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Networks in Production: Asset Pricing Implications

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ABSTRACT

In this paper, I examine asset pricing in a multisector model with sectors connected through an input-output network. Changes in the network are sources of systematic risk reflected in equilibrium asset prices. Two characteristics of the network matter for asset prices: network concentration and network sparsity. These two production-based asset pricing factors are determined by the structure of the network and are computed from input-output data. Consistent with the model predictions, I find return spreads of 4.6% and −3.2% per year on sparsity and concentration beta-sorted portfolios, respectively.

FIRMS USE A VARIETY OF inputs to build their products, collectively spending trillions of dollars and designing a network of input-output linkages. As technology evolves, industries use different inputs to produce their products. For example, since the 1970s, plastics have become a more suitable substitute for wood and metal materials, reshaping the production process for manufacturing and construction. Changes in the input-output network have implications for the overall economy as they alter sectoral input-output linkages. In this paper, I investigate the implications of changes in the input-output network for asset prices and aggregate quantities such as consumption and GDP. I show

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that changes in the network are a source of systematic risk that is priced in equilibrium. To the best of my knowledge, I am the first to explore the asset pricing implications of a sectoral network model.

The main result of this paper is that two key network factors matter for asset prices: network *concentration* and network *sparsity*. These network factors describe specific attributes of the sectoral linkages, based on the fundamentals of the economy. I demonstrate that concentration and sparsity are sufficient statistics for aggregate risk. Thus, while the entire input-output linkage network is multidimensional, we may focus on these two characteristics when assessing systematic risk. I derive concentration and sparsity from a general equilibrium model and show that they determine the dynamics of aggregate output and consumption. When I compute innovations in concentration and sparsity from the data and empirically test these new asset pricing factors, the return data show that exposure to these network factors is reflected in average returns as predicted by my model.

Network concentration measures the degree to which equilibrium output is dominated by a few large sectors. It is a measure of concentration over sectors' output shares in equilibrium. An individual sector's equilibrium output share captures the importance of the sector's output to all other sectors as an input. If the output of a sector is widely used as an input by other sectors, then it has high output share in equilibrium. Whether a sector has high or low output share depends on the network and therefore concentration is an attribute of the network.

Network sparsity measures the distribution of sectoral linkages. Sectoral linkages capture the input flow in the economy and are directly related to the importance of each input to a particular sector. Sparsity thus measures the degree of input specialization in the economy and how crowded or dense these linkages are in the network. A network with high sparsity has fewer linkages, but these linkages are stronger and, on average, firms rely on fewer sources of input.

The Bureau of Economic Analysis (BEA) Input-Output Accounts provide a picture of the production network of the U.S. economy. Figure 1 provides a network representation of the input-output linkages, in which nodes (circles) represent sectors and edges (arrows) represent input flows between sectors—an arrow from sector j to sector i shows the input flow from sector j to sector i. The size of a node represents the sector's output share, and the thickness of an edge represents the input expenditure share. Concentration, which captures the degree to which aggregate output is dominated by few sectors, is reflected in the concentration over nodes' size. If there are a few large nodes (sectors with large output share), as the graph illustrates for the U.S. economy, then concentration is greater than in an economy in which the nodes have the same size. Sparsity, which captures the degree of input specialization, is reflected in the thickness and scarcity of the network edges. An economy with high sparsity and therefore high input specialization has fewer edges, but these edges are thicker. Hence, concentration is a characteristic of the nodes' size distribution, whereas sparsity is a characteristic of the edges' thickness distribution.

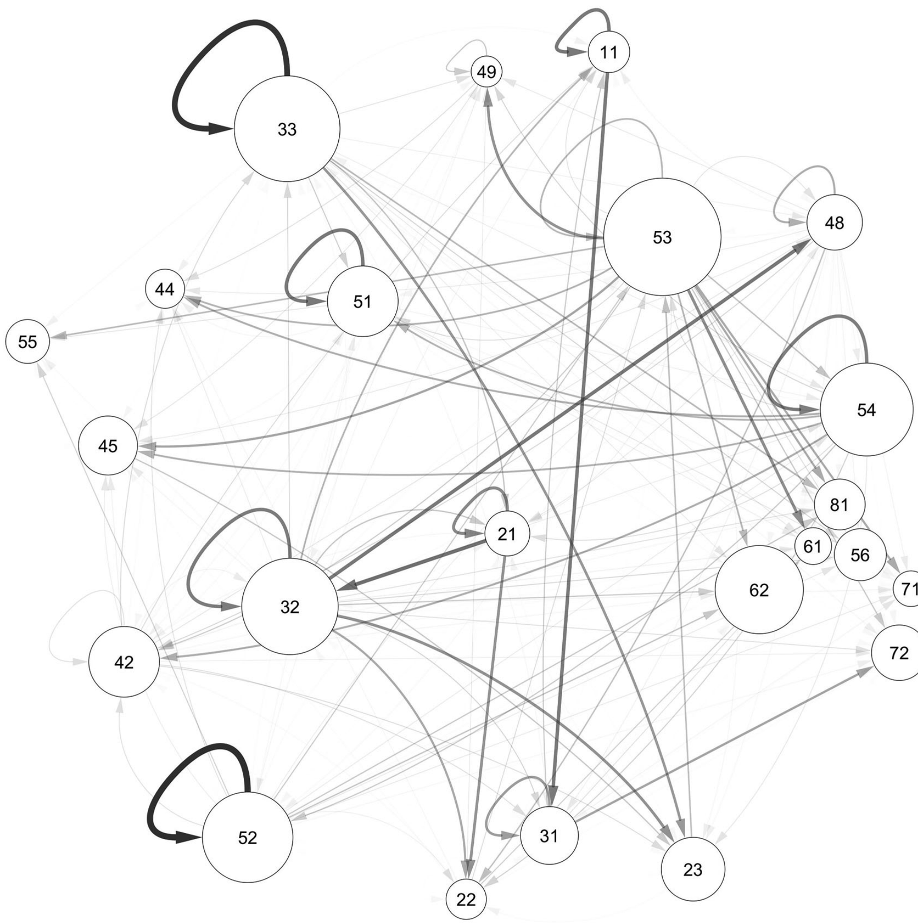


Figure 1. Input-output network at the sector level. This picture contains a network representation of the Bureau of Economic Analysis (BEA) Input-Output Accounts for 2012 at the sector level, that is, two-digit North American Industry Classification System (NAICS) code level. An arrow from sector j to sector i means that j is selling to i; the intensity of the arrow (transparency and width) indicates how much i is buying from j relative to other suppliers. Each node (circle) represents a different sector in the economy, with the size of nodes representing output shares. Node labels specify the two-digit NAICS sector.

When production is subject to diminishing returns, an economy with high concentration has a few large sectors with lower returns on investment. The lower productivity of large sectors of an economy affects other sectors through equilibrium prices. As a result, high concentration leads to lower aggregate consumption and higher marginal utility. Innovations in concentration therefore carry a negative price of risk. Assets that have high returns when concentration increases, that is, assets with high concentration beta, are hedges against a decline in aggregate consumption and hence should have lower expected returns. A portfolio that goes long high-concentration-beta stocks and short low-concentration-beta stocks should have negative average returns.

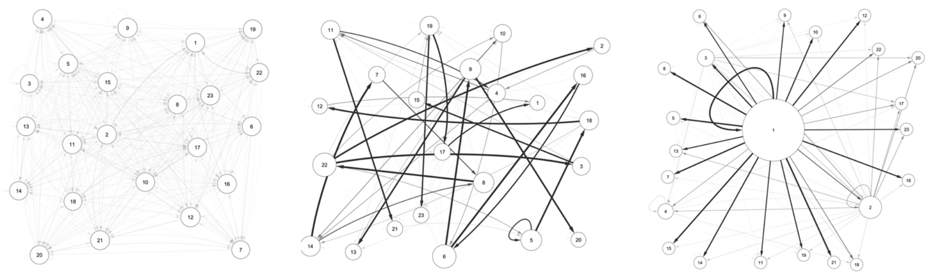
Sparsity is directly related to productivity gains due to sectors' connectivity. In my model, firms have a Cobb-Douglas production technology.[1] They use each others' inputs to produce their final output, with the network specifying the importance of each input to the final output. In particular, for each sector, the network defines the elasticity of its output with respect to each input as well as the marginal product of inputs. Therefore, the network delimits the shape of the production function.

When network sparsity increases, firms reoptimize inputs based on changes in their marginal productivity, substituting inputs that have lower marginal product with those that have higher marginal product. The updated allocation of inputs has two immediate implications for firms' final output. On the one hand, firms observe efficiency improvement from using more inputs with higher marginal product and as a result produce more. On the other hand, firms substitute inputs at their relative spot market prices, changing input combinations and marginal cost of production. When sparsity increases, a firm may use inputs that are relatively more (less) expensive, causing the marginal cost of production to increase (decrease) and its final output to decrease (increase). Therefore, changes in marginal cost may have a positive or negative effect on output depending on both the spot market prices and the specific network changes. The efficiency gain, however, always increases output. Thus, the aggregate effect of an increase in sparsity on the output of a firm depends on which effect dominates.

When network concentration is constant, changes in marginal cost due to different input combinations aggregate to zero. This is because some firms use more expensive inputs while other firms use less expensive inputs. Thus, aggregate output and consumption increase when sparsity increases. When sparsity increases, the input-output linkages are rearranged, increasing aggregate consumption and decreasing marginal utility. Innovations in network sparsity carry a positive price of risk. Assets that have high returns when network sparsity increases, that is, assets with high sparsity beta, are risky assets and their expected returns should be higher to compensate the investor for such risk. A portfolio that goes long high-sparsity-beta stocks and short low-sparsity-beta stocks should have positive average returns.

To illustrate the difference between concentration and sparsity, Figure 2 shows three simulated networks with different network factors. The network in Panel A has uniform edges, meaning that sectors' input expenditures are evenly distributed across inputs. Similarly, the nodes are of similar size, meaning that output shares are roughly the same. This network has low sparsity and low concentration. The network in Panel B has fewer edges, but they are thicker. Each sector's input expenditure concentrates on a few sectors. As a result, the network in Panel B has higher sparsity than that in Panel A, although

[1] For the remainder of the paper, the words "firm" and "sector" are used interchangeably, as each sector features a representative firm in the model.



Panel A. Low sparsity and low concentration

Panel B. High sparsity and low concentration

Panel C. High sparsity and high concentration

Figure 2. Changes in network sparsity and network concentration. This figure shows three simulated networks with 23 sectors. Panel A presents a network with low network sparsity and low network concentration. Panel B presents a network with low network concentration, but high network sparsity. Panel C presents a network with high sparsity and high concentration.

concentration is the same in both networks. The network in Panel C presents an increase in the concentration factor. The input expenditure of all other sectors is highly concentrated on Sector 1, which results in a higher output share for sector 1 and a lower share for the other sectors in equilibrium. As a result, the network in Panel C has a higher concentration than in Panels A and B. However, the edges of the networks in Panels B and C are just as scattered and the degree of input specialization is the same, meaning that sparsity is the same in both networks.

