Federal Reserve Bank of Dallas

Upstream, Downstream & Common Firm Shocks

Everett Grant and Julieta Yung

Globalization Institute Working Paper 360

Research Department

https://doi.org/10.24149/gwp360

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Everett Grant[†] and Julieta Yung[‡]

April 12, 2019

Abstract

We develop a multi-sector DSGE model to calculate upstream and downstream industry exposure networks from U.S. input-output tables and test the relative importance of shocks from each direction by comparing these with estimated networks of firms' equity return responses to one another. The correlations between the upstream exposure and equity return networks are large and statistically significant, while the downstream exposure networks have lower — but still positive — correlations that are not statistically significant. These results suggest a low short-term elasticity of substitution across inputs transmitting shocks from suppliers, but more flexible ties with downstream firms. Additionally, both the DSGE model and simulations of our empirical approach highlight the importance of accounting for common factors in network estimation, which become more important over our 1989-2017 sample period, explaining 11.7% of equity return variation over the first ten years and 35.0% over the final ten.

Keywords: upstream versus downstream, input-output linkages, firm networks, shock propagation, aggregate shocks.

JEL Codes: C32, D85, E23, E44, G01

[*] We thank Alex Chudik, Pavel Kapinos, Christoffer Koch, Karen Lewis, Karel Mertens, Jorge Miranda-Pinto, Alex Richter, Mike Sposi, Kei-Mu Yi, Eric Young, and attendees of the 2018 Federal Reserve Bank of Dallas Banking and Finance Workshop, and 2019 SNDE conferences for helpful comments and suggestions, and Daniel Crowley for phenomenal research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

[†] Everett Grant, Federal Reserve Bank of Dallas, 2200 N. Pearl Street, Dallas, TX 75201, EGrant.Econ@gmail.com, +1 214 922 5622.

[‡] Julieta Yung, Bates College, 4 Andrews Road, Lewiston, ME 04240, JYung@Bates.edu, +1 207 786 6184.

Several crisis episodes and natural disasters over the past decade have seen the broad transmission of economic shocks across firms and industries. The frequency and severity of these events has driven research on what channels transmit shocks as they spread across firms and how these mechanisms have evolved over time. The literature has focused on bilateral input-output, financial, and trade relationships; however, it remains unclear whether the co-movements experienced during these events arise from network linkages versus exposure to common underlying factors.[1]

The recent experience of ZTE Corp illustrates the importance of firms' upstream connections with suppliers. When the Commerce Department announced a prohibition on U.S. firms selling to the Chinese telecommunications firm for its failing to comply with prior sanctions, its equity price declined over 60% and it neared insolvency.[2] This event can also be viewed as an exogenous downstream shock for U.S. firms such as Qualcomm, Intel, and AT&T that supplied ZTE and experienced significant contagion, with several suppliers having equity declines over 35% or appreciably deteriorated financial conditions.

This paper evaluates the importance of upstream versus downstream exposures, as well as the role of common factors. We develop a multi-sector DSGE model to measure upstream and downstream sectoral exposures from input-output tables. The model indicates that after common factors are removed, equity returns reflect firms' idiosyncratic responses to shocks through these two exposure networks. We therefore propose an empirical approach to estimate both common factors and the inter-firm network from daily equity returns for U.S. firms over 1989-2017. These inter-firm networks capture the realized responses of firms to one another, and we compare their network adjacency matrices with those of the upstream and downstream exposure networks to gauge the importance of each direction for shock propagation in the U.S. economy over the past three decades.

Exposure to suppliers is economically important and statistically significant with a 0.62 average correlation between the upstream exposure networks derived from U.S. input-output tables and the defactored equity return response networks. However, the downstream exposure networks have statistically insignificant average network correlations of only 0.22 with the equity response networks. These are suggestive of a low short-term elasticity of substitution across inputs passing shocks downstream but greater flexibility with customers.

On the common factor side, the DSGE model indicates firm equity returns depend on three aggregates — the overall growth of the economy, the price level, and the supply of raw inputs. The empirical model agrees in finding three significant common factors, and they correlate with those from the theoretical model. These common factors — especially the growth, or broad market beta factor — become more important over the period we study, explaining 11.7% of the equity return variation over the first ten years of the sample and 35.0% over the final ten.

The literature studying common shocks, and upstream and downstream inter-industry connections has grown significantly in the past several years.[3] To evaluate these three potential transmis-

[1] The importance of these channels and common shocks at the country and sector levels has been explored in many papers, including Brooks and Del Negro (2006), Burstein et al. (2008), di Giovanni and Levchenko (2010), Grant (2016), Imbs (2004), Johnson (2014) and Loayza et al. (2001).

[2] For details see https://www.wsj.com/articles/in-zte-battle-u-s-suppliers-are-collateral-damage-1524562201 and https://www.wsj.com/articles/ztes-operations-shutdown-stymies-major-phone-customers-1525957596.

[3] Recent papers on endogenous network formation and input-output linkages are Atalay et al. (2011), Gabaix (2011), Acemoglu et al. (2012), Acemoglu et al. (2016), Acemoglu et al. (2017), Acemoglu and Azar (2017), Taschereau-Dumouchel (2017), Oberfield (2018), and Bernard et al. (2019). See Carvalho and Tahbaz-Salehi (2019)

sion channels, we expand the model of Baqaee (2018) from a one period setting to a multi-sector DSGE model with inter-temporal assets. In the model, heterogeneous monopolistically competitive firms may either sell their goods to the household sector or to other firms as intermediate inputs. The model serves two purposes. It provides the method to calculate upstream and downstream exposure networks from U.S. input-output data and gives us a basis for the equity return network estimation.

The empirical approach to estimate inter-firm networks from daily equity return data capturing these influences consists of several steps. We first estimate the common factors from the equity return series using principal component analysis, finding evidence of three significant common factors that appear to correspond with the three suggested by the DSGE model. The first is the average daily return across firms in our sample, which is highly correlated with U.S. economic growth as measured by industrial production or GDP. We label the second factor the price one as it is highly correlated with U.S. PPI, CPI, the value of the dollar, and 10-year breakeven inflation. The third factor has a strong correlation with commodities, particularly oil.

In the second step we get the residual, idiosyncratic firm returns by subtracting the contributions of the common factors. Third, we estimate inter-firm networks from these defactored returns, following the work of Bonaldi et al. (2015), Demirer et al. (2018), Diebold and Yilmaz (2009, 2014, 2016), Grant and Yung (2017), and Scida (2017) in deriving them from vector-autoregressions (VAR), being the first to ground such analysis in a structural DSGE model to enhance interpretation. We utilize the variable selection method from Chudik et al. (2018) to deal with the curse of dimensionality and avoid over-fitting the data in such a large VAR. We apply our method to daily equity returns for samples of 500 to $1,600$ U.S. firms from 1989 to 2017 to obtain a comprehensive picture of idiosyncratic and aggregate connections across all industries in the U.S. economy.

Finally, once we have the common factors, their loadings, and the VAR of idiosyncratic equity returns, we estimate networks across them using generalized forecast error variance contributions to infer the magnitude and direction of these relationships.[4] We estimate firm networks at both the actual return level inclusive of the effects of the common factors in the individual firms' returns, and at the idiosyncratic returns level.[5] Using simulations we show that the former networks that do not separate out the effects of common factors produce networks similar to others in the literature. These approaches are more reflective of similar loadings on common factors than of the bilateral relationships they are often purported to estimate, while the idiosyncratic return based networks reflect the bilateral network connections that they are intended to capture well.

We compare inter-firm networks from equity returns with input-output based networks to assess the relative importance of upstream/supply side versus downstream/demand side shocks for explaining firms' equity responses to one another. We do so by aggregating the estimated equity return networks at the sector level and comparing them with several types of input-output table based networks. These include the raw input-output tables, their Leontief inverses, and the theo-

for further literature relating production networks to macroeconomic aggregate fluctuations.

[4]These are similar to the standard generalized forecast error variance decompositions of Pesaran and Shin (1998), however, we do not divide through by the equity variance adjustment in the denominator. We do this because that adjustment varies by firm and over time, and we would like the edge weights to be comparable across both.

[5]In a similar vein, Hale and Lopez (2018) study bank holding company networks, extracting common factors that affect all firms within the network and then identifying idiosyncratic shocks that include any remaining connections between the firms to demonstrate how recent methodologies can produce useful measures of connectedness from large amounts of available data at mixed frequencies.

retical upstream and downstream exposures. We treat these tables as sectoral network adjacency matrices and calculate their correlations using a procedure to bootstrap the expected correlation distributions over networks of similar structure and calculate statistical significance. We find that upstream exposures (shocks to a firm's suppliers) are more important than downstream exposures (shocks to customers), as the correlations are economically and statistically significant between the equity networks and the upstream networks; however, that is not the case for the downstream ones. For example, a manufacturer facing a disruption from a supplier going bankrupt might be unable to produce in the short-term because of frictions in retooling its production process to substitute the use of parts from another source; however, if there were a bankruptcy of a customer then it could adjust its sales strategy to other clients, with less business impact.

Further, the supplier exposure networks have higher correlations with the equity response networks than do the Leontief inverses, suggesting an important role for market structure, the demand elasticities across goods, and the markups priced into the former networks. The defactored equity response networks on average have 34% higher correlations with the upstream exposure networks than those that include the common factors — as past network estimation procedures implicitly do — suggesting that they better reflect the underlying firm connections. These results support the use of the defactored network estimation method to study transmission across firms, especially towards the end of our sample when common factors become a greater driver of the equity returns, skewing the networks estimated inclusive of common factors that have declining correlations with the input-output derived networks over time.

In Section 4.3 we provide a discussion of these findings in the context of the relevant theoretical and empirical literatures, and their implications. Our results on upstream versus downstream shock transmission are important for the theoretical literature following Long and Plosser (1983) in examining multi-sector economies, since it differs on which of these two channels are operational. One important point here is that our findings provide support for the many papers that rely on Cobb-Douglas input aggregation or other modeling simplifications that cut-off the downstream exposure channel.[6] These results are also consistent with the empirical literature finding strong exposures to suppliers, such as Boehm et al. (2019) and Carvalho et al. (2016) analyzing the ramifications of the 2011 Tohoku earthquake. We contribute the result that the reverse direction does not appear to be as relevant.

Using our equity based networks, we can estimate connections at a higher frequency and more granular level than input-output tables and assess the impact of shocks in real-time. We present an application of how the estimated firm networks can be used to analyze the impact of aggregate productivity and commodity price shocks across firms. This analysis shows that financial, consumer cyclical and commodity firms would be most affected by a market beta/growth shock, with the former at the center of the network in close proximity to the growth factor. A negative commodity price shock would unsurprisingly most adversely affect energy and base materials companies, while an airline in the network is expected to have the largest positive response. That an airline would be affected in this manner likely reflects the high fuel costs faced by the industry and is an example of how an understanding of these inter-firm networks can be used by its managers and investors to hedge or neutralize its commodity exposure.

[6] There is no upstream propagation of shocks under Cobb-Douglas because the price and quantity effects cancel out (Shea (2002)).

1 Modeling Firm Upstream and Downstream Exposures

We model a firm's upstream and downstream exposures to demand and productivity shocks by extending the one-period DSGE model of Baqaee (2018) to a multi-sector, dynamic, stochastic setting with inter-temporal assets. The model has two sets of agents acting in discrete time: a unit continuum of identical households; and heterogeneous firms divided across N industries, each producing a single differentiated product in a monopolistically competitive environment. Every period, firms choose how much of their goods to sell to the household sector and to other firms as intermediate inputs.[7]

Each period proceeds in three stages. In the first stage, the households — who are the sole owners of inter-period capital — determine how to allocate their labor, and their capital holdings across renting to the firms and a technology to produce further capital for tomorrow. Each firm determines how much labor and capital to employ, the amount of other firms' output to use as intermediate inputs in its production process, and the price it will charge. In the second stage, production of goods and next period capital occur, and the productivity (v_{t+1k}) and taste shocks (β_{t+1k}) for $t+1$ are realized. In the final stage, the firms pay the households their wages, return on capital, and profits as equity dividends. The households also make their consumption purchases and trade firm equities then.

1.1 Household's Problem

The representative household maximizes expected discounted utility:

$$E_0 \sum_{t=0}^{\infty} \rho^t U_t$$

where

$$U_t = \left(\sum_{k=1}^{N} \beta_{tk}^{\frac{1}{\sigma}} c_{tk}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

U_t is the total consumption index discounted at ρ^t, c_{tk} is the composite consumption index for industry $k \in \{1, 2, ..., N\}$, the β_{tk} are consumer taste weights across industries' goods and services, and σ is the inter-industry elasticity of substitution. The industry k composite consumption index is defined as:

$$c_{tk} = \left(\int_{M_k} c_t(k,i)^{\frac{\epsilon_k - 1}{\epsilon_k}} di \right)^{\frac{\epsilon_k}{\epsilon_k - 1}},$$

where $c_t(k,i)$ is consumption of the output from firm i in industry k, $M_k = 1$ is the mass of firms in industry k, and ϵ_k is the intra-industry elasticity of substitution across varieties.[8]

At the beginning of each period the household must choose how to allocate its capital holdings across investing in further capital for tomorrow and renting it to firms, K_t^f, at a market rate of r_t. The household inelastically supplies one unit of labor each period, and both the labor and capital

[7] See Appendix Section D for an extended version of the model with industry total factor productivity, credit, varied market size and commodity price shocks.

[8] The simplifying assumption that households' and firms' elasticities are the same is chosen for mathematical tractability.

markets are perfectly competitive, with all participants taking prices as given. Post-production, the household makes its consumption and firm equity purchases, constrained by the following budget:

$$\sum_{k=1}^{N} \int p_t(k,i)c_t(k,i)di = w_t + K_t^f r_t + \sum_{k=1}^{N} \int s_t(k,i)q_t(k,i)di - \sum_{k=1}^{N} \int s_{t+1}(k,i)[q_t(k,i) - \pi_t(k,i)]di.$$

w_t is the wage per unit of labor, and $p_t(k,i)$ is the price of the good from firm i in industry k. The wage is the numeraire in the economy, with $w_t = 1$ for all periods. The $q_t(k,i)$ are the cum-dividend firm equity prices, $s_t(k,i)$ are the holdings of those equities and $\pi_t(k,i)$ are the profits repaid as dividends to the equity holders. There is a unit supply of each firm's equity, with initial equal holdings across the households.

Iterating the household's first order condition for $s_{t+1}(k,i)$ over periods, along with the equity transversality condition, yields the cum-dividend equity price equation as a function of expected discounted dividends in real terms:

$$\frac{q_t(k,i)}{P_{ct}} = E_t \sum_{\tau=0}^{\infty} \rho^{\tau} \frac{\pi_{t+\tau}(k,i)}{P_{c,t+\tau}},$$

where P_{ct} is the aggregate consumption price index:

$$P_{ct} \equiv \left(\sum_{k=1}^{N} \beta_{tk} P_{tk}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

1.2 Firms' Problem

Within each industry k there is a unit continuum of firms, and the firms use labor, capital, and other firms' goods as inputs to their production processes. Since the firms do not have any inter-period choice variables, they solve a series of independent problems each period seeking to maximize profits:

$$\pi_t(k,i) = p_t(k,i)\left[c_t(k,i) + D_t(k,i)\right] \\ - \left[w_t L_t(k,i) + r_t K_t(k,i) + \textstyle\sum_{l=1}^{N} \int p_t(l,j) x_t(k,i,l,j) dj \right].$$

Firm i in industry k makes its intermediate input decision for purchases of good j from industry l, $x_t(k,i,l,j)$, and agrees to pay prices for those, $p_t(l,j)$, before production occurs. $D_t(k,i) \equiv \sum_{l=1}^{N} \int x_t(l,j,k,i)dj$ is the total demand for good i from other firms to use as an intermediate input. The amount of labor, $L_t(k,i)$, and capital, $K_t(k,i)$, employed by firm i are also decided upon in the first stage.

The firm's output, $y_t(k,i)$, is given by the following production function:

$$y_t(k,i) = \left[v_{tk}^{\frac{1}{\sigma}} \left(K_t(k,i)^{\gamma} L_t(k,i)^{1-\gamma} \right)^{\frac{\sigma-1}{\sigma}} + \sum_{l=1}^{N} \omega_{kl}^{\frac{1}{\sigma}} x_t(k,i,l)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where γ is the production process' capital share and $x_t(k,i,l)$ is the intermediate input index of goods from industry l used by firm i in industry k:

$$x_t(k,i,l) = \left(\int x_t(k,i,l,j)^{\frac{\epsilon_l - 1}{\epsilon_l}} dj \right)^{\frac{\epsilon_l}{\epsilon_l - 1}}.$$

The v_{tk} industry productivity parameters are realized during production in the prior period, which can be thought of as firms learning or improving fabrication techniques during production that they implement the following period. The amount that firm i sells to the households will be its final output minus the quantity it already sold to other firms, $c_t(k,i) = y_t(k,i) - D_t(k,i)$.

Finally, the ω_{kl} are share parameters for the goods of industry l in production for industry k, and the $N \times N$ matrix of these entries, Ω, drives the real firm network of the economy — that is, the input-output structure of the firms' production processes.

1.3 Industry Centralities

Each firm in our model makes three choices each period about where to place itself in the production network: how much to consume of others' goods as intermediate inputs; how much to sell to other firms as a supplier of intermediate inputs; and how much to sell as final goods directly to the households. From these choices each firm will act both as a "consumer" of raw inputs (i.e., labor and capital) and a "supplier" of final goods, though they may do so either directly or indirectly through other firms in one or more production chains. The degrees to which firms in each industry act as consumers of inputs and suppliers of output through the full input-output network are captured by the two centralities that we introduce in this section. Consumer centrality measures the degree to which a firm consumes raw inputs itself and through others, and with that its exposure to its own and other upstream firms' productivity parameters. Likewise, supplier centrality measures how a firm is exposed to household demand for its own and other downstream firms' goods. This also represents exposure to shocks to the demand parameters for a firm and those downstream from it. These supplier and consumer centralities can be used to measure how exposed each industry is to the demand and productivity shocks of others downstream or upstream from it in the input-output network.

1.3.1 Consumer Centrality

Using within industry symmetry, and the ratio between firm prices and marginal costs, the industry price indices (P_{tk}) can be related to the quantity and prices of the raw capital and labor inputs through upstream input-output connections:

$$P_t^{1-\sigma} = \underbrace{\left[I_N - \mu^{1-\sigma}\Omega\right]^{-1} \mu^{1-\sigma}}_{\equiv \Psi_d} v_t \tilde{z}_t^{\sigma-1} R_t^{1-\sigma} \equiv \tilde{\alpha}_t \tilde{z}_t^{\sigma-1} R_t^{1-\sigma} \tag{2}$$

where P_t is a vector of the industry k price indices:

$$P_{tk} \equiv \left(\int p_t(k,i)^{1-\epsilon_k} di \right)^{\frac{1}{1-\epsilon_k}},$$

$\tilde{z}_{ts}$ is the labor-capital aggregate:

$$\tilde{z}_t \equiv K_t^{f\gamma} L_t^{1-\gamma},$$

and R_t is the price for this composite of raw inputs:

$$R_t \equiv r_t K_t^f + w_t L_t = \frac{1}{1-\gamma}.$$

Additionally, v_t is a vector of the productivity parameters, and μ is a square matrix with the industries' $\mu_k \equiv \frac{\epsilon_k}{\epsilon_k - 1}$ values on the diagonal. Ψ_d is a function of the firms' positions within the production network from Equation (1) and can be thought of as a markup adjusted Leontief inverse. The vector of consumer centralities for the labor-capital aggregate is defined as $\tilde{\alpha}_t \equiv \Psi_d v_t$, suggesting that a firm's direct and indirect demand for raw inputs depends on the economy's production capabilities (v_t), the technology (Ω), and the elasticities of substitution. The $\tilde{\alpha}_{tk}$ consumer centrality term captures the importance of sector k as a user of raw inputs and measures the sector's network adjusted factor use.

1.3.2 Supplier Centrality

The supplier centrality can be calculated by examining the total downstream demand for a firm's goods from other industries and consumers. The supplier centrality is determined from the following system of the stacked total demand equations:

$$(P_t^\sigma y_t)' = \beta_t' \underbrace{\left[I_N - \mu^{-\sigma}\Omega\right]^{-1}}_{\equiv \Psi_S} P_{ct}^\sigma U_t \equiv \tilde{\beta}_t' P_{ct}^\sigma U_t \tag{3}$$

where y_{tk} is the industry k aggregate output:

$$y_{tk} \equiv \left(\int y_t(k,i)^{\frac{\epsilon_k - 1}{\epsilon_k}} di \right)^{\frac{\epsilon_k}{\epsilon_k - 1}}.$$

The supplier centrality vector is defined as $\tilde{\beta}_t \equiv \Psi_S' \beta_t$, which relates a firm's role as a supplier in the network to the consumer preferences for goods and services of itself and downstream industries that it directly and indirectly supplies. $\tilde{\beta}_{tk}$ therefore reflects the network adjusted final consumption share of firms in industry k.

1.3.3 Firm Profits and Centralities

The standard constant elasticity of substitution and monopolistic competition result holds for all firms, with their profits being a fixed markup over sales:

$$\pi_t(k,i) = \frac{1}{\epsilon_k} P_{tk} y_{tk}.$$

Multiplying Equations (2) and (3) gives $P_{tk}y_{tk}$ on the left hand side and allows us to derive profits in terms of economy wide aggregates and the industry centralities:

$$\pi_t(k,i) = \underbrace{\underbrace{P_{ct}U_t}_{\substack{\text{GDP /}\\ \text{Aggregate}\\ \text{Demand}}} \underbrace{\left(\frac{P_{ct}}{R_t}\right)^{\sigma-1}}_{\substack{\text{Real Price}\\ \text{Level}}} \underbrace{\tilde{z}_t^{\sigma-1}}_{\substack{\text{Raw}\\ \text{Input}\\ \text{Supply}}}}_{\text{Aggregate Exposures}} \underbrace{\underbrace{\frac{1}{\epsilon_k}}_{\substack{\text{Market}\\ \text{Structure}}} \underbrace{\tilde{\alpha}_{tk}}_{\substack{\text{Consumer}\\ \text{Centrality}}} \underbrace{\tilde{\beta}_{tk}}_{\substack{\text{Supplier}\\ \text{Centrality}}}}_{\text{Industry Specific Exposures}} .$$

Changes in firm profits depend on common (or aggregate) factors and industry specific dynamics, which vary according to each firm's downstream and upstream exposures within the network. Firm-specific profit movements net of the common factors are captured by changes in the firm's consumer and supplier centralities, with idiosyncratic changes in firm profitability reflecting their heterogeneous exposures to shocks propagating upstream and downstream through the input-output network.

1.4 Firm Equity Return Responses to Upstream and Downstream Shocks

In this section, we examine firm equity returns relative to productivity and demand shocks. We specifically want to focus on the idiosyncratic aspect of each firm's equity return, and what this can tell us about its proximity through the inter-firm network to the source of a shock.[9] The log of the steady-state equity price of firm i in industry k is given by:

$$ln(q_t(k,i)) = \underbrace{ln\left(\frac{1}{\epsilon_k(1-\rho)}\right)}_{\substack{\text{Discount Factor}\\ \text{\& Markup}}} + \underbrace{ln(P_{ct}U_t) + ln\left(\frac{P_{ct}}{R_t}\right)^{\sigma-1} + ln\tilde{z}_t^{\sigma-1}}_{\text{Common Variation}} + \underbrace{ln\left(\tilde{\alpha}_{tk}\right) + ln\left(\tilde{\beta}_{tk}\right)}_{\text{Idiosyncratic Variation}} . \quad (4)$$

If there is a shock, the first term is a constant that will be unaffected, and the next three represent variation that will be common across firms: GDP growth; changes in the real price level; and changes to the supply of raw inputs. The idiosyncratic return response of a firm's equity price ($q_t^*(k,i)$) to shocks can be approximated by the log change to the final two "idiosyncratic variation" components, reflecting firms' centrality to the source of the shock(s) as a ratio of the total centralities for a firm. The response of a firm in industry k to innovations in a source industry s would be:

$$dln(q_t^*(k,i)) = \underbrace{\frac{\iota_k'\Psi_d\iota_s}{\tilde{\alpha}_{tk}}}_{\substack{\mathcal{U}_{ks}\equiv\text{Upstream}\\ \text{Exposure}}} dv_s + \underbrace{\frac{\iota_k'\Psi_S'\iota_s}{\tilde{\beta}_{tk}}}_{\substack{\mathcal{D}_{ks}\equiv\text{Downstream}\\ \text{Exposure}}} d\beta_s, \quad (5)$$

where ι_k is a selection vector with a one in the k^{th} position and zeroes elsewhere. The first term of Equation (5) captures the exposure of firm i to productivity shocks via the upstream exposure matrix, $\mathcal{U}$. In this matrix, each entry measures the exposure of the row sector to a productivity shock from the column sector, both directly and possibly indirectly through other sectors whose products

[9] Herskovic (2018) also studies the asset pricing implications of sectoral input-output networks, finding return spreads of 4.6% and -3.2% per year on sparsity and concentration beta-sorted portfolios.

are between theirs in a production chain.[10] The second term provides the exposure of a firm in industry k to demand shocks through the downstream exposure matrix, $\mathcal{D}$. The supplier centrality quantifies the intensity with which the household consumes from an industry, both directly and indirectly through its downstream sales. The downstream exposure matrix captures the potential for propagation of taste shocks for downstream goods to each industry as the ratio of its centrality to a particular downstream industry relative to its total downstream exposure.

The model indicates that firms' equity returns reflect their exposures to upstream and downstream shocks once common factors are removed. In the next section, we use model simulations to illustrate the extent to which aggregate factors prevent us from estimating the true input-output relationships between firms from equity returns, and how once they are removed, equity returns reveal network exposures to demand and productivity shocks. This provides the motivation for our empirical method to estimate inter-firm networks from daily equity returns. Additionally, this DSGE framework allows us to model the theoretical upstream and downstream network exposures of industries from input-output table data, which we do for the U.S. in Section 1.5. Finally, we compare the equity return based networks with these input-output based exposure networks to evaluate which direction — upstream or downstream — has been more important for shock propagation in the U.S. economy over the past three decades.

1.4.1 Simulated Equity Responses to Demand & Productivity Shocks

We simulate equity responses in the DESGE model for a set of firms to productivity (v_{tk}) and taste (β_{tk}) shocks and measure the extent to which changes in equity returns reflect the centralities between firms. The top panel of Figure 1 shows the relationships between five firms in different industries and the household sector in the canonical "X-network," often used as an example in the network literature.[11] Sector 2 consumes inputs from Sectors 1 and 4 and supplies its output to Sectors 3 and 5, who sell their final products to the household.

The four bottom plots show the effects of productivity shocks in the first column and a demand shock in the second. Note that to simplify the presentation we do not show the results for sectors with symmetric positions in the network. In each case, the y-axis measures the equity return between being in steady-state at the initial parameter levels and the new steady-state after the shock. The x-axis measures the relevant upstream ($\mathcal{U}$) or downstream ($\mathcal{D}$) exposure to the sector in which the shock originates, multiplied by the change in that sector's specified parameter. For the productivity shocks, this is $\frac{\iota_k' \Psi_d \iota_s}{\tilde{\alpha}_{tk}} * \Delta v_s$, and for the taste shock it is $\frac{\iota_k' \Psi_S' \iota_s}{\tilde{\beta}_{tk}} * \Delta \beta_s$. These are the network adjusted use of raw inputs through the shock source sector in the first term measured by Ψ_d and the indirect sales through the shock source sector measured by Ψ_S' in the second, scaled by the overall network adjusted raw input use and sales of a firm in industry k, respectively. The gray lines in the plots are the 45-degree lines equating these two, and the source sector for each shock is denoted with an x-marker.

[10]This accords with the results of Grant and Yung (2017), who find that greater overall firm network connectedness has a positive correlation with firm outcomes, possibly matching Equation (5) and reflecting that more connected firms are able to benefit from the productivity improvements of a wider array of industries.

[11]We selected this network because it is simple but is also rich enough to demonstrate the importance of both the consumer and supplier centralities to shock transmission. Appendix Section B contains the results for numerous other canonical firm networks from the literature — including the examples from the Baqaee (2018) and Acemoglu et al. series of network papers — with qualitatively similar relationships.

These plots show that the centralities do a reasonable job of capturing the change in log equity prices to shocks, $dln(q_t(k,i))$; however, they do not precisely correlate to the returns as they deviate from the 45-degree lines. Equation (5) provides the answer as to why this is — the common factors need to be removed in order to isolate responses to shocks transmitted through the consumer and supplier centralities. Therefore, in Figure 2 we present the same results for the idiosyncratic log price changes instead, $dln(q_t^*(k,i))$. It is immediately apparent that the observations all move towards the 45-degree lines. Starting at the top of the productivity shock column, the sector being shocked, Sector 1, has the largest centrality to itself and the greatest equity response. Sectors farther down the production process (Sectors 2 and 3) have lower centralities to the productivity of Sector 1 and commensurately lower idiosyncratic returns, with Sector 4 having a zero idiosyncratic return because Sector 1 is not upstream from it. In the second plot down, Sectors 3 and 5 are equally affected by a productivity shock to Sector 2, reflecting that they have symmetric downstream positions from it, while both Sectors 1 and 4 have no response since they are upstream. Finally, a productivity shock to Sector 3 has zero effect on the other sectors outside of its impact on the common factors since it has no downstream customer sectors, making the consumer centralities of the other sectors to it zero. These results demonstrate the importance of downstream propagation of productivity shocks in the model. On the other side, the final plot on the bottom right shows the effect of a taste shock to the output of Sector 3. Sector 5's only relationship to Sector 3 is as direct competitor in the final goods market, so it has a zero centrality to Sector 5 as a supplier. Alternately, the other three sectors are all direct or indirect suppliers to Sector 5 to similar degrees and see analogous changes to their idiosyncratic returns.

These simulations confirm our theoretical insights: the importance of removing common factors to unwind the connections between firms; and that once the aggregate or common factors are removed, equity returns reflect the centralities between and proximity of firms.

1.5 U.S. Sectors' Upstream & Downstream Exposures

We estimate the upstream and downstream exposure matrices ($\mathcal{U}$ and $\mathcal{D}$) from our theoretical model using U.S. input-output data from the Bureau of Economic Analysis (BEA) for 1997 through 2015.[12] These tables provide the expenditures on commodities from each sector by households and firms as intermediate inputs, valued in dollars. The commodities or products used are in the rows, and the consumer is in the column. The entries in each row sum to the output of that commodity. The columns also contain the components of value added — employee compensation, taxes, and profits. Therefore, including these values, the sum of the entries in a column equal that sector's output.[13] The BEA refers to the use table as a "recipe" matrix because it shows the inputs that are necessary to produce the output of each sector.

We generate six types of networks from these U.S. input-output use tables at the BEA sector level. The matrices are left so that the supplier of an input is in the column and the user is in the

[12] The BEA input-output tables we use throughout are North American Industry Classification System based, with surveys at the establishment level. We also tried using the older Standard Industrial Classification based data that is at the firm level in case the discrepancy between the level of our equity networks and the input-output networks skewed our results; however, this change makes little difference for the years where we have both use table types.

[13] We exclude the "Other services, except government" and "Government" sectors as the former does not cleanly match the sectors of the firms we analyze, and we wish to focus on the private sector.

row, as this appears to best align with the orientation of our equity based networks.[14] First, we take the raw input-output use tables, which we call the "Raw IO" network. Second, we use those tables with the input expenditures divided by the total output of the using sector to get a measure of the share of value derived from the other sectors as intermediate inputs. We label these networks as "IO Output Normalized." The third network is the standard Leontief inverse calculated using the IO Output Normalized matrices. The fourth and fifth networks are the upstream and downstream exposures, $\mathcal{U}$ and $\mathcal{D}$. We match the input-output data to our model parameters by assuming a Cobb-Douglas form ($\sigma = 1$).[15] The upstream and downstream exposures are calculated as matrices of the two respective terms in the idiosyncratic equity return Equation (5). Finally, to match that equation we add the two exposures together to see how the combined centralities compare in our "Upstream + Downstream Exposures" network.

In the next two sections we provide our method for using daily U.S. equity return data to empirically estimate inter-firm networks, and then compare them to the above input-output based networks to evaluate the relative importance of upstream and downstream sector exposures.

2 Estimating Inter-Firm Networks from Equity Return Data

Following the notion that firms' equity returns are affected by both aggregate shocks and the states of other firms in the network, we build an empirical model of firm returns that allows return series to be split into influences from systemic factors and firms' idiosyncratic returns. Consider a panel dataset with T daily observations and N firms, where $R_t^A = \left(R_{1t}^A, R_{2t}^A, ..., R_{Nt}^A\right)'$ represents the vector of actual observed daily log equity returns for each firm. While some portion of a firm's equity return is driven by K systemic factors, the remaining variation is attributed to idiosyncratic or firm-specific factors, denoted by $R_t^I = \left(R_{1t}^I, R_{2t}^I, ..., R_{Nt}^I\right)'$:

$$R_t^A = \Lambda F_t + R_t^I. \tag{6}$$

$F_t = (F_{1t}, F_{2t}, \ldots, F_{Kt})'$ is a vector of the common shocks and Λ is an $N \times K$ loading matrix capturing the exposure of firms to them. The F_t may reflect economy-wide macroeconomic shocks, or those for individual industries, regions, etc. as they are directly recovered from the data with minimal econometric restrictions used for identification.

Firms' idiosyncratic returns, R_t^I, influence one another reflecting the interconnectedness of the system and are subject to firm-specific innovations, captured by the $N \times 1$ vector ϵ_t:

$$R_t^I = \beta_0 + \beta R_{t-1}^I + \epsilon_t; \quad \epsilon_t \overset{iid}{\sim} \mathcal{N}(0, \Sigma), \tag{7}$$

[14] This is not a critical assumption due to the large degree of symmetry in both the input-output and equity return based networks we examine. Our correlation results are changed by less than 0.02 if we transpose the raw equity based networks. The normalized equity networks see significant reductions in the correlations; however, these differences are only because one network in the comparison is then normalized by row while the other is normalized by column. Normalizing after transposing remedies this issue.

[15] We make this assumption because otherwise we run into the issue that the industry-level prices cannot be cleanly separated from their output quantities in the data, while with a Cobb-Douglas structure, only the expenditures matter not the breakdown between prices and quantities. If we take the parameters as estimated assuming a Cobb-Douglas form and then vary σ, we find that our results are minimally affected by changes to this parameter, so beyond helping us take the model to the data, this assumption does not appear to be a crucial one.

where β_0 is a constant vector of firm fixed effects and β is an $N \times N$ influence matrix.[16] Since not all firms are likely to directly influence each other, the β matrix is expected to include many zero elements. Firms' innovations, ϵ_t, may be cross-sectionally correlated within a period, reflecting exposure to similar underlying economic dynamics, but are assumed to be serially uncorrelated, as equity prices quickly adjust to reflect new information.[17]

The individual firms are assumed to be small enough relative to the whole economy that their idiosyncratic components do not influence the aggregate factors, which follow a vector-autoregressive process:

$$F_t = \Gamma(L)F_{L,t-1} + \eta_t; \quad \eta_t \overset{iid}{\sim} \mathcal{N}(0, \Upsilon), \tag{8}$$

where $\Gamma(L)$ represents the $K \times KL$ matrix of coefficients on the L-order lag process, $F_{L,t-1} = (F'_{t-1}, F'_{t-2}, \ldots, F'_{t-L})'$ is a $KL \times 1$ vector of lagged factors, and η_t is a $K \times 1$ vector of shocks to the aggregate system.[18]

2.1 Common Factor and VAR Estimates

We estimate the system defined by Equations (6)-(8) in several stages, combining two major tools from big data estimation problems: principal components analysis (PCA) and variable selection methods.[19]

2.1.1 Estimating the Common Factors & Idiosyncratic Firm Return Series

Solving Equation (6) by least squares under a known F_t via seemingly unrelated regressions analysis yields consistent model estimates, and the calculations are directly analogous to the problem of extracting the principal components of the actual return series, R_t^A, with unknown F_t. Both circumstances require solving the following minimization problem:

$$\min_{\{\Lambda, F_t\}} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(R_{it}^A - \lambda_i F_t\right)^2,$$

with the difference being whether the F_t are known or objects to be solved for. Given that in our case $\Lambda \equiv \{\lambda'_1, \lambda'_2, ..., \lambda'_N\}'$ and F_t are unobservable, we implement PCA to estimate the common variation of equity returns. We use the panel BIC information criteria method from Bai and Ng

[16]That the idiosyncratic returns depend on firm specific constants and the vector of lagged returns can be micro-founded by many data generating processes for the productivity and demands shocks in our DSGE model. We provide two such examples in Appendix Section F.

[17]In our empirical analysis we find no evidence of serial correlation in the errors, supporting this assumption. Moreover, we allow for lags of the idiosyncratic returns of up to ten days and find that lags of more than one day are rarely selected by different information criteria and variable selection methods, and therefore we use one lag in our model specification.

[18]We also estimated the factor VAR with potentially non-zero constants; however, they were generally estimated to be small and not statistically significant so we omit them from the model.

[19]Foerster et al. (2011) point out that there may be estimation issues when trying to calculate inter-industry shock propagation due to the effects of common factors on all industries. In their work they use input-output and inter-sectoral capital network data to adjust for this. However, our goal is to estimate inter-firm networks without imposing any ex-ante network assumptions, so we make the trade-off to not apply their adjustments and estimate the common factors with PCA instead. They find that aggregate factors contribute less volatility over their sample period, while sectoral shocks do not change in importance and therefore become relatively more significant after the mid-1980s.

(2002) to select the number of factors to include, which is the form they suggest to account for potential correlation in the idiosyncratic errors. Once the common variation in the data (ΛF_t) is estimated, the R_t^I are obtained as the residual firm returns from Equation (6).

When calculating the common factors we use the return series' covariance matrix and calculate common factor series inclusive of the means so that they capture the broad trends. Let R^A be the $T \times N$ matrix of combined R_t^A vectors, μ the $T \times N$ matrix of the firms' R^A return series' means repeated along each column, and R_0^A the demeaned return series ($R^A - \mu$). Also, V is the $N \times K$ matrix of the first K eigenvectors of the returns' covariance matrix (in descending order of sample variance explained). There are also similar stacked matrices for the factors and idiosyncratic firm returns, namely F ($T \times K$) and R^I ($T \times N$).

The formula to recover the original data using the standard PCA approach involves projecting the data series without their means into the reduced dimension space and back again. The means are excluded so that the directions of maximal variation are captured, rather than the return series' means driving the newly created factors. The means are then added to these series after they are projected back to the original space:

$$\text{Standard PCA Recovery Formula: } \hat{R^A} = \mu + R_0^A V V'$$

The recovery error — or the variation explained by the excluded eigenvectors — is:

$$R^A - \hat{R^A} = R_0^A (I_N - VV')$$

As more eigenvectors are included in V, the VV' term will approach the identity matrix and the recovery error will go to zero.

In our analysis, if there are broad common trends then we wish to capture them in the factors, rather than allocating them to the individual firm return series. Therefore, we calculate the factor series with the full — rather than the demeaned — data, with $F = R^A V$ and $\Lambda = V$. R^I is then:

$$R^I = R^A - F\Lambda' = \underbrace{\mu}_{\substack{\text{Average}\\ \text{Returns}}} + \underbrace{R_0^A (I_N - VV')}_{\substack{\text{Standard PCA}\\ \text{Recovery Error}}} - \underbrace{\mu VV'}_{\substack{\text{Broad Trends}\\ \text{Captured in Factors}}}.$$

These idiosyncratic returns include each firm's average return plus the variation not explained by the K included eigenvectors, minus the shared trend already accounted for in the factors.

2.1.2 Estimating the Idiosyncratic Firm Return Sub-VAR

To deal with the curse of dimensionality and avoid over-fitting the data in such a large VAR, we implement the One Covariate at a time Multiple Testing (OCMT) procedure of Chudik et al. (2018) for variable selection to estimate the idiosyncratic firm return VAR in Equation (7). The prior literature following Diebold and Yilmaz's work has generally used LASSO or adaptive elastic-net for the variable shrinkage and selection, however, the OCMT procedure has several benefits over those algorithms: it is computationally faster and more efficient; it is statistically founded with clear individual variable inclusion rules; it is not as reliant on the initial parameter settings; and there is not the randomness that can occur with the other methods due to cross-validation sampling selection and optimizer seeding.[20]

The OCMT procedure is intuitive in that one need only run individual OLS regressions of the dependent variable on each of the potential explanatory variables, testing whether they have a statistically significant relationship with the dependent variable using a critical value adjusted for the fact that this test will be repeated for all of the potential explanatory variables. The OCMT procedure is based on evaluating the net impact of each of N potential explanatory variables, $R^I_{1,t-1}, R^I_{2,t-1}, \ldots, R^I_{N,t-1}$, on a dependent variable, $R^I_{i,t}$, in a linear model of the form:

$$R^I_{i,t} = \beta_{i0} + \sum_{j=1}^{N} \beta_{ij} R^I_{j,t-1} + \epsilon_{it}, \text{ for } t = 1, 2, \ldots, T \tag{9}$$

where N is small relative to T and a subset of the β_{ij} coefficients are non-zero. The analysis is based on the idea that if an explanatory variable's coefficient is non-zero, then its mean net impact on $R^I_{i,t}$ should be significantly different from zero, where the mean net impact of variable $R^I_{j,t-1}$ is:

$$\theta_j = \sum_{l=1}^{N} \beta_{il}\sigma_{jl} = \sum_{l=1}^{N} I(\beta_{il} \neq 0)\beta_{il}\sigma_{jl}$$

and $\sigma_{jl} = cov(R^I_{j,t-1}, R^I_{l,t-1})$. Each variable is considered individually through a series of bivariate regressions of $R^I_{i,t}$ on each $R^I_{j,t-1}$ series and a constant estimated with OLS. The t-ratio of $\hat{\beta}_{ij}$ from this simple regression is then compared to a critical value that takes into account the multiple testing aspect of this approach. The OCMT test of $\beta_{ij} \neq 0$ is:

$$I[\hat{\beta}_{ij} \neq 0] = I\left[|t_{\hat{\beta}_{ij}}| > \Phi^{-1}\left(1 - \frac{p}{2N^{\delta}}\right)\right]$$

where p is the size of the test, and Φ^{-1} is the inverse of the cumulative standard normal distribution. The denominator of the second term can take a number of functional forms, but we choose this simple form and $\delta = 1$ for the first iteration. We then add the included variables to the test regressions along with a constant and repeat the test with $\delta = 2$ until no further variables are added.[21] The final step is to then estimate Equation (9) using OLS with only the selected variables and a constant included, setting the coefficients on all of the other variables to zero.

To estimate Equation (7), we perform this analysis on each row of the VAR and then combine the estimated coefficient vectors to arrive at our estimate of β_0 and β. Finally, the residuals of these regressions are used to derive our estimate of Σ.

2.1.3 Estimating the Common Factor VAR Process

The factors capturing aggregate shocks to the system in Equation (8) are assumed to follow a vector-autoregressive process of order L. We assume that the error terms are uncorrelated over time, though they may be correlated across the F_t and the factors may influence one another, with

[20] For example, OCMT is over twenty times faster than adaptive elastic-net when estimating the simulated networks in Section 2.3.

[21] These values for δ are the lower bound to asymptotically select the proper variables, and in untabulated results we repeat our main analysis for a series of alternate values finding similar conclusions.

the $\Gamma(L)$ coefficient matrices being non-diagonal. Without autocorrelation of the disturbances, the system in Equation (8) is a seemingly unrelated regression model with identical regressors making single-equation OLS the efficient estimator, which we use.

2.2 Firm Network Estimation

Once we estimate Equations (6)-(8), we then derive the inter-firm network from generalized forecast error variance contributions (GFEVc) across the system. We calculate the GFEVc's from the reduced form of the VAR created by stacking the three sets of estimated regressions:

$$\begin{bmatrix} R_t^A \\ R_t^I \\ F_t \end{bmatrix} = \begin{bmatrix} \beta_0 \\ \beta_0 \\ 0_{K\times 1} \end{bmatrix} + \begin{bmatrix} 0_N & \beta & \Lambda\Gamma \\ 0_N & \beta & 0_{N\times K} \\ 0_{K\times N} & 0_{K\times N} & \Gamma \end{bmatrix} \begin{bmatrix} R_{t-1}^A \\ R_{t-1}^I \\ F_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t + \Lambda\eta_t \\ \epsilon_t \\ \eta_t \end{bmatrix}.$$

We call the coefficient matrix of this reduced form system A_1 and the covariance of the errors is:

$$\Theta = \begin{bmatrix} \Sigma + \Lambda\Upsilon\Lambda' & \Sigma & \Lambda\Upsilon \\ \Sigma & \Sigma & 0_{N\times K} \\ \Upsilon\Lambda' & 0_{K\times N} & \Upsilon \end{bmatrix}.$$

By construction the innovations in ϵ_t are independent of those in η_t, yielding the zero blocks in Θ.

Other papers, including several in the Diebold-Yilmaz network series, have used generalized forecast error variance decompositions to derive network edges given an estimated VAR system, the formula for which we provide in the appendix. We instead adjust these to create our GFEVc's. The difference is that in our GFEVc's we do not divide through by the equity variance adjustment in the denominator. We do this because those adjustments vary by firm and over time, and we would like the edge weights to be comparable across both. The formula for our one period ahead GFEVc network is:

$$GFEVc(1) = \left[\Theta^2 + (A_1\Theta)^2\right] Diag(\Theta)^{-1}, \tag{10}$$

where the exponents are all applied to the individual elements of the matrices, and the *Diag* operation yields a square matrix with the diagonal entries of the given matrix along the diagonal and zeroes elsewhere.[22] This formula provides a matrix with the edge sources along the columns and the destinations along the rows. We then create three distinct types of networks from this matrix.

2.2.1 R^A to R^A Networks

In our first approach, the nodes in the network represent the individual firms' actual observed returns, R_t^A. The edges from each source firm, s, to each destination one, d, are the response of the latter's actual returns, R_t^A, when there are shocks affecting the former's. In Equation (10) this would mean the entry for column s and row d. This specification forms a weighted, directed network capturing the way that firms' returns respond to one another, regardless of whether the

[22]In addition to the GFEVc based networks in the main text, we also estimate the GFEVD (Appendix Figures C.7 - C.10) and GIRF (Appendix Figures C.11 - C.14) based networks with similar results.

innovations are to the firms' idiosyncratic returns or the aggregate factors. These networks are similar to those in Demirer et al. (2018) and Grant and Yung (2017) in this way.

2.2.2 R^I to R^I Networks

Our second network approach focuses on the responses of firms' idiosyncratic returns to other firms' idiosyncratic returns. In this case, the edge from firm s to firm d is the entry of Equation (10) in column $N + s$ and row $N + d$.

2.2.3 R^I & Factors to R^A & Factors Networks

In our third approach, we distinguish the effects of firms' idiosyncratic shocks from those to the common factors. When doing so, we explicitly treat the factors as nodes in the network. In these networks there are $N + K$ nodes, with one for each of the firms and factors. The edge from firm s to firm d will be the expected variance contribution to d's returns when shocks affect firm s's idiosyncratic returns, and likewise for a shock affecting factor k. In these cases, we take the entry for column $N + s$ and row d of Equation (10) as the inter-firm edge, and the entry for column $2N + k$ and row d for the edge from a factor to a firm. In the case where the destination is factor k, then the edge from firm s to it will be the entry in column $N + s$ and row $2N + k$ — giving a zero effect — and the edge from another factor, f, to it will be the entry in column $2N + f$ and row $2N + k$.

2.3 Network Estimation Simulation

To illustrate the above estimation procedure, we apply it to simulated data given a known data generating process.[23] The simulated data has nine distinct groups where the observations within each group depend on one-another's lagged values and idiosyncratic shocks, giving β a block diagonal form. These groups can be thought to model distinct industries. There are also three common factors, with the first portion of simulated series only loading on the first factor, the second loading on the first two factors, the third loading on the second factor, the fourth loading on the second and third factors, and the fifth loading only on the third factor.

Figure 3 shows how this network system can be interpreted when including or separating out the effects of common factors in our three approaches. These plots use the ForceAtlas2 method from Bastian et al. (2014). ForceAtlas2 is a force-directed layout algorithm to display network spatialization, transforming a network into a map where nodes with greater connectedness are closer together. At a high level, all of the nodes are repulsed from one another like charged particles, while edges attract their nodes like springs — yielding the name for this class of algorithms, spring plots — with greater edge weights producing greater attraction. The final node positions provide a balanced state, helping to interpret the data without having to incorporate any other attributes of the nodes. To read these plots, think of a map without a key showing the direction of true north nor a scale. In that case, as with these plots, the precise orientation of the figures is not informative and rotations do not have a clear meaning, but the relative proximity of features on the plots to one another and the center of the figure do, as do any clusters that arise and inform the underlying

[23] The details of how the data were simulated can be found in Appendix Section G.

topology. This technique is superior to other network visualization methods such as heat maps primarily because the number of network members makes many other methods hard to read, and the spring plots are able to capture third party or greater relationships.

Each row in the figure has the same network plotted with one of our three different approaches derived from Equation (10). The first row provides the connections between the R^A series with a "R^A to R^A" actual return network. The network plotted in the second row is an attempt to isolate the bilateral inter-firm connections in an "R^I to R^I" idiosyncratic return network. Finally, the third row's network has edge weights between firms and factors based on the expected response of one firm's actual returns when a shock affects other firms or factors in an R^I & Factors to R^A & Factors network. This allows us to simultaneously examine the roles of shocks to firms and aggregate factors.

The columns of Figure 3 differ in the legends used for the plots. The first column has the nodes colored based on the factor(s) directly affecting each node. The second column is colored based on the nine blocks of non-zero β coefficient groups. To understand the results of the estimation process, we start by analyzing the "R^A to R^A" networks in the first row. It is evident in the left plot that our procedure has grouped the nodes by the factors that each firm is directly affected by, with those loading on the first factor only at the bottom right in red, then those loading on the first two factors just to the left of that group in green, followed by those directly affected by only the second factor adjacent to that group, and so on. These actual return networks are similar to those uncovered using the approach common in other papers in the literature of applying a version of adaptive elastic-net and then calculating network edges from either the raw or standardized GFEVDs or GIRFs — as can be seen in Appendix Figure A.3 versus the first row of Figure 3 — with those also being driven by the common factor loadings.

The right plot in the first row shows the same network with each node in the identical position as the first plot. Here, the β coefficient groups can be seen in the clustering; however, it is their overlap with the factor loading groups that drives the patterns in them — all of the nodes in the first β coefficient group load only on the first factor so they are in the bottom right group, those in the second β coefficient group are mixed between those loading only on the first factor and those loading on both of the first two factors so they are split between the first two clusters, and so on.

The spring plots in the second and third rows demonstrate how our procedure is able to extract and separate the direct inter-firm connections captured in the β coefficient groups from the common factors. The plots in these two rows are extremely similar because the factors have roughly even total influences on the network and are near the center of the figures in the third row, so the major dynamics of these figures are determined by the R^I based edges. When looking at the left column of these two rows it at first appears that the firm factor groups are central to their organization; however, it is clear from the right column and perfect clustering by the β coefficient groups that they in fact are the drivers. The clustering in these two networks is governed by the β coefficient group structure, unlike the "R^A to R^A" network.[24]

Combined, the results from Figure 3 are quite striking — the "R^A to R^A" networks identify the organization of the system around the factors very well, while the next two types of plots that

[24] Note that using our estimation approach but calculating the network edge weights with either GFEVDs or GIRFs instead of the GFEVcs yields similar results, with the actual return networks being driven by the common factors and the idiosyncratic networks by the β matrix coefficients. See Appendix Figures A.1 and A.2 for spring plots using these approaches.

first isolate the factors' influence are able to effectively estimate the bilateral node relationships.[25] Finally, we compare our estimated network matrices with the ones we would expect theoretically given the simulation model constants. The correlation for the actual return network is 0.996, and that for the idiosyncratic network is 0.98 with both statistically significant at the 1% level, indicating that the output of our estimation procedure is similar to the networks that we wish to uncover.

3 U.S. Equity Common Factors & Inter-Firm Networks

In this section, we apply our methodology to daily U.S. log equity returns from 1989 through 2017 in order to estimate the U.S. inter-firm network. To select our sample of U.S. firms, we take the union of the top 25% of firms by market capitalization over each year of the past two and a half decades. If a firm is in our sample at any point then we follow it for the full time that there is equity pricing data for it from Bloomberg. Our focus is on the largest firms in order to ensure that they all have actively traded, liquid equity securities that are highly researched and followed, providing them with accurate price discovery. Our data set includes the daily Bloomberg closing prices for $5,454$ firms from December 30$^{\text{th}}$, 1988 through June 20$^{\text{th}}$, 2017. The closing equity values are total return indices inclusive of returns from dividends to avoid spurious price jumps when dividends are paid that do not reflect a change in the valuation of the underlying firm. One of the benefits of our methodology is that it can be implemented using easily obtainable data. We also gathered the BEA sector and Bloomberg industry for each firm.

We analyze several samples of firms to study the long-term firm network, and others to account for changes to it from companies entering and exiting. Specifically, we examine the set of 524 firms continuously traded throughout our whole sample — both over the full period and in rolling 10-year periods — and on broader rolling samples of firms continuously traded over each 10-year window.

3.1 Common Factors in Equity Returns

Our analysis produces three common factor series for the firms' daily log equity returns, which combined account for 27% of the cross-sectional variation in the entire dataset.[26] Subsequent factors each contribute less than 2%, so we favor a parsimonious approach that is also consistent with the scree plot test typically used to infer the number of factors in PCA.[27] Refer to Table 1 for details of the PCA results.[28]

[25] These simulation results are in line with the main argument of Bailey et al. (2016) that one needs to account for common factors before estimating a network in order to properly recover the bilateral connections between its members.

[26] Our finding that equities are roughly 70% driven by idiosyncratic firm shocks is in line with Campbell et al. (2001), who find that over the period from 1962 to 1997 U.S. equities were 17% market driven, 12% by industry developments, and 71% by idiosyncratic considerations.

[27] The Bai and Ng (2002) panel information criteria suggest a range between one and three common factors in the data, with a mode of three. Although we focus on the first three factors for our main network specification, in untabulated analysis we explore variations in which we include one to five common factors yielding similar results.

[28] In principle, the choice of three factors selected by PCA is consistent with the seminal work of Fama and French (1993, 1995, 1996), who are able to explain more than 95% of the return in a diversified stock portfolio when accounting for returns' sensitivity to the beta, size and value factors.

The first factor loads positively on all firms in the sample, as can be seen in Figure 4.[29] This implies that positive shocks to the first factor translate into higher equity returns for all firms, thus representing the equity market beta, akin to the Fama and French market risk factor identified as the excess return of the market portfolio (Fama and French, 1995).[30] In fact, because we use covariance based PCA to uncover the factors, the first factor series is almost identical to the sample average of all log returns in the panel for each day, as can be observed in the top row of Figure 5, both in levels and in year-over-year changes. The second row shows how the first factor compares to another average measure of the market, the S&P 500 Index. The correlation between the series is 0.89 in levels and 0.83 in year-over-year changes. Intuitively, the first factor can be interpreted as economic growth in the aggregate U.S. economy, with booms and busts corresponding to higher and lower average equity returns. The third and fourth rows in Figure 5 show that our first factor co-moves with the U.S. industrial production index and GDP, with year-over-year change correlations above 0.50. Therefore, we match this factor to the growth common factor in our DSGE model. Below we focus on the year-over-year changes in the other two factors and real series, as the trends in levels may lead to spuriously high correlations.

The second factor loads negatively on the energy, financial, basic materials, and utilities sectors, and positively on the technology sector.[31] In Figure 6 we compare the factor with different measures of the price level, including the Producer Price Index (PPI), Consumer Price Index (CPI), the value of the dollar, and U.S. 10-Year Breakeven Inflation (BEI) calculated from TIPs and nominal U.S. treasury bonds.[32] The correlation between year-over-year changes in the second factor and PPI is 0.60, that with CPI is 0.51, and those with the dollar range around 0.40, either when taking into account the trade-weighted value of the dollar or looking at several major currencies individually. Note that that PPI matters more than CPI fits with our results below that the transmission of shocks through the firm network is more from upstream than downstream. These patterns suggest that fluctuations in the second factor closely align with movements of the U.S. price level, matching the price level factor from our DSGE model. In the last figure, it can be seen that breakeven inflation is positively correlated with our factor at 0.48. Further, if the breakeven inflation rate is lagged six months then the correlation increases to 0.71, suggesting that the forward looking market implied inflation level has predictive power for the price level factor in our sample.

The third factor has a large positive average loading on the energy sector, followed by the technology and base materials sectors.[33] Figure 7 displays the movements of the third factor relative to the price of Brent crude oil and the Goldman Sachs Commodity Index. These series indicate that the third factor is similar to the raw input factor from our DSGE model, with the correlation

[29] As shown in Appendix Table C.1, the firms with the highest loadings are predominantly from the technology, consumer cyclical and financial sectors, while those with the lowest loadings are royalty trusts, consumer non-cyclical and utility firms. This makes intuitive sense as the former are pro-cyclical sectors, while the latter are generally considered passive, acyclical investment sectors.

[30] Relatedly, Kose et al. (2003) studied business-cycle fluctuations in output, consumption, and investment for a 60 country sample, with results indicating that a common world factor is an important source of volatility for aggregates in most countries, providing evidence for a world business cycle.

[31] Appendix Table C.2 shows that all of the top ten firms loading on the second factor are technology companies, and the bottom ten consists of nine energy firms and a petroleum shipping company.

[32] A role for price pressures in the inter-firm network is supported by Smets et al. (2019), who found evidence of inflation being passed through production networks.

[33] Nine of the top ten firms by their loadings on the third factor in Appendix Table C.3 are energy related, and the bottom ten with negative loadings are all financial firms.

between oil and this factor especially high at 0.64.[34] Additionally, around 2009 commodities seem to go from the third to the second most important common factor in our sub-sample analyses — possibly because of a lower inflation environment making the price level less important.[35] If one looks on either side of this break then the pertinent factor has a greater correlation with commodity prices. For example, when looking at all firms in our sample traded continuously from 2008 through 2017, the correlation of the year-over-year changes in the second factor with oil is 0.77, and that for the Goldman Sachs Commodity Index is 0.79. Overall, these results support the existence and strong influence of the factors from our theoretical model for actual U.S. equity prices. This decomposition of equity returns also shows that the first factor loads relatively evenly across sectors while the second and third have the largest loadings in absolute value on the energy and technology sectors, indicating that they are key sources of industry specific variance in our sample.

The importance of these factors increased significantly over time.[36] Figure 8 plots the cumulative shares of the sample variance explained by the factors in rolling ten year windows for all firms traded continuously throughout each period.[37] The variance share of these three factors increased from around 12% at the start of our sample period in the early 1990s to over 35% towards the end in the mid-2010s. Further, the 2010-2017 variance shares for these factors remained near the elevated levels in the figure — they explained 25.1%, 2.4%, and 1.2% of the variance, respectively — even when not including the 2008-2009 crisis period with particularly high equity correlations. The variance share for the first factor, in particular, increased from 8.6% over the 1989-1998 period to 31.2% over 2008-2017, with the largest increase occurring when 2008 entered the rolling windows. The second and third factors saw their variance shares increase by just over a fifth with 0.5% and 0.2% increases. These results suggest a significant change in the importance of the broad market beta following the Global Financial Crisis, with meaningful implications for the scope for portfolio diversification.[38]

3.2 Equity Return Based Firm Networks

The inter-firm network of the 524 firms continuously traded from 1989-2017 is shown in spring plots in Figure 9.[39] These plots also use the ForceAtlas2 algorithm to determine the node locations. The top two rows contain only the firm nodes, with the R^A to R^A networks in the first row, and the R^I to R^I in the second. The third row contains the R^I & Factors to R^A & Factors network, with

[34] See the Appendix for similar plots of the third factor against various components of the GSCI index. The correlations are positive except for cocoa and generally economically significant in magnitude. The highest correlations are with the petroleum based energy commodities, followed by industrials and then precious metals.

[35] See Appendix Figures C.19, C.20 and C.21 for the sum of the edge weights of the factors to each sector and one-another over time. These make the transition of commodities between the second and third factors clear, as well as some other interesting behavior like the greatly increased influence of the first two factors on the finance sector beginning in 2009. Additionally, Appendix Figures C.17 and C.18 expand this to include all bilateral weight sums between sectors and factors over time.

[36] Bartram et al. (2018) also find an increasing share of firm level equity returns from common rather than idiosyncratic factors. Studying the period 1965-2017, they find that average idiosyncratic risk declined to an all-time low at the end of their sample.

[37] Appendix Figure C.1 has the same plot for the balanced 524 firm sample from 1989-2017, with similar results.

[38] Note that the structures of the idiosyncratic networks before and after the Global Financial Crisis were highly correlated at around 95%; however, the inter-sector sums increased about 2.8× on average.

[39] Appendix Figure C.6 has these same networks with several other legends based on the edge weight relationships (e.g., the total weights in and out from a firm). Appendix Figure C.15 shows these networks estimated using correlation based PCA in place of covariance PCA, with broadly similar results.

our novel approach to visualize the firms and the common factors driving them together. The first column has the firms colored by Bloomberg industry, while the second column has the firms in the same positions but with a BEA sector legend. We also separate REITs in these plots from the remainder of the financial sector given their distinct return profiles and separate cluster. These plots capture both direct relationships between firms, and those through others. For example, if two tire manufacturers both have strong ties to Ford but weak ones with each other, then they would still be close in these figures because they would both be near Ford. The parameters entered into the ForceAtlas2 algorithm for these and the subsequent firm network figures are the same, so they should be comparable.

Starting with the R^A to R^A networks at the top, it is clear that industry clusters are an important feature of the network. Additionally, finance, consumer cyclical, and industrial diversified firms are near the center of the network. This observation coincides with the fact that the top firms by the sum of their weights out to others are predominantly financial firms, as in Grant and Yung (2017) examining global firm networks derived from equity prices. Additionally, the number two and three firms are industrial diversified firms, and that third firm — General Electric — was designated a nonbank systemically important financial institution by the Financial Stability Oversight Council due to its high level of financial dealings up until it significantly changed its businesses in June 2016.[40]

The lower two networks remove the effects of the common factors, and in so doing they "unfold" the networks to better view and analyze the firm to firm connections. For example, in the R^I & Factors to R^A & Factors network one can see that the first factor — the market beta — is at the center of the network, and that finance firms are near that center. What can be further seen from the bottom figures is that REITs form a distinct grey cluster farther from the center of the network, unlike in the top row where they are nearly dead center and indistinguishable in location from the other financial firms. Additionally, the commodity firms are on the periphery of the network, near the third commodity factor at the top of the plot. This implies that the energy, base material, and utility firms near it do not co-move as much with the broad market, and that the commodity factor is influential for them.

The evolution of the U.S. firm network can be seen across Figures 10, 11, and 12. These figures have the networks of all firms continuously traded within each of the past three decades, with about $1,500$ firms in each plot.[41] Finance is at the center in all three decades, and these figures suggest a progression of the U.S. inter-firm network over this period. First, the R^A to R^A networks show firms becoming more tightly grouped over time, suggesting greater equity market integration and matching the increased factor variance shares mentioned above. Along with this, these plots — and the other network estimation methods used in the past in this literature — become less informative as all of the equities move more with the common factors in one compact cluster. On the other hand, the industry clusters become more pronounced over time in the defactored networks, possibly reflecting increased specialization and more integrated within industry production processes, or the rise in sector specific investment funds.[42] As with the longer run plots in Figure 9, the REITs

[40]See Appendix Table C.4 for the list of top firms by their sum of weights out to others.

[41]When estimating networks over rolling samples, the factors are calculated using only data from the estimating sample period and do not include future or out of sample information.

[42]Evidence of changing production processes — with increases in production fragmentation and specialization along the production chain — is especially strong in the trade literature given the high quality data on cross-border goods

are a distinct cluster from the remainder of the financial firms. They are close to the utility firm cluster, which is interesting as both are often seen as safe, acyclical dividend oriented sectors. The commodity factor can be seen to move between the second and third factors, with energy becoming more related with it than base materials over time. Finally, the price factor appears to be heavily influential for ICT firms.

As a further method to study how the firm networks changed over this period, Figure 13 has plots of the GFEVc edge values summed by industry and for each factor for rolling 10-year windows of the continuously traded 524 firm set. The top figure has the weights out from each sector and factor, while the lower figure has the net of the weights out and in to each. From both plots, it is again clear that the importance of the factors increased over this period. This is especially true for the first factor, with a large increase when 2008 enters the rolling windows after which the weights out remain high, even when looking at windows after that year. Additionally, the weights out from finance increased, however, the net weights for finance went significantly negative towards the end of the period. This difference is caused by finance becoming much more sensitive to the market beta factor. There is similar, though less extreme, behavior for the consumer cyclical and industrial diversified sectors. Note that in a corresponding figure for the R^A to R^A networks, Appendix Figure C.16, much of the increase in weights out comes from the finance, consumer cyclical and industrial diversified sectors, suggesting that the increased role of the market beta is an artifact of these pro-cyclical sectors leading greater movements in the market.

3.3 Growth & Commodity Factors Shock Analysis

In this section, we demonstrate how our network estimation can be used to analyze responses to common shocks. Using our networks, we can estimate connections at a higher frequency than in input-output tables and assess the impacts of shocks in real-time. Further, we can use visualization algorithms to study how firms are connected to one another and how these linkages have evolved over time, with the novel addition of including common factors as separate nodes in the networks.

We focus on the network of $1,416$ firms continuously traded over 2008-2017.[43] In the spring plots in Figures 14 and 15 the location of each firm is the same, though the colors are scaled based on their expected log returns over the given period following a shock to one of the common factors, with the darkest green for returns over 1% and the darkest red for those below -1%. Most of the price movement comes on impact, with some moderate returns for a few firms the day after, and virtually zero impact in the following days, as equity markets are quick to incorporate new information. The spring plots with industry and BEA sector legends are also included for reference.

Figure 14 shows that financial, consumer cyclical and commodity companies would be most affected by a one standard deviation positive growth shock at $T = 0$. The financial firms are at the center of the network in close proximity to the first factor, and a positive move in the first factor

flows. Timmer et al. (2014) find that cross-border intermediate input trade — measured as the foreign value-added content of production — has rapidly increased since the early 1990s, and Bridgman (2012) points to a rapid expansion of manufactured parts trade over the past forty years. For other important contributions to this long literature see Balassa (1967), Findlay (1978), Dixit and Grossman (1982), Sanyal (1983), Krugman et al. (1995), Feenstra and Hanson (1997), Arndt (1997), Feenstra (1998), Hummels et al. (2001) and Bems et al. (2011).

[43] Appendix Figures C.22 and C.23 have the results of applying this same analyis over our balanced 1989-2017 sample, with similar results.

correlates with a negative move in the second factor associated with a commodity price increase.[44] This suggests these firms are most driven by the market beta factor — both directly and indirectly through other firms and factors — and that the central finance firms have a high degree of influence on the network, in agreement with our findings that the majority of the top 25 firms by actual return network weights out are financial firms (see Appendix Table C.4). Further, all of the firms' cumulative returns through $T = 2$ are positive, consistent with the findings in Figure 4 that all of the firms had positive loadings on the first factor.

Figure 15 shows the effect of a commodity price drop as measured by a one standard deviation move in the second factor. Lower commodity prices would unsurprisingly most adversely affect energy and base materials companies. In fact, the top 10 declining equities following the shock are for firms in the oil and gas extraction sub-sector. On the other hand, United Continental Holdings — the parent company of United Airlines — would be expected to have the largest positive response. This result likely reflects the high fuel costs faced by airlines, and recognizing this could be used by an airline's managers as an indicator that it should hedge its commodity exposure. The other firms in the top ten highest expected equity returns are banks and REITs, possibly because lower commodity prices benefit firms in other sectors of the economy that would be passed onto them. It is not only these central sectors mentioned that increase, but the consumer cyclical firms also have positive returns, supporting this interpretation. Overall, the responses to a shock to commodity prices have more variation in firm returns than those to the first factor, with some cumulative returns positive and some negative.

These observations of the expected inter-firm dynamics can help managers and policymakers analyze potential exposures to common shocks, and inform investors' diversification choices to confront the systemic risk they face, as in the case of a fund that is long airlines recognizing the latent commodity risk factor in that investment.

4 U.S. Upstream & Downstream Exposures

Our equity based networks quantify how firms' equity prices co-move as a consequence of shocks to the economy. Using these networks that reflect firms' realized responses to shocks, our goal in this section is to evaluate the significance of upstream/supplier and downstream/demand side shocks over the past three decades. Specifically, how the equity response networks aggregated at the sector level compare with the U.S. input-output table based networks from Section 1.5, especially the upstream and downstream exposure matrices from our DSGE model.

In this analysis we study both our R^A to R^A (actual return) and R^I to R^I (idiosyncratic return) equity networks, estimated over various time frames. The R^I to R^I networks are identical to the firm-to-firm portions of the R^I & Factors to R^A & Factors ones by construction, so we only include results for the former. The edge weights are summed at the BEA sector level to create response matrices at the level of the U.S. input-output tables.[45] In these matrices, the source of an edge is

[44] Over this period the raw inputs are captured by the second factor, with price increases correlating with declines in the factor. It has a year-over-year change correlation of -0.79 with Brent crude oil and -0.74 with the Goldman Sachs Commodity Index. The level correlations with these are -0.77 and -0.79, respectively.

[45] The correlation between the number of firms in our 1989-2017 sample in each BEA sector and the output shares of those sectors is 0.85-0.9 over time suggesting that our sample has representative coverage of the broad economy, so we do not apply sampling weights when aggregating the networks to the BEA sector level.

in the column and the destination in the row. Additionally, as an alternate aggregation we scale the networks so that the edges into each sector sum to 100%, excluding self-loops from firms to themselves. This alternative accounting is meant to produce edge weight shares to parallel the sectoral output normalization that we apply in some of our input-output network comparisons below.

To compare these networks with the input-output derived networks, we use the element-by-element correlations between the equity and input-output based networks. To calculate the significance of these correlations we utilize a network correlation distribution bootstrapping method from the machine learning literature, the Quadratic Assignment Procedure (QAP).[46] This algorithm creates a distribution of network correlations by randomly reassigning the order of the nodes in one of the networks and moving the adjacency matrix entries accordingly. The new order will be the same for the rows and columns in that network, creating a hypothetical network with similar structure to that observed. We repeat this procedure ten thousand times for each network comparison that we do, saving the set of correlations and then calculating the p-value for the actual network correlation based on the simulated distribution. Making this adjustment rather than using the standard procedure to calculate the significance of correlations is particularly important given the structure of the networks we study, where the weights from sectors to themselves are all expected to be substantial (i.e., the correlations are ex-ante expected to be sizable and positive due to the large diagonal entries). The QAP bootstrapping procedure will retain this property of the networks, and provide correlations for distributions of networks with this trait. The QAP procedure also implicitly accounts for the sparsity of the network, the scale (i.e., range of edge weight magnitudes), and whether there are star nodes with outsized weights in or out of them from many other agents.

4.1 Long-Run Network Upstream & Downstream Exposures Analysis

The results of these network comparisons over our full sample period can be seen in two ways in the panels of Table 2. The top panel shows the results of comparing our 1989-2017 balanced panel network with the input-output data from the middle of that period in 2001, and the averages for broader rolling member 10-year networks ending in 1998 through 2017 against the input-output year with data available nearest their midpoints. The stars in Panel A indicate statistical significance as calculated using the QAP procedure. The results are similar for the two methods of looking across the sample period, so we focus on Panel A.

The first column contains the correlations of the equity networks with the Raw IO tables. We provide these correlations to demonstrate that the underlying input-output tables are positively related to our equity networks; however, we do not focus on these as the correlations are potentially spurious being driven by a handful of entries due to the skewed nature of the Raw IO tables. Specifically, the diagonal elements. For example, the R^I to R^I network for 1989-2017 has a correlation of 0.89 with the 2001 Raw IO network; however, if the manufacturing self usage entry on the diagonal is dropped then this declines by 38% to 0.55. If that entry and the finance self usage entry are dropped the correlation declines by 78% to 0.19. If no diagonal entries are included the correlation has a 63% decline to 0.32.[47] Nevertheless, we provide these as a baseline to demonstrate that the

[46]See Baker and Hubert (1981) for the first use of this procedure on a social network.

[47]Note that this issue is far greater for the Raw IO matrices than the other networks given the large concentration of values along the diagonals, and we do not believe that it materially affects our main results. If we remove the diagonal

equity based networks are reflective of the unadulterated input-output data.

The next column contains the IO Output Normalized networks against our equity networks. These values are economically and statistically significant, indicating a strong correlation between both types of equity networks and the standardized input-output tables. In this case there is no clear frontrunner between the two equity network types; however, when taking into account the full, network-adjusted relationships inclusive of pass-through via the Leontief inverse in the next column the idiosyncratic networks come out ahead. The correlation of the R^A to R^A network with the Leontief inverse is 0.39, while that for the idiosyncratic network is 56% higher at 0.61. The correlations for the upstream exposures exhibit a similar pattern: the R^A to R^A network has a correlation of 0.45, while that for the idiosyncratic network is 38% higher at 0.62. These correlations are statistically significant, and demonstrate that the equity based networks — particularly the idiosyncratic ones — strongly reflect the underlying macroeconomic relationships between sectors.[48]

For the downstream exposures the idiosyncratic networks also yield higher results than the R^A to R^A networks; however, none of these are statistically significant. The actual return network correlation with the downstream exposures is only 0.04 (0.06 for the normalized network), while that for the idiosyncratic network is 0.21 (0.30 for the normalized network). In the final column, we study the Upstream + Downstream Exposures to match Equation (5) and examine whether including both terms unearths a further association with the equity responses. In these cases, it appears that the poor fit of the downstream exposures dominates the better fit of the upstream exposures, with correlations very similar to those for the downstream exposures and not statistically significant. Together, these results indicate that shocks from upstream suppliers of which a firm is a customer either directly or indirectly matter more for short-term equity responses as measured by our networks than shocks from downstream in the production process. This is suggestive of low short-term elasticities of substitution across inputs with more flexibility on the downstream, customer side. Finally, removing the common factors is an important step to uncover the inter-sectoral connections.

These relationships not only hold for the changes in market expectations captured in the one day equity return based networks, but also for networks calculated using longer return periods. Appendix Table C.6 analyzes the same network correlations for monthly equity return based networks against the input-output networks. The results are similar, reflecting persistence in the importance of shocks to upstream firms over those to downstream firms. As further robustness, we repeat our analysis for networks where the edge weights are the bilateral daily equity return correlations between each firm pair, with the results in Table C.5. These simple networks are highly correlated with the actual return networks from our econometric model (0.95-0.99 correlations when aggregated at the BEA sector level) and have similar correlations with the IO based networks.

elements from the analysis for the unnormalzied equity networks then the correlations decline to about a third of their values for the Raw IO and IO Output Normalized networks. However, the upstream exposure and Leontief inverse measures decline by only about half, with the upstream exposure correlations remaining substantially greater than those for the Leontief inverse. The downstream exposure correlations continue to be positive but minimal. Excluding the diagonal elements for the normalized equity networks sees the Raw IO correlations marginally decrease, and the IO Output Normalized correlations slightly increase. The upstream exposure and Leontief inverse correlations increase to the upper 0.6's, while downstream exposure correlations double, remaining positive but low. All of these results are in line with our main findings.

[48] This similarity in results for the upstream exposure and Leontief inverse is not surprising as they are strongly related. In fact, the two are the same under our Cobb-Douglas assumption if the μ_k values are all one, which occurs in the case of perfect competition ($\lim_{\epsilon_k \to \infty}\ \forall\, k$).

4.2 Evolution of Upstream & Downstream Exposures

In this section we examine changes in how our equity based networks compare to input-output derived networks over time. Table 3 lists the correlations between rolling ten year equity networks ending in 1998 through 2017 and those derived from the input-ouput tables closest to their mid-points. These networks include the same 524 firms over time to remove the impact of a changing sample on the correlations. The top panel contains these correlations for the actual return and idiosyncratic return networks. For reference, the bottom panel contains the amount by which the idiosyncratic return correlations exceed those of the R^A to R^A networks on the left, and the percentage improvement in fit for the model based Leontief inverse and upstream exposure networks over the basic IO Output Normalized networks on the right.

From Panel A there are a few lessons to be learned. First, the correlations for the idiosyncratic return networks are consistently higher than for the actual return networks, across all of the input-output table based network transformations. This again suggests improved fit for the idiosyncratic return networks with the underlying real economic relationships, and the need to account for common factors. Second, the idiosyncratic return network correlations are relatively static over time, while those for the actual return networks decline. This is likely a result of the common factors becoming more influential over our period as shown in Figure 8. For example, the improvement of the idiosyncratic network over the actual return one in terms of correlation hovered near 0.1 for upstream exposure at the start of the sample, doubling to around 0.2 in the last six years. These two facts support the use of our procedure to measure inter-firm networks over those previously proposed in the literature and indicate that these network relationships have been remarkably consistent over time.

Finally, the improvement of the correlations for the idiosyncratic network with the model based Leontief inverse and upstream exposure networks over the simple IO Output Normalized networks emphasizes the importance of considering propagation through the full network and not just to immediate neighbors. The right section of Panel B shows the percentage increase in the correlations for these two model based networks over the IO Output Normalized one. These are especially large for networks towards the end of sample, possibly reflecting production processes involving more specialization and intermediate input use. The correlations for the upstream exposures are consistently greater than those for the Leontief inverses for both equity return network types, possibly implying a meaningful role for market competition, the demand elasticities across goods and markups in the structure of inter-firm networks.

4.3 Upstream & Downstream Exposure Discussion & Implications

Our results on upstream versus downstream exposures and the importance of common factors can be placed in several literatures. The relative significance of the upstream exposures indicate a low short-term elasticity of substitution across inputs with near Leontief production functions, which matches work at the country level. Examining trade across 30 countries, Ng (2010) found that bilateral trade in complements/upstream intermediate goods contributes to cross-country business-cycle co-movement, while trade in substitutes/downstream final goods reduces it, with a net positive impact of trade on co-movement. Additionally, Burstein et al. (2008) and Johnson (2014) identified that low elasticities of substitution between inputs is key to explaining the degree of synchronization in international business cycles.[49] Relatedly, Loayza et al. (2001) analyzed output fluctuations in emerging economies, finding a central role for sectoral interdependence. Barrot and Sauvagnat (2016) found that production elasticities near zero best match real world shock amplifications in a calibrated network model, and Atalay (2017) found strong input complemenetarities play an important role in the transmission of industry level shocks.

Our results are consistent with the empirical analysis of the Tohoku earthquake in Boehm et al. (2019) that found strong downstream propagation of the shock there to firms abroad that were reliant on imports from the affected areas of Japan. They found that Japanese affiliates abroad saw output drop about one for one with imports of intermediate goods from Japan in the wake of the disaster, suggesting extremely low elasticities of substitution for inputs in the short-term. Carvalho et al. (2016) also found quantitatively large upstream and downstream spillovers in Japan after the Tohoku quake. They assessed that the propagation of the shock over input-output linkages accounted for a 1.2% decline in Japanese GDP in the year following the earthquake. Similarly, Jones (2011) studied production linkages and intermediate input use, finding that problems along a production chain can sharply reduce output under input complementarity.

That upstream exposure is greater than downstream exposure is also in line with much of the theoretical literature on multi-sector firm models following Long and Plosser (1983), which generally agrees on the importance of propagation from upstream, with a more muted role for transmission from downstream. For example, our results match the model implications of Acemoglu et al. (2012), who concluded that under Cobb-Douglas intermediate input aggregation, an industry's impact on the aggregate economy depends only on its role as a supplier of inputs through downstream propagation, and not as a consumer. Further, Section 4 of Baqaee (2018) showed these results hold under a more general set of models than those with Cobb-Douglas intermediate input aggregation. The models of Johnson (2014), Barrot and Sauvagnat (2016), and Baqaee and Farhi (2017) likewise have downstream but not upstream shock propagation. Alternately, Baqaee (2018) and Luo (2018) achieved both downstream and upstream shock propagation by including firm entry-and-exit and a credit channel, respectively.

Our results support these papers, and further suggest that there appears to be less shock propagation from a firm's direct and indirect customers, possibly reflecting more substitutability across buyers or price adjustments. Understanding such short-run dynamics about the spread of shocks across firms has important implications for policymakers, managers and investors seeking to prevent or contend with possible contagion, such as from a firm facing bankruptcy or loss of productive capacity due to a natural disaster.

5 Conclusion

There has been a documented increase in the co-movement of firms over the past few decades, particularly during crisis events. This is true both within and across industries. Given the increased risks associated with this environment, we evaluate the relative importance of upstream, downstream and common factor exposures that may lead to these co-movements.

We develop a multi-sector DSGE model with inter-temporal assets to analyze the macroeco-

[49] Similarly, intermediate input complemenetarity is shown to synchronize cross-country business cycles in Backus et al. (1994) and Heathcote and Perri (2002).

nomic factors driving equity returns, and to study supply chains and their role in the propagation of shocks. Our theoretical framework reveals that the common factors that influence equity returns are economic growth, the price level, and the supply of raw inputs. Further, equity returns net of these common factors represent the upstream and downstream exposures of firms in the network to those experiencing productivity and demand shocks.

We then apply a machine learning VAR estimation method to study the inter-firm response network accounting for common factors using daily U.S. equity prices from 1989 to 2017. Supporting the relationships in our theoretical model, our empirical work reveals that the same three common factors — especially economic growth — are important stock market drivers and have become more important over time, explaining 11.7% of equity return variation during the 1990s versus 35.0% post-2007. As the movements in equity prices attributable to common factors can be sizable, their influence may mask the underlying connections between firms, with many prior methods in the network estimation literature conflating the two.

Turning to the inter-firm portion of these networks, the empirical literature has yet to reconcile theoretical models' discrepancies as to the importance of upstream and downstream propagation, so we compare these equity based networks with upstream and downstream exposure networks calculated using U.S. input-output data in the framework of our DSGE model. We find upstream exposure (shocks to a firm's direct and indirect suppliers) to be more significant than downstream exposure (shocks to its direct and indirect customers) by analyzing the correlations between the equity, upstream and downstream exposure networks. These findings have meaningful implications for understanding the reactions of firms relative to one another and suggest that macroeconomic linkages can be proxied well with financial market data, potentially allowing for the real-time monitoring of economic developments at a more disaggregated level of data that would otherwise be difficult to measure.

Our work yields several insights that warrant further investigation. First, the common factors that drive equity returns have increased in influence and finding their root causes would have implications for portfolio diversification, as well as firm management and public policy strategies. Delving into the precise channels through which firms are connected — e.g., intermediate goods, services or credit — to understand contagion would also be fruitful. Finally, recognizing the greater importance of upstream firms relative to downstream ones could be applied to businesses hedging risks, trade and international economic policies, and the design of bailout schemes during future crises.

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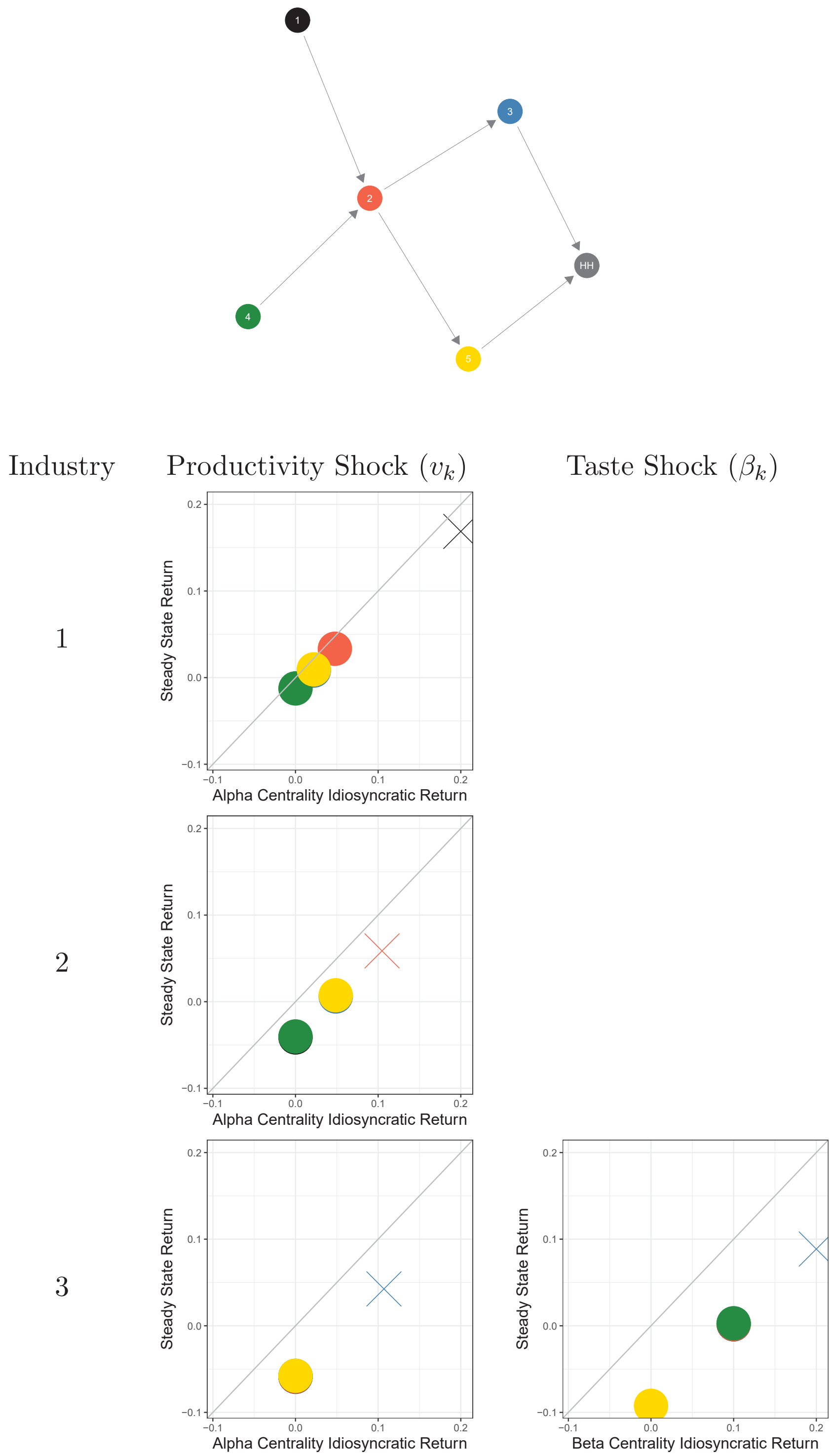
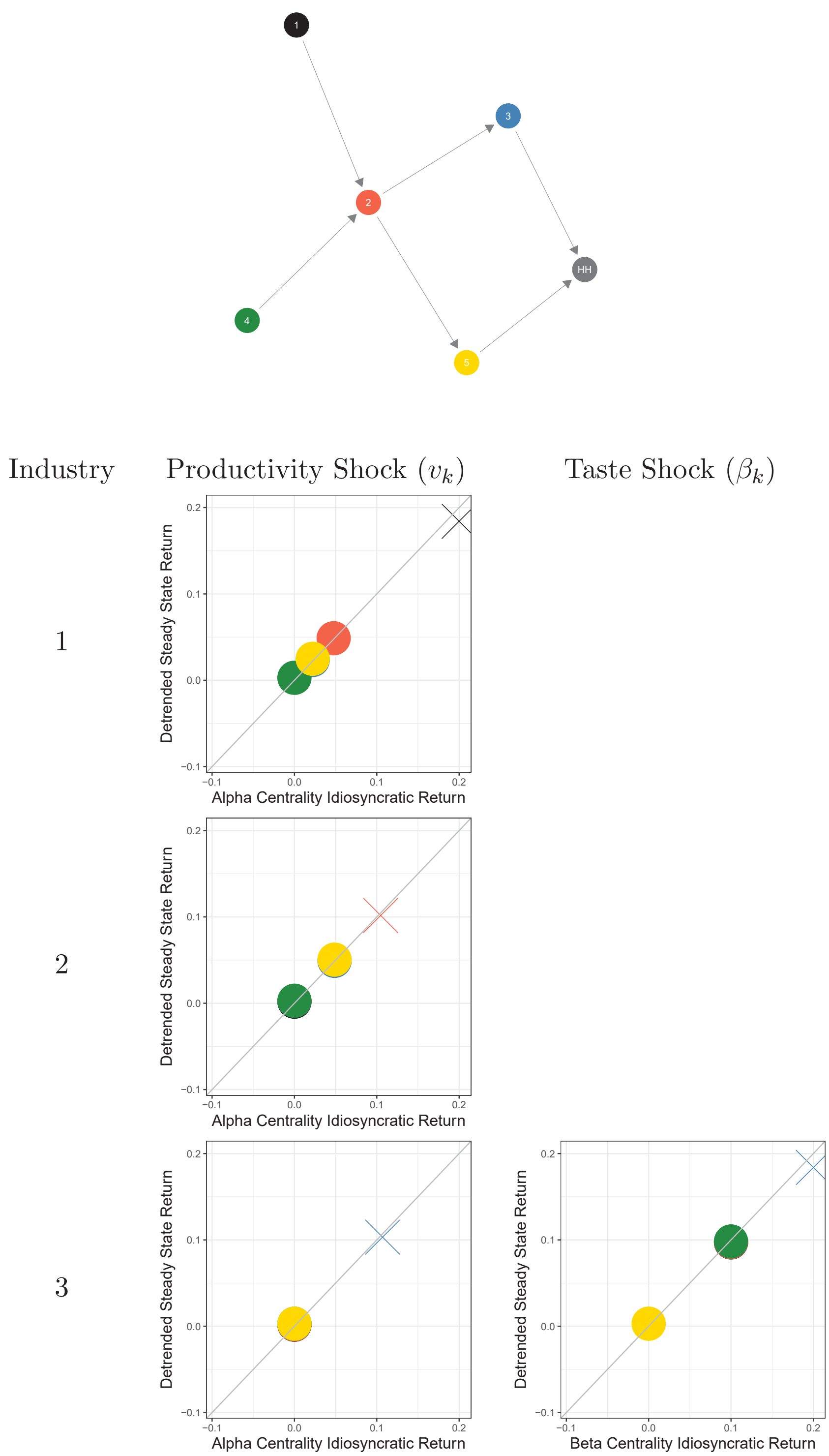
Figures and Tables

Figure 1: Simulated Equity Responses to Shocks by Centrality



Note: The y-axis measures the return from being in steady-state at the initial parameter levels to moving to a steady-state after the shock. The x-axis measures the upstream or downstream exposure to the source sector multiplied by the change in that sector's specified parameter. The lines in the lower plots are the 45-degree lines equating these two. The source firm is denoted with an x-marker. The industry legend is 1-black, 2-red, 3-blue, 4-green, and 5-yellow. Gray is the household.

Figure 2: Simulated Idiosyncratic Equity Responses to Shocks by Centrality

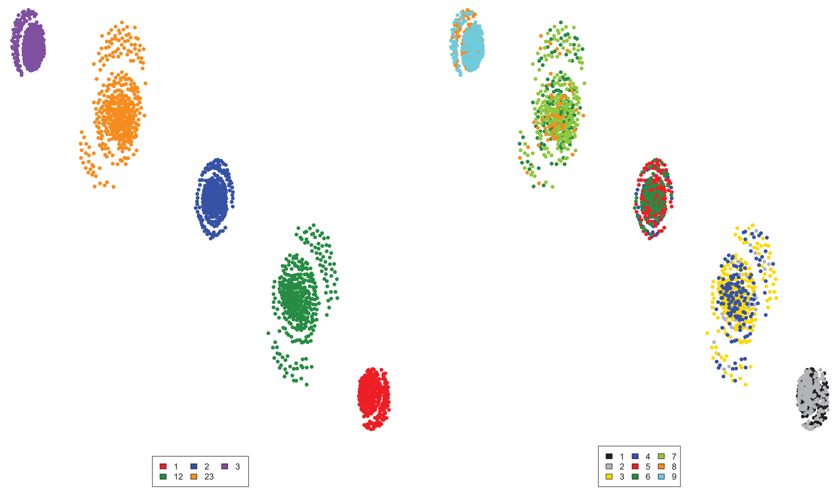


Note: The y-axis measures the idiosyncratic return from being in steady-state at the initial parameter levels to moving to a steady-state after the shock. The x-axis measures the upstream or downstream exposure to the source sector multiplied by the change in that sector's specified parameter. The lines in the lower plots are the 45-degree lines equating these two. The source firm is denoted with an x-marker. The industry legend is 1-black, 2-red, 3-blue, 4-green, and 5-yellow. Gray is the household.

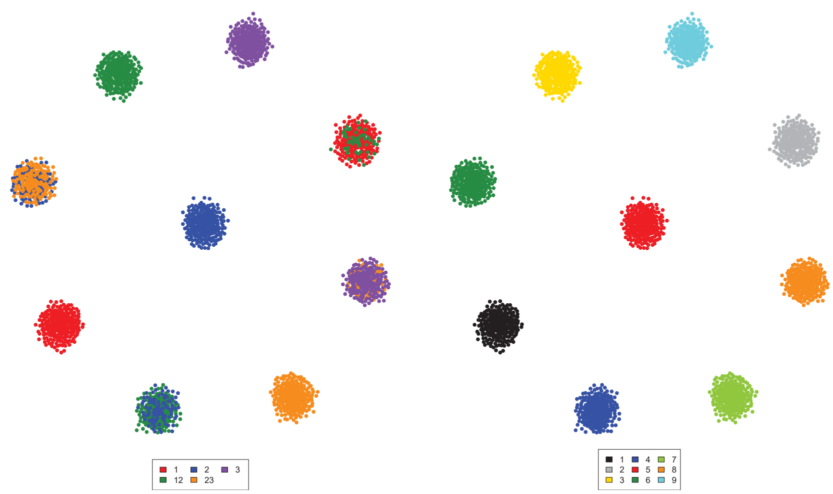
Figure 3: Spring Plots of Simulated Networks

Network Type	Λ Factors Loaded on	β Coefficient Groups

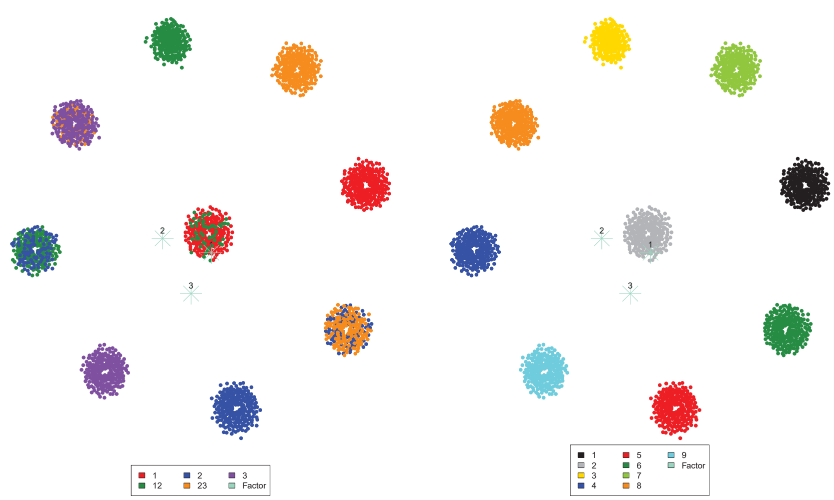
R^A to R^A



R^I to R^I

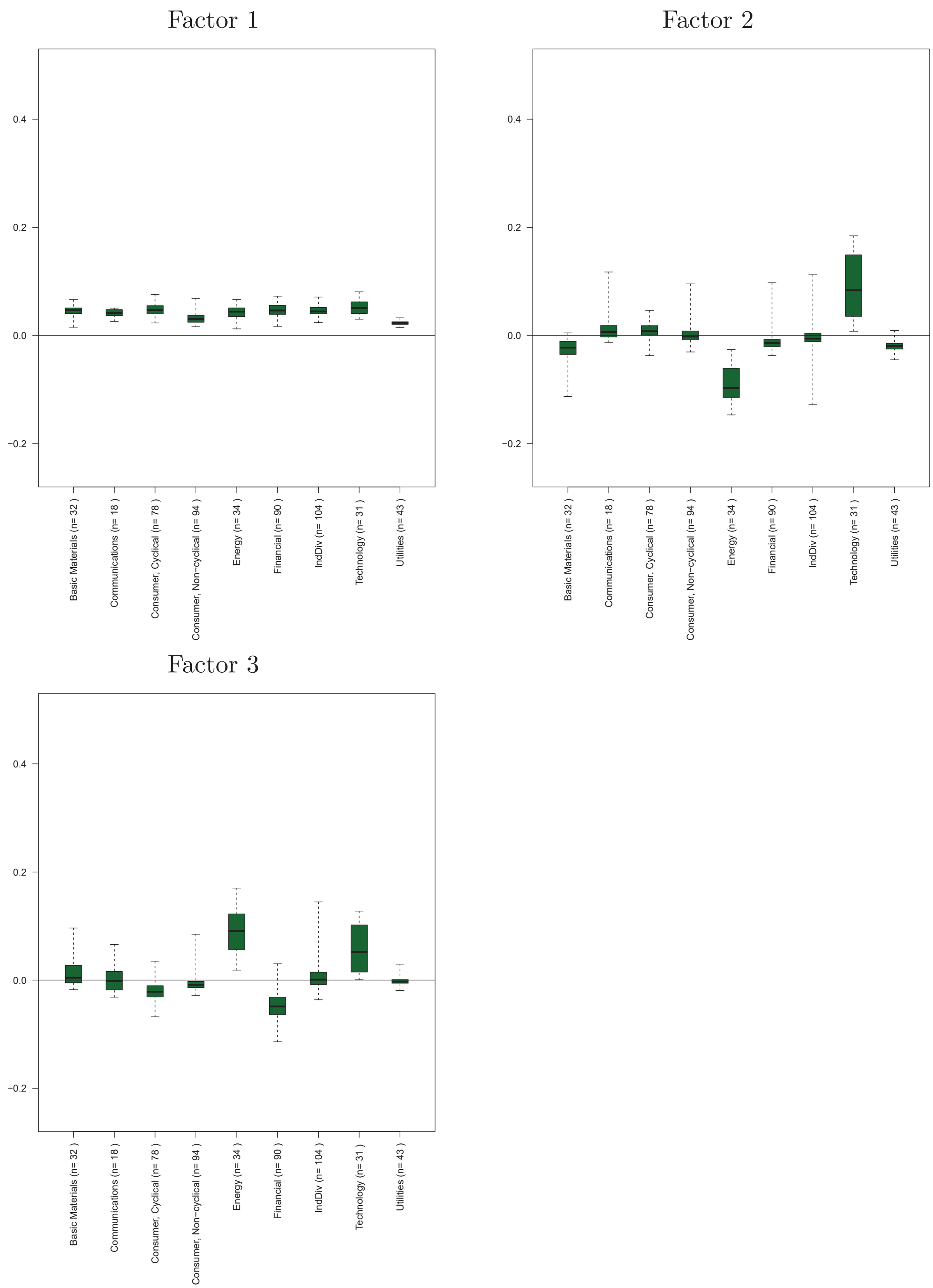


R^I & Factors to R^A & Factors



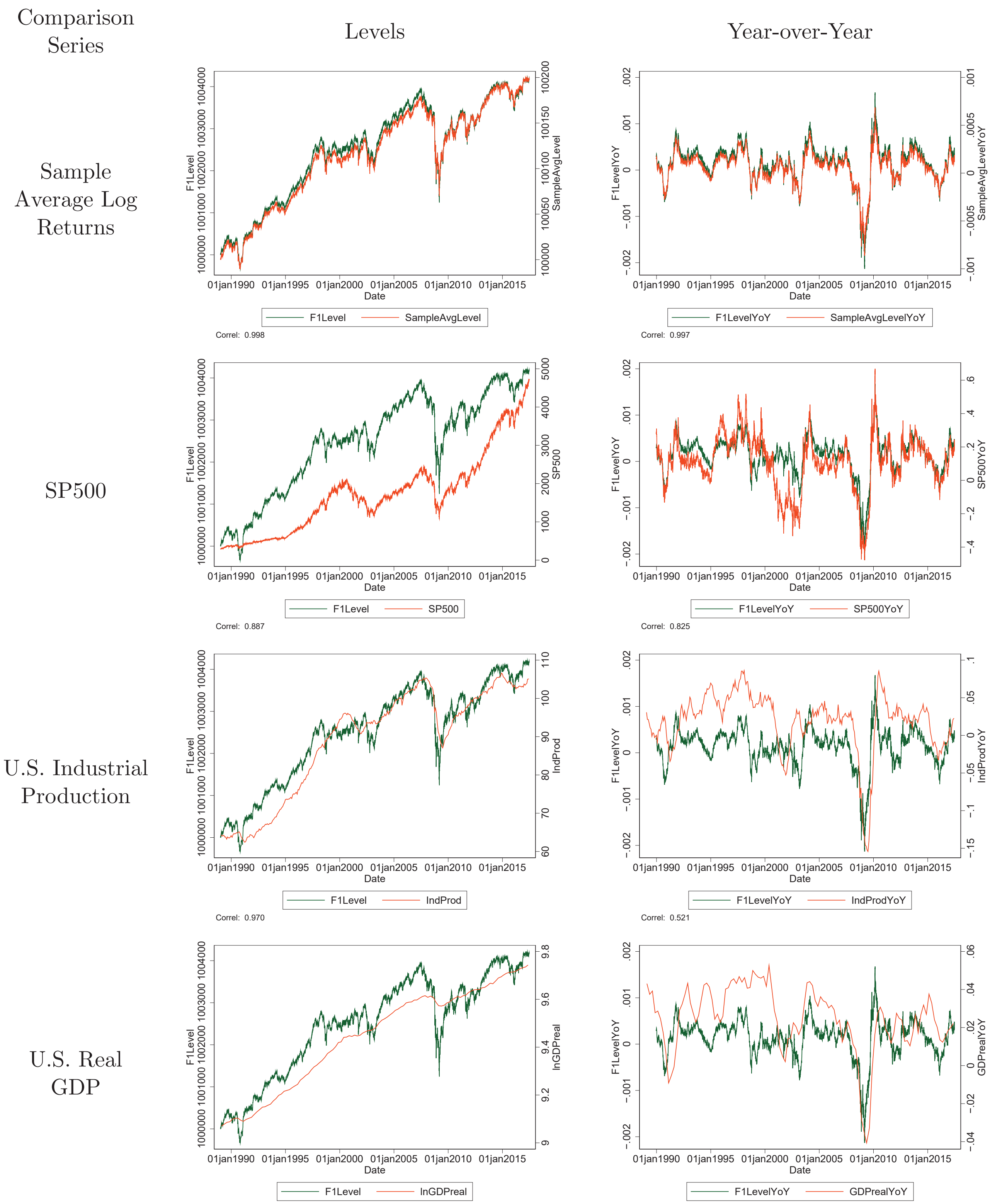
Note: Estimated GFEVc networks from data simulations with 3 common factors. See Section G for details on how the data was generated.

Figure 4: U.S. Factor Λ Coefficient Distributions by Industry (1989-2017)



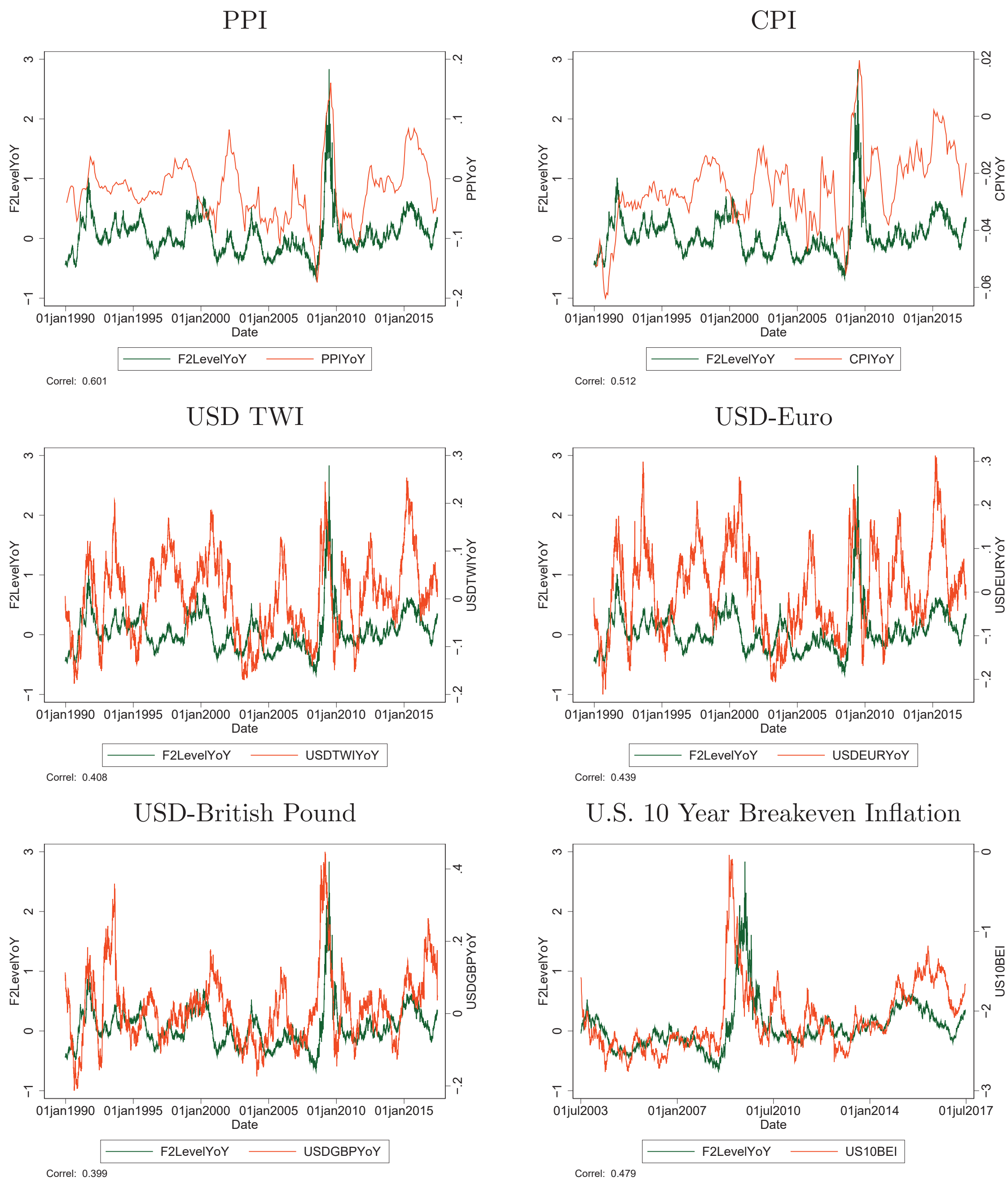
Note: Loadings on the first three factors extracted by principal component analysis on the covariance matrix of U.S. daily log equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524).

Figure 5: First Factor and Growth of the U.S. Economy (1989-2017)



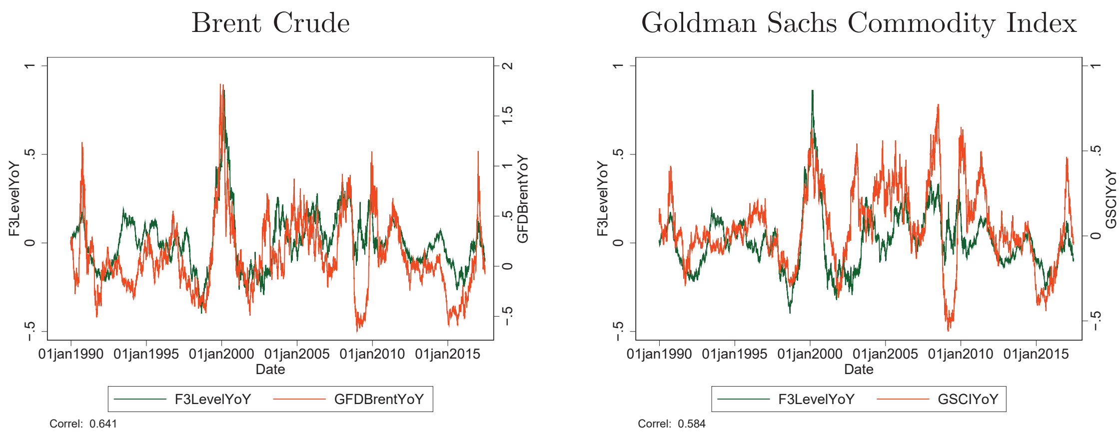
Note: F1Level is the cumulative sum of the first factor extracted by principal component analysis on the covariance matrix of U.S. daily log equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524).

Figure 6: Second Factor and U.S. Prices, Year-over-Year Plots (1989-2017)



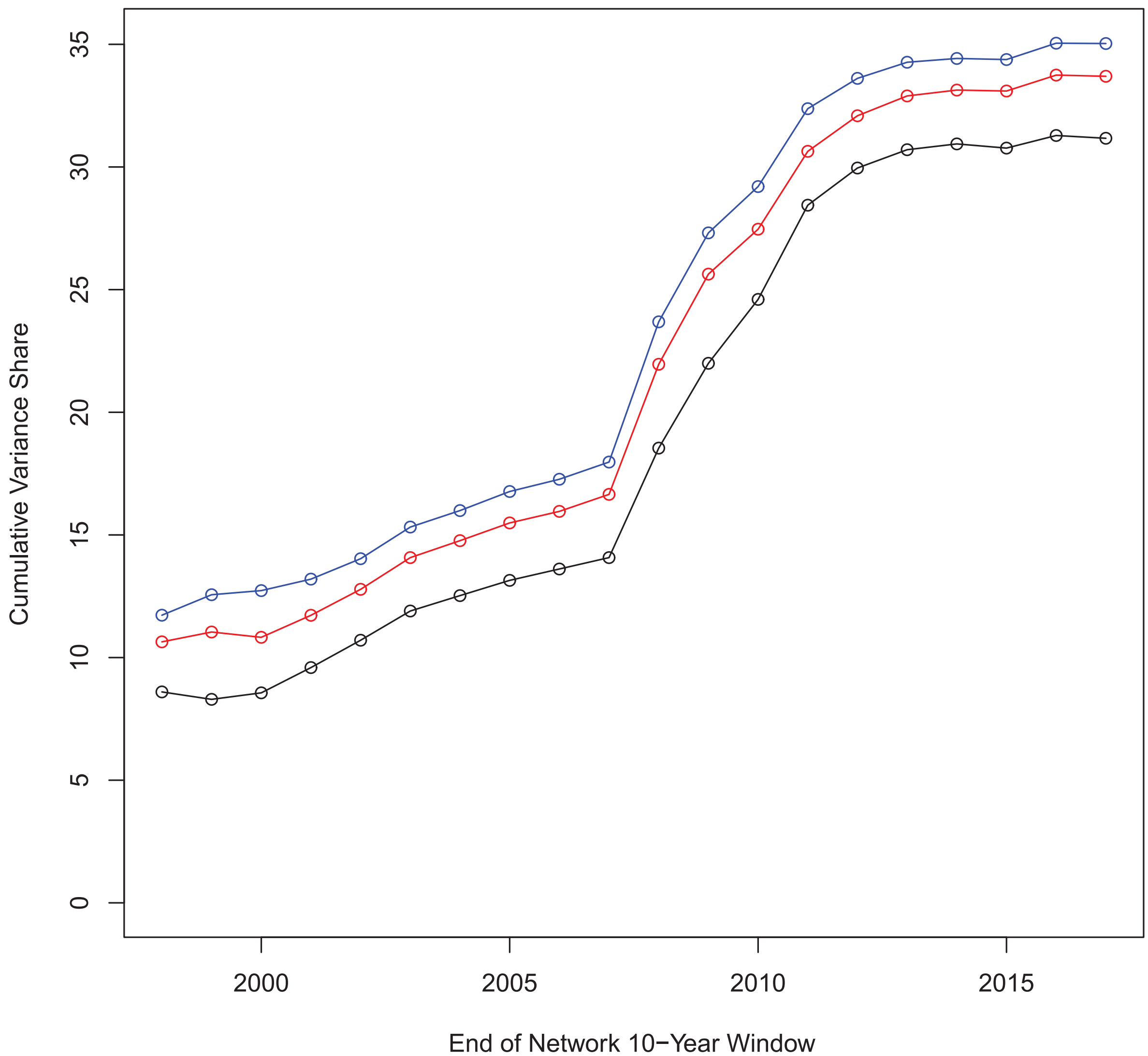
Note: F2Level is the cumulative sum of the second factor extracted by principal component analysis on the covariance matrix of U.S. daily log equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524). The PPI and CPI return series are inverted to match the direction of the factor series.

Figure 7: Third Factor and Commodities, Year-over-Year Plots (1989-2017)



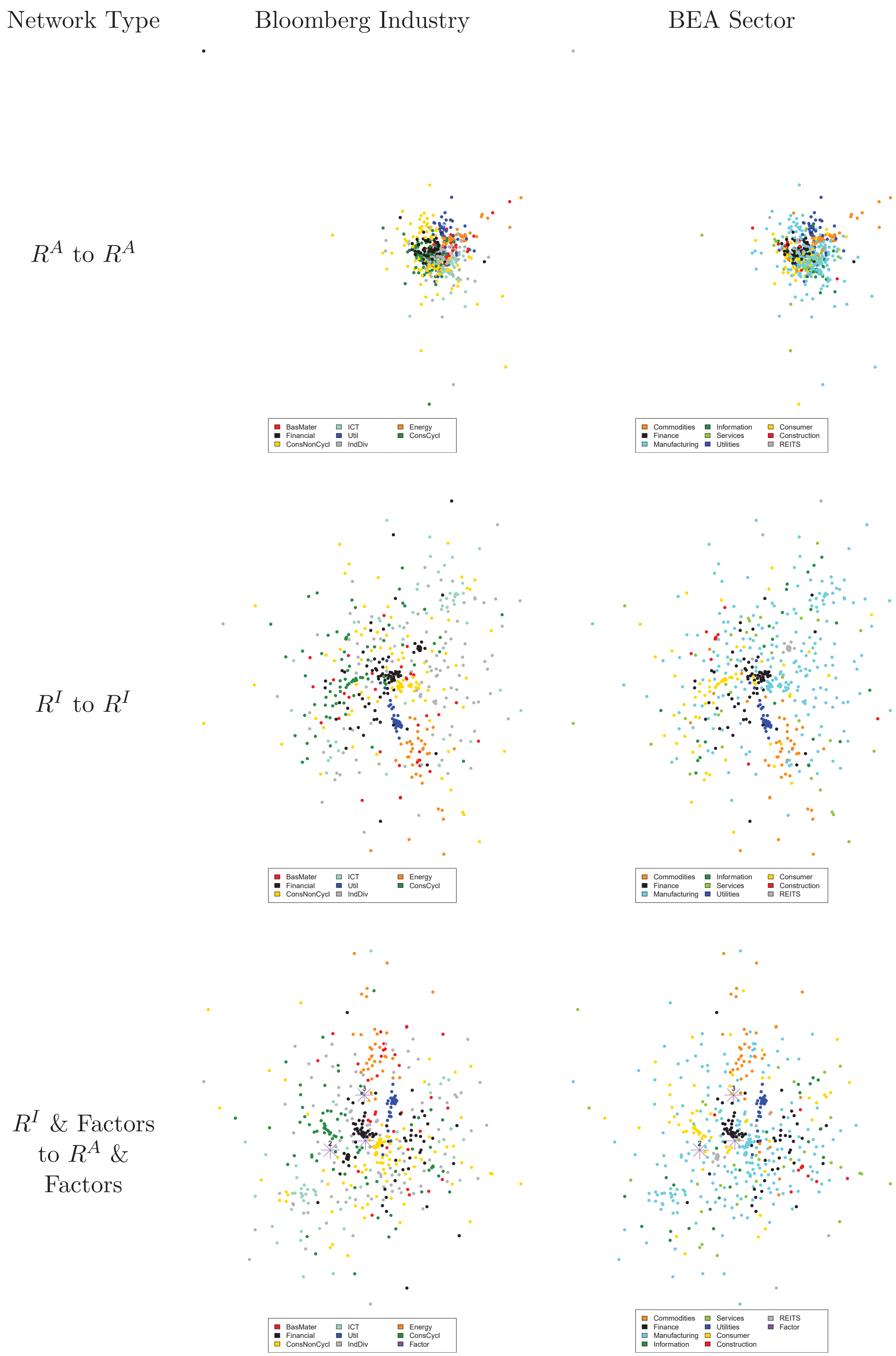
Note: F3Level is the cumulative sum of the third factor extracted by principal component analysis on the covariance matrix of U.S. daily log equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524).

Figure 8: Variance Share Explained by Top 3 Factors, Rolling 10-Year Samples



Note: Factor variance shares for rolling 10-year samples with all firms continuously traded within each time period, with factors extracted by principal component analysis on the variance-covariance matrix of the daily log equity returns.

Figure 9: U.S. Firm Network Spring Plots (1989-2017)



Note: Networks of the U.S. daily log equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524). Network edges are calculated using generalized forecast error variance contributions and 3 common factors.

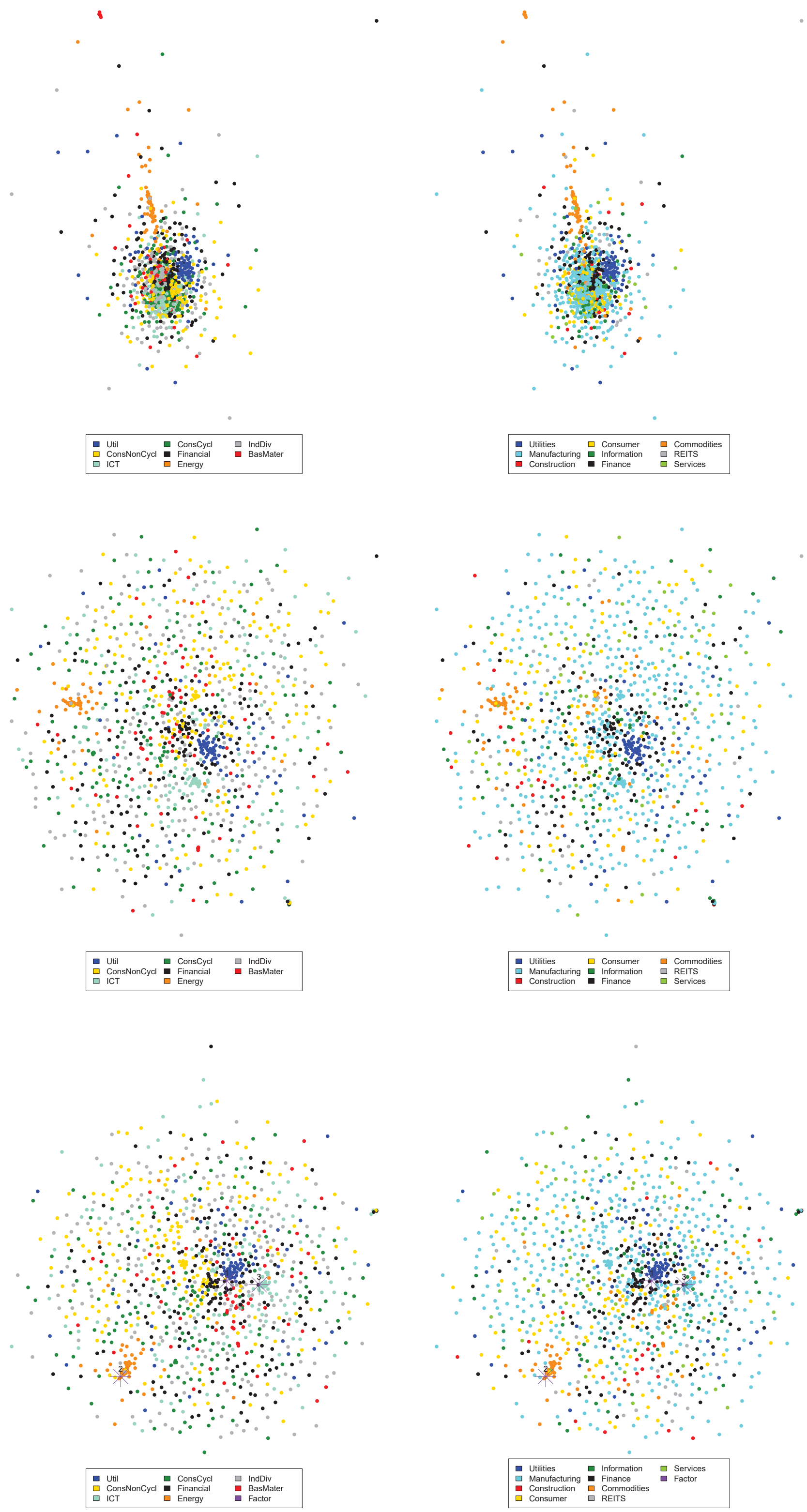
Figure 10: U.S. Firm Network Spring Plots (1990-1999)

Network Type | Bloomberg Industry | BEA Sector

R^A to R^A

R^I to R^I

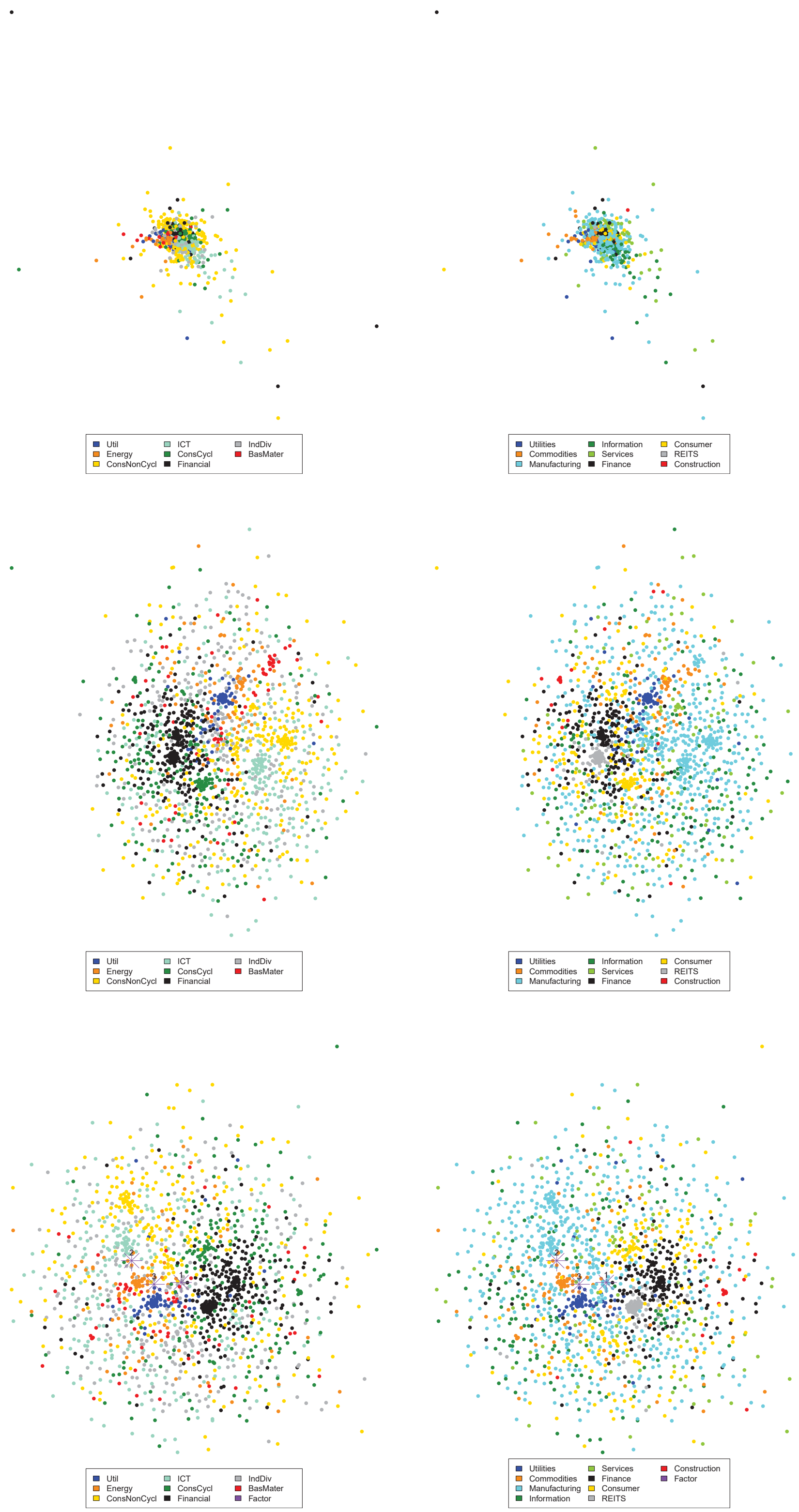
R^I & Factors to R^A & Factors



Note: Networks of the U.S. daily log equity returns for the portion of our sample continuously traded from 1990 through 1999. Network edges are calculated using generalized forecast error variance contributions and 3 common factors.

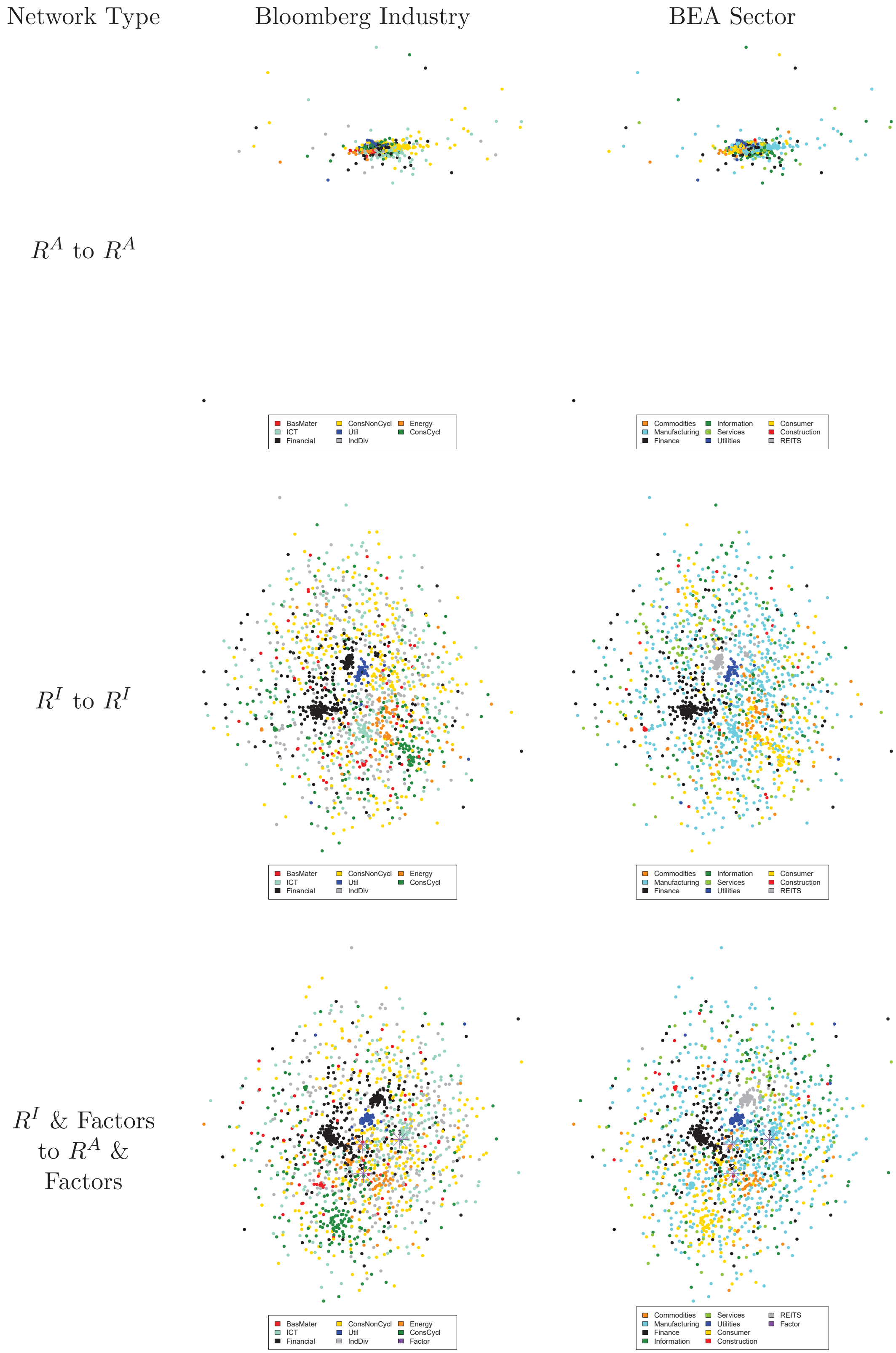
Figure 11: U.S. Firm Network Spring Plots (2000-2009)

Network Type	Bloomberg Industry	BEA Sector
R^A to R^A		
R^I to R^I		
R^I & Factors to R^A & Factors		



Note: Networks of the U.S. daily log equity returns for the portion of our sample continuously traded from 2000 through 2009. Network edges are calculated using generalized forecast error variance contributions and 3 common factors.

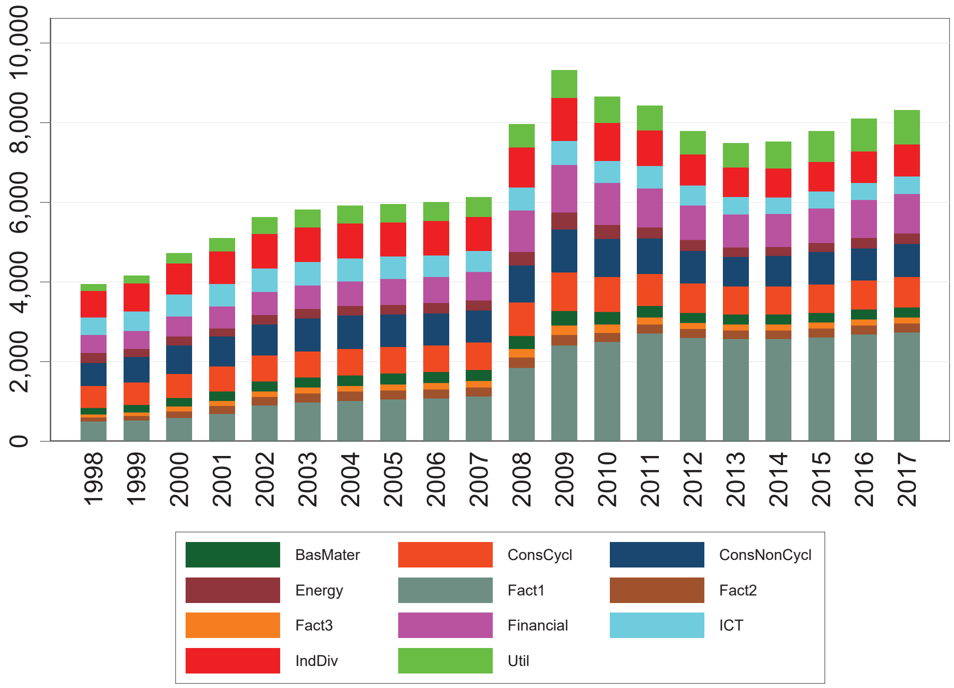
Figure 12: U.S. Firm Network Spring Plots (2010-2017)



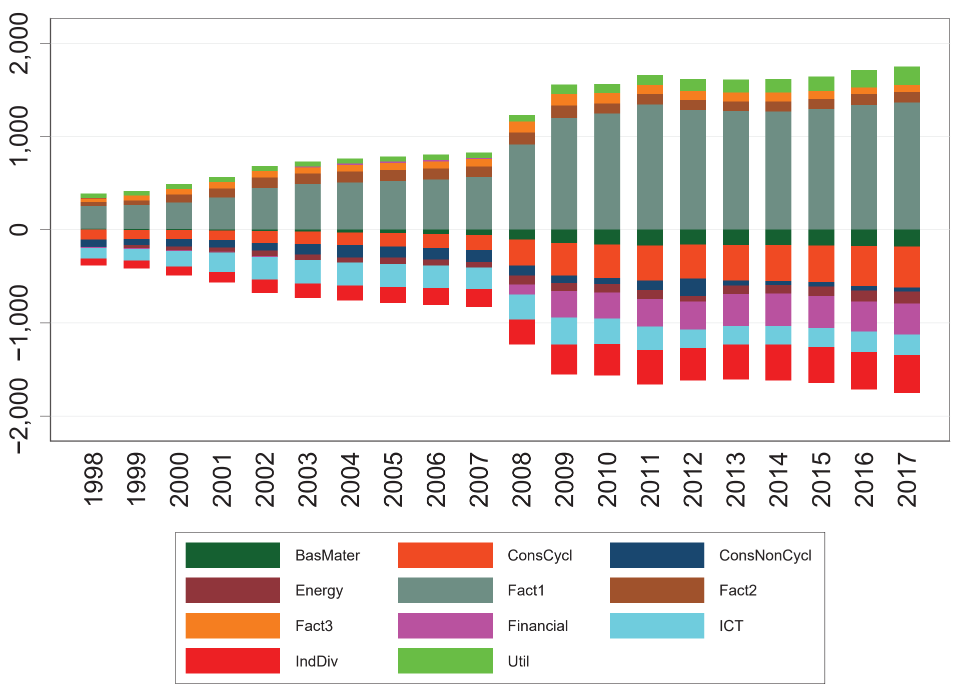
Note: Networks of the U.S. daily log equity returns for the portion of our sample continuously traded from 2010 through 2017. Network edges are calculated using generalized forecast error variance contributions and 3 common factors.

Figure 13: U.S. Firm Network Aggregate Industry Edge Weights (1989-2017)

(a) Sum of Industry Weights Out to All Firms

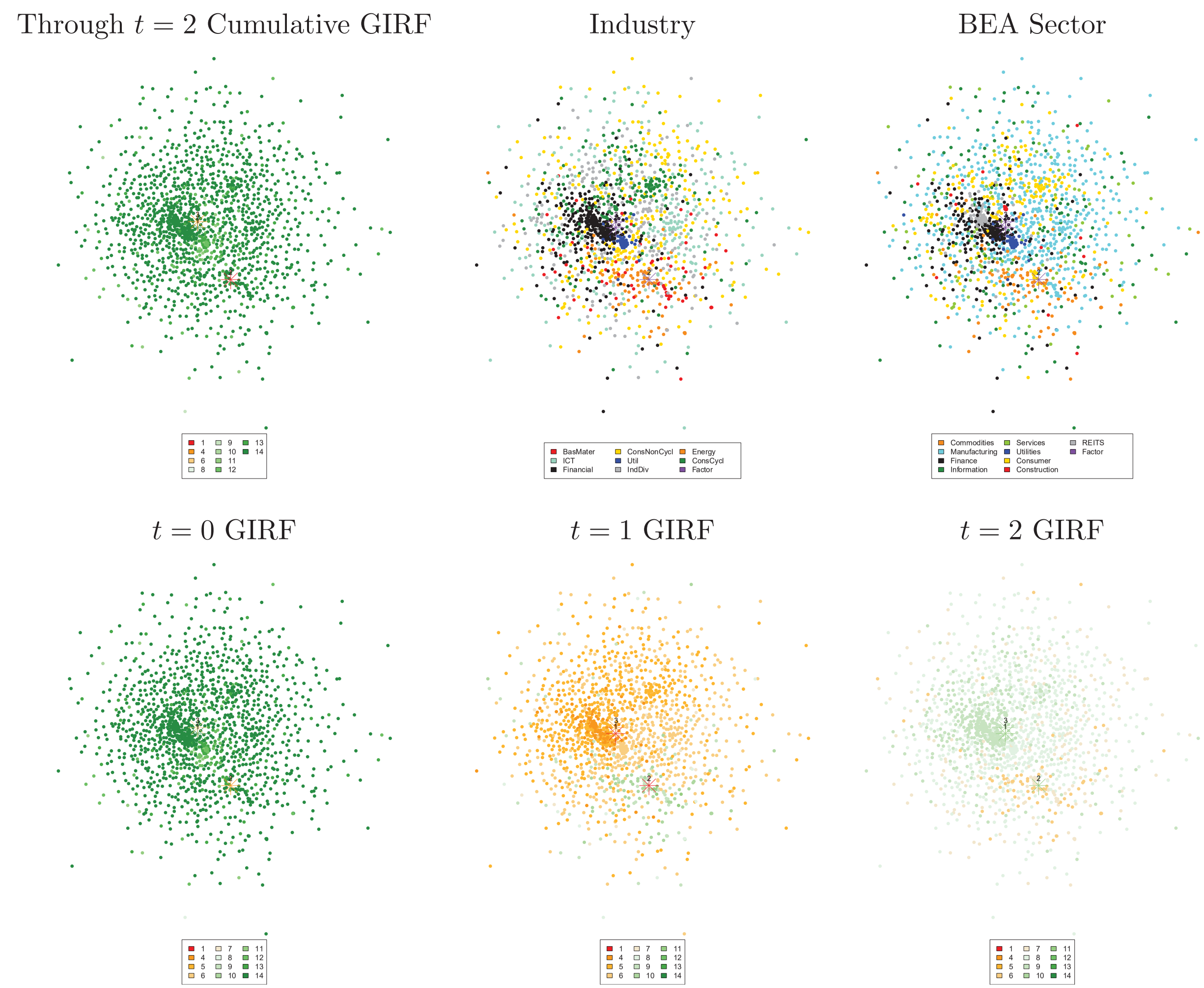


(b) Net Industry Edge Weights



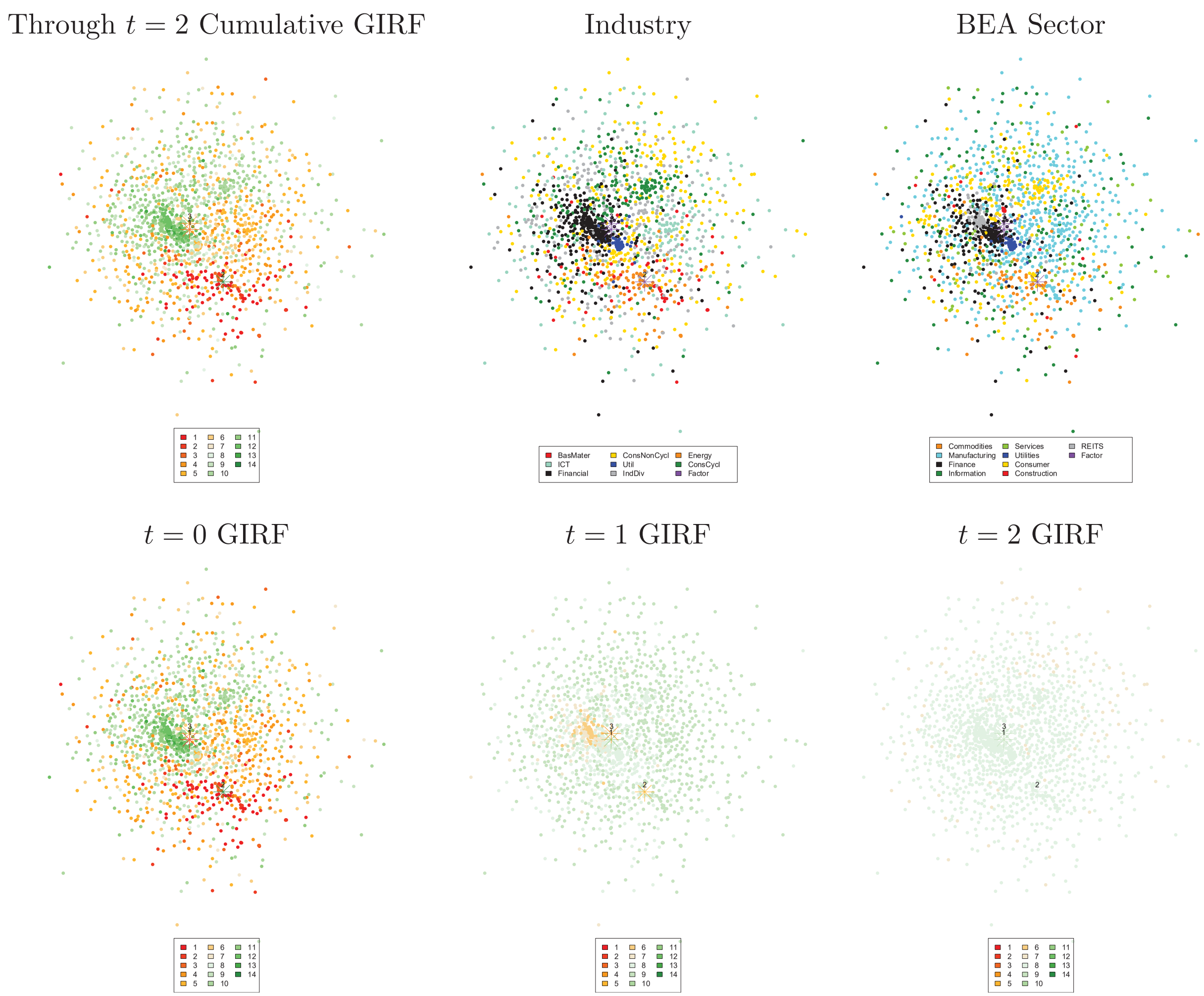
Note: Aggregate edge weights of the R^I & Factors to R^A & Factors GFEVc networks for the portion of our sample continuously traded from 1989 through 2017 with 3 common factors (T = 7424 and N = 524). Factors extracted by principal component analysis on the covariance matrix of the daily log equity returns.

Figure 14: Positive Growth Shock for the U.S. Firm Network (2008-2017)



Note: Networks are for the portion of our sample continuously traded from 2008-2017 with 3 factors. Factors extracted by covariance PCA on the matrix of daily log equity returns. The shock is a positive one to the first factor, correlating with a positive growth shock.

Figure 15: Commodity Price Decline Shock for the U.S. Firm Network (2008-2017)



Note: Networks are for the portion of our sample continuously traded from 2008-2017 with 3 factors. Factors extracted by covariance PCA on the matrix of daily log equity returns. The shock is a positive one to the second factor, correlating with a negative commodity price shock.

Table 1: 20 Largest Eigenvalues by PCA for U.S. Equity Returns (1989-2017)

Top	Value	%	Cum. %	Top	Value	%	Cum. %
1	692.99	22.63	22.63	*11*	23.00	0.75	34.68
2	70.03	2.29	24.91	*12*	22.07	0.72	35.40
3	66.17	2.16	27.07	*13*	21.18	0.69	36.09
4	39.82	1.30	28.37	*14*	20.65	0.67	36.76
5	34.68	1.13	29.51	*15*	19.92	0.65	37.41
6	32.10	1.05	30.55	*16*	18.90	0.62	38.03
7	28.68	0.94	31.49	*17*	18.12	0.59	38.62
8	27.52	0.90	32.39	*18*	17.71	0.58	39.20
9	24.10	0.79	33.17	*19*	17.20	0.56	39.76
10	23.03	0.75	33.93	*20*	16.82	0.55	40.31

Note: Eigenvalue decomposition of the covariance matrix of log daily equity returns for the portion of our sample continuously traded from 1989 through 2017 (T = 7424 and N = 524). Only the largest 20 values are shown.

Table 2: Firm Equity vs. Input-Output Based Networks

Panel A: 1989-2017 Network

Equity Network Type	Raw IO	IO Output Normalized	Leontief Inverse	Upstream Exposure	Downstream Exposure	Upstream + Downstream Exposure
R^A to R^A	0.83***	0.49**	0.39**	0.45***	0.04	0.07
R^I to R^I	0.89***	0.54**	0.61**	0.62***	0.21	0.24
R^A to R^A, No Self-Loops and Scaled by Destination	0.39***	0.55***	0.27***	0.38***	0.06	0.08
R^I to R^I, No Self-Loops and Scaled by Destination	0.40*	0.51**	0.53**	0.59**	0.30	0.32

Panel B: Average Across 10-Year Networks with Maximum Number of Firms Ending 1998-2017

Equity Network Type	Raw IO	IO Output Normalized	Leontief Inverse	Upstream Exposure	Downstream Exposure	Upstream + Downstream Exposure
R^A to R^A	0.78	0.47	0.38	0.44	0.04	0.06
R^I to R^I	0.88	0.56	0.59	0.61	0.19	0.22
R^A to R^A, No Self-Loops and Scaled by Destination	0.38	0.56	0.28	0.40	0.07	0.09
R^I to R^I, No Self-Loops and Scaled by Destination	0.41	0.54	0.51	0.58	0.31	0.34

Note: The firms in each sample are those that are continuously traded throughout that period. GFEVc 3 factor networks. In the top panel, *** p<0.01, ** p<0.05, * p<0.1. Note that the results for the "R^I & Factors to R^A & Factors" and "R^I to R^I" networks are identical by construction, so we only include results for the latter.

Table 3: Firm Equity vs. Input-Output Based Networks Over Time

Panel A: Firm Equity Network Correlations with BEA Sector Level Input-Output Based Networks

		R^A to R^A Network Correlations					R^I to R^I Network Correlations				
EQ Network Period	IO Year	IO Output Normalized	Leontief Inverse	Upstream Exposure	Downstream Exposure	Upstream + Downstream Exposure	IO Output Normalized	Leontief Inverse	Upstream Exposure	Downstream Exposure	Upstream + Downstream Exposure
1989-1998	1997	0.55**	0.46**	0.50***	0.08	0.11	0.58**	0.60**	0.61***	0.20	0.23
1990-1999	1997	0.55**	0.47**	0.51***	0.10	0.13	0.57**	0.59**	0.60***	0.19	0.22
1991-2000	1997	0.55**	0.48**	0.52***	0.11	0.14	0.57**	0.59**	0.60***	0.19	0.22
1992-2001	1997	0.55**	0.47**	0.51***	0.11	0.14	0.57**	0.59**	0.60***	0.20	0.23
1993-2002	1998	0.54**	0.45**	0.49***	0.09	0.11	0.57**	0.59**	0.61***	0.20	0.22
1994-2003	1999	0.53**	0.43**	0.47***	0.07	0.10	0.56**	0.60**	0.61***	0.19	0.22
1995-2004	2000	0.52**	0.43**	0.47***	0.07	0.09	0.55**	0.59**	0.60***	0.19	0.22
1996-2005	2001	0.50**	0.42**	0.45***	0.07	0.09	0.54**	0.59**	0.60***	0.19	0.22
1997-2006	2002	0.51**	0.41**	0.45***	0.07	0.09	0.54**	0.59**	0.60***	0.20	0.22
1998-2007	2003	0.50**	0.41**	0.45***	0.07	0.09	0.53**	0.59**	0.60***	0.21	0.24
1999-2008	2004	0.49**	0.40**	0.45***	0.05	0.08	0.54**	0.60**	0.62***	0.22	0.25
2000-2009	2005	0.48**	0.39**	0.46***	0.03	0.06	0.53**	0.61**	0.63***	0.21	0.24
2001-2010	2006	0.48**	0.38**	0.45***	0.03	0.05	0.53**	0.61**	0.63***	0.21	0.24
2002-2011	2007	0.47**	0.38**	0.45***	0.02	0.05	0.53**	0.61**	0.63***	0.22	0.25
2003-2012	2008	0.45**	0.37**	0.44***	0.03	0.06	0.51**	0.61**	0.63***	0.22	0.26
2004-2013	2009	0.44**	0.35**	0.41***	0.03	0.05	0.51**	0.60**	0.62***	0.23	0.26
2005-2014	2010	0.45**	0.35**	0.42***	0.02	0.05	0.50**	0.60**	0.63***	0.25	0.28
2006-2015	2011	0.46**	0.36**	0.43***	0.03	0.06	0.50**	0.61**	0.63**	0.29	0.32
2007-2016	2012	0.45**	0.36**	0.44***	0.03	0.05	0.50**	0.61**	0.63**	0.30	0.32
2008-2017	2013	0.46**	0.36**	0.44***	0.03	0.06	0.50**	0.61**	0.63**	0.30	0.33
Average		0.50	0.41	0.46	0.06	0.08	0.54	0.60	0.62	0.22	0.25
Std. Dev.		0.04	0.04	0.03	0.03	0.03	0.03	0.01	0.01	0.04	0.04

Panel B: Correlation Comparisons

		R^I Minus R^A Correlations					% Improvement Over IO Output Normalized for R^I	
EQ Network Period	IO Year	IO Output Normalized	Leontief Inverse	Upstream Exposure	Downstream Exposure	Upstream + Downstream Exposure	Leontief Inverse	Upstream Exposure
1989-1998	1997	0.03	0.14	0.11	0.12	0.12	3%	5%
1990-1999	1997	0.02	0.12	0.09	0.09	0.09	4%	5%
1991-2000	1997	0.02	0.11	0.08	0.08	0.08	4%	5%
1992-2001	1997	0.02	0.12	0.09	0.09	0.09	4%	5%
1993-2002	1998	0.03	0.14	0.12	0.11	0.11	4%	7%
1994-2003	1999	0.03	0.17	0.14	0.12	0.12	7%	9%
1995-2004	2000	0.03	0.16	0.13	0.12	0.13	7%	9%
1996-2005	2001	0.04	0.17	0.15	0.12	0.13	9%	11%
1997-2006	2002	0.03	0.18	0.15	0.13	0.13	9%	11%
1998-2007	2003	0.03	0.18	0.15	0.14	0.15	11%	13%
1999-2008	2004	0.05	0.20	0.17	0.17	0.17	11%	15%
2000-2009	2005	0.05	0.22	0.17	0.18	0.18	15%	19%
2001-2010	2006	0.05	0.23	0.18	0.18	0.19	15%	19%
2002-2011	2007	0.06	0.23	0.18	0.20	0.20	15%	19%
2003-2012	2008	0.06	0.24	0.19	0.19	0.20	20%	24%
2004-2013	2009	0.07	0.25	0.21	0.20	0.21	18%	22%
2005-2014	2010	0.05	0.25	0.21	0.23	0.23	20%	26%
2006-2015	2011	0.04	0.25	0.20	0.26	0.26	22%	26%
2007-2016	2012	0.05	0.25	0.19	0.27	0.27	22%	26%
2008-2017	2013	0.04	0.25	0.19	0.27	0.27	22%	26%
Average		0.04	0.19	0.16	0.16	0.17	12%	15%
Std. Dev.		0.01	0.05	0.04	0.06	0.06	7%	8%

Note: Rolling GFEVc 3 factor networks of 524 firms continuously traded over 1989-2017. *** p<0.01, ** p<0.05, * p<0.1. Results for the "R^I & Factors to R^A & Factors" and "R^I to R^I" networks are identical by construction, so we only include results for the latter.