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

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Abstract

Hulton's Theorem argues that in the presence of input-output linkages, a sector's role in deciding the impact of microeconomic shocks on the aggregate economy is entirely captured by its size, regardless of its position in the production network. This paper proposes the idea that the production network in isolation represents an essential channel in shaping macroeconomic fluctuations in the United States. First, based on the data from the BEA input-output account, this paper shows that as the empirical production network is getting sparser over the past five decades, namely, a majority of industries are dominated by a few central input suppliers, GDP growth tends to decline and is more volatile. Motivated by these facts, this paper embeds the input-output network into a multisector real business cycle model with CES technologies. In order to highlight the role of the input-output network, this paper characterizes sectoral total factor productivity (TFP) shocks' impact on macroeconomic aggregates nonlinearly. Finally, this paper measures realized sector-level productivity shocks from the data, feeds them into the model, and observes that the calibrated model can quantitatively generate observed empirical patterns. Overall, this paper gauges the crucial role of the production network structure in deciding aggregate fluctuations empirically and quantitatively.

JEL classification: C67, E23, E32
Keywords: production network structure, centrality variation, GDP growth, growth volatility, nonlinearity

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1 Introduction

In the modern economy, to produce any good or service always needs corporation among a wide range of industries or firms. For instance, to make a cellphone, a manufacturing company needs not only raw materials such as electrical components, plastics, screens, but also services like transportation and banking services, etc[1]. In this example, the company acts as a consumer. However, if it then sells cellphones to a wholesaler, it would become a supplier itself. This example is an epitome of a production network or an input-output network[2] that the production of goods and services relies on a complex web of transactions between a bunch of suppliers and consumers in the economy. Based on this network view of the production process, shocks to particular industries or firms might spread to their neighbors, neighbors' neighbors, and so forth via input-output linkages. As a result, microeconomic level distortions might possibly be aggregated up to the overall economy. Furthermore, the production network in the U.S. economy varies over time. Therefore, it raises the question of how does the network structure relates to business cycle fluctuations.

This paper puts forth the idea that the production network structure in isolation represents an essential channel in shaping both GDP growth and volatility. I make this argument in three steps. First, I document features of the production network of the United States and show that the network structure has changed substantially over the past five decades. Moreover, this changing nature of the U.S. production network significantly correlates with macroeconomic fluctuations, such as aggregate GDP growth and volatility. Second, I embed the input-output network into a constant elasticity of substitution (CES) multisector real business cycle model to study the impact of industry-level technology shocks, i.e., changes in factor productivity on the aggregate economy when propagating through different networks. In order to highlight the role of inter-industrial linkages and resource reallocation, I solve the model nonlinearly. Finally, I construct realized sectoral productivity shocks from the data, feed them into the model, and simulate GDP growth and growth volatility. I observe that aggregate GDP growth in more recent years, where the economy is dominated by a few central input suppliers or industries, tends to be slow and more volatile. Specifically, the model-implied relationship between input-output network structure and macroeconomic aggregates is of an order of magnitude similar to that observed in the data.

In the first step of the analysis, this paper provides evidence that both GDP growth and growth volatility are significantly related to the heterogeneous input-output network structure of the U.S. economy. Initially, I use the summary-level input-output data from the Bureau of Economic Analysis (BEA) to construct annual production networks of the United States from 1970 to 2017 and document network

[1]In the example, the intermediate goods used to produce cellphones are provided by the following industries: Electrical equipment, appliances, and components, Plastics and Rubber Products, Transportation and Warehousing, and Finance and Insurance.

[2]Throughout this paper, I use the production network and the input-output network interchangeably. I also use macroeconomic fluctuations and macroeconomic aggregates interchangeably, in this paper they both refer to aggregate GDP growth and growth volatility.

features regarding the diameter and distance, network density, and Katz-Bonacich centrality. The evidence shows that network diameter and average distance are relatively stable over time, but the other two measures tend to fluctuate. According to the Katz-Bonacich centrality measure, which describes one industry's relative importance as an input supplier in the economy, the U.S. production network or industry's centrality is becoming sparser. For example, the centrality of a few industries, such as Finance & Insurance and Professional Services, has risen substantially, meaning those industries are supplying more outputs to the rest of the economy. In contrast, like Paper Products and Mining, some other industries have become more isolated in the production network.

Observing the changing nature of the U.S. input-output network, this paper gauges the role of an input-output network in shaping aggregate fluctuations. In order to capture the heterogeneity of network structure across years, I develop a measure of centrality variation or dispersion, that is, the unweighed cross-sectional standard deviation of centrality. Specifically, I estimate the correlation between the network structure or centrality variation and GDP growth and volatility, respectively, in a panel of 46 industries for the period 1970−2017. The empirical observations suggest that: (i) industries with a broader connection to the rest of the economy are likely to produce more output; (ii) an economy or a production network, where industries are dominated by a few major input suppliers, displays relatively low GDP growth rate, even after controlling for other macroeconomic features; (iii) in an economy or a production network with a greater industrial centrality variation, GDP growth tends to be more volatile.

Motivated by these empirical observations, in the second step, I build a CES real business cycle model embedded with intersectoral linkages to quantitatively assess the role of network structure in determining GDP growth and growth volatility. In the model, each sector produces output using labor and a bundle of intermediate goods purchased from other sectors. According to Hulten's Theorem, in an efficient economy, Domar weight is sufficient statistics in determining the impact of idiosyncratic productivity shocks on GDP (see Acemoglu et al. (2012), Gabaix (2011), V. Carvalho & Gabaix (2013), and among others). In other words, in the presence of input-output linkages, a sector's role in deciding macroeconomic aggregates is entirely captured by its size, regardless of its position in the production network or reallocations of other factors, i.e., labor. However, this paper argues that it might not be true empirically as intersectoral linkages are significantly correlated with GDP growth and growth volatility, respectively, even after controlling for the Herfindahl-Hirschman index (HHI) of sectoral sales shares. Therefore, in order to highlight the sole role of network structures, this paper shares the spirit of theorems in D. R. Baqaee & Farhi (2019) and quantitatively analyzes the nonlinear impact of sectoral productivity shocks on the aggregate economy. In particular, I measure realized sectoral productivity shocks from the data, feed them into the model, and simulate aggregate GDP growth and growth volatility.

The main findings of this paper are as follows. First, when sector-specific productivity shocks propagate through various input-output networks, the aggregate impact on the economy is quantitatively different. On the one hand, the model suggests that relatively sparse economies, where most sectors are linked to a few central suppliers like "Finance and insurance", are less likely to encounter negative growth rates and less volatile than those with a group of "equally" important sectors[3]. On the other hand, I estimate the impact of the Covid-19 crisis, measured as sectoral labor supply shocks, on real GDP. The model predicts a reduction of real GDP of around 10.5%, which is in line with the decline in real GDP in the second quarter of 2020. Second, I feed the technology process into the model, allow the model to grow stochastically, and study the quantitative predictions of the model regarding the empirical correlations between input-output network structure and two macroeconomic aggregates. The model-implied coefficients are of an order of magnitude similar to that observed in the data. Therefore, the nonlinear characterization allows the model to replicate the observed empirical patterns decently.

The rest of the paper is organized as follows. In section 2, I review three strands of literature and present the contributions of this paper. Then I measure empirical input-output production networks and document characteristics of the U.S. network structure over time in section 3. In section 4, I show that the changing nature of the network structure correlates significantly with aggregate fluctuations. Motivated by those observations, in section 5, I develop a multisector real business cycle model with CES technologies and inter-sectoral linkages and calibrate the model. In section 6, I simulate the model in a nonlinear fashion, conduct three quantitative experiments both statically and stochastically, and gauge the role of input-output linkages in deciding macroeconomic aggregates. Section 7 concludes.

2 Literature Review

This paper relates to several extensive pieces of literature studying the origin of macroeconomic fluctuations, the role of an input-output network in propagating sectoral idiosyncratic shocks into the aggregate economy, and how structural transformation determines economic growth.

In the branch of literature that studies the network origin of macroeconomic fluctuations, the canonical work of Gabaix (2011) and Acemoglu et al. (2012) point out that aggregate volatility is primarily the result of microeconomic shocks; also see Long & Plosser (1987), Horvath (2000), Dupor (1999), V. M. Carvalho (2007), and Di Giovanni et al. (2014). Gabaix (2011) and V. Carvalho & Gabaix (2013) show that the *fundamental volatility*, which is constructed as the weighted[4] idiosyncratic firm-level shocks, is able to track the fluctuations of macroeconomic volatility over time. This is because, with the existence of *granular* firms (or large firms), the impact of firm-level TFP shocks will not be canceled out, resulting in aggregate fluctuations. Acemoglu et al. (2012) argue that idiosyncratic shocks to industries that are more important input suppliers propagate more widely through the input-output network and thus do not wash out with shocks to small sectors, generating sizeable aggregate movements.

[3]The results are simulated subjecting to the same sectoral productivity shocks.

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

Atalay (2017) deviates the work of A. T. Foerster et al. (2011) from a Cobb-Douglas economy to the one with CES technologies and preferences to find out the sources of business cycle fluctuations. They both conclude that the interplay of idiosyncratic shocks and the input-output network can account for at least half of the aggregate volatility. This paper shares the spirit of previous literature and identifies sectoral (independent) productivity shocks as the origin of aggregate fluctuations. However, I study a different research question, that is, the role of the production network in propagating microeconomic shocks and shaping macroeconomic aggregates over time.