In addition to a time-varying network, the model features an aggregate productivity factor, a common feature of production-based models. However, in the model, this productivity factor arises endogenously from aggregating sector-specific productivity shocks. The network structure governs the extent to which these productivity shocks are diversifiable and how they generate systematic risk. The general equilibrium model therefore boils down to a three-factor model: aggregate productivity, network concentration, and network sparsity. These three factors fully determine the dynamics of aggregate output and consumption in equilibrium, and innovations in concentration and sparsity represent two new candidate asset pricing factors that I take to the data.

I test whether high-sparsity-beta assets have higher expected returns than those with low sparsity beta, and whether high-concentration-beta assets have lower expected returns than assets with low concentration beta. The network factors are computed from Compustat data over the period 1979 to 2013, and the Center for Research in Security Prices (CRSP) stocks are sorted into portfolios based on their exposures to the innovations in the network factors. The high-sparsity-beta portfolio has higher returns than the low-sparsity-beta portfolio, with a return difference of 4.6% per year. Furthermore, the high-concentration-beta portfolio has lower returns than the low-concentration-beta portfolio, with a return spread of 3.2% per year. These return spreads are economically meaningful and statistically significant. Moreover, neither the capital asset pricing model (CAPM) nor the Fama and French (1993) three-factor model explain these return differences.

In addition to studying network-beta-sorted portfolios return spreads, I use a comprehensive set of test assets and verify that sparsity and concentration are priced in the cross-section of stocks returns. I also investigate macroeconomic implications of the model. I find that sparsity innovations are associated with higher aggregate dividend growth, while innovations in network concentration are associated with lower aggregate dividend growth.

The rest of paper is organized as follows. In the next subsection, I discuss the related literature. In Section I, I present the model and discuss the network factors. In Section II, I discuss the empirical evidence. Finally, I conclude in Section III.

A. Related Literature

The literature that applies network theory to macroeconomics and finance has focused mostly on documenting stylized facts and building a microfoundation for business cycles, financial contagion, and other macroeconomic phenomena.[2] The asset pricing implications of sectoral linkages, however, have been largely neglected. This paper contributes to a recent but growing literature on customer-supplier linkages and asset prices. I extend this literature by identifying new asset pricing factors constructed from the input-output network.

Using input-output data, Ahern (2013) shows that industries occupying a more central position in the network earn higher returns on average. The centrality of an industry is a property of a node (sector) in the network as opposed to a property of the entire network. In my model, sparsity and concentration factors are properties of the whole network. Another related paper is Herskovic et al. (2017), which investigates the relation between firm size distribution and firm-level volatility through the lens of a customer-supplier network model. However, the authors do not investigate the asset pricing implications of customer-supplier linkages as I do have. Herskovic et al. (2016) documents a common factor structure in idiosyncratic firm-level return volatility and shows that the common idiosyncratic volatility factor is priced. Unlike these papers, I derive network factors from a general equilibrium model in which these factors originate from sectoral linkages and are a source of systematic risk.

This paper is also closely related to the literature on the importance of sectoral shocks for economic aggregates. The multisector model developed in this

[2] Recent contributions to the literature on networks and finance include Hou and Robinson (2006), Cohen, Frazzini, and Malloy (2008), Cohen and Frazzini (2008), Carvalho (2010), Gofman (2011), Carvalho and Gabaix (2013), Li and Schürhoff (2013), Ahern and Harford (2014), Aobdia, Caskey, and Ozel (2014), Carvalho and Voigtlander (2014), Carvalho (2014), Farboodi (2014), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015a, 2015b), Carvalho and Grassi (2015), Neklyudov and Sambalaibat (2015), Babus and Parlatore (2016), Eisfeldt et al. (2018), Babus (2016), Babus and Kondor (2016), Biggio and La'O (2016), Carvalho et al. (2016), Pasten, Schoenle, and Weber (2016), Richmond (2016), Wu (2016), Babus and Hu (2017), Denbee et al. (2017), Gofman (2017), Hollifield, Neklyudov, and Spatt (2017), Malamud and Rostek (2017), and Ozdagli and Weber (2017). Allen and Babus (2009) present a detailed review of network models applied to finance.

paper is based on Long and Plosser (1983). Their model generates comovement of sectors' output because each sector relies on the output of other sectors for inputs. My model does not have the same degree of comovement, however, because the production technology represented by the network changes over time and therefore the sectoral shares also change over time. My model is also closely related to the work of Acemoglu et al. (2012). They show that aggregate fluctuations can be generated from sectoral idiosyncratic shocks when sectors are connected by input-output linkages.[3] However, the network in my model changes over time, while theirs is static. Network sparsity and concentration factors are therefore absent from their analysis. Also, their paper focuses on the origins of aggregate fluctuations, while I am interested in identifying priced sources of systematic risk due to network changes.[4]

This paper also contributes to the production-based asset pricing literature by providing asset pricing factors computed directly from the input-output network.[5] Papanikolaou (2011) studies how investment shocks are priced, and Loualiche (2012) investigates aggregate entry cost as a priced risk factor. Although my model has neither entry cost nor investment shocks, both the concentration factor and the sparsity factor are related to changes in how much firms produce in aggregate. Changes in the network reflect not only changes in the sectoral relations, but also changes in investment opportunities. However, changes in the network factors are due to technological rearrangements that reshape the input-output network, which is different from changes in the cost of producing new capital.

This paper further relates to a line of research on how technological innovation is priced. Kung and Schmid (2015) study asset pricing in a general equilibrium framework with endogenous technological growth. In my model, changes in network sparsity and concentration can be interpreted as reflecting technological innovation—they are distinct risk factors that result from changes in technology. Corhay, Kung, and Schmid (2017) study time-variation in industry competitiveness and its implication for the equity premium. My model features perfect competition and the network factors are priced, as they reflect changes in the production technology rather than changes in industry competition.

Finally, this paper sheds light on the literature on network formation. Oberfield (2012) develops an input-output network formation model. In his model, firms choose from whom they buy their inputs and the network is endogenous.[6]

[3] The idea of aggregate shocks originating from idiosyncratic shocks is also discussed by Jovanovic (1987), Bak et al. (1993), and Gabaix (2011).

[4] Carvalho (2010) presents a dynamic version of the model in Acemoglu et al. (2012), but the network itself is fixed over time.

[5] Related work in production-based asset pricing includes Jermann (1998, 2010, 2013), Yogo (2006), Gomes, Kogan, and Yogo (2009), Kuehn (2009), Lochstoer (2009), Belo (2010), Gomes and Schmid (2012), Kuehn and Schmid (2014), Kogan, Papanikolaou, and Stoffman (2017), and Binsbergen (2016).

[6] One interesting result is the existence of star suppliers as an endogenous outcome of his model, that is, suppliers who are simultaneously used by many other firms. In a recent set of

In my model, the network formation is exogenous and the network evolves stochastically over time.

I. Multisector Network Model

In this section, I present the theoretical model and discuss its predictions. I start by presenting the setup of the model and the equilibrium conditions. I then solve the model in closed form and discuss the network factors. Finally, I provide examples to illustrate the differences between concentration and sparsity.

A. Setup

Time is discrete and indexed by $t = 1, 2, \ldots$. There are n distinct goods and n sectors. Each sector has one representative firm producing the good of that particular sector. Firm i buys inputs from other sectors, and these inputs combined are transformed into the final output of sector i. Firms buy inputs and produce at the same time, that is, firm i buys inputs from other sectors at period t and produces at period t as well.[7] The model also features a representative household with constant relative risk aversion preference that owns all firms and lives off their dividends. Next, I describe the optimization problem of the firms and how they connect to each other through input-output linkages. Then, I present the representative household problem as well as all market-clearing conditions.

A.1. Firms

Consider the optimization problem of firm i. The input bought from firm j in period t is denoted by $y_{ij,t}$. All inputs acquired from other firms are combined and transformed into a single investment variable given by

$$I_{i,t} = \prod_{j=1}^{n} y_{ij,t}^{w_{ij,t}}, \tag{1}$$

where $w_{ij,t}$ is the weight on, or the importance of, input j. The weights $w_{ij,t}$ are nonnegative and sum to one, that is,

$$w_{ij,t} \geq 0 \quad \text{and} \quad \sum_{j=1}^{n} w_{ij,t} = 1.$$

studies, endogenous network formation results in a network with a core-periphery structure when agents choose their connections unilaterally (Bala and Goyal (2000), Galeotti and Goyal (2010)). Herskovic and Ramos (2017) show that, under general conditions, a hierarchical network structure emerges endogenously in a network formation game.

[7] Production in the model is based on Long and Plosser (1983), but the time dimension is collapsed: firms buy inputs and produce at the same time. Acemoglu et al. (2012) use the same modeling approach.

The investment variable $I_{i,t}$ in equation (1) is further transformed into the final output of sector i according to

$$Y_{i,t} = \varepsilon_{i,t} I_{i,t}^{\eta}, \tag{2}$$

where $\eta \in (0, 1)$ captures decreasing returns to input investments and $\varepsilon_{i,t}$ represents the sector-specific productivity level.[8]

Although firms maximize all future discounted dividends, their optimization problem is time-separable and it is sufficient to maximize per-period profits. Firm i chooses how much to invest and which inputs to acquire to maximize profits, taking both spot market prices and input weights as given. This implies the following optimization problem:

$$D_{i,t} = \max_{\{y_{ij,t}\}_j, I_{i,t}} P_{i,t} Y_{i,t} - \sum_{j=1}^{n} P_{j,t} y_{ij,t}$$

subject to equations (1) and (2), where $P_{i,t}$ is the spot market price of good i and $D_{i,t}$ is the dividend paid by firm i in period t.

The cum-dividend value of firm i, denoted by $V_{i,t}$, is defined recursively by

$$V_{i,t} = D_{i,t} + \mathbb{E}_t[M_{t+1} V_{i,t+1}],$$

where M_{t+1} is the stochastic discount factor (SDF) that prices all assets in the economy.

A.2. Network

The network consists of all weights $w_{ij,t}$, which are taken as given by firms when maximizing profits. Formally, the network in period t is characterized by the $n \times n$ matrix

$$W_t \equiv \begin{pmatrix} w_{11,t} & \dots & w_{1n,t} \\ \vdots & \ddots & \vdots \\ w_{n1,t} & \dots & w_{nn,t} \end{pmatrix}.$$

The network represents how production is interconnected. It shows how much a firm may influence or be influenced by other firms. Furthermore, the network defines the production technology through equation (1). The network weight $w_{ij,t}$ is the elasticity of the investment of sector i with respect to input j. Therefore, $w_{ij,t}$ is informative about the responsiveness of output i

[8] The decreasing returns to scale is interpreted as the return to scale to capital, $I_{i,t}$. One may assume that each sector faces inelastic labor (or land) supply, $L_{i,t} = 1$ for every i and t. Thus, the output function can be stated as $Y_{i,t} = \varepsilon_{i,t} I_{i,t}^{\eta} L_{i,t}^{1-\eta} = \varepsilon_{i,t} I_{i,t}^{\eta} 1^{1-\eta}$. Under this interpretation, the firm's profit is exactly equal to the wage (rent) payment to the representative household, which owns the entire labor (land) supply. In Section IV of the Internet Appendix, I discuss a version of the model that features a competitive labor (land) market. The Internet Appendix may be found in the online version of this article.

regarding changes in the amount of input that firm i uses from j. The network and the productivity shocks evolve over time according to a stochastic process known to all agents.[9]

A.3. Representative Household

The representative household has a CRRA Bernoulli utility function with respect to a consumption aggregator,

$$u_t = \frac{\mathcal{C}_t^{1-\gamma} - 1}{1-\gamma}, \tag{3}$$

where γ is risk aversion and $\mathcal{C}_t$ is a consumption aggregator.

