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Working Paper

Producer price inflation connectedness and input-output networks

Working Paper, No. 1813

Provided in Cooperation with:

Koç University - TÜSİAD Economic Research Forum, Istanbul

Suggested Citation: Bilgin, N. Melisa; Yilmaz, Kamil (2018) : Producer price inflation connectedness and input-output networks, Working Paper, No. 1813, Koç University-TÜSİAD Economic Research Forum (ERF), Istanbul

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**PRODUCER PRICE INFLATION CONNECTEDNESS
AND INPUT-OUTPUT NETWORKS**

N. Melisa Bilgin
Kamil Yılmaz

Working Paper 1813
September 2018

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Producer Price Inflation Connectedness and Input-Output Networks*

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August 31, 2018

Abstract: We analyze the transmission of producer price inflation shocks across the U.S. manufacturing industries from 1947 to 2018 using the Diebold-Yilmaz Connectedness Index framework, which fully utilizes the information in generalized variance decompositions from vector autoregressions. The results show that the system-wide connectedness of the input-output network Granger-causes the producer price inflation connectedness across industries. The input-output network and the inflation connectedness nexus is stronger during periods of major supply-side shocks, such as the global oil and metal price hikes, and weaker during periods of aggregate demand shocks, such as the Volcker disinflation of 1981-84 and the Great Recession of 2008. These findings are consistent with Acemoglu et al. (2016)'s conjecture that supply shocks are transmitted downstream, whereas demand shocks are transmitted upstream. Finally, preliminary results show that Trump tariffs caused an increase in the system-wide inflation connectedness in the first half of 2018, due to shocks mostly transmitted from tariff-targeted industries, namely, basic metals, fabricated metals and machinery.

Key Words: Input-output networks, Inflation, Connectedness, Supply-side shocks, Commodity prices, Business cycles, Vector autoregression, Variance decomposition.

JEL codes: E3, D57, C32.

*For helpful comments on an earlier draft, we thank Umut Akovali, Vasco M. Carvalho, Francis X. Diebold, M. Furhan Karaca, Ayhan Kose and Muhammed Ali Yildirim and seminar participants at Koç University.

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1 Introduction

The fact that idiosyncratic microeconomic shocks can affect the aggregate economy has already attracted attention in macroeconomic theory. In the earlier and perhaps the more straightforward contribution, Long and Plosser (1983) 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. (2012), Acemoglu et al. (2016), Atalay (2017), Baqaee and Farhi (2017)).

Among the contributions to this emerging literature, Acemoglu et al. (2012) 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. (2016), on the other hand, show empirically that supply-side shocks (including productivity shocks) are transmitted downstream from intermediate goods-producing industries to the final goods-producing industries, while demand-side shocks are likely to be transmitted upstream from final goods-producing to intermediate goods-producing 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. (2016) 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. (2016) instead only focus on the spillover of shocks across industries through the output levels only.

In this paper we take up from where Acemoglu et al. (2016) left off. In particular, we focus on how shocks to the prices rather than the quantities are transmitted across industries. Using the simple general equilibrium model of Acemoglu et al. (2012), we show that the input-output linkages across industries form the underlying network through which the price shocks are transmitted. 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 an intermediate input. The firms in

the downstream industry will eventually have to reflect this cost increase in their product prices.

Measures of the producer price inflation shock transmission across industries are obtained using the Diebold-Yilmaz Connectedness Index (DYCI) framework. With this methodology, we measure the extent of the change in sectoral producer price inflation 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 measure are quite useful in gauging how much of price shocks are transmitted across sectors, the total and pairwise directional connectedness measures are used to distinguish between sectors that on average transmit inflation shocks to others from the ones that on average receive inflation 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. Muntaz and Surico (2009) and Monacelli and Sala (2009) use factor models to analyze the transmission of inflation shocks across countries. Ciccarelli and Mojon (2010) 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 (2010), Auer and Saure (2013), and Antoun de Almeida (2016) 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 as well as the inflation correlations across sectors. 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.

The remainder of the paper is structured as follows. After a brief literature review in the next section, section 2 outlines the general equilibrium model of inflation transmission through input-output linkages. Section 3 provides information about the DYCI methodology and the data used in the paper. Sections 4 and 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 6. Section 7 concludes the paper.

2 A Model of Perfect Competition

The multi-sector static competitive economy model of Acemoglu et al. (2016) takes into account the input-output structure of the manufacturing industry to analyze how input and/or output quantity shocks are transmitted across industries. This model is flexible enough to be used in the analysis of how product price shocks rather than the quantity shocks are transmitted across of industries.

Each sector has the following Cobb-Douglas production function, where labor and

intermediate inputs are used to produce the output of industry i :

$$y_i = e^{z_i} l_i^{\alpha_i} \prod_{j=1}^n x_{ij}^{a_{ij}} \quad (1)$$

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

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 :

$$y_i = c_i + \sum_{j=1}^n x_{ij} \quad (2)$$

where c_i is the final consumption of the product of industry i . As equation (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 :

$$u(c_1, c_2, \dots, c_n, l) = \gamma(l) \prod_{i=1}^n c_i^{\beta_i} \quad (3)$$

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

$$\sum_{i=1}^n p_i c_i = w l \quad (4)$$

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, \dots, p_n) , wage rate w , consumption bundle (c_1, c_2, \dots, 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 in 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, $dz_i < 0$):

$$dlnp_i = \sum_{j=1}^n a_{ij} dlnp_j - dz_i \quad (5)$$

Both the adverse productivity shock and the input price increase causes the average cost of production cost to increase, which in return leads to an increase in the producer price of industry i .

Intuitively, equation 5 captures the fact that the impact of the price change dp_j in industry j would 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. (2016), 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}).

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.

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 $\text{VAR}(p)$ model, $x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. Covariance stationarity of $\text{VAR}(p)$ 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 $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$, with

A_0 an $N \times N$ 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 $i = 1, 2, \dots, N$, 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 $i, j = 1, 2, \dots, N$, $i \neq j$. 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. (1996) and Pesaran and Shin (1998) 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

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, \dots, \quad (6)$$

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 (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:

$$C_{i \leftarrow j}^H = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}. \quad (7)$$

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

$$C_{i \leftarrow \bullet}^H = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N C_{i \leftarrow j}^H}{\sum_{i,j=1}^N C_{i \leftarrow j}^H} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N C_{i \leftarrow j}^H}{N}. \quad (8)$$

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

$$C_{\bullet \leftarrow i}^H = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N C_{j \leftarrow i}^H}{\sum_{i,j=1}^N C_{j \leftarrow i}^H} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N C_{j \leftarrow i}^H}{N}. \quad (9)$$

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

$$C_i^H = C_{\bullet \leftarrow i}^H - C_{i \leftarrow \bullet}^H. \quad (10)$$

The net total directional connectedness index, equation 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:

$$C^H = \frac{\sum_{\substack{i,j=1 \\ j \neq i}}^N C_{i \leftarrow j}^H}{\sum_{i,j=1}^N C_{i \leftarrow j}^H} = \frac{\sum_{\substack{i,j=1 \\ j \neq i}}^N C_{i \leftarrow j}^H}{N}. \quad (11)$$

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 71 years, from February 1947 to June

2018.

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.

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 January 1960 to December 2016. We first calculate the average annual input-output network over the 1960-2016 period. Then we analyze it along with the inflation connectedness network over the same period to draw conclusions about the possible relationship between the inflation and input-output connectedness over the full sample.

Table 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 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 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 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 81.2 and 79.0, respectively,

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 A.