An adjacent strand of literature builds on the seminal multisector model of Long Jr & Plosser (1983), which provide a theoretical framework to study the role of an input-output network in propagating shocks. Acemoglu et al. (2012) employ a Cobb-Douglas model and observes that the aggregate volatility depends on the interconnection of an input-output network. D. R. Baqaee & Farhi (2019) quantify the macroeconomic impact of sectoral productivity shocks with a multisector CES model and emphasizes the crucial role of network linkages under the nonlinear characterization. There are other papers studying the role of inter-sectoral linkages in spreading microeconomic distortions by deviating from an efficient economy. Jones (2011) argues that the misallocation of resources at the micro-level can aggregate up to TFP through the input-output network. Liu (2019) shows that the effect of market imperfections in the form of deadweight losses accumulate through input-output linkages to upstream supplying sectors, causing resource distortions across sectors. Therefore, there is an incentive for well-meaning governments to subsidize those sectors, thus improve social welfare. D. R. Baqaee & Farhi (2020), working with a CES multisector production function, find that by eliminating mark-up misallocation in such an environment, aggregate TFP would rise by about 15%. In addition, Bigio & La'o (2020) investigate that, with Cobb-Douglas technologies, sector-level financial shocks distort industries input-output decisions away from efficiency levels, and the impact manifests at the aggregate level over production networks. This paper makes two contributions to this strand of literature. First, I develop a unique measure of industry centrality dispersion of a production network to capture network heterogeneity. Second, I use a dynamic model to study quantitative predictions of the model regarding the empirical correlations between heterogeneous network structure and GDP growth and growth volatility, respectively.

My paper also relates to the empirical literature exploring the impact of structural change on economic growth. Koren & Tenreyro (2013) develop a model with endogenized technological diversification to show that firms in rich economies tend to use a large variety of inputs, which mitigate their exposure to productivity shocks and thus reduce aggregate volatility. Herrendorf et al. (2014) document that service sales to GDP ratio increases with income across various countries, and they develop a multisector growth model to account for these salient features. Moro (2012) and Moro (2015) construct a two-sector model of structural transformation to study the impact of sectoral composition of GDP on cross-country differences in GDP growth and volatility. In particular, an increase in the share of services in GDP reduces both aggregate TFP growth and volatility, thus reducing GDP growth and volatility. Miranda-Pinto (2019) builds a multisector model with CES technologies and shows that GDP growth volatility declines with production network diversification. My paper contributes to the previous literature from the following two aspects. From an empirical standpoint, this paper provides evidence that production network structure, as measured by industry centrality variation or dispersion within a network, significantly correlates with two macroeconomic variables. These results hold even after controlling for the HHI of sectoral service shares, indicating that the production network (structure) in isolation can determine aggregate fluctuations. From a more theoretical standpoint, I apply a multisector real business cycle model embedded with CES technologies and input-output linkages to offer a detailed interconnection among all 46 industries.

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

In this section, I present some salient features of the U.S. production network. I observe that the network structure in the United States has changed substantially over the past five decades due to changes either in inter-industrial connections or in one industry's position as an input supplier in the economy. I start by describing the data.

3.1 Data

The U.S. economy includes various industries linked by the goods and services they exchange with one another during production. To measure the intersectoral production network of the U.S. economy, I use the summary-level input-output data from the BEA, which is compiled annually for the period 1970−2017. In particular, I combine the BEA's Make and Use tables[5] to derive the Commodity-by-Commodity Direct Requirements (CCDR) table for each year over my sample period. The Make table documents the value of each commodity produced in each industry (in producer's price). The Use table reports the consumption of commodities by each industry or the final user. Each CCDR table includes 46 industries[6] that are classified at a three-digit industry level according to the North American Industry Classification System

[5]The Make and Use tables used in this paper 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 Horowitz et al. (2006). 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.

[6]The BEA defined 46 broad industries in the year 1947, then it revised the data collection mechanism and redefined 65 and 71 industries in 1963 and 1997, respectively. Therefore, to ensure the total number and classification of industries are consistent over my sample period, I aggregate several industries back into the original 46-industry definition, see details in A. Foerster & Choi (2017). Additionally, I choose the 46-industry classification to access input-output tables at an annual frequency from 1970 to 2017.

(NAICS)[7]. Each nonzero entry (i, j) in the table denotes a directed edge from a supplying industry i to its customer industry j in the network, implying the value of spending on good i per dollar of the production of good j. Each column j is normalized to one, as total intermediate input expenditures must be allocated to all (or at least some) sectors in the economy. Thus, the sum of values of row i, presented as the share of its customers' total intermediate purchases on good i, captures sector i's position as an input supplier in the production network. Table 1 lists the 46 industries included in the following analysis.

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

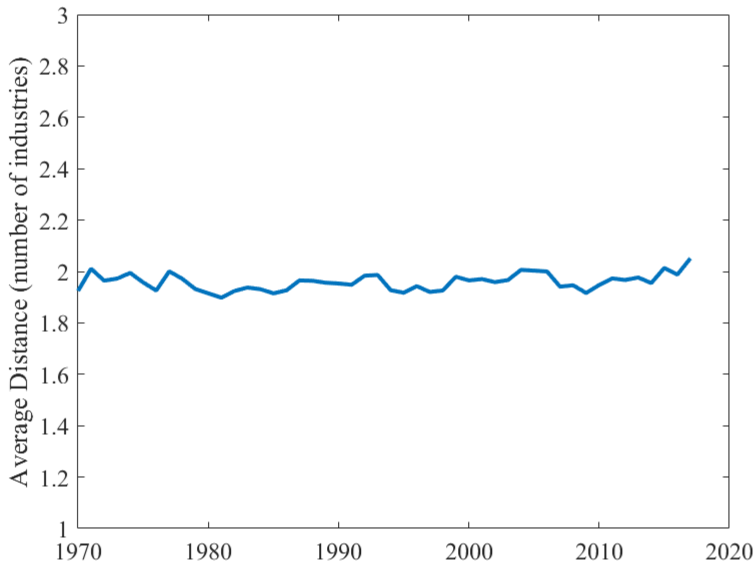
3.2 A Small World of Input Flows: Distance and Diameter

According to V. M. Carvalho (2014), a small-world network is the 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. Therefore, an economy with a small-world network feature might be vulnerable when exposed to sector-level

[7] The BEA collects two-digit and three-digit industry-level data at an annual frequency from 1974 to 2017 and five-digit industry-level data in a five-year interval from 1972 to 2012.

idiosyncratic shocks. Since it takes only a few steps for a sector to reach the other, the impact of shocks might propagate more effectively and quickly within such a network.

Figure 1: Average Distance of the U.S. Input-output Network, 1970−2017.



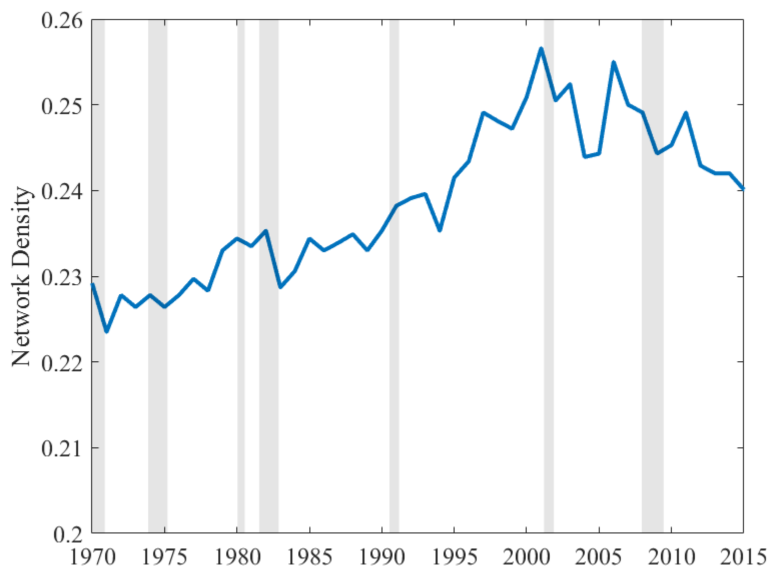
Formally define the diameter of a network, d, as the maximum length of all ordered entries (i, j) of the shortest path from i to j. The average distance, l, represents the average length of the shortest path for all entries (i, j). On average, the diameter of the U.S. production network is about four, and this number is very stable across years. Also shown in Figure 1, the average distance of the network has a mean of two over the sample period. In other words, when the U.S. economy is categorized into 46 industries, it takes about two steps on average for one industry to reach any other industry within the network. Both the small diameter and the short average distance imply a small-world network feature of the U.S. economy over time. Therefore, industries with indirect demand-supply relationships are very likely to be connected through a few central nodes or input suppliers in the economy, consistent with the findings in V. M. Carvalho (2013). For example, imagine an economy where two industries, A and B, do not trade with each other directly. Obviously, there is no direct linkage between them. However, an indirect connection is formed if both industries simultaneously trade with industry C. The existence of the common trade partner C shortens the distance between A and B within the network. When negative shocks, say shutdown or default, hitting a primary input supplier in such a small-world economy, the adverse impact might be spread rapidly to other industries due to short distances among them, generating aggregate fluctuations.

Besides, considering that the diameter and the average distance are relatively stable across years, respectively, the U.S. network structure has barely changed.

3.3 A Measure of Network Interconnection: Density

Network density measures the degree of inter-industrial connection within a network, that is, the portion of all potential linkages among industries that are actually connected. As defined by A. Foerster & Choi (2017), an economy with N industries has a network density of L/N^2, where N^2 is the number of all possible links, and L indicates the actual interconnection. Thus, the value of network density ranges from 0 to 1. The lower limit corresponds to an economy without any inter-industrial connection, while the upper limit refers to the network with all possible sectoral relationships. On average, industries in a denser production network tend to trade with a broader range of other industries. As a result, adverse shocks to such a network are highly likely to affect more sectors in the economy.

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



Note: Shaded area refers to National Bureau of Economic Research (NBER) recessions.

Figure 2 plots the U.S. input-output network density from 1970 to 2017. I assume a link exists between industry i and j if the value of j's intermediate goods purchased from i is at least one percent of its total input expenditures. Over the sample period, the U.S. network density has a mean of 0.239, implying that on average, 506 out of 2,116 direct linkages[8] existed among industries. The standard deviation of network density is 0.0086. This 18-link deviation reveals that the variation of network interconnection is relatively small over time. In addition, although the network density varies over time, it is always below 0.3, meaning the actual inter-sectoral connections are less than 30% of all possible relationships. Concerning this, the U.S. input-output network might not be very efficient in transmitting shocks' impact, as the impact has

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

to be propagated indirectly. Or, oppositely, industries in the economy are connected by a few central nodes or input suppliers, leading to a more effective network structure in propagating shocks.