The consumption aggregator is Cobb-Douglas and given by

$$\mathcal{C}_t = \prod_{i=1}^{n} c_{i,t}^{\alpha_i}, \tag{4}$$

where $c_{i,t}$ is the consumption of good i in period t and α_i is the preference weight on good i. The preference weights are assumed to be constant over time and they sum to one.

The household budget constraint is

$$\sum_{i=1}^{n} P_{i,t} c_{i,t} + \sum_{i=1}^{n} (V_{i,t} - D_{i,t})\varphi_{i,t+1} = \sum_{i=1}^{n} V_{i,t}\varphi_{i,t}, \tag{5}$$

where $V_{i,t}$ is the cum-dividend value of firm i in period t, $\varphi_{i,t}$ is the ownership of firm i in period t, and $D_{i,t}$ is the dividend paid by firm i in period t. In the budget constraint, total expenditure in consumption goods and firms' shares net of dividends (left-hand side) must equal shares' value (right-hand side).

In each period, the representative agent chooses how much to consume of each good in the current period, $\{c_{i,t}\}_i$, and how much of each firm to own next period, $\{\varphi_{i,t+1}\}_i$, to maximize the sum of her future discounted utility. The household cannot store goods from one period to another and therefore cannot save. There is a risk-free asset in zero net supply, and in equilibrium the household has a zero net position to satisfy clearing conditions. Thus, I do not include this asset in equation (5).

[9] The number of sectors and therefore the size of the network are fixed over time. However, the model accommodates the introduction of new sectors. To add a sector, we have to assume that the sector is already represented in the network, but that it is inactive with zero weight, as neither the household nor any other sector consumes its product as an input or final good. In equilibrium, the production of this sector would be zero. As the network changes and other sectors start using its product as a source of input, the new sector starts to have a positive output in equilibrium and there would be a new sector in the economy.

The household's problem may be stated as follows:

$$J_t = \max_{\{c_{i,t}\varphi_{i,t+1}\}_i} \frac{\mathcal{C}_t^{1-\gamma} - 1}{1-\gamma} + \beta \mathbb{E}_t[J_{t+1}]$$

subject to equations (4) and (5).

A.4. Market Clearing

There are two sets of market-clearing conditions. First, all good markets clear

$$c_{i,t} + \sum_{j=1}^{n} y_{ji,t} = Y_{i,t}, \quad \forall i, t, \tag{6}$$

where $c_{i,t}$ is household consumption of good i, $\sum_{j=1}^{n} y_{ji,t}$ is total demand for good i as a source of input in the economy, and $Y_{i,t}$ is the total supply of good i. Second, all asset markets clear

$$\varphi_{i,t} = 1, \quad \forall i, t, \tag{7}$$

and the household owns all firms. Hence, the household is a representative shareholder as well.

B. Competitive Equilibrium

The competitive equilibrium is defined as follows":

DEFINITION 1: *A competitive equilibrium consists of spot market prices $(P_{1,t}, \ldots, P_{n,t})$, consumption bundle $(c_{1,t}, \ldots, c_{n,t})$, shareholdings $(\varphi_{1,t}, \ldots, \varphi_{n,t})$, and input bundles $(y_{ij,t})_{ij}$ such that, in every period t, (i) the household and firms optimize, taking the network and spot market prices as given, and (ii) the market-clearing conditions in equations (6) and (7) hold.*

To solve the multisector model for the competitive equilibrium, we have to define agents' optimality conditions. On the production side, the first-order conditions of firm i are

$$y_{ij,t} = \mu_{i,t} \frac{w_{ij,t} I_{i,t}}{P_{j,t}}, \tag{8}$$

$$I_{i,t} = \left(\frac{\eta P_{i,t} \varepsilon_{i,t}}{\mu_{i,t}} \right)^{\frac{1}{1-\eta}}, \tag{9}$$

and

$$\mu_{i,t} = \prod_{j=1}^{n} \left(\frac{P_{j,t}}{w_{ij,t}} \right)^{w_{ij,t}}, \tag{10}$$

where $\mu_{i,t}$ is a network-weighted average of spot market prices and is the shadow price of investment, that is, $\mu_{i,t}$ is the Lagrange multiplier on the $I_{i,t}$ constraint (equation (1)). Equation (8) specifies the optimal input allocation for a given investment and equation (9) specifies the investment level itself.[10]

For the household, the intraperiod consumption rule is given by

$$c_{i,t} = \alpha_i \frac{\sum_{j=1}^{n} D_{j,t}}{P_{i,t}}, \tag{11}$$

which is a direct implication of the Cobb-Douglas consumption aggregator, which implies that the household spends a share α_i of its income on good i. The first-order condition for the intertemporal consumption allocation problem is

$$\mathbb{E}_t \left[\underbrace{\beta \left(\frac{\mathcal{C}_{t+1}}{\mathcal{C}_t} \right)^{-\rho} \frac{\frac{\partial \mathcal{C}_{t+1}}{\partial c_{1,t+1}} / P_{1,t+1}}{\frac{\partial \mathcal{C}_t}{\partial c_{1,t}} / P_{1,t}}}_{\equiv M_{t+1}} \underbrace{\frac{V_{i,t+1}}{V_{i,t} - D_{i,t}}}_{\equiv R_{i,t+1}} \right] = 1. \tag{12}$$

Equation (12) is the first-order condition for investing in firm i, where M_{t+1} is the SDF and $R_{i,t+1}$ is the one-period return on holding firm i's share from t to $t+1$. The household chooses asset holdings $\{\varphi_{i,t+1}\}_i$ such that equation (12) holds for every asset i.

Therefore, the competitive equilibrium is fully determined by the optimality conditions of firms (equations (8), (9), and (10)), the household's first-order conditions (equations (11) and (12)), and the market-clearing conditions (equations (6) and (7)).

In addition, spot market prices are normalized. When spot market prices satisfy

$$\prod_{j=1}^{n} P_{j,t}^{\alpha_j} = \prod_{j=1}^{n} \alpha_j^{\alpha_j}, \quad \forall t, \tag{13}$$

the consumption aggregator becomes the numeraire of the economy and the utility aggregator equals the household's consumption expenditure, $\mathcal{C}_t = \sum_{i=1}^{n} P_{i,t} c_{i,t}$. The price normalization is useful not only to interpret the numeraire of the economy, but also to simplify the pricing kernel of the assets. Under this price normalization, the marginal aggregator term in the SDF equals one, that is, $\frac{1}{P_{1,t}} \partial \mathcal{C}_t / \partial c_{1,t} = 1$ for every t.[11]

Thus, the normalization considerably simplifies the expression of the SDF. Lemma 1 shows that it may be written in terms of the consumption expenditure growth.

[10] Detailed derivations are in Section I of the Internet Appendix.

[11] See Section II of the Internet Appendix for a detailed discussion and derivation.

LEMMA 1: *If the consumption aggregator is homogeneous of degree one and the price normalization from equation (13) holds, then the SDF can be written as*

$$M_{t+1} = \beta \left(\frac{\omega_{t+1}}{\omega_t} \right)^{-\gamma}, \tag{14}$$

where $\omega_t = \sum_{i=1}^{n} P_{i,t} c_{i,t}$ *is period t total expenditure on consumption goods.*

C. Closed-Form Expressions

In this subsection, I develop closed-form expressions for output shares and consumption expenditure growth.[12]

C.1. Output Shares

The solution to the system of market-clearing conditions in equation (6) determines equilibrium output shares.[13] The output share of sector j is given by

$$\delta_{j,t} = \frac{P_{j,t} Y_{j,t}}{\sum_{i=1}^{n} P_{i,t} Y_{i,t}},$$

where $P_{j,t}$ and $Y_{j,t}$ are the price of good j and the aggregate quantity of good j, respectively. Although $P_{j,t}$ and $Y_{j,t}$ are endogenous, in equilibrium the output shares are completely determined by the network and household preferences. In fact, the output shares are equal to the network centrality of Katz (1953), which captures the relative importance of each node (firm) in a network, that is, the relative importance of each firm to the aggregate economy. The Katz centrality measure further captures the indirect effects that each sector has on the other sectors,

$$\delta_t = (1 - \eta) \left[\mathrm{I} - \eta W_t' \right]^{-1} \alpha = (1 - \eta) \left[\mathrm{I} + \eta W_t' + \eta^2 W_t'^2 + \eta^3 W_t'^3 + \dots \right] \alpha, \tag{15}$$

where δ_t is a column vector of output shares, α is a column vector of preference weights, and the return-to-scale parameter is the decaying rate of the feedback effects.

The output share of firm j may be defined recursively and decomposed into two parts, a preference component and a network component:

$$\delta_{j,t} = \underbrace{(1 - \eta)\alpha_j}_{\text{preference component}} + \underbrace{\eta \sum_{i=1}^{n} w_{ij,t} \delta_{i,t}}_{\text{network component}}.$$

[12] Detailed derivations are in Section III of the Internet Appendix.

[13] The derivation of output share is similar to that in Acemoglu et al. (2012). However, my derivation is for a consumption aggregator with different preference weights, and in the Internet Appendix I solve the model under a general constant elasticity of substitution (CES) production function.

The preference component represents the household's direct demand for goods from sector j, and the network component captures the demand for good j when used as input. The specific contribution of sector i to j's output share depends on sector i's own share, $\delta_{i,t}$, and on the network weight connecting both sectors, $w_{ij,t}$.

The recursive expression of output shares can be iterated to obtain a representation capturing all indirect effects along the network linkages:

$$\delta_{j,t} = \underbrace{(1-\eta)\alpha_j}_{\text{preference component}} + \underbrace{\eta\left[\sum_{i=1}^{n}\alpha_i w_{ij,t} + \eta\sum_{i=1}^{n}\sum_{k=1}^{n}\alpha_i w_{ik,t}w_{kj,t} + \eta^2\sum_{i=1}^{n}\sum_{k=1}^{n}\sum_{s=1}^{n}\alpha_i w_{ik,t}w_{ks,t}w_{s,j,t} + \dots\right]}_{\text{network component}}.$$

The first term of the network component captures the importance of sector j to its immediate customers, firms that are directly connected to j. The second term captures the indirect importance of j through firms that buy inputs from j's customers, that is to say, the customers of the customers of firm j. The third term captures the importance of j through customers that are a step further removed, two customers away from j to be precise, and so on. All of these indirect effects decay at the rate given by the returns to scale η. As firms increase production, the marginal product decreases and the demand of a particular customer has a decaying effect along the production chain.

