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Equilibrium Asset Pricing in Directed Networks

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Non-Technical Summary

The notion of an economy as a network of more or less tightly linked units has received considerable attention in the finance and economics literature. Links in a network usually have a direction, i.e., it makes a difference whether a link goes from node i to node j or the other way around. In this paper, we study whether directedness in a network at the cash flow level has implications for asset prices. To this end, we introduce a general equilibrium asset pricing model, in which negative cash flow shocks in some industries can increase the probability of subsequent cash flow shocks in other industries.

We introduce the variable "shock propagation capacity" (spc) to measure directedness. Industries with a high spc are by definition those industries whose shocks substantially increase the risk of subsequent shocks throughout the economy. Based on a series expansion of the closed-form solution of our model, we analyze the impact of spc on the main equilibrium asset pricing quantities. Specifically, we prove the following two cross-sectional statements: (i) Cash flow shocks in industries with high spc command a high market price of risk. (ii) The response of an industry's price to its own cash flow shocks is less pronounced for industries with higher spc. Importantly, however, when it comes to expected excess returns, these two effects work in opposite directions, so that the overall impact of spc on risk premia depends on the tradeoff between them. To illustrate our theoretical findings, we estimate an empirical network from industry cash flows and find support for these predictions.

The innovative combination of self and mutually exciting jump processes with recursive preferences allows for the integration of directed networks into a tractable equilibrium asset pricing model. Cash flow shocks propagate with a time lag, but, of course, equilibrium prices react immediately to any shock in the economy since markets are efficient. It is this instantaneous reaction of prices to cash flow shocks propagating slowly over time that is at the heart of our equilibrium model. Our results indicate that it is necessary to decompose expected returns into their constituents in order to understand the implications of directed cash flow shock propagation.

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Equilibrium Asset Pricing in Directed Networks

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ABSTRACT

Directed links in cash flow networks affect the cross-section of price exposures and market prices of risk in equilibrium. In an asset pricing model featuring mutually exciting jumps, we measure directedness through an asset's shock propagation capacity (*spc*). In the model, we prove: (i) Cash flow shocks of high *spc* assets command high market prices of risk, (ii) the price reaction of an asset to its own cash flow shocks is less pronounced for high *spc* assets. Our results indicate it is necessary to decompose excess returns into their constituents to understand the implications of directed cash flow shock propagation.

Keywords: Directed cash flow networks, directed shocks, mutually exciting processes, recursive preferences

JEL: G01, G12, D85

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The notion of an economy as a network of more or less tightly linked units has received considerable attention in the finance and economics literature. Links in a network usually have a direction, i.e., it makes a difference whether a link goes from node i to node j or the other way around. In this paper, we document that directedness in a network at the cash flow level is of first-order importance for asset prices. We propose an equilibrium asset pricing model, in which negative cash flow shocks in some industries can increase the probability of *subsequent* cash flow shocks in other industries.[1] The direction and the magnitude of this "timing of shocks" characterize the network in our model and we introduce the variable "shock propagation capacity" (*spc*) that measures this directedness. Industries with a high *spc* are by definition those industries whose shocks substantially increase the risk of subsequent shocks throughout the economy. Based on a series expansion of the closed-form solution of our model, we analyze the impact of *spc* on the main equilibrium asset pricing quantities. Specifically, we prove the following two cross-sectional statements: (i) Cash flow shocks in industries with high *spc* command a high market price of risk. (ii) The response of an industry's price to its own cash flow shocks is less pronounced for industries with higher *spc*. Finally, when it comes to expected excess returns, these two effects work in opposite directions, so that the overall impact of *spc* on risk premia depends on the tradeoff between them.

The intuition behind statement (i) is as follows. High *spc* industries have more links or stronger links to other industries, relative to their low *spc* counterparts. Hence, shocks originating from a high *spc* industry have a more pronounced impact on the rest of the economy. They increase the aggregate risk of subsequent shocks by a larger amount, hence they are more systematic and carry a higher market price of risk.

Statement (ii) builds on the general intuition that price-to-cash flow ratios throughout the economy decrease in response to any cash flow shock that increases the aggregate risk. However, we document that industry i's price reaction to a shock to industry j's cash flow is the result of a tradeoff between two opposing forces: (1) the direct spillover of shocks from j to i causes a price decline reflecting that the risk of subsequent shocks in industry i's cash flows increased after the initial shock to industry j, and (2) an equilibrium hedge effect. The more shocks to industry j spill over to other industries $k \neq i$, the more "attractive" (in relative terms) will be industry i after the initial shock to j. This latter effect is always positive, irrespective of the representative investor's preference parameters, and becomes more pronounced, the larger the *spc* of asset j. In particular, if a shock to a high *spc* industry increases the probability of subsequent shocks only in other, low *spc* industries,

[1]We will use the term "industry" to refer to a node in the network throughout the paper. Of course, nodes can also represent individual firms, countries, or any other economic unit.

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the equity of the "originating" industry itself serves as a hedging device against the risk of further propagation of cash flow shocks throughout the economy. The positive price-to-cash flow ratio reaction due to the hedge effect (2) dampens the price decline due to the direct effect (1). In particular when it comes to shocks in their own cash flows, high *spc* industries thus have a less negative price reaction than their low *spc* counterparts.

Our stylized consumption-based equilibrium asset pricing model features an arbitrary number of industries whose cash flows are linked via self and mutually exciting jump processes, and a representative investor with recursive preferences. An initial negative cash flow shock of industry i increases the *probability* of future cash flow shocks to connected industries $j \neq i$ (and potentially also to i itself), but it is unknown when (and if at all) these shocks will *materialize*. The network thus manifests itself only indirectly via the dynamics of jump intensities as state variables, but not directly through contemporaneous shocks to the levels of several cash flows. Aggregate consumption is driven by all individual jumps, but a given jump affects the cash flow of only one industry at a time. The investor's preference for early resolution of uncertainty, i.e., the fact that she cares about the risk associated with future values of the state variables, implies that the price-to-cash flow ratios of all assets will react to a jump in any individual cash flow, and it is the structure of the network which determines the sign and the magnitude of these reactions.

We choose this model for the following three reasons. First, mutually exciting processes naturally feature directed links, with a shock going from i to j, but not necessarily vice versa. Second, the model belongs to the exponentially affine class for which there is a well-developed solution theory, and thus it remains tractable with at least semi-closed form expressions for all equilibrium quantities. A series expansion allows us to rewrite the market prices of jump risk and jump exposures as functions of *spc* for *arbitrary directed networks*. Third, the crucial model feature that cash flow shocks to one node in the network affect other nodes only with a certain time lag has been documented empirically. In a recent paper, Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) provide rich empirical evidence for such a delayed propagation of cash flow shocks at the firm level in a natural experiment setting around the nuclear incident of Fukushima in 2011. They summarize the intuition behind their result as follows: "When faced with a supply-chain disruption, individual firms are unable to find suitable alternatives in order to completely insulate themselves from the shock (at least in the short run). This is consistent with an emerging literature [...] that emphasizes the importance of search frictions and relation-specific investments along supply chains." (p.34). However, even though the cash flow shocks propagate with a time lag, equilibrium prices react immediately to any shock in the economy since markets are efficient. It is precisely this instantaneous reaction of prices to cash flow shocks propagating slowly over time that is at the heart of

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our equilibrium model.

We close the paper by presenting some suggestive empirical evidence for our theoretical channels. Since we propose a consumption-based asset pricing model, industry cash flow data are the quantity to be modeled in this exercise.[2] We estimate an empirical cash flow network by applying the generalized variance decomposition method suggested by Diebold and Yilmaz (2014) to the earnings time series of 14 NAICS industries. Given *spc* for these industries, we regress Sharpe ratios (as a proxy for the market prices of risk), return volatilities (as a proxy for price exposures), and average excess returns of value-weighted industry portfolios on this measure. In line with the model, we find in cross-sectional regressions positive coefficients for Sharpe ratios, negative coefficients for return volatilities, and insignificant coefficients for average excess returns.

Our paper is linked to several strands of literature. First, there are papers studying the asset pricing implications of networks at the production level. Herskovic (2018) extends the input-output framework of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) to a time-varying network and highlights the role of sparsity and concentration of an entire network for capturing aggregate risk. Gofman, Segal, and Wu (2018) determine a firm's vertical position in the supply chain and calculate a top-minus-bottom spread which they explain in a production economy with layer-specific capital. In an international context, Richmond (2016) relies on Katz centrality and finds that more central countries have lower interest rates and currency risk premia. The purely empirical papers by Ahern (2013) and Aobdia, Caskey, and Ozel (2014) link equity returns to trade flows between industries. However, none of these papers focus explicitly on the impact of directedness, i.e., the magnitude and the direction of all the links of an asset, which is the key aspect we emphasize.[3] Second, Buraschi and Tebaldi (2018) model cash flows via jumps which are not mutually exciting. However, their focus is not on directed links, but on systemic risk in banking networks. A third strand of literature analyzes networks estimated from return data. An example for such papers

[2] We restrain from using input-output production data to construct our cash flow network. While it is intuitive to assume that a firm or industry which is *central* in the production input-output network is also *central* in the cash flow network, it is not clear at all whether a similar relation also holds with respect to *direction*. Empirically, Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) document that cash flow shocks can propagate both upstream and downstream along the supply chain. Consequently, directed links at the cash flow level cannot necessarily be traced back to links of the same direction at the production level.

[3] There is also a strand of literature on production or supply chain networks in economics, however, they do not focus on the asset pricing implications of network structures. Examples include, among others, Long and Plosser (1983), Gabaix (2011), Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), Carvalho and Voigtländer (2015), Wu (2015), Acemoglu, Akcigit, and Kerr (2016), Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016), Barrot and Sauvagnat (2016), Wu (2016), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017), Ozdagli and Weber (2017), and Tascherau-Dumouchel (2018). Carvalho (2014) provides an excellent review of this literature.

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is Diebold and Yilmaz (2014). Many papers dealing with the measurement of systemic risk also follow this route, e.g., Billio, Getmansky, Lo, and Pelizzon (2012) and Demirer, Diebold, Liu, and Yilmaz (2017). The main difference between these papers and ours is that we model the underlying fundamentals, i.e., cash flows, and prices and returns are then endogenously determined in equilibrium.

Finally, Aït-Sahalia, Cacho-Diaz, and Laeven (2015) are the first to discuss the role of mutually exciting jumps in finance applications. The methodological framework of our equilibrium model goes back to the paper by Eraker and Shaliastovich (2008). Besides, there is an increasing literature about consumption-based asset pricing models with stochastic jump intensities in the endowment process. For instance, Wachter (2013) and Gabaix (2012) analyze the equity premium puzzle and the excess volatility puzzle in an economies with a stochastic intensities for rare consumption disasters, but do so in models with only one endowment stream, which obviously does not lend itself to any network applications.[4]

1. Model

1.1. Fundamental dynamics

We assume a Lucas endowment economy. Log aggregate consumption $y_t \equiv \ln Y_t$ follows

$$dy_t \;=\; \mu\, dt + \sum_{j=1}^{n} K_j\, dN_{j,t},$$

where μ is the constant drift rate and the $N_{j,t}$ $(j = 1, \ldots, n)$ are self and mutually exciting jump processes with constant jump sizes $K_j < 0$.[5] Their stochastic jump intensities $\ell_{j,t}$ have dynamics

$$d\ell_{j,t} \;=\; \kappa_j \left(\bar{\ell}_j - \ell_{j,t}\right) dt + \sum_{i=1}^{n} \beta_{j,i}\, dN_{i,t}. \tag{1}$$

[4]This framework is extended to a two-sector economy with jump intensities driven by correlated Brownian motions in Tsai and Wachter (2016) and towards CDS pricing in Seo and Wachter (2018). Benzoni, Collin-Dufresne, Goldstein, and Helwege (2015) analyze defaultable bonds subject to contagion risk in a general equilibrium model. Nowotny (2011) investigates a one-sector economy with consumption following a self exciting process. Branger, Kraft, and Meinerding (2014) show that self exciting processes can endogenously evolve in a framework with learning about latent disaster intensities. A comprehensive summary of the disaster risk literature is provided by Tsai and Wachter (2015).

[5]We do not include diffusion terms in the dynamics of aggregate consumption for parsimony. One could of course generalize the model to incorporate additional types of diffusive risk premia, e.g., by making the expected consumption growth rate time-varying, as long as the framework remains affine.

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The coefficients $\beta_{j,i}$ represent discrete changes in $\ell_{j,t}$ induced by a jump in $N_{i,t}$. The parameters $\beta_{j,i}$, collected in what we call the "beta matrix" or the connectivity matrix, completely determine the structure of a given network.[6] To preclude negative intensities we assume $\beta_{j,i} \geq 0$ for all pairs (j, i).

There are n industries in the economy, indexed by i, with the following dynamics for log cash flows $y_{i,t}$:

$$dy_{i,t} \;=\; \mu_i \, dt + L_i \, dN_{i,t} \qquad (i = 1, \ldots, n). \tag{2}$$

We do not link aggregate consumption to the sum of cash flows, but model cash flows as claims on certain risk factors in the consumption process. The difference can be thought of, e.g., as the investor's implicit labor income. Note that this specification is consistent with empirical data, e.g., Santos and Veronesi (2006) point out that the sum of cash flows is only a fraction of aggregate consumption. This assumption is present in asset pricing models like Campbell and Cochrane (1999), Longstaff and Piazzesi (2004), Bansal and Yaron (2004), Backus, Chernov, and Martin (2011), or Barberis, Greenwood, Jin, and Shleifer (2015).

Equations (1) and (2) formalize how the beta matrix gives rise to a dynamic shock propagation mechanism by which negative shocks to one cash flow stream can spread across the economy. With $\beta_{j,i} > 0$, a downward jump in cash flow i immediately increases the jump intensity of cash flow j by the amount $\beta_{j,i}$. Once the increased intensity $\ell_{j,t}$ indeed leads to a jump in cash flow j and there is a nonzero coefficient $\beta_{k,j}$, the initial shock is passed on to asset k and can in this way be propagated through the whole network. Note that our specification is general in the sense that it also allows for "feedback loops", i.e., depending on the structure of the network, an initial shock to node i can, after a number of intermediate steps, eventually reach node i itself again. Nevertheless, each jump only affects one cash flow directly, so that network connectivity is captured exclusively via linkages in the dynamics of the state variables, not at the cash flow level itself.

Mutually exciting jumps provide certainly not the only, but a very lean and reduced-form modeling tool to capture exactly the above intuition. An initial cash flow shock in industry i increases the *probability* of future cash flow shocks to a connected industry $j \neq i$ (and potentially also firm i itself), but it is unknown when (and if at all) these shocks will *materialize*. Stated differently, a cash flow shock of one firm changes the conditional distribution of future cash flows of other firms, but does not affect the level of these cash flows instantaneously. The structure of the jump processes in our model thus differs in a

[6]Our network is weighted in the sense that the links between nodes are represented by (positive) real numbers, not just by the binary 0-1 information whether two nodes are linked or not.

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time series and in a cross-sectional dimension from, for instance, contemporaneous jumps in many assets. Representing this time dimension of shock propagation alternatively by, e.g., a discrete-time vector autoregressive model would lead to the problem that the sum of AR(1) processes is not necessarily an AR(1) process itself (see Granger and Morris (1976)).