Table 1: Inflation Connectedness Table (1960-2016)

| | 321 | 327 | 331 | 332 | 333 | 335 | 3361 | 337 | 339 | 311 | 313 | 315 | 322 | 323 | 324 | 325 | 326 | From |
|-------------------------|------|------|------|------|-------|-------|------|------|------|------|------|------|------|------|------|------|-------|-------------|
| 321 - Wood | 89.6 | 0.2 | 1.6 | 0.3 | 0.2 | 0.1 | 2.6 | 0.3 | 0.3 | 0.1 | 2.5 | 0.3 | 0.3 | 0.9 | 0.1 | 0.3 | 0.5 | 10.4 |
| 327 - Minerals | 0.3 | 48.6 | 3.8 | 6.4 | 1.7 | 5.4 | 0.0 | 9.9 | 2.8 | 0.7 | 0.5 | 4.4 | 3.3 | 2.2 | 1.4 | 5.6 | 2.8 | 51.4 |
| 331 - Basic Metals | 0.3 | 1.9 | 70.1 | 7.9 | 0.3 | 0.7 | 0.4 | 0.4 | 0.1 | 0.6 | 0.8 | 1.3 | 2.0 | 1.2 | 2.0 | 9.6 | 0.4 | 29.9 |
| 332 - Fabricated Metals | 0.4 | 6.3 | 15.9 | 36.9 | 1.0 | 3.2 | 0.1 | 2.7 | 1.2 | 1.0 | 0.2 | 3.8 | 5.1 | 4.4 | 3.3 | 8.8 | 5.8 | 63.1 |
| 333 - Machinery | 0.2 | 4.4 | 4.1 | 5.9 | 44.4 | 6.8 | 4.4 | 6.6 | 1.4 | 0.3 | 0.2 | 2.7 | 3.3 | 3.5 | 2.5 | 5.3 | 4.1 | 55.6 |
| 335 - Electric Eq. | 0.1 | 7.0 | 4.1 | 5.4 | 3.5 | 45.2 | 0.7 | 11.1 | 2.8 | 0.4 | 0.2 | 3.7 | 3.3 | 2.3 | 1.4 | 5.4 | 3.4 | 54.8 |
| 3361 - Motor Veh. | 2.6 | 0.4 | 0.7 | 0.3 | 2.2 | 1.4 | 88.1 | 1.2 | 0.5 | 0.1 | 0.0 | 0.2 | 0.3 | 0.7 | 0.4 | 0.7 | 0.3 | 11.9 |
| 337 - Furniture | 0.2 | 9.6 | 4.2 | 5.0 | 3.5 | 7.6 | 0.5 | 43.1 | 4.7 | 1.0 | 0.3 | 3.3 | 3.1 | 2.3 | 1.8 | 5.4 | 4.4 | 56.9 |
| 339 - Other | 0.1 | 4.1 | 0.7 | 0.7 | 1.0 | 3.2 | 0.1 | 9.4 | 75.7 | 0.3 | 0.3 | 0.5 | 0.7 | 0.3 | 0.4 | 1.4 | 1.1 | 24.3 |
| 311 - Food & Bev. | 0.0 | 0.9 | 0.6 | 1.0 | 0.0 | 0.3 | 0.0 | 1.4 | 0.2 | 88.8 | 0.1 | 0.7 | 1.9 | 2.1 | 0.1 | 2.0 | 0.0 | 11.2 |
| 313 - Textiles | 2.5 | 1.0 | 3.4 | 0.3 | 0.3 | 0.3 | 0.1 | 0.3 | 0.3 | 0.3 | 88.1 | 0.6 | 1.1 | 0.1 | 0.1 | 1.1 | 0.2 | 11.9 |
| 315 - Apparels | 1.6 | 5.7 | 3.7 | 2.7 | 0.8 | 3.2 | 0.1 | 2.3 | 1.6 | 1.5 | 1.5 | 65.4 | 2.9 | 0.5 | 0.5 | 3.8 | 2.4 | 34.6 |
| 322 - Paper | 0.1 | 3.5 | 5.8 | 4.1 | 0.4 | 1.9 | 0.0 | 1.7 | 0.4 | 1.4 | 0.5 | 3.2 | 45.4 | 19.3 | 0.9 | 7.6 | 3.7 | 54.6 |
| 323 - Printing | 0.1 | 2.8 | 2.9 | 4.2 | 0.4 | 1.5 | 0.3 | 1.6 | 0.3 | 1.4 | 0.1 | 1.1 | 22.8 | 50.3 | 1.1 | 4.8 | 4.2 | 49.7 |
| 324 - Petroleum & Coal | 0.1 | 1.9 | 3.1 | 3.1 | 0.1 | 0.6 | 0.3 | 1.9 | 0.3 | 0.2 | 0.0 | 0.6 | 1.0 | 1.4 | 82.7 | 1.6 | 1.2 | 17.3 |
| 325 - Chemicals | 0.1 | 4.6 | 16.7 | 6.6 | 1.1 | 2.7 | 0.2 | 1.8 | 0.5 | 1.4 | 0.2 | 2.5 | 4.4 | 3.3 | 1.3 | 49.1 | 3.6 | 50.9 |
| 326 - Plastics | 0.4 | 4.9 | 9.8 | 5.7 | 0.4 | 2.2 | 0.0 | 3.0 | 1.1 | 0.5 | 0.6 | 5.6 | 5.3 | 4.2 | 1.4 | 15.7 | 39.3 | 60.7 |
| To Others | 9.1 | 59.1 | 81.2 | 59.8 | 16.7 | 41.1 | 9.8 | 55.6 | 18.4 | 10.9 | 8.0 | 34.4 | 60.7 | 48.5 | 18.7 | 79.0 | 38.3 | 38.2 |
| Net to Others | -1.4 | 7.7 | 51.3 | -3.3 | -38.9 | -13.6 | -2.2 | -1.3 | -6.0 | -0.3 | -3.9 | -0.2 | 6.1 | -1.1 | 1.4 | 28.1 | -22.4 | |

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. The last row is the difference between 'to connectedness' and 'from connectedness' and documented as net connectedness. The bottom-right element is the mean of the 'to connectedness' between all thirteen industries.

basic metals and chemical products are the two industries that generated the highest inflation connectedness to other industries. They are followed by plastics (60.7), fabricated metal products (59.8) and nonmetallic mineral products (59.1), furniture (55.6), printing (48.5), electrical equipment (41.1), plastics (38.3), apparels (34.4), petroleum and coal products (18.7), other (18.4), machinery (16.7) and food and beverages (10.9).

Industries with higher ‘from connectedness’ are the receivers of inflation shocks that originated in other sectors. With corresponding ‘from connectedness’ values of 63.1 and 60.7, fabricated metals and plastics are the industries that receive the largest inflation shocks from other industries. They are followed by chemicals (43.9), minerals (40.6), paper (39.4) and basic metals (35.1). 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.

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 9.6 percent, the connectedness from basic metals to chemicals amounts to 16.7 percent. Actually, the basic metals industry’s net pairwise connectedness with all 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 (16.7), it is the plastics that receives the highest inflation connectedness from the chemicals industry (15.7).

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 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.

Table 2: Input-Output Network Table (1960-2016)