C.2. Consumption Growth

The SDF, however, depends on changes in the log consumption aggregator, $\log(\frac{\mathcal{C}_{t+1}}{\mathcal{C}_t})$, according to Lemma 1. Changes in the log consumption aggregator are identical to changes in the log aggregate output,

$$\log\left(\frac{\mathcal{C}_{t+1}}{\mathcal{C}_t}\right) = \log\left(\frac{z_{t+1}}{z_t}\right),$$

where $z_t = \sum_{i=1}^{n} P_{i,t}Y_{i,t}$ is aggregate output. The above equality holds because the consumption aggregator is proportional to aggregate output:

$$\mathcal{C}_t = \sum_j P_{i,t}c_{i,t} = \sum_j D_{j,t} = (1-\eta)\sum_j P_{j,t}Y_{j,t} = (1-\eta)z_t.$$

The first equality holds as the consumption aggregator equals consumption expenditure when price normalization in equation (13) is satisfied. The second equality comes from the budget constraint and the clearing conditions combined. The third equality is based on firms' optimality conditions, and the last equality the definition of aggregate output.

Aggregate output is part of the solution of all market-clearing conditions and agents' first-order conditions. To solve the model for the aggregate output, we have to solve firms' optimality conditions. Their first-order conditions can be simplified to

$$\left(\delta_{i,t} z_t\right)^{1-\eta} = \mu_{i,t}^{-\eta} P_{i,t} \varepsilon_{i,t} \eta^{\eta}, \quad \forall\ i, t, \tag{16}$$

where $\delta_{i,t}$ is the equilibrium output shares from equation (15) and $\mu_{i,t}$ is the shadow price of investment from equation (10). Equation (16) along with price normalization in equation (13) are sufficient to determine the equilibrium spot market prices and output. Therefore, equations (13) and (16) together result in a system of $n+1$ equations and $n+1$ unknowns $(z_t, P_{1,t}, \ldots, P_{n,t})$ for each period t that fully characterizes the equilibrium solution of the model. The following theorem shows that this system of equations can be solved analytically.

THEOREM 1: *The equilibrium consumption expenditure growth is given by*

$$\log \mathcal{C}_{t+1} - \log \mathcal{C}_t = \tfrac{1}{1-\eta}\left[\eta \Delta \mathcal{N}_{t+1}^{\mathcal{S}} - (1-\eta)\Delta \mathcal{N}_{t+1}^{\mathcal{C}} + \Delta e_{t+1}\right], \tag{17}$$

where $\Delta \mathcal{N}_{t+1}^{\mathcal{S}} = \mathcal{N}_{t+1}^{\mathcal{S}} - \mathcal{N}_t^{\mathcal{S}}$, $\Delta \mathcal{N}_{t+1}^{\mathcal{C}} = \mathcal{N}_{t+1}^{\mathcal{C}} - \mathcal{N}_t^{\mathcal{C}}$, $\Delta e_{t+1} = e_{t+1} - e_t$,

$$\begin{aligned} \mathcal{N}_t^{\mathcal{S}} &= \textstyle\sum_i \delta_{i,t} \sum_j w_{ij,t} \log w_{ij,t}, \\ \mathcal{N}_t^{\mathcal{C}} &= \textstyle\sum_i \delta_{i,t} \log \delta_{i,t}, \end{aligned}$$

and

$$e_t = \sum_i \delta_{i,t} \log \varepsilon_{i,t}.$$

This is the main result of the general equilibrium model. Equation (17) shows that the consumption expenditure growth rate can be decomposed into three distinct factors: innovations in network concentration ($\Delta \mathcal{N}_{t+1}^{\mathcal{C}}$), innovations in network sparsity ($\Delta \mathcal{N}_{t+1}^{\mathcal{S}}$), and innovations in residual total factor productivity (TFP) (Δe_{t+1}). According to equation (17), changes in sparsity and residual TFP increase consumption and output growth, while changes in concentration have the opposite effect.[14]

Combining Lemma 1 and Theorem 1, we have that the log SDF is given by

$$m_{t+1} = \log \beta - \gamma \frac{1}{1-\eta}\left[\eta \Delta \mathcal{N}_{t+1}^{\mathcal{S}} - (1-\eta)\Delta \mathcal{N}_{t+1}^{\mathcal{C}} + \Delta e_{t+1}\right], \tag{18}$$

[14] A key assumption in the model is that the elasticity of substitution between inputs equals one. Atalay (2017) estimates the elasticity of substitution between inputs and finds that it should be less than one (their point estimate is 0.034) when these inputs are not used to accumulate capital, whereas it should be greater than one (2.87) when these inputs are used for investment or to build capital. This means that inputs are more substitutable when they are used to build capital than when they are used as raw materials. In my model, there is no capital accumulation. Firms buy inputs from each other and these are immediately transformed into effective investment or capital ($I_{i,t}$), which is then used to produce the final output. Thus, neither of the two elasticities estimated by Atalay (2017) fully represents the elasticity of substitution between inputs in my model. In Section V of the Internet Appendix, I set up a version of a model in which the investment aggregator function features CES and I solve a first-order approximation of the model around the unit-elastic case.

which means that sparsity carries a positive price of risk while concentration carries a negative price of risk.

D. Network Factors

In this subsection, I discuss the residual TFP, network concentration, and network sparsity factors in detail.

D.1. Residual TFP

Productivity of firms is combined into one aggregate variable given by

$$e_t \equiv \sum_{i=1}^{n} \delta_{i,t} \log \varepsilon_{i,t}, \tag{19}$$

which is an average of sector-specific productivities weighted by the sector-specific output share.

Since the model does not feature a labor market or capital accumulation, output growth is net of capital and labor utilization, which is exactly what econometricians estimate as TFP in the data. Therefore, residual TFP, e_t, is TFP net of network factors. Innovations in the residual TFP, Δe_{t+1}, positively affect consumption growth because firms become more productive on average.

D.2. Network Concentration

The network concentration factor is given by

$$\mathcal{N}_t^{\mathcal{C}} \equiv \sum_{i=1}^{n} \delta_{i,t} \log \delta_{i,t}. \tag{20}$$

This is the average of firms' log output share weighted by their own output share. This factor is the negative entropy of output shares' distribution and captures output shares' concentration. In equilibrium, sectoral shares depend primarily on the input-output network, and the dynamics of concentration depend only on the input-output network dynamics.[15] As discussed earlier, the output shares in equilibrium are equal to firms' centrality in the network. Therefore, the network concentration factor measures the concentration of nodes' centrality, which is equivalent to the concentration over the size of the network nodes.

Changes in concentration *negatively* affect consumption growth given that $\eta < 1$ (equation (17)). An economy with a high network concentration has few

[15] The fact that changes in concentration depend on changes in the network relies on the assumption that preference weights are constant over time. However, in the data, network concentration using time-varying preference weights is almost identical to the concentration factor, assuming constant preference weights over time, with over 99% correlation between the two series (see the two dashed lines in Figure IA.4 in Section IX of the Internet Appendix).

large sectors. More importantly, these large sectors face lower returns to input investments due to decreasing returns to scale. In equilibrium, these sectors' lower productivity spreads across other sectors through prices, and as a result, aggregate consumption and output decrease. Thus, high concentration leads to lower aggregate consumption.[16]

D.3. Network Sparsity

The network sparsity factor is given by

$$\mathcal{N}_t^S \equiv \sum_{i=1}^{n} \delta_{i,t} \underbrace{\sum_{j=1}^{n} w_{ij_t} \log w_{ij,t}}_{\equiv \mathcal{N}_{i,t}^S}. \tag{21}$$

Sparsity measures the thickness and scarcity of network linkages. Similar to the network concentration factor, the term $\mathcal{N}_{i,t}^S = \sum_{j=1}^{n} w_{ij_t} \log w_{ij,t}$ measures the concentration of $\{w_{ij,t}\}_j$. Hence, $\mathcal{N}_{i,t}^S$ measures sector i's input specialization, which is high when network weights $\{w_{ij,t}\}_j$ are close to zero but have a few values that are relatively large or even close to one. Network sparsity is the average of $\mathcal{N}_{i,t}^S$ weighted by sectors' output shares. High network sparsity implies that sectors specialize in using fewer input sources by spending more resources on fewer inputs. Graphically, a low-sparsity network is represented by the network in Panel A of Figure 2, while Panels B and C provide two examples of high-sparsity networks.

Based on equation (17), changes in sparsity positively affect consumption growth, holding both the residual TFP and the concentration factors fixed. To explain the intuition behind this result, I focus on a partial equilibrium example in which firms are exogenously endowed with some resource to make their input investments. This example allows us to show how sparsity affects the aggregate economy.

Consider a partial equilibrium example in which firm i has $\$k_{i,t}$ units of the numeraire to invest in acquiring inputs to maximize profits. For a given network W_t, firm i's optimal input allocation is given by

$$y_{ij,t} = \frac{w_{ij,t} k_{i,t}}{P_{j,t}} \tag{22}$$

and firm i's output is given by

$$Y_{i,t} = \varepsilon_{i,t} \left(\frac{\prod_{j=1}^{n} w_{ij,t}^{w_{ij,t}}}{\prod_{j=1}^{n} P_{j,t}^{w_{ij,t}}} \right)^{\eta} k_{i,t}^{\eta}. \tag{23}$$

[16] In Section IV of the Internet Appendix, I show that a competitive labor (or land) market diminishes the effect that network concentration has on aggregate output. In this case, the additional production factor (labor or land) is endogenously allocated toward sectors with the highest marginal product, which mitigates the effects of decreasing returns to scale on input investments.

When sparsity increases, the shape of the investment function changes, which affects the marginal product of each input. The network weights represent the output elasticity with respect to different inputs, and the dispersion of these output elasticities increases when sparsity increases. In equilibrium, firms optimally spend less (more) on inputs from sectors whose network weights decreased (increased). In other words, firms specialize in using inputs with high output elasticity. This results in input specialization gains, represented by the term $\prod_{j=1}^{n} w_{ij,t}^{w_{ij,t}}$ in equation (23).

However, whether a particular firm produces more or less depends on changes in sparsity and spot market prices because firms substitute inputs at the relative spot market prices. For example, if firms specialize in using inputs that are more expensive, then the marginal cost of production increases and output decreases. Because firms use different input configurations, input specialization changes their marginal cost of production. The final effect on output is represented by the term $\prod_{j=1}^{n} P_{j,t}^{w_{ij,t}}$ in equation (23).

Therefore, changes in the network weights $\{w_{ij,t}\}$ toward a more sparse network have two immediate effects. On the one hand, sparsity increases total output as the economy benefits from input specialization. Firms substitute inputs toward a more productive input allocation and there are input specialization gains from more dispersion in output elasticities. On the other hand, firms substitute inputs at their relative spot market prices, and changes in their production function affect firms' marginal cost of production as firms may specialize in inputs that are relatively more or less expensive. Changes in marginal cost can be either positive or negative depending on the firm and on the specific change in the network. Therefore, the aggregate effect of an increase in sparsity on firm output depends on the input specialization gain and the changes in firms' marginal cost.

When network concentration and residual TFP are held constant, changes in marginal cost are averaged out to zero and have no aggregate effect in equilibrium. The intuition may be obtained by calculating aggregate output growth using the following approximation:[17]

$$\begin{aligned}\log z_{t+1} - \log z_t &\approx \sum_{i=1}^{n} \delta_{i,t} \left[\log(P_{i,t+1}Y_{i,t+1}) - \log(P_{i,t}Y_{i,t})\right] \\ &\approx \sum_{i=1}^{n} \delta_{i,t+1} \log(P_{i,t+1}Y_{i,t+1}) - \sum_{i=1}^{n} \delta_{i,t} \log(P_{i,t}Y_{i,t}),\end{aligned}$$

where a first-order approximation of $\log z_{t+1}$ is used in the first line, and constant output shares is used in the second line, which is consistent with the idea of holding network concentration constant.

