The Importance of Input-Output Network Structure in the U.S. Economy*

Shuoshuo Hou
Temple University

October, 2022

Abstract

Hulton's Theorem states that in the presence of input-output linkages, the impact of an industry-level shock on the aggregate economy is entirely captured by the size of this industry, regardless of its position in the network. This paper argues that the production network structure in isolation represents an essential channel in shaping GDP growth and growth volatility. First, I show evidence that as industries in the U.S. economy became sparsely connected from 1970 to 2017, that is, many more industries relied on a few central input suppliers for production, GDP growth slowed and became more volatile. Motivated by these empirical facts, I embed input-output linkages into a multisector real business cycle model and provide a nonlinear characterization of the macroeconomic impact of sector-specific productivity shocks to highlight the key role of production network structures. Finally, I measure realized sector-level productivity shocks from the data, feed them into the model, and study model-implied relationships between production network structure, GDP growth, and growth volatility. Our calibrated model is able to explain about 20% of the business cycle fluctuations as observed in the data. Moreover, our results imply that network connections matter beyond industry sizes.

JEL classification: C67, E23, E32, L16

Keywords: production or input-output network structure, centrality dispersion, concentration centrality, GDP growth, growth volatility, nonlinearity

*I would like to extend my sincere thanks for the guidance and supports from my committee members: Pedro Silos (Chair), Charles Swanson, Martin Lopez-Daneri, and Olga Timoshenko. My gratitude also goes to Catherine Maclean and Michael Leeds for providing me with tremendous comments on research and assistance in job market preparation. Finally, I appreciate the academic discussions with my colleagues: You Du, Mark Robinson, Elisheva Stern, and Huilin Zhu.

1 Introduction

In the modern economy, the production of any good or service always needs cooperation among a wide range of industries or firms. Industries buy goods and services from different suppliers to produce and sell their products to various consumers, which then form a particular structure of an input-output network or a production network.[1] Based on this network view of the production process, shocks to any industry or firm can spread to its neighbors, sectors directly connected to it, its neighbors' neighbors, and so forth via input-output linkages. For example, in September 2021, a record number of cargo ships were stuck at the port of Los Angeles and waited to unload due to a shortage of trucks and drivers. In this example, not only was the transportation sector affected, but many other sectors waited for this cargo for production, such as apparel manufacturing and wholesale trade, as well as their consumers. As a result, industry-level distortions will be propagated and amplified through the production network and cause aggregate fluctuations. However, what is the role of the production network structure in explaining an economy's aggregate outcomes?

This paper puts forth the idea that the production network structure in isolation represents an essential channel in shaping GDP growth and growth volatility in the United States. I make this argument in three steps. First, I develop a new measure of production network structure, named centrality dispersion, and show that industries in the U.S. economy have become sparsely connected from 1970 to 2017, that is, a few highly central input supplier industries combined with an isolated group of less important industries. With such changes in the network structure, I observe that aggregate GDP growth tended to slow down and became more volatile. Second, I embed inter-sectoral linkages into a constant elasticity of substitution (CES) multisector real business cycle model and study the nonlinear impact of industry-specific productivity shocks on the aggregate economy. In this theoretical environment, the production network structure (or centrality dispersion) plays a key role in the propagation and amplification of sectoral shocks. Finally, I construct realized sectoral productivity shocks from the data, feed them into the model, and study quantitative predictions of the model regarding the empirical correlations between input-output network structures, GDP growth, and growth volatility. The calibrated model can deliver the observed empirical patterns in the U.S. economy moderately well, while a Cobb-Douglas model fails to deliver.

In the first step, this paper reveals the changing nature of the U.S. input-output network structure and provides empirical evidence of a significant correlation between the network structure and GDP growth and growth volatility, respectively. Specifically, I first use the summary-level input-output data from the Bureau of Economic Analysis (BEA) to construct

[1] Throughout this paper, I use terms "production network" and "input-output network" interchangeably.

annual input-output tables of the U.S. economy over the 1970−2017 period. Each input-output table captures the flows of intermediate inputs from a supplying industry to its consumer industries. Next, I develop a new measure of production network structure named centrality dispersion, describing the extent to which an economy has a group of important input suppliers, and identify a gradually sparsely connected network structure of the U.S. economy across the years. For example, a few industries, such as "Finance and insurance" and "Professional services", have become more central suppliers within the network, meaning many more industries rely on their services to produce, while other industries, like "Paper products" and "Mining", have become more isolated. Last, I study the empirical relationship between changes in the network structure and aggregate fluctuations. The evidence shows that as the U.S. input-output network structure becomes sparsely connected over time, aggregate GDP growth tends to slow down and be more volatile.

Motivated by these empirical observations, in the second step, I build a multisector real business cycle model embedded with intersectoral linkages to understand the role of the production network structure in propagating industry-specific productivity shocks. In our model, each industry produces a distinct product using labor and a bundle of intermediate inputs purchased from other industries. All the inputs are aggregated by a CES production function, which characterizes the empirical input-output network. Hulten's theorem states that, in an efficient economy, *Domar weights*, defined as an industry's total sales to aggregate GDP ratio, are sufficient statistics in explaining the impact of sector-specific productivity shocks on GDP (see **?**, **?**, **?**, and among others). In other words, in the presence of input-output linkages, the impact of a sector-level shock on the aggregate economy is entirely captured by the size of this sector, regardless of its position in a production network. Therefore, in order to highlight the importance of production network structure in propagating shocks and shaping macroeconomic outcomes, I provide a nonlinear approximation of sectoral productivity shocks' impact on GDP, as in **?** and **?**.

The final step of our analysis is to use the calibrated model to perform several quantitative exercises assessing the role of input-output network structure in shaping GDP growth and growth volatility under nonlinear characterization. In the first exercise, I measure the realized industry-specific productivity shocks from the data using the Solow residual approach, feed them into the model, and study the quantitative predictions of the model regarding the empirical correlations between the input-output network structure and two macroeconomic aggregates. Overall, our model is able to deliver the observed empirical patterns moderately well, while a Cobb-Douglas model fails to deliver. In particular, our model implies that a more sparsely connected network structure is associated with lower GDP growth and higher growth volatility. Nevertheless, the model-estimated key coefficients[2] are about one-quarter as big as those observed in the data. To ensure the changes in GDP growth and growth volatility are not purely driven by variations in industry sizes, in the second exercise, I build two three-sector economies with identical Domar weights but different inter-sectoral linkages to disentangle the contribution of network interconnections. In the last exercise, I use our model to estimate the impact of the Covid-19 shocks, measured as the reduction in sectoral labor supply from March 2020 to June 2020, on the real economy. Our model predicts a roughly 10.5% reduction in real GDP, which is in line with the data in the second quarter of 2020 from the BEA.

The rest of the paper is organized as follows. In section 2, I review three strands of related literature and present the contributions of this paper. In section 3, I first measure the empirical input-output production network of the United States spanning the 1970−2017 period and document several stylized facts about the network structure. Then I show evidence that the changing network structure significantly correlates with the U.S. economy's aggregate performance. Motivated by these empirical observations, in section 4, I incorporate inter-sectoral linkages into a multisector real business cycle model to study the role of network structure in propagating and amplifying sectoral productivity shocks under nonlinear characterization. In section 5, I use the calibrated model to perform several quantitative exercises. Section 6 concludes.

2 Literature Review

This paper relates to several strands of literature that study: i) the origin of macroeconomic fluctuations, ii) the role of an input-output network in propagating idiosyncratic shocks into the aggregate economy, and iii) how structural transformation determines economic growth.

In the branch of theoretical literature that studies the network origin of macroeconomic fluctuations, the canonical work of **?** and **?** point out that aggregate volatility is the primarily result of microeconomic shocks propagating through input-output networks; also see **?**, **?**, **?**, **?**, and **?**. At the firm level, **?** and **?** show that *fundamental volatility*, defined as the weighted[3] sum of firm-level idiosyncratic shocks, is able to track the volatility of macroeconomic variables over time. As with the existence of large firms, the impact of firm-level total factor productivity (TFP) shocks will not be canceled out, resulting in aggregate fluctuations. At the industry level, **?** argue that idiosyncratic shocks to important input

[2] Key coefficients refer to the estimated coefficients of model-implied centrality dispersion and concentration centrality, respectively.

[3] Following Hulten's theorem, weights are the Domar weights of selected large firms in the U.S. economy.

suppliers (industries) propagate more widely through the input-output network, thus do not wash out with shocks to small sectors, generating sizeable aggregate movements. Moreover, **?** generalizes **?**'s theoretical framework from a Cobb-Douglas economy to accommodate flexible substitution patterns in production functions and quantifies the contribution of sectoral and aggregate shocks to business cycle fluctuations. Both papers conclude that the interplay of idiosyncratic shocks and the input-output network can account for at least half of the aggregate volatility. Sharing the spirit of previously mentioned papers, I study the impact of industry-specific productivity shocks on macroeconomic aggregates when propagating through different input-output networks.

My paper also contributes to a growing literature on assessing the role of an input-output network in shaping macroeconomic fluctuations with a multisector real business cycle model initiated by **?**. **?** employ this framework with Cobb-Douglas technologies and argue that in a linear economy, Domar weights are sufficient statistics in determining an economy's aggregate performance, not the intricate details of the network. Nevertheless, **?** incorporate CES production functions and preferences into a multisector model and provide a nonlinear characterization of the impact of sectoral productivity shocks on the aggregate economy. The authors emphasize that in the presence of nonlinearity, network linkages do matter. **?** also clarify how network interactions function as a mechanism for propagating and amplifying microeconomic shocks by providing the first- and second-order approximation of the structure of equilibrium. Other papers (see **?**, **?**, **?**, and **?**) explore the role of an input-output network in an inefficient economy and illustrate that market imperfections, for example, misallocation of resources, sectoral mark-ups, financial distortions, etc., can accumulate through the input-output network, causing systematic influences.

More broadly, my paper adds to the empirical literature on the relationship between structural change and economic growth. For example, **?** develop a model with endogenized technological diversification and show that firms in rich economies tend to use a larger variety of inputs, which mitigate their exposure to productivity shocks and thus reduce aggregate volatility. **?** document the fact that the service sales to GDP ratio increases with income across countries and develop a multisector growth model to account for it. **?** and **?** provide cross-country evidence that high-income countries, or the countries that have experienced an increase in the share of services in GDP over time, tend to grow slower and be less volatile than middle-income ones. Moreover, Moro constructs a two-sector general equilibrium model to study the impact of structural change on cross-country differences in GDP growth and volatility. More recently, **?** shows that GDP growth volatility declines with production network diversification—as measured by the fraction of input-output connections within a network.

Compared to the aforementioned papers, my paper's contributions are as follows. First, from an empirical standpoint, I develop a new measure of production network structure, centrality dispersion, to describe the extent to which an economy consists of a group of star sectors. I show that the production network structure is significantly associated with the economic growth and volatility of the United States, complementing **?**'s work. Moreover, I generalize **?** and **?**'s theoretical results and show that centrality dispersion (our network structure measure) play an essential role in explaining the impact of sector-specific productivity shocks on the aggregate economy up to the second-order approximation. Last, I construct two three-sector economies with identical Domar weights to disentangle the contribution of network linkages in determining GDP growth and growth volatility.

3 Data and Stylized Facts

In this section, I study the empirical relationship between the production network structure of the U.S. economy and real GDP growth and growth volatility, respectively. I start by describing the data and then document several empirical facts to reveal the changing nature of the U.S. production network structure from 1970 to 2017. Last, I estimate the correlation between the network structure and the economy's aggregate performance with panel regressions.

3.1 Data

To map the U.S. production network to data, I use the summary-level input-output data from the BEA, which measures the input transactions among the 46 U.S. industries[4,5] over a long time span at an annual frequency. Table 1 lists the 46 industries included in our analysis. In particular, I first combine the BEA's Make and Use tables[6] to derive the Commodity-by-Commodity Direct Requirements (CCDR) table for each year over the 1970−2017 period. Each nonzero entry (i, j) in the CCDR table denotes a flow of inputs from a supplying indus-

[4] This paper only focuses on the flow of inputs between the U.S. industries, ignoring input trading with the rest of the world.

