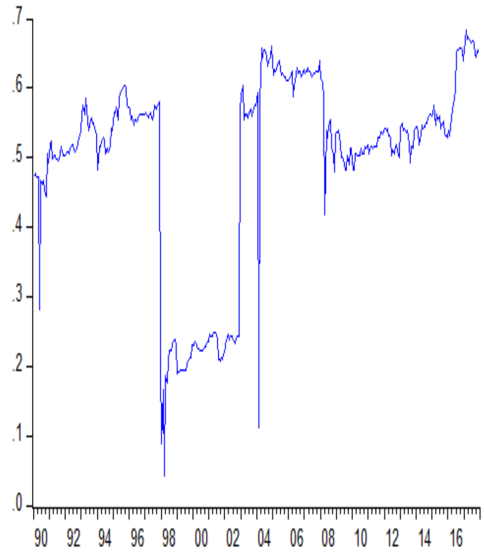
parts as domestic and import. Domestic IO refers to the trade across industries in the local market, and import IO presents the material provided by the international markets. To be more precise, we are checking whether there is a relation between industry i's shock contribution to industry j with the supplied amount of input from industry i to j.

We start by conducting regressions with estimated inflation and connectedness network for each linkage starting from 1990 to 2017. Estimates of industry-level inflation connectedness regressions on both domestic and imported production networks with year and industry fixed effects reported in Table 3.3. According to these results, the empirical evidence is consistent with our model findings. A well-documented result in Table 3.3 is that IO linkages are responsible for inflation connectedness, as expected in theory. For the estimation period, 55 percent of producer price inflation propagated through the domestic IO linkages. Industries that are dependent on each other's intermediate products tend to spread price changes more than the other industries with the less common raw material. Yet, the role of the imported input is also significant and it is a part of this mechanism. However, the propagation of inflation through imported intermediate inputs is relatively small than the domestic linkages.

Table 3.3 explains that inflation circulated through production networks. We repeat the identical exercise over the rolling windows to explore the variation of the relationship between pairwise inflation connectedness and input-output linkages of Korean industries over time. We begin with performing dynamic regressions of connectedness on both local and import input-output linkages to investigate whether this mechanism is time-varying or constant over time. Due to data availability, we assume production networks remain constant over a year. Then, we report the monthly calculated R^2 values and statistically significant coefficients of this mechanism for each month.



(a) β_D



(b) R^2

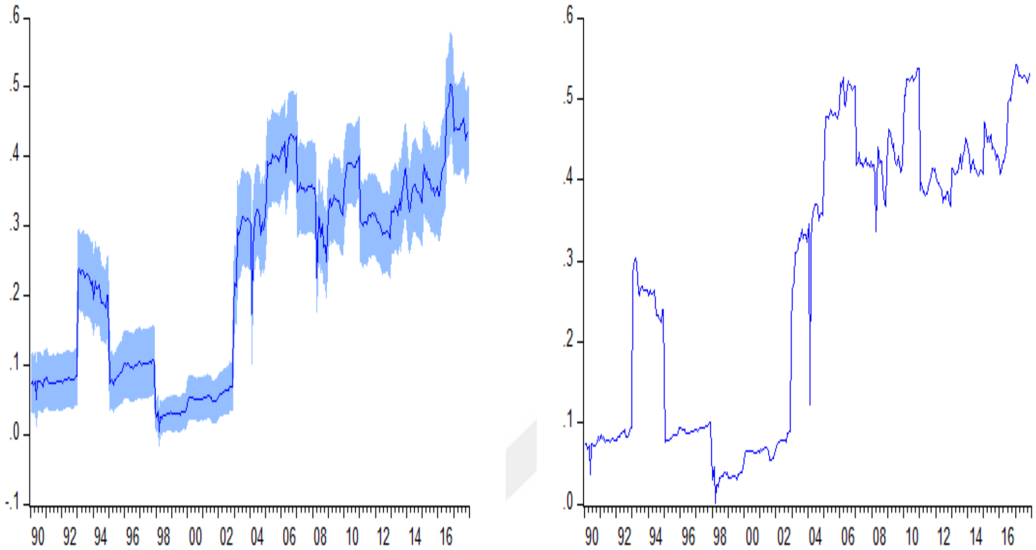
Figure 3.5: Dynamic Pairwise Connectedness Regressions - Domestic IO Coefficients Only. *Notes: Domestic input-output coefficients are used as explanatory variables*

Figure 3.5 represents the coefficient and R^2 calculated from regressions that derived from the domestic production networks. Figure 3.5.a shows the coefficient of interest with the confidence intervals, whereas Figure 3.5.b is the R^2 values of each regression. The time-varying regression underlines the importance of the period for the mechanism. During the tranquil periods, inflation propagation through domestic IO linkages varies between thirty and sixty percent. These supply-side shocks propagate from input-supplier industries to downstream industries. Still, there is a significant decrease following 1997. Even our proposed approach performs well to clarify inflation connectedness, input-output tables are inadequate to explain this phenomenon during risky times such as the East Asian crisis. Because Korea was one of the countries that were hugely affected by currency depreciation and stock market collapse. Thus, the regression coefficient declines significantly during the East Asian Crisis of 1997, which was effectively an aggregate demand shock rather than a supply-shock to upstream industries. Hence, the amplification of inflation shocks such as demand and currency crises are not due to production linkages between industries as anticipated. The IO linkages transmit the supply-side shocks faced by customer industries except for this period. Keeping this in mind, inflation propagation is not due to raw material flow between sectors during a demand-side shock. Moreover, there is a second shock to the Korean economy during that period: Global financial crisis. Once the global financial crisis hit, the coefficient of production networks' significance decreased. Hence, production networks are successful to explain PPI transmission as a supply-side shock from upstream industries to downstream industries except for the years that cover the East Asian Financial Crises and the Global Financial Crises.

Our model proposes that price fluctuations as a form of supply-side shock, diffuse from input-supplier industries to customer industries. Further, during the shocks that are originated from the demand side, the relationship between inflation and production networks are not as strong as expected.

Further, another key issue is that whether importing the intermediate goods for an industry generates a variation in inflation transmission. To clarify this, the identical exercise repeated by working with only the import IO matrix as the explanatory variable. The results of coefficients computed and R^2 values reported in Figure 3.6.a and 3.6.b .

Lastly, to distinguish the differences between domestic and import IO directly, we run a similar regression by using both data set. (namely, estimated coefficients of the domestic and imported input-output coefficients as well as regression R^2) in Figures 3.7.a, 3.7.b and 3.7.c. Importantly, there are critical variations between the two explanatory variables. First, the import IO coefficient is very small and external product flow has a negligible effect when we consider the coefficients of the domestic production network. Second, the coefficient of imported products is not meaningful. Third, the impact of the domestic network decreases during the years 2008-9. Imported production network undertakes the role of domestic part and inflation transmitted across local producers. All in all, demand-side shocks are not delivered by production networks like the supply-side shocks and the underlying mechanism behind the PPI connectedness is the domestic production network of



(a) β_M (b) R^2

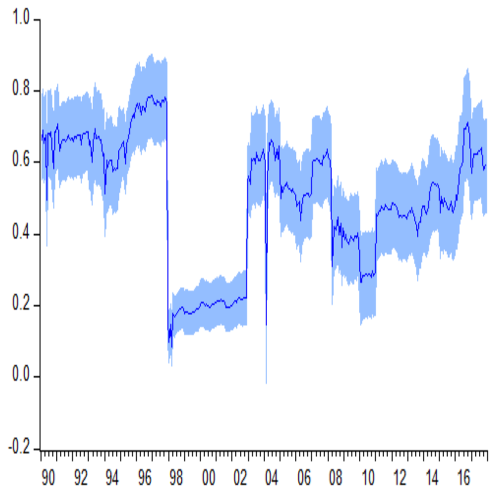
Figure 3.6: Dynamic Pairwise Connectedness Regressions - Imported IO Coefficients Only. *Notes: Imported transactions across industries are used as explanatory variables*

Korea.

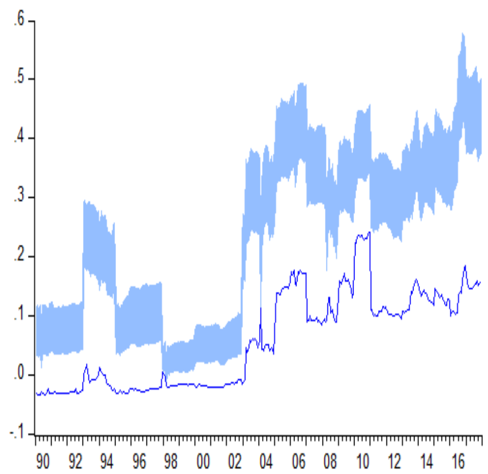
3.8 Conclusion

In this study, we focus on the propagation and amplification of inflation shocks. First, we developed the theoretical implications of shock transmission through input-output linkages. Theoretically, we show that when the preferences and production functions are Cobb-Douglas, supply-side shocks generate downstream propagation. To be more precise, supply-side shocks change the prices faced by customer industries. Thus, inflation circulation across manufacturing sectors relies upon the underlying production network.

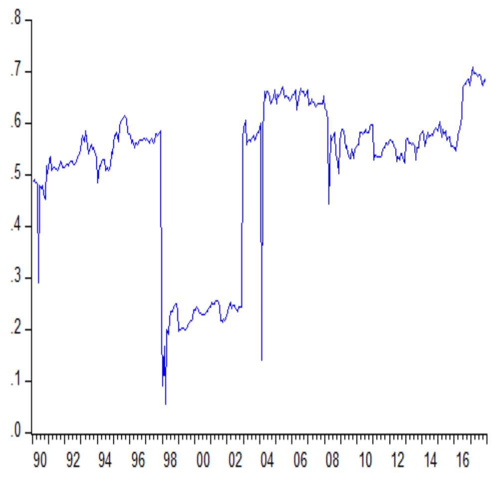
The illustration of the inflation spillovers estimated with the Diebold-Yilmaz framework that provides the bilateral inflation spillovers. Both production and inflation connectedness networks of Korean manufacturing industries indicate that upstream sectors have higher out-degree distributions by playing a more crucial role in the center. On the contrary, downstream sectors located in the periphery demonstrating less impact on inflation shock transmission. Besides, the resemblances of both networks are compatible with our model predictions.