| | 321 | 327 | 331 | 332 | 333 | 335 | 3361 | 337 | 339 | 311 | 313 | 315 | 322 | 323 | 324 | 325 | 326 | From |
|-------------------------|------|------|------|------|-------|-------|-------|-------|-------|------|------|-------|------|-------|------|------|------|-------------|
| 321 - Wood | 19.5 | 1.2 | 0.7 | 3.4 | 0.7 | 0.8 | 0.7 | 0.7 | 0.3 | 0.0 | 0.5 | 0.0 | 0.5 | 0.0 | 0.9 | 2.1 | 0.8 | 13.5 |
| 327 - Minerals | 0.5 | 11.8 | 0.9 | 1.6 | 0.5 | 0.2 | 0.3 | 0.0 | 0.2 | 0.1 | 0.3 | 0.0 | 2.2 | 0.0 | 1.1 | 3.7 | 1.0 | 12.5 |
| 331 - Basic Metals | 0.2 | 0.8 | 26.3 | 2.1 | 1.0 | 0.9 | 0.3 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.3 | 0.0 | 0.8 | 1.4 | 0.3 | 8.1 |
| 332 - Fabricated Metals | 0.2 | 0.5 | 23.7 | 9.1 | 1.2 | 0.6 | 0.3 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.7 | 0.2 | 0.5 | 1.9 | 0.9 | 31.0 |
| 333 - Machinery | 0.2 | 0.5 | 10.3 | 7.1 | 7.4 | 3.8 | 3.1 | 0.1 | 0.4 | 0.0 | 0.1 | 0.0 | 0.5 | 0.0 | 0.5 | 0.9 | 2.0 | 29.5 |
| 335 - ElectricalEquip | 0.3 | 1.4 | 12.7 | 4.5 | 1.2 | 7.2 | 0.5 | 0.0 | 0.3 | 0.0 | 0.1 | 0.0 | 1.1 | 0.0 | 0.6 | 2.5 | 2.1 | 27.2 |
| 3361 - Motor Vehicles | 0.3 | 0.9 | 8.3 | 5.7 | 2.2 | 0.9 | 28.4 | 0.0 | 0.2 | 0.0 | 0.9 | 0.2 | 0.3 | 0.1 | 0.2 | 0.9 | 3.3 | 24.3 |
| 337 - Furniture | 9.2 | 0.9 | 5.3 | 5.6 | 0.2 | 0.1 | 0.2 | 2.4 | 0.2 | 0.1 | 4.7 | 0.2 | 1.5 | 0.0 | 0.4 | 1.9 | 5.0 | 35.7 |
| 339 - Other | 1.3 | 0.8 | 6.7 | 3.1 | 0.5 | 0.7 | 0.2 | 0.1 | 6.7 | 0.2 | 2.2 | 0.3 | 2.4 | 0.1 | 0.6 | 3.8 | 3.7 | 26.7 |
| 311 - Food & Bev. | 0.0 | 1.0 | 0.3 | 2.6 | 0.2 | 0.1 | 0.1 | 0.0 | 0.0 | 17.6 | 0.0 | 0.0 | 2.7 | 0.3 | 0.3 | 0.8 | 1.6 | 10.1 |
| 313 - Textiles | 0.1 | 0.4 | 0.2 | 0.5 | 0.4 | 0.1 | 0.1 | 0.0 | 0.2 | 0.1 | 24.3 | 0.9 | 0.9 | 0.0 | 0.4 | 16.9 | 0.9 | 22.1 |
| 315 - Apparels | 0.1 | 0.0 | 0.0 | 0.4 | 0.1 | 0.1 | 0.0 | 0.0 | 1.5 | 1.6 | 21.5 | 13.9 | 0.6 | 0.3 | 0.2 | 1.5 | 0.9 | 28.9 |
| 322 - Paper | 2.1 | 0.1 | 0.4 | 1.4 | 0.5 | 0.1 | 0.2 | 0.0 | 0.0 | 0.5 | 1.0 | 0.0 | 24.2 | 0.1 | 1.4 | 5.5 | 1.7 | 15.1 |
| 323 - Printing | 0.0 | 0.0 | 0.2 | 0.7 | 1.7 | 0.1 | 0.1 | 0.0 | 0.4 | 0.3 | 0.7 | 0.9 | 17.5 | 5.9 | 1.2 | 4.0 | 1.2 | 29.1 |
| 324 - Petroleum & Coal | 0.0 | 0.2 | 0.2 | 0.4 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.2 | 0.0 | 5.1 | 1.4 | 0.1 | 2.7 |
| 325 - Chemicals | 0.1 | 0.4 | 0.7 | 1.7 | 0.7 | 0.1 | 0.1 | 0.0 | 0.1 | 0.8 | 0.2 | 0.0 | 1.6 | 0.2 | 2.0 | 23.4 | 1.8 | 10.4 |
| 326 - Plastics | 0.3 | 0.7 | 0.7 | 1.9 | 0.6 | 0.3 | 0.1 | 0.1 | 0.2 | 0.0 | 2.6 | 0.0 | 2.1 | 0.0 | 0.6 | 21.2 | 5.7 | 31.3 |
| To Others | 14.9 | 9.7 | 71.1 | 42.4 | 11.8 | 8.9 | 6.5 | 1.1 | 4.0 | 3.9 | 34.9 | 2.9 | 35.2 | 1.5 | 11.8 | 70.2 | 27.3 | 21.1 |
| Net to Others | 1.4 | -2.8 | 63.0 | 11.5 | -17.8 | -18.3 | -17.8 | -34.6 | -22.7 | -6.2 | 12.8 | -26.0 | 20.0 | -27.6 | 9.2 | 59.9 | -4.0 | |

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.

The diagonal elements in Table 2 provides a measure of the use of inputs within the same industry, whereas the off-diagonal elements measure the use of products as inputs across 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’ (71.1 and 70.2, respectively) and ‘net connectedness’ (63.0 and 59.9) measures in Table 2, basic metals and chemicals industries appear to be the two top upstream industries, followed by fabricated metals (42.4 and 11.5), paper (35.2 and 20.0), textiles (34.9 and 12.8), petroleum and coal (11.8 and 9.2) and wood (14.9 and 1.4). All other industries have negative net input-output network connectedness measures. Among these furniture (-34.6), printing (-27.6), apparels (-26), other industries (-22.7), electrical equipment (-18.3), machinery (-17.8), motor vehicles (-17.8), food and beverages (-11.2) are the downstream industries (in descending order) that depend on intermediate inputs from other industries.

Tables 1 and 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 (23.7), electrical equipment (12.7), machinery (10.3), motor vehicles (8.3), others (6.7) and furniture (5.3). 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 57 years of data.

Even though displaying the estimated static inflation connectedness measures and 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. (2018).

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. (2014) 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

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.

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 1: Color Spectrum of the Networks

Inflation connectedness and input-output network graphs created with the conventions listed above are presented in Figures 2 and 3, respectively.

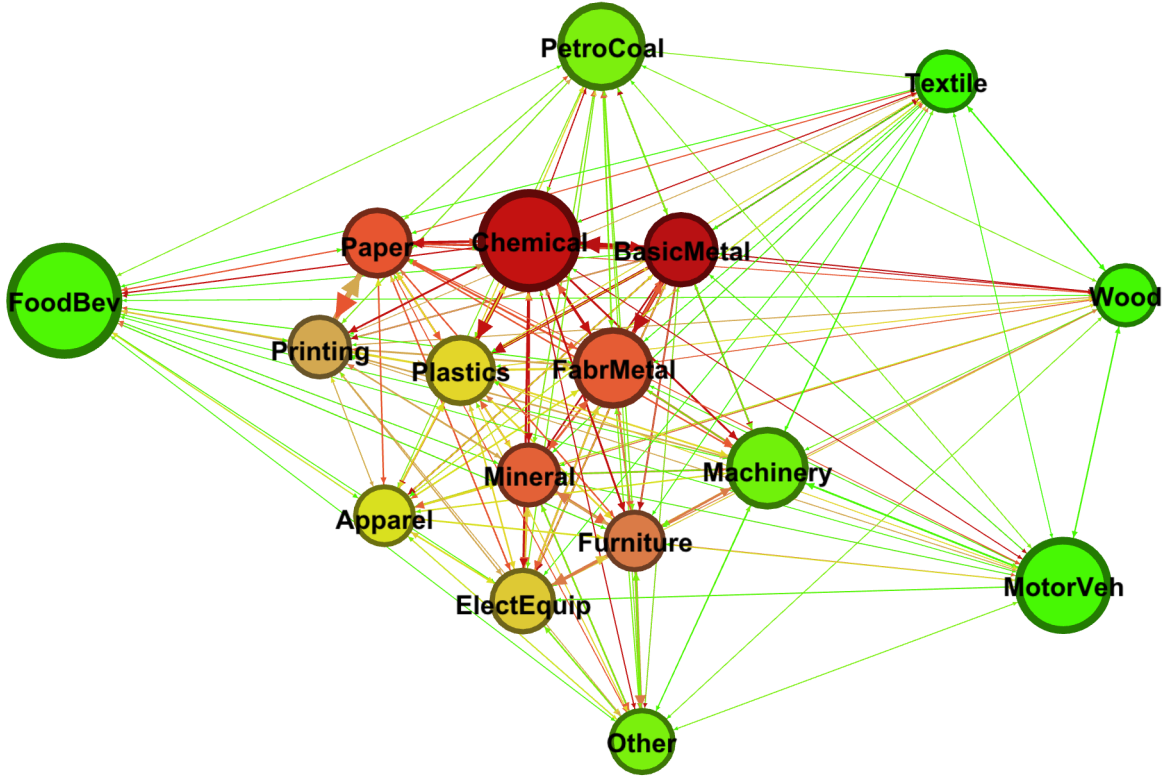


Figure 2: Inflation Connectedness Network (1960–2016)

Node labels are short acronyms of the industry names listed in Appendix Table D.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

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.

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.

green (lowest) to luminous vivid yellow, whiskey sour, bright red and dark red (highest). The node color spectrum is presented in Figure 1.

We have three major takeaways from Figures 2 and 3. First, in Figure 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.