[5] The 46 industries in the sample were classified according to the North American Industry Classification System (NAICS) in 1947. However, in 1963 and 1997, the BEA revised the data collection mechanism and reclassified the economy into 65 and 71 industries, respectively. Therefore, I aggregate several industries back into the original 46-industry definitions to ensure consistency in measurement, see details in **?**.

[6] The Make and Use tables used to construct CCDR tables are collected before redefinitions of secondary products. A redefinition is a transfer of a secondary product from the industry that produced it to the industry in which it is primary, as described in **?**. Thus, for example, the output and associated inputs for restaurants located in hotels are moved from the hotels and lodging places industry to the eating and drinking places industry.

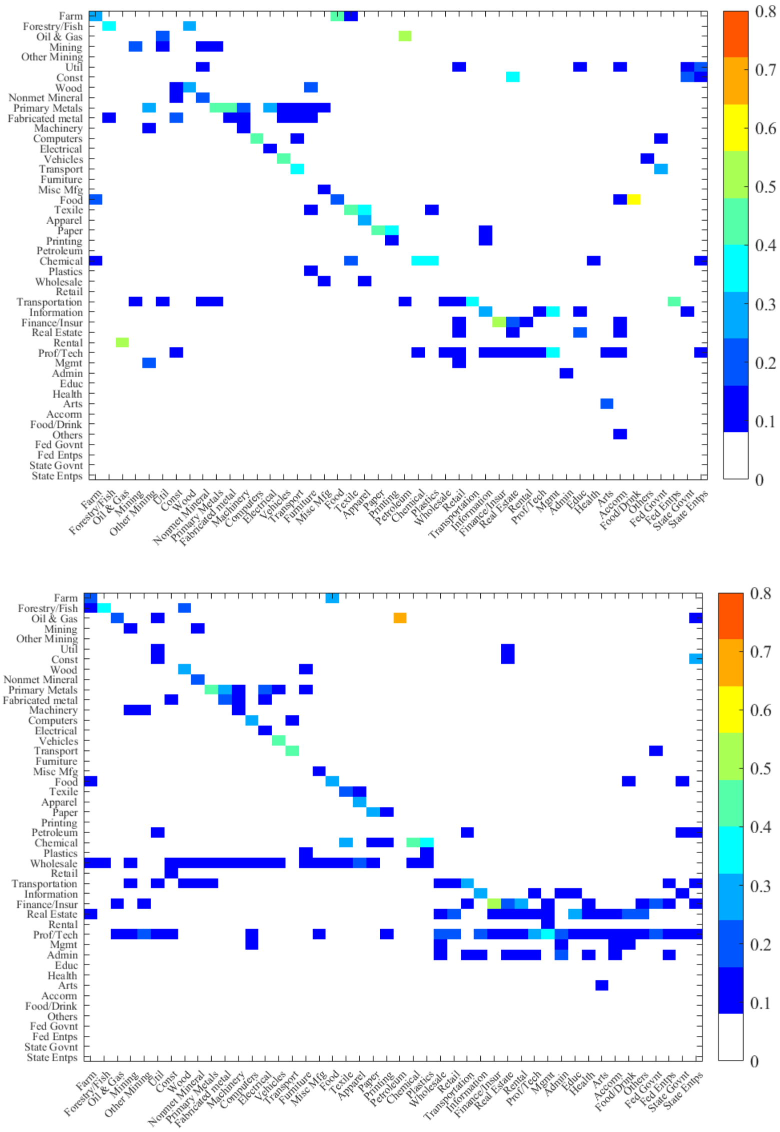
Table 1: The 46 Industries Used in the Analysis.

Farms	Petroleum and coal products
Forestry, fishing, and related activities	Chemical products
Oil and gas extraction	Plastics and rubber
Mining, except oil and gas	Wholesale trade
Support activities for mining	Retail trade
Utilities	Transportation and warehousing
Construction	Information
Wood products	Finance and Insurance
Nonmetallic mineral products	Real estate
Primary metals	Rental and leasing services
Fabricated metal products	Professional, scientific, and technical services
Machinery	Management of companies and enterprises
Computer and electronic products	Administrative and waste management services
Electrical equipment, and components	Educational services
Motor vehicles, bodies and trailers	Health care and social services
Other transportation equipment	Arts, entertainment, and recreation
Furniture and related products	Accommodation
Miscellaneous manufacturing	Food services and drinking places
Food and beverage and tobacco products	Other services, except government
Textile mills and textile product mills	Federal general government
Apparel and leather and allied products	Federal government enterprise
Paper products	State and local general government
Printing and related support activities	State and local government enterprise

try i to a demanding industry j within the network, while zero means no input transactions. Then I normalize all column industries j to sum to one, as j's total intermediate input expenditures must be allocated to all (or at least some) industries in the economy. Therefore, the entry (i, j) in our final table implies the value of spending on good i per dollar of the production of good j, and I refer to the final table as the empirical input-output network. In addition, the sum of values in rows i, presented as total purchases of good i in shares of the demanding industry, captures sector i's importance as an input supplier in the production network.

Figure 1 illustrates the U.S. empirical input-output network structure in 1970 (top panel) and 2017 (bottom panel) with heatmaps. Each row represents an industry supplying intermediate inputs for production to the others, while each column represents industries demanding the inputs. I report each small rectangle in the heatmap as industries' intermediate input purchases from each supplier as a fraction of their total input expenditures. White (cool) colors denote small shares, and bright colors denote large shares. As shown in the figure, a

Figure 1: The U.S. Input-Output Network in 1970 (top) and 2017 (bottom)



Note: Heatmaps of empirical input-output networks. Entry (i, j) computes the share of total intermediate input expenditure in sector j that is purchased from sector i.

few industries, such as “Wholesale trade (row 27)” and “Professional, scientific, and technical services (row 34)”, became more central suppliers in 2017 as they were connected to many more industries. This is represented by more blue dots in a row. In contrast, other industries like “Utilities” became more isolated within the network.

3.2 The Changing Input-Output Network Structure of the U.S. Economy

3.2.1 A Small World of Input Flows: Distance and Diameter

According to **?**, a small-world network is a type of network in which most nodes are not neighbors of one another but where most nodes can be reached from every other by a small number of hops or steps. If so, when shocks hit a sector in such a network, especially a star supplier, the impact would fast propagate to its neighbors, then to the rest of the economy, generating aggregate fluctuations.

To identify such features, I measure the distance and diameter of the U.S. input-output network over time. Define *network diameter* as the maximum length of all ordered entries (i, j) of the shortest path from i to j and *average distance* as the average length of the shortest path for all entries (i, j). Over the 1970−2017 period, the diameter and average distance of the U.S. production network have a mean of four and two, respectively.[7] When the U.S. economy is categorized into 46 industries, it takes two steps on average for one industry to reach any other industry within the network, which implies a small world of production networks. In other words, industries with indirect demand-supply relationships are highly likely to link through a few star input suppliers as they shorten the distance between industries.

3.2.2 A Measure of Network Interconnection: Density

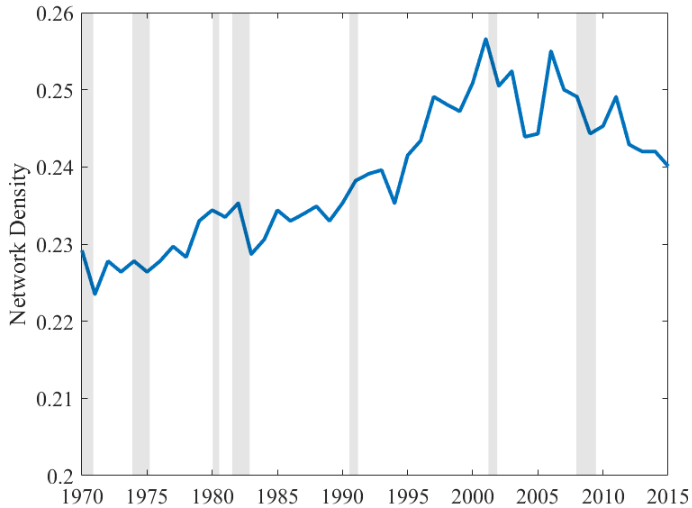
Network density measures the degree of inter-industrial connections within a network. In line with **?**, an economy with N industries has a network density of L/N^2, where N^2 indicates the number of all possible links, and L is the number of existing links. This measure ranges from 0 to 1, with the lower limit corresponding to an economy with completely isolated sectors, while the upper limit refers to the network with all possible sectoral interconnections. Moreover, network density can vary over time, as inter-sectoral linkages might emerge or vanish due to changes in suppliers' productivity, international competition, consumers' preferences, etc.

Figure 2 plots the network density of the United States from 1970 to 2017 with 46 industries. I assume a link exists between industry i and j if i's supply of good i can account for at least one percent of j's total input expenditures. In our analysis, the average network density is 0.239, implying that 506 out of 2,116 possible linkages[8] existed in any given year. However, even with such a highly disaggregated industry classification, the number of links varies over time. The network density has a standard deviation of is 0.0086, which is roughly

[7] The standard deviation of network diameter and distance are 0.03 and 0.4, respectively.

[8] Since I choose the 46-industry classification in the analysis, the number of all potential links is $N^2 = 2116$.

Figure 2: Network Density of the U.S. Economy from 1970 to 2017.



Note: Shaded areas refer to the National Bureau of Economic Research (NBER) defined recessions in the United States.

18 links. Therefore, although the degree of network interconnection has varied over time, the variation is relatively small.

As shown in Figure 2, network density trended up until early 2000, indicating industries have become more interconnected during that period, but it started to decline afterward. One possible reason might lie in the rapid growth of international trade since the 1980s, especially with Asian countries. The easier accessibility and comparative advantage of producing in Asian countries have boosted U.S. firms' offshoring activities, making them less connected with domestic trade partners. Moreover, the network density tended to decline during economic recessions. Intuitively, firms or industries tend to reduce production during economic downturns and thus become less connected with others.

3.2.3 A Measure of an Industry's Relative Importance within the Network: Katz−Bonacich Centrality

The Katz-Bonacich (KB for short) centrality is one way of measuring an industry's relative importance as an input supplier in a production network. It takes into account both direct and indirect (higher-order) connections between industries, as well as the strength of these connections. In general, industries are considered more central (a higher centrality) if their neighbors are well-connected industries.

Define the KB centrality $Centrality_{(j)}$ of an industry j as proportional to the weighted sum of its neighbors' centralities, which is given by

$$Centrality_{(j)} = \mu \sum_{i=1}^{N} w_{ij} Centrality_{(i)} + \eta,$$

where $N = 46$ is the number of industries defined in my sample, and w_{ij} corresponds to the (i, j) element of an empirical input-output matrix $\mathbf{W}$ as described in section 3.1, representing the expenditure on input i per dollar of the production of good j. μ is the baseline centrality level that is identical across industries, and $\eta > 0$ is an attenuation factor. Recall the KB centrality captures both direct and indirect inter-sectoral connections within the network. A longer distance, say more than a one-edge distance between industries i and j, will be penalized through the attenuation factor μ (**?**). An industry's centrality can range from 0 to 1 and sum up to one over all industries in a given year. A higher centrality implies this sector is a more important input supplier in the network and more influential over the entire economy. For instance, an industry with a centrality of 0.2 has twice as much influence as a $0.1-$centrality industry.