(a) β_D



(b) β_M



(c) R^2

Figure 3.7: Dynamic Pairwise Connectedness Regressions

We consider the time-varying evolution of shocks between the dates January 1968 and December 2019. The system-wide index remained high during the promotion of upstream industries as a government policy including heavy-chemical industry drive. After determining the connectedness of each industry, we argue that promoted industries demonstrate higher connectedness for each period. By rotating industry focus to high-tech industries which are essentially downstream, the connectedness index remained low and stable. Additionally, this index captures the turning points of the Korean economy. We also report the robustness of the connectedness index to the fluctuations in the exchange rate, oil price and gold price with the VARX model. These various controls generated different robust connectedness indices.

According to the empirical tests, the propagation of inflation shocks through the input-output linkages. These linkages account for 30-60 % inflation propagation across industries. Still, the distribution of inflation is not stable over time. Even input-linkages amplify the inflation transmission, and they are insufficient to clarify this phenomenon in case of aggregate demand shocks such as the East Asian Financial Crisis and Global Financial Crisis. More, domestic and import IO linkages act differently.

As a final remark, our work has critical policy-making implications for central banks and institutions especially for inflation forecasting and optimal monetary policy. For the producer price inflation studies, the role of input-output linkages is crucial. Industries participate in the inflation transmission mechanism asymmetrically depending on their role in the production networks.

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Appendix A

PRODUCTION NETWORKS AND LEARNING-BY-NETWORKING

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. (2006) correction. The correlation matrix below shows that TFP methodology that 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

Appendix B. Proof of Propositions

P1. Firms that only operate in domestic market

Firms that trade only in domestic market,

Profit of firm i,

$$\pi_i = p_i y_i - w l_i - \sum_{j=1}^{n} p_j x_{ij} \tag{A.1}$$

The production function of the firm,

$$y_i = A_i {L_i}^{\alpha_i} \prod_{j=1}^{n} X_{ij}^{a_{ij}} \tag{A.2}$$

By taking the first-order conditions ,

For x_{ij}

$$a_{ij}y_ip_i - x_{ij}p_j = 0 \tag{A.3}$$

$$a_{ij}y_ip_i = x_{ij}p_j \tag{A.4}$$

$$a_{ij} = \frac{x_{ij}p_j}{y_ip_i} \tag{A.5}$$

For l_i,

$$\alpha_i p^y_i{}_i - wl_i = 0 \tag{A.6}$$

$$\alpha_i = \frac{w_il_i}{p_iy_i} \tag{A.7}$$

Logarithm of the production function,

$$dlny_i = dz_i + \alpha^l_i + dlnl_i + \sum_{j=1}^{n} a_{ij}x_{ij} \tag{A.8}$$

Differentiating equation A.5 yields,

$$dlny_i + dlnp_i = dlnx_{ij} + dlnp_j \tag{A.9}$$

Differentiating equation A.7 yields,

$$dlny_i + dlnp_i = dlnw_i + dlnl_i \tag{A.10}$$

As the wages are chosen to be numeraire $dlnw_i = 0$

$$dlny_i + dlnp_i = dlnl_i \tag{A.11}$$

Replacing for the $dlnl_i$ and $dlnx_{ij}$ for equation A.8,

$$dlny_i = dz_i + \alpha^l_i(dlny_i + dlnp_i) + \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i - dlnp_j) \tag{A.12}$$

$$dlny_i = dz_i + (\alpha^l_i + \sum_{j=1}^{n} a_{ij})dlny_i + (\alpha^l_i + \sum_{j=1}^{n} a_{ij})dlnp_i - \sum_{j=1}^{n} a_{ij}dlnp_j \tag{A.13}$$

Market clearing condition $\alpha^l_i + \sum_{j=1}^{n} a_{ij} = 1$

$$dlny_i = dz_i + dlny_i + dlnp_i - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.14}$$

$$0 = dz_i + dlnp_i - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.15}$$

By relying on the equation A.11 and l_i remains constant,

$$0 = dz_i - dlny_i + \sum_{j=1}^{n} a_{ij} dlny_j \tag{A.16}$$

$$dlny_i = dz_i + \sum_{j=1}^{n} a_{ij} dlny_j \tag{A.17}$$

P2. Firms that export

The definition of a firm depends on whether firm its a domestic seller or exporter,

$$\pi = \begin{cases} \pi_d & \text{if firm } i \text{ does not export } t \\ \pi_d + \pi_e(1-\tau) - f_{ex} & \text{if firm } i \text{ exports to international markets} \end{cases} \tag{A.18}$$

Profit of the exporter firm,

$$\pi = \pi_d + \pi_e(1-\tau) - f_{ex} \tag{A.19}$$

$$\pi_e = p_i^H y_i \delta + p_i^F y_i (1-\delta)(1-\tau) - wl_i - \sum_{j=1}^{n} p_j x_{ij} - f_{ex} \tag{A.20}$$

where δ is the amount of the firm's output that is exported and is assumed to be given for calculation purposes.

The production function of the firm,

$$y_i = A_i {L_i}^{\alpha_i} \prod_{j=1}^{n} X_{ij}^{a_{ij}} \tag{A.21}$$

Taking the first-order conditions for l_i, x_{ij} and δ yields,

For x_{ij}

$$a_{ij} y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau)) - x_{ij} p_j = 0 \tag{A.22}$$

$$x_{ij} = \frac{a_{ij} p_j}{y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau))} \tag{A.23}$$

$$a_{ij} = \frac{x_{ij} p_j}{y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau))} \tag{A.24}$$

and for l_i,

$$\alpha_i p_i^H y_i \delta + \alpha_i p_i^F y_i (1-\delta)(1-\tau) - w l_i = 0 \tag{A.25}$$

$$\alpha_i y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau)) = w l_i \tag{A.26}$$

$$\alpha_i = \frac{w_i l_i}{y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau))} \tag{A.27}$$

and δ,

$$p_i^H y_i - p_i^F y_i (1-\tau) = 0 \tag{A.28}$$

$$p_i^H - p_i^F (1-\tau) = 0 \tag{A.29}$$

$$p_i^H = p_i^F (1-\tau) \tag{A.30}$$

Totally differentiating equation A.24 yields by using $log(X+Y) = log(x) + log(1 + Y/X)$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F (1-\delta)(1-\tau)}{p_i^H \delta}) \tag{A.31}$$

By replacing the p_i^H according to eqn A.30

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F (1-\delta)(1-\tau)}{p_i^F (1-\tau)\delta}) \tag{A.32}$$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\psi + dln(1 + \frac{(1-\delta)}{\delta}) \tag{A.33}$$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\psi + dln(\frac{\delta + 1 - \delta}{\delta}) \tag{A.34}$$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\psi + dln(\frac{1}{\delta}) \tag{A.35}$$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H + dln\delta - dln\delta \tag{A.36}$$

$$dlnx_{ij} + dlnp_j = dlny_i + dllnp_i^H \tag{A.37}$$

Totally differentiating equation A.27 yields

$$dlnl_i + dlnw_i = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F(1-\delta)(1-\tau)}{p_i^H\delta}) \tag{A.38}$$

Since wages are chosen as numeraire $dlnw_i = 0$

$$dlnl_i = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F(1-\delta)(1-\tau)}{p_i^H\delta}) \tag{A.39}$$

After replacing the p_i^H as in eqn A.32, we obtain

$$dlnl_i = dlny_i + dllnp_i^H \tag{A.40}$$

Utility maximization in turn yields

$$\frac{p_i c_i}{\delta_i} = \frac{p_j c_j}{\delta_j} \tag{A.41}$$

Household budget constraint,

$$\sum_{i=1}^{n} p_i c_i = wl \tag{A.42}$$

yields

$$p_i c_i = \delta_i wl \tag{A.43}$$

Also, first-order condition for labor supply

$$-\frac{\gamma(l)'l}{\gamma(l)} = 1 \tag{A.44}$$

implying labor supply is determined independent of the equilibrium wage rate

Taking logarithm of the production function for exporter firms and totally differentiating yields

$$dlny_i = dz_i + \alpha_i^l dlnl_i + \sum_{j=1}^{n} a_{ij} dlnx_{ij} \tag{A.45}$$

Replacing $dlnx_{ij}$ and $dlnl_i$ in equation C.7 yields

$$dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) + \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j) \tag{A.46}$$

Since $\alpha_i^l + \sum_{j=1}^{n} a_{ij} = 1$

$$dlny_i = dz_i + (\alpha_i^l + \sum_{j=1}^{n} a_{ij})dlny_i + \alpha_i^l dlnp_i^H + \sum_{j=1}^{n} a_{ij} dlnp_i^H - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.47}$$

$$0 = dz_i + \alpha_i^l dlnp_i^H + \sum_{j=1}^{n} a_{ij} dlnp_i^H - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.48}$$

$$0 = dz_i + (\alpha_i^l + \sum_{j=1}^{n} a_{ij})dlnp_i^H - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.49}$$

Using for $\alpha_i^l + \sum_{j=1}^{n} a_{ij} = 1$

$$0 = dz_i + dlnp_i^H - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.50}$$

By relying on the equation A.30, $dnp_i^H = dlnp_i^F + dln(1-\tau)$ and replacing for $dlnp_i^H$,

$$0 = dz_i + dlnp_i^F + dln(1-\tau) - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.51}$$

As the $dlny_i = -dlnp_i$,

$$0 = dz_i - dlny_i^F + dln(1-\tau) + -\sum_{j=1}^{n} a_{ij} dlnp_j \tag{A.52}$$

Replacing for $dlnp_j$

$$dlny_i^F = dz_i + dln(1-\tau) + \sum_{j=1}^{n} a_{ij} dlny_j \tag{A.53}$$

Writing $dlny_i$ in terms of $dlny_i^F$

$$dlny_i(1-\delta) = dz_i + dln(1-\tau) + \sum_{j=1}^{n} a_{ij} dlny_j \tag{A.54}$$

$$dlny_i = \frac{dz_i + dln(1-\tau) + \sum_{j=1}^{n} a_{ij} dlny_j}{(1-\delta)} \tag{A.55}$$

P3. Firms that import

Profit of the importer firm,

$$\pi = p_i^H y_i - wl_i - \lambda \sum_{i=1}^{n} a_{ij} X_{ij}^H - (1-\lambda) \sum_{i=1}^{n} a_{ij} X_{ij}^F \tag{A.56}$$