[17] The first-order approximation of $\log z_{t+1}$ around $\{\log(P_{i,t}Y_{i,t})\}_i$ is

$$\log z_{t+1} = \log \sum_i P_{i,t+1}Y_{i,t+1} \approx \log z_t + \sum_i \underbrace{\frac{P_{i,t}Y_{i,t}}{\sum_j P_{j,t}Y_{j,t}}}_{=\delta_{i,t}} \left[\log(P_{i,t+1}Y_{i,t+1}) - \log(P_{i,t}Y_{i,t})\right].$$

We can substitute the expression for sectors' output from equation (23) to understand the aggregate output growth approximation:

$$\sum_{i=1}^{n} \delta_{i,t} \log(P_{i,t} Y_{i,t}) = \underbrace{\sum_{i=1}^{n} \delta_{i,t} \log \varepsilon_{i,t}}_{=e_t} + \eta \sum_{i=1}^{n} \delta_{i,t} \log k_{i,t} + \eta \underbrace{\sum_{i=1}^{n} \delta_{i,t} \sum_{j=1}^{n} w_{ij,t} \log w_{ij,t}}_{=\mathcal{N}_t^S}$$

$$+ \underbrace{\log P_{i,t} - \eta \sum_{i=1}^{n} \delta_{i,t} \sum_{j=1}^{n} w_{ij,t} \log P_{j,t}}_{=(1-\eta)\sum_{i=1}^{n} \alpha_i \log \alpha_i}.$$

The first term on the right-hand side of this equation is the residual TFP factor, that is, e_t. The second term is an affine transformation of the concentration factor because the total amount that firm i invests in equilibrium is given by $k_{i,t} = \eta \delta_{i,t} z_t$. The third term is the network sparsity factor, that is, $\mathcal{N}_t^S$. Finally, the last term is a constant that can be derived using the price normalization and the market-clearing conditions.

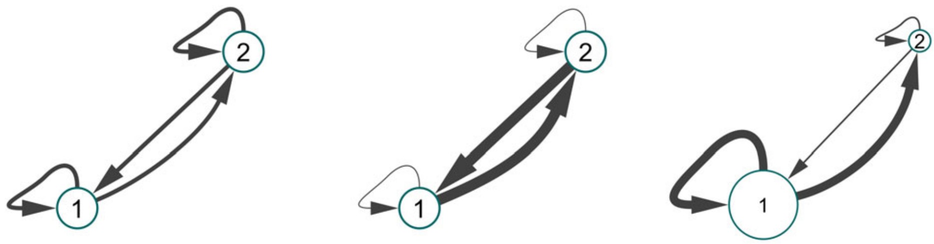
By keeping concentration and residual TFP constant, the only term on the right-hand side of the above equation that changes from t to $t+1$ is network sparsity. Thus, output growth is given approximately by

$$\log z_{t+1} - \log z_t \approx \eta(\mathcal{N}_{t+1}^S - \mathcal{N}_t^S).$$

Since this is a partial equilibrium derivation with an exogenously given investment endowment, it ignores general equilibrium feedback effects. As firms produce more, they buy more inputs from other firms, which in turn makes customers produce more and so forth. These equilibrium feedback effects make the aggregate economy produce even more, but they die off with diminishing returns to scale, which explains the denominator $(1-\eta)$ in the consumption growth expression in equation (17). At the aggregate level, sparsity innovations are associated with specialization gains. When sparsity is high, the input-output linkage changes cause aggregate consumption and output to increase.

E. Examples

Concentration and sparsity are distinct attributes of a network. To show this, in this subsection I provide an example of networks with the same concentration but different sparsity level, and an example in which concentration varies but sparsity is held constant. However, in discussing a third example of two distinct networks that have exactly the same network factors, I show that it is not possible to infer the entire network based on concentration and sparsity alone.



Panel A. Network 1 Panel B. Network 2 Panel C. Network 3

Figure 3. Network factors and network representation. This picture contains representations of three different networks. In Panel A, the weights in Network 1 are $w_{1,1} = w_{1,2} = w_{2,1} = w_{2,2} = 0.5$. In Panel B, the weights in Network 2 are $w_{1,1} = w_{2,2} = 0.1$ and $w_{1,2} = w_{2,1} = 0.9$. In the Panel C, the weights in Network 3 are $w_{1,1} = w_{2,1} = 0.9$ and $w_{1,2} = w_{2,2} = 0.9$. Network edges (arrows) represent input flows, with the width of edges representing network weights. Each node (circle) represents a different sector in the economy, with the size of nodes representing output shares. (Color figure can be viewed at wileyonlinelibrary.com)

EXAMPLE 1 (Change in network sparsity): This economy has two sectors. I assume that the household preference weights on each good are the same. Moreover, I consider two networks:

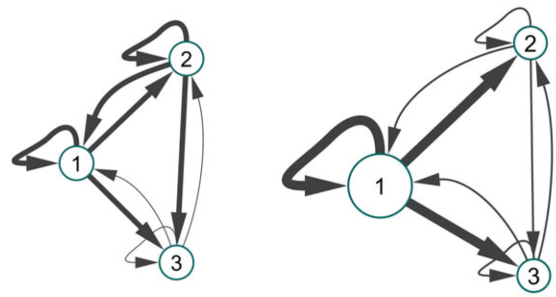
$$W_1 = \begin{pmatrix} 0.5 & 0.5 \\ 0.5 & 0.5 \end{pmatrix} \quad \text{and} \quad W_2 = \begin{pmatrix} 0.1 & 0.9 \\ 0.9 & 0.1 \end{pmatrix}.$$

Networks 1 and 2 are represented graphically in Panels A and B of Figure 3. In Network 1, Sectors 1 and 2 equally spend their input investment in the two inputs. In Network 2, Sector 1 spends 90% of its input investment on inputs from Sector 2 and only 10% on inputs from Sector 1, while Sector 2 does exactly the opposite. Networks 1 and 2 are symmetric and sectors have the same output share in equilibrium, with each sector having 50% of the market. Therefore, Networks 1 and 2 have the same concentration factor of -0.69. However, Network 2 has more input specialization with its sparsity equal to -0.33, while that of Network 1 is -0.69.

EXAMPLE 2 (Change in network concentration): Keeping the structure of Example 1, Network 3 is given by

$$W_3 = \begin{pmatrix} 0.9 & 0.1 \\ 0.9 & 0.1 \end{pmatrix}.$$

A representation of Network 3 is shown in Panel C of Figure 3. In this case, Sectors 1 and 2 both use fewer inputs from Sector 2 and more inputs from Sector 1. Sectors 1 and 2 spend 90% of their input investment in goods from Sector 1 and only 10% in goods from Sector 2. As a result, Sector 1 has 64% of output share, while Sector 2 has 36%, assuming $\eta = 0.35$. In the figure, sectoral shares are represented by nodes' size. Network 3 has a concentration of -0.65 and sparsity of -0.33. Therefore, Network 3 has the same sparsity and more concentration, compared to Network 2.



Panel A. Network 4 Panel B. Network 5

Figure 4. Different networks with same factors. This figure plots two distinct networks that have the same network factors. In Panel A, the weights in Network 4 are $w_{1,1} = w_{1,2} = w_{2,1} = w_{2,2} = w_{3,1} = w_{3,2} = 0.4$ and $w_{1,3} = w_{2,3} = w_{3,3} = 0.2$. In Panel B, the weights in Network 5 are $w_{1,1} = w_{2,1} = w_{3,1} = 0.48$ and $w_{1,2} = w_{1,3} = w_{2,2} = w_{2,3} = w_{3,2} = w_{3,3} = 0.26$. Network edges (arrows) represent input flows, with the width of edges representing network weights. Each node (circle) represents a different sector in the economy, with the size of nodes representing output shares. (Color figure can be viewed at wileyonlinelibrary.com)

EXAMPLE 3 (Same network factors, but different networks): Finally, given the two network factors, it is not possible to recover the entire network. Figure 4 depicts Networks 4 and 5, which have the same network factors. In Network 4, Sectors 1 and 2 are the largest ones, with an output share of 0.4 each, the network concentration factor is -1.09, and the network sparsity factor is -1.05. In Network 5, Sector 1 is the largest sector with 48% output share and Sectors 2 and 3 split the remaining output share, at 26% each. Although Network 5 is different from Network 4, they have the same network factors.

II. Evidence

According to the multisector network model, consumption growth depends positively on sparsity and negatively on concentration. A positive shock to sparsity is associated with higher consumption and lower marginal utility, while a positive shock to concentration is associated with lower consumption and higher marginal utility. Therefore, the model has a clear-cut prediction regarding how innovations in the network factors are priced: innovations in sparsity carry a positive price of risk while innovations in concentration carry a negative price of risk.[18]

[18] To price assets, we need the marginal utility of an agent who chooses asset holdings without constraint and whose Euler equation holds with equality. However, some studies show that consumption may not be properly measured in the data (Attanasio, Battistin, and Leicester (2004), Koijen, Van Nieuwerburgh, and Vestman (2013), Carroll, Crossley, and Sabelhaus (2015)). Concentration and sparsity are based on the fundamentals of a production economy and are related to the consumption of shareholders, as discussed earlier in Section I. Thus, instead of consumption data, I use concentration and sparsity as asset pricing factors.

In this section, I verify the asset pricing prediction of the model. In Section II.B, I sort portfolios based on stocks' exposure to innovations in the network factors, and I show that investors are compensated for the exposure to innovations in the network factors. In Section II.C, I estimate factors' prices of risk. Finally, in Section II.D, I investigate the macroeconomic implications of the model by showing that sparsity (concentration) innovations are associated with higher (lower) aggregate dividend growth.

A. Data

The concentration factor can be computed directly from sectors' output shares, but sparsity requires the entire input-output network. The main input-output data source is the BEA Input-Output Accounts. However, these data are available on an annual basis only from 1997 to 2012. Due to the length of the BEA sample, I use an alternative data set to compute estimates of the input-output tables using Compustat segment customer data, which are available from 1979 to 2013. If a customer represents more than 10% of its sellers' revenue, then the customer's name is reported in Compustat, as well as the sales amount for that particular customer.[19] Combining this information with total sales, it is possible to reconstruct the network for each year and compute a time series for the network factors. Firms are aggregated at the two-digit North American Industry Classification System (NAICS) code level (sector level). This process generates an input-output network for every year in the sample, from which network factors are directly computed.[20]

The two network factors are plotted in Figure 5. Interestingly, since the late 1990s there has been a decline in concentration and an increase in sparsity. Concentration decreased because small sectors expanded while some large sectors shrunk. For instance, between 1997 and 2012, the bottom five sectors in output share expanded their combined output share by 54% from 4.39% to 6.74%. We can break this number down as follows: Warehousing (NAICS 49) expanded 67%, from 0.22% to 0.36%; Education (NAICS 61) expanded 43%, from 0.7% to 1%; Arts and Entertainment (NAICS 71) expanded 20%, from

[19] See Regulation SFAS No. 14 and SFAS No. 131.