Rewriting the previous equation into the matrix form, we have

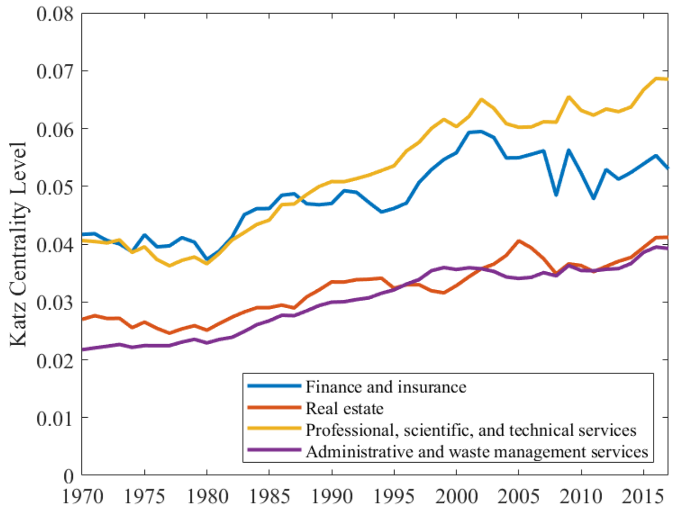
$$\Psi = \eta[\mathbf{I} - \mu \mathbf{W}']^{-1},$$

where Ψ denotes a $N \times N$ industry centrality matrix, and $\mathbf{I}$ is the identity matrix. Each element $\Psi = [\psi_{ij}]$ measures sector i's total reliance on its input supplier j, which is proportional to the Leontief inverse elements. Therefore, the centrality of j is computed as the sum of the jth column $Centrrality_{(j)} = \sum_{i=1}^{N} \psi_{ij}$. Last, following **?**, I set the attenuate factor $\mu = 0.5$, and $\eta = (1 - \mu)/N$.

Using the above equation, I calculate each industry's centrality from 1970 to 2017. Figure 3 highlights four industries that increased in centrality over the past fifty years. They are "Finance and insurance", "Real estate", "Professional, scientific, and technical services", and "Administrative and waste management services."[9] An industry with increasing centrality means that many more sectors, directly and indirectly, rely on it for their own production process. For example, "Professional, scientific, and technical services (yellow line)" (PST services for short) and "Administrative and waste management services (purple line)" exhibited a more than 50% increase in centrality since 1970. One possible explanation for such increases is outsourcing. Rather than hiring accountants, statisticians, or cleaning persons to produce in-house, more firms or industries were increasingly contracting out these jobs

[9] I choose these four industries as they experienced the largest rise in centrality across all industries over the sample period.

Figure 3: Selected Industries that Increased in Centrality.



to specialized companies, thus making them more central over time (?). Imagine the same adverse shock hitting "PST services" in 1970 and 2010 separately. It will have a more devastating impact on 2010's economy as "PST services" has become a more influential input supplier.

On the other hand, "Finance and insurance (blue line)" and "Real estate (red line)" in Figure 3 present similar periodic patterns throughout the sample, despite their centralities being different in magnitude. In particular, two sectors experienced a sharp increase in centrality level from the mid-1990s to 2005, which coincided with the U.S. real estate boom. The continuous growth in housing demand had boomed financial and real estate-related services, making the two industries more central in the economy. However, their centralities started declining around 2007, possibly due to the 2008-2010 financial crisis.

In contrast, Figure 4 depicts four selected industries with no substantial gains in centrality. For example, "Primary metal (blue line)" and "Paper products (red line)" experienced a declining centrality over time.[10] Since the 1980s, the U.S. government has started imposing stringent environmental regulations on manufacturing industries. As a result, it largely increased firms' production costs as old equipment needed to be replaced by new environment-friendly ones (?). Meanwhile, foreign companies entered the U.S. market with cheaper imports. Both situations weakened the competitiveness of domestic manufacturers (?) and thus reduced their centralities. In addition, the centrality of "Oil and gas extraction (yellow line)" and "Petroleum and coal products (purple line)" peaked in the early 1980s and late 2000s but maintained a similar level at the beginning and the end of the sample

[10] In my analysis, the majority of industries that experienced a declining centrality belong to manufacturing.

Figure 4: Selected Industries that Did Not Increase in Centrality.

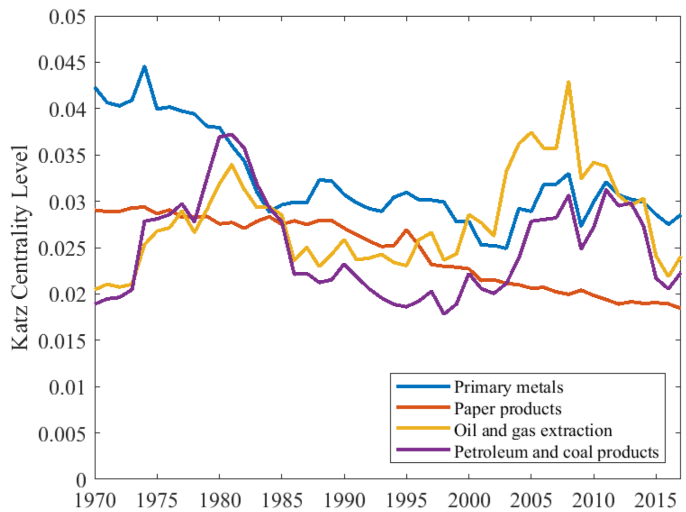
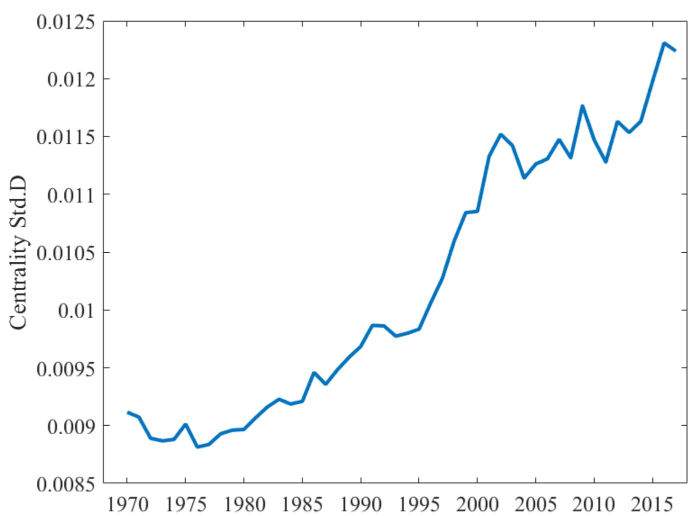


Figure 5: Centrality Std.D , 1970−2017.

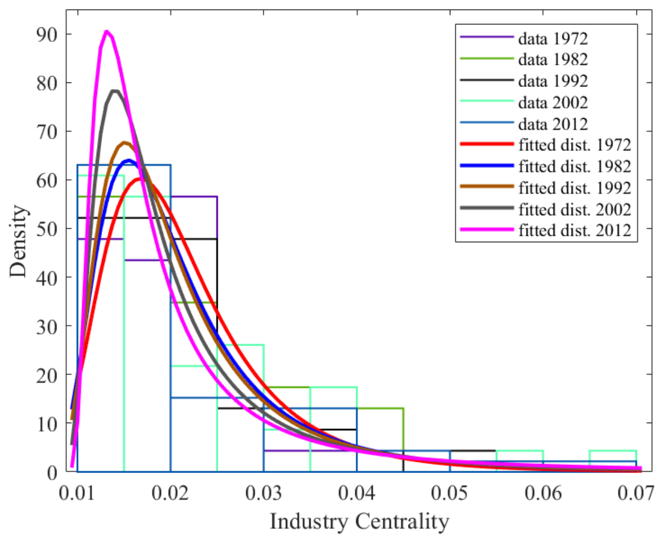


period.

3.2.4 A Measure of Network Structure: Centrality Dispersion

In this paper, I use *centrality dispersion* to characterize the production network structure of the U.S. economy, which is defined as the unweighted cross-sectional standard deviation of the KB centrality in a given year. This measure is closely related to what **?** has found theoretically, which characterizes how sectoral productivity shocks amplify and propagate through inter-sectoral linkages and lead to (second-order) aggregate impact. Centrality dis-

Figure 6: Fitted GEV Distribution of Centrality in Five Selected Years.



persion describes the extent to which an economy contains a group of star intermediate input suppliers. Thus, a more dispersive production network structure (or a larger standard deviation of centrality) implies an economy consisting of a few highly central industries. And such an economy could be more vulnerable to shocks. Because shocks to a sector, especially a star supplier, would propagate to more sectors via network linkages, then generate greater aggregate volatility.

Figure 5 plots the centrality dispersion (the standard deviation of the KB centrality) spanning 1970 to 2017. The increasing trend in the figure indicates that industry centrality has spread further from the mean, leaving (both right and left) tails of centrality distribution fatter over the years. A fatter right tail implies an economy with more central input suppliers. That is to say, over time, many more industries relied on these star suppliers for their own production process. Analogously, a heavier left tail suggests that relatively unimportant industries (or low-centrality industries) have maintained a weak interconnection with most other industries throughout the sample period. The coexistence of a few highly central industries and an isolated group of less central industries identifies the U.S. economy as a gradually sparsely connected production network. Last, in Figure 6, I plot the centrality distribution[11] in 1972, 1982, 1992, 2002, and 2012 to provide a clear vision of how the U.S. production network structure has changed over time.

In Appendix A, I will provide an alternative measure of production network structure, concentration centrality, and show its significant correlations with GDP growth and volatility.

[11]Since I only have 46 centralities each year, I plot the generalized extreme value (GEV) distribution that best fits the limited data.

3.3 Input-Output Network Structure and Aggregate Fluctuations

In this subsection, I will show empirical evidence of how input-output network structure shapes aggregate fluctuations in the United States from 1970 to 2017. In particular, I examine the conditional correlation between centrality dispersion, the production network structure measure described in Section 3.2.4, and real GDP growth and growth volatility, respectively.

3.3.1 Centrality Dispersion and real GDP Growth

First, I estimate the relationship between centrality dispersion, specified as the unweighted cross-sectional standard deviation of the KB centrality, and aggregate real GDP growth using the following regression:

$$\Delta\log(RGDP_T) = \beta_1\log(Std.centrality_T) + \bar{\mathbf{X}}_T'\gamma_1 + \bar{e}_T \tag{1}$$

where $\Delta\log(RGDP_T)$ denotes real GDP growth in year T, measured by the first difference of annual real GDP in logarithm. The key regressor $Std.centrality_T$ stands for centrality dispersion, which describes year T's network structure. The vector $\bar{\mathbf{X}}_T$ contains control variables (in logarithm) used in the literature: service[12] sales share in GDP (**?**), $\log(Serv./GDP_T)$, and intermediate input sales to gross output ratio (**?**), $\log(Int.m/output_T)$. I also include $\log(Int.m/output_T)^2$, denoted as the squared input sales ratio, to capture the potential non-linearity in explaining output growth.

Observation 1 *As industries in the U.S. economy become sparsely connected over time, aggregate real GDP growth tends to slow down.*

Table 2 illustrates the results of estimating equation (1), which indicates a strong negative correlation between centrality dispersion and real GDP growth. As the production network structure becomes sparser across years, that is, a few highly central supplier industries combined with an isolated group of less important industries, GDP growth tends to slow down. To have an idea of the economic significance of the coefficient in the first column of Table 2, for a one-standard-deviation increase in centrality dispersion, real GDP growth rate declines by about 0.007 on average. The intuition underlying this negative coefficient is that, on the one hand, most service-related industries in the United States were becoming

[12] 21 out of 46 industries are selected to be the members of the broad service sector, including Utility, sixteen private service-producing industries, and four government-related industries.

Table 2: Real GDP Growth and Centrality Dispersion, 1970−2017.

Variables	(1) $\Delta\log(RGDP_T)$	(2) $\Delta\log(RGDP_T)$	(3) $\Delta\log(RGDP_T)$
$\log(Std.centrality_T)$	-0.798***	-0.861***	-0.831***
	(0.299)	(0.280)	(0.300)
$\log(Int.m/output_T)$		-0.423***	-0.703**
		(0.156)	(0.353)
$\log(Int.m/output_T)^2$		-27.378***	–29.741***
		(4.587)	(4.321)
$\log(Serv./GDP_T)$		-0.663*	-0.791*
		(0.396)	(0.485)
$\log(HHI_T)$			1.772
			(2.311)
R-squared	0.157	0.497	0.511
Observations	48	48	48

[1] This table presents the OLS regression results, using real GDP growth rate as the dependent variable. All variables except real GDP growth are HP-filtered with a smoothing parameter of 6.25.
[2] ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, and robust standard errors are in the parentheses.

more central suppliers. However, on the other hand, these service sectors tend to have low productivity growth to grow over time,[13] thus causing an economic slowdown. Also shown in column (2), results are robust when including the aforementioned control variables.