The first order conditions,

For l_i,

$$\alpha_i p_i^H y_i - wl_i = 0 \tag{A.57}$$

$$\alpha_i = \frac{wl_i}{p_i^H y_i} \tag{A.58}$$

For x_{ij},

$$a_{ij} y_i p_i^H - \lambda x_{ij}^H p_j^H - (1-\lambda) x_{ij}^F p_j^F = 0 \tag{A.59}$$

$$a_{ij} = \frac{\lambda x_{ij}^H p_j^H + (1-\lambda) x_{ij}^F p_j^F}{y_i p_i^H} \tag{A.60}$$

For δ_i,

$$x_{ij}^H p_j^H - x_{ij}^F p_j^F = 0 \tag{A.61}$$

$$x_{ij}^H p_j^H - x_{ij}^F \epsilon p_j^H = 0 \tag{A.62}$$

$$x_{ij}^H = \epsilon x_{ij}^F \tag{A.63}$$

where ϵ is the exchange rate.

$$dlny_i + dlnp_i^H = dln(\lambda X_{ij}^H p_j^H + (1-\lambda) X_{ij}^F p_j^F) \tag{A.64}$$

After replacing equation A.63 into equation A.64,

$$dlny_i + dlnp_i^H = dln(\lambda \epsilon X_{ij}^F p_j^H + X_{ij}^F \epsilon p_j^H - \lambda X_{ij}^F \epsilon p_j^H) \tag{A.65}$$

$$dlny_i + dlnp_i^H = dln(\lambda \epsilon X_{ij}^F p_j^H + X_{ij}^F \epsilon p_j^H - \lambda X_{ij}^F \epsilon p_j^H) \tag{A.66}$$

$$dlny_i + dlnp_i^H = dln(X_{ij}^F \epsilon p_j^H) \tag{A.67}$$

$$dlny_i + dlnp_i^H = dln(X_{ij}^F p_j^F) \tag{A.68}$$

$$dlny_i + dlnp_i^H = dlnX_{ij}^F + dlnp_j^F \tag{A.69}$$

Going back to equation A.64 and replacing for the domestic inputs,

$$dlny_i + dlnp_i^H = dln(\lambda X_{ij}^H p_j^H + (1-\lambda) X_{ij}^F p_j^F) \tag{A.70}$$

$$dlny_i + dlnp_i^H = dln(\lambda X_{ij}^H p_j^H + (1-\lambda) \frac{X_{ij}^H}{\epsilon} p_j^H \epsilon) \tag{A.71}$$

$$dlny_i + dlnp_i^H = dlnX_{ij}^H + dlnp_j^H \tag{A.72}$$

Taking the logarithm of production function for importer firms and totally differentiating yields,

$$dlny_i = dz_i + \alpha_i^l dlnl_i + \lambda \sum_{j=1}^{n} a_{ij} dlnx_{ij}^H + (1-\lambda) \sum_{j=1}^{n} a_{ij} dlnx_{ij}^F \tag{A.73}$$

After replacing the $dlnl_i$ according to the equation A.40

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l(dlnp_i^H + dlny_i) + \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^H) + \\ (1-\lambda)\sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F) \end{aligned} \tag{A.74}$$

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l(dlnp_i^H + dlny_i) + \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^H) + \\ \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F) - \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F) \end{aligned} \tag{A.75}$$

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l(dlnp_i^H + dlny_i) - \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^H + \sum_{j=1}^{n} a_{ij} dlny_i \\ + \sum_{j=1}^{n} a_{ij} dlnp_i^H + \sum_{j=1}^{n} a_{ij} dlnp_i^F + \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^F \end{aligned} \tag{A.76}$$

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l(dlnp_i^H + dlny_i) + \sum_{j=1}^{n} a_{ij}(dlnp_i^H + dlny_i) \\ - \sum_{j=1}^{n} a_{ij} dlnp_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^F - \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^H \end{aligned} \tag{A.77}$$

since

$$\alpha_i^l + \sum_{j=1}^{n} a_{ij} = 1 \tag{A.78}$$

$$dlny_i = dz_i + dlnp_i^H + dlny_i - \sum_{j=1}^{n} a_{ij} dlnp_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^F - \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^H \tag{A.79}$$

Recall that $dlny_i = -dlnp_i$

$$0 = dz_i + dlnp_i^H + \sum_{j=1}^{n} a_{ij} dlny_j^F - \lambda \sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \tag{A.80}$$

$$dlny_i = dz_i + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda sum_{j=1}^{n} a_{ij} dlny_j^H \tag{A.81}$$

$$dlny_i = dz_i + \sum_{j=1}^{n} a_{ij}[\lambda dlny_j^H + (1-\lambda)dlny_j^F] \tag{A.82}$$

P4. Firms that both export and import

Profit of the firm,

$$\pi = \pi_d + \pi_e(1-\tau) - f_{ex} \tag{A.83}$$

$$\pi = p_i^H y_i \delta + p_i^F y_i (1-\delta)(1-\tau) - wl_i - \lambda \sum_{i=1}^{n} a_{ij} X_{ij}^H - (1-\lambda) \sum_{i=1}^{n} a_{ij} X_{ij}^F - f_{ex} \tag{A.84}$$

First-order conditions,

l_i,

$$\alpha_i p_i^H y_i \delta + \alpha_i p_i^F y_i (1-\delta)(1-\tau) - wl_i = 0 \tag{A.85}$$

$$\alpha_i y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau)) = wl_i \tag{A.86}$$

$$\alpha_i = \frac{l_i y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau))}{w_i} \tag{A.87}$$

X_{ij},

$$\alpha_i y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau)) - [(\lambda X_{ij}^H p_j^H) + ((1-\lambda) X_{ij}^F p_j^F)] = 0 \tag{A.88}$$

$$\alpha_i y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau)) = [(\lambda X_{ij}^H p_j^H) + ((1-\lambda) X_{ij}^F p_j^F)] \tag{A.89}$$

$$a_{ij} = \frac{[(\lambda X_{ij}^H p_j^H) + ((1-\lambda) X_{ij}^F p_j^F)]}{y_i (p_i^H \delta + p_i^F (1-\delta)(1-\tau))} \tag{A.90}$$

β,

$$X_{ij}^H p_j^H - X_{ij}^F p_j^F = 0 \tag{A.91}$$

$$X_{ij}^H p_j^H = X_{ij}^F p_j^F \tag{A.92}$$

$$X_{ij}^H = \epsilon X_{ij}^F \tag{A.93}$$

δ,

$$p_i^H y_i - p_i^F y_i(1-\tau) = 0 \tag{A.94}$$

$$p_i^H - p_i^F(1-\tau) = 0 \tag{A.95}$$

$$p_i^H = p_i^F(1-\tau) \tag{A.96}$$

By using log(X+Y) =log(X) + log (1+Y/X)) and totally differentiating equation A.90,

$$0 = dlny_i + dllnp_i^H + dln\delta + dln(1+\frac{p_i^F(1-\delta)(1-\tau)}{p_i^H\delta}) - dln(\lambda X_{ij}^H p_j^H + (1-\lambda)X_{ij}^F p_j^F) \tag{A.97}$$

$$dlny_i + dllnp_i^H + dln\delta + dln(1+\frac{p_i^F(1-\delta)(1-\tau)}{p_i^H\delta}) = dln(\lambda X_{ij}^H p_j^H + (1-\lambda)X_{ij}^F p_j^F) \tag{A.98}$$

Replacing p_i^H, $p_i^H = p_i^F(1-\tau)$

$$dlny_i + dllnp_i^H + dln\delta + dln(1+\frac{p_i^F(1-\delta)(1-\tau)}{p_i^F(1-\tau)\delta}) = dln(\lambda X_{ij}^H p_j^H + (1-\lambda)X_{ij}^F p_j^F) \tag{A.99}$$

$$dlny_i + dllnp_i^H + dln\delta + dln(1+\frac{1-\delta}{\delta}) = dln(\lambda X_{ij}^H p_j^H + (1-\lambda)X_{ij}^F p_j^F) \tag{A.100}$$

$$dlny_i + dllnp_i^H + dln\delta + dln(\frac{1}{\delta}) = dln(\lambda X_{ij}^H p_j^H + (1-\lambda)X_{ij}^F p_j^F) \tag{A.101}$$

$$dlny_i + dllnp_i^H + dln\delta + dln1 - dln\delta = dln(\beta X_{ij}^H p_j^H + (1-\beta)X_{ij}^F p_j^F) \tag{A.102}$$

$$dlny_i + dllnp_i^H = dln(\beta X_{ij}^H p_j^H + (1-\beta)X_{ij}^F p_j^F) \tag{A.103}$$

By relying on the equation A.93, $X_{ij}^H = \epsilon X_{ij}^F$

$$dlny_i + dllnp_i^H = dln(\beta X_{ij}^H p_j^H + X_{ij}^F p_j^F - \beta X_{ij}^F p_j^F) \tag{A.104}$$

$$dlny_i + dllnp_i^H = dln(\beta \epsilon X_{ij}^F p_j^H + X_{ij}^F p_j^F - \beta X_{ij}^F \epsilon p_j^H) \tag{A.105}$$

$$dlny_i + dllnp_i^H = dln(X_{ij}^F p_j^F) \tag{A.106}$$

$$dlny_i + dllnp_i^H = dlnX_{ij}^F + dlnp_j^F \tag{A.107}$$

Writing the same equation for the domestic inputs,

$$dlny_i + dllnp_i^H = dln(\beta X_{ij}^H p_j^H + (1-\beta)X_{ij}^F p_j^F) \tag{A.108}$$

Replacing for X_{ij}^H and p_j^H

$$dlny_i + dllnp_i^H = dln(\beta X_{ij}^H p_j^H + (1-\beta)\frac{X_{ij}^H}{p_j^H} p_i^H \epsilon) \tag{A.109}$$

$$dlny_i + dllnp_i^H = dln(X_{ij}^H p_j^H) \tag{A.110}$$

$$dlny_i + dllnp_i^H = dlnX_{ij}^H + dlnp_j^H \tag{A.111}$$

Differentiating equation A.87 yields

$$dlnl_i + dlnw_i = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F(1-\delta)(1-\tau)}{p_i^H \delta}) \tag{A.112}$$