As stated above, our specification ensures that the vector $X_t = (y_t, \ell_{1,t}, \dots, \ell_{n,t}, y_{1,t}, \dots, y_{n,t})'$ follows an affine jump process.[7] The joint process (N_t, ℓ_t) is Markov. In all applications of the model, we assume $\kappa_i > \beta_{i,i}$ for $i = 1, \dots, n$, so that the vector of intensities ℓ is stationary.[8]

In the following analyses, we refer to one particular measure for the directedness of cash flow shocks. The *shock propagation capacity*, *spc*, of asset i is defined as the respective column sum of the beta matrix without the diagonal entry:[9]

$$spc_i \;=\; \sum_{\substack{j=1 \\ j\neq i}}^{n} \beta_{j,i}. \tag{3}$$

This measure has been proposed by, e.g., Jackson (2008) and Diebold and Yilmaz (2014) and represents the total strength of the network links going from node i to all other nodes in the network. In the framework of our model, the higher the *spc* of a given node, the more a shock to its cash flow increases the jump intensities of other nodes.[10]

1.2. Market prices of jump risk

Our economy is populated by a representative agent with an infinite planning horizon. We assume that the agent has recursive preferences so that the risk generated by state variables (in this case the intensities $\ell_{i,t}$) will be priced in equilibrium.

The derivation of the model solution closely follows Eraker and Shaliastovich (2008).[11] They show that the continuous-time dynamics of the pricing kernel M_t can be written as

$$d\ln M_t \;=\; -\delta\,\theta\,dt - (1-\theta)\;d\ln R_t - \frac{\theta}{\psi}\,dy_t,$$

where δ is the subjective time preference rate, γ is the coefficient of relative risk aversion,

[7] See Appendix A for details.

[8] See, e.g., Aït-Sahalia, Cacho-Diaz, and Laeven (2015) for details about mutually exciting processes, in particular, concerning conditions for stationarity.

[9] Disregarding the diagonal entry is standard practice in the literature, see Diebold and Yilmaz (2014).

[10] Although we call *spc* a measure of *directedness*, it can of course also be applied in an *undirected* network, i.e., in a network where the connectivity matrix is symmetric.

[11] Details are presented in Appendix A.

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ψ is the elasticity of intertemporal substitution (EIS), and $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$. We assume that the representative agent has a preference for early resolution of uncertainty, implying $\gamma > \frac{1}{\psi}$ and thus $\theta < 1$.

The return on the consumption claim R_t satisfies the following continuous-time version of the Euler equation

$$0 = \frac{1}{dt}\,\mathbb{E}_t\left[\frac{d\left(e^{\ln M_t + \ln R_t}\right)}{e^{\ln M_t + \ln R_t}}\right],$$

and follows from the dynamics of the log wealth-consumption ratio v and aggregate consumption. To compute R_t, we use the Campbell-Shiller log-linear approximation $d\ln R_t = k_{v,0}\,dt + k_{v,1}\,dv_t - (1-k_{v,1})\,v_t\,dt + dy_t$ with linearizing constants $k_{v,0}$ and $0 < k_{v,1} < 1$. Employing the usual affine guess for the log wealth-consumption ratio v_t, i.e., assuming $v_t = A + B'\,\ell_t$ with $B = (B_1, \ldots, B_n)'$ and $\ell_t = (\ell_{1,t}, \ldots, \ell_{n,t})'$, we can solve numerically for the coefficients A and B as well as for the linearizing constants.

The dynamics of the pricing kernel are

$$\frac{dM_t}{M_t} = -r_t\,dt - \sum_{i=1}^{n} \mathrm{MPJR}_i\,(dN_{i,t} - \ell_{i,t}dt),$$

where r_t is the equilibrium risk-free rate and MPJR_i is the market price of risk for the jump process N_i. These in general negative market prices of jump risk are given as

$$\mathrm{MPJR}_i = 1 - \exp\left\{-\gamma\,K_i + k_{v,1}\,(\theta-1)\,\left[\sum_{j=1}^{n} B_j\,\beta_{j,i}\right]\right\}, \tag{4}$$

with $k_{v,1} = \frac{e^{\bar{v}}}{1+e^{\bar{v}}}$, where $e^{\bar{v}}$ is the steady-state wealth-consumption ratio. The exponential term is a product of two factors. The first one, $\exp\{-\gamma\,K_i\}$, represents the compensation for the immediate shock caused by the jump in cash flow i. Since $K_i < 0$ these market prices of jump risk are in general negative. The second one with the remaining exponents is the compensation for the risk caused by variations in the state variables and is one of the key features of our model. It depends on the impact of the intensities ℓ_i on the equilibrium wealth-consumption ratio, represented by the components of the vector B.

The coefficients in B depend on the structure of the network, and they are in general not equal across all $j = 1, \ldots, n$. Therefore, we cannot immediately formulate the market prices of risk as functions of network measures such as *spc* just from Equation (4). To obtain predictions for how the structure of the network affects the market prices of risk, we derive

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the following proposition through a first-order approximation.[12]

Proposition 1. *Assume that $\kappa_1 = \ldots = \kappa_n = \kappa$ and $K_1 = \ldots = K_n = K$. Then, the market price of jump risk $MPJR_i$ satisfies*

$$MPJR_i \;\; = \;\; 1 - \exp\left\{\mathcal{A} + \mathcal{B} \cdot (\beta_{i,i} + spc_i) + O\left(\beta^2\right)\right\},$$

where the coefficients $\mathcal{A}$ and $\mathcal{B}$ are given by

$$\begin{aligned} \mathcal{A} &= -\gamma\, K \\ \mathcal{B} &= \frac{(\theta - 1)\; (1 - \exp\{K\; (1 - \gamma)\})}{\theta\, \left[(1 - \kappa) - \frac{1}{k_{v,1}}\right]} \end{aligned}$$

and $O(\beta^2)$ denotes polynomial terms of order 2 or higher in the coefficients of the network matrix. Defining the first-order approximation

$$MPJR_i^{**} \;\; \equiv \;\; 1 - \exp\left\{\mathcal{A} + \mathcal{B} \cdot (\beta_{i,i} + spc_i)\right\} \tag{5}$$

and assuming $\gamma > 1$, $\theta < 0$, $0 < \kappa < 1$, and $K < 0$, we obtain the following results:

(1) $\mathcal{A} > 0$ and $\mathcal{B} > 0$.

(2) If $spc_i > spc_j$, then $|MPJR_i^{**}| > \left|MPJR_j^{**}\right|$.

Proof: See Appendix B.1.

The second exponential factor on the right-hand side of (5) is one of the key features of our model. The *spc* of an asset is the main driver of the equilibrium market price of risk. The proposition states that the market prices of risk for jumps associated with high *spc* assets are larger (in absolute terms) than those of low *spc* assets (note that $\mathcal{A}$ and $\mathcal{B}$ do not depend on i).[13]

The economic intuition behind this key result is the following. By definition, high *spc* industries have more links or stronger links to other industries, relative to their low *spc*

[12]First-order approximations are used, e.g., in Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) or Walden (2018) to make statements about general network structures. A different strategy to obtain closed-form solutions for equilibrium quantities as functions of network measures is to focus on special cases in which the connectivity matrix is very sparse. For instance, in Online Appendix A, we derive such closed-form solutions *without approximations* in so-called star (or core-periphery) networks.

[13]In Appendix B.3, we analyze the quality of the first-order approximation in Proposition 1 by regressing the approximate solution (5) on the exact solution (4) for the empirical network estimated in Section 2. The R^2 of this regression is 0.98, the ordering of the assets, and the signs of the market prices of risk are all preserved. The slope of the regression line is 0.26, implying that the higher-order terms omitted in the approximation are quantitatively sizable, but do not change any of our model results qualitatively.

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counterparts. Hence, cash flow shocks originating from a high *spc* industry have a more pronounced impact on the rest of the economy, i.e. they increase the aggregate risk of subsequent shocks by a larger amount. In models with stochastic cash flow jump intensities and recursive preferences, the wealth-consumption ratio is generally decreasing in the aggregate jump risk.[14] The wealth-consumption ratio in our economy thus reacts more negatively to cash flow shocks of high *spc* assets. These shocks are thus more "systematic" and carry a higher (i.e. more negative) market price of risk in equilibrium.

The proposition explicates that a necessary condition for this key result is that $\mathcal{B} > 0$, and this condition is satisfied under some mild preference parameter restrictions like $\theta < 0$, which implies $\psi > 1$ (if $\gamma > 1$). In this situation, the intertemporal substitution effect dominates the income effect, so that the investor wants to consume more and save less in bad times with high jump intensities. The proposition also shows that in the special case of CRRA utility ($\theta = 1$, implying $\mathcal{B} = 0$), the second term in Equation (5) vanishes, implying that state variable risk is not priced and that the market prices of risk do not depend on the network structure. Finally, MPJR_i is the larger, the larger the impact of jumps in asset i on aggregate consumption, as measured by K.

1.3. Jump exposures

In analogy to the return on the consumption claim, the returns $R_{i,t}$ on the individual cash flow claims satisfy the continuous-time Euler equations

$$0 \;=\; \frac{1}{dt}\,\mathbb{E}_t\left[\frac{d\left(e^{\ln M_t + \ln R_{i,t}}\right)}{e^{\ln M_t + \ln R_{i,t}}}\right].$$

To compute the expected excess return on asset i, we proceed as in the case of the consumption claim, i.e., we employ an affine guess for the log price-to-cash flow ratio of asset i, $v_{i,t} = A_i + C_i'\ell_t$ with $C_i = (C_{i,1}, \ldots, C_{i,n})'$, and use the Campbell-Shiller approximation $d\ln R_{i,t} = k_{i,0}\,dt + k_{i,1}\,dv_{i,t} - (1 - k_{i,1})\,v_{i,t}\,dt + dy_{i,t}$ with linearization constants $k_{i,0}$ and $0 < k_{i,1} < 1$. Again, we solve for the coefficients A_i and $C_{i,j}$ $(j = 1, \ldots, n)$ as well as for the linearization constants $k_{i,0}$ and $k_{i,1}$ numerically.

The return on the i-th individual cash flow claim is then given by

$$dR_{i,t} \;=\; \ldots dt + \sum_{j=1}^{n} \text{JEXP}_{i,j}\,dN_{j,t},$$

[14] This has been shown, e.g., by Wachter (2013).

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with the jump exposures

$$\mathrm{JEXP}_{i,j} \;=\; \begin{cases} \exp\left(L_i + k_{i,1}\sum_{k=1}^{n} C_{i,k}\,\beta_{k,i}\right) - 1 & \text{for } j = i \\ \exp\left(k_{i,1}\sum_{k=1}^{n} C_{i,k}\,\beta_{k,j}\right) - 1 & \text{for } j \neq i. \end{cases} \tag{6}$$

The exponential term in the exposure of asset i to jumps in its own cash flow, $\mathrm{JEXP}_{i,i}$, has two components. First, there is the price change due to the immediate cash flow shock, represented via the jump size L_i. By assumption this component is only present in the exposure of asset i to jumps in its own cash flow i because y_i is exclusively affected by N_i, i.e., jumps in other intensities do not have a direct impact on the cash flow y_i. The second term is a special feature of models with recursive utility and captures the effect of a shock in cash flow j on asset i's price-to-cash flow ratio. For $j \neq i$, the exposure $\mathrm{JEXP}_{i,j}$ only consists of this valuation ratio effect.

In Equation (6), the coefficients $C_{i,k}$ depend on the network structure. Since they will not coincide for all $k = 1, \ldots, n$ in general, we cannot simply factor out *spc* in Equation (6). Therefore, we again apply a first-order approximation allowing us to formulate the following proposition.[15]

Proposition 2. *Assume that $\kappa_1 = \ldots = \kappa_n = \kappa$ and $K_1 = \ldots = K_n = K$. Then, the jump exposures $JEXP_{i,j}$ of asset i against shocks to cash flow j satisfy the equation*

$$JEXP_{i,j} \;=\; \begin{cases} \exp\left\{\mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,j} + \mathcal{D}_i \cdot \beta_{i,j} + O\left(\beta^2\right)\right\} - 1 & \textit{for } j \neq i \\ \exp\left\{L + \mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,i} + \mathcal{D}_i \cdot \beta_{i,i} + O\left(\beta^2\right)\right\} - 1 & \textit{for } j = i, \end{cases}$$

where the coefficients $\mathcal{C}_i$ and $\mathcal{D}_i$ are given by

$$\mathcal{C}_i \;=\; \frac{1 - \exp\{-K\,\gamma\} - \frac{\theta-1}{\theta}\left[1 - \exp\{K\,(1-\gamma)\}\right]}{1 - \kappa - \frac{1}{k_{i,1}}}$$

$$\mathcal{D}_i \;=\; \frac{1 - \exp\{L - K\,\gamma\} - \frac{\theta-1}{\theta}\left[1 - \exp\{K\,(1-\gamma)\}\right]}{1 - \kappa - \frac{1}{k_{i,1}}}$$

and $O(\beta^2)$ denotes polynomial terms of order 2 or higher in the network coefficients. Defining the first-order approximation

$$JEXP^{**}_{i,j} \;:=\; \begin{cases} \exp\left\{\mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,j} + \mathcal{D}_i \cdot \beta_{i,j}\right\} - 1 & \textit{for } j \neq i \\ \exp\left\{L + \mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,i} + \mathcal{D}_i \cdot \beta_{i,i}\right\} - 1 & \textit{for } j = i \end{cases} \tag{7}$$

[15] In Online Appendix A, we show that qualitatively similar closed-form solutions for the return volatility can be obtained *without approximations* in so-called star (or core-periphery) networks.

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and assuming $\gamma > 1$, $0 < \kappa < 1$, and $-\log(2) < K < 0$, we obtain $\mathcal{C}_i > 0$ for all i. Additionally assuming $\theta < 0$, we obtain

(1) $\mathcal{D}_i < 0$, and $\mathcal{D}_i - \mathcal{C}_i < 0$ for all i.

(2) If $JEXP^{**}_{i,i}$, $JEXP^{**}_{j,j} < 0$, $k_{i,1} = k_{j,1}$, and $spc_i > spc_j$, then $\left|JEXP^{**}_{i,i}\right| < \left|JEXP^{**}_{j,j}\right|$.

Proof: See Appendix B.2.[16]

For $j \neq i$, the expression for $\text{JEXP}^{**}_{i,j}$ comprises two terms. The quantity $\mathcal{D}_i\, \beta_{i,j}$ describes a price effect through direct spillover of shocks from j to i. A jump in asset j increases the jump intensity of asset i by $\beta_{i,j}$. Since $\mathcal{D}_i < 0$, the reaction of the price-dividend ratio of i due to this direct effect, $\exp\{\mathcal{D}_i\, \beta_{i,j}\} - 1$, is negative.

The term $\mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,j}$ represents an equilibrium "hedge effect". A jump in asset j increases the jump intensities of (some or all) other assets $k \neq i$, and the price of asset i *increases* through this mechanism, since $\mathcal{C}_i > 0$. This hedge effect is always positive, irrespective of the preference parameter θ. Intuitively, the hedge effect makes assets which are not directly affected by a jump in asset j's cash flow *relatively* more attractive. For $j \neq i$, we can rewrite

$$\text{JEXP}^{**}_{i,j} \;=\; \exp\left\{\mathcal{C}_i \cdot \text{spc}_j + \mathcal{C}_i \cdot \beta_{j,j} + (\mathcal{D}_i - \mathcal{C}_i)\; \beta_{i,j}\right\} - 1, \tag{8}$$

which implies that the hedge effect is larger for shocks originating from high *spc* assets than from low *spc* assets.