Last, I add an additional regressor, the Herfindahl-Hirschman index (HHI) of sectoral sales shares $\log(HHI_T)$ (**?**),[14] and re-estimate the correlation. As shown in column (3), the relationship between centrality dispersion and real GDP growth holds even after controlling for the HHI of sectoral sales shares. This result suggests that network structure affects real GDP growth beyond sectoral sales shares. In other words, sectoral interconnection in isolation can account for aggregate economic growth. Our empirical evidence complements **?**'s theoretical findings that Domar weights (sectoral sales shares) are insufficient statistics for characterizing the nonlinear impact of sectoral productivity shocks on economic outcomes.

Nevertheless, there is a potential reverse causality problem as aggregate GDP growth might reversely affect how sectors trade with one another. Regarding this issue, I conduct the Granger causality test, and the results suggest that reverse causality should not be a primary concern here.

[13] In Appendix B.1, I show empirical evidence of a negative correlation between an industry's centrality and sectoral real output growth over my sample period, which is similar to **?**'s finding.

[14] For each period T, I calculate $HHI_T = \sqrt{\sum_{i=1}^{N}(\frac{S_{i,T}}{GDP_T})^2}$, where $S_{i,T}$ are sector i's total sales at time T.

Table 3: Real GDP Growth Volatility and Centrality Dispersion, 1970−2017.

Variables	(1) *Growth volatility*$_T$	(2) *Growth volatility*$_T$	(3) *Growth volatility*$_T$
$\log(Std.centrality_T)$	0.370**	0.397**	0.440**
	(0.200)	(0.210)	(0.126)
$\log(Serv./GDP_T)$		0.345	0.537**
		(0.271)	(0.205)
$\log(Std.domar_T)$			-0.355
			(0.330)
$Growth\ volatility_{T-1}$	-0.319**	-0.292**	0.350***
	(0.148)	(0.132)	(0.122)
R-squared	0.176	0.217	0.250
Observations	48	48	48

[1] This table presents the coefficients of estimating equation (2), using the standard deviation of real GDP growth as the dependent variable.
[2] All variables have been HP-filtered with a smoothing parameter of 6.25.
[3] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

3.3.2 Centrality Dispersion and Growth Volatility

Next, I estimate the relationship between centrality dispersion and macroeconomic volatility using the equation below:

$$Growth\ volatility_T = \rho_2 Growth\ volatility_{T-1} + \beta_2 \log(Std.centrality_T) + \tilde{\mathbf{X}}_T'\gamma_2 + \tilde{e}_T \quad (2)$$

where $Growth\ volatility_T$ denotes the standard deviation of real GDP growth at time T, as in **?** and **?**, which is referred to as growth volatility. $Std.centrality_T$ still represents our production network structure measure, which is the centrality dispersion in period T. Three control variables in $\tilde{\mathbf{X}}$ are the one-period lag of growth volatility $Growth\ volatility_{T-1}$, service sales over GDP ratio $\log(Serv./GDP_T)$ and the standard deviation of Domar weights $\log(Std.domar_T)$. Recall that *Domar weight* is defined as an industry's total sales to the economy's GDP ratio.

Observation 2 *As the U.S. input-output network structure becomes sparser over time, aggregate real GDP growth tends to be more volatile.*

Table 3 presents the results of estimating equation (2). There is a strong positive correlation between the production network structure and real GDP growth volatility over the sample period. The coefficient in column (1) indicates that a 1% increase in centrality dispersion is associated with a 0.37% increase in aggregate volatility. It also implies that a one-standard-deviation increase in centrality dispersion rises growth volatility by about 0.004. Intuitively, shocks hitting central supplier industries do not wash out with shocks to less important industries. Therefore, shocks to a more dispersive network structure will have a more disproportionate impact on the macroeconomy, thus making it more volatile.

The results are robust when adding previously mentioned control variables. In particular, I re-estimate the equation conditional on the standard deviation of sectoral sales shares, $log(Std.domar_T)$, to control for potential variations caused by Domar weights. The significant coefficient in column (3) suggests that even in the absence of sectoral sales shares, production network structure is still strongly correlated with aggregate volatility, which empirically accentuates the role of intersectoral linkages in determining macroeconomic fluctuations.

4 Theoretical Framework

Motivated by the stylized facts, I develop a theoretical framework by embedding intersectoral linkages into a multisector real business cycle model with CES technologies, as in **?** and **?**. Moreover, I solve the model nonlinearly in order to highlight the role of production network structure (centrality dispersion) in propagating and amplifying industry-level productivity shocks to the macroeconomy. Throughout this section, variables with overlines are normalizing constants equal to their steady-state values.[15]

4.1 A Model of Input-Output Networks

Firms' Productions

In our economy, time is discrete and infinite. There are $N = 46$ competitive industries. Each industry $i \in \{1, 2, ..., N\}$ produces a distinct good with a single factor of production (labor) and an intermediate input bundle within one CES nest. The production function is given by

$$\frac{y_{it}}{\bar{y}_{it}} = A_{it}\left[a_{it}\left(\frac{L_{it}}{\bar{L}_{it}}\right)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}} + (1-a_{it})\left(\frac{X_{it}}{\bar{X}_{it}}\right)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}}\right]^{\frac{\varepsilon_Y}{\varepsilon_Y-1}} \tag{3}$$

where y_{it} denotes industry i's output, and L_{it} is the amount of labor used by i at time T. Note that an industry's total output will be sold either to other industries as intermediate inputs for production or to households as final consumption goods. X_{it} indicates a bundle of

[15]Since this paper focuses on percentage changes in GDP, the normalizing constants are irrelevant.

intermediate inputs purchased from other industries and used for production. The elasticity of substitution parameter ε_Y measures how easily factors of production (that is, labor and intermediate inputs) are substituted, and I assume it is identical across industries. Parameter a_{it} reflects industry i's usage of labor in the total value of production. Last, I assume that industry-specific TFP A_{it} follows a random walk:

$$\log A_{it} = \log A_{it-1} + \kappa_{it} \tag{4}$$

where sectoral productivity shocks κ_{it} are lognormally distributed.

The intermediate input bundle X_{it} consists of industry i's purchases of intermediate inputs from other sectors for production, aggregated through an input-output network:

$$\frac{X_{it}}{\bar{X}_{it}} = \left(\sum_{j=1}^{N} \gamma_{ijt} \left(\frac{x_{ijt}}{\bar{x}_{ijt}} \right)^{\frac{\varepsilon_X - 1}{\varepsilon_X}} \right)^{\frac{\varepsilon_X}{\varepsilon_X - 1}} \tag{5}$$

where x_{ijt} is the inputs purchased by industry i from its supplier j in year t. The $N \times N$ matrix $\mathbf{\Gamma} = [\gamma_{ij}]$ sumerizes the input-output linkages between various industries, and we refer to as the input-output network structure of the economy. I also assume the constant returns to scale technology of firms in sector i such that $\sum_{j=1}^{N} \gamma_{ij} = 1$. The elasticity of substitution ε_X parameterizes the substitutability across intermediate inputs demanded by sector i and is set to be identical across industries.

Following **?**, I allow for two types of labor[16] in the model: specific labor $l_{is_i,t}$ and general labor $l_{ig,t}$. Whereas the specific labor can only work in sector i, general labor can move across sectors flexibly without any transaction cost. Total labor demanded in industry i's production L_{it} is organized as

$$\frac{L_{it}}{\bar{L}_{it}} = \Big(\frac{l_{is_i,t}}{\bar{l}_{is_i,t}}\Big)^{\beta_i} \Big(\frac{l_{ig,t}}{\bar{l}_{ig,t}}\Big)^{1-\beta_i}, \tag{6}$$

where the two types of labor are in fixed supplies, such that $\bar{l}_{s_i,t} = \bar{l}_{is_i,t}$ and $\bar{l}_{g,t} = \sum_{i=1}^{N} \bar{l}_{ig,t}$. Parameter β_i denotes the portion of specific labor in total labor used by industry i. As a result, $\beta_i = 1$ means the economy only consists of specific labor, which cannot be reallocated to other sectors, while with $\beta_i = 0$, all labor can move flexibly within the network.

[16]**?** argue that the degree of factor (labor) reallocation can affect sectoral TFP shocks' impact on the aggregate economy when characterizing the model nonlinearly.

Household's Preferences

The representative household maximizes utility over leisure and N different final consumption goods (or services)

$$U(C_t, L_{St}) = C_t - \frac{\varepsilon_{LS}}{\varepsilon_{LS}+1} L_{St}^{\frac{\varepsilon_{LS}+1}{\varepsilon_{LS}}} \tag{7}$$

subject to the budget constraint

$$w_t L_{St} + \sum_{i=1}^{N} \pi_{it} = P_{c,t} C_t \tag{8}$$

where C_t represents the household's aggregate consumption bundle at time t, consisting of different final goods c_{it} and L_{St} is the total labor supply to all sectors. In the household budget constraint, w_t is wage, π_{it} is the profit in sector i ($\pi_{it} = 0$ for each i at the equilibrium), and $P_{c,t}$ represents the associated ideal price index of the consumption bundle C_t, assumed to be a numeraire. The Frisch elasticity of labor supply $\varepsilon_{LS} > 0$ describes the sensitivity of household's desired labor supply to a given wage rate.

Moreover, the household's aggregate consumption function is constructed as

$$\frac{C_t}{\bar{C}_t} = \left(\sum_{i=1}^{N} b_i \left(\frac{c_{it}}{\bar{c}_{it}}\right)^{\frac{\varepsilon_C - 1}{\varepsilon_C}} \right)^{\frac{\varepsilon_C}{\varepsilon_C - 1}} \tag{9}$$

where parameter b_i illustrates the consumption share of good i, which satisfies $\sum_{i=1}^{N} b_i = 1$. The elasticity of substitution among different consumption goods is denoted as ε_C.

Competitive Equilibrium

I characterize the competitive equilibrium of our multisector CES economy using the social planner's problem. For each industry i, goods market clearing ensures that i's output is used for final consumption or intermediate inputs for production: $y_{it} = c_{it} + \sum_{j=1}^{N} x_{jit}$. Recall that labors are in fixed supplies, so the market-clearing conditions for the specific labor and the general labor are $\bar{l}_{s_i,t} = l_{is_i,t}$ and $\bar{l}_{g,t} = \sum_{i=1}^{N} l_{ig,t}$.

Solution Method

I solve the model nonlinearly in order to characterize the second-order impact of sectoral TFP shocks on the aggregate economy, as in **?** and **?**. The advantage of our characterization is to highlight the key role of inter-sectoral linkages or the network structure in determining shocks' effect on aggregate GDP growth and growth volatility. First-order conditions of the social planner's problem is provided in the Appendix C.

4.2 Network Propagation Mechanism

In this subsection, I study the model's implications for the relationship between the network structure and GDP growth.

First, the second-order approximation of aggregate real GDP with respect to productivity shocks to several industries i and j is:

$$\begin{aligned}\log\frac{Y}{\bar{Y}} \approx & \sum_{i=1}^{N}\frac{d\ \log Y}{d\ \log A_i}\log A_i \\ & + \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{d^2\ \log Y}{d\ \log A_i d\ \log A_j}(\log A_i \log A_j),\end{aligned} \tag{10}$$

where Y represents aggregate real GDP, and $\bar{Y}$ denotes the steady-state value of Y. A_i are industry-specific productivity shocks to industry i. In particular, the first line of equation (10) shows shocks' first-order (linear) impact on aggregate GDP, while the second line captures shocks' second-order (nonlinear) impact.