Since wages are chosen as numeraire $dlnw_i = 0$

$$dlnl_i = dlny_i + dllnp_i^H + dln\delta + dln(1 + \frac{p_i^F(1-\delta)(1-\tau)}{p_i^H \delta}) \tag{A.113}$$

After replacing the p_i^H , we obtain

$$dlnl_i = dlny_i + dllnp_i^H \tag{A.114}$$

Taking the logarithm of the production function,

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l dlny_i + \lambda \sum_{j=1}^{n} a_{ij} dlnx_{ij}^H \\ + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlnx_{ij}^F \end{aligned} \tag{A.115}$$

$$\begin{aligned} dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) + \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^H) \\ - (1-\lambda)\sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F) \end{aligned} \tag{A.116}$$

$$
\begin{aligned}
dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) + \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^H) \\
+ \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F) \\
- \lambda \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H - dlnp_j^F)
\end{aligned} \tag{A.117}
$$

$$
\begin{aligned}
dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) - \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^H + \sum_{j=1}^{n} a_{ij} dlny_i \\
+ \sum_{j=1}^{n} a_{ij} dlnp_j^H - \sum_{j=1}^{n} a_{ij} dlnp_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^F
\end{aligned} \tag{A.118}
$$

$$
\begin{aligned}
dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) + \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H) + \sum_{j=1}^{n} a_{ij} dlnp_j^F \\
+ \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^F - \lambda \sum_{j=1}^{n} a_{ij} dlnp_j^H
\end{aligned} \tag{A.119}
$$

since $dlnp_j^F = -dlny_j^F$ and $dlnp_j^H = -dlny_j^H$

$$
\begin{aligned}
dlny_i = dz_i + \alpha_i^l(dlny_i + dlnp_i^H) + \sum_{j=1}^{n} a_{ij}(dlny_i + dlnp_i^H) \\
+ (1-\lambda) \sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H
\end{aligned} \tag{A.120}
$$

By using market clearing condition $\alpha_i^l + \sum_{j=1}^{n} a_{ij} = 1$,

$$
dlny_i = dz_i + dlny_i + dlnp_i^H + (1-\lambda) \sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \tag{A.121}
$$

$$
0 = dz_i + dlnp_i^H + (1-\lambda) \sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \tag{A.122}
$$

Replacing for $dlnp_i^H = dlnp_i^F + dln(1-\tau)$

$$
0 = dz_i + dlnp_i^F + dln(1-\tau) + (1-\lambda) \sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \tag{A.123}
$$

By using $dlny_i = -dlnp_i$,

$$0 = dz_i - dlny_i^F + dln(1-\tau) + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \quad (A.124)$$

$$dlny_i^F = dz_i + dln(1-\tau) + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \quad (A.125)$$

Writing $dlny_i$ in terms of $dlny_i^F$

$$(1-\tau)dlny_i = dz_i + dln(1-\tau) + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H \quad (A.126)$$

$$dlny_i = \frac{dz_i + dln(1-\tau) + (1-\lambda)\sum_{j=1}^{n} a_{ij} dlny_j^F + \lambda \sum_{j=1}^{n} a_{ij} dlny_j^H}{(1-\delta)} \quad (A.127)$$

Appendix C. Countries

MENA	**Western Europe**	**Southern Europe**	**East Asia**	**North America**
	WE	**SEB**	**EA**	**NA**
Algeria	Austria	Albania	China	Canada
Bahrain	Belgium	Belarus	Hong Kong	U.S.
Djibouti	Denmark	Bosnia	Japan	Mexico
Egypt	Finland	Bulgaria	Philippines	Costa Rica
Ethiopia	France	Croatia	Singapore	Cuba
Iran	Germany	Czech Republic	South Korea	
Iraq	Iceland	Estonia	Taiwan	
Israil	Ireland	Greece	Vietnam	
Jordan	Italy	Hungary		
Kuwait	Luxembourg	Latvia		
Lebanon	Monaco	Lithuania		
Libya	Netherlands	Moldavia		
Morocco	Norway	Montenegro		
Oman	Portugal	Poland		
Qatar	Spain	Romania		
Saudi Arabia	Sweden	Russia		
Syria	Switzerland	Serbia		
Tunisia	U.K.	Slovakia		
Yemen		Ukraine		
		Yugoslavia		

Appendix D. 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

	[1]	**[2]**	**[3]**	**[4]**	**[5]**
β_{Di}	0.88^{**}				0.53^{*}
	(0.08)				(0.08)
$\beta_{I,NA}$		5.99^{*}			4.34^{*}
		(1.89)			(1.59)
$\beta_{I,WA}$		5.69			3.81
		(4.90)			(2.78)
$\beta_{I,WE}$		-208.7			-168.8
		(254.2)			(212.2)
$\beta_{I,SEB}$		-1.52			-1.94^{+}
		(2.37)			(0.78)
$\beta_{I,MENA}$		1.75^{**}			1.15^{+}
		(0.28)			(0.35)
$\beta_{I,Oth}$		2.21^{**}			0.82
		(0.39)			(0.33)
β_{Dq}			0.60^{*}		0.18^{+}
			(0.03)		(0.07)
$\beta_{E,NA}$				2.16	-0.61
				(2.36)	(1.21)
$\beta_{E,EA}$				5.45	0.37
				(4.04)	(1.01)
$\beta_{E,WE}$				2.20^{**}	0.35
				(0.49)	(0.35)
$\beta_{E,SEB}$				-1.10	0.38
				(3.28)	(1.34)
$\beta_{E,MENA}$				6.68^{+}	0.81
				(2.61)	(0.45)
$\beta_{E,Oth}$				5.27^{*}	1.31
				(1.79)	(0.67)
R^2	0.32	0.29	0.41	0.18	0.51
# of Obs.		——	1,066,818	——	

Table A.1: Propagation of Shocks through Value-added with Different Trade Partners

Notes: This table presents estimates from regressing firms' real value-added levels rates on different trade partners. All regressions include fixed effects for 4-digit industry code, size and year. The robust standard errors are reported in the parentheses. $+$, $*$, and $**$ denote the significance of the coefficients at %10, %5 and %1.

Appendix E. Trade Partners

Appendix F. Other 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)
PetroCoke	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)
BasicMetals	-0.90	0.61	0.85
	(1.09)	(1.02)	(0.77)
ComputerElectronic	-0.24	0.97	0.19
	(0.84)	(1.45)	(0.82)
ElectricalEquip	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)
MotorVech	0.16	0.31	0.71
	(0.19)	(0.49)	(0.61)
OtherTrans	4.33	0.45	1.05
	(6.74)	(0.84)	(3.34)
OtherManu	0.86	0.09	0.34
	(1.51)	(0.24)	(0.41)
RepairInstall	0.74	0.12	0.19
	(0.45)	(0.16)	(0.16)

Table A.2: 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 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 presented in parentheses and the third row provides the R^2 of each estimation.

Appendix G. Production Network at 4-digit Level

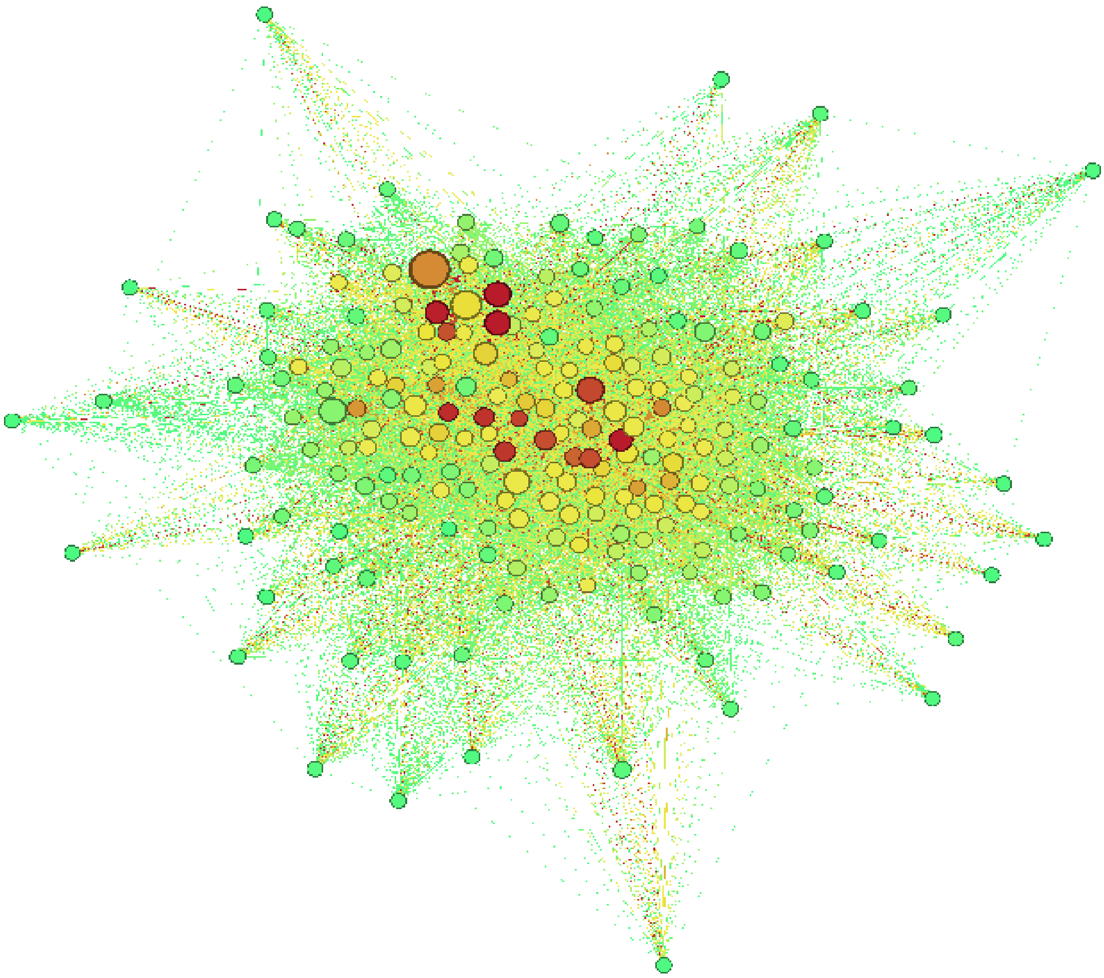


Figure A.1: Domestic Production Network *Notes:* Turkish Manufacturing Industries aggregated according to 4-digit NACE Rev 2. Classification, colors turn from green to dark red depending on the out-degrees of industries. Nodes locations estimated with the ForceAtlas2 algorithm Jacomy et al. (2014a).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

Appendix B

CONNECTEDNESS AND THE PROPAGATION OF SHOCKS THROUGH THE INPUT-OUTPUT NETWORK

B.1 Robustness

In this Appendix, we check whether the results reported in the main body of the paper are robust to alternative specifications and parameter choices.