For $j = i$, this positive hedge effect reduces the negative cash flow effect of a jump in i on the price of asset i itself, represented by $\exp\{L\} - 1$. Again, we can write

$$\text{JEXP}^{**}_{i,i} \;=\; \exp\{L + \mathcal{C}_i \cdot \text{spc}_i + \mathcal{D}_i \cdot \beta_{i,i}\} - 1,$$

i.e., the hedge effect is more pronounced for a high *spc* asset than for a low *spc* asset.

The ultimate sign of $\text{JEXP}^{**}_{i,j}$ depends on the trade-off between the hedge effect, $\mathcal{C}_i \cdot \sum_{k=1,k\neq i}^{n} \beta_{k,j}$, and the direct price effect, $\mathcal{D}_i \cdot \beta_{i,j}$, and thus on the network structure. Despite the fact that the hedge effect is positive for any network structure and any preference parameter θ, the choice of preferences is still very important for the overall properties

[16] In Appendix B.3, we analyze the quality of the first-order approximation in Proposition 2 by regressing the approximate solution on the exact solution of Equation (6) for the network estimated in Section 2. The R^2 of this regression is 0.98, the ordering of the assets, and the signs of the jump exposures are all preserved. The slope of the regression line is 0.77, implying that the higher-order terms omitted in the approximation are quantitatively sizeable, but do not change any of our results qualitatively.

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of the model. For $L > K\,\gamma$, CRRA preferences ($\theta = 1$) will lead to all cross-exposures $\mathrm{JEXP}^{**}_{i,j} > 0$ being positive, so that here the hedging effect massively outweighs the direct negative effect. With recursive preferences, on the other hand, there will also be pairs of assets with $\mathrm{JEXP}^{**}_{i,j} < 0$, i.e., there will be cases when the hedging effect is not strong enough to dominate the direct negative effect. For $i = j$, the exposure $\mathrm{JEXP}^{**}_{i,i}$ comprises a third component, L, and if this parameter is chosen strongly negative, then $\mathrm{JEXP}^{**}_{i,i}$ will be negative.

1.4. Expected excess returns

Finally, the local expected excess return of asset i can be written as

$$\frac{1}{dt}\,\mathbb{E}_t\left[dR_{i,t}\right] - r_t \;\; = \;\; \sum_{j=1}^{n} \ell_{j,t}\,\mathrm{MPJR}_j\,\mathrm{JEXP}_{i,j}, \tag{9}$$

i.e., the risk premium of asset i is given by the sum of the products of jump intensity, market price of risk, and jump exposure over all n jump components.

Although the expected excess return depends on all market prices and all exposures, the summand $\mathrm{MPJR}_i\,\mathrm{JEXP}_{i,i}$ is usually the largest in this sum because the exposure $\mathrm{JEXP}_{i,i}$ also comprises the direct cash flow effect captured by the cash flow jump size L, as shown in Equation (7). Propositions 1 and 2 show that MPJR_i is higher for high *spc* assets than for low *spc* assets, whereas the relation is the other way around for $\mathrm{JEXP}_{i,i}$. Thus, we cannot obtain unambiguous cross-sectional predictions regarding the impact of *spc* on expected excess returns.

For this insight, recursive preferences are crucial. With CRRA utility, the market price of risk on all jumps would be identical, and all cross exposures would be positive for $L > K\,\gamma$. So the trade-off outlined above does not exist and high *spc* assets earn larger expected excess returns than low *spc* assets in a CRRA economy.

2. Suggestive empirical evidence

To present suggestive evidence for the theoretical channels outlined above, we use a time series of log earnings growth rates for 14 industry portfolios which we constructed based on the NAICS code of all firms in the CRSP/Computstat merged (CCM) fundamentals quarterly database over the sample from 1966-Q2 to 2014-Q4. This time series allows us to estimate the directed earnings network following the procedure proposed by Diebold and

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Yilmaz (2014).[17] The first step is to estimate a 14-dimensional VAR(1) process based on our earnings growth time series, i.e., $z_t = \phi_0 + \phi_1 z_{t-1} + \varepsilon_t$. From the coefficient matrix ϕ_1 and the covariance matrix of the shocks ε, we compute generalized variance decompositions of quarterly earnings with a forecast horizon of $H = 4$ quarters.[18] We denote the fraction of H-quarter forecast error variance of industry i's earnings explained by shocks in industry j's earnings by $d_{i,j}$. This gives us a 14×14 matrix $(d_{i,j})_{i,j=1,\dots,14}$, which Diebold and Yilmaz (2014) refer to as the *connectedness table*. This matrix serves as our empirical network matrix from which we compute the shock propagation capacity spc_j for industry j analogous to Equation (3) as $spc_j = \sum_{\substack{i=1 \\ i \neq j}}^{N} d_{i,j}$. Diebold and Yilmaz (2014) call this measure *total directional connectedness to others from* j.

According to the firm's NAICS code, we form value-weighted industry portfolios and we calculate three variables over the whole sample, which serve as dependent variables in our regressions. The average excess return of an industry portfolio is the mean of the difference between its log return and the log three-month Treasury bill return. Return volatilities are calculated as the standard deviations of log returns. Sharpe ratios are computed as average excess returns divided by return volatilities.

The Sharpe ratio of an industry serves as a proxy for the market price of risk for cash flow shocks of the respective industry, MPJR, because these market prices of risk are not observable empirically. Recall from Equation (9) that the expected excess return on asset i is given as $\frac{1}{dt}\mathbb{E}\left[dR_i\right] - r = \sum_{j=1}^{n} \ell_j \, \mathrm{JEXP}_{i,j} \, \mathrm{MPJR}_j$. The i-th summand is by the far the largest on the right-hand side, since $\mathrm{JEXP}_{i,i}$ is the only exposure containing the direct cash flow effect represented by the jump size L. The expected excess return of an asset is thus mostly driven by the response of its price and of the pricing kernel to *its own cash flow shocks*. Therefore we use the Sharpe ratio of asset i as a proxy for MPJR_i and the return volatility as a proxy for $\mathrm{JEXP}_{i,i}$.

Panel A in Table 1 reports the results from this exercise. In the cross-sectional regressions, the independent variables are the industry shock propagation capacities and the dependent variables are return volatilities, Sharpe ratios, and average excess returns.[19] In line with the model, we find positive and significant coefficients for Sharpe ratios, negative

[17] We thank Francis Diebold and Kamil Yilmaz for sharing their code.

[18] There is no clear guidance towards the optimal choice of the forecast horizon H. As documented by Diebold and Yilmaz (2014), who choose $H = 12$ days for their daily stock return data, a very short horizon produces noisy estimates, but the estimates stabilize with longer horizons. We find similar, albeit weaker, effects of the forecast horizon in our estimation and, therefore, report results for $H = 4$ quarters in the following and present those for $H = 1, 2, 3$ in Online Appendix C. There we also explain the details of the data construction process, provide plots for the empirical cash flow networks for different forecast horizons, and report summary statistics for *spc* and the industry portfolio returns.

[19] Although one of the three regressions is redundant, we report all three for the sake of completeness.

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and significant coefficients for return volatilities, and insignificant coefficients for average excess returns. Since the effects of *spc* on the market price of jump risk and on price exposures have opposite signs, the impact of directedness on expected excess returns can only be assessed appropriately when the two opposing effects described above are disentangled. Finally, the coefficients in the Sharpe ratio and return volatility regressions are also economically significant. A one-standard-deviation difference in *spc* leads to a difference in Sharpe ratios of roughly $8.18 \cdot 0.16 \approx 1.31$ percentage points monthly or $-4.41 \cdot 0.16 \approx -0.71$ for return volatilities.

The existing literature on network linkages and cross-sectional asset pricing features a different approximation for the relative importance of a node in a network, namely eigenvector centrality.[20] Therefore, Panel B in Table 1 presents the results of regressions analogous to those shown in Panel A, but now with *evc* as additional regressor where we orthogonalize *evc* with respect to *spc* to quantify its *additional* explanatory power beyond *spc*.[21] While *evc* remains insignificant for Sharpe ratios, it seems to have explanatory power beyond *spc* for the cross-section of return volatilities for industry portfolios. Finally, in the bivariate regressions for average excess returns, *evc* yields negative and significant coefficients. Overall, we conclude that our theoretically motivated measure of directedness *spc* indeed contains additional information above and beyond the information captured by *evc*.

3. Conclusion

Networks have received considerable attention in the finance and economics literature. In this paper, we analyze the implications of directed links in cash flows networks for equilibrium returns. Our analysis is motivated by Carvalho, Nirei, Saito, and Tahbaz-Salehi (2016) who provide rich empirical evidence for a delayed propagation of cash flow shocks, both at the firm and at the industry level, in a natural experiment setting around the nuclear incident of Fukushima in 2011. We model this delayed propagation with mutually exciting processes which naturally feature directedness and capture the intuition that cash flow shocks to one node in the network affect other nodes only with a certain time lag.

In our equilibrium model, we combine these self and mutually exciting jump processes for cash flows with a representative investor with recursive preferences. We prove the following cross-sectional statements for arbitrary directed networks: (i) Cash flow shocks in industries

[20] We provide more details on this concept, which has been introduced by Bonacich (1972a,b) and applied, e.g., by Demirer, Diebold, Liu, and Yilmaz (2017) and Walden (2018), in Appendix C.

[21] For the sake of brevity, we again report the results for $H = 4$ quarters in the following and present those for $H = 1, 2, 3$ in Online Appendix C.6 which also contains the summary statistics for *evc*.

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with high shock propagation capacity (*spc*) have a high market price of risk. (ii) The response of the price-to-cash flow ratio of an industry to its own cash flow shocks is less pronounced for industries with higher *spc*. Importantly, when it comes to expected excess returns, the effects of *spc* on market prices of risk and on exposures work in opposite directions, so that the overall impact of *spc* on risk premia depends on the tradeoff between these two forces.

We close the paper by presenting some suggestive empirical evidence for our theoretical channels, where we estimate an empirical network from industry cash flows by applying the Diebold and Yilmaz (2014) generalized variance decomposition methodology. In line with the model, we find that high *spc* industries have lower return volatilities and higher Sharpe ratios than their low *spc* counterparts. Regression coefficients for average excess returns are, however, insignificant.

To sum up, the innovative combination of self and mutually exciting jump processes with recursive preferences allows for the integration of directed networks into a tractable equilibrium asset pricing model. Our results indicate that it is necessary to decompose equilibrium asset prices and returns into their constituents in order to understand the implications of directed cash flow shock propagation.

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APPENDIX

A. Model solution

To solve for the equilibrium we apply the approach proposed in Eraker and Shaliastovich (2008). The vector $X \equiv (y, \ell_1, \ldots, \ell_n, y_1, \ldots, y_n)'$ follows the affine jump process

$$dX_t \quad = \quad \mu\,(X_t)\; dt + \xi_t\, dN_t,$$

where we use the following notation:

- $\mu(X_t) = \mathcal{M} + \mathcal{K}\, X_t$
  with $\mathcal{M} = \begin{pmatrix} \mu \\ \kappa_1\,\bar{\ell}_1 \\ \vdots \\ \kappa_n\,\bar{\ell}_n \\ \mu_1 \\ \vdots \\ \mu_n \end{pmatrix}$ and $\mathcal{K} = \begin{pmatrix} 0 & 0 & \ldots & 0 & \ldots & 0 \\ 0 & -\kappa_1 & \ldots & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & -\kappa_n & \ldots & 0 \\ 0 & 0 & \ldots & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 0 & \ldots & 0 \end{pmatrix}$,
- $\ell_t = l_0 + l_1\, X_t$
  with $l_0 = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix}$ and $l_1 = \begin{pmatrix} 0 & 1 & \ldots & 0 & 0 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & 1 & 0 & \ldots & 0 \end{pmatrix}$,
- $\xi_t = \begin{pmatrix} \xi_{1,t}, & \ldots, & \xi_{n,t} \end{pmatrix} = \begin{pmatrix} K_1 & \ldots & K_n \\ \beta_{1,1} & \ldots & \beta_{1,n} \\ \vdots & \ddots & \vdots \\ \beta_{n,1} & \ldots & \beta_{n,n} \\ L_1 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & L_n \end{pmatrix}$.

The jump transform $\varrho\,(u) \equiv \mathbb{E}\left[\left(e^{u'\xi_{1,t}}, \ldots, e^{u'\xi_{n,t}}\right)\right]'$ is in our case simply equal to $\left(e^{u'\xi_{1,t}}, \ldots, e^{u'\xi_{n,t}}\right)'$, since the jump sizes are all constant.

We define the selection vectors δ_y, $\delta_{\ell_{i,t}}$ $(i = 1, \ldots, n)$, and $\delta_{y,i}$ $(i = 1, \ldots, n)$ implicitly via $dy_t = \delta_y'\, dX_t$, $d\ell_{i,t} = \delta_{\ell,i}'\, dX_t$, and $dy_{i,t} = \delta_{y,i}'\, dX_t$.

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The continuous-time version of the Euler equation can be written as

$$0 = \frac{1}{dt}\,\mathbb{E}_t\left[\frac{d\left(e^{\ln M_t + \ln R_t}\right)}{e^{\ln M_t + \ln R_t}}\right], \tag{A.1}$$

where R is the return on the claim to aggregate consumption. The logarithm of the pricing kernel has the dynamics

$$d\ln M_t = -\delta\,\theta\,dt - (1-\theta)\;d\ln R_t - \frac{\theta}{\psi}\,dy_t.$$

We apply the usual affine conjecture for the log wealth-consumption ratio

$$\begin{aligned} v_t &= A + (0, B_1, \ldots, B_n, 0, \ldots, 0)\;X_t \\ &= A + (B_1, \ldots, B_n)\,\ell_t, \end{aligned}$$

and use the Campbell-Shiller approximation for the return on the consumption claim

$$d\ln R_t = k_{v,0}\,dt + k_{v,1}\,dv_t - (1-k_{v,1})\;v_t\,dt + dy_t.$$

Combining the Campbell-Shiller approximation, the affine guess for v_t, and the dynamics of the log pricing kernel, we get

$$\begin{aligned} \frac{d\left(e^{\ln M_t + \ln R_t}\right)}{e^{\ln M_t + \ln R_t}} &= \left\{-\delta\,\theta + \theta\,k_{v,0} - \theta\;(1-k_{v,1})\;\left(A + B'\,X_t\right) + \chi_y'\;(\mathcal{M} + \mathcal{K}\,X_t)\right\}\;dt \\ &\quad + \left\{e^{\chi_y'\,\xi_t} - \mathbb{1}\right\}\;dN_t, \end{aligned} \tag{A.2}$$

where

$$\begin{aligned} \chi_y &= \theta\left[\left(1 - \frac{1}{\psi}\right)\;\delta_y + k_{v,1}\,B\right] \\ &= \left(-\theta\,\left(\frac{1}{\psi} - 1\right), \theta\,k_{v,1}\,B_1, \ldots, \theta\,k_{v,1}\,B_n, 0, \ldots, 0\right)', \end{aligned}$$

and where $\mathbb{1}$ is a vector of ones with length n. We plug expression (A.2) into the Euler equation (A.1) to get a system of equations for A and B:

$$0 = \theta\;[-\delta + k_{v,0} - (1-k_{v,1})\;A] + \mathcal{M}'\,\chi_y + l_0'\;[\varrho\,(\chi_y) - \mathbb{1}] \tag{A.3}$$

$$0 = \mathcal{K}'\,\chi_y - \theta\;(1-k_{v,1})\;B + l_1'\;[\varrho\,(\chi_y) - \mathbb{1}]\,. \tag{A.4}$$

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We have two additional equations for the loglinearization constants $k_{v,0}$ and $k_{v,1}$:

$$0 = -k_{v,0} - \ln k_{v,1} + (1 - k_{v,1}) \left[A + B' \mu_X\right] \tag{A.5}$$

$$0 = A + B' \mu_X - \ln (k_{v,1}) + \ln (1 - k_{v,1}), \tag{A.6}$$

where μ_X is a vector with i-th component $\mathbb{E}[X_i]$ if that expectation is finite and 0 otherwise. Due to the presence of the mutually exciting jump terms, the long-run means $\bar{\bar{\ell}}_i$, i.e., the unconditional expectations, are not equal to the respective mean reversion levels $\bar{\ell}_i$, as it would be the case, e.g., for a standard square-root process. According to Aït-Sahalia, Cacho-Diaz, and Laeven (2015), the $\bar{\bar{\ell}}_i$ are the solution to the following system of equations:

$$\bar{\bar{\ell}}_i = \frac{\kappa_i \bar{\ell}_i + \sum_{j \neq i} \beta_{i,j} \bar{\bar{\ell}}_j}{\kappa_i - \beta_{i,i}} \qquad (i = 1, \ldots, n). \tag{A.7}$$

We assume $\kappa_i > \beta_{i,i}$ for $i = 1, \ldots, n$ to ensure that all the $\bar{\bar{\ell}}_i$ are positive.