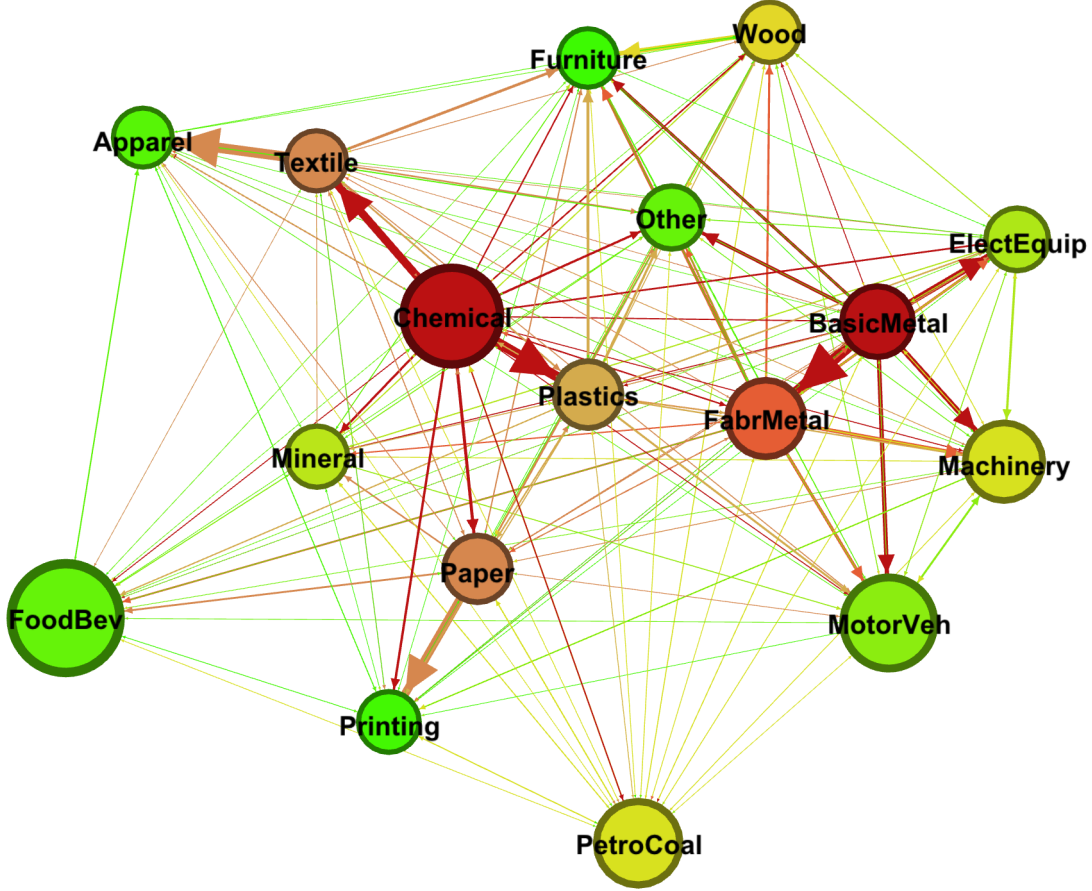


Figure 3: Input-Output Network, Domestic Inputs plus Imports (1960–2016)

Similarly, in Figure 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 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 industries are located around the basic metals industry again with sizeable input use from that industry.

Second, having a closer look at Figure 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.

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.

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 ?? along with the World Bank commodity price index for metals and minerals. As we will discuss the system-wide connectedness index is influenced significantly during times of metal and mineral price

increases. The system-wide connectedness is based on the Lasso estimation of a first-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. Not only does inflation shock transmission fluctuates over time, but it also increases significantly during the periods of major supply-side inflationary shocks.

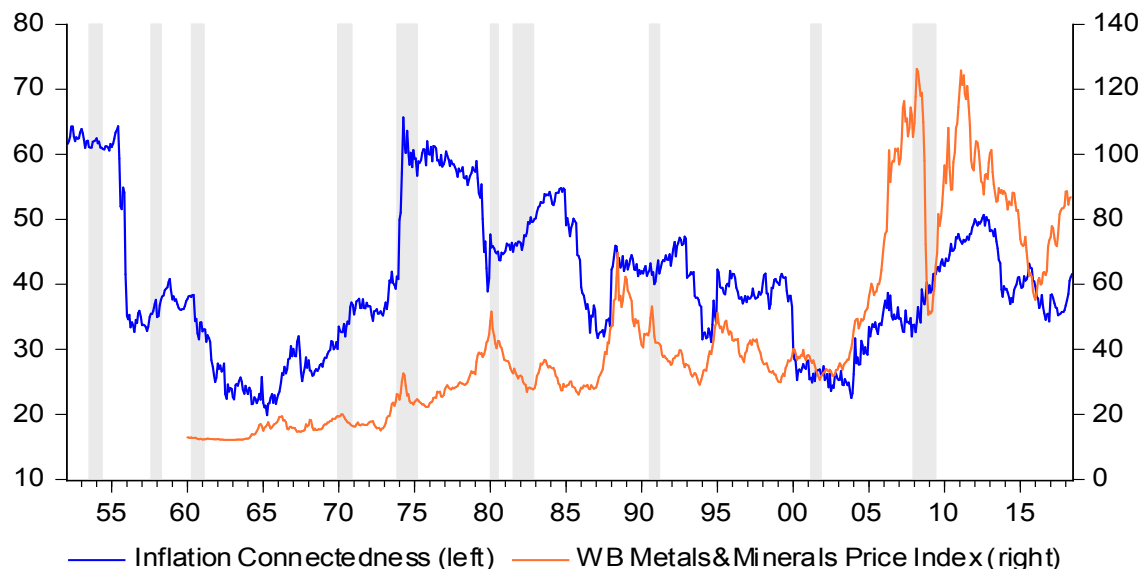


Figure 4: System-wide Connectedness Index Three-digit NAICS industries; Based on LASSO estimates of VAR(1) model, rolling window length of 60 months and forecast horizon of 12 months

Let us analyze the behavior of the index over time. 1950 was an exceptionally high inflation year. 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 the second half of 1950 and early 1951 are dropped out of the sample window, the producer price inflation connectedness recorded a major 30 percentage points drop.

After a brief upward move in the second half of the 1950s, the index follows a gradual path that lasts until mid-1960s. These are the years of rather stable commodity prices. However, starting from 1963 to 1966 the metal commodity prices increased by

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

another 40% (see Figure 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 swings, 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. From October 1973 onwards, 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. Global oil prices increased by a factor of three as can be seen in the spot crude oil price of West Texas Intermediate (WTI) increasing from \$3.56 per barrel in August 1973 to \$10.1 in January 1974 and further to \$11.2 in October 1974.

The impact of the second oil price shock on the inflation connectedness index is observed following the 1979 Islamic Revolution in Iran, one of the world's major oil producers. The spot price for WTI went up from \$14.9 in January 1979 to \$26.5 in September 1979. However, following the outbreak of the hostage crisis in early November (where 52 American diplomats were taken hostage) the spot price of WTI oil continued to climb as high as \$39.5 per barrel in May 1980.

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 oil price increases in 1979-1980 was much less than the one in the first round of increases in 1974-1975 because the first round of increases was rather an unexpected development that had caught almost all industries off guard. The jump in the index followed the oil price shock rather than the U.S. recession that in January 1980.

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 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 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 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 also increased, from 23 to 38 (see Figure 4).

After a 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 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 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, we should also note that the index goes 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.

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 5 and 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, primary (basic) metals (see Figure 5) and chemical products (see Figure 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 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%).

The net inflation connectedness of the chemical products industry (Figure 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 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