First, we focus on whether the system-wide connectedness index is robust to the choice of the variance decomposition method. Throughout the paper, generalized variance decomposition is used to obtain the connectedness measures. Even though, generalized variance decomposition allows one to obtain directional connectedness measures, one could use the Cholesky variance decomposition to obtain the system-wide connectedness index, which is not robust to the ordering of variables and hence cannot be used to obtain directional measures.

Figure B.1 presents the dynamic system-wide connectedness index obtained with the generalized as well as the Cholesky decomposition approaches.[1] As expected, the generalized variance decomposition based index is always higher than the Cholesky variance decomposition based index. As the time series behavior of the two indices are very much the same, we can conclude that the presence of simultaneous inflation shocks to different industries does not affect the dynamic behavior of the system-wide connectedness index significantly.

Next, the robustness of the system-wide connectedness index to the choice of the VAR model order is analyzed. The system-wide connectedness index reported in the main body of the paper was obtained from the estimation of a VAR(2) model of inflation for seventeen U.S. manufacturing industries. Here the VAR model order is varied from one month to four months and the resulting system-wide connectedness index is plotted in Figure B.2. It is clear from the figure that the choice of the VAR model order does not make much of a difference in terms of the overall connectedness of inflation shocks across industries.

Following the analysis of robustness of the results to the choice of the VAR order,

[1] The Cholesky variance decomposition based index is calculated for the ordering of variables as in Table D.1.

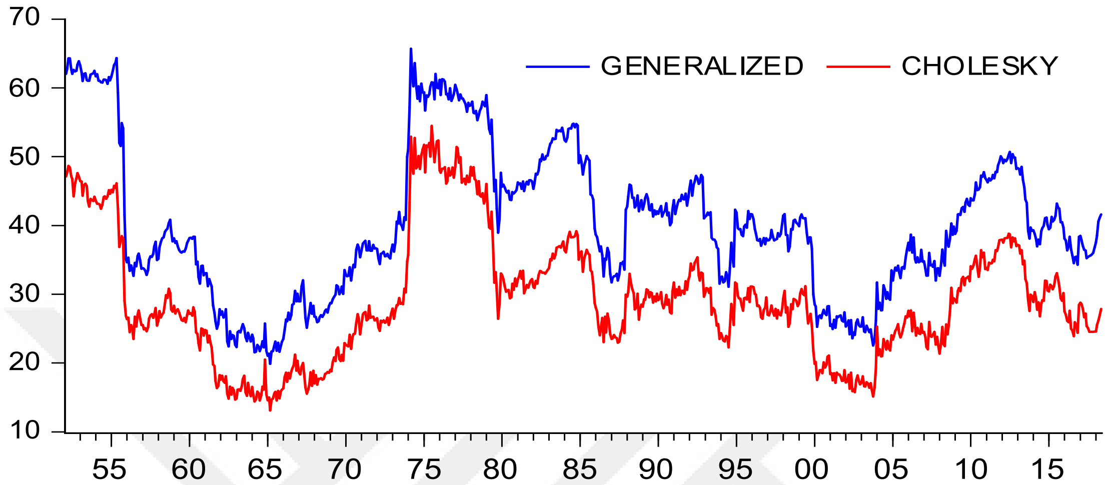


Figure B.1: System-wide Connectedness Index and Variance Decomposition Methods

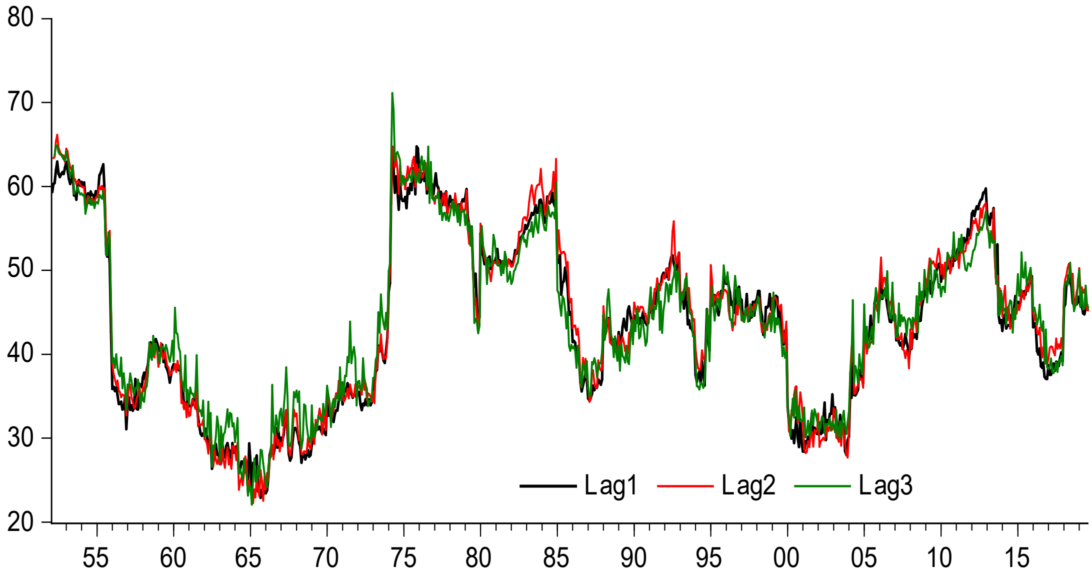


Figure B.2: Sensitivity of the Connectedness Index to the VAR Order we study the robustness of our results to the rolling window size. Fixing the VAR model order at two months, four alternative rolling sample window sizes, namely 48, 72, 84 and 96 months, are considered. Along with the choice of the 60-month long window size in the paper, the system-wide connectedness index for all five alternative windows sizes are obtained. Rather than plotting each of these separately, it makes more sense to plot the minimum, maximum and median values of the five resulting system-wide connectedness indices in Figure B.3.

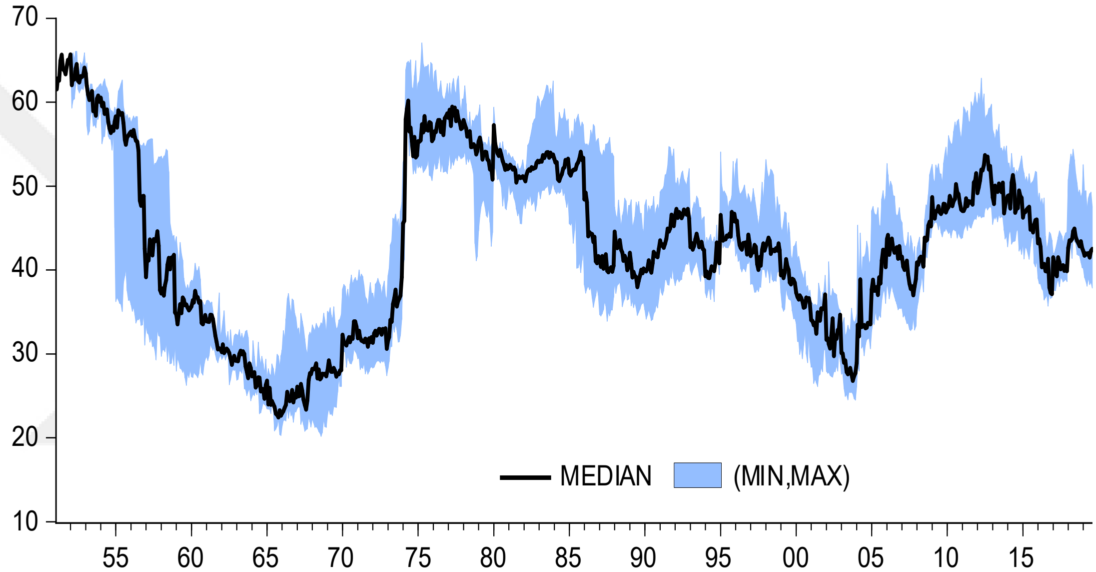


Figure B.3: Sensitivity of the Connectedness Index to the Window Size The median, minimum and maximum values of connectedness index with five different window sizes: 48, 60, 72, 84 and 96 months.

Clearly, the choice of the window size makes a big difference for the system-wide connectedness index than the choice of the VAR model order. The upward jumps in the connectedness index takes place exactly at the same time for all five window sizes when the systemically important events (such as the first oil price shock of 1974 and the global financial crisis of 2008-2009) are included in the rolling sample windows, with a very narrow band of minimum and maximum values The drops in the index, however, take place with a twelve month delay as we move from the 48 to 60, 72, 84 and 96 month-long rolling sample windows. This is clearly visible in the drop of mid-1950s, which has a very wide minimum-maximum band for the system-wide connectedness index as the inflation data for 1950 are dropped out of the sample window. First, the connectedness index for the 48-month long sample window drops close to 30 percentage points, followed by others with 12-month lag each time. Over the whole sample, the system-wide connectedness indices obtained in five different window sizes form a maximum bandwidth of 10-15 percentage points. Despite that fact, however, the overall trends of the system-wide index and its major turning points are not affected by the choice of the window size.