Definition 1 *Define $\Gamma = [\gamma_{ij}]$ as the $N \times N$ model-implied input-output matrix, the model-implied centrality matrix is*

$$\Phi = \eta[\boldsymbol{I} - \mu\Gamma]^{-1}, \tag{11}$$

where each element in the centrality matrix $\Phi = [\phi_{ij}]$ describes sector i's direct and indirect reliance on j as an input supplier. Thus, the model-implied centrality of sector j is given by $\tilde{Centrality}_{(j)} = \sum_{i=1}^{N}\phi_{ij}$.

Proposition 1 *The first-order effect of an industry-specific productivity shock A_i on aggregate GDP is given by*

$$\frac{d\ \log Y}{d\ \log A_i} = \lambda_i, \tag{12}$$

where $\lambda_i = \frac{p_i y_i}{GDP}$ denotes Domar weights, that is, industry i's total sales to GDP ratio.

Assume that $\eta = \mu = 1$,[17] *and the elasticity of substitution of intermediate inputs ε_X is common across all industries. I specify the second-order approximation of aggregate real*

[17] When $\eta = \mu = 1$, the model-implied centrality matrix is essentially the model-implied Leontief inverse matrix $\Phi = [\mathbf{I} - \Gamma]^{-1}$.

GDP as

$$\log\frac{Y}{\bar{Y}} \approx \sum_{i=1}^{N} \lambda_i \log A_i$$
$$+ \frac{1}{2}(\varepsilon_X - 1) \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N} \lambda_l \phi_{li}\phi_{lj} \log A_i \log A_j \tag{13}$$
$$- \frac{1}{2}(\varepsilon_X - 1) \sum_{i=1}^{N}\sum_{j=1}^{N} \tilde{Centrality}_{(i)} \tilde{Centrality}_{(j)} \log A_i \log A_j.$$

Proof: See Appendix D.

Proposition 1 generalizes **?** and **?**'s results by building a connection between centrality dispersion (our network structure measure) and aggregate GDP. Consistent with Hulton's theorem, the first line of equation (13) implies that Domar weights λ_k, sector k's sales to GDP ratio, are sufficient statistics in determining the impact of microeconomic shocks on GDP up to the first-order approximation.

However, Hulton's theorem no longer holds when considering shocks' nonlinear (high-order) effect. The last two lines of equation (13) exhibits the second-order impact of sector-level productivity shocks on GDP. On the one hand, when $i = j$, $\sum_{l=1}^{N} \lambda_l \phi_{li}^2$ in the second line is closely related to our concentration centrality measure, which describes the variation in the extent to which industry i influences other industries within the network. In other words, how evenly an industry's impact is distributed across its consumers within the network. On the other hand, the last line of equation (13) implies that the variance of industry centrality plays a key role in determining aggregate GDP. When $i = j$, $\sum_{i=1}^{N} \tilde{Centrality}_{(i)}^2$ is essentially our empirical network structure measure of centrality dispersion. For example, consider the effect of a negative productivity shock $d\,\log A_i < 0$ only on sector i. If $\varepsilon_X < 1$, a greater centrality dispersion leads to a smaller second-order approximation, and thus a smaller negative impact on aggregate GDP, ceteris paribus. In other words, a more dispersive network structure itself would mitigate aggregate GDP growth.

5 Quantitative Applications

In this section, I first calibrate a set of parameters, set the value of elasticities of substitution, and construct empirical industry-specific TFP shocks from the data. Second, I apply several quantitative exercises to assess the role of production network structures in shaping GDP growth and growth volatility. As discussed earlier, the model-simulated results are obtained by solving the model nonlinearly.

5.1 Calibration Targets

First, in firms' production functions, intermediate input shares γ_{ij} are calibrated so that the steady-state input cost ratios match the elements in the empirical input-output matrix $\mathbf{W}$. Then I calibrate labor shares a_i to be the value added over gross output ratio by sector. I assume the two elasticities of substitution in the production function to be common across industries, respectively.[18] Specifically, I set the elasticity of substitution between labor and intermediates $\varepsilon_Y = 0.4$, as **?** estimates its value to range from 0.4 to 0.8. **?** also argues that with a relatively broad industry classification, industries can barely find close substitutes for inputs in production, so the elasticity of substitution across intermediate inputs ε_X should be close to zero. Therefore, I set $\varepsilon_X = 0.001$ for our model with 46 industries.

Next, I calibrate sectoral expenditure shares b_i in the representative household's consumption function to match the empirical input-output table. I set the elasticity of substitution across final consumption goods to be $\varepsilon_C = 0.9$ since the estimated parameter should be slightly less than one (**?** and **?**). A higher ε_C implies that the household responds to an increase in the relative price of a product by substituting away from it. In addition, following **?**, I set the Frisch elasticity of labor supply $\varepsilon_{LS} = 2$ in the utility function.

Finally, the process of sectoral productivity follows a random walk as in Equation (4). I specify sectoral TFP shocks κ_i to be lognormally distributed so that $\log\kappa_i \sim N(-\Sigma_{ii}/2,\ \Sigma_{ii})$, where Σ_{ii} represents the sample variance of log TFP growth in industry i. In our analysis, I work with uncorrelated sectoral productivity shocks.[19] To calibrate the sample variance of log TFP growth, I first combine the US KLEMS data compiled by **?** and the BEA's annual input-output tables with 46 industries from 1970 to 2017. Then I measure sectoral productivity growth as sectoral Solow residuals following **?** and calculate the variance.

5.2 Model-Simulated Regression

In this subsection, I study the quantitative predictions of the model regarding the empirical correlations between the production network structure, real GDP growth, and growth volatility, as documented in Section 3.3.

To begin with, I simulate the series of sectoral productivities of $T = 50$ years for the U.S. economy by $S = 300$ times. The process for sectoral productivity follows a random walk as in equation (4), in which shocks κ_i are independent and lognormally distributed with $\log\kappa_i \backsim N(-\sum_{ii}/2, \sum_{ii})$. For each simulation $s \subseteq S$, I match the initial steady-state

[18] The estimation of sectoral elasticity of substitution might not be applicable with a level of disaggregation of 46 industries due to data availability (**?**).

[19] **?** argue that the average correlation between sectoral growth rates is small (less than 5%) with a similar level of industry disaggregation as in this paper.

Table 4: Model-implied Real GDP Growth and Centrality Dispersion.

Variables	(1) Data	(2) Model (0.9, 0.4, 0.001)	(3) Model (0.999, 0.999, 0.999)
$\log(Std.centrality_T)$	-0.861***	-0.181***	2.770**
	(0.280)	(0.009)	(1.267)
$\log(Int.m/output_T)$	-0.423***	-1.132***	-0.868***
	(0.156)	(0.030)	(0.012)
$\log(Int.m/output_T^2)$	-27.378***	5.288***	-3.974***
	(4.587)	(1.035)	(0.260)
$\log(Serv./GDP_T)$	-0.142***	-0.889***	-0.001
	(0.396)	(0.051)	(0.006)
Observations	48	15,000	15,000

[1] Using $\Delta\log(RGDP_T)$ as the dependent variable, column (1) presents the empirical results from Table 2, while column (2) and (3) present the OLS regression results estimated from the model-simulated variables. All model-implied variables except real GDP growth have been HP-filtered with a smoothing parameter of 6.25. The number of observations used in model is computed as $T \times S$.
[2] $***p < 0.01$, $**p < 0.05$, $*p < 0.1$, and robust standard errors are in the parentheses.

input-output matrix to the empirical input-output table of 1970, as 1970 is the first year in the sample. The rest of the parameters are calibrated to match year 1970's economy. I also assume workers can flexibly move across industries. Because I simulate the model economy for 50 years, the full reallocation assumption is considered more appropriate in this scenario. Next, I feed each productivity process into the model. With the model-implied path for aggregate real GDP and input-output matrix, I calculate the time series of real GDP growth, growth volatility, centrality dispersion, as well as other control variables included in the empirical regressions. Last, I re-estimate the correlation between the model-simulated input-output network structure, real GDP growth, and growth volatility over S simulations.

The results of re-estimating equation (1) and (2) with model-simulated variables are shown in the second column of Table 4 and 5, respectively. I include the empirical results in column (1) in each table for comparison. Overall, with the calibration $(\varepsilon_C, \varepsilon_Y, \varepsilon_X) = (0.9, 0.4, 0.001)$, our model is able to deliver the observed empirical patterns. In particular, the model predicts a negative relationship between centrality dispersion and real GDP growth in Table 4, implying that as the production network becomes sparsely connected, GDP growth tends to slow down. However, the estimated coefficient on centrality dispersion $\log(Std.centrality_T)$ is only about one-quarter as big as observed in the data. On the other

Table 5: Model-implied Growth Volatility and Centrality Dispersion.

Variables	(1) Data	(2) Model $(0.9, 0.4, 0.001)$	(3) Model $(0.999, 0.999, 0.999)$
$\log(Std.centrality_T)$	0.397**	0.168***	-7.987***
	(0.210)	(0.004)	(0.792)
$\log(Serv./GDP_T)$	0.345	-0.059**	-0.022***
	(0.271)	(0.003)	(0.004)
$Growth\ volatility_{T-1}$	-0.292**	-0.345***	-0.301***
	(0.132)	(0.007)	(0.009)
Observations	48	15,000	15,000

[1] Using $Growth\ volatility_T$ as the dependent variable, column (1) presents the empirical results as in Table 3, while column (2) and (3) present the OLS regression results estimated from the model-simulated variables. All model-implied variables have been HP-filtered with a smoothing parameter of 6.25. The number of observations used in model is computed as $T \times S$.

[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

hand, as presented in Table 5, the calibrated model is able to capture the positive correlation between centrality dispersion and growth volatility as empirically, except that the estimated coefficient is of an order magnitude smaller, which is 0.168 compared to 0.397. One possible explanation for the smaller estimated coefficients is that our parsimonious model has inelastic labor supply and abstracts from capital accumulation. As argued by **?**, elastic capital and labor supply would further amplify TFP shocks.

Finally, in column (3) of Table 4 and 5, I report the model's implied regression coefficients for a (near) log-linear Cobb-Douglas economy by setting $(\varepsilon_C, \varepsilon_Y, \varepsilon_X) = (0.999, 0.999, 0.999)$. As Proposition 1 predicts, the Cobb-Douglas model is unable to replicate the empirical facts.

5.3 The Role of Network Linkages in Propagating Shocks

The previous quantitative exercise highlights the crucial role of production network structure in explaining business cycle fluctuations in the United States over a long time horizon. To ensure the changes in GDP growth and growth volatility are not purely driven by variations in industry sizes, I construct two economies with identical Domar weights but different intersectoral linkages to disentangle the contribution of network interconnections. Without loss of generality, I study a three-sector economy to avoid complexity in the calculation.

In this exercise, I choose year 2002 as the benchmark economy. In particular, I aggregate the original 46 industries into three broadly defined sectors: Agriculture, Manufacturing, and

Table 6: Simulated GDP Moments in the Benchmark and Counterfactual Economies.

$(\varepsilon_C, \varepsilon_Y, \varepsilon_X)$	Mean ($\times 10^4$)	Standard Deviation ($\times 10^2$)	Skewness	Ex-Kurtosis
Panel A: No Labor Reallocation				
Benchmark Economy $(0.9, 0.4, 0.001)$	-5.68	0.20	-2.52	10.92
Counterfactual Economy $(0.9, 0.4, 0.001)$	-2.68	0.15	-1.20	3.04
Benchmark Economy $(0.999, 0.999, 0.999)$	-0.36	0.13	0.01	-0.02
Counterfactual Economy $(0.999, 0.999, 0.999)$	-0.36	0.13	0.01	-0.02
Panel B: Full Labor Reallocation				
Benchmark Economy $(0.9, 0.4, 0.001)$	0.22	0.24	0.23	0.03
Counterfactual Economy $(0.9, 0.4, 0.001)$	0.07	0.22	0.18	0.01
Benchmark Economy $(0.999, 0.999, 0.999)$	0.00	0.00	0.32	0.11
Counterfactual Economy $(0.999, 0.999, 0.999)$	0.00	0.00	0.25	0.09

[1] All simulated moments of log GDP are calculated from 80,000 draws.