Also shown in Figure 2, the network density exhibits an increasing trend until early 2000, which indicates that the U.S. industries tended to build trade relationships with one another until 2000 but started to break previous connections afterward. One possible reason for breaking inter-sectoral linkages might lie in the rapid technological improvement since the late 1990s, which allowed industries to alter their production processes towards more efficient ones. More specifically, rather than buying various raw materials to produce in-house, industries started to buy inputs from firms or sectors with specialties, leading to a less interconnected network structure. This sharp decline might also be the consequence of changing global trade patterns. As China joined the World Trade Organization (WTO) by the end of 2001, U.S. firms were more accessible to trade with firms in China. They switched from buying domestic products to cheaper Chinese imports, therefore, lost (at least some) connections with domestic trade partners. There are other large drops in network density that occurred in 1970, 1982, 2001, and 2008, which correspond to historical U.S. recessions. A decline in network density suggests a loss in interconnection among industries. During economic downturns, firms are more likely to encounter liquidity contractions on their budgets and temporarily stop trading with previous partners.

There are potential drawbacks of the density measurement. First, it only measures the number of existing links within a network but not which specific industries are actually connected. For instance, although some industries have changed their trading partners over time, the network density might still be the same and not be able to identify their neighbors. Second, recall that the U.S. economy is classified into 46 industries in this paper, which is highly disaggregated. Therefore, industries are more likely to change the volume of trading with others rather than breaking or building linkages.

3.4 A Measure of the Relative Importance of an Industry: Katz-Bonacich Centrality

Network centrality is used to identify the "key" nodes in a network. While among several different centrality measures, I choose the Katz-Bonacich (Katz for short) centrality in this paper, which captures each industry's relative importance as an input supplier in an economy. According to the Katz centrality, industries are considered more central (with a higher centrality level) if their neighbors are themselves well-connected industries. More importantly, this measure captures both direct and higher-order indirect connections between two random industries. For instance, an industry with a centrality value of 0.2 has twice as much influence as a 0.1 centrality value industry.

Formally, the Katz centrality of an industry j, c_j, is proportional to the weighted sum of its neighbors' centralities, which is given by

$$c_j = \lambda \sum_{i=1}^{N} w_{ij} c_i + \eta$$

where $N = 46$ is the total number of industries defined in my sample, and w_{ij} is the (i, j) element of a $N \times N$ input-output matrix $\mathbf{W}$, referring to a directed link from a supplying sector i to its consumer j. The input-output matrix $\mathbf{W}$ corresponds to the BEA's CCDR table described in section 2.1. In addition, η is a baseline centrality level that is identical across industries, and $\lambda > 0$ is an attenuation factor. Recall that the Katz centrality measures both direct and indirect interconnections within the network. Therefore, longer distance, i.e., more steps or edges between industry i and j, will be penalized through the attenuation factor λ (Zhan et al. (2017)).

Rewrite previous equation into a matrix form,

$$\mathbf{c} = \lambda \mathbf{W}'\mathbf{c} + \eta \mathbf{1}$$

therefore,

$$\mathbf{c} = \eta [\mathbf{I} - \lambda \mathbf{W}']^{-1} \mathbf{1}$$

where $\mathbf{c}$ is a $N \times 1$ vector of industrial centralities, $\mathbf{1}$ is a vector of ones, and $\mathbf{I}$ is the identity matrix. Following V. M. Carvalho (2014), I set the attenuate factor $\lambda = 0.5$, and $\eta = (1 - \lambda)/N$.

Using the above algorithm, I calculate the Katz centrality of all 46 industries from 1970 to 2017, respectively. In each year, the sum of overall industry centrality is normalized to one. Figure 3 plots four selected industries[9] that have increased in the centrality levels over the past fifty years. They are "Finance and Insurance", "Real Estate", "Professional, scientific, and technical services", and "Administrative and waste management services."

On the one hand, "Professional, scientific, and technical services (Professional services for short)" and "Administrative and waste management services" exhibited a more than 50% increase in their centrality levels since 1970, indicating many more industries directly and indirectly rely on them for their own production process. One possible explanation is that rather than hiring accountants, statisticians, or cleaning persons to produce in-house, firms or industries prefer outsourcing those jobs to professional companies (Yuskavage et al. (2008)). Consequently, industries (or firms) that offer specialized services are more desirable by others, thus have their centralities risen over time. Suppose a series of technological shocks hitting "Professional services" in 1970 and 2010, respectively. It is reasonable to expect a more significant spillover impact on the rest of the economy in the latter year since more other industries relied on "Professional services" in 2010 than in 1970.

On the other hand, "Finance and insurance" and "Real estate" present similar periodic patterns throughout the sample, despite the fact that their centralities are different in magnitude. Figure 3 shows that their centrality levels grew relatively

[9] Of all industries that increased in centrality throughout the sample, these four sectors saw the largest gains in centrality.

smoothly up to the early 1990s and started to jump afterward. This jump coincided with the U.S. real estate boom from the mid-1990s to 2005. The continuous growth in the demand for houses had boomed financial and real estate-related services, making these two industries more influential in the economy. However, the centrality of "Finance and insurance" declined sharply in 2007, when the recent financial crisis occurred. As subprime mortgage defaults triggering the financial system to collapse, banks stopped providing funds to the real economy, leaving some inter-sectoral connections vanished.

Figure 3: Selected Industries that Increased in Centrality.

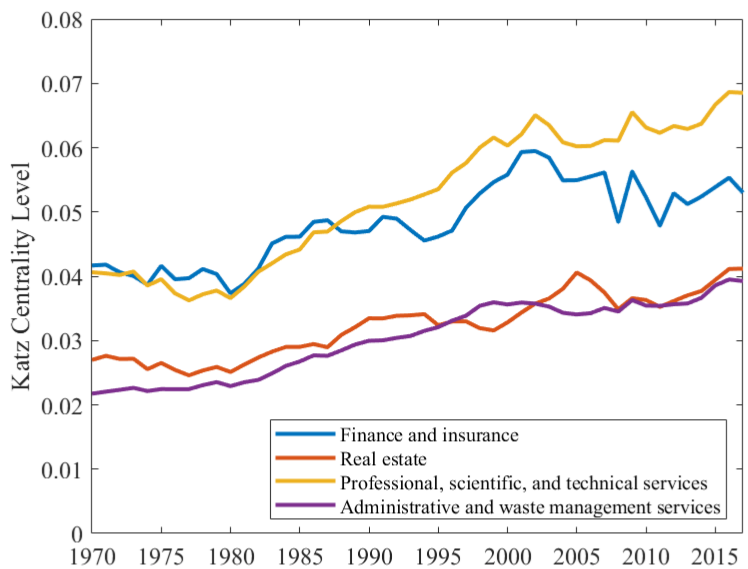


Figure 4 depicts four selected industries that have decreased in centralities. Among all U.S. industries with a declining centrality over time, most of them fall into the manufacturing category. In other words, the manufacturing sector as a whole has been gradually supplying fewer inputs to the real economy. For instance, starting from the 1980s, more stringent environmental regulations were imposed on the "Primary metal" industry, which increased its costs of production as old equipment needed to be replaced by new environment-friendly ones (Andres et al. (1995)). Furthermore, foreign companies entered the U.S. market with cheaper imports. Both situations weaken "Primary metal" competitiveness in the domestic market (Peden et al. (1998)) and reduce its centrality.

In Figure 5, the centrality of three selected industries has similar cyclical patterns but with a lower frequency than the business cycle. Three industries have maintained (roughly) the same centrality levels between 1970 and 2017. They also experienced spikes in the centrality level in both the early 1980s and late 2000s.

Considering the Katz centrality, all 46 industries throughout the sample changed their importance as an input supplier in a production network.

Figure 4: Selected Industries that Decreased in Centrality.

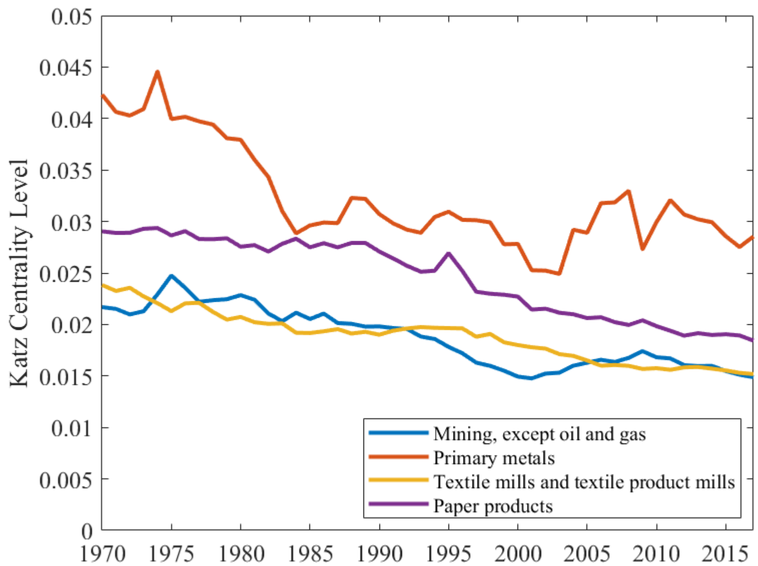
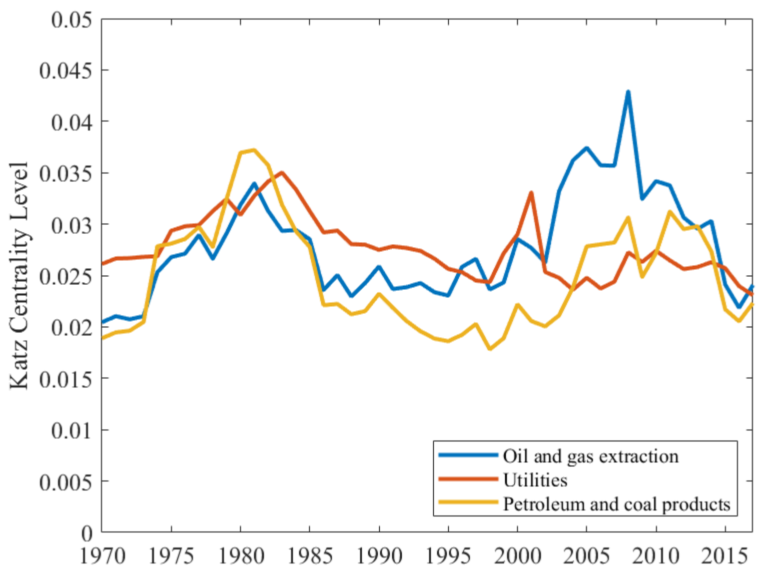