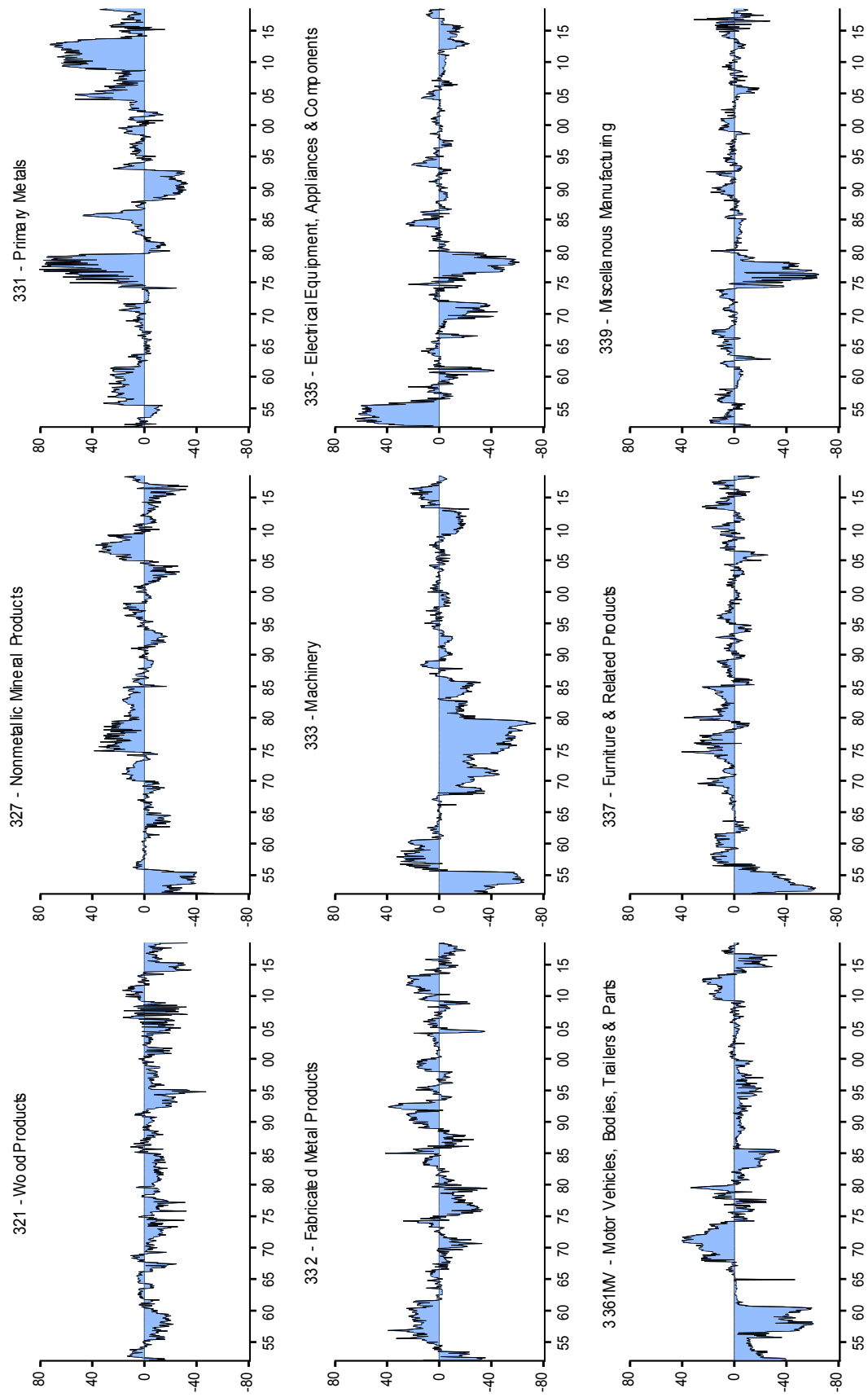


Figure 5: Net Directional Inflation Connectedness – U.S. Manufacturing Industries

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 5 and 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

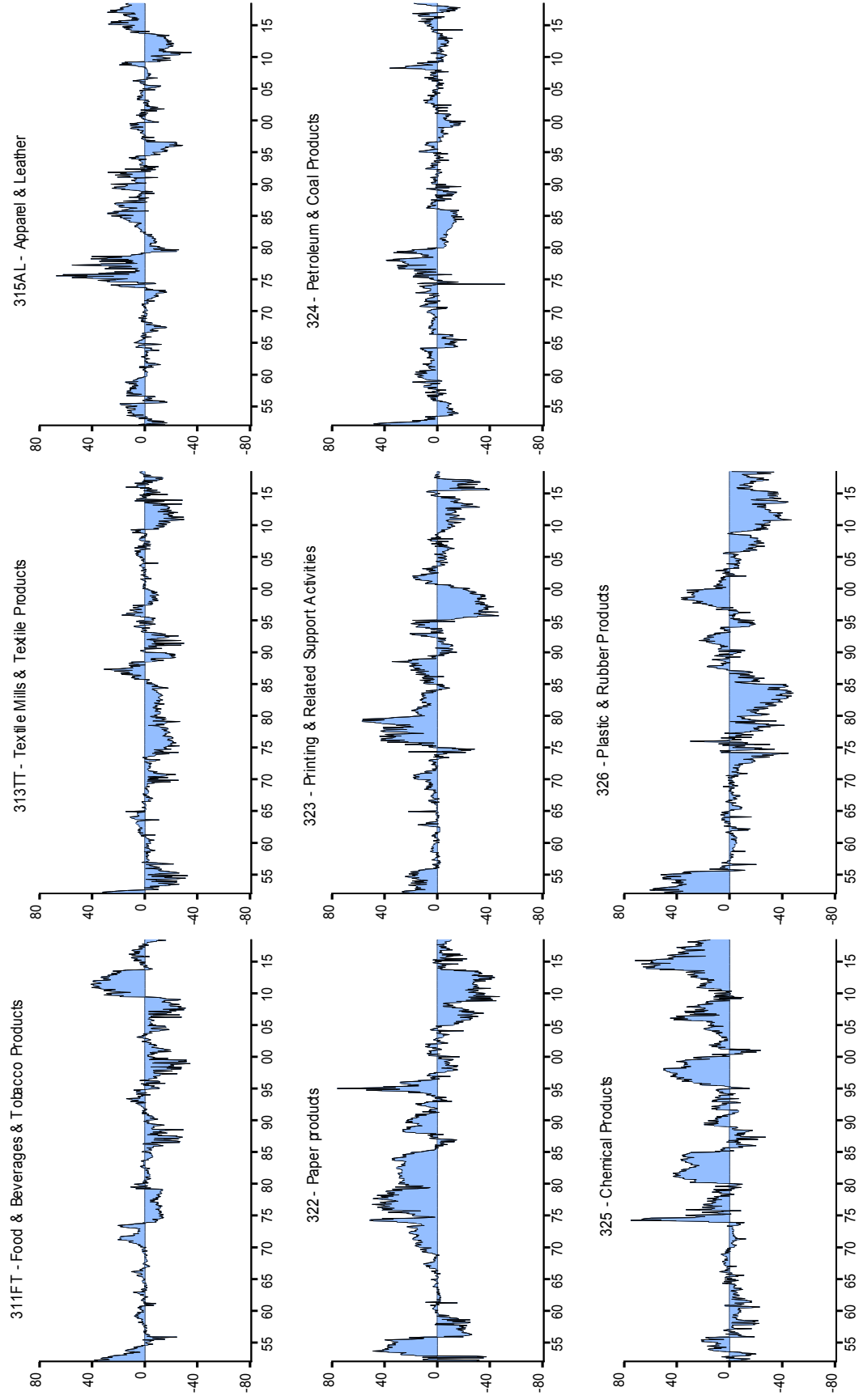


Figure 6: Net Directional Inflation Connectedness – U.S. Manufacturing Industries (cont'd)

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.

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.

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).⁷

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.

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.

6.1 System-wide Connectedness

In Figure 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.⁸

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 change substantially in a

⁷In order to save space, we presented the “to connectedness” graphs in Appendix B, Figures B.1 and B.2, highlighting the jump in these industries ‘to connectedness’ measures in the first half of 2018 with a red oval shape.

⁸As 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 available only until 2016, the joint annual analysis of the two connectedness measures covers the period until 2016.

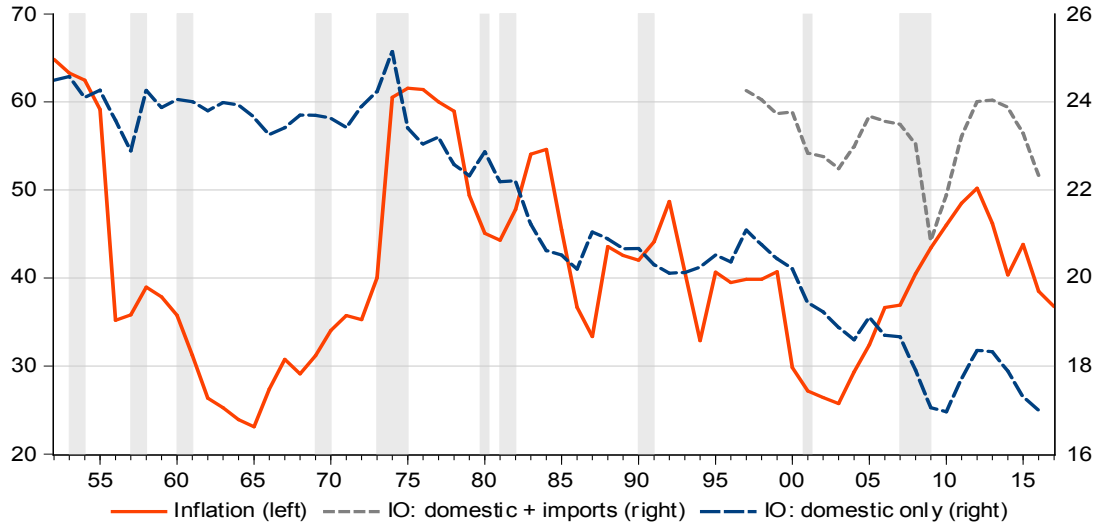


Figure 7: System-wide Connectedness: Inflation vs Input-Output Networks (Annual) Three-digit NAICS industries; Based on VAR(1) model, rolling window length of 60 months and forecast horizon of 12 months