We solve the four equations (A.3), (A.4), (A.5), and (A.6) via an iterative procedure. We initialize $k_{v,1}$ by setting it equal to δ, then compute $k_{v,0}$, A, and B. Given these we then compute $k_{v,1}$ again and iterate forward until the system converges.

The pricing kernel has dynamics

$$\frac{dM_t}{M_t} = -r_t \, dt - [\mathbb{1} - \varrho(-\lambda)]' \, (dN_t - \ell_t dt)$$

with

$$\begin{aligned} \lambda &= \gamma \, \delta_y + (1 - \theta) \, k_{v,1} \, B \\ &= (\gamma, (1-\theta) \, k_{v,1} \, B_1, \ldots, (1-\theta) \, k_{v,1} \, B_n, 0, \ldots, 0)', \end{aligned}$$

so that we can immediately read off the risk-free rate and the market prices of risk. The risk-free rate is given as

$$r_t = \Phi_0 + \Phi_1' \, X_t$$

with

$$\Phi_0 = \theta \, \delta + (\theta - 1) \left[\ln k_{v,1} + (k_{v,1} - 1) \, B' \mu_X\right] + \mathcal{M}' \lambda - l_0' \, [\varrho(-\lambda) - \mathbb{1}]$$

and

$$\Phi_1 = (1 - \theta) \, (k_{v,1} - 1) \, B + \mathcal{K}' \lambda - l_1' \, [\varrho(-\lambda) - \mathbb{1}].$$

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The market prices of jump risk are given as

$$\begin{pmatrix} \mathrm{MPJR}_1 \\ \vdots \\ \mathrm{MPJR}_n \end{pmatrix} = [\mathbb{1} - \varrho(-\lambda)]$$
$$= \begin{pmatrix} 1 - \exp\left(-\gamma K_1 + k_{v,1} \, (\theta - 1) \, [B_1 \, \beta_{1,1} + \ldots + B_n \, \beta_{n,1}]\right) \\ \vdots \\ 1 - \exp\left(-\gamma K_n + k_{v,1} \, (\theta - 1) \, [B_1 \, \beta_{1,n} + \ldots + B_n \, \beta_{n,n}]\right) \end{pmatrix}.$$

The return on the consumption claim is given by

$$dR_t = \{\ldots\} \, dt + \{\varrho(\delta_y + k_{v,1} \, B) - \mathbb{1}\} \, dN_t$$

with jump exposures

$$\begin{pmatrix} \mathrm{JEXP}_{y,1} \\ \vdots \\ \mathrm{JEXP}_{y,n} \end{pmatrix} = \varrho(\delta_y + k_{v,1} \, B) - \mathbb{1},$$

where

$$\mathrm{JEXP}_{y,i} = \exp\left[K_1 + k_{v,1} \, (B_1 \, \beta_{1,1} + \ldots + B_n \, \beta_{n,1})\right] - 1$$

for $i = 1, \ldots, n$.

To obtain the expected excess returns on the cash flow claims, we follow the same approach as for the consumption claim. The continuous-time Euler equation again reads

$$0 = \frac{1}{dt} \mathbb{E}_t \left[\frac{d\left(e^{\ln M_t + \ln R_{i,t}}\right)}{e^{\ln M_t + \ln R_{i,t}}} \right].$$

Applying the Campbell-Shiller approximation

$$d \ln R_{i,t} = k_{i,0} \, dt + k_{i,1} \, dv_{i,t} - (1 - k_{i,1}) \, v_{i,t} \, dt + dy_{i,t}$$

and the usual affine guess for the log price-to cash flow ratio

$$\begin{aligned} v_{i,t} &= A_i + (0, C_{i,1}, \ldots, C_{i,n}, 0, \ldots, 0) \, X_t \\ &= A_i + (C_{i,1}, \ldots, C_{i,n}) \, \ell_t, \end{aligned}$$

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we arrive at

$$
\begin{aligned}
\frac{d\left(e^{\ln M_t+\ln R_{i,t}}\right)}{e^{\ln M_t+\ln R_{i,t}}} &= \left\{-\delta\,\theta-(1-\theta)\,\left[k_{v,0}-(1-k_{v,1})\,\left(A+B'\,X_t\right)\right]+k_{i,0}\right.\\
&\quad\left.-(1-k_{i,1})\,\left[A_i+C_i'\,X_t\right]+\chi_{y,i}'\,\left(\mathcal{M}+\mathcal{K}\,X_t\right)\right\}\,dt\\
&\quad+\left\{e^{\chi_{y,i}'\,\xi_t}-\mathbb{1}\right\}\,dN_t,
\end{aligned}
\tag{A.8}
$$

where $\chi_{y,i}=k_{i,1}\,C_i+\delta_{y,i}-\lambda$. Plugging (A.8) into the Euler equation yields a system of equations for the coefficients A_i and C_i:

$$
\begin{aligned}
0 &= -\theta\,\delta+(1-\theta)\,\left[\ln k_{v,1}-(1-k_{v,1})\,B'\,\mu_X\right]-\ln k_{i,1}+(1-k_{i,1})\,C_i'\,\mu_X\\
&\quad+\mathcal{M}'\,\chi_{y,i}+l_0'\,\left[\varrho\left(\chi_{y,i}\right)-\mathbb{1}\right] &\text{(A.9)}\\
0 &= \mathcal{K}'\,\chi_{y,i}+(1-\theta)\,(1-k_{v,1})\,B-(1-k_{i,1})\,C_i+l_1'\,\left[\varrho\left(\chi_{y,i}\right)-\mathbb{1}\right]. &\text{(A.10)}
\end{aligned}
$$

The two additional equations for the log-linearization constants $k_{i,0}$ and $k_{i,1}$ are

$$
\begin{aligned}
0 &= -k_{i,0}-\ln k_{i,1}+(1-k_{i,1})\,\left(A_i+C_i'\,\mu_X\right) &\text{(A.11)}\\
0 &= A_i+C_i'\,\mu_X-\ln k_{i,1}+\ln\left(1-k_{i,1}\right). &\text{(A.12)}
\end{aligned}
$$

The return of the individual cash flow claim i is then given by

$$
dR_{i,t} = \{\ldots\}\,dt+\left\{\varrho\left(\delta_{y,i}+k_{i,1}\,C_i\right)-\mathbb{1}\right\}\,dN_t
$$

so that the jump exposure of the return is thus given by

$$
\begin{aligned}
\begin{pmatrix}\mathrm{JEXP}_{i,1}\\ \vdots\\ \mathrm{JEXP}_{i,i}\\ \vdots\\ \mathrm{JEXP}_{i,n}\end{pmatrix} &= \left[\varrho\left(\delta_{y,i}+k_{i,1}\,C_i\right)-\mathbb{1}\right]\\
&= \begin{pmatrix}\exp\left(k_{i,1}\,\left[C_{i,1}\,\beta_{1,1}+\ldots+C_{i,n}\,\beta_{n,1}\right]\right)-1\\ \vdots\\ \exp\left(L_i+k_{i,1}\,\left[C_{i,1}\,\beta_{1,i}+\ldots+C_{i,n}\,\beta_{n,i}\right]\right)-1\\ \vdots\\ \exp\left(k_{i,1}\,\left[C_{i,1}\,\beta_{1,n}+\ldots+C_{i,n}\,\beta_{n,n}\right]\right)-1\end{pmatrix}.
\end{aligned}
$$

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The expected return on the claim to cash flow i can then be written as

$$\begin{aligned}\frac{1}{dt}\,\mathbb{E}_t\left[dR_{i,t}\right] &= -\ln k_{i,1} + (1-k_{i,1})\; C_i'\;(\mu_X - X_t) + \left[\delta_i + k_{i,1}\,C_i\right]'\;(\mathcal{M} + \mathcal{K}\,X_t)\\ &\quad + \left[\varrho\left(\delta_{y,i} + k_{i,1}\,C_i\right) - \mathbb{1}\right]\;(l_0 + l_1\,X_t)\,.\end{aligned}$$

The expected excess return is given by

$$\frac{1}{dt}\,\mathbb{E}_t\left[dR_{i,t}\right] - r_t \;=\; (l_0 + l_1\,X_t)'\;\left[\varrho\left(\chi_{y,i} + \lambda\right) + \varrho\left(-\lambda\right) - \varrho\left(\chi_{y,i}\right) - \mathbb{1}\right]$$

which can be represented as

$$\frac{1}{dt}\,\mathbb{E}_t\left[dR_{i,t}\right] - r_t \;=\; \sum_{j=1}^{n} \ell_{j,t}\,\mathrm{MPJR}_j\,\mathrm{JEXP}_{i,j}.$$

B. Approximation for general network structures

B.1. Market prices of jump risk

B.1.1. First approximation step

Rewriting Equation (A.4) for $\kappa_1 = \ldots = \kappa_n = \kappa$ and $K_1 = \ldots = K_n = K$ gives the following system of equations

$$\begin{aligned}0 &= B_1\,\theta\,\left[k_{v,1}\;(1-\kappa) - 1\right] + \exp\left\{K\;(1-\gamma) + \theta\,k_{v,1}\;(B_1\,\beta_{1,1} + \ldots + B_n\,\beta_{n,1})\right\} - 1\\ &\;\;\vdots\\ 0 &= B_n\,\theta\,\left[k_{v,1}\;(1-\kappa) - 1\right] + \exp\left\{K\;(1-\gamma) + \theta\,k_{v,1}\;(B_1\,\beta_{1,n} + \ldots + B_n\,\beta_{n,n})\right\} - 1\end{aligned}$$

and translating this into matrix notation yields

$$\mathbb{1} \;=\; \theta\,\left[k_{v,1}\;(1-\kappa) - 1\right]\;B + \exp\left\{K\;(1-\gamma)\right\}\;\exp\left\{\theta\,k_{v,1}\,\beta'\,B\right\},$$

where now and in the following, the "exp" operator, applied to a vector, stands for element-wise application of the "exp" operator to the vector.

Next, we apply the approximation $\exp(x) = 1 + x + O\left(x^2\right)$ and solve for B:

$$\begin{aligned}B &= \left(I_{n\times n} + \frac{\exp\left\{K\;(1-\gamma)\right\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta'\right)^{-1}\;\frac{1}{\theta\,\left[k_{v,1}\;(1-\kappa)-1\right]}\;\left[\mathbb{1} - \exp\left\{K\;(1-\gamma)\right\}\right]\\ &\quad + O\left(\beta^2\right)\end{aligned} \tag{B.1}$$

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where $I_{n\times n}$ denotes an $n \times n$ identity matrix and $\frac{\exp\{K\,(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}} < 0$ since $\frac{1}{k_{v,1}} > 1-\kappa$ (due to $\frac{1}{k_{v,1}} = \frac{1+e^{\bar{v}}}{e^{\bar{v}}} > 1 > 1-\kappa$ for $0 < \kappa < 1$).

To conclude the first approximation step, we define

$$B^* \;=\; \left(I_{n\times n} + \frac{\exp\{K\;(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta'\right)^{-1} \frac{1}{\theta\,[k_{v,1}\;(1-\kappa)-1]}\,[\mathbb{1}-\exp\{K\;(1-\gamma)\}]\,. \qquad \text{(B.2)}$$

B.1.2. Second approximation step

Since the inverse term in Equation (B.1) has the structure of a Leontief inverse, $(I-A)^{-1} = I + A^1 + A^2 + \ldots$, we rewrite (B.1) as:

$$\begin{aligned} B \;&=\; \left[I_{n\times n} - \frac{\exp\{K\;(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta' - \left(\frac{\exp\{K\;(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta'\right)^2 - \ldots\right] \frac{1}{\theta\,[k_{v,1}\;(1-\kappa)-1]} \\ &\quad \times [\mathbb{1}-\exp\{K\;(1-\gamma)\}] + O\left(\beta^2\right) \\ &=\; \left(I_{n\times n} - \frac{\exp\{K\;(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta'\right) \frac{1}{\theta\,[k_{v,1}\;(1-\kappa)-1]}\,[\mathbb{1}-\exp\{K\;(1-\gamma)\}] \\ &\quad + O\left(\beta^2\right) \end{aligned} \qquad \text{(B.3)}$$

To conclude the second approximation step, we define

$$B^{**} \;=\; \left(I_{n\times n} - \frac{\exp\{K\;(1-\gamma)\}}{1-\kappa-\frac{1}{k_{v,1}}}\,\beta'\right) \frac{1}{\theta\,[k_{v,1}\;(1-\kappa)-1]}\,[\mathbb{1}-\exp\{K\;(1-\gamma)\}]\,. \qquad \text{(B.4)}$$

Plugging (B.3) into the market price of risk from Equation (4) and rewriting this in matrix notation yields:

$$\begin{aligned} \text{MPJR} \;&=\; 1-\exp\left\{-\gamma\,K + \frac{k_{v,1}\;(\theta-1)}{\theta\,[k_{v,1}\;(1-\kappa)-1]}\;\left[\beta'\;[\mathbb{1}-\exp\{K\;(1-\gamma)\}] + O\left(\beta^2\right)\right]\right\} \\ &=\; 1-\exp\left\{-\gamma\,K + \frac{(\theta-1)\;(1-\exp\{K\;(1-\gamma)\})}{\theta\,\left[(1-\kappa)-\frac{1}{k_{v,1}}\right]}\;(\beta_{\text{diag}}+\text{spc}) + O\left(\beta^2\right)\right\} \\ &=\; 1-\exp\left\{\mathcal{A}+\mathcal{B}\;(\beta_{\text{diag}}+\text{spc}) + O\left(\beta^2\right)\right\} \end{aligned}$$

with $\mathcal{A}$ and $\mathcal{B}$ given in Proposition 1. Thus we define

$$\text{MPJR}^{**} \;=\; 1-\exp\{\mathcal{A}+\mathcal{B}\;(\beta_{\text{diag}}+\text{spc})\}\,. \qquad \text{(B.5)}$$

For $\gamma > 1$, $\theta < 0$, $0 < \kappa < 1$, and $K < 0$, we have $\mathcal{A} > 0$ and $\mathcal{B} > 0$ since $\frac{1}{k_{v,1}} > 1-\kappa$.