Service, to construct a new 3×3 input-output network. Then I construct a counterfactual economy where the three industries have identical industry sizes (Domar weights) as the benchmark one but are connected differently. I shut down the Domar weights channel in the model, so the only source of variation in GDP fluctuations comes from the change in production network structures (or network interconnections).

Moreover, I specify two sets of elasticity of substitution parameters in our analysis: one is the benchmark calibration $(\varepsilon_C, \varepsilon_Y, \varepsilon_X) = (0.9, 0.4, 0.001)$, as described in Section 5.1, and the other is $(\varepsilon_C, \varepsilon_Y, \varepsilon_X) = (0.999, 0.999, 0.999)$ to perform a (near) log-linear Cobb-Douglas model. I also consider two extreme possibilities for the labor market: the case with no labor reallocation, meaning each labor works for a specific industry and cannot be reallocated, and the case with full labor reallocation, where labor can move costlessly across industries. Intuitively, workers cannot move easily across industries within a short time horizon after shocks, so I assume no reallocation for studying shocks' short-run impact. Alternatively, I view the full reallocation assumption as more appropriate to model the long-run impact of productivity shocks. Last, the rest of the parameters are calibrated to match the two economies separately.

Table 6 displays the mean, standard deviation,[20] skewness, and excess kurtosis[21] of model-simulated log aggregate GDP under different specifications. The first two rows in each panel present the results of our CES model with non-unitary elasticities, while the last two rows illustrate the results of a log-linear Cobb-Douglas model. The moments are calculated from 80,000 draws.[22]

I start by explaining the simulated moments under no labor reallocation assumption in Panel A. With non-unitary elasticities $(0.9, 0.4, 0.001)$, all four simulated moments in the benchmark economy are at least twice as much as those in the counterfactual economy in magnitude. Loosely speaking, since the only distinction between the two economies is industry interconnections−ceteris paribus−variations in the simulated GDP moments would attribute to various network structures. For example, a productivity shock to "Agriculture" in the benchmark economy causes a greater loss in the mean of log GDP $(5.68 - 2.68 = 3)$ and higher volatility $(0.20 - 0.15 = 0.05)$ than in the counterfactual economy. These quantitative results are consistent with Proposition 1's prediction that a more dispersive network structure itself dampens the negative impact on GDP growth. On the other hand, great skewness and excess kurtosis imply that the benchmark economy is more vulnerable to adverse shocks.[23]

In contrast, I set parameters $(\varepsilon_C, \varepsilon_Y, \varepsilon_X) = (0.999, 0.999, 0.999)$ to perform a Cobb-Douglas model and re-calculate GDP moments, listed in the third and fourth rows of Panel A. As Hulton's Theorem predicted, simulated results are identical for both economies. This is to say, up to the first-order approximation, the impact of industry-specific productivity shocks on aggregate GDP can be entirely captured by the size of industries, meaning network linkages do not matter. Last, I compare the simulated GDP moments of our benchmark economy between two sets of parameters (in row one and three). The differences in results, e.g., $5.68 - 0.36 = 5.32$ in the mean, capture shocks' nonlinear (higher-order) impact on aggregate output.

A qualitatively similar pattern holds for the model with full labor reallocation assumption, as shown in Panel B. On the one hand, the simulated moments are different under two labor market assumptions, which suggests that the degree of labor reallocation could also affect productivity shocks' impact on GDP. On the other hand, with full labor reallocation, the

[20] In the model, the steady-state value of $Y/\bar{Y}$ equals one, which yields a log value of zero. Therefore, I calculate the standard deviation of model-implied log $(Y/\bar{Y})$ as the model-implied GDP growth volatility.

[21] Excess kurtosis refers to the difference between the kurtosis of log GDP and 3, which is the kurtosis of log GDP distribution against the kurtosis of a normal distribution.

[22] All exercises are simulated with respect to the same agriculture-specific productivity shock with mean 0 and the variance calibrated from the data.

[23] Figure 7 in Appendix C.1 shows the distribution of simulated GDP for the benchmark economy and counterfactual economy. As seen in the figure, the left tail of the aggregate GDP distribution for the benchmark economy is fatter than that for the counterfactual economy.

gap in each simulated between the benchmark and counterfactual economies is smaller. For instance, the reduction in the mean is $0.22 - 0.07 = 0.15$, which is less than 3 under the no-reallocation assumption. Intuitively, given $\varepsilon_X = 0.01 < 1$, if workers are allowed to move freely across industries, a negative productivity shock to an industry will trigger a reallocation of workers towards the hit industry, then mitigate the shock's adverse effect on GDP. Unsurprisingly, a Cobb-Douglas model behaves similarly regardless of interconnections.

5.4 The Aggregate Impact of the Covid-19 Crisis

In the last exercise, I study the quantitative impact of the Covid-19 Crisis on the real economy in our parsimonious model with input-output linkages.[24] I assume the Covid-19 shock is a labor supply shock, meaning it only affects the labor supply in each industry $\bar{L}_{it}$. There are practical reasons for this assumption during the Covid-19 pandemic period. It could be driven by government actions, such as stay-at-home orders, mandated shutdowns, and reduced seating capacity in inner areas that prevent people from working. It might also be households' unwillingness to work due to concerns about their health or unemployment benefits. Although the shock initially hit the labor market, it might affect industries' production decisions, then generate macroeconomic fluctuations via inter-sectoral connections.

The labor supply shock is calibrated to match the changes in the number of employees in each industry in the United States from March 2020 to June 2020. The data comes from the June 2020 Economic News Release compiled by the U.S. Bureau of Labor Statistics. I observe that each industry experienced a 9% reduction in employees on average, whereas "Accommodation" and "Food services and drinking places" lost more than half of their workers. Moreover, I assume no labor mobility across industries since I am interested in the shock's impact on the aggregate economy within a quarter. In response to the labor supply shocks, our model predicts a reduction of real aggregate GDP by 10.5%, which aligns with the decline in real GDP in the second quarter of 2020 measured by the BEA. Therefore, this model does a good job of predicting the aggregate performance of the U.S. economy.

6 Conclusion

This paper argues that the input-output network structure in isolation plays an essential role in propagating sectoral productivity shocks and shaping aggregate fluctuations in the U.S. economy from 1970 to 2017. First, I develop a new measure of network structure,

[24] There are other papers studying economic effects of the Covid-19 crisis on multi-sector Keynesian models with nominal rigidities, see **?**, **?** among others.

named centrality dispersion, to capture the extent to which an economy has a group of star input suppliers. Then I provide empirical evidence that as the U.S. production network has become sparsely connected over the years, such that many more industries rely on a few central input suppliers to produce, leaving the rest of industries more isolated, GDP growth tended to slow down and be more volatile. Second, I build a multisector real business cycle model incorporating CES production functions and preferences and inter-industrial linkages and show that under the nonlinear characterization, production network structure plays a crucial role in propagating sectoral productivity shocks onto aggregate fluctuations. Finally, I measure sector-level productivity shocks from the data, feed them into the model, and study quantitative predictions of the model regarding the empirical correlations between production network structure, GDP growth, and growth volatility. Overall, the calibrated model is able to deliver observed empirical patterns reasonably well, while a Cobb-Douglas model fails to deliver. Our main finding suggests that the U.S. economy has been dominated by a few central input suppliers, so adverse shocks to the economy, especially these star industries, will have a more damaging impact on the real economy. As a result, ex-ante regulations and supportive policies targeting large sectors or corporations, such as the Stress Test, could be desirable to prevent them from catastrophic failure.

In order to emphasize the role of the production network structure, I have embedded inter-sectoral linkages into a purposely simple multisector real business cycle model. A natural next step would be to incorporate the rich set of nominal rigidities and market frictions, which literature has argued are relevant for shock propagation and amplification within the network. I also kept the quantitative exercise simple by focusing on sector-level productivity shocks measured as a simple Solow residual. Another next step would be to incorporate other shocks and understand what drives variations in the production network structure.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2016). Networks and the macroeconomy: An empirical exploration. *Nber macroeconomics annual 30*(1), 273–335.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica 80*(5), 1977–2016.

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Networks, shocks, and systemic risk. Technical report, National Bureau of Economic Research.

Andres, A., I. Ortiz, J. Viguri, and A. Irabien (1995). Long-term behaviour of toxic metals in stabilized steel foundry dusts. *Journal of Hazardous Materials 40*(1), 31–42.

Atalay, E. (2017). How important are sectoral shocks? *American Economic Journal: Macroeconomics 9*(4), 254–80.

Baqaee, D. and E. Farhi (2020a). Supply and demand in disaggregated keynesian economies with an application to the covid-19 crisis. Technical report, National Bureau of Economic Research.

Baqaee, D. R. and E. Farhi (2019). The macroeconomic impact of microeconomic shocks: beyond hulten's theorem. *Econometrica 87*(4), 1155–1203.

Baqaee, D. R. and E. Farhi (2020b). Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics 135*(1), 105–163.

Bigio, S. and J. La'o (2020). Distortions in production networks. *The Quarterly Journal of Economics 135*(4), 2187–2253.

Carvalho, V. and X. Gabaix (2013). The great diversification and its undoing. *American Economic Review 103*(5), 1697–1727.

Carvalho, V. M. (2007). Aggregate fluctuations and the network structure of intersectoral trade.

Carvalho, V. M. (2014). From micro to macro via production networks. *Journal of Economic Perspectives 28*(4), 23–48.

Cecchetti, S. G., A. Flores-Lagunes, and S. Krause (2006). Assessing the sources of changes in the volatility of real growth. Technical report, National Bureau of Economic Research.

Di Giovanni, J., A. A. Levchenko, and I. Mejean (2014). Firms, destinations, and aggregate fluctuations. *Econometrica 82*(4), 1303–1340.

Dupor, B. (1999). Aggregation and irrelevance in multi-sector models. *Journal of Monetary Economics 43*(2), 391–409.

Foerster, A. and J. Choi (2017). The changing input-output network structure of the us economy. *Economic Review-Federal Reserve Bank of Kansas City 102*(2), 23–49.

Foerster, A. T., P.-D. G. Sarte, and M. W. Watson (2011). Sectoral versus aggregate shocks: A structural factor analysis of industrial production. *Journal of Political Economy 119*(1), 1–38.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*(3), 733–772.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Technical report, National Bureau of Economic Research.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2013). Two perspectives on preferences and structural transformation. *American Economic Review 103*(7), 2752–89.

Herrendorf, B., R. Rogerson, and A. Valentinyi (2014). Growth and structural transformation. In *Handbook of economic growth*, Volume 2, pp. 855–941. Elsevier.

Horowitz, K. J., M. A. Planting, et al. (2006). Concepts and methods of the us input-output accounts. Technical report, Bureau of Economic Analysis.

Horvath, M. (2000). Sectoral shocks and aggregate fluctuations. *Journal of Monetary Economics 45*(1), 69–106.

Jones, C. I. (2011). Misallocation, economic growth, and input-output economics. Technical report, National bureau of economic research.

Jorgenson, D., F. M. Gollop, and B. Fraumeni (2016). *Productivity and US economic growth.* Elsevier.

Jorgenson, D. W., M. S. Ho, and J. D. Samuels (2017). Educational attainment and the revival of us economic growth. In *Education, Skills, and Technical Change: Implications for Future US GDP Growth*, pp. 23–60. University of Chicago Press Chicago.

Koren, M. and S. Tenreyro (2013). Technological diversification. *American Economic Review 103*(1), 378–414.

Liu, E. (2019). Industrial policies in production networks. *The Quarterly Journal of Economics 134*(4), 1883–1948.

Long, J. B. and C. I. Plosser (1983). Real business cycles. *Journal of political Economy 91*(1), 39–69.

Long, J. B. and C. I. Plosser (1987). Sectoral vs. aggregate shocks in the business cycle. *The American Economic Review 77*(2), 333–336.

McConnell, M. M. and G. Perez-Quiros (2000). Output fluctuations in the united states: What has changed since the early 1980's? *American Economic Review 90*(5), 1464–1476.

Miranda-Pinto, J. (2019). Production network structure, service share, and aggregate volatility.