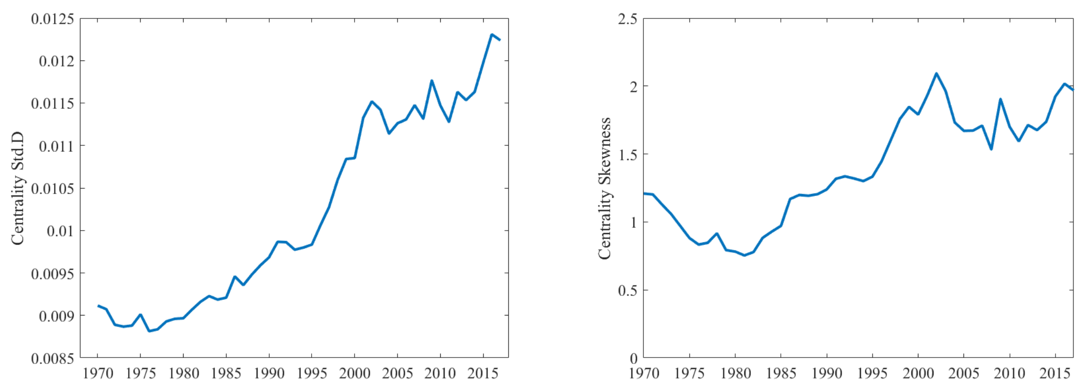
Figure 5: Selected Industries that Fluctuate in Centrality.



3.5 Production Network Heterogeneity

After calculating the Katz centrality of each individual industry in each year, I form annual centrality distributions spanning 1970 to 2017. I choose two statistics, the unweighted cross-sectional standard deviation and skewness of industry centrality distribution, to describe the structure of a production network[10] in a given year. Two statistics are depicted in Figure 6. Whereas standard deviation measures the industry centrality dispersion in a network, skewness quantifies the asymmetry of a random centrality about its mean in a probability distribution. Intuitively, an increase (or a decrease) in the standard deviation of a centrality distribution implies more (or less) dispersive centralities across sectors from its mean. Moreover, skewness reveals whether this economy contains more central suppliers or a bunch of relatively unimportant sectors instead. Untangling how U.S. production network structure has changed over time is crucial, as sector-level (idiosyncratic) shocks might be propagated differently through various networks, generating distinct aggregate impacts. Throughout this paper, I use the unweighted cross-sectional standard deviation of centrality to measure heterogeneous network structures across years.

Figure 6: Centrality Std.D (left panel) and Skewness (right panel), 1970−2017.



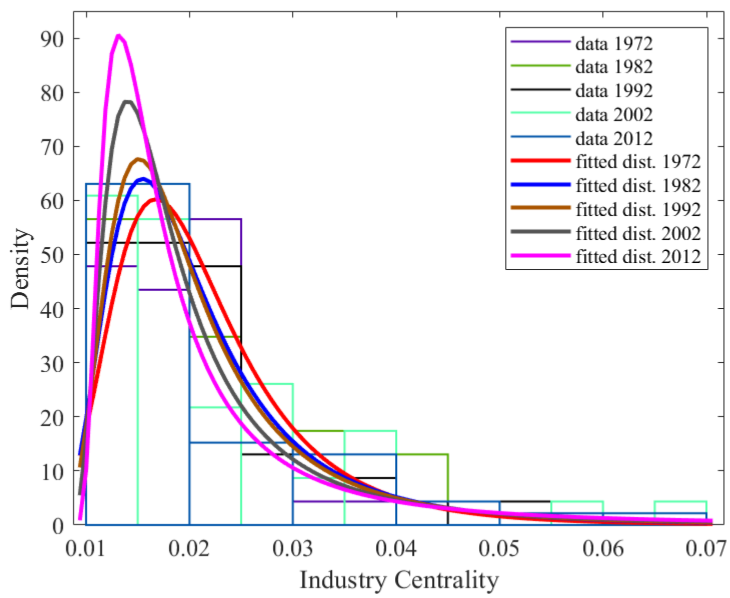
As plotted in the left panel of Figure 6, the increasing trend of standard deviation suggests that over time centralities across industry spread further from their mean. Also, the rising value in skewness (in the right panel) indicates a progressively right-skewed centrality distribution. In other words, the "body" of the distribution gradually shifts to the left, which makes its right tail heavier. They both imply that, with a higher probability, those central industries or important input suppliers would emerge in the latter years in the US economy than in the earlier ones.

To provide a clear vision of how the U.S. production network structure changes over time, I plot generalized extreme value (GEV) distributions of industry centrality in five different years in Figure 7. First, I find the probability distribution that best fits the limited data (with a number of 46 industry centralities in each year) in my sample, which is the GEV distribution. Second, I plot fitted distributions for the following five years: 1972, 1982, 1992, 2002, and 2012.

In general, the fitted centrality distribution skewed right and obtained fatter tails. On the one hand, they suggest that more important input suppliers emerged in the latter years, or alternatively, some particular industries became more influential. For

[10]Network structure describes the inter-industrial connection among U.S. industries in a production network.

Figure 7: Fitted GEV Distribution of Industry Centrality in Five Years.



example, as mentioned in section 3.4, "Professional services" has increased its centrality substantially from about 0.4 in 1972 to 0.6 in 2012, indicating that more other sectors directly and indirectly purchased inputs from it. On the other hand, as the bulk of centrality shifting to the left, it also implies that relatively unimportant industries have maintained a weak interconnection with others over time. Two features jointly identify that industries in the U.S. production network are getting more "dispersed" throughout the sample, where most industries are linked by a few major input suppliers. Therefore, adverse productivity shocks might cause a more damaging impact on the aggregate economy when hitting a critical supplier in more recent years.

4 Aggregate Fluctuations and the Production Network Structure

In this section, I study how the changing network structure accounts for aggregate fluctuations. In particular, I confirm that variations in network structure are significantly correlated with sectoral real output, aggregate real GDP growth and growth volatility, respectively.

4.1 Sectoral Real Output and the an Industry's Relative Importance in the Production Network

First, I estimate the correlation between sectoral real output and its centrality level by running the following regression on a panel of 46 industries spanning from 1970 to

2017 with industry fixed effects:

$$\log(real\ output_{iT}) = \beta_1 * \log(centrality_{iT}) + \mathbf{X'_{iT}}\gamma_1 + e_{iT} \tag{1}$$

where $real\ output_{iT}$ is the chain-type quantity index of gross output[11] in sector i at time T, and $centrality_{iT}$ represents the centrality level of industry i in period T. I select the logarithm of intermediate sales to gross output ratio as the control variable in vector $\mathbf{X_{iT}}$ since changes in goods supplied to other sectors might affect its output level, as in Miranda-Pinto (2019).

Table 2: Sectoral Real Output and Centrality, 1970−2017.

Variables	(1) log $real\ output_{iT}$	(2) log $real\ output_{iT}$
$\log(centrality_{iT})$	0.991***	0.880***
	(0.092)	(0.090)
$\log(int.m/g.\ output_{iT})$		0.683***
		(0.068)
Industry Fixed Effects	Yes	Yes
R-squared	0.506	0.528
Observations	2208	2208

[1] Column (1) and (2) present the results of fixed effects regression. There is one observation for each industry every year, which lead to a total number of 2028 observations (48×46).
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

Observation 1 *There is a positive relationship between sectoral real output and its centrality.*

Table 2 presents the estimated results of a fixed effects regression, revealing a significant positive correlation between sectoral centrality and its real output (presented in Observation 1). On average, a one-percent increase in the sector's centrality level leads to a 0.99-percent rise in its real output. Since an industry with a greater centrality means that more customers or sectors directly and indirectly rely on it for their production process; therefore, it supplies more products (greater real output). Besides, I estimate a similar correlation but using sectoral real value-added as the independent variable instead, and the results are also robust.

[11] The gross output by industry data is adjusted using year 2002's prices and is available at `https://apps.bea.gov/iTable/` from the BEA.

4.2 Aggregate Real GDP Growth and the Production Network Structure

As mentioned in subsection 3.5, I calculate the unweighted cross-sectional standard deviation of industry centrality distribution, which is a measure of centrality variation or dispersion of a network, to capture production network heterogeneity. The values are listed in the independent variable *Std.centrality*.

Next, I estimate the correlation between aggregate real GDP growth and centrality variation. Consider the following OLS regression:

$$RGDP\ growth_T = \beta_2 * \log(Std.centrality_T) + \bar{\mathbf{X}}'_{\mathbf{T}}\gamma_2 + \bar{e}_T \tag{2}$$

where $RGDP\ growth_T$ represents the U.S. real GDP growth rate at time T, and the independent variable $Std.centrality_T$ represents the centrality dispersion in period T. The vector $\bar{\mathbf{X}}$ contains three control variables of other determinants of real GDP growth from previous literature: the share of service[12] sales in gross output (Moro (2012)), $int.m/g.\ output_T$, the intermediate input sales to gross output ratio (Miranda-Pinto (2019)), $serv./g.\ output_T$, and the HHI of sectoral sales shares[13], HHI_T.

Table 3: Real GDP Growth and the Standard Deviation of Centrality, 1970−2017.

Variables	$RGDP\ growth_T$			
	(1)	(2)	(3)	(4)
$\log(Std.centrality_T)$	-0.519***	-0.608**	-0.371**	-0.347**
	(0.155)	(0.245)	(0.215)	(0.203)
$int.m/g.\ output_T$		-0.079	-0.409***	-1.064***
		(0.128)	(0.122)	(0.262)
$serv./g.\ output_T$			-2.532***	-3.189***
			(0.671)	(0.730)
HHI_T				4.717***
				(1.399)
R-squared	0.113	0.120	0.345	0.481
Observations	48	48	48	48

[1] This table presents the OLS regression results, using real GDP growth rate 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.

[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.

[13] 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.