[20] The output shares (δ) and network matrix (W) used in the construction of the network factors in the data are from Compustat customer segment data. Since the model is at the sector level, I aggregate Compustat customer sales data at the two-digit NAICS code level (sector level). To calculate output shares, I used sales shares, that is, δ_i is sector i's sales divided by total sales. For the (i, j) entry in the network matrix, I calculated how much sector i sells to each sector and divided by sector i's total sales. Finally, I equally divided the remaining weights in order to have each row sum to one. These calculations are done each year from 1979 to 2013. Details on data construction are provided in Section VII of the Internet Appendix. Cohen and Frazzini (2008) located the CRSP permanent number, PERMNO, of customers until 2009. I updated their data set by locating the customer identification numbers up to 2013. The level of aggregation chosen makes the network factors constructed from the BEA and Compustat data compatible with each other. For the overlapping sample (16 years), the network factors from the two data sets are positively correlated: the concentration values from BEA and from Compustat share a correlation of 86%, while the sparsity series have a correlation of 54%.

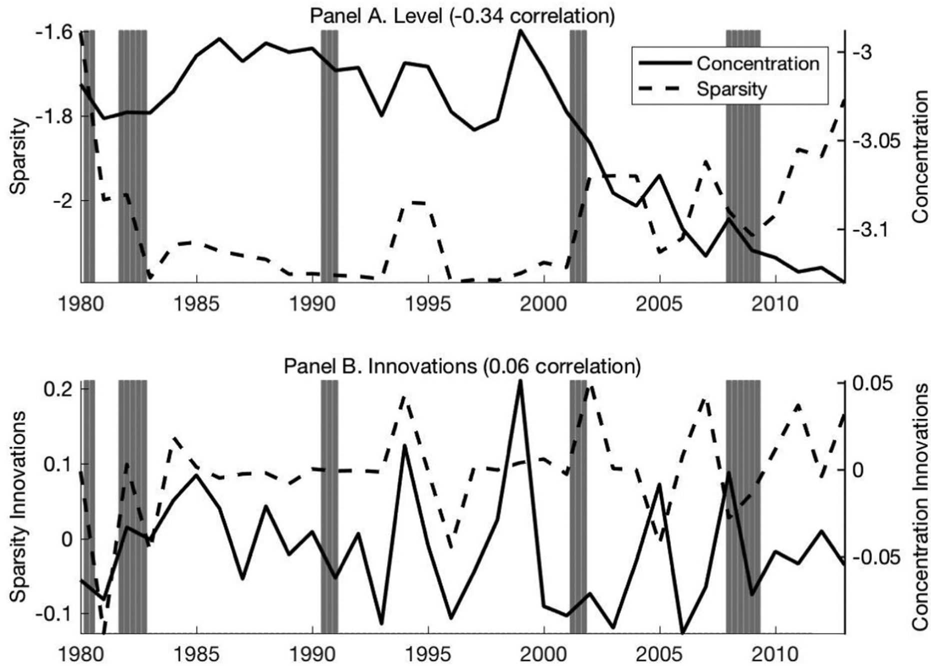


Figure 5. Network factors. This figure shows the time series of concentration (solid line) and sparsity (dashed line) computed from Compustat. Panel A shows the factor levels, while Panel B shows the innovations (one period difference). The sample is from 1980 to 2013 at an annual frequency.

0.87% to 1.05%; Mining (NAICS 21) expanded 83%, from 1.24% to 2.27%; and Management (NAICS 55) increased output share by 50%, from 1.37% to 2.06%. At the same time, large sectors such as manufacturing shrunk over the same period.

Sparsity increased because there was an economywide increase in input specialization. From equation (21), the term $\mathcal{N}^{\mathcal{S}}_{i,t}$ captures the input specialization of sector i. From 1997 to 2013, this sector-specific degree of input specialization (i.e., $\mathcal{N}^{\mathcal{S}}_{i,t}$) increased for most sectors in the economy. For example, for the Transportation sector (NAICS 48), this measure increased from -2.48 in 1997 to -2.12 in 2013, which was the steepest increase across all sectors. In 1997, the Transportation sector spent 18% of its input investment on inputs from Manufacturing (NAICS 32) and another 18.57% on inputs from the transportation sector itself. These were the sector's highest input expenditure shares in 1997. In 2013, the Transportation sector spent 34.57% of its input investment on inputs from Manufacturing (NAICS 32) and another 20.44% on inputs from the transportation sector itself. Therefore, in 1997 inputs from these two sectors represented 36.58% of transportation's input expenditure, while in 2013 they represented 55%. This captures significant input specialization in the Transportation sector. Other sectors experienced a similar pattern. Taken together,

Table I
Network Factors Statistics

This table reports statistics for the network factors in levels and changes (Innov.). AC(j) stands for the j^{th} autocorrelation.

	Sparsity		Concentration	
	Level	Innov.	Level	Innov.
Mean	−3.10	−0.00	−1.83	−0.02
Standard Deviation	0.0360	0.0277	0.1817	0.0757
AC(1)	0.67	−0.09	0.91	−0.07
AC(2)	0.25	0.02	0.82	−0.20
AC(3)	0.09	−0.12	0.77	−0.06
AC(4)	0.04	0.14	0.73	−0.01
AC(5)	0.08	0.08	0.70	0.06

an overall increase in input specialization from 1997 to 2013 led to an increase in network sparsity.

The correlation between the two factors in levels is -34% (p-value $= 0.04$). The factors' innovations are computed as the difference from one year to another, and the correlation between the innovations is 6% (p-value $= 0.72$). This suggests that factors' innovations are not correlated with each other and that innovations in sparsity and concentration represent two distinct sources of risk. Table I reports the mean, standard deviation, and autocorrelation of the network factors, both in levels and innovations. The factors are autocorrelated in levels but not in changes.

For stock returns, I consider all stocks from the CRSP with share codes 10, 11, and 12. Penny stocks are removed from the sample and delisting returns are taken into account. Due to the trailing window, I consider stocks with at least 15 years of data. The annual risk-free rate and the annual market return both come from Kenneth French's website.[21]

B. Sorted Portfolios and Trading Strategy

To verify the positive price of risk for sparsity innovations and the negative price of risk for concentration innovations, I sort stocks based on their exposure to these innovations and form portfolios by terciles on a trailing window.

For every stock i, I regress its excess return on a constant and on innovations in network factors controlling for changes in residual TFP, as well as the network factors in levels from the previous period:[22]

$$r_t^i = \alpha^i + \beta^i_{\mathcal{N}^{\mathcal{S}}} \Delta \mathcal{N}_t^{\mathcal{S}} + \beta^i_{\mathcal{N}^{\mathcal{C}}} \Delta \mathcal{N}_t^{\mathcal{C}} + Controls + \xi_t^i. \tag{24}$$

[21] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[22] Changes in the residual TFP factor, Δe_{t+1}, are computed as the residual from regressing TFP growth on factor innovations. The TFP used is from the Federal Reserve Bank of San Francisco (Basu, Fernald, and Kimball (2006), Fernald and Matoba (2009), Fernald (2012)).

Table II
One-Way Sorted Portfolios

This table reports average excess returns, alphas, volatility, average book-to-market ratio, and average market capitalization (in billions of dollars, inflation adjusted to 2013 dollars) of sparsity-beta-sorted portfolios (Panel A) and concentration-beta-sorted portfolios (Panel B). Columns (1) to (3) report portfolios sorted from low (L) to high (H) network beta. Columns (4) and (5) report the characteristics and t-statistics of a portfolio that goes long high-network-beta portfolio and short the low-network-beta portfolio. The sample period is from January 1995 to December 2013 at a monthly frequency (228 months). Returns, alphas, and volatilities are annualized.

Panel A: Sparsity-Beta-Sorted Portfolios

	L (1)	(2)	H (3)	H−L (4)	t-Stat. (5)
Average excess returns (%)	6.42	8.35	11.03	4.61	2.08
α_{CAPM}	−1.50	2.25	4.68	6.18	2.91
α_{FF}	−1.82	1.27	3.66	5.49	2.65
Volatility (%)	16.48	13.41	14.46	9.64	–
Average book-to-market	0.79	0.76	0.75	–	–
Average market value ($bn)	6.16	7.10	4.22	–	–

Panel B: Concentration-Beta-Sorted Portfolios

	L (1)	(2)	H (3)	H−L (4)	t-Stat. (5)
Average excess returns (%)	10.28	7.82	7.10	−3.18	−2.02
α_{CAPM}	2.98	1.85	−0.31	−3.30	−2.07
α_{FF}	1.97	0.95	−0.76	−2.74	−1.72
Volatility (%)	15.65	13.21	15.25	6.87	–
Average book-to-market	0.77	0.77	0.77	–	–
Average market value ($bn)	3.11	6.44	7.94	–	–

The coefficients $\beta^i_{\mathcal{N}^S}$ and $\beta^i_{\mathcal{N}^C}$ measure the exposure of stock i to the factors' innovations. The controls used in the benchmark estimation are not crucial for the sorted portfolio results, as discussed in the robustness section below (Section II.B.1).

If sparsity carries a positive price of risk, then stocks with high sparsity beta, that is, high $\beta^i_{\mathcal{N}^S}$, are risky assets and should have higher expected returns. Similarly, high-concentration-beta stocks should have lower expected return. For every year t, I compute stocks' exposure to innovations in the network factors using the regression in equation (24) over a 15-year window from $t-14$ to t. I then sort stocks based on each beta separately (one-way sort). Given that stocks are properly sorted, valued-weighted portfolios are formed over the subsequent year ($t+1$). I repeat this procedure as a trailing window until the last year of the sample.

The average returns of the one-way-sorted portfolios are reported in Table II, along with return volatilities, average book-to-market ratio, average market value, and postsample alphas from the CAPM and Fama and French (FF) three-factor model. Panel A reports these moments when portfolios are sorted based on stocks' exposure to network sparsity innovations. The high-sparsity-beta portfolio earned a 4.6% higher return than the low-sparsity-beta portfolio (Column (4)), consistent with a positive price of risk for sparsity innovations. Panel B reports portfolios sorted by their exposure to concentration innovations. Here, the return spread is −3.2% (Column (4)), consistent with a negative price of risk for concentration innovations. Both spreads are statistically significant (Column (5)). Interestingly, neither the CAPM nor the FF three-factor model explain these return gaps, as the postsample alpha spreads are statistically significant. This suggests that innovations in network factors represent a source of risk that is not captured by the market return (CAPM) or by the FF factors. For each trailing window, I compute the correlation between the sparsity and concentration betas estimated from the regression in equation (24). The average correlation is −9%, which means that the network betas are not very correlated and the two network factors represent distinct sources of risk.

The sorted portfolios are roughly similar to each other. The first tercile for the sparsity-beta-sorted portfolios has slightly higher book-to-market ratios (0.79) than the other two terciles (roughly 0.75 each). The average market value of stocks is reported in the last row of each panel.

Taken together, there is compelling evidence that innovations in concentration and sparsity factors constitute priced sources of risk. Moreover, the two factors represent distinct sources of risk that cannot be explained by standard asset pricing models such as the CAPM or the FF three-factor model.