Moro, A. (2012). The structural transformation between manufacturing and services and the decline in the us gdp volatility. *Review of Economic Dynamics 15*(3), 402–415.

Moro, A. (2015). Structural change, growth, and volatility. *American Economic Journal: Macroeconomics 7*(3), 259–94.

Peden, J., G. D. Miller, E. Burke, L. Case, C. Harris, T. C. Lindsey, L. Merrifield, J. Brown, L. L. Barnes, and L.-C. Shen (1998). Pollution prevention in the primary metals industry: A manual for pollution prevention technical assistance providers. Technical report, Illinois Waste Management and Research Center.

Yuskavage, R. E., E. H. Strassner, and G. W. Medeiros (2008). Outsourcing and imported inputs in the us economy: Insights from the integrated economic accounts. In *World Congress on National Accounts and Economic Performance Measures for Nations, held in Arlington, VA, May*, pp. 12–17.

Zhan, J., S. Gurung, and S. P. K. Parsa (2017). Identification of top-k nodes in large networks using katz centrality. *Journal of Big Data 4*(1), 1–19.

A Concentration Centrality

A.1 A Measure of an Industry's Influence across Consumers: Concentration Centrality

I choose concentration centrality as the second network structure measure in our analysis. Whereas KB centrality captures an industry's systematic importance as an input supplier, concentration centrality describes the variation in the extent to which one industry can influence the others. In other words, how evenly an industry's impact is distributed across its consumers within the network. This measure is theoretically founded by **?** and determines the second-order effect of sectoral productivity shocks on an economy's aggregate performance, such as GDP growth and volatility.

The concentration centrality of industry i is defined as follows:

$$Concentration\ Centrality_{(i)} = \sum_{k=1}^{N} \lambda_k Variance_{\mathbf{W}^{(k)}}(\Psi_{(i)}),$$

and

$$Variance_{\mathbf{W}^{(k)}}(\Psi_{(i)}) = \sum_{l=1}^{N} w_{kl}\psi_{li}^2 - \Big(\sum_{l=1}^{N} w_{kl}\psi_{li}\Big)^2,$$

where λ_k denotes sectoral Domar weights, that is, industry k's sales to GDP ratio. $Variance_{\mathbf{W}^{(k)}}(\Psi_{(i)})$ measures the variance of the ith column of centrality matrix Ψ, using the kth row of the empirical input-output matrix $\mathbf{W}$ as the distribution. Recall that each element in the centrality matrix $\Psi = [\psi_{li}]$ measures sector l's total reliance on its input supplier i, while $\mathbf{W} = [w_{kl}]$ captures sector k's input expenditure on good l over its total input expenditures in production. Intuitively, a smaller variance means that sector i's influence is more evenly distributed throughout the economy, thus having a lower concentration centrality. In the following subsection, I will provide evidence for the relevance of concentration centrality and an economy's aggregate performance.

A.2 Concentration Centrality, Growth, and Volatility

In Section 3.3, I show empirical evidence of a significant relationship between centrality dispersion and real GDP growth and growth volatility, respectively, and highlight the sole role of network structure in shaping aggregate fluctuations. Next, I will explore the role of concentration centrality, our second measure of network structure, in shaping economic outcomes.

Table 7: Real GDP Growth and the Concentration Centrality of "Management", 1970−2017.

Variables	(1) $\Delta\log(RGDP_T)$	(2) $\Delta\log(RGDP_T)$
$\log(Concent.centrality_{Manage,T})$	0.196***	0.184***
	(0.061)	(0.048)
$\log(Int.m/output_T)$		-0.217***
		(0.156)
$\log(Serv./GDP_T)$		-2.108*
		(0.396)
R-squared	0.128	0.654
Observations	48	48

[1] This table presents the estimated coefficients of the relationship between real GDP growth and the concentration centrality of "Management of companies and enterprises".
[2] All variables except real GDP growth are HP-filtered with a smoothing parameter of 6.25.
[3] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

Table 8: Growth Volatility and the Concentration Centrality of "Retail trade", 1970−2017.

Variables	(1) $Growth\ volatility_T$	(2) $Growth\ volatility_T$
$\log(Concent.centrality_{iT})$	-0.080**	-0.083**
	(0.029)	(0.035)
$\log(Serv./GDP_T)$		0.472
		(0.374)
$Growth\ volatility_{T-1}$	-0.431***	-0.506**
	(0.145)	(0.124)
R-squared	0.222	0.297
Observations	48	48

[1] This table presents the estimated coefficients of the relationship between real GDP growth volatility and the concentration centrality of "Retail trade".
[2] All variables have been HP-filtered with a smoothing parameter of 6.25.
[3] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

Observation 3 *An industry's concentration centrality significantly correlates with real GDP growth and growth volatility.*

To achieve this goal, I first regress aggregate real GDP growth on each industry's concentration centrality separately using the following equation:

$$\Delta\log(RGDP_T) = \beta_3\log(Concent.centrality_{iT}) + \bar{\mathbf{X}}_T'\gamma_3 + \bar{e}_{iT} \tag{14}$$

where $\Delta\log(RGDP_T)$ represents real GDP growth at time T, and $Concent.centrality_{iT}$ is the concentration centrality of sector i of year T. I add the same control variables[25] as in Section 3.3.1: log of service sales share in GDP, $\log(Serv./GDP_T)$, and log of intermediate input sales to gross output ratio, $\log(Int.m/output_T)$.

Table 7 illustrates the estimated results of the "Management of companies and enterprises (Management for short)" sector. The positive coefficients (0.196 and 0.184) imply that a greater concentration centrality of "Management" is associated with faster real GDP growth. In other words, as the influence of "Management" is more unevenly distributed amongst its consumers within the network, it accounts for greater aggregate fluctuations. In our analysis, about half of the 46 industries exhibit a significant relationship between their concentration centrality and aggregate GDP growth.[26]

Next, I estimate the conditional relationship between an industry's concentration centrality and real GDP growth volatility using the equation below:

$$Growth\ volatility_T = \rho_4 Growth\ volatility_{T-1} + \beta_4\log(Concent.centrality_{iT}) + \tilde{\mathbf{X}}_T'\gamma_4 + \tilde{e}_{iT} \tag{15}$$

where $Growth\ volatility_T$ denotes growth volatility, which is the standard deviation of real GDP growth at time T, and the key regressor $Concent.centrality_{iT}$ refers to sector i's concentration centrality in year T. The two control variables in $\tilde{\mathbf{X}}$ are one-period lag of growth volatility, $Growth\ volatility_{T-1}$, and log of service sales over GDP ratio, $\log(Serv./GDP_T)$.

Table 8 lists the results of estimating the correlation between growth volatility and the concentration centrality of "Retail trade" and shows a strong negative correlation between the two variables throughout the sample period. It implies that GDP growth volatility decreases as "Retail" affect its customers more unevenly. As our final result, I find that 17 out of the 46 industries defined in this paper reveal such a significant relationship.[27]

A.3 Model-Simulated Regression

I re-estimate the relationship between model-simulated industry concentration centrality, GDP growth, and growth volatility as in equation (15) and (16), respectively, and list the

[25] I did not include the squared input sales ratio in the regression because the corresponding estimated coefficient is not significant.

[26] Note that although I obtain a positive estimated coefficient for "Management," the sign of the estimated coefficient is not consistent across industries.

[27] See footnote 28.

Table 9: Model-implied Real GDP Growth and Concentration Centrality of "Management".

Variables	(1)	(2)	(3)	(4)
	Data: $\Delta\log(RGDP_T)$		Model: Simulated $\Delta\log(RGDP_T)$	
$\log(Concent.centrality_{Manage,T})$	0.196***	0.184***	-0.022	0.486***
	(0.061)	(0.048)	(0.029)	(0.014)
$\log(Int.m/output_T)$		-0.217***		-1.379***
		(0.156)		(0.036)
$\log(Serv./GDP_T)$		-2.108*		-1.087***
		(0.396)		(0.114)
Observations	48	48	16,500	16,500

[1] Column (1) and (2) present the empirical results as in Table 7, while Column (3) and (4) present the OLS regression results estimated from the model-simulated variables. All model-implied variables except real GDP growth have been HP-filtered with a smoothing parameter of 6.25. The number of observations used in model is computed as $T \times S$.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

Table 10: Model-implied Growth Volatility and Concentration Centrality of "Retail trade".

Variables	(1)	(2)	(3)	(4)
	Data: $Growth\ volatility_T$		Model: Simulated $Growth\ volatility_T$	
$\log(Concent.centrality_{iT})$	-0.080**	-0.083**	-0.195***	-0.094***
	(0.029)	(0.035)	(0.055)	(0.014)
$\log(Serv./GDP_T)$		-0.070		-0.750***
		(0.374)		(0.272)
$Growth\ volatility_{T-1}$	-0.431***	-0.506**	-0.303***	-0.359**
	(0.145)	(0.124)	(0.099)	(0.089)
Observations	48	48	16,500	16,500

[1] Column (1) and (2) present the empirical results as in Table 8, while Column (3) and (4) present the OLS regression results estimated from the model-simulated variables. All model-implied variables except real GDP growth have been HP-filtered with a smoothing parameter of 6.25. The number of observations used in model is computed as $T \times S$.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

results of "Management" and "Retail trade" in Table 9 and Table 10. In each table, the model-implied results (in the last two columns) replicate the empirical results (in the first two columns) reasonably well, especially for the coefficient signs. Broadly speaking, our model is able to replicate the observed correlation between concentration centrality and GDP growth for 17 out of 23 industries.[28] Meanwhile, it reproduces the empirical concentration

[28] I observe a significant relationship between concentration centrality and GDP growth for 23 of the 46 industries in the sample.

Table 11: Sectoral Real Output Growth and Centrality Growth, 1970−2017.

Variables	(1) $\Delta\log(real\ output_{iT})$	(2) $\Delta\log(real\ output_{iT})$	(3) $\Delta\log(real\ output_{iT})$
$\Delta\log(centrality_{iT})$	0.391***	-0.089***	-0.393***
	(0.040)	(0.031)	(0.034)
$\Delta\log(real\ int.m_{iT})$		0.459***	0.285***
		(0.011)	(0.014)
$\Delta\log(Domar\ weight_{iT})$			0.357***
			(0.021)
$\Delta\log(real\ output_{iT-1})$	0.189***	0.071***	0.056***
	(0.021)	(0.016)	(0.015)
R-squared	0.081	0.512	0.573
Observations	2116	2116	2116

[1] Column (1)-(3) present the results of an OLS regression in first differences.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

centrality−volatility correlations for 10 of the 17 industries with significant estimates.

B Industry's Centrality and Real Output Growth

In this section, I study the relationship between an industry's centrality and its real output growth by running the following regression on a panel of 46 industries spanning the 1970−2017 period:

$$\Delta\log(Real\ output_{iT}) = \rho\Delta\log(Real\ output_{iT-1}) + \beta\Delta\log(Centrality_{iT}) + \Delta\log(\mathbf{X'_{iT}})\gamma + e_{iT} \tag{16}$$

where $Real\ ouput_{iT}$ represents the real output in sector i at time T, measured as the chain-type quantity index of sectoral gross output. Therefore, $\Delta\log(Real\ output_{iT})$ refers to sectoral real output growth. $Centrality_{iT}$ denotes the centrality of industry i in year T. Vector $\mathbf{X_{iT}}$ contains two variables: real intermediate inputs $real\ int.m_{iT}$ used by sector i in year T and Domar weights[29] $Domar\ weight_{iT}$. I also include the one-period lag of output growth in the regression to capture the possibility of persistent changes in output (?).

Observation 4 *An industry with a higher centrality tends to have a slower growth rate to grow over time.*

[29] I include Domar weights in the regression for the same reason specified in Section 3.2.2.

Table 11 presents the regression results of estimating equation (20), which reveal a significant negative correlation between sectoral centrality growth and real output growth. In other words, as an industry becomes a more central input supplier over the years, i.e., many more network customers rely on it for their own production process, it tends to have slower (gross output) growth rate to grow. To understand the economic significance of the result in column (3), for a one-standard-deviation increase in an industry's centrality growth, its real output growth declines by about 0.004.