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 3.⁹

Table 3: **Granger Causality: System-wide Inflation vs I-O Network Connectedness (Annual, 1960-2016)**

| Lags | Dependent Variable: IC | | | | Dependent Variable: ION | | | |
|------|------------------------|------------------|-------|-----------------|-------------------------|-------------------|-------|-----------------|
| | IC | ION | R^2 | GC test p-value | IC | ION | R^2 | GC test p-value |
| 1 | 0.747** (0.05) | 1.25* (0.35) | 0.834 | $8x10^{-4}$ | -0.010 (0.011) | 0.978** (0.07) | 0.958 | 0.378 |
| 2 | 0.519** (0.08) | 2.11** (0.61) | 0.666 | $4x10^{-4}$ | -0.012 (0.011) | 0.921** (0.07) | 0.912 | 0.44 |
| 3 | 0.386** (0.08) | 2.22** (0.59) | 0.528 | $4x10^{-4}$ | -0.010 (0.018) | 0.779** (0.13) | 0.874 | 0.56 |
| 4 | 0.261* (0.08) | 2.12** (0.53) | 0.418 | $2x10^{-4}$ | -0.012 (0.013) | 0.701** (0.08) | 0.863 | 0.51 |
| 5 | 0.156 (0.08) | 1.71* (0.50) | 0.317 | 0.001 | -0.013 (0.017) | 0.689** (0.09) | 0.883 | 0.44 |
| 6 | 0.103 (0.09) | 1.46* (0.47) | 0.345 | 0.003 | -0.019 (0.017) | 0.681* (0.06) | 0.899 | 0.25 |

Notes: As the World Bank Metals and Minerals Commodity Price Index starts in 1960, regressions are based on data for 1960-2016 period; t statistics in parentheses; * $p < 0.01$, ** $p < 0.001$.

In the ION equation, the coefficient estimates of the one- to five-year lagged IC variable 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 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 causality 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. (2016) 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 .

⁹As 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.

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 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.

Table 4: **Pairwise Inflation and I-O Network Connectedness (1952-2016)**

| Dependent Variable: Pairwise Inflation Connectedness | | | | | |
|--|-------------------|-------------------|-------------------|-------------------|--------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Input-Output Linkages | 1.766** (46.0) | – | 1.766** (46.2) | 1.766** (46.1) | 1.979** (50.73) |
| GDP Share (Source/Target Ind.) | – | 0.455** (15.7) | 0.435** (13.6) | 0.437** (13.6) | 0.367* (6.63) |
| R^2 | 0.394 | 0.005 | 0.399 | 0.399 | 0.443 |
| Year FE | N | N | N | Y | Y |
| Source Industry FE | N | N | N | N | Y |
| Target Industry FE | N | N | N | N | Y |

Notes: Number of observations: 18785; t statistics in parentheses. * $p < 0.01$, ** $p < 0.001$

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 goodness of fit measure, R^2 , in Figure 8 and the coefficient estimate of the input-output network connectedness in Figure 9.

Figure 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 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.

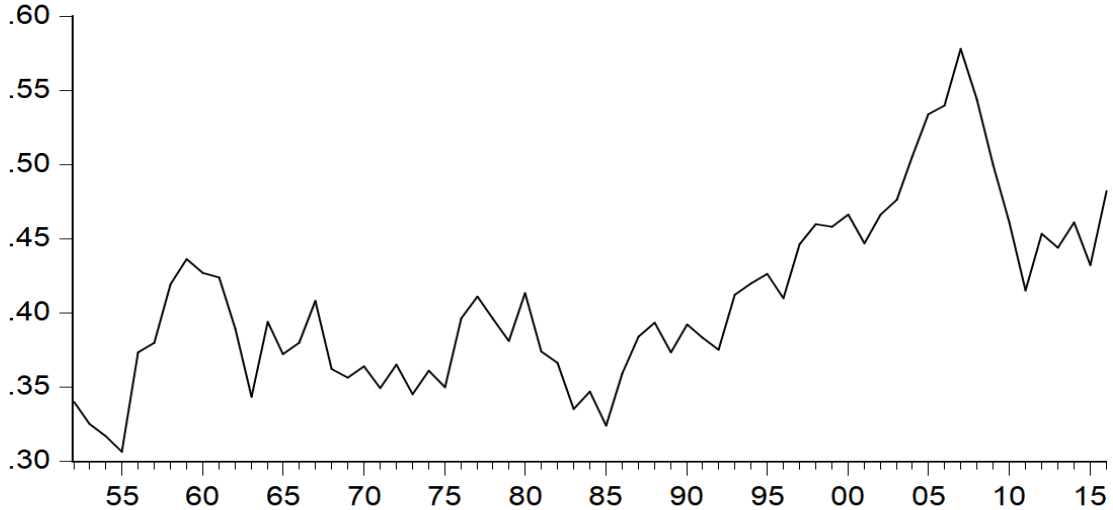


Figure 8: Dynamic Pairwise Connectedness Regression Fit. R^2 values obtained from the secondary regression; domestic input-output coefficients are used as explanatory variables

Figure 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.

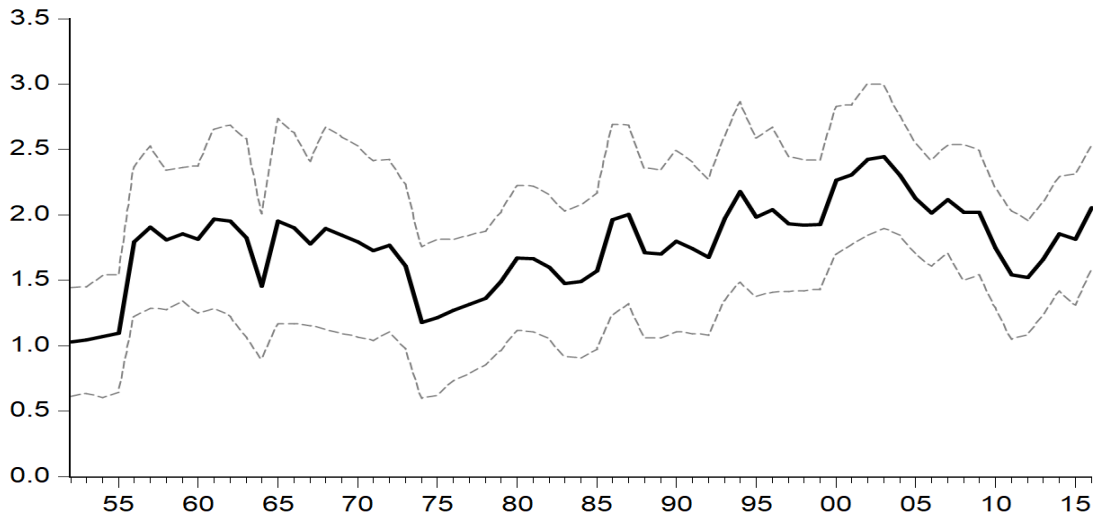


Figure 9: Dynamic Pairwise Connectedness Regressions - Domestic IO Coefficients Only. Statistically significant values of β obtained from the secondary regressions; domestic input-output coefficients are used as explanatory variables.

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.

7 Conclusion

We analyzed the producer price inflation connectedness across the U.S. manufacturing industries. We first used Acemoglu et al. (2012)’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.

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Appendices

A 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 A.1 presents the dynamic system-wide connectedness index obtained with the generalized as well as the Cholesky decomposition approaches.¹⁰ 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.

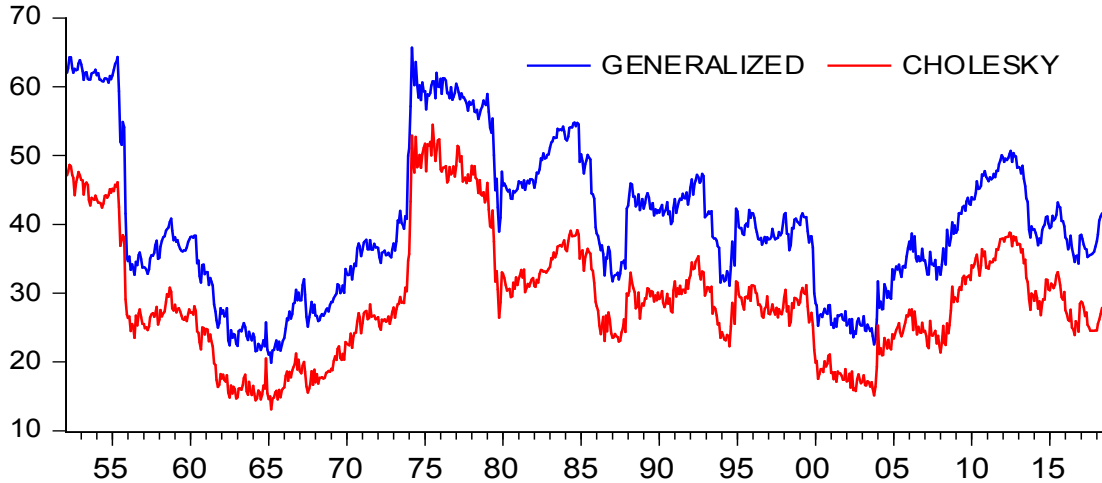


Figure A.1: System-wide Connectedness Index and Variance Decomposition Methods

Next, the robustness of the system-wide connectedness index to the choice of the

¹⁰The Cholesky variance decomposition based index is calculated for the ordering of variables as in Table D.1.