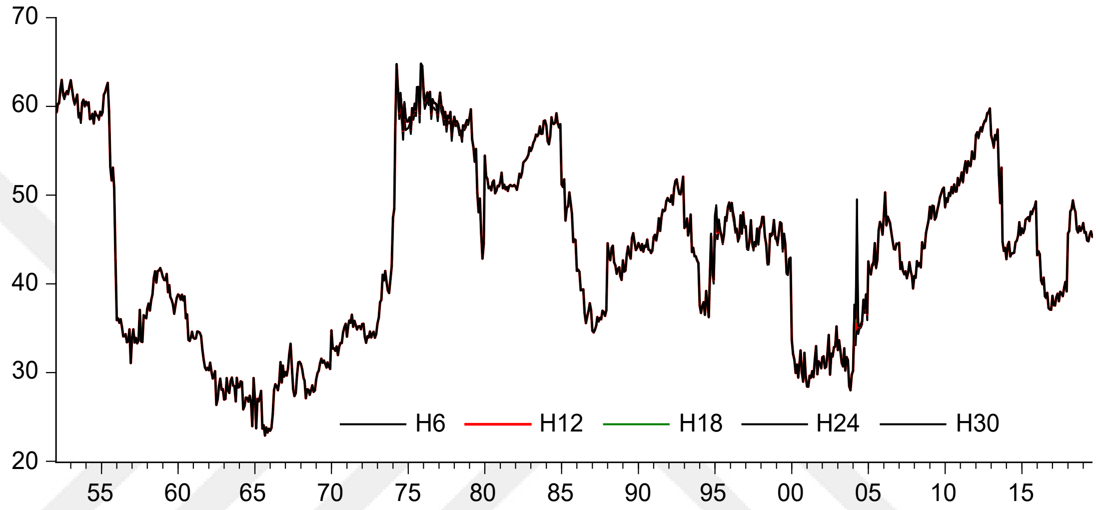


Figure B.4: Sensitivity of the Connectedness Index to the Forecast Horizon

Finally, the system-wide connectedness index values are also robust to the choice of the forecasting horizon. The forecast horizon is allowed to vary from 6 to 12, 18, 24 and 30 months and the resulting system-wide connectedness index in obtain. The resulting connectedness indices for five different forecast horizons are plotted in Figure B.4. It is clearly visible in Figure B.4 that there is very little variation in the system-wide connectedness index as the forecast horizon is increased from 6 months to all the way to 30 months.

B.2 Plots: Inflation Connectedness "To Others"

In this Appendix, we present the directional inflation connectedness "to others" measures for all 17 U.S. manufacturing industries.

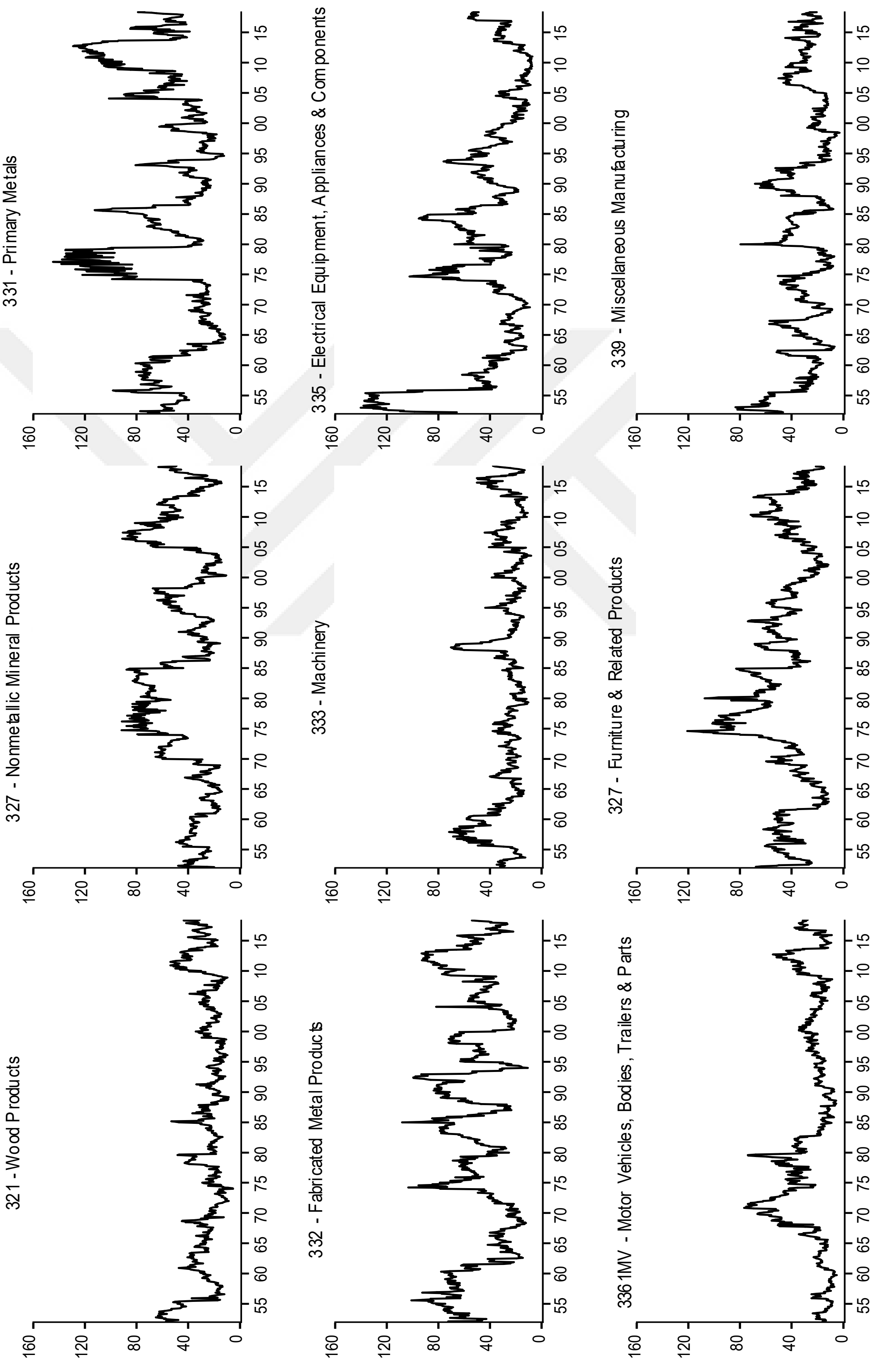


Figure B.1: Inflation Connectedness "To Others" – U.S. Manufacturing Industries

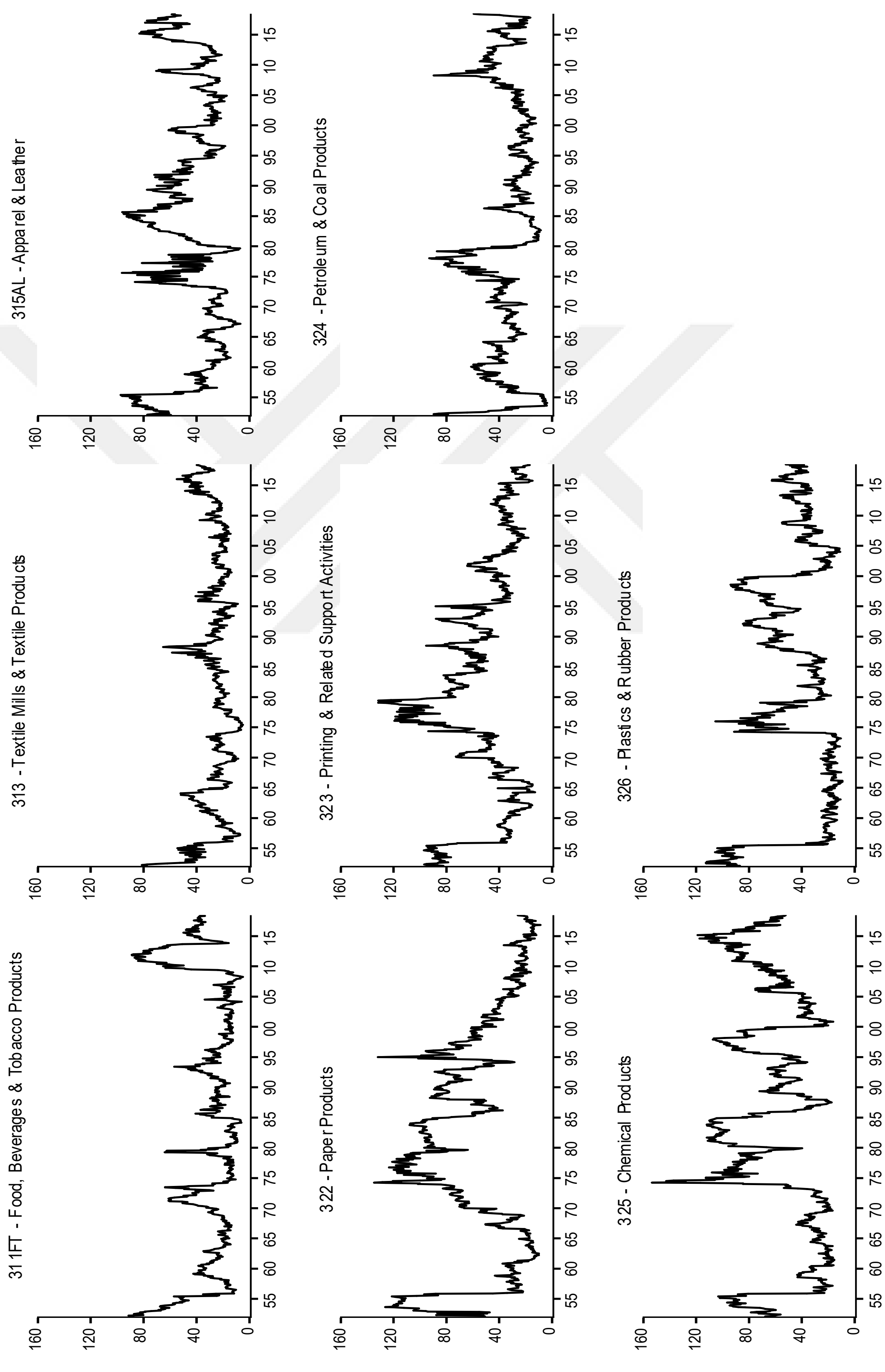


Figure B.2: Inflation Connectedness "To Others" – U.S. Manufacturing Industries (cont'd)