C First-Order Conditions and Steady-State Values

In this section, I spell out the solution of our model. In particular, I write out the constrained maximization problem of a social planner, take first-order conditions, and specify the conditions that characterize the steady state.

C.1 The Social Planner's Problem

The Lagrangian is specified as follows:

$$\begin{aligned}\mathcal{L} = \bar{C}_t\Bigg(\sum_{i=1}^{N} b_i\big(\frac{c_{it}}{\bar{c}_{it}}\big)^{\frac{\varepsilon_C-1}{\varepsilon_C}}\Bigg)^{\frac{\varepsilon_C}{\varepsilon_C-1}} - \frac{\varepsilon_{LS}}{\varepsilon_{LS}+1}L_{St}^{\frac{\varepsilon_{LS}+1}{\varepsilon_{LS}}} \\ + \sum_{i=1}^{N} p_{it}(y_{it} - c_{it} + \sum_{j=1}^{N} x_{jit}) \\ + \sum_{i=1}^{N} w_{ist}(\bar{l}_{is,t} - l_{is,t}) + w_{gt}(\bar{l}_{g,t} - \sum_{i=1}^{N} l_{ig,t}),\end{aligned} \tag{17}$$

where p_{it} is the Lagrangian multiplier on good i's market-clearing condition. w_{st} and w_{gt} represent the Lagrangian multipliers on the specific and general labors, respectively.

Re-stating the expressions

$$y_{it} = \bar{y}_{it}A_{it}\Bigg[a_{it}\Bigg(\frac{L_{it}}{\bar{L}_{it}}\Bigg)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}} + (1-a_{it})\Bigg(\frac{X_{it}}{\bar{X}_{it}}\Bigg)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}}\Bigg]^{\frac{\varepsilon_Y}{\varepsilon_Y-1}},$$

$$L_{it} = \bar{L}_{it}\big(\frac{l_{is_i,t}}{\bar{l}_{is_i,t}}\big)^{\beta_i}\big(\frac{l_{ig,t}}{\bar{l}_{ig,t}}\big)^{1-\beta_i},$$

$$X_{it} = \bar{X}_{it}\Bigg(\sum_{j=1}^{N}\gamma_{ijt}\Bigg(\frac{x_{ijt}}{\bar{x}_{ijt}}\Bigg)^{\frac{\varepsilon_X-1}{\varepsilon_X}}\Bigg)^{\frac{\varepsilon_X}{\varepsilon_X-1}},$$

$$C_t = \bar{C}_t\Bigg(\sum_{i=1}^{N} b_i\big(\frac{c_{it}}{\bar{c}_{it}}\big)^{\frac{\varepsilon_C-1}{\varepsilon_C}}\Bigg)^{\frac{\varepsilon_C}{\varepsilon_C-1}}.$$

The first-order conditions are:

$$[c_{it}]: \quad c_i = C_t\left(\frac{p_{it}}{P_c}\right)^{-\varepsilon_C} b_{it}^{\varepsilon_C}\left(\frac{\bar{C}_t}{\bar{c}_{it}}\right)^{\varepsilon_C-1}. \tag{18}$$

$$[x_{ijt}]: \quad \frac{p_{jt}}{p_{it}} = A_{it}^{\frac{\varepsilon_Y-1}{\varepsilon_Y}}\left(\frac{(1-a_{it})y_{it}}{X_{it}}\right)^{\frac{1}{\varepsilon_Y}}\left(\frac{(1-a_{it})\bar{y}_{it}}{\bar{X}_{it}}\right)^{1-\frac{1}{\varepsilon_Y}}\left(\frac{\gamma_{ijt}X_{it}}{x_{ijt}}\right)^{\frac{1}{\varepsilon_X}}\left(\frac{\gamma_{ijt}\bar{X}_{it}}{\bar{x}_{ijt}}\right)^{1-\frac{1}{\varepsilon_X}}. \tag{19}$$

$$[l_{ist}]: \quad w_{ist} = p_{it}\bar{y}_{it}A_{it}\left(\frac{y_{it}}{\bar{y}_{it}A_i}\right)^{\frac{1}{\varepsilon_Y}} a_{it}\beta_i\left(\frac{L_{it}}{\bar{L}_{it}}\right)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}} l_{ist}^{-1}. \tag{20}$$

$$[l_{igt}]: \quad w_{gt} = p_{it}\bar{y}_{it}A_{it}\left(\frac{y_{it}}{\bar{y}_{it}A_i}\right)^{\frac{1}{\varepsilon_Y}} a_{it}(1-\beta_i)\left(\frac{L_{it}}{\bar{L}_{it}}\right)^{\frac{\varepsilon_Y-1}{\varepsilon_Y}} l_{igt}^{-1}. \tag{21}$$

Assume the model economy only contains one type of labor l_i for simplicity and w denotes the corresponding wage rate. Substituting the first-order conditions into the production function implies that

$$p_{it} = A_{it}^{-1}[a_{it}w_t^{1-\varepsilon_Y} + (1-a_{it})\Bigg(\sum_{j=1}^{N}\gamma_{ijt}p_{jt}^{1-\varepsilon_X}\Bigg)^{\frac{1-\varepsilon_Y}{1-\varepsilon_X}}]^{\frac{1}{1-\varepsilon_Y}}. \tag{22}$$

C.2 Steady-State Values

To obtain the steady-state value of key variables in the first-order conditions, we need to ensure that the shares of bar variables in equations to be equal to the corresponding long-run ratios: $P_c = 1$, $A_i = 1$, $p_i\bar{c}_i/\bar{C} = b_i$, $q_i\bar{X}_i/p_i\bar{y}_i = 1-a_i$, $p_j\bar{x}_{ij}/p_i\bar{y}_i = \gamma_{ij}$, $w\bar{L}_i/p_i\bar{y}_i = a_i$. Towards the goal of solving for the steady-state, I drop time subscripts and re-arrange the selected first-order conditions of industry i as follows:

$$x_{ij} = (1-a_i)\gamma_{ij}y_ip_ip_j^{-\varepsilon_X}\Bigg(\sum_{k=1}^{N}\gamma_{ikt}p_{kt}^{1-\varepsilon_X}\Bigg)^{-1}, \tag{23}$$

$$l_i = a_ip_iy_i/w. \tag{24}$$

D Proof of Proposition 1

According to equation (18), the envelope theorem implies that

$$\frac{d\ \mathcal{L}}{d\ A_i} = p_i y_i \tag{25}$$

where $\mathcal{L}$ is equivalent to aggregate GDP, Y. Therefore, equation (29) yields

$$\frac{d\ \log Y}{d\ \log A_i} = \frac{p_i y_i}{Y} = \lambda_i. \tag{26}$$

Next, recall that the market-clearing condition for good i is given by $y_i = c_i + \Sigma_{j=1}^n x_{ji}$, and define $g_{ij} \equiv p_j x_{ij}/p_i y_i$. Multiplying both sides by p_i and dividing by aggregate GDP implies that

$$\lambda_i = b_i + \sum_{k=1}^{n} g_{ki}\lambda_k, \tag{27}$$

where $\lambda_i = p_i y_i / Y$ is the Domar weight of industry i and $b_i = p_i c_i / Y$ are consumption shares in household's first-order condition. Differentiating both sides of the above equation with respect to $\log A_j$ implies that

$$\frac{d\lambda_i}{d\log A_j} = \sum_{k=1}^{n} g_{ki}\frac{d\lambda_k}{d\log A_j} + \sum_{k=1}^{n} \lambda_k \frac{dg_{ki}}{d\log A_j} \tag{28}$$

On the one hand, by Shephard's lemma, differentiating both sides of equation (23) with respect to $\log A_k$ and evaluating it at $\log A = 0$ leads to

$$\frac{d\ \log\hat{p}_i}{d\ \log A_k} = -\mathbf{1}(i=k) + \sum_{j=1}^{n} \gamma_{ij}\frac{d\ \log\hat{p}_j}{d\ \log A_k} \tag{29}$$

where $\hat{p}_i \equiv p_i / w$.

Recall that the model-implied Leontief inverse matrix is $\Phi = (I - \Gamma)^{-1}$, and $\Phi = [\phi_{ij}]$ denotes the element in the matrix, the above equation can be rewritten as

$$\left.\frac{d\ \log\hat{p}_i}{d\ \log A_k}\right|_{\log A = 0} = -\phi_{ik} \tag{30}$$

On the other hand, equation (23) implies that $g_{ij} = (1-a_i)\gamma_{ij} y_i p_i^{1-\varepsilon_X} / \left(\sum_{k=1}^{N} \gamma_{ikt} p_{kt}^{1-\varepsilon_X} \right)$. Hence, differentiating both sides of this expression, evaluating them at $\log A = 0$, and plugging the resulting expression back into equation (28) implies that

$$\frac{d\lambda_i}{d\log A_j} = \sum_{k=1}^{n} \gamma_{ki} \frac{d\lambda_k}{d\log A_j} + \sum_{k=1}^{n} (1-\varepsilon_X)\gamma_{ki}\lambda_k \left(\frac{d\log \hat{p}_i}{d\log A_j} - \frac{1}{1-a_k} \sum_{r=1}^{n} \gamma_{kr} \frac{d\log \hat{p}_r}{d\log A_j} \right) \tag{31}$$

Thus, using equation (30), we obtain

$$\frac{d\lambda_i}{d\log A_j} - \sum_{k=1}^{n} \gamma_{ki} \frac{d\lambda_k}{d\log A_j} = \sum_{k=1}^{n} (\varepsilon_X - 1)\gamma_{ki}\lambda_k \left(\phi_{ij} - \frac{1}{1-a_k} \sum_{r=1}^{n} \gamma_{kr} \phi_{ij} \right) \tag{32}$$

Multiplying both sides of the above equation by ϕ_{is}, summing over all i leads to

$$\frac{d^2 \log Y}{d \log A_i d \log A_j} = \frac{d\ \lambda_i}{d \log A_j} = \sum_{k=1}^{N} (\varepsilon_X - 1)\lambda_k \Big(\sum_{l=1}^{N} \gamma_{kl}\phi_{li}\phi_{lj} - \frac{1}{1-a_k} \sum_{s=1}^{N} \gamma_{ks}\phi_{si} \sum_{l=1}^{N} \gamma_{kl}\phi_{lj} \Big), \tag{33}$$

which implies the second-order effect on aggregate GDP with respect to shocks to sector i and j. In particular, when $i = j$,

$$\frac{d^2 \log Y}{d \log A_i^2} = \frac{d\ \lambda_i}{d \log A_i} = \sum_{k=1}^{N} (\varepsilon_X - 1)\lambda_k \Big(\sum_{l=1}^{N} \gamma_{kl}\phi_{li}^2 - \frac{1}{1-a_k} (\sum_{l=1}^{N} \gamma_{kl}\phi_{li})^2 \Big). \tag{34}$$

Recall that the model-implied centrality of industry j is $Cent\tilde{r}ality_{(j)} = \sum_{i=1}^{N} \phi_{ij}$, thus $Cent\tilde{r}ality_{(i)} Cent\tilde{r}ality_{(j)} \propto \sum_{s=1}^{N} \phi_{si} \sum_{l=1}^{N} \phi_{lj} \sum_{k=1}^{N} \frac{\lambda_k}{1-a_k} \gamma_{ks}\gamma_{kl}$. Re-writing equation (33) leads to

$$\frac{d^2 \log Y}{d \log A_i d \log A_j} \approx (\varepsilon_X - 1) \Big(\sum_{l=1}^{N} \lambda_l \phi_{li}\phi_{lj} - Cent\tilde{r}ality_{(i)} Cent\tilde{r}ality_{(j)} \Big). \tag{35}$$

E Simulated GDP Distributions for Application One

In Figure 7, I provide two histograms to visually illustrate model-simulated GDP in the benchmark (blue bars) and counterfactual (orange bars) economies under different assumptions on the labor market.

Figure 7: Simulated GDP in the Benchmark Economy and the Counterfactual Economy.