Observation 2 *Aggregate real GDP growth and the centrality dispersion are negatively correlated.*

The estimated regression coefficients are exhibited in Table 3. In column (1), the coefficient suggests that for a one-percent increase in the standard deviation of centrality, the expected mean of real GDP growth rate declines by about 0.005 or 0.5%. This negative relationship (summarized in Observation 2) states that as the production network is getting sparser, or equivalently, as many more sectors are linked by a few major suppliers, the output growth slows down. In the United States, service sectors have been expanding for over decades and forming more connections with the rest of the economy. However, although service sectors account for a larger share in GDP, they are less productive compared to manufacturing (Moro (2015)). Therefore, it is reasonable to expect a declining aggregate GDP growth over time. Also shown in columns (2) and (3), results are robust when including selected control variables.

Moreover, in order to highlight the sole role of input-output linkages in determining real GDP growth, I re-estimate the correlation by adding a third control variable, the HHI of sectoral sales shares. Hulton's Theorem argues that in the presence of input-output linkages, an industry's role in deciding the impact of microeconomic shocks on the aggregate economy is entirely captured by its size, regardless of its position in the production network. However, the estimated coefficients listed in column (4) are statistically significant. The fact that the network structure matters even after controlling for industries' sales shares suggests that sectoral interconnection in isolation might account for aggregate GDP growth. This finding can also be seen as an empirical complement to D. R. Baqaee & Farhi (2019), who argue that theoretically, Domar weight[14] is not a sufficient statistics in explaining the impact of sectoral productivity shocks on the aggregate economy.

In addition, there might be a potential reverse causality problem in regression since GDP growth might also affect the inter-industrial connection among sectors. Regarding this issue, I conduct the Granger causality test, and the results suggest that the reverse causality issue should not be a primary concern for this paper.

4.3 Real GDP Growth Volatility and the Production Network Structure

In this subsection, I estimate the relationship between centrality dispersion and the volatility of real GDP growth using the equation below.

$$Growth\ volatility_T = \beta_3 * \log(Std.centrality_T) + \mathbf{\tilde{X}'_T}\gamma_3 + \tilde{e}_T \tag{3}$$

where $Growth\ volatility_T$ denotes the standard deviation of the U.S. real GDP growth at time T. $Std.centrality_T$ captures a particular network structure in period T. I include three controls in the regression, which are the same ones as in the previous subsection.

[14] *Domar weight* is defined as sector's sales to GDP ratio.

To measure real GDP growth volatility, I follow the technique provided by Cecchetti et al. (2006). Specifically, I regress the first difference of log real GDP on its first lags spanning the 1970-2017 period and obtain a series of estimated residuals, $\hat{\varepsilon}_t$. As argued by McConnell & Perez-Quiros (2000), if residual $\hat{\varepsilon}_t$ follows a normal distribution, the transformed residuals, $\sqrt{\frac{\pi}{2}}\,|\hat{\varepsilon}_t|$, are unbiased estimators of the standard deviation of true residual, ε_t. Therefore, I calculate transformed residual as the real GDP growth volatility and denote it as $Growth\ volatility_T$.

Table 4: Real GDP Growth Volatility and the Standard Deviation of Centrality, 1970−2017.

Variables	$Growth\ Volatility_T$			
	(1)	(2)	(3)	(4)
$\log(Std.centrality_T)$	0.179**	0.304***	0.321***	0.323**
	(0.086)	(0.109)	(0.117)	(0.126)
$int.m/g.\ output_T$		0.110*	0.087	0.134
		(0.068)	(0.095)	(0.205)
$serv./g.\ output_T$			-0.182	-0.139
			(0.450)	(0.507)
HHI_T				-0.345
				(0.722)
R-squared	0.059	0.079	0.083	0.097
Observations	48	48	48	48

[1] This table presents the coefficients of estimating equation (3), 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.

Observation 3 *The relationship between real GDP growth volatility and the centrality dispersion is positive.*

Table 4 presents the regression results of equation (3). The results indicate a strong positive correlation between the cross-sectional standard deviation of centrality or centrality dispersion and real GDP growth volatility. For example, a one percent increase in centrality variation is associated with an about 0.2 percent increase in the expected mean of aggregate volatility. When industries within a production network have more diffused centralities, GDP growth tends to be more volatile. In other words, the network structure in the latter years might be more vulnerable to (positive and negative) shocks. The results are robust when adding control variables such as the share of services in total output, $serv./g.\ output_T$, and the intermediate sales to GDP ratio, $int.m/g.\ output_T$.

Similar to the previous subsection, I re-estimate equation (3) conditional on the HHI of sectoral sales shares. The estimated results also confirm that intersectoral linkages significantly correlate with aggregate volatility even in the absence of sectoral sales shares (Domar weight).

5 Model and Calibration

To model the economy, I embed intersectoral linkages into a multisector real business cycle model with CES technologies, as in Atalay (2017) and D. R. Baqaee & Farhi (2019). Throughout this section, variables with overlines are normalizing constants equal to their steady-state values. Since I focus on percentage changes in GDP, the normalizing constants are irrelevant.

5.1 The Benchmark Nested-CES Network

Firms

In the benchmark 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), an intermediate input bundle, and one CES nest. The production function is given by

$$\frac{y_{it}}{\bar{y}_{it}} = A_{it}\left[a_{it}\left(\frac{L_{it}}{\bar{L}_{it}}\right)^{\frac{\theta_i-1}{\theta_i}} + (1-a_{it})\left(\frac{X_{it}}{\bar{X}_{it}}\right)^{\frac{\theta_i-1}{\theta_i}}\right]^{\frac{\theta_i}{\theta_i-1}} \tag{4}$$

where y_{it} is sector i's output, and L_{it} is the amount of labor used by i. X_{it} is a bundle of intermediate inputs used in production that are purchased from other sectors. The elasticity of substitution parameter θ_i measures how easily factors of production are substituted, while parameter a_{it} reflects the usage of labor in i. A_{it} is total factor productivity (TFP), which follows a random walk:

$$\log A_{it} = \log A_{it-1} + \kappa_{it} \tag{5}$$

where κ_{it} are innovations, referred to as sectoral productivity shocks.

The intermediate input bundle X_{it} consists goods or services purchased from other sectors by industry i, aggregated through the economy's input-output network:

$$\frac{X_{it}}{\bar{X}_{it}} = \left(\sum_{j=1}^{N}\gamma_{ijt}\left(\frac{x_{ijt}}{\bar{x}_{ijt}}\right)^{\frac{\varepsilon_i-1}{\varepsilon_i}}\right)^{\frac{\varepsilon_i}{\varepsilon_i-1}} \tag{6}$$

where x_{ijt} is the quantity of inputs purchased by i from its supplier j in year t. Parameter $\gamma_{ijt} \geq 0$ is the element of model-implied input-output matrix $\mathbf{\Gamma}$, which is designated as the share of good j in the total intermediate input usage by sector i. I assume that sector i's intermediate good bundle is produced with constant returns to scale technology such that $\sum_{j=1}^{N}\gamma_{ij} = 1$. γ_{ij} also corresponds to the (j, i) element of the empirical input-output matrix $\mathbf{W}$, which measures the expenditure on input j per dollar of production of good i. The elasticity of substitution parameter ε_i captures the substitutability across intermediate goods demanded by sector i.

Following D. R. Baqaee & Farhi (2019), I allow for two types of labor[15] in the economy, specific labor $l_{is_i,t}$ and general labor $l_{ig,t}$. Whereas the specific labor can only be used by sector i thus cannot be reallocated anywhere else, the general labor can be flexibly moved across sectors without any transaction cost. Total labor supplied in industry i is organized as

$$\frac{L_{it}}{\bar{L}_{it}} = \left(\frac{l_{is_i,t}}{\bar{l}_{is_i,t}}\right)^{\beta_i} \left(\frac{l_{ig,t}}{\bar{l}_{ig,t}}\right)^{1-\beta_i} \tag{7}$$

where β_i is the portion of specific labor in total labor supplied in sector i. In addition, two types of labor are in fixed supplies, such that $\bar{l}_{s_i,t} = \bar{l}_{is_i,t}$ and $\bar{l}_{g,t} = \sum_{i=1}^{N} \bar{l}_{ig,t}$.

There are two extreme cases. When $\beta_i = 1$, only industry-specific labor exists; no labor can be reallocated to other sectors. When $\beta_i = 0$, all labor can move flexibly. As labor is hard to adjust in a short time horizon, I might expect a lower degree of labor reallocation accordingly.

Household's Preferences

There is one representative household who has a preference over leisure and N different consumption goods (or services) at time t. The utility function is specified as follows

$$U(C_t, L_t) = C_t - \frac{\varepsilon_{LS}}{\varepsilon_{LS}+1} L_t^{\frac{\varepsilon_{LS}+1}{\varepsilon_{LS}}} \tag{8}$$

subject to the budget constraint

$$w_t L_t + \sum_{i=1}^{N} \pi_{it} = P_{c,t} C_t \tag{9}$$

where C_t represents the household's aggregate consumption over different types of final goods c_{it}. $P_{c,t}$ is the associated ideal price index, and is assumed to be a numeraire. The household supplies a total amount of labor L_t to all sectors, and receives a profit of π_{it} from each sector i ($\pi_{it} = 0$ for each i at equilibrium). The Frisch elasticity of labor supply, $\varepsilon_{LS} > 0$, describes the sensitivity of household's desired labor supply to a given wage w_t.

The aggregate consumption function is constructed as

$$\frac{C_t}{\bar{C}_t} = \left(\sum_{i=1}^{N} b_i \left(\frac{c_{it}}{\bar{c}_{it}}\right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{10}$$

where parameter b_i illustrates the importance of good i in his or her preference, which satisfies $\sum_{i=1}^{N} b_i = 1$. The elasticity of substitution σ describes how easily different consumption goods are substituted by the representative household.

[15] This paper allows for two types of labor in the model since D. R. Baqaee & Farhi (2019) argue that the degree of factor (labor) reallocation can affect sectoral TFP shocks' impact on the aggregate economy when characterizing the model nonlinearly.