B.3 Commodity Prices: Metals & Minerals and Oil

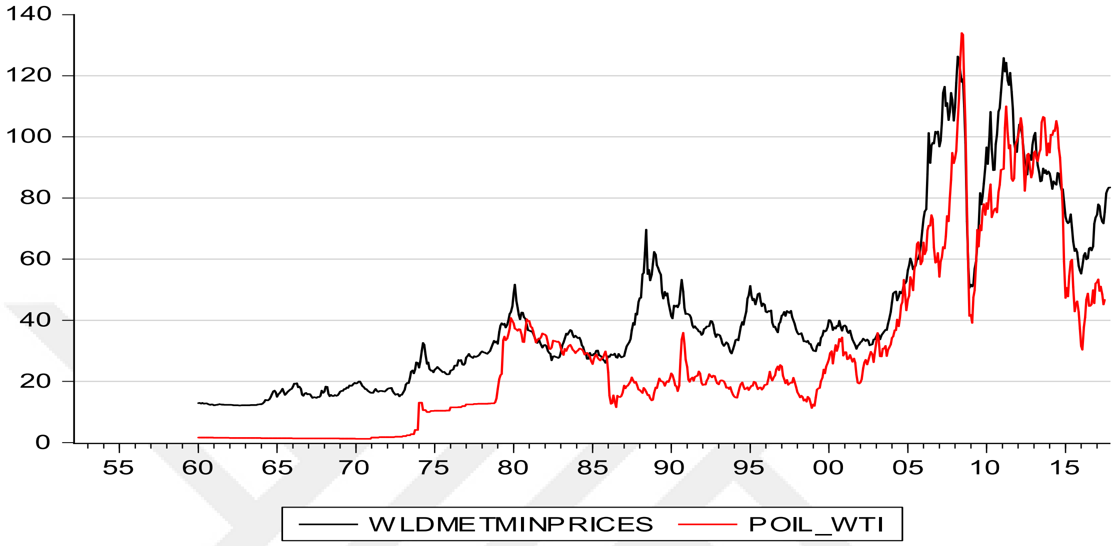


Figure C.1: Metals & Minerals Price Index and Price of Crude Oil (WTI, $ per barrel)

B.4 U.S. Manufacturing Industries

Table D.1: U.S. Manufacturing Industries

NAICS	**Acronym**	**Sector**
321	Wood	Wood Products
327	Mineral	Nonmetallic Mineral Products
331	BasicMetal	Primary Metals
332	FabrMetal	Fabricated Metal Products
333	Machinery	Machinery
335	ElectricEquip	Electrical Equipment, Appliances, & Components
3361MV	MotorVech	Motor Vehicles, Bodies, Trailers & Parts
337	Furniture	Furniture and Related Products
339	Other	Miscellaneous Manufacturing
311FT	FoodBEv	Food and Beverage and Tobacco Products
313TT	Textiles	Textiles Mills and Products
315AL	Apparel	Apparel and Leather
322	Paper	Paper Products
323	Printing	Printing and Related Support Activities
324	PetroCoal	Petroleum and Coal Products
325	Chemical	Chemical products
326	Plastics	Plastics and Rubber Products

Appendix C

INFLATION IMPLICATIONS OF PRODUCTION NETWORKS IN SOUTH KOREA

Appendix A. Proof of Proposition 1

Profit maximization implies

$$a_{ij} = \frac{p_j x_{ij}}{p_i y_i} \tag{C.1}$$

and

$$\alpha_i = \frac{w l_i}{p_i y_i} \tag{C.2}$$

Utility maximization in turn yields

$$\frac{p_i c_i}{\beta_i} = \frac{p_j c_j}{\beta_j} \tag{C.3}$$

Household budget constraint,

$$\sum_{i=1}^{n} p_i c_i = wl \tag{C.4}$$

yields

$$p_i c_i = \beta_i w l \tag{C.5}$$

Also, first-order condition for labor supply

$$-\frac{\gamma(l)' l}{\gamma(l)} = 1 \tag{C.6}$$

implying labor supply is determined independent of the equilibrium wage rate

Taking the logarithm of the production function and differentiating yields

$$dlny_i = dz_i + \alpha_i^l dlnl_i + \sum_{j=1}^{n} a_{ij} dlnx_{ij} \tag{C.7}$$

Differentiating equation C.1 yields

$$dlny_i + dlnp_i = dlnx_{ij} + dlnp_j \tag{C.8}$$

Differentiating equation C.2 yields

$$dlny_i + dlnp_i = dlnl_i + dlnw_i \tag{C.9}$$

Since wages are chosen as numeraire $dlnw_i = 0$

$$dlny_i + dlnp_i = dlnl_i \tag{C.10}$$

Replacing $dlnx_{ij}$ and $dlnl_i$ in equation C.7 yields

$$dlny_i = dz_i + \alpha_i^l (dlny_i + dlnp_i) + \sum_{j=1}^{n} a_{ij} (dlny_i + dlnp_i - dlnp_j) \tag{C.11}$$

$$dlny_i = dz_i + \alpha_i^l dlny_i + \alpha_i^l dlnp_i + \sum_{j=1}^{n} a_{ij} dlny_i + \sum_{j=1}^{n} a_{ij} dlnp_i - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{C.12}$$

$$dlny_i = dz_i + dlny_i(\alpha_i^l + \sum_{j=1}^{n} a_{ij}) + dlnyp_i(\alpha_i^l + \sum_{j=1}^{n} a_{ij}) - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{C.13}$$

By using market clearing condition,

$$\alpha_i{}^l + \sum_{i=1}^{n} \alpha_{ij} = 1 \tag{C.14}$$

$$dlny_i = dz_i + dlny_i + dlnyp_i - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{C.15}$$

$$0 = dz_i + dlnyp_i - \sum_{j=1}^{n} a_{ij} dlnp_j \tag{C.16}$$

$$\sum_{j=1}^{n} a_{ij} dlnp_j = dlnp_i + dz_i \tag{C.17}$$

Appendix B1. Korean Manufacturing Industries

Code	Name of Sector	Acronym
C01	Food, beverages and tobacco products	Food and Beverages
C02	Textile and leather products	Textile and Leather
C03	Wood and paper products, printing and reproduction of media	Wood and Paper
C04	Petroleum and coal products	Petroleum and Coal
C05	Chemical Products	Chemicals
C06	Non-metallic mineral products	Minerals
C07	Basic metal products	Primary Metals
C08	Fabricated metal products, except machinery and furniture	Metal Products
C09	Computing machinery, electronic equipment and optical instruments	Electronics
C10	Electrical equipment	Electrical
C11	Machinery and equipment	Machinery
C12	Transport equipment	Transport
C13	Other manufactured products	Other

Appendix B2. Robustness Assessment

In this paper, we employed the estimation window as sixty months and forecast horizon as 12 months with the VAR order of one. In the following estimations, we provide the robustness of the rolling window and forecast horizon.

Appendix B3. To Connectedness of Korean Manufacturing Industries

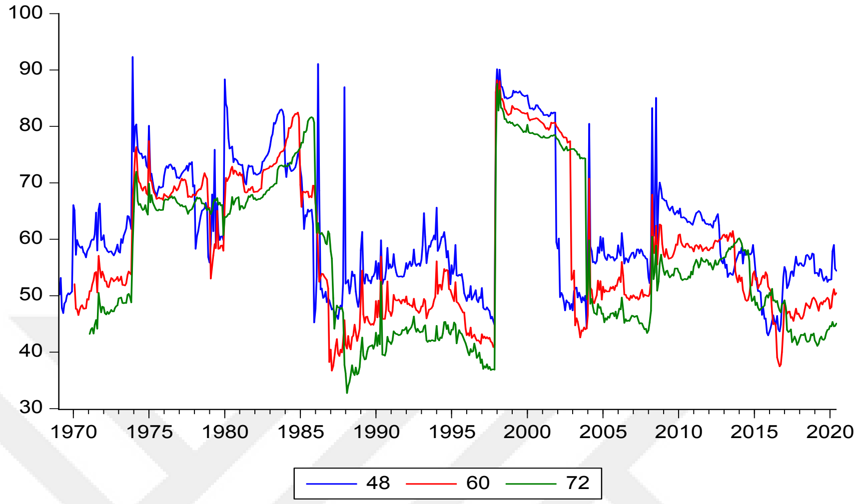


Figure C.1: Robustness of different rolling windows

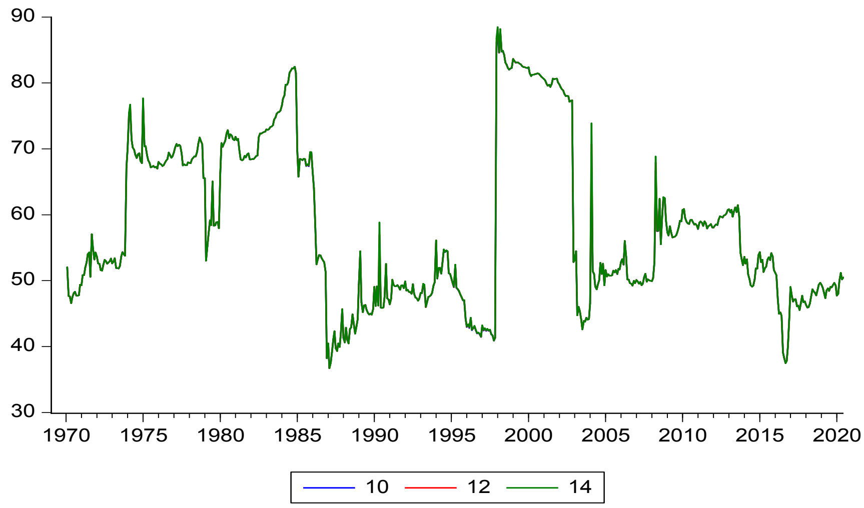
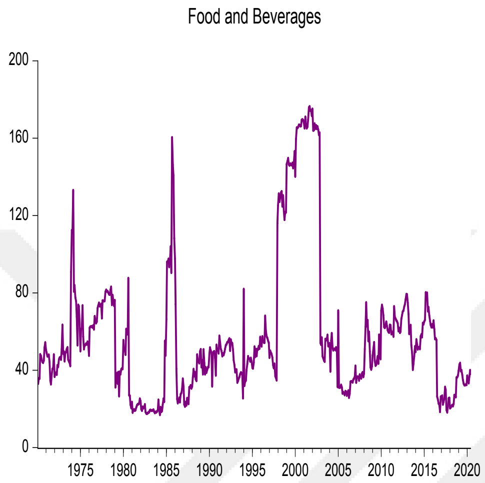
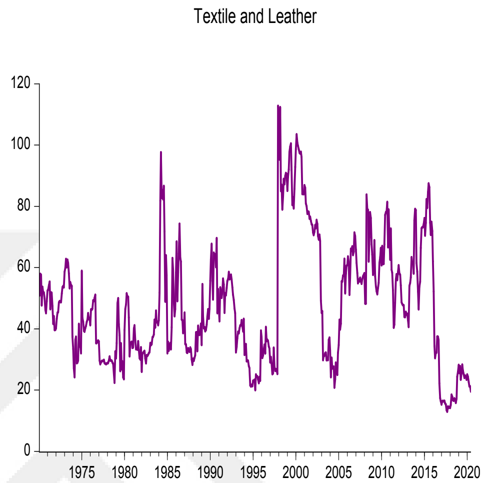