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 A.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.

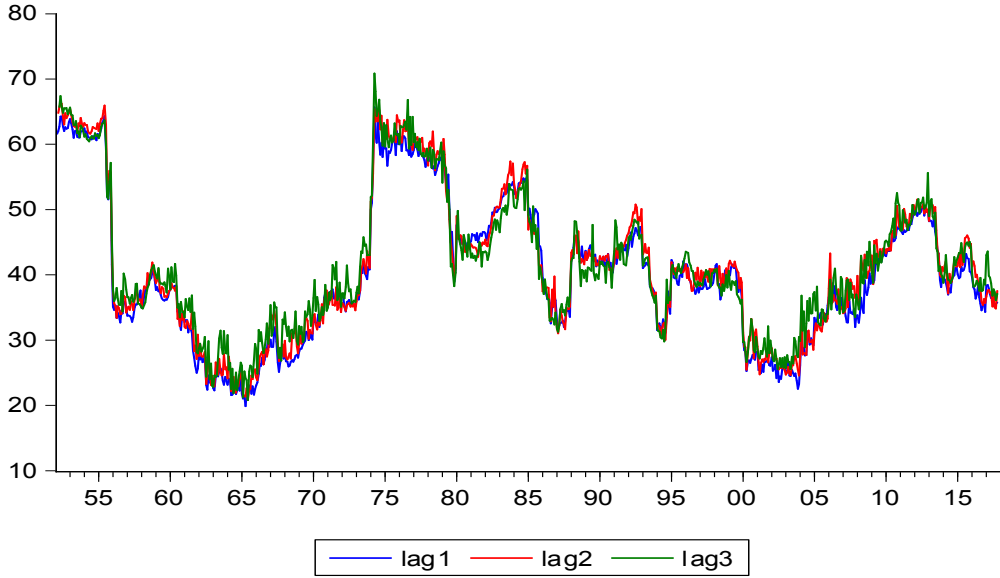


Figure A.2: Sensitivity of the Connectedness Index to the VAR Order

Following the analysis of robustness of the results to the choice of 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 A.3.

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

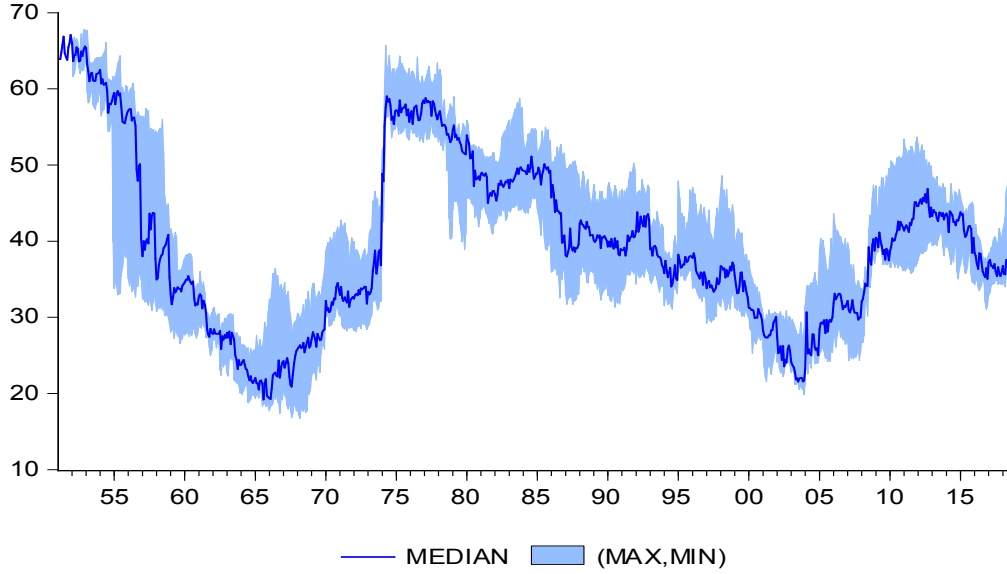


Figure A.3: Sensitivity of the Connectedness Index to the Window Size The median, minimum and maximum values of connectedness index with five different window sizes: 48, 60, 72, 84 and 96 months.

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.

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 is obtained. The resulting connectedness indices for five different forecast horizons are plotted in Figure A.4. It is clearly visible in Figure A.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.

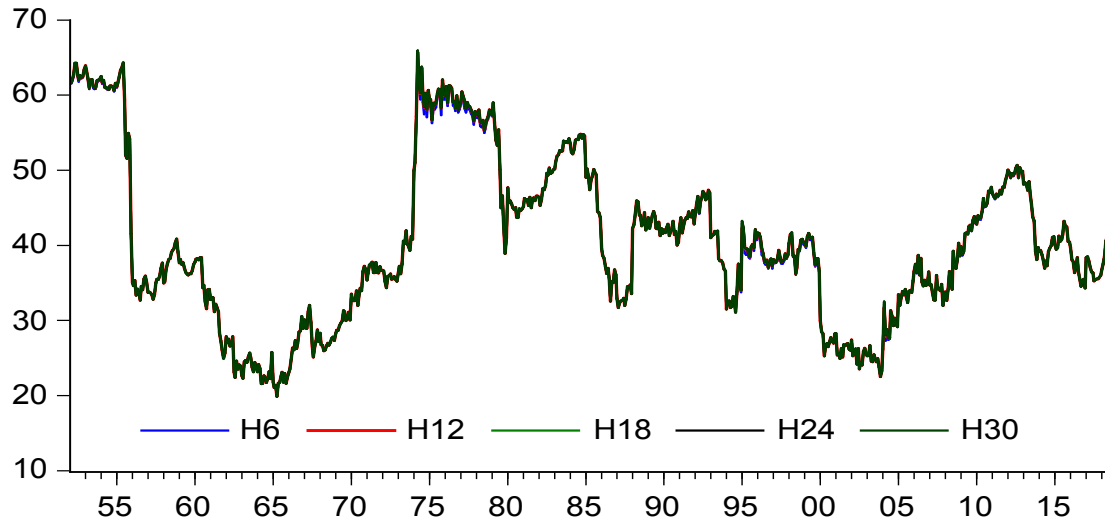


Figure A.4: Sensitivity of the Connectedness Index to the Forecast Horizon

B Plots: Inflation Connectedness “To Others”