For the market portfolio, I compute the factor betas using the regression in equation (24) and employing the market return instead of individual stock returns. The market sparsity beta is 0.40 and the market concentration beta is −0.08. The betas are not significant, but their signs are consistent with the model. If aggregate consumption growth depends positively on sparsity innovations and negatively on concentration innovations, then the market sparsity beta should be positive while the market concentration beta should be negative.

The theoretical model features perfect competition, hence it is uninformative about network beta heterogeneity at the firm level. For this reason, my mechanism is different from Loualiche (2012) and Corhay, Kung, and Schmid (2017). Industry competition may be related to changes in the network factors, but the interplay between competition and exposure to network factors is beyond the scope of this paper.

B.1. Robustness

The results above are robust to different specifications of the estimation procedure.[23] First, I verify whether the results are robust to double-sorting. In this robustness exercise, I sort stocks on both factors simultaneously and build

[23] Tables IA.IV to IA.VIII in the Internet Appendix report the results. In Section VIII of the Internet Appendix, I also conduct truncation analysis to mitigate concerns regarding the fact that I construct network factors based on Compustat segment customer data.

double-sorted portfolios. Table IA.IV reports returns as well as CAPM and FF alphas for the double-sorted portfolios. The return spread on sparsity-beta-sorted portfolios is 8.32% per year among stocks with high concentration betas; for lower concentration betas, however, the return spread is lower and not significant. The return on the concentration beta-sorted portfolio loses significance for all sparsity beta terciles. Thus, the sparsity factor seems to survive double-sorting.

Second, I consider an alternative set of controls for the regression in equation (24) by removing the network factors in levels. In this case, the control variables only include the changes in the residual TFP factor. The results, reported in Table IA.V, show that the return spread as well as the CAPM and FF alpha spreads are positive and significant for the sparsity-beta-sorted portfolios. For the concentration-beta-sorted portfolios, the return spread is negative but not significant, but the CAPM alpha spread is negative and significant.

Third, I verify whether changes in the residual TFP calculation affect the results. In Table IA.V, I consider two alternative specifications as robustness checks: I reestimate the network betas without controlling for TFP, and I use aggregate consumption growth rather than TFP growth. For both sparsity- and concentration-beta-sorted portfolios, the results remain roughly unchanged.

Fourth, I check whether trailing length matters for the return spreads. In the benchmark estimation, the trailing window is 15 years. Table IA.V shows that the quantitative results are robust to using trailing windows from 16 years and 20 years.

Finally, I double-sort stocks on network factors and other portfolio characteristics. Table IA.VII reports portfolios double-sorted on sparsity and seven other factors: market value, book-to-market ratio, total volatility (over one year of daily data), idiosyncratic volatility from the CAPM (over one year of daily data), idiosyncratic volatility from the FF three-factor model (over one year of daily data), volume, and turnover (volume divided by market value). Table IA.VIII reports portfolios double-sorted on concentration and the seven factors considered above. Both the sparsity- and concentration-beta-sorted portfolio return spreads have the correct sign and are statistically significant among stocks with high market value, low book-to-market ratio, low volatility, high volume, and low turnover.

C. *Prices of Risk*

In this section, I examine whether the network factors are priced in other portfolios. I build a sparsity factor-mimicking portfolio that goes long the high-sparsity-beta portfolio and short the low-sparsity-beta portfolio. I follow the same procedure to create concentration and residual TFP factor-mimicking portfolios. I use these factor-mimicking portfolios as asset pricing factors and run Fama and MacBeth (1973) regressions at a monthly frequency to verify whether concentration and sparsity are priced in different assets.

This is a two-stage procedure. For a given set of test assets and a given set of asset pricing factors, I first regress the time-series excess returns on

Table III
Fama and MacBeth Analysis: Network Factors

This table reports the estimated prices of risk for three asset pricing factors: sparsity and concentration network factor-mimicking portfolios, along with the residual TFP factor-mimicking portfolio. In terms of test assets, I consider seven different test assets. Column (1) uses 25 portfolios double-sorted on size and book-to-market. Column (2) adds 10 momentum-sorted portfolios. Column (3) adds 10 long- and 10 short-term reversal sorted portfolios. Column (4) adds 10 investment and 10 operating profitability sorted portfolios. Column (5) adds 10 accruals, 10 cash flow, 10 dividend yield, 10 earning-price ratio, 10 net issuance, 10 residual variance, and 10 total variance sorted portfolios. Column (6) adds four corporate bond portfolios sorted by credit rating. Different from the previous columns, Column (7) uses only 30 industry-sorted portfolios. All the portfolio data come from Kenneth French's website, except for the corporate bond portfolios, which are from Citibank's Yield Book for four investment-grade portfolios: AAA, AA, A, and BBB. The last row reports the cross-sectional R^2. t-statistics are based on Newey and West (1987) standard errors. The sample period is from January 1995 to December 2013 at a monthly frequency (228 months), except for the corporate bond portfolio sample, which ends on May 2013. All coefficients are annualized.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Residual TFP	12.66	5.45	8.35	8.09	3.13	4.84	−0.44
t-Stat.	2.86	1.37	2.84	3.10	2.20	3.16	−0.28
Sparsity	−3.95	1.97	1.02	1.66	2.47	1.95	2.83
t-Stat.	−1.34	0.74	0.55	1.10	2.62	1.94	1.96
Concentration	−9.63	−11.51	−9.91	−9.18	−6.53	−7.31	−3.95
t-Stat.	−3.50	−3.53	−4.34	−5.00	−5.10	−5.35	−1.83
R^2	0.38	0.35	0.27	0.29	0.18	0.21	0.28

the factors considered, that is, one time-series regression for each asset. In the second stage, I regress the time-series average of the excess returns on the estimated coefficients from the first stage, that is, one cross-sectional regression for all assets. The coefficients from the second stage, reported in Table III, are the prices of risk of the asset pricing factors.

We can conduct this test for any set of portfolios to verify whether innovations in sparsity and concentration are priced. Following Lewellen, Nagel, and Shanken (2010), I use a comprehensive set of portfolios from Kenneth French's website to identify risk prices. I start by estimating prices of risk among the 25 portfolios double-sorted by size and book-to-market (25 FF portfolios). The estimation results are displayed in Column (1) of Table III. Network concentration is priced among the 25 FF portfolios with a negative price of risk, which is consistent with the theoretical model. However, for this first set of test assets, sparsity is not significant. In Column (2), I include 10 momentum-sorted portfolios in addition to the 25 portfolios used in Column (1), and network concentration still carries a significant negative price of risk. Column (3) adds 10 portfolios sorted on long-term reversal and 10 portfolios sorted on short-term reversal to the set of test assets, and the results remain unchanged. In Column (4), I add 10 investment and 10 operating profitability sorted portfolios to the set of test assets, and in Column (5) I also include 10 accruals, 10 cash flow, 10 dividend yield, 10 earnings-price ratio, 10 net issuance, 10 residual variance, and 10 total variance sorted portfolios. Finally, in Column (6), I add corporate bond portfolios for four investment grades: AAA, AA, A, and BBB. As we add more portfolios to the set of test assets in Columns (1) to (6), network sparsity becomes statistically significant with a positive price of risk, while network concentration is priced with a negative price of risk, among all six sets of test assets.

Finally, in Column (7), I use only 30 industry-sorted portfolios as test assets. In this estimation, the price of risk is positive for sparsity and negative for concentration, which is consistent with the model's prediction. However, residual TFP is not significantly priced among the industry portfolios. In a robustness test in the Internet Appendix, I recalculate these prices of risk controlling for other asset pricing factors. I show that the results are similar when controlling for the three factors from the FF three-factor model, namely, the market return, the small minus big, and the high minus low factors.

The Fama and MacBeth (1973) analysis suggests that concentration and sparsity are priced in the cross-section of stock returns. As we increase the dimensionality of risk and include different test assets in the analysis, both network concentration and sparsity are significantly priced in the cross-section (Columns (5) and (6)). This analysis, in addition to the network-beta-sorted portfolio, provides solid evidence that both network factors are priced sources of systematic risk.

D. Additional Macroeconomic Evidence

According to the model, aggregate dividend should be positively related to changes in sparsity and negatively related to changes in concentration (Theorem 1) because equation (17) specifies not only the consumption expenditure growth but also the aggregate dividend growth. I, therefore, use data from the National Income and Product Accounts (NIPA) Table 1.10 to construct a time series for aggregate dividend growth and test how the network factors relate to aggregate dividends.

In Table IV, I regress aggregate dividend growth on changes in sparsity and concentration, controlling for aggregate TFP, and find that sparsity innovations are associated with higher dividend growth, while concentration innovations are associated with low dividend growth rates. The regression coefficient on concentration is -0.85 ($t = -2.27$) and on sparsity it is 1.35 ($t = 1.31$), which is consistent with the model prediction of a positive coefficient for sparsity innovations and a negative coefficient for concentration innovations. Furthermore, the R^2 is 22%.

Alternatively, we can calculate the dividend growth rate using ex- and cum-dividend return data for the market portfolio and rerun the same regressions. In this case, the R^2 is 19% and the regression coefficients are -0.53 ($t = -1.67$) and 0.70 ($t = 0.66$) for concentration and sparsity, respectively.

Changes in network factors are also correlated with the shareholder's consumption growth at a lower frequency. Using shareholder consumption data

Table IV

Network Factors and Dividends

This table reports the coefficients and t-statistics from the regression of aggregate dividend growth on the network factors and a constant, controlling for the residual TFP factor. The last row reports the R^2. The first column uses the dividend growth rate implied by cum- and ex-dividend returns from the CRSP market return, and the second column uses dividend growth rate from National Income and Product Accounts (NIPA) Table 1.10. The sample is at an annual frequency from 1979 to 2013.

	Aggregate Dividend (CRSP)	Aggregate Dividend (NIPA)
Sparsity	0.70	1.35
t-Stat.	0.66	1.31
Concentration	−0.53	−0.85
t-Stat.	−1.67	−2.27
R^2	0.19	0.22

from Annette Vissing-Jørgensen's website[24] and regressing the consumption growth of the top shareholders on the two network factors, I find that sparsity is associated with higher consumption growth and concentration is associated with lower growth rates, over the next four to five years. The fact that the network factors' effects on top-shareholder consumption align with the model predictions is consistent with the empirical findings for the cross-section of stock returns. This is because both shareholder consumption and the network factors capture cross-sectional variation on average assets' returns (Malloy, Moskowitz, and Vissing-Jørgensen (2009)).

III. Conclusion

In this paper, I develop a multisector network model that predicts that two key characteristics of the network—sparsity and concentration—matter for both asset prices and aggregate quantities such as consumption and GDP. Changes in these two factors constitute an aggregate source of risk that is priced in equilibrium. Using return data, I find supportive evidence that innovations in the network factors are priced. By sorting stocks on their exposure to network factor innovations and forming portfolios by terciles, I find that there is a significant return gap that cannot be explained by standard asset pricing models such the CAPM or the FF three-factor model. Specifically, sparsity-beta-sorted portfolios have a return spread of 4.6% per year and concentration-beta-sorted portfolios have a return spread of −3.2% per year.

The literature on networks and macrofinance has documented stylized facts and has built a microfoundation for business cycles, financial contagion, and other macroeconomic phenomena. In this paper, I explore the asset pricing implications of a sectoral network model, and I identify new asset pricing factors constructed from the input-output network.

[24] See http://faculty.haas.berkeley.edu/vissing/.

Future work might extend this paper by focusing on a less aggregated level, ideally the firm level, to endogenize the network formation process. An immediate implication of endogenous network formation is that the equilibrium may become inefficient as firms form their connections ignoring the effects on other firms (network externality). Moreover, endogenous network formation can potentially amplify the effects of network concentration and sparsity depending on firms' incentives to form their connections. Future work might also introduce frictions in the credit market. In this case, the standard Long and Plosser (1983) aggregation result would no longer hold and sectors' output will not comove as much for any given network. This extension would allow for an analysis of the relation between firm-level volatility and network characteristics through the lens of an equilibrium model.

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REFERENCES

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012, The network origins of aggregate fluctuations, *Econometrica* 80, 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2015a, Systemic risk and stability in financial networks, *American Economic Review* 105, 564–608.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2015b, Systemic risk in endogenous financial networks, Columbia Business School Research Paper 15–17.

Ahern, Kenneth, 2013, Network centrality and the cross section of stock returns, Working paper.

Ahern, Kenneth, and Jarrad Harford, 2014, The importance of industry links in merger waves, *Journal of Finance* 69, 527–576.

Allen, Franklin, and Ana Babus, 2009, Networks in finance, in Paul R. Kleindorfer, and Yoram R. Wind, eds., *The Network Challenge* (Prentice Hall Publishing, Upper Saddle River, NJ).

Aobdia, Daniel, Judson Caskey, and N. Bugra Ozel, 2014, Inter-industry network structure, information transfers, and the cross-predictability of earnings and stock returns, *Review of Accounting Studies* 19, 1191–1224.

Atalay, Enghin, 2017, How important are sectoral shocks? *American Economic Journal: Macroeconomics* 9, 254–280.

Attanasio, Orazio, Erich Battistin, and Andrew Leicester, 2004, Inequality, poverty, and their evolution in the US: Consumption and income information in the Consumer Expenditure Survey, Notes prepared for the National Poverty Center's ASPE-Initiated Workshop on Consumption among Low-Income Families, Washington, DC, November 5.

Babus, Ana, 2016, The formation of financial networks, *RAND Journal of Economics* 47, 239–272.

Babus, Ana, and Tai-Wei Hu, 2017, Endogenous intermediation in over-the-counter markets, *Journal of Financial Economics* 125, 200–215.

Babus, Ana, and Péter Kondor, 2016, Trading and information diffusion in over-the-counter markets, *Econometricia* (forthcoming).

Babus, Ana, and Cecilia Parlatore, 2016, Strategic fragmented markets, Working paper.

Bak, Per, Kan Chen, José Scheinkman, and Michael Woodford, 1993, Aggregate fluctuations from independent sectoral shocks: Self-organized criticality in a model of production and inventory dynamics, *Ricerche Economiche* 47, 3–30.

Bala, Venkatesh, and Sanjeev Goyal, 2000, A noncooperative model of network formation, *Econometrica* 68, 1181–1229.

Basu, Susanto, John Fernald, and Miles Kimball, 2006, Are technology improvements contractionary? *American Economic Review* 96, 1418–1448.

Belo, Frederico, 2010, Production-based measures of risk for asset pricing, *Journal of Monetary Economics* 57, 146–163.
Biggio, Saki, and Jennifer La'O, 2016, Financial frictions in production networks, NBER Working Paper No. 22212.
Binsbergen, Jules H., 2016, Good-specific habit formation and the cross-section of expected returns, *Journal of Finance* 71, 1699–1732.
Carroll, Christopher, Thomas Crossley, and John Sabelhaus, 2015, *Improving the Measurement of Consumer Expenditures* (University of Chicago Press, Chicago).
Carvalho, Vasco M., 2010, Aggregate fluctuations and the network structure of intersectoral trade, Working Paper No. 1206, Universitat Pompeu Fabra.
Carvalho, Vasco M., 2014, From micro to macro via production networks, *Journal of Economic Perspectives* 28, 23–48.
Carvalho, Vasco M., and Xavier Gabaix, 2013, The great diversification and its undoing, *American Economic Review* 103, 1697–1727.
Carvalho, Vasco M., and Basile Grassi, 2015, Large firm dynamics and the business cycle, CEPR Discussion Paper No. DP10587.
Carvalho, Vasco M., Makoto Nirei, Yukiko Saito, and Alireza Tahbaz-Salehi, 2016, Supply chain disruptions: Evidence from the Great East Japan Earthquake, Columbia Business School Research Paper No. 17–5.
Carvalho, Vasco M., and Nico Voigtlander, 2014, Input diffusion and the evolution of production networks, NBER Working Paper No. 20025.
Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, *Journal of Finance* 63, 1977–2011.
Cohen, Lauren, Andrea Frazzini, and Christopher Malloy, 2008, The small world of investing: Board connections and mutual fund returns, *Journal of Political Economy* 116, 951–979.
Corhay, Alexandre, Howard Kung, and Lukas Schmid, 2017, Competition, markups and predictable returns, SSRN Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2550981.
Denbee, Edward, Christian Julliard, Ye Li, and Kathy Yuan, 2017, Network risk and key players: A structural analysis of interbank liquidity, Columbia Business School Research Paper No. 17–6.
Eisfeldt, Andrea L., Bernard Herskovic, Emil Siriwardane, and Sriram Rajan, 2018, OTC intermediaries, Working paper.
Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.
Farboodi, Maryam, 2014, Intermediation and voluntary exposure to counterparty risk, SSRN Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2535900.
Fernald, John, 2012, A quarterly, utilization-adjusted series on total factor productivity, FRBSF Working Paper 2012–19.
Fernald, John, and Kyle Matoba, 2009, Growth accounting, potential output, and the current recession, FRBSF Economic Letter 2009–26. Available at https://pdfs.semanticscholar.org/b098/2a8b94e25c70fa4dd57035c120302c8cc112.pdf.
Gabaix, Xavier, 2011, The granular origins of aggregate fluctuations, *Econometrica* 79, 733–772.
Galeotti, Andrea, and Sanjeev Goyal, 2010, The law of the few, *American Economic Review* 100, 1468–1492.
Gofman, Michael, 2011, A network-based analysis of over-the-counter markets, AFA 2012 Chicago Meetings Paper.
Gofman, Michael, 2017, Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions, *Journal of Financial Economics* 124, 113–146.
Gomes, Joao, Leonid Kogan, and Motohiro Yogo, 2009, Durability of output and expected stock returns, *Journal of Political Economy* 117, 941–986.

Gomes, Joao, and Lukas Schmid, 2012, Equilibrium credit spreads and the macroeconomy, The Wharton School Research Paper No. 42.

Herskovic, Bernard, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh, 2016, The common factor in idiosyncratic volatility: Quantitative asset pricing implications, *Journal of Financial Economics* 119, 249–283.

Herskovic, Bernard, Bryan Kelly, Hanno Lustig, and Stijn Van Nieuwerburgh, 2017, Firm volatility in granular networks, CEPR Discussion Papers No. 12284.

Herskovic, Bernard, and Joao Ramos, 2017, Information through peers, SSRN Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2613202.

Hollifield, Burton, Artem Neklyudov, and Chester Spatt, 2017, Bid-ask spreads, trading networks, and the pricing of securitizations, *Review of Financial Studies* 30, 3048–3085.

Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *Journal of Finance* 61, 1927–1956.

Jermann, Urban J., 1998, Asset pricing in production economies, *Journal of Monetary Economics* 41, 257–275.

Jermann, Urban J., 2010, The equity premium implied by production, *Journal of Financial Economics* 98, 279–296.

Jermann, Urban J., 2013, A production-based model for the term structure, *Journal of Financial Economics* 109, 293–306.

Jovanovic, Boyan, 1987, Micro shocks and aggregate risk, *Quarterly Journal of Economics* 102, 395–409.

Katz, Leo, 1953, A new status index derived from sociometric analysis, *Psychometrika* 18, 39–43.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman, 2015, Winners and losers: Creative destruction and the stock market, NBER Working Paper No. 18671.

Koijen, Ralph, Stijn Van Nieuwerburgh, and Roine Vestman, 2013, Judging the quality of survey data by comparison with “truth” as measured by administrative records: Evidence from Sweden, in Christopher D. Carroll, Thomas F. Crossley, and John Sabelhaus, eds., *Improving the Measurement of Consumption Expenditures*, NBER Book Series in Income and Wealth (National Bureau of Economic Research).

Kuehn, Lars-Alexander, 2009, Disentangling investment returns and stock returns: The importance of time-to-build, AFA 2010 Atlanta Meetings Paper.

Kuehn, Lars-Alexander, and Lukas Schmid, 2014, Investment-based corporate bond pricing, *Journal of Finance* 69, 2741–2776.

Kung, Howard, and Lukas Schmid, 2015, Innovation, growth and asset prices, *Journal of Finance* 70, 1001–1037.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

Li, Dan, and Norman Schürhoff, 2013, Dealer networks: Market quality in over-the-counter markets, Working paper. Available at https://finance.uni-mannheim.de/fileadmin/files/areafinance/files/HWS_2013/Schuerhoff_2013_DealerNetworks.pdf.

Lochstoer, Lars A., 2009, Expected returns and the business cycle: Heterogeneous goods and time-varying risk aversion, *Review of Financial Studies* 22, 5251–5294.

Long, John B., and Charles I. Plosser, 1983, Real business cycles, *Journal of Political Economy* 91, 39–69.

Loualiche, Erik, 2012, Asset pricing with entry and imperfect competition, Working paper, Sloan School of Management, MIT. Available at https://loualiche.gitlab.io/www/docs/AP_entry.pdf.

Malamud, Semyon, and Marzena Rostek, 2017, Decentralized exchange, *American Economic Review* 107, 3320–3362.

Malloy, Christopher J., Tobias J. Moskowitz, and Annette Vissing-Jørgensen, 2009, Long-run stockholder consumption risk and asset returns, *Journal of Finance* 64, 2427–2479.

Neklyudov, Artem, and Batchimeg Sambalaibat, 2015, Endogenous specialization and dealer networks, SSRN Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2676116.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Oberfield, Ezra, 2012, Business networks, production chains, and productivity: A theory of input-output architecture, FRB of Chicago Working Paper No. 2011–12.

Ozdagli, Ali K., and Michael Weber, 2017, Monetary policy through production networks: Evidence from the stock market, NBER Working Paper No. 23424.

Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639–685.

Pasten, Ernesto, Raphael Schoenle, and Michael Weber, 2016, The propagation of monetary policy shocks in a heterogeneous production economy, Working paper, Chicago Booth. Available at http://faculty.chicagobooth.edu/michael.weber/research/pdf/monetaryPolicyShocks.pdf.

Richmond, Robert J., 2016, Trade network centrality and currency risk premia, SSRN Working Paper. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2607735.

Wu, Di, 2016, Shock spillover and financial response in supply chain networks: Evidence from firm-level data, Working paper. Available at http://fbe.usc.edu/seminars/papers/RECR_1-29-16_F_WUjmp.pdf.

Yogo, Motohiro, 2006, A consumption-based explanation of expected stock returns, *Journal of Finance* 61, 539–580.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.