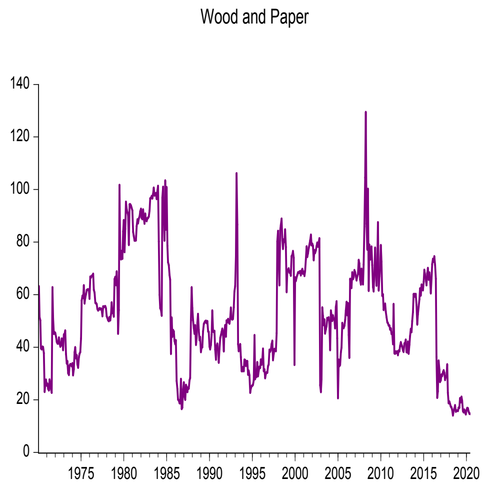
Figure C.2: Robustness of different forecast horizons



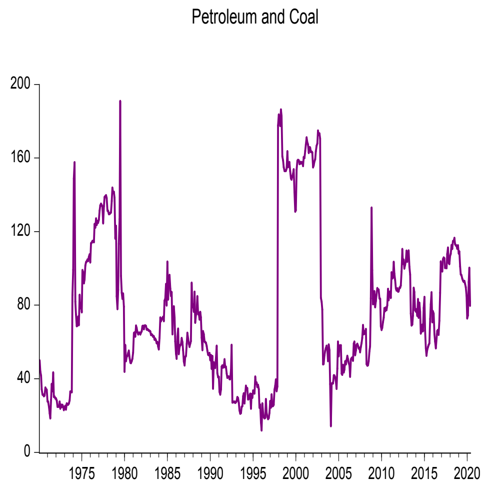
(a) Exogeneous Variable: Exchange Rate



(b) Exogeneous Variable: Oil Price



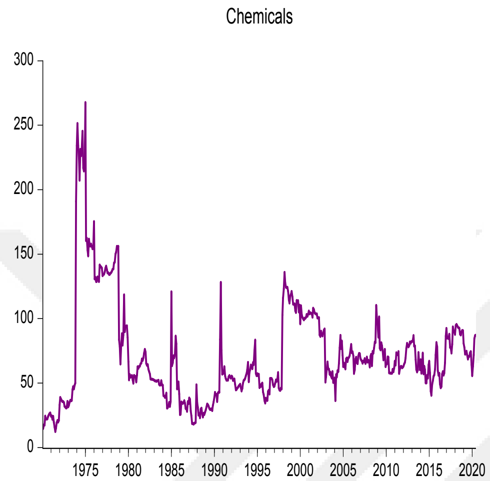
(c) Annual TFP growth



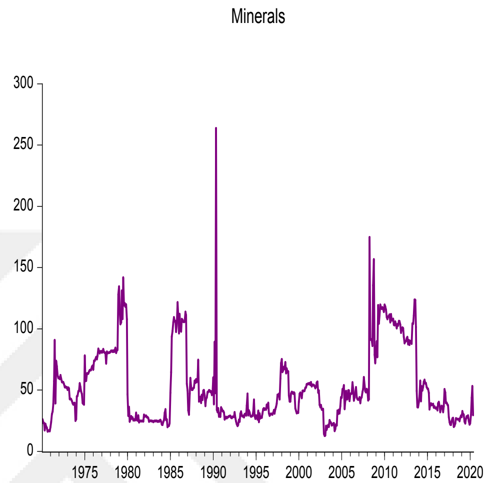
(d) Inclusion of All Exogenous Variables

Figure C.3: "To" Connectedness of Korean manufacturing industries - 1

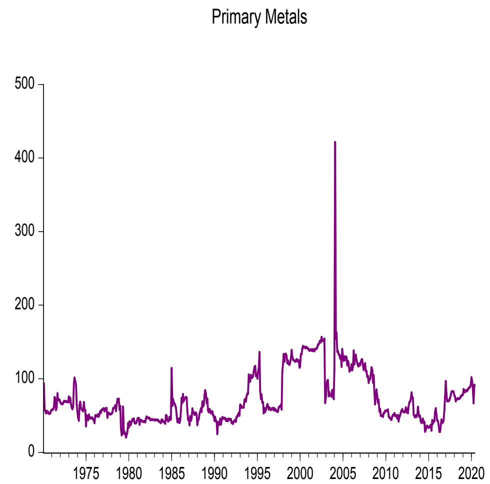
Notes: The rolling window is 60 months, and VAR(1) forecast horizon is twelve months for each run.



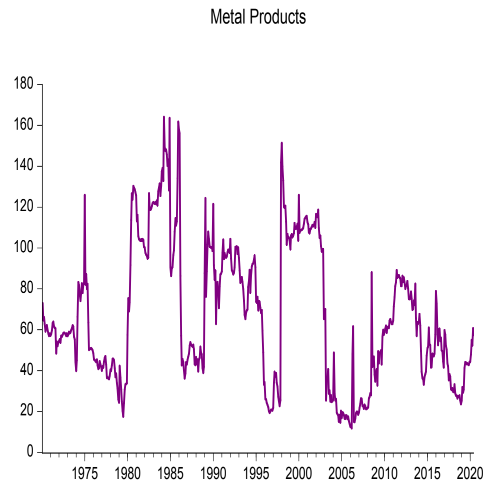
(a) Exogeneous Variable: Exchange Rate



(b) Exogeneous Variable: Oil Price



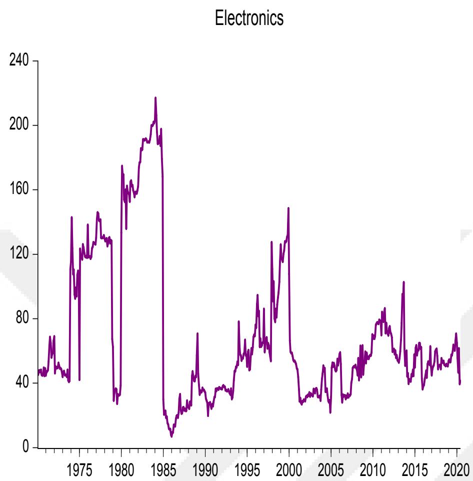
(c) Annual TFP growth



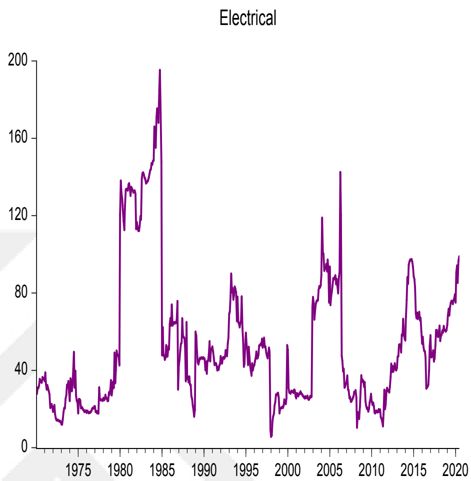
(d) Inclusion of All Exogenous Variables

Figure C.4: "To" Connectedness of Korean manufacturing industries - 2

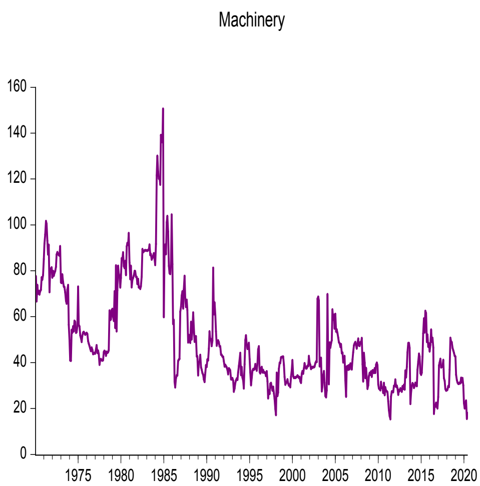
Notes: The rolling window is 60 months, and VAR(1) forecast horizon is twelve months for each run.



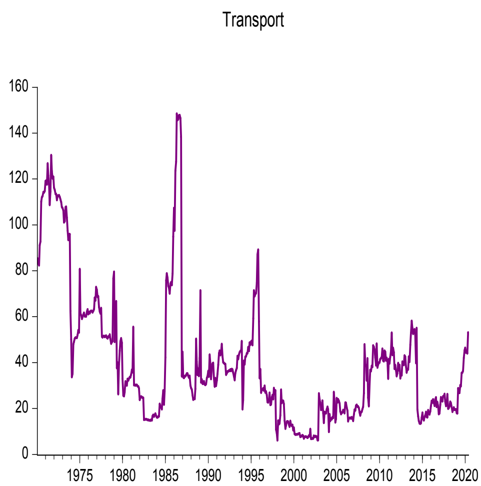
(a) Exogeneous Variable: Exchange Rate



(b) Exogeneous Variable: Oil Price



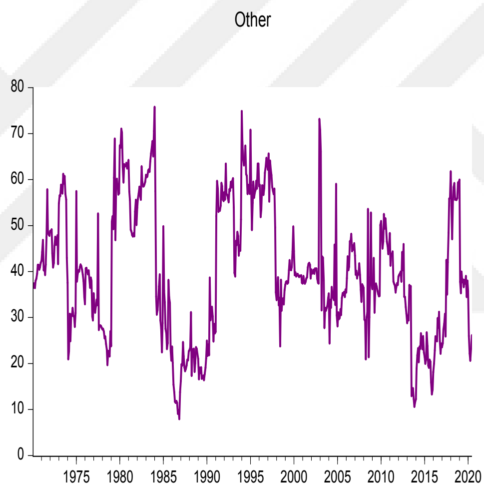
(c) Annual TFP growth



(d) Inclusion of All Exogenous Variables

Figure C.5: "To" Connectedness of Korean manufacturing industries - 3

Notes: The rolling window is 60 months, and VAR(1) forecast horizon is twelve months for each run.



(a) Other

Figure C.6: "To" Connectedness of Korean manufacturing industries - 4

Notes: The rolling window is 60 months, and VAR(1) forecast horizon is twelve months for each run.