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

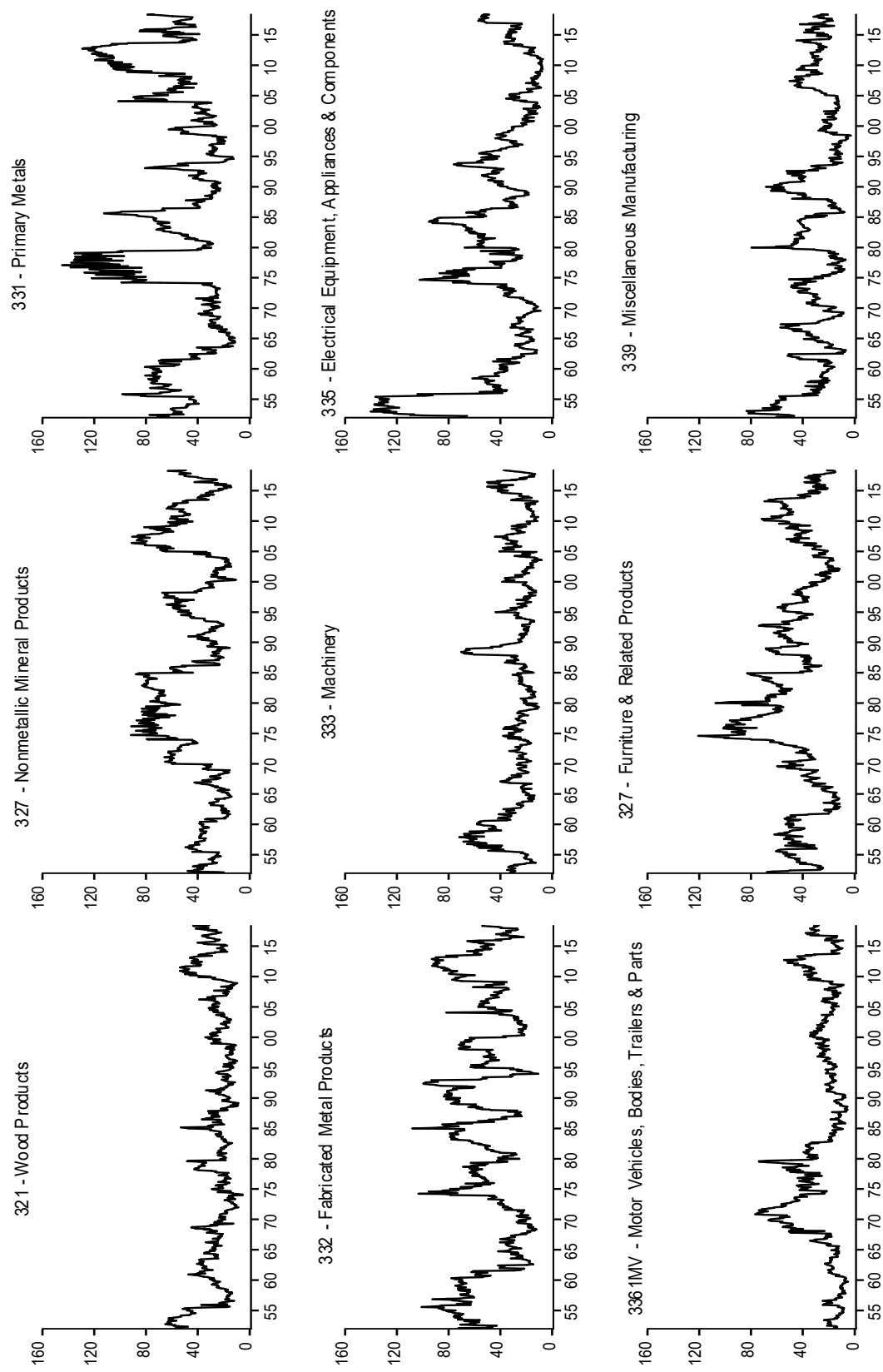


Figure B.1: Inflation Connectedness “To Others” – U.S. Manufacturing Industries

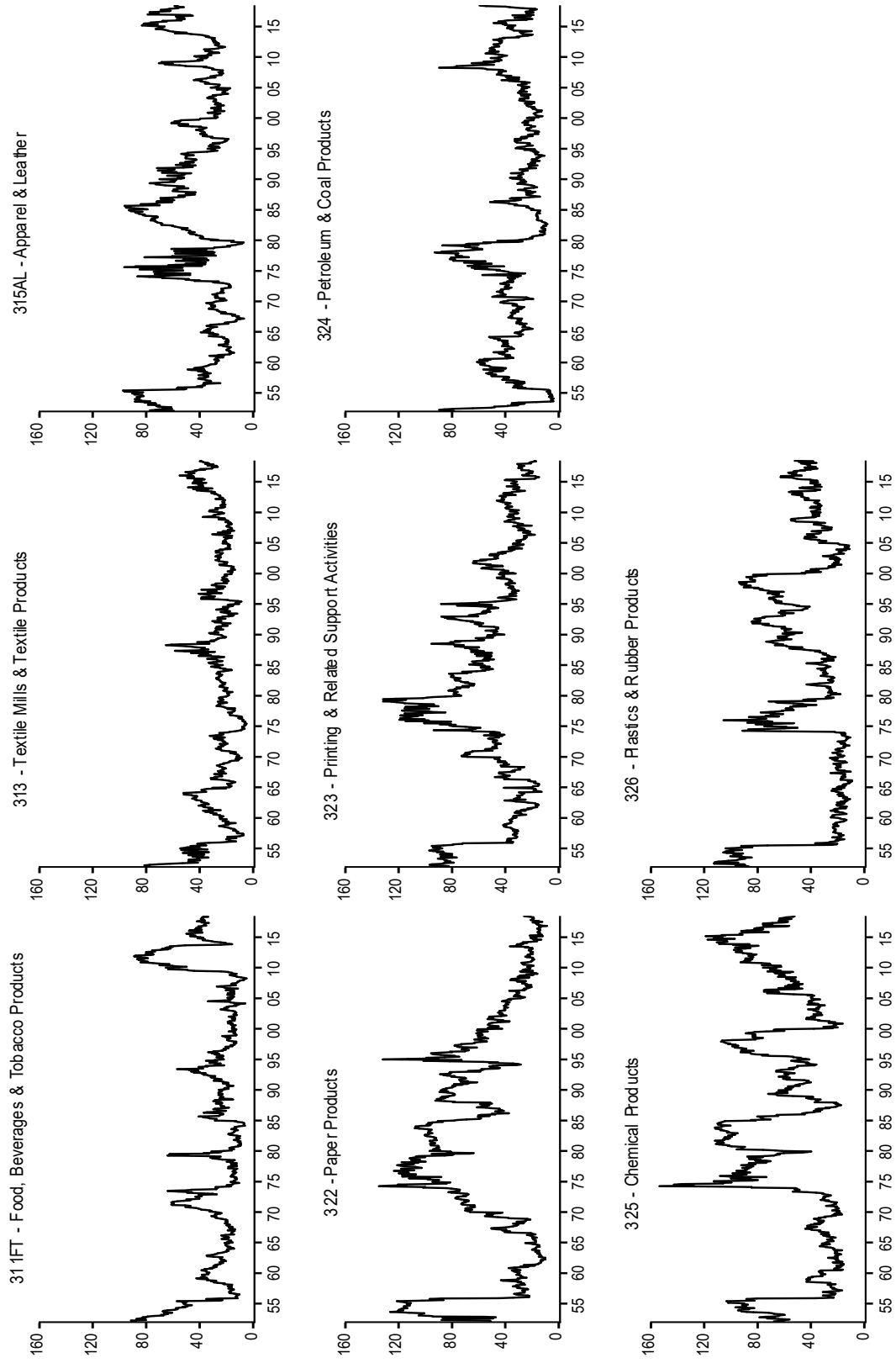


Figure B.2: Inflation Connectedness “To Others” – U.S. Manufacturing Industries (cont’d)

C Commodity Prices: Metals & Minerals and Oil

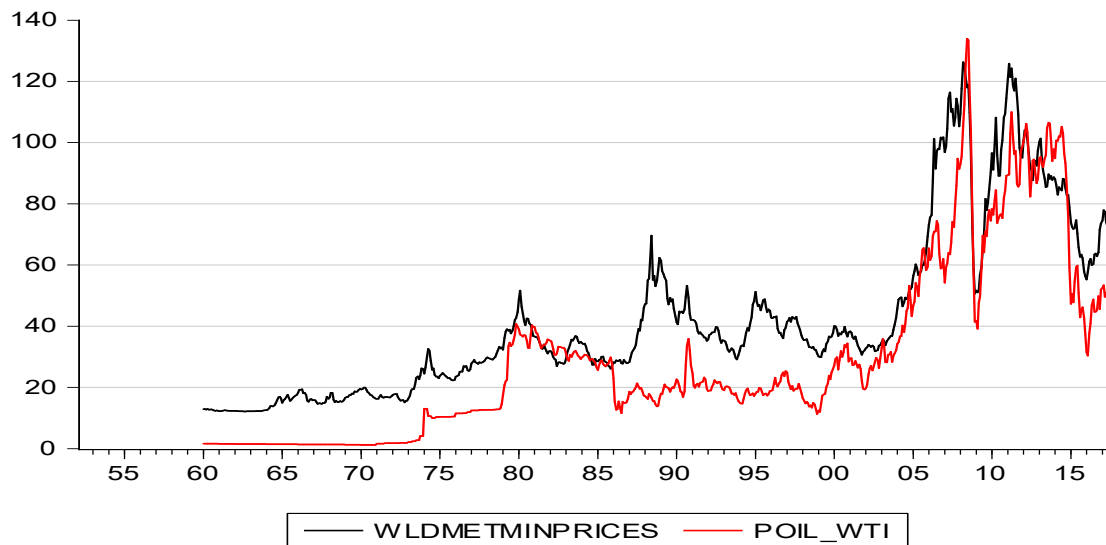


Figure C.1: Metals & Minerals Price Index and Price of Crude Oil (WTI, \$ per barrel)

D 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 |