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B.2. Jump exposures

B.2.1. First approximation step

Rewriting Equation (A.10) for $\kappa_1 = \ldots = \kappa_n = \kappa$ and $K_1 = \ldots = K_n = K$ gives a system of equations for each i, exemplified in the following for $i = 1$:

$$\begin{aligned}
0 &= B_1\,(k_{v,1}-1)\,(\theta-1) + C_{1,1}\,(k_{1,1}-1) - \kappa\,[B_1\,k_{v,1}\,(\theta-1) + C_{1,1}\,k_{1,1}] \\
&\quad + \exp\{L - K\,\gamma + \beta_{1,1}\,[B_1\,k_{v,1}\,(\theta-1) + C_{1,1}\,k_{1,1}] + \ldots + \beta_{n,1}\,[B_n\,k_{v,1}\,(\theta-1) + C_{1,n}\,k_{1,1}]\} - 1 \\
&\;\;\vdots \\
0 &= B_n\,(k_{v,1}-1)\,(\theta-1) + C_{1,n}\,(k_{1,1}-1) - \kappa\,[B_n\,k_{v,1}\,(\theta-1) + C_{1,n}\,k_{1,1}] \\
&\quad + \exp\{-K\,\gamma + \beta_{1,n}\,[B_1\,k_{v,1}\,(\theta-1) + C_{1,1}\,k_{1,1}] + \ldots + \beta_{n,n}\,[B_n\,k_{v,1}\,(\theta-1) + C_{1,n}\,k_{1,1}]\} - 1.
\end{aligned}$$

Collecting terms and introducing matrix notation yields the following system for each i:

$$\begin{aligned}
\mathbb{1} &= B\,(\theta-1)\,[k_{v,1}\,(1-\kappa)-1] + C_i\,[k_{i,1}\,(1-\kappa)-1] \\
&\quad + [\exp\{-K\,\gamma\}\,\mathbb{1} + (\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\})\,I_{n\times 1,i}] \bullet \exp\left\{k_{v,1}\,(\theta-1)\,\beta'\,B + k_{i,1}\,\beta'\,C_i\right\},
\end{aligned}$$

where now and in the following, $\bullet$ represents element-wise multiplication of the vectors. $I_{n\times 1,i}$ is an $n\times 1$ vector with the i-th entry equal to 1 and zeros otherwise.

Again, we employ $\exp(x) = 1 + x + O\left(x^2\right)$ and solve for C_i:

$$\begin{aligned}
C_i &= \left(I + \frac{\exp\{-K\,\gamma\}\,\mathbb{1} + (\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\})\,I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta'\right)^{-1} \frac{1}{k_{i,1}\,(1-\kappa)-1} \\
&\quad \times \Big[\mathbb{1} - (\theta-1)\,[k_{v,1}\,(1-\kappa)-1]\,B \\
&\qquad - [\exp\{-K\,\gamma\}\,\mathbb{1} + (\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\})\,I_{n\times 1,i}] \bullet k_{v,1}\,(\theta-1)\,\beta'\,B \\
&\qquad - \exp\{-K\,\gamma\}\,\mathbb{1} - (\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\})\,I_{n\times 1,i}\Big] + O\left(\beta^2\right),
\end{aligned} \tag{B.6}$$

where $\frac{\exp\{-K\,\gamma\}\,\mathbb{1} + (\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\})\,I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} < 0$ since $\frac{1}{k_{i,1}} > 1-\kappa$ (due to $\frac{1}{k_{i,1}} = \frac{1+e^{\bar{v}_i}}{e^{\bar{v}_i}} > 1 > 1-\kappa$ for $0 < \kappa < 1$).

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To conclude the first approximation step, we define

$$
\begin{aligned}
C_i^* \;=\; & \left(I + \frac{\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L - K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta'\right)^{-1} \frac{1}{k_{i,1}\ (1-\kappa)-1} \\
& \times \Big[\mathbb{1} - (\theta-1)\ \left[k_{v,1}\ (1-\kappa)-1\right]\ B \\
& \quad - \left[\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\right] \bullet k_{v,1}\ (\theta-1)\ \beta'\, B \\
& \quad - \exp\{-K\,\gamma\}\ \mathbb{1} - \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\Big]. \qquad \text{(B.7)}
\end{aligned}
$$

B.2.2. Second approximation step

Again the inverse term in Equation (B.6) has the structure of a Leontief inverse, and we rewrite (B.6) as:

$$
\begin{aligned}
C_i \;=\; & \Bigg[I_{n\times n} - \frac{\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L - K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta' \\
& - \left(\frac{\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L - K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta'\right)^2 - \ldots\Bigg]\ \frac{1}{k_{i,1}\ (1-\kappa)-1} \\
& \times \Big[\mathbb{1} - (\theta-1)\ \left[k_{v,1}\ (1-\kappa)-1\right]\ B \\
& \quad - \left[\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\right] \bullet k_{v,1}\ (\theta-1)\ \beta'\, B \\
& \quad - \exp\{-K\,\gamma\}\ \mathbb{1} - \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\Big] + O\left(\beta^2\right) \\
=\; & \left(I_{n\times n} - \frac{\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L - K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta'\right) \frac{1}{k_{i,1}\ (1-\kappa)-1} \\
& \times \Big[\mathbb{1} - (\theta-1)\ \left[k_{v,1}\ (1-\kappa)-1\right]\ B \\
& \quad - \left[\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\right] \bullet k_{v,1}\ (\theta-1)\ \beta'\, B \\
& \quad - \exp\{-K\,\gamma\}\ \mathbb{1} - \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\Big] + O\left(\beta^2\right). \qquad \text{(B.8)}
\end{aligned}
$$

To conclude the second approximation step, we define

$$
\begin{aligned}
C_i^{**} \;=\; & \left(I_{n\times n} - \frac{\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L - K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}}{1-\kappa-\frac{1}{k_{i,1}}} \bullet \beta'\right) \frac{1}{k_{i,1}\ (1-\kappa)-1} \\
& \times \Big[\mathbb{1} - (\theta-1)\ \left[k_{v,1}\ (1-\kappa)-1\right]\ B \\
& \quad - \left[\exp\{-K\,\gamma\}\ \mathbb{1} + \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\right] \bullet k_{v,1}\ (\theta-1)\ \beta'\, B \\
& \quad - \exp\{-K\,\gamma\}\ \mathbb{1} - \left(\exp\{L-K\,\gamma\} - \exp\{-K\,\gamma\}\right)\ I_{n\times 1,i}\Big] \qquad \text{(B.9)}
\end{aligned}
$$

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Plugging (B.8) into the jump exposures from Equation (6) and rewriting them in matrix notation yields:

$$\begin{aligned}\mathrm{JEXP}_i &= \exp\Bigg\{L\, I_{n\times 1,i} + \frac{1-\frac{\theta-1}{\theta}\,\left(1-\exp\left\{K\,\left(1-\gamma\right)\right\}\right)-\exp\left\{-K\,\gamma\right\}}{1-\kappa-\frac{1}{k_{i,1}}}\,\beta'\,\mathbb{1}\\ &\qquad -\frac{\exp\left\{-K\,\gamma\right\}\,\left(\exp\left\{L\right\}-1\right)}{1-\kappa-\frac{1}{k_{i,1}}}\,\beta'\,I_{n\times 1,i}+O\left(\beta^2\right)\Bigg\}-1.\end{aligned}$$

Breaking this expression down into the jump exposures $\mathrm{JEXP}_{i,j}$ yields:

$$\begin{aligned}\mathrm{JEXP}_{i,j} &= \begin{cases}\exp\left\{\mathcal{C}_i\cdot\sum_{k=1,k\neq i}^{n}\beta_{k,j}+\mathcal{D}_i\cdot\beta_{i,j}+O\left(\beta^2\right)\right\}-1 & \text{for } j\neq i\\ \exp\left\{L+\mathcal{C}_i\cdot\sum_{k=1,k\neq i}^{n}\beta_{k,i}+\mathcal{D}_i\cdot\beta_{i,i}+O\left(\beta^2\right)\right\}-1 & \text{for } j=i\end{cases}\\ &= \begin{cases}\exp\left\{\mathcal{C}_i\cdot\mathrm{spc}_j+\mathcal{C}_i\cdot\beta_{j,j}+\left(\mathcal{D}_i-\mathcal{C}_i\right)\,\beta_{i,j}+O\left(\beta^2\right)\right\}-1 & \text{for } j\neq i\\ \exp\left\{L+\mathcal{C}_i\cdot\mathrm{spc}_i+\mathcal{D}_i\cdot\beta_{i,i}+O\left(\beta^2\right)\right\}-1 & \text{for } j=i\end{cases}\end{aligned}$$

where

$$\begin{aligned}\mathcal{C}_i &= \frac{1-\frac{\theta-1}{\theta}\,\left[1-\exp\left\{K\,\left(1-\gamma\right)\right\}\right]-\exp\left\{-K\,\gamma\right\}}{1-\kappa-\frac{1}{k_{i,1}}}\\ \mathcal{D}_i &= \frac{1-\frac{\theta-1}{\theta}\,\left[1-\exp\left\{K\,\left(1-\gamma\right)\right\}-\exp\left\{L-K\,\gamma\right\}\right]}{1-\kappa-\frac{1}{k_{i,1}}}\\ \mathcal{D}_i-\mathcal{C}_i &= \frac{\exp\left\{-K\,\gamma\right\}\,\left(1-\exp\left\{L\right\}\right)}{1-\kappa-\frac{1}{k_{i,1}}}.\end{aligned}$$

Note that $\frac{1}{k_{i,1}}>1-\kappa$ (see above). For $\gamma>1$, $0<\kappa<1$, and $-\log(2)<K<0$, we have $\mathcal{C}_i>0$. Additionally assuming $\theta<0$, we obtain $\mathcal{D}_i<0$, and $\mathcal{D}_i-\mathcal{C}_i<0$.

Proof that $\mathcal{C}_\mathbf{i}>\mathbf{0}$: We rewrite $\mathcal{C}_i$ as follows:

$$\begin{aligned}\mathcal{C}_i &= \frac{1-\frac{\theta-1}{\theta}\,\left[1-\exp\left\{K\,\left(1-\gamma\right)\right\}\right]-\exp\left\{-K\,\gamma\right\}}{1-\kappa-\frac{1}{k_{i,1}}}\\ &= \frac{\exp\left\{-K\,\gamma\right\}\,\left[\frac{1}{\theta}\,\left(\exp\left\{K\,\gamma\right\}-1\right)+\exp\left\{K\right\}-1\right]}{1-\kappa-\frac{1}{k_{i,1}}}\end{aligned}$$

Here, we have $1-\kappa-\frac{1}{k_{i,1}}<0$ by assumption (since $0<\kappa<1$). Moreover, we have $\exp\left\{-K\,\gamma\right\}>0$ and $\frac{1}{\theta}\,\left(\exp\left\{K\,\gamma\right\}-1\right)+\exp\left\{K\right\}-1<0$.

To see the last inequality, define

$$\begin{aligned}f\left(K\right) &= \exp\left\{K\,\gamma\right\}-1-\left(\exp\left\{K\right\}+\gamma\right)\,\left(\exp\left\{K\right\}-1\right)\\ &= \exp\left\{K\,\gamma\right\}-1-\exp\left\{2\,K\right\}-\gamma\,\exp\left\{K\right\}+\exp\left\{K\right\}+\gamma\end{aligned}$$

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Then $f(0) = 0$ and

$$\begin{aligned} f'(K) &= \gamma \exp\{K\gamma\} - 2\exp\{2K\} - \gamma\exp\{K\} + \exp\{K\} \\ &= \gamma\left(\exp\{K\gamma\} - \exp\{K\}\right) + \exp\{K\} - 2\exp\{2K\} \end{aligned}$$

If $\gamma > 1$ and $-\ln(2) < K < 0$, then $f'(K) < 0$ which implies $f(K) > 0$. In particular,

$$\frac{\exp\{K\gamma\} - 1}{\exp\{K\} - 1} \; < \; \exp\{K\} + \gamma < -\theta$$

from where the statement then follows. Altogether, we thus get $\mathcal{C}_i > 0$.

Proof that $\mathcal{D}_\mathbf{i} < \mathbf{0}$: We rewrite $\mathcal{D}_i$ as follows:

$$\begin{aligned} \mathcal{D}_i &= \frac{1 - \frac{\theta - 1}{\theta}\left[1 - \exp\{K\,(1-\gamma)\}\right] - \exp\{L - K\gamma\}}{1 - \kappa - \frac{1}{k_{i,1}}} \\ &= \frac{\frac{1}{\theta} + \exp\{-K\gamma\}\left[\left(1 - \frac{1}{\theta}\right)\exp\{K\} - \exp\{L\}\right]}{1 - \kappa - \frac{1}{k_{i,1}}} \end{aligned}$$

Again, we have $1 - \kappa - \frac{1}{k_{i,1}} < 0$. Moreover, we have

$$\begin{aligned} & \frac{1}{\theta} + \exp\{-K\gamma\}\left[\left(1 - \frac{1}{\theta}\right)\exp\{K\} - \exp\{L\}\right] \; > \; 0 \\ \Leftrightarrow \quad & \exp\{-K\gamma\}\left[\left(1 - \frac{1}{\theta}\right)\exp\{K\} - \exp\{L\}\right] \; > \; -\frac{1}{\theta} \\ \Leftrightarrow \quad & \left(1 - \frac{1}{\theta}\right)\exp\{K\} + \frac{1}{\theta}\exp\{K\gamma\} - \exp\{L\} \; > \; 0 \\ \Leftrightarrow \quad & \left(\exp\{K\} - \exp\{L\}\right) + \frac{1}{\theta}\left(\exp\{K\gamma\} - \exp\{K\}\right) \; > \; 0 \end{aligned}$$

which is true if $L < K$, $\gamma > 1$ and $\theta < 0$. This completes the proof.

B.3. Approximation quality

In this section, we assess the quality of the first-order approximations derived in the Propositions 1 and 2. More precisely, we compare those against the results from the numerical solution of the model using the empirical network for $H = 4$ determined in Section 2 and the following parametrization. For the representative investor, we assume a relative risk aversion $\gamma = 10$, an intertemporal elasticity of substitution $\psi = 1.5$, and a subjective time discount rate $\delta = 0.02$. The expected growth rate μ and the jump size $K_1 = \ldots = K_{14}$ of log aggregate consumption are set equal to 0.02 and -0.004. For the industry cash flows, the expected growth rates $\mu_1 = \ldots = \mu_{14}$ and the jump sizes $L_1 = \ldots = L_{14}$ are chosen to be 0.02 and -0.04. With respect to the stochastic jump intensities, we assume mean reversion speeds of $\kappa_1 = \ldots = \kappa_{14} = 0.85$ and mean reversion levels of $\bar{\ell}_1 = \ldots = \bar{\ell}_{14} = 0.05$.