Competitive Equilibrium

A decentralized competitive equilibrium of this CES-nested economy contains a set of prices $\{w_t, p_{it}, p_{it}^X\}_{i=1}^N$, an allocation $\{C_t, L_t, c_{it}\}_{i=1}^N$ for the representative household, and an allocation $\{L_{it}, y_{it}, \{x_{ijt}\}_{j=1}^N\}_{i=1}^N$ for industries given a vector of sectoral productivity shocks $\{A_{it}\}_{i=1}^N$, such that

- Each industry maximizes profits.
- The representative household maximizes utility as in equation (8) subject to the budget constraint.
- Goods and labor markets clear

$$y_{it} = c_{it} + \sum_{j=1}^{N} x_{jit},$$

$$L_t = \sum_{i=1}^{N} L_{it}.$$

Solution Method

I solve this model nonlinearly to characterize sectoral TFP shocks' impact on the aggregate economy up to a second- and higher-order approximation. The key advantage of nonlinearization is that it emphasizes the role of inter-sectoral linkages $\mathbf{\Gamma}$ and the degree of labor reallocation β_i in determining the impact of sector-level productivity shocks on aggregate GDP growth and growth volatility (D. R. Baqaee & Farhi (2019)). First order conditions will be provided in the appendix.

5.2 Calibration Targets

In this subsection, I calibrate a set of parameters, set up values of three elasticities of substitution, and construct empirical sectoral productivity shocks from the data. In the benchmark calibration, two elasticities of substitution parameters in production function are assumed to be structural parameters[16]; they are time-invariant and identical across industries, respectively.

First, in the firm's production function, intermediate input shares γ_{ij} are calibrated so that steady-state input cost ratios match the empirical input-output matrix $\mathbf{W}$[17] at a level of disaggregation of 46 sectors. Then I calibrate labor shares a_i to match the ratio of sectoral value added over its gross output in a given year. For the elasticity of substitution between value added and intermediate inputs, I set $\theta = 0.4$, as Atalay (2017) estimates this parameter to be from 0.4 to 0.8. Also, following Atalay (2017), I set the elasticity of substitution across intermediate goods to be $\varepsilon = 0.01$.

[16] The estimation of sectoral elasticity of substitution might not be applicable with a level of disaggregation of 46 industries due to data availability (D. R. Baqaee & Farhi (2019)). Therefore, i subscript will be dropped.

[17] The empirical counterpart of $\mathbf{W}$ is the U.S. CCDR table derived from the BEA.

With such a disaggregated classification employed by this paper, industries might not easily substitute one type of intermediate input for others.

Next, in the household's utility function, I calibrate expenditure shares b_i to match the input-output table in a given year. Then I set the elasticity of substitution across final consumption goods to be $\sigma = 0.9$ since the estimated parameter might be slightly less than one (Atalay (2017) and Herrendorf et al. (2013)). A higher σ implies that the representative household responds to an increase in the relative price of a good by substituting away from it. In addition, the Frisch elasticity of labor supply, which includes the changes in hours worked per worker, employment, and effort (V. Carvalho & Gabaix (2013)), is set to be $\varepsilon_{LS} = 2$.

Finally, the process of sectoral productivity follows a random walk as in Equation (5), in which sectoral TFP shocks κ_i are independent and lognormally distributed in the way that $\log\kappa_i \sim N(-\Sigma_{ii}/2,\ \Sigma_{ii})$, where Σ_{ii} is the sample variance of log TFP growth in industry i. In particular, I combine the 46 sector US KLEMS data compiled by D. W. Jorgenson et al. (2017) and the BEA's annual input-output tables spanning the 1970-2017 period and calibrate the variance for sectoral productivities following the methodology developed by D. Jorgenson et al. (2016). In general, sectoral TFP shocks are identified as sectoral Solow residuals. I also assume that sectoral productivity shocks are uncorrelated[18].

6 Quantitative Application

In this section, I apply several quantitative exercises to assess the role of U.S. production network structure in shaping aggregate GDP growth and growth volatility, statically and dynamically. As discussed earlier, the results are simulated by solving the benchmark model nonlinearly to highlight the inter-sectoral linkages.

6.1 Role of Production Network in Propagating Shocks

Application One: the Economy of 1982 v.s. 2002

In the first quantitative experiment, I feed the realized sector-level productivity shocks[19] specified in section 5.2 into the benchmark model and estimate aggregate GDP growth for two different economies of 1982 and 2002, respectively. Two years are chosen as they present salient input-output network structures. Recall that the centrality distribution in the year 2002 has the highest skewness values over the sample period, while 1982 is the reverse. Table 5 displays the mean, standard deviation, and skewness of log aggregate GDP under different specifications. The model-simulated moments are calculated from 20,000 draws. For comparison, this table also displays the standard deviation of real GDP growth from 1970 to 2017.

[18] D. R. Baqaee & Farhi (2019) argue that the average correlation between sectoral growth rates is small (less than 5%) with a similar level of industry disaggregation as this paper.

[19] TFP shocks series are cross-sectional uncorrelated and drawn from a multivariate log-normal distribution.

Table 5: Simulated and Estimated Moments in 1982 and 2002.

$(\sigma, \theta, \varepsilon)$ $(0.9, 0.4, 0.01)$	Mean ($\times$100)	Standard Deviation ($\times$100)	Skewness
Data			
Real GDP growth	-	2.20	-
Year 1982			
No Reallocation	-0.21	2.24	-0.10
Full Reallocation	0.71	0.77	0.27
Year 2002			
No Reallocation	-0.11	1.41	0
Full Reallocation	0.30	0.51	0.12
Without IO Linkages			
No Reallocation	0.07	1.13	0.01
Full Reallocation	0.42	1.06	0.53

[1] For the data, I use the HP-filtered real GDP growth rate with the smoothing parameter of 6.25.
[2] For the model, I calculate three moments of model-implied log GDP from 20,000 draws.

First, I start with the mean. When industries trade as the year 1982's production network[20], the mean of simulated log aggregate GDP is -0.0021 in the case without labor reallocation. This value indicates that, on average, shocks induce a 0.21% loss of real output from the steady-state level. However, with 2002's network structure, the same shocks only reduce real output by 0.11%, which is substantially lower than in the previous case. A qualitatively similar pattern holds for estimated results with complete labor reallocation, besides the fact that sectoral shocks' impact on real GDP growth is positive in both economies, which are 0.0071 in 1982 and 0.003 in 2002, respectively.

Second, I calculate the standard deviation of log GDP[21] as GDP growth volatility for two years. Regardless of specifications in labor reallocation, the model-implied aggregate GDP growth in 2002 is always about 60% as volatile as in 1982. Moreover, with the input-output network structure of 1982, the simulated second moment replicates the GDP growth volatility observed in the data. In Figure 8, I provide a visual representation of two frequency distributions of model-simulated aggregate real GDP[22]. The blue bars represent the simulated results of 1982's economy, while the

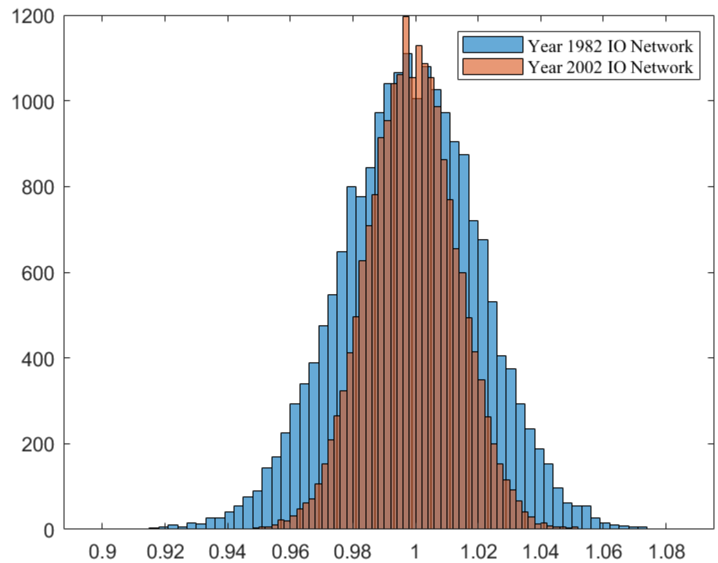
[20] The production or input-output network is built into the model exogenously.

[21] 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 simulated real GDP growth volatility.

[22] Real GDP is simulated from 20,000 draws according to the benchmark calibration without labor reallocation.

orange bars plot the year 2002's. As seen in the figure, a greater standard deviation combined with a negatively skewed distribution in 1982 indicates that industries in 1982's economy might be more likely to encounter adverse shocks than in 2002's.

Figure 8: Model-Simulated Aggregate GDP in 1982 and 2002.



Finally, I compare model-implied moments in 1982 and 2002 with the ones in a horizontal economy. The results are exhibited in the last three rows of Table 5. A *pure horizontal economy* is defined as one in which industries have no external purchases of intermediate goods. Therefore, there are no inter-sectoral connections with other sectors; all sectors sell their output directly to the representative household. Specifically, I construct the horizontal economy as follows. First, I calibrate expenditure shares b_i so that the steady-state input-output matrix is an identity matrix. Then I remove all input-output linkages by setting each sector's labor share to be one. A positive mean of simulated GDP growth[23] implies that the same sectoral shocks induce positive economic growth to a horizontal economy. Moreover, GDP growth is significantly less volatile than the other two networks. The results are intuitive as, without any interconnection, idiosyncratic shocks might generate less comovement across industries, resulting in smaller aggregate volatility. Therefore, production network structure does shape aggregate fluctuations.

Application Two: The Effect of Financial Shocks

In the second quantitative exercise, I study the capability of one particular sector in propagating shocks to the overall economy. Intuitively, the aggregate impact is expected to be stronger if the shocked sector has a greater centrality (a wider direct

[23] I focus on the results estimated without labor reallocation to minimize the impact of labor movement on the variation of growth volatility.

and indirect connections with the rest of the economy) since the effect is highly likely to be spread to other sectors and aggregated into macroeconomic fluctuations.

In this exercise, I estimate the impact of financial shocks on two different economies. The *financial shocks* is defined as the TFP shocks to the "Finance and insurance" sector. To measure the size of financial shocks, I demean the log growth rate of gross output[24] of "Finance and insurance" from 2007 to 2009 and construct the shocks to be cumulative changes in demeaned growth rate, which yields a one-time shock of -11.7%. Next, I apply realized financial shocks to the "Finance and insurance" sector in the economies of 2002 and 2007 and compare GDP declines induced by adverse financial shocks. I choose 2002 for comparison since "Finance and insurance" had a higher centrality level in 2002 than in 2007, which is 0.059 versus 0.056. For the benchmark model without labor reallocation, financial shocks reduce aggregate GDP by 4.9% in 2007, while with 2002's production network, aggregate output declines by 5.4% ($> 4.9\%$). Subjecting to the same shocks, since "Finance and insurance" played a more central role in 2002, it caused a more significant aggregate effect in the earlier year. To put it in another way, if the recent Financial Crisis would happen in 2002, it might lead to a more damaging impact on the entire economy.

Therefore, an industry's role as an input supplier in the production network indeed determines shocks' impact and results in different aggregate outcomes.

Application Three: The Aggregate Impact of the Covid-19 Crisis

In this exercise, I study the quantitative impact of the Covid-19 Crisis on the aggregate economy in our parsimonious model with input-output linkages[25]. I consider the Covid-19 shocks as shocks to labor supplies and assume that the supply-side shocks only reduce potential labor used by each industry $\bar{L}_{it}$. There are reasons for reductions in the labor supply. They could be driven directly from government actions, such as stay-at-home orders, mandated shutdowns, and reduced seating capacity in inner areas. They could also be because of households' unwillingness to work due to their health concerns or unemployment benefit. Although shocks originally take place in the labor market, they also affect the industry's production decision. Therefore, the impact might be aggregated to macroeconomic fluctuations through inter-industrial connections.

The Covid-19 or labor supply shocks are calibrated to match the changes in the number of employees by sector from March 2020 to June 2020 (Q2, 2020) from the June 2020 BLS Economic News release. On average, industries experienced a 9% reduction in employees, whereas "Accommodation" and "Food services and drinking places" suffered more than 50% loss in workers. Since I measure employment changes of the second quarter of 2020, I also assume that there is no labor mobility across sectors. At the aggregate level, the model predicts a reduction of real GDP of around 10.5%, which is in line with the decline in real GDP measured by the BEA for the

[24]I use the chain-type quantity indexes for gross output by industry from the BEA.

[25]There are other papers studying economic effects of the Covid-19 crisis on multi-sector Keynesian models with nominal rigidities, see D. Baqaee & Farhi (2020), Guerrieri et al. (2020) among others.

calibrated period. Therefore, this model does a decent job predicting sectoral shocks' impact on the macro economy.

6.2 Model-Simulated Regression

This subsection aims to study the quantitative predictions of the model regarding the empirical correlations among production network structure, intermediate input share, service share, real GDP growth, and volatility documented in Section 4.

Initially, I feed realized sectoral TFP shocks into the model and simulate aggregate real GDP for the U.S. economy of size $T = 50$ years for $S = 100$ periods, starting from 1970[26]. I set 1970 as the initial year by matching the steady-state input-output matrix to the 1970's input-output table. The model grows stochastically as productivity shocks follow a random walk specified in equation (5). With the model-implied path for real GDP, I then calculate real GDP growth and growth volatility using the same method specified in the empirical section. I also calculate the independent variable, $Std.cen_T$, and control variables, $int.m/g.\ output_T$ and $serv./g.\ output_T$, based on the model-implied input-output matrix[27]. Last, I re-estimate the correlation between the input-output network variation and (i) real GDP growth and (ii) growth volatility. Recall that in the benchmark calibration, the set of structural elasticity of substitution $(\sigma, \theta, \varepsilon) = (0.9, 0.4, 0.01)$, and labor is allowed to be reallocated to other sectors for my sample period, $\beta_i = 0$. I also provide estimated results with no labor mobility assumption in Table 8 and Table 9 in Appendix A.4.

Table 6: Model-implied Real GDP Growth and the Centrality Variation.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Data: $RGDP\ growth_T$			Model: Simulated $RGDP\ growth_T$		
$log(Std.cen_T)$	-0.519***	-0.608**	-0.371**	0.191***	-0.722***	-0.702***
	(0.155)	(0.245)	(0.215)	(0.017)	(0.018)	(0.019)
$int.m/g.\ output_T$		-0.079	-0.409***		6.311***	6.071***
		(0.128)	(0.122)		(0.095)	(0.131)
$serv./g.\ output_T$			-2.532***			-0.084***
			(0.671)			(0.032)
Observations	48	48	48	5000	5000	5000

[1] Column (4)-(6) present the OLS regression results, using model-simulated real GDP growth rate as the dependent variable. Model implied control variables are also applied as in the empirical section. All variables have been 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.

The results of estimating equation (2) using model-implied real GDP growth as the dependent variable are in columns (4)-(6) in Table 6. I control for intermediate

[26]As 1970 is the first year in my sample, I set it to be the initial year for simulation.
[27]In each period $s \subseteq S$, I simulate the model for 50 times ($T = 50$) as there are about 50 years in my sample and obtain one input-output matrix for each year.

input shares and service shares, as in the empirical section. When I re-estimate the correlation between simulated real GDP growth and centrality variation with controls, the model under nonlinear characterization delivers negative coefficients as an order of magnitude similar to the empirical one. The model predicts that as the network structure getting dispersive, GDP growth will slow down, which is consistent with the empirical relationship.

Table 7: Model-implied Growth Volatility and the Centrality Variation.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Data: $Growth\ volatility_T$			Model: Simulated $Growth\ volatility_T$		
$log(Std.cen_T)$	0.179**	0.304***	0.321***	0.049***	0.146***	0.144***
	(0.086)	(0.109)	(0.117)	(0.012)	(0.018)	(0.020)
$int.m/g.\ output_T$		0.11*	0.087		-0.668***	-0.647***
		(0.068)	(0.095)		(0.101)	(0.140)
$serv./g.\ output_T$			-0.182			-0.007
			(0.671)			(0.034)
Observations	48	48	48	5000	5000	5000

[1] Column (4)-(6) present the OLS regression results, using model-simulated growth volatility as the dependent variable. Model implied control variables are also applied as in the empirical section. All variables have been HP-filtered with the smoothing parameter of 6.25.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.

The estimated correlation coefficients between model-simulated network variation and growth volatility are presented in Table 7. In general, the calibrated model is quantitatively decent in replicating the observed empirical patterns under the non-linear characterization. The model-implied centrality-volatility relationship implies that a sparser network tends to be more volatile, thus more vulnerable to shocks. However, the estimated coefficients are smaller compared to the data. The reason might be that this parsimonious model abstracts from capital accumulation so that labor and intermediate inputs cannot fully account for GDP growth and volatility.

7 Conclusion

This paper argues that the U.S. input-output network plays an essential role in propagating sectoral shocks and shaping aggregate fluctuations, such as GDP growth and growth volatility. First, I show that industries in the U.S. production network are getting more dispersive over the past five decades, such that more sectors rely on a few central input suppliers for their own production process. This changing nature of network structure significantly correlates with business cycle fluctuations. Precisely, an economy with a greater industrial centrality variation displays relatively low GDP growth and tends to be more volatile. Second, I build a multisector real business cycle model with general CES technologies to account for inter-industrial linkages. Third, I measure sector-level productivity shocks from the data, feed them into the model, and solve the model nonlinearly in order to highlight the role of an input-output network in propagating shocks. Finally, this paper finds that the production network structure has a quantitatively significant effect in explaining GDP growth and volatility.

The results might have important policy implications. Essentially, the reason for the U.S. production network structure getting sparser over time is to have a few input suppliers played a central role in the network. Therefore, adverse shocks to those central sectors might have a more damaging impact on the entire economy. As a result, policymakers might impose relatively strict regulations on those sectors in normal times, such as the Stress Test, or have supportive policies at the early stage of the recession, to prevent large enterprises from catastrophic failure.

There are some extensions for future work. On the one hand, the correlation of the production network structure and aggregate GDP growth is different during the pre-1984 and post-1984 period[28]. Thus, the changing network structure might be a source of the Great Moderation. On the other hand, this paper provides evidence of the expansion in the service sector. One possible reason for the expansion is outsourcing, to have intermediate inputs produced by specialized companies rather than in-house. I am also interested in studying the role of outsourcing in explaining labor productivity in the context of the input-output network.

[28] This evidence is not presented in this paper and might be used for future projects.

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A Theoretical Framework

In this section, I start by presenting a non-parametric general equilibrium model of production network, which will be used to demonstrate the Hulten's theorem and the second-order approximation of the impact of an idiosyncratic shock on the aggregate economy. This static model is also used and analysed by Baqaee and Farhi (2019).

A.1 The Hulten Theorem

Consider a static economy consisting of N competitive industries, each industry $i \in \{1, 2, ..., N\}$ produces a distinct good using different factors of production and intermediate inputs. The production function is given by

$$y_i = A_i F_i(l_{i1}, ..., l_{iF}, x_{i1}, ..., x_{iN})$$

where A_i is the Hicks-neutral technology, l_{if} is the type$-f \in \{1, 2, ..., F\}$ factor used by industry i, and x_{ij} are the intermediate goods purchased by i from its directed supplier j. The profits π_i earned by industry i are

$$\pi_i = p_i y_i - \sum_{f=1}^{F} w_f l_{if} - \sum_{j=1}^{N} p_j x_{ij}$$

with p_i being good i's price, and w_f denoting the wage of type$-f$ factor.

The economy is also populated with one representative household. The aggregate final demand of the economy Y is the maximized final demand of all consumption goods

$$Y = \max_{\{c_1,...,c_N\}} D(c_1, ..., c_N)$$

subject to a budget constraint

$$\sum_{i=1}^{N} p_i c_i = \sum_{f=1}^{F} w_f \bar{l}_f + \sum_{i=1}^{N} \pi_i$$

where c_i is the final consumption of good i, and each type of factor $\bar{l}_f$ offered by the household is in fixed supply.

In a competitive equilibrium, all prices are given. The markets for each good i and each type of factor f clear at

$$y_i = \sum_{j=1}^{N} x_{ji} + c_i \ \ and \ \ \bar{l}_f = \sum_{i=1}^{N} l_{if}$$

Theorem 1 (The Hulten's Theorem) *In any efficient economy, the impact of an idiosyncratic shock to industry i on the aggregate economy is i's Domar weight up to a first-order approximation.*

$$\frac{d\ logY}{d\ logA_i} = \lambda_i \tag{11}$$

where $\lambda_i = p_i y_i / \sum_{j=1}^{N} p_j c_j$ *is i's total sales over GDP ratio, which is defined as the Domar weight of industry i.*

According to Hulten's Theorem, when the economy is efficient, Domar weight is a sufficient statistics in determining the impact of an industry-specific TFP shock on GDP. In other words, other microeconomic details, such as the structure of a production network, household's perefernce over consumption goods, and the elasticities of substitution in production, are irrelevant. However, it seems implausible when you consider the following example. Construction and Finance industries have very similar gross sales, so does the Domar weights (about 7 percent in 2010). If Hulten's Theorem holds true, industry-specific productivity shocks should generate analogous macroeconomic impacts. But in reality, as the Finance sector supplies to a wider range of sectors than Construction, the adverse effects caused by negative productivity shocks to Finance will be more damaging. This example emphasizes that an industry's network interconnection does matter in translating the impact of idiosyncratic shocks to aggregate outputs, which is missing from the first-order approximation.

A.2 The Role of Network Structure in Shaping Second-Order Aggregate Impact

In this section, I will study model implications for the relationship between the network structure and the aggregate impact of sector-specific productivity shocks. The impact is estimated up to a second-order approximation where the network structure plays in crucial role.

I start by presenting the definition of the input-output covariance operator, proposed by D. R. Baqaee & Farhi (2019).

Definition 1 *The input-output covariance operator is defined as*

$$cov_{\Gamma^k}(\Psi_i, \Psi_j) = \sum_{r=1}^{N} \gamma_{kr} \Psi_{ri} \Psi_{rj} - \left(\sum_{r=1}^{N} \gamma_{kr} \Psi_{ri} \right) \left(\sum_{r=1}^{N} \gamma_{kr} \Psi_{rj} \right). \tag{12}$$

The operator illustrates the covariance between ith and jth columns of the Leontief inverse using the kth row of an input-output matrix as the distribution. The economy's Leontief inverse is defined as $\Psi = (I - \Gamma)^{-1}$, where Γ is the model-implied input-output matrix. Intuitively, Ψ_{ij} captures industry i's total (directed and indirected) reliance on j as its input supplier. Moreover, the element γ_{ij} is specified as the steady-state value of $\frac{p_j x_{ij}}{p_i y_i}$.

Proposition 1 *In any efficient economy, the impact of an idiosyncratic TFP shock to industry i on the aggregate economy is i's Domar weight up to a first-order approximation.*

$$\frac{d\ logY}{d\ logA_i} = \lambda_i \tag{13}$$

where $\lambda_i = p_i y_i / \sum_{j=1}^{N} p_j c_j$ is i's total sales over GDP ratio, which is defined as the Domar weight of industry i.

Hulten (1978) states that as long as an economy is efficient, Domar weight is a sufficient statistics in determining the impact of industry-specific TFP shocks on aggregate GDP. In other words, other microeconomic details, such as the inter-industrial linkages, etc., are completely irrelevant. However, it seems implausible when you consider the following example. In 2010, Construction and Finance industries had very similar gross sales, so does the Domar weights, which was about 7 percent. If Hulten's Theorem holds true, productivity shocks should generate analogous fluctuations on GDP. But it is more persuasive, as the Finance sector supplies to more sectors than Construction, adverse productivity shocks to Finance will be more damaging to the whole economy. This example tells us that industries interconnection might play an important role in modelling the macroeconomic impact of productivity shocks, which has been ignored by a first-order approximation.

Proposition 2 *In a nested-CES economy with only one factor of production, the second-order aggregate impact of idiosyncratic shocks is*

$$\frac{d^2\ logY}{d\ logA_j\ d\ logA_i} = \frac{d\ \lambda_i}{d\ logA_j} = \sum_{k=1}^{N} (\varepsilon_k - 1) \lambda_k cov_{\Gamma^k}(\Psi_i, \Psi_j). \tag{14}$$

Proposition 2 specifies three key microeconomic determinants in analysing the aggregate impact on GDP up to a second-order approximation. They are the elasticity of substitution across intermediates used by industry k, ε_k, Domar weight of k, λ_k, and the input-output covariance operator defined earlier.

As shown in equation (10), the second-order impact can also be expressed by the change in i's Domar weight in response to a productivity shock to industry j. Intuitively, the change in i's sales depends on how much i's direct and indirect customers are exposed to j's productivity shocks simultaneously. Suppose there are negative TFP shocks $d\ logA_j < 0$ hitting industry j, which leads to an increase in good j's price. Now considering any given producer k, if $\varepsilon_k > 1$, the producer will substitute away from the intermediates that are (directly or indirectly) affected by negative shocks. In other words, industry k will decrease its demanding expenditures on good j-related inputs[29] and switch to cheaper substitutes. Meanwhile, if those affected inputs are also (directly or indirectly) related to industry i, the demand of i's output will be affected as well, which is measured by Ψ_i.

Again, the covariance operator is calculated with the input-output matrix Γ, which is also used in the Katz-Bonacich centrality measure. Therefore, the network structure (inter-sectoral linkages) does matter in shaping the second-order macroeconomic fluctuation.

A.3 The Role of Elasticity of Substitution in Deciding Macroeconomic Fluctuations

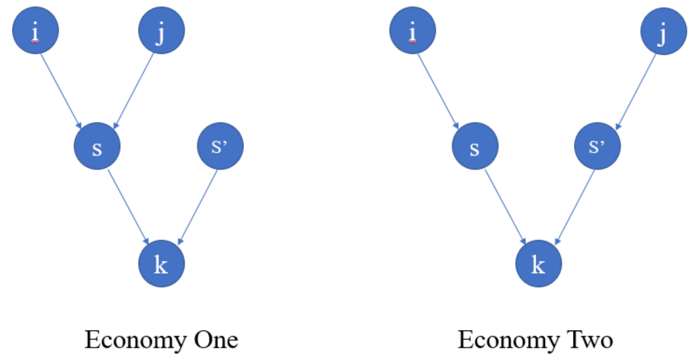
To begin with, I illustrate the impact of elasticity of substitution among intermediate goods on the aggregate economy through different input-output network structures. In general, negative productivity shocks to industry i can be propagated through the production network in two different channels. It leads to an increase in good i's price. Consequently, all sectors using good i as intermediate inputs in production, either directly or indirectly, will be affected negatively. Alternatively, shocks to i might also cause reallocations in the demand for good j as intermediates, depending on the complementarity across two sectors.

To elaborate the second channel, let's consider two simple economies in Figure 8. In each economy, producer (or industry) k has two (potential) indirect suppliers i and j ($j \neq i$). Then I present how the productivity shocks to sector j affect i's sales differently, given k's complementarity across inputs in production.

In economy one, sector i and j share a common customer s, which is also a direct supplier of producer k. When sector j suffered negative productivity shocks, j's output price rises. Suppose the elasticity of substitution across producer k's intermediate inputs is greater than one, $\varepsilon_k > 1$, therefore, k will substitute away from s and purchase more of good s' instead. This reallocation of inputs between s and s' might lead to a decline in the demand for good i as well, since i is an ingredient in the production of good s. However, if good s and s' are complements to producer

[29] The total reliance on good j by all industries in the network is captured by Ψ_j, the jth column of Leontief inverse.

Figure 9: Two Simple Economies



k, the need for i might stay the same or decline with much less amount than in the substitutes case.

In the second economy, industry i and j connect with k through two separate supply chains. i and j are also direct suppliers of s and s', respectively. Again, negative TFP shocks to j make j-related goods more expensive. When $\varepsilon_k > 1$, k will purchase good s instead of s', as they are gross substitutes. As a result, the demand for good i will increase. But when $\varepsilon_k < 1$, i's sales will probably drop.

This example illustrates that given different complementarity values, the reallocation of the demand for inputs in production (by sector k) changes correspondingly subject to productivity shocks. Differences in reallocation pattern lead to various input-output network structures. Thus, the correlation between elasticities of substitution across intermediates and the network structure can be confirmed. Recall that inter-sectoral linkages[30] is one of the key features of the second-order aggregate impact. Therefore, elasticity of substitution does play a non-trivial role in deciding macroeconomic fluctuations.

A.4 Model-Simulated Regression with no labor mobility assumption

In appendix A.4, I present the estimated results of model-simulated regression. In particular, I assume that labor cannot be reallocated across sectors.

[30]The network structure again is defined as the way of industries being connected or trading with one another, which is specified by the input-output matrix.

Table 8: Model-implied Real GDP Growth and the Std. of Centrality.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Data: $RGDP\ growth_T$			Model: Simulated $RGDP\ growth_T$		
$\log(Std.cen_T)$	-0.519***	-0.608**	-0.371**	-0.754***	1.817***	1.267***
	(0.155)	(0.245)	(0.215)	(0.063)	(0.057)	(0.046)
$int.m/g.\ output_T$		-0.079	-0.409***		-8.953***	-4.894***
		(0.128)	(0.122)		(0.137)	(0.139)
$serv./g.\ output_T$			-2.532***			-4.304***
			(0.671)			(0.094)
Observations	48	48	48	5000	5000	5000

[1] Column (4)-(6) present the OLS regression results, using model-simulated real GDP growth rate as the dependent variable. Model implied control variables are also applied as in the empirical section. All variables have been 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.

Table 9: Model-implied Growth Volatility and the Std. of Centrality.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Data: $Growth\ volatility_T$			Model: Simulated $Growth\ volatility_T$		
$\log(Std.cen_T)$	0.179**	0.304***	0.321***	0.121***	0.399***	0.507***
	(0.086)	(0.109)	(0.117)	(0.043)	(0.059)	(0.061)
$int.m/g.\ output_T$		0.11*	0.087		-0.970***	-1.768***
		(0.068)	(0.095)		(0.141)	(0.182)
$serv./g.\ output_T$			-0.182			0.847***
			(0.671)			(0.124)
Observations	48	48	48	5000	5000	5000

[1] Column (4)-(6) present the OLS regression results, using model-simulated growth volatility as the dependent variable. Model implied control variables are also applied as in the empirical section. All variables have been HP-filtered with the smoothing parameter of 6.25.
[2] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, and robust standard errors are in the parentheses.