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As explained in Appendix B.1, MPJR** is based on two approximation steps, B^* and B^{**}. The left part of Figure 1 shows the result of the first approximation step graphically by plotting B^* against the exact solution B of Equation (4). The middle part shows similar results for the second approximation step, B^{**} given in Equation (B.4). Finally, the right part of Figure 1 depicts the full approximation of the market prices of risk MPJR** against the exact MPJR.

Regressing B^* (or B^{**}, resp.) on B yields the following parameter estimates, t-stats, R^2, and correlations:

$$\begin{array}{lcccccccc} B_i^* & = & -0.0003 & + & 0.8993 & B_i & + & u_i, & \\ & & (-8.5) & & (125.3) & & & & R^2 = 0.9992, \quad \text{Corr} = 0.9996 \\ B_i^{**} & = & -0.0015 & + & 0.2524 & B_i & + & u_i, & \\ & & (-41.1) & & (28.2) & & & & R^2 = 0.9848, \quad \text{Corr} = 0.9924. \end{array}$$

Performing a similar regression of MPJR** on MPJR gives:

$$\begin{array}{lcccccccc} \text{MPJR}_i^{**} & = & -0.0377 & + & 0.2576 & \text{MPJR}_i & + & u_i, & \\ & & (-40.4) & & (27.7) & & & & R^2 = 0.9848, \quad \text{Corr} = 0.9924. \end{array}$$

Altogether, we see from the figures that the first approximation step hardly affects the B coefficients at all. The second approximation step (approximating the Leontief inverse) changes all coefficients quantitatively, but not qualitatively. The ordering of the coefficients is preserved, the sign is preserved, the correlation between approximated and exact coefficients is 99%. Only the size and the dispersion is reduced.

Similarly, JEXP** is based on two approximation steps, C^* and C^{**}, and its approximation quality is shown in Figures 2. The corresponding regressions yield

$$\begin{array}{lcccccccc} C_i^* & = & -0.0054 & + & 0.9578 & C_i & + & u_i, & \\ & & (-59.8) & & (390.3) & & & & R^2 = 0.9970, \quad \text{Corr} = 0.9985. \\ C_i^{**} & = & -0.0036 & + & 0.7668 & C_i & + & u, & \\ & & (-24.1) & & (53.6) & & & & R^2 = 0.9879, \quad \text{Corr} = 0.9939. \\ \text{JEXP}_i^{**} & = & -0.0010 & + & 0.7665 & \text{JEXP}_i & + & u_i, & \\ & & (-10.7) & & (53.9) & & & & R^2 = 0.9884, \quad \text{Corr} = 0.9942. \end{array}$$

Again, we see that the second approximation step is more severe than the first one. However, it does not change the coefficients qualitatively. The ordering of the coefficients as well as the sign are preserved and the correlation between approximated and exact coefficients is 99%.

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C. Eigenvector centrality

Let the network matrix β be diagonalized as follows:

$$\beta \quad = \quad S \cdot \operatorname{diag}(\phi_1, \ldots, \phi_n) \cdot S^{-1}, \tag{C.1}$$

where the ϕ_i's are the eigenvalues, ordered by absolute size, the columns of S are the eigenvectors of β, and the rows of S^{-1} are the eigenvectors of the transposed matrix β' (usually all normalized to have unit length). The eigenvector centrality of node i is defined as the i-th entry of the first column vector in S (the so-called principal eigenvector), i.e, $evc_i = S_{i,1}$.[22] Loosely speaking, a node has a high eigenvector centrality when it is linked to many other nodes, to other central nodes, or both.

Both *evc* and *spc* are approximations, condensing the entire network matrix into one value per node. Although *evc* can also be viewed as a "directed measure", in the sense that it changes when the network matrix is transposed, we view *spc* as the more natural quantity when it comes to capturing directedness in the context of our model for the following reason. An approximation of our equilibrium asset pricing results using *evc* would combine the principal eigenvectors of both β and β', hence mixing up the impact of incoming and outgoing links. To see this, let evc_i denote the eigenvector centrality of node i, and let evc_i' denote the eigenvector centrality of node i based on the transposed matrix β'. Defining the approximation β^{***} of β via

$$\beta^{***} \quad := \quad S \cdot \operatorname{diag}(\phi_1, 0, \ldots, 0) \cdot S^{-1},$$

i.e., replacing all non-principal eigenvalues by 0, one can easily show that

$$\beta^{***} \quad = \quad \phi_1 \cdot \begin{pmatrix} \mathrm{evc}_1\, \mathrm{evc}_1' & \ldots & \mathrm{evc}_1\, \mathrm{evc}_n' \\ \vdots & \ddots & \vdots \\ \mathrm{evc}_n\, \mathrm{evc}_1' & \ldots & \mathrm{evc}_n\, \mathrm{evc}_n' \end{pmatrix}.$$

spc, on the other hand, offers a straightforward interpretation of directedness, given the additive structure of our model with mutually exciting processes.

[22]Further technical details about the construction of eigenvector centrality are given in Online Appendix C.6.

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Panel A: Univariate regressions on *spc*			
	Sharpe ratios	Return volatilities	Average excess returns
spc	8.1778**	-4.4060***	-0.3203
	[2.46]	[-4.14]	[-1.15]
const.	14.8382***	7.1776***	1.0972***
	[16.03]	[17.44]	[13.59]
$\bar{R}^2$	0.2236	0.4039	0.0162

Panel B: Bivariate regressions on *spc* and *evc*			
	Sharpe ratios	Return volatilities	Average excess returns
spc	8.1778***	-4.4060***	-0.3203
	[2.83]	[-4.40]	[-1.42]
evc	-4.0006	-3.2633**	-0.7237**
	[-0.57]	[-2.03]	[-1.96]
const.	14.8382***	7.1776***	1.0972***
	[17.38]	[17.96]	[15.57]
$\bar{R}^2$	0.1759	0.4328	0.0848

Table 1
Cross-sectional regressions on *spc* and *evc*

The table reports the results of cross-sectional regressions of Sharpe ratios, return volatilities, and average excess returns of the 14 industry portfolios on their shock propagation capacity (*spc*) and eigenvector centrality (*evc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 4$, applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *spc* is defined in Equation (3), *evc* in Equation (C.1). In bivariate regressions, we orthogonalize *evc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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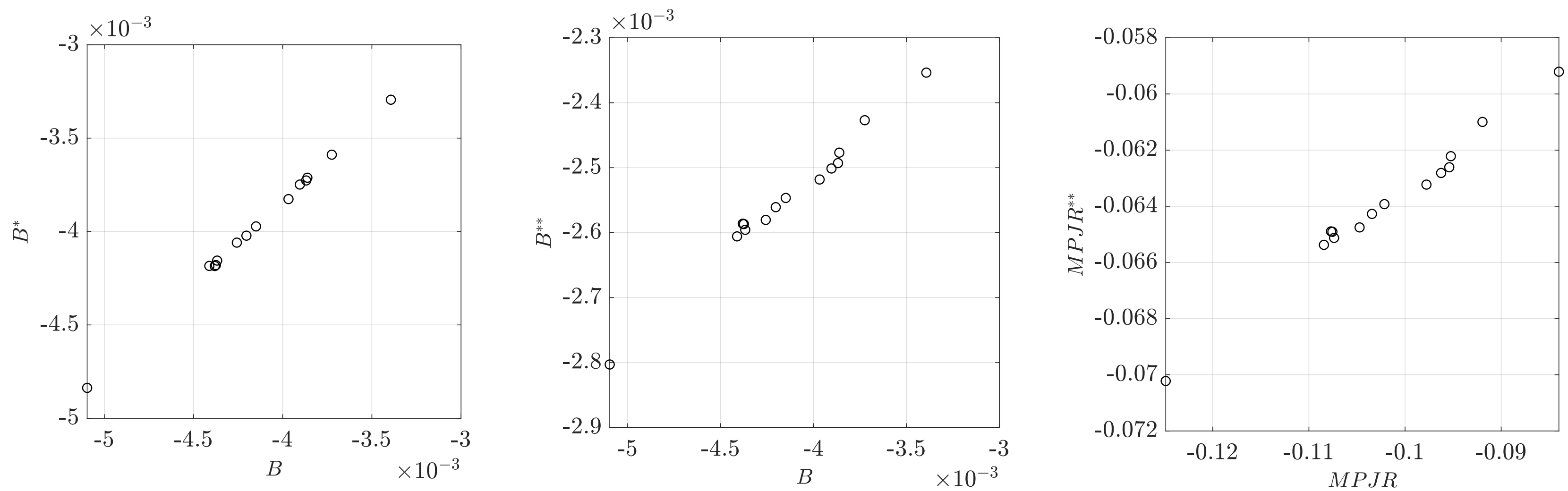

Figure 1
Approximation quality of B^*, B^{**}, and MPJR**

The graph on the left (in the middle) plot the coefficients B^* (B^{**}) as a function of the coefficients B. The graph on the right plots the approximation of the market price of jump risk as stated in Proposition 1, i.e., MPJR**, as a function of the market prices of risk MPJR for which the B coefficients have been computed numerically. The coefficients B^* and B^{**} are defined in Appendix B.1. The regression results are discussed in Appendix B.3. We use the empirical network determined in Section 2 for a forecast horizon of $H = 4$ quarters as the beta matrix. The remaining parameters are given in Appendix B.3.

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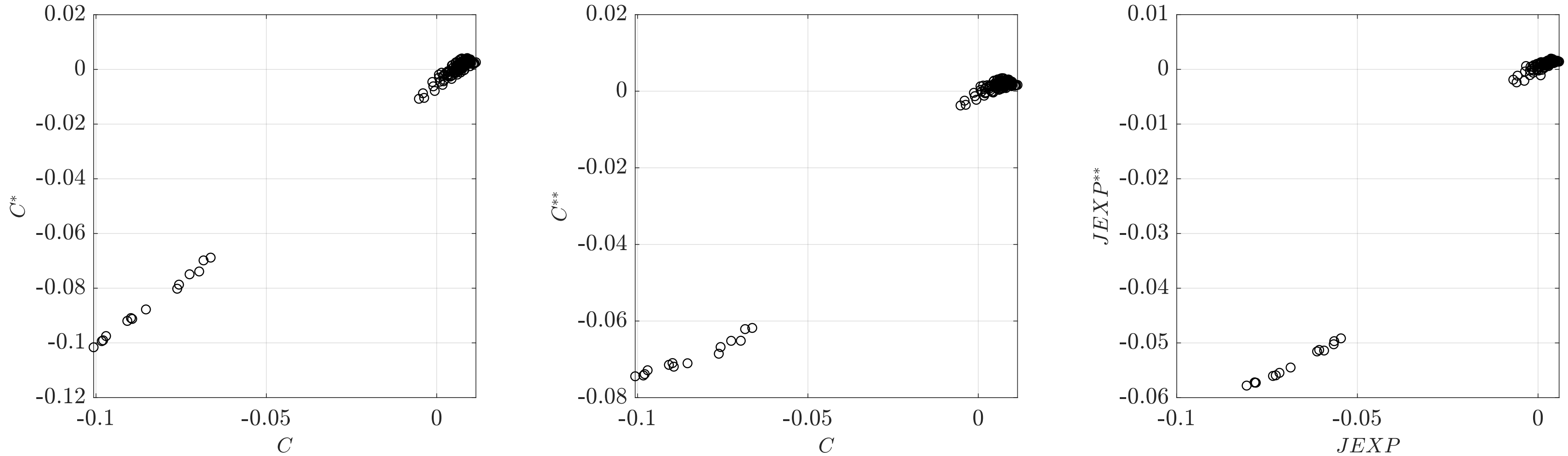

Figure 2
Approximation quality of C^*, C^{**}, and JEXP**

The graph on the left (in the middle) plots the coefficients C^* (C^{**}) as a function of the coefficients C. The graph on the right plots the approximation of the jump exposures as stated in Proposition 2, i.e., JEXP**, as a function of the jump exposures JEXP for which the C coefficients have been computed numerically. The coefficients C^* and C^{**} are defined in Appendix B.2. The regression results are discussed in Appendix B.3. We use the empirical network determined in Section 2 for a forecast horizon of $H = 4$ quarters as the beta matrix. The remaining parameters are given in Appendix B.3.

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ONLINE APPENDIX

Equilibrium Asset Pricing in Directed Networks

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Abstract

This Online Appendix serves as a companion to our paper "Equilibrium Asset Pricing in Directed Networks". It provides additional results and explanations not reported in the main text due to space constraints.

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A. Star networks: Exact formulas

1. Shock propagation capacity

Theoretically appealing special cases can be constructed by assuming sparse beta matrices, the most prominent examples being the so-called "star networks" which we are going to analyze in the following. These networks feature a classic core-periphery structure. They are motivated by the theoretical analysis in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and illustrated graphically in Figure A.1.

The economy here consists of n industries, i.e., there are n equity claims ("assets"). Asset (industry) 1 is labeled "core asset" because it is linked to all other assets in the economy. Assets 2 to n are called "periphery assets" because they are linked only to the core asset, but to none of the other periphery assets.

We distinguish two versions of such star networks which differ with respect to the direction of the links. In the "outward star" (superscript "OS"), shocks can propagate from the core asset to the periphery asset, but not the other way around. Vice versa, in the "inward star" (superscript "IS"), shocks can only propagate from the periphery assets to the core asset. The two networks can be represented using the following two beta matrices

$$\beta^{\mathrm{OS}} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ \beta_{\mathrm{per,core}} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{\mathrm{per,core}} & 0 & \cdots & 0 \end{pmatrix}, \quad \beta^{\mathrm{IS}} = \begin{pmatrix} 0 & \beta_{\mathrm{core,per}} & \cdots & \beta_{\mathrm{core,per}} \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{pmatrix}. \tag{A.1}$$

Since these matrices are sparse, we can show the basic effects of shock propagation on jump exposures, local return volatilities, market prices of jump risk, and local expected excess returns.

In particular, the general formula

$$spc_j \;=\; \sum_{\substack{i=1 \\ i\neq j}}^{n} \beta_{i,j} \tag{A.2}$$

simplifies for the two special cases to

$$\begin{aligned} spc^{\mathrm{OS}}_{\mathrm{core}} &= (n-1)\cdot\beta_{\mathrm{per,core}} \qquad & spc^{\mathrm{OS}}_{\mathrm{per}} &= 0 \\ spc^{\mathrm{IS}}_{\mathrm{core}} &= 0 \qquad & spc^{\mathrm{IS}}_{\mathrm{per}} &= \beta_{\mathrm{core,per}}. \end{aligned} \tag{A.3}$$

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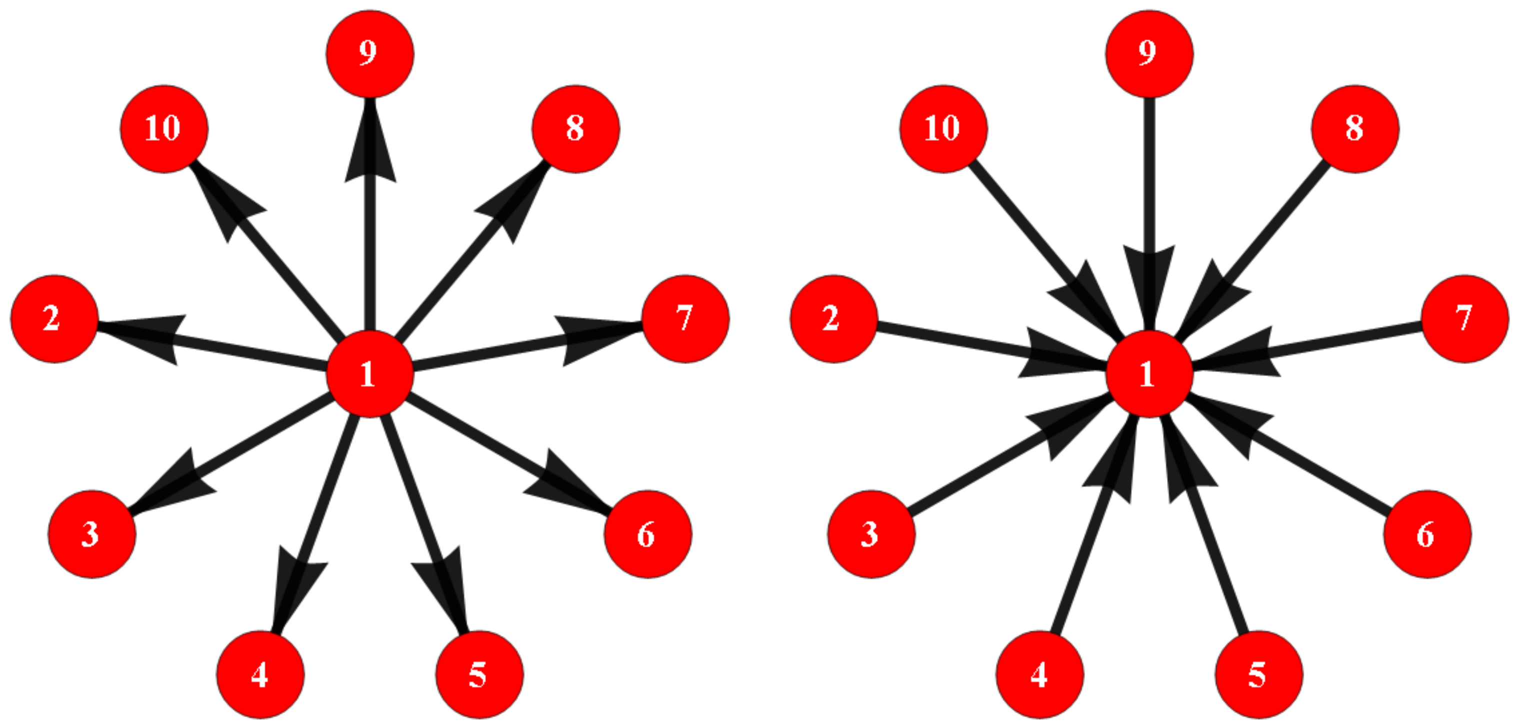

Figure A.1
Outward and inward star network

The pictures show the outward (left) and the inward star network (right) discussed in Online Appendix A. An arrow from node i to node j implies that a jump in the cash flow of industry i increases the jump intensity of industry j, i.e., $\beta_{j,i} > 0$.

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2. Market prices of jump risk

In the two stylized star networks, we can derive model predictions for market prices of risk and jump exposures in closed form.

Proposition 1. *Assume that* $\gamma > 1$*,* $\theta < 0$*,* $K_1 = \ldots = K_n = K < 0$*,* $\kappa_1 = \ldots = \kappa_n = \kappa$*,* $0 < \kappa < 1$*, and* $k_{v,1} > \frac{1}{1-\kappa}$*. Then, in the outward and the inward star network, the market prices of risk for jumps in the cash flows of shock-propagating assets are increasing (in absolute values) in these assets' spc:*

$$\begin{aligned} \frac{\partial |MPJR^{OS}_{core}|}{\partial spc_{core}} &> 0 \\ \frac{\partial |MPJR^{IS}_{per}|}{\partial spc_{per}} &> 0. \end{aligned}$$

The market prices of risk for jumps in the cash flows of non-propagating assets are independent of the spc of any asset:

$$\begin{aligned} MPJR^{OS}_{per} &= 1 - \exp\{-\gamma\, K\} \\ MPJR^{IS}_{core} &= 1 - \exp\{-\gamma\, K\} \end{aligned}$$

and they are lower (in absolute terms) than the market prices of jump risk for the corresponding shock-propagating assets:

$$\begin{aligned} |MPJR^{OS}_{per}| &< |MPJR^{OS}_{core}| \\ |MPJR^{IS}_{core}| &< |MPJR^{IS}_{per}|. \end{aligned}$$

A proof is given in Online Appendix B.

The market prices of jump risk are in general negative: a negative cash flow shock increases the risk of subsequent shocks to the cash flows of the other assets and to aggregate consumption and therefore leads to an increase in the pricing kernel. By definition, the market price of jump risk is the negative of this pricing kernel response to the jump. When we refer to the market price of risk being increasing in *spc*, such a statement is meant to refer to the absolute value of the market price of risk.

In the outward star network, the intuition behind this result is that shocks to the core asset increase all periphery jump intensities, so these shocks are the most "systematic" in the sense that they affect the whole economy and the distribution of future consumption growth the most. Shocks to the periphery assets do not spill over to other assets and hence do not have an additional effect on the wealth-consumption ratio. This can also be seen from the expressions for the market prices

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of risk given above which simplify to

$$\begin{aligned}
\mathrm{MPJR}^{\mathrm{OS}}_{\mathrm{core}} &= 1-\exp\left\{-\gamma\, K + k_{v,1}\ (\theta-1)\ B_{\mathrm{per}}\, spc^{\mathrm{OS}}_{\mathrm{core}}\right\} \\
\mathrm{MPJR}^{\mathrm{OS}}_{\mathrm{per}} &= 1-\exp\left\{-\gamma\, K + k_{v,1}\ (\theta-1)\ B_{\mathrm{core}}\, spc^{\mathrm{OS}}_{\mathrm{per}}\right\} \ = \ 1-\exp\left\{-\gamma\, K\right\}
\end{aligned}$$

in the outward star network. As already noted above, $k_{v,1} > 0$. Moreover, $\theta - 1$ is negative if the representative agent has a preference for early resolution of uncertainty. B_{per} captures the response of the wealth-consumption ratio to the jump intensity of one of the (assumed identical) periphery assets. It is negative for the given parameters, since the wealth-consumption ratio is decreasing in all jump intensities, due to the fact that higher jump intensities imply higher future consumption risk. Altogether, shocks to the core asset have the highest (in absolute terms) market price of risk, and this market price of risk is increasing in absolute terms (i.e., becoming more negative) in the core asset's *spc*.

In the inward star network, the analogous intuition applies, but the other way around. The market prices of jump risk are given as

$$\begin{aligned}
\mathrm{MPJR}^{\mathrm{IS}}_{\mathrm{core}} &= 1-\exp\left\{-\gamma\, K + k_{v,1}\ (\theta-1)\ B_{\mathrm{per}}\, spc^{\mathrm{IS}}_{\mathrm{core}}\right\} \ = \ 1-\exp\left\{-\gamma\, K\right\} \\
\mathrm{MPJR}^{\mathrm{IS}}_{\mathrm{per}} &= 1-\exp\left\{-\gamma\, K + k_{v,1}\ (\theta-1)\ B_{\mathrm{core}}\, spc^{\mathrm{IS}}_{\mathrm{per}}\right\}.
\end{aligned}$$

Cash flow shocks in the periphery can spread to the core and this makes them more systematic, implying a higher (i.e., more negative) market price of risk.

Altogether, market prices of jump risk in these two star networks are thus increasing in shock propagation capacity. Finally, note that the result documented here hinges critically on the assumption of a preference for early resolution of uncertainty. In an economy with CRRA preferences ($\theta = 1$), the wealth-consumption ratio does not enter the pricing kernel, state variable risk is not priced, and the market prices of jump risk are the same for all jump processes.

3. Return volatilities

For return volatilities in the IS and OS network, we have the following result.

Proposition 2. *Assume that $\gamma > 1$, $\theta < 0$, $K_1 = \ldots = K_n = K < 0$, $L_1 = \ldots = L_n = L < 0$, $\kappa_1 = \ldots = \kappa_n = \kappa$, $0 < \kappa < 1$, and $k_{core,1} > \frac{1}{1-\kappa}$. Then in the outward and inward star networks, conditional on the jump intensities ℓ_j and assuming that $\ell_1 = \ldots = \ell_n$, the local return volatilities of shock-propagating assets are decreasing in their spc:*

$$\begin{aligned}
\frac{\partial |RVol^{OS}_{core}|}{\partial spc_{core}} &< 0 \\
\frac{\partial |RVol^{IS}_{per}|}{\partial spc_{per}} &< 0.
\end{aligned}$$

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A proof is given in Online Appendix B.

To get the intuition behind this result, note that in a pure jump model like ours, the local return volatility of asset j, RVol_j, is given as

$$\mathrm{RVol}_j = \sqrt{\sum_{i=1}^{n} \ell_i \, \mathrm{JEXP}_{j,i}^2}, \tag{A.4}$$

and thus depends on two components: the conditional jump intensities ℓ_i and the (squared) exposures to jumps.[1] We want to focus on the exposure effect because this is an equilibrium pricing effect that endogenously arises within the model, whereas the dynamics of jump intensities are exogenous. Therefore the following analysis is performed conditional on the current values of the ℓ_i and assuming that $\ell_1 = \ldots = \ell_n$.

As shown in Online Appendix B, the local return volatility of the core asset in the outward star network can be written as

$$\mathrm{RVol}_{\mathrm{core}}^{\mathrm{OS}} = \sqrt{\ell_{\mathrm{core}} \left[\underbrace{e^{L + k_{\mathrm{core},1} \, C_{\mathrm{core,per}} \, spc_{\mathrm{core}}^{\mathrm{OS}}} - 1}_{\mathrm{JEXP}_{\mathrm{core,core}}} \right]^2}.$$

It is decreasing in the core asset's shock propagation capacity spc_{core}. The reason is that, given positive $k_{\mathrm{core},1}$ and $C_{\mathrm{core,per}}$ and negative L, a larger (and positive) spc_{core}^{OS} makes the exponent less negative and thus the expression in square brackets smaller in absolute terms. The coefficient $C_{\mathrm{core,per}}$ measures the reaction of the price-to-cash flow ratio of the core asset to changes in the jump intensity of one of the periphery assets. $C_{\mathrm{core,per}}$ is in general positive due to the hedging effect described above.[2] When the jump intensity of one of the periphery assets increases, the core asset becomes relatively less risky compared to the periphery, and therefore its equilibrium price-to-cash flow ratio goes up.

Symmetrically, we find that in the inward star network the local return volatility of the periphery asset decreases in its shock propagation capacity. For this special network structure, the return volatility simplifies to

$$\mathrm{RVol}_{\mathrm{per}}^{\mathrm{IS}} = \sqrt{\ell_{\mathrm{per}} \left[\underbrace{e^{L + k_{\mathrm{per},1} \, C_{\mathrm{per,core}} \, spc_{\mathrm{per}}^{\mathrm{IS}}} - 1}_{\mathrm{JEXP}_{\mathrm{per,per}}} \right]^2 + (n-2) \, \ell_{\mathrm{other\ per}} \left[\underbrace{e^{k_{\mathrm{per},1} \, C_{\mathrm{per,core}} \, spc_{\mathrm{other\ per}}^{\mathrm{IS}}} - 1}_{\mathrm{JEXP}_{\mathrm{per,other\ per}}} \right]^2}$$

where $spc_{\mathrm{other\ per}}$ denotes the spc of the other periphery assets. The first square under the square root is the dominating term, so that the result of the return volatility decreasing in spc follows

[1] In the remainder of this section, we suppress the time index to simplify the notation.

[2] A proof that $C_{\mathrm{core,per}} > 0$ for reasonable parameter choices is given in Online Appendix B.

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from an argument analogous to the one presented for the OS case above. In particular, $C_{\text{per,core}}$ is positive in the inward star network.

To sum up, in both star networks the local return volatility of an asset is decreasing in its own shock propagation capacity.

B. Proof of Propositions 1 and 2

The two stylized cases of the outward star and the inward star network are represented by the sparse beta matrices

$$\beta^{OS} = \begin{pmatrix} 0 & 0 & \cdots & 0 \\ \beta_{\text{per,core}} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{\text{per,core}} & 0 & \cdots & 0 \end{pmatrix}, \quad \beta^{IS} = \begin{pmatrix} 0 & \beta_{\text{core,per}} & \cdots & \beta_{\text{core,per}} \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{pmatrix}. \tag{B.1}$$

In the "outward star" (superscript "OS"), shocks can propagate from the core asset to the periphery asset, but not the other way around. In the "inward star" (superscript "IS"), it is exactly the other way around.

We obtain for the market prices of risk and jump exposures in the star networks:

$$\begin{aligned} \text{MPJR}^{\text{OS}}_{\text{core}} &= 1 - \exp\left\{-\gamma\, K + k_{v,1}\,(\theta - 1)\; B_{\text{per}}\, spc^{\text{OS}}_{\text{core}}\right\} \\ \text{MPJR}^{\text{OS}}_{\text{per}} &= 1 - \exp\left\{-\gamma\, K + k_{v,1}\,(\theta - 1)\; B_{\text{core}}\, spc^{\text{OS}}_{\text{per}}\right\} &&= 1 - \exp\left\{-\gamma\, K\right\} \\ \text{MPJR}^{\text{IS}}_{\text{core}} &= 1 - \exp\left\{-\gamma\, K + k_{v,1}\,(\theta - 1)\; B_{\text{per}}\, spc^{\text{IS}}_{\text{core}}\right\} &&= 1 - \exp\left\{-\gamma\, K\right\} \\ \text{MPJR}^{\text{IS}}_{\text{per}} &= 1 - \exp\left\{-\gamma\, K + k_{v,1}\,(\theta - 1)\; B_{\text{core}}\, spc^{\text{IS}}_{\text{per}}\right\} \end{aligned} \tag{B.2}$$

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and

$$
\begin{aligned}
\mathrm{JEXP}^{\mathrm{OS}}_{\mathrm{core,core}} &= \exp\left\{L + k_{\mathrm{core},1}\, C_{\mathrm{core,per}}\, spc^{\mathrm{OS}}_{\mathrm{core}}\right\} - 1 \\
\mathrm{JEXP}^{\mathrm{OS}}_{\mathrm{per,core}} &= \exp\left\{k_{\mathrm{per},1}\, C_{\mathrm{per,per}}\, spc^{\mathrm{OS}}_{\mathrm{core}}\right\} - 1 \\
\mathrm{JEXP}^{\mathrm{OS}}_{\mathrm{core,per}} &= 0 \\
\mathrm{JEXP}^{\mathrm{OS}}_{\mathrm{per,per}} &= \exp\{L\} - 1 \\
\mathrm{JEXP}^{\mathrm{OS}}_{\mathrm{per,other\ per}} &= 0 \\
\mathrm{JEXP}^{\mathrm{IS}}_{\mathrm{core,core}} &= \exp\{L\} - 1 \\
\mathrm{JEXP}^{\mathrm{IS}}_{\mathrm{per,core}} &= 0 \\
\mathrm{JEXP}^{\mathrm{IS}}_{\mathrm{core,per}} &= \exp\left\{k_{\mathrm{core},1}\, C_{\mathrm{core,core}}\, spc^{\mathrm{IS}}_{\mathrm{per}}\right\} - 1 \\
\mathrm{JEXP}^{\mathrm{IS}}_{\mathrm{per,per}} &= \exp\left\{L + k_{\mathrm{per},1}\, C_{\mathrm{per,core}}\, spc^{\mathrm{IS}}_{\mathrm{per}}\right\} - 1 \\
\mathrm{JEXP}^{\mathrm{IS}}_{\mathrm{per,other\ per}} &= \exp\left\{k_{\mathrm{per},1}\, C_{\mathrm{per,core}}\, spc^{\mathrm{IS}}_{\mathrm{other\ per}}\right\} - 1.
\end{aligned}
$$

To prove the propositions, it is therefore sufficient to show that (i) in the outward star network the coefficients B_{per}, $C_{\mathrm{core,per}}$, and $C_{\mathrm{per,per}}$ do not depend on $spc^{\mathrm{OS}}_{\mathrm{core}}$, (ii) in the inward star network the coefficients B_{core}, $C_{\mathrm{per,core}}$, and $C_{\mathrm{core,core}}$ do not depend on $spc^{\mathrm{IS}}_{\mathrm{per}}$, and (iii) to determine the signs of these coefficients.

To see (i) and (ii) for the outward star, one has to plug the sparse beta matrices given in Equation (B.1) into the following Equations (A.4) and (A.10) from the Appendix of the main text:

$$
\begin{aligned}
0 &= \mathcal{K}'\, \chi_y - \theta\, (1 - k_{v,1})\, B + l_1'\, \left[\varrho\left(\chi_y\right) - \mathbb{1}\right] \\
0 &= \mathcal{K}'\, \chi_{y,i} + (1 - \theta)\, (1 - k_{v,1})\, B - (1 - k_{i,1})\, C_i + l_1'\, \left[\varrho\left(\chi_{y,i}\right) - \mathbb{1}\right].
\end{aligned}
$$

For the coefficients B_{core} and B_{per} in the outward star, this results in the system of equations

$$
\begin{aligned}
0 &= -\kappa\, \theta\, k_{v,1}\, B_{\mathrm{core}} - \theta\, (1 - k_{v,1})\, B_{\mathrm{core}} + \exp\left\{-K\, \theta\, \left(\frac{1}{\psi} - 1\right) + \theta\, k_{v,1}\, B_{\mathrm{per}}\, spc^{\mathrm{OS}}_{\mathrm{core}}\right\} - 1 \\
0 &= -\kappa\, \theta\, k_{v,1}\, B_{\mathrm{per}} - \theta\, (1 - k_{v,1})\, B_{\mathrm{per}} + \exp\left\{-K\, \theta\, \left(\frac{1}{\psi} - 1\right)\right\} - 1. \qquad \text{(B.3)}
\end{aligned}
$$

Assuming that the linearization coefficient $k_{v,1}$ is given exogenously and independent of $spc^{\mathrm{OS}}_{\mathrm{core}}$, the solution B_{per} does not depend on $spc^{\mathrm{OS}}_{\mathrm{core}}$. The previous assumption is justifiable, since the method of Eraker and Shaliastovich (2008) works independent of the particular point of expansion in the Campbell-Shiller loglinearization, and so we essentially assume the point of expansion to be held constant throughout this section. Moreover, rearranging Equation (B.3) as

$$
B_{\mathrm{per}} = \frac{1}{\theta}\, \frac{\exp\left\{(1 - \gamma)\, K\right\} - 1}{1 - k_{v,1}\, (1 - \kappa)},
$$

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one can see that $B_{\text{per}} < 0$ for the given parameter choices $\gamma > 1$, $\theta < 0$, $K < 0$, $0 < \kappa < 1$, and $k_{v,1} > \frac{1}{1-\kappa}$

For the inward star, we obtain

$$\begin{aligned}
0 &= -\kappa\,\theta\,k_{v,1}\,B_{\text{core}} - \theta\,(1-k_{v,1})\,B_{\text{core}} + \exp\left\{-K\,\theta\,\left(\frac{1}{\psi}-1\right)\right\} - 1 \\
0 &= -\kappa\,\theta\,k_{v,1}\,B_{\text{per}} - \theta\,(1-k_{v,1})\,B_{\text{per}} + \exp\left\{-K\,\theta\,\left(\frac{1}{\psi}-1\right) + \theta\,k_{v,1}\,B_{\text{core}}\,spc^{\text{IS}}_{\text{per}}\right\} - 1.
\end{aligned}$$

Based on arguments analogous to those above we conclude that $B_{\text{core}} < 0$.

For the coefficients $C_{i,j}$ we obtain the following set of equations in the outward star network:

$$\begin{aligned}
0 &= (-1 + k_{\text{core},1} - \kappa\,k_{\text{core},1})\,C_{\text{core,core}} - \kappa + (1-\theta)\,(1 - k_{v,1} + \kappa\,k_{v,1})\,B_{\text{core}} \\
&\quad + \exp\left\{k_{\text{core},1}\,C_{\text{core,per}}\,spc^{\text{OS}}_{\text{core}} - (1-\theta)\,k_{v,1}\,B_{\text{per}}\,spc^{\text{OS}}_{\text{core}} - \gamma K\right\} - 1 \\
0 &= (-1 + k_{\text{per},1} - \kappa\,k_{\text{per},1})\,C_{\text{per,core}} + (1-\theta)\,(1 - k_{v,1} + \kappa k_{v,1})\,B_{\text{core}} \\
&\quad + \exp\left\{k_{\text{per},1}\,[C_{\text{per,per}}\,\beta_{\text{core,per}} + (n-2)\,C_{\text{per,other per}}\,\beta_{\text{core,per}}] + \beta_{\text{core,per}}\right. \\
&\qquad\quad \left. -\,(1-\theta)\,k_{v,1}\,B_{\text{per}}\,spc^{\text{OS}}_{\text{core}} - \gamma K\right\} - 1 \\
0 &= (-1 + k_{\text{core},1} - \kappa\,k_{\text{core},1})\,C_{\text{core,per}} + (1-\theta)\,(1 - k_{v,1} + \kappa\,k_{v,1})\,B_{\text{per}} + \exp\{-\gamma\,K\} - 1 \\
0 &= (-1 + k_{\text{per},1} - \kappa\,k_{\text{per},1})\,C_{\text{per,per}} - \kappa + (1-\theta)\,(1 - k_{v,1} + \kappa\,k_{v,1})\,B_{\text{per}} + \exp\{-\gamma\,K\} - 1 \\
0 &= (-1 + k_{\text{per},1} - \kappa\,k_{\text{per},1})\,C_{\text{per,other per}} + (1-\theta)\,(1 - k_{v,1} + \kappa\,k_{v,1})\,B_{\text{per}} + \exp\{-\gamma\,K\} - 1
\end{aligned}$$

which leads to the conclusion that $C_{\text{core,per}}$, and $C_{\text{per,per}}$ do not depend on $spc^{\text{OS}}_{\text{core}}$ when the Campbell-Shiller coefficients $k_{\text{i},1}$ and $k_{v,1}$ are exogenous. Moreover, the third equation, reformulated as

$$\begin{aligned}
C_{\text{core,per}} &= \frac{(1-\theta)\,[1 + k_{v,1}\,(\kappa-1)]\,B_{\text{per}} + \exp\{-\gamma K\} - 1}{1 + k_{\text{core},1}\,(\kappa-1)} \\
&= \frac{\frac{1-\theta}{\theta}\,[\exp\{-K\,(\gamma-1)\} - 1] + \exp\{-\gamma K\} - 1}{1 - k_{\text{core},1}\,(1-\kappa)}
\end{aligned}$$

reveals that $C_{\text{core,per}} > 0$ because $\frac{1-\theta}{\theta} \approx -1$ for the given preference parameters.

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Similarly, for the inward star network, we have the system

$$
\begin{aligned}
0 &= (-1+k_{\text{core},1}-\kappa\, k_{\text{core},1})\; C_{\text{core,core}} - \kappa + (1-\theta)\;(1-k_{v,1}+\kappa\, k_{v,1})\; B_{\text{core}} + \exp\{-\gamma\, K\} - 1 \\
0 &= (-1+k_{\text{per},1}-\kappa\, k_{\text{per},1})\; C_{\text{per,core}} + (1-\theta)\;(1-k_{v,1}+\kappa\, k_{v,1})\; B_{\text{core}} + \exp\{-\gamma\, K\} - 1 \\
0 &= (-1+k_{\text{core},1}-\kappa\, k_{\text{core},1})\; C_{\text{core,per}} + (1-\theta)\;(1-k_{v,1}+\kappa\, k_{v,1})\; B_{\text{per}} \\
&\quad + \exp\left\{k_{\text{core},1}\, C_{\text{core,core}}\, spc^{\text{IS}}_{\text{per}} + spc^{\text{IS}}_{\text{per}} - (1-\theta)\; k_{v,1}\, B_{\text{core}}\, spc^{\text{IS}}_{\text{per}} - \gamma\, K\right\} - 1 \\
0 &= (-1+k_{\text{per},1}-\kappa\, k_{\text{per},1})\; C_{\text{per,per}} - \kappa + (1-\theta)\;(1-k_{v,1}+\kappa\, k_{v,1})\; B_{\text{per}} \\
&\quad + \exp\left\{k_{\text{per},1}\, C_{\text{per,core}}\, spc^{\text{IS}}_{\text{per}} + spc^{\text{IS}}_{\text{per}} - (1-\theta)\; k_{v,1}\, B_{\text{core}}\, spc^{\text{IS}}_{\text{per}} - \gamma\, K\right\} - 1 \\
0 &= (-1+k_{\text{per},1}-\kappa\, k_{\text{per},1})\; C_{\text{per,other per}} + (1-\theta)\;(1-k_{v,1}+\kappa\, k_{v,1})\; B_{\text{per}} \\
&\quad + \exp\left\{k_{\text{per},1}\, C_{\text{per,core}}\, spc^{\text{IS}}_{\text{per}} + spc^{\text{IS}}_{\text{per}} - (1-\theta)\; k_{v,1}\, B_{\text{core}}\, spc^{\text{IS}}_{\text{per}} - \gamma\, K\right\} - 1,
\end{aligned}
$$

whose solutions $C_{\text{per,core}}$ and $C_{\text{core,core}}$ do not depend on $spc^{\text{IS}}_{\text{per}}$. Similar to the outward star, we also see from the second equation that $C_{\text{per,core}} > 0$ since $B_{\text{core}} < 0$.

In a pure jump model like ours, the local return volatilities are given by

$$
\text{RVol}_j \;=\; \sqrt{\sum_{i=1}^{n} \ell_i\, \text{JEXP}^2_{j,i}}.
$$

In the sparse star networks, this expression becomes

$$
\begin{aligned}
\text{RVol}^{\text{OS}}_{\text{core}} &= \sqrt{\ell_{\text{core}}\,\Big[\underbrace{e^{L+k_{\text{core},1}\, C_{\text{core,per}}\, spc^{\text{OS}}_{\text{core}}} - 1}_{\text{JEXP}_{\text{core,core}}}\Big]^2} \\
\text{RVol}^{\text{IS}}_{\text{per}} &= \sqrt{\ell_{\text{per}}\,\Big[\underbrace{e^{L+k_{\text{per},1}\, C_{\text{per,core}}\, spc^{\text{IS}}_{\text{per}}} - 1}_{\text{JEXP}_{\text{per,per}}}\Big]^2 + (n-2)\;\ell_{\text{other per}}\,\Big[\underbrace{e^{k_{\text{per},1}\, C_{\text{per,core}}\, spc^{\text{IS}}_{\text{other per}}} - 1}_{\text{JEXP}_{\text{per,other per}}}\Big]^2}
\end{aligned}
$$

From the discussion above, we know that the relevant coefficients $C_{\text{core,per}}$ in the outward star and $C_{\text{per,core}}$ in the inward star are both negative and independent from the *spc*'s, which concludes the proof.

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C. Empirical illustration

1. Data on industry earnings

In the following, we perform several illustrative exercises to present suggestive empirical evidence for the theoretical channels outlined in Section 2 of the main paper. We start by constructing quarterly time series of industry earnings following Irvine and Pontiff (2009). The sample comprises all firms in the CRSP/Compustat merged (CCM) fundamentals quarterly database from 1966-Q2 to 2014-Q4. In principle, the data is available from 1964 onwards, but before 1966-Q2 not all industries are represented in the sample. We work with firms' earnings per share (item EPSPXQ) and require a firm to have at least four consecutive data entries to be included in our sample. Following the procedure outlined in Irvine and Pontiff (2009), we winsorize the EPS data.

Based on the NAICS code dictionary from the Bureau of Economic Analysis, we sort in each quarter firms into 15 industry portfolios as in Menzly and Ozbas (2010). Following Aobdia, Caskey, and Ozel (2014), and Menzly and Ozbas (2010), we exclude the government sector. We multiply firms' earnings per share by the number of shares to obtain total earnings, sum up the total earnings across all firms in a given industry, and divide by the number of firms in that industry to account for variation over time. We then calculate log earnings growth rates for each industry.[3] We adjust each time series for seasonality using the method proposed in Hamilton (2018).[4] Eventually, we end up with a time series of 49 log earnings growth rates for each of the 14 industries, i.e., 686 quarterly observations in total.

2. Measurement of directed cash flow links

Having constructed quarterly industry earnings time series allows us to estimate the directed earnings network following the procedure proposed by Diebold and Yilmaz (2014).[5] The first step is to estimate a 14-dimensional VAR(1) process based on our earnings growth time series:

$$\begin{bmatrix} z_{1,t} \\ \vdots \\ z_{14,t} \end{bmatrix} = \begin{bmatrix} \phi_1 \\ \vdots \\ \phi_{14} \end{bmatrix} + \begin{bmatrix} \phi_{1,1} & \cdots & \phi_{1,14} \\ \vdots & \ddots & \vdots \\ \phi_{14,1} & \cdots & \phi_{14,14} \end{bmatrix} \begin{bmatrix} z_{1,t-1} \\ \vdots \\ z_{14,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{14,t} \end{bmatrix}.$$

From the coefficient matrix ϕ and the covariance matrix of the shocks ε, we compute generalized variance decompositions of quarterly earnings with a forecast horizon of $H = 1, 2, 3, 4$ quarters.

[3]We follow Lochstoer and Tetlock (2018) and winsorize log earnings growth rates at $\log(0.01)$ when earnings growth rates are below -0.99.

[4]Running a Dickey and Fuller (1979) test on each resulting time series, we can reject the null hypothesis of a unit root at the 1% significance level.

[5]We thank Francis Diebold and Kamil Yilmaz for sharing their code.

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We denote the fraction of H-quarter forecast error variance of industry i's earnings explained by shocks in industry j's earnings by $d^H_{i,j}$. This gives us a 14×14 matrix $(d^H_{i,j})_{i,j=1,\ldots,14}$, which Diebold and Yilmaz (2014) refer to as the *connectedness table*. In the following, this matrix serves as our empirical network matrix at the cash flow level.

There is no clear guidance towards the optimal choice of the forecast horizon H. As documented by Diebold and Yilmaz (2014), a very short horizon produces noisy estimates, but the estimates stabilize with longer horizons. Diebold and Yilmaz (2014), thus, choose $H = 12$ days for their daily stock return data. We find similar, albeit weaker, effects of the forecast horizon in our estimation and, therefore, report results for $H = 1, 2, 3, 4$ quarters in the following.

Figure C.1 presents graphical illustrations of the estimated networks, where the arrowheads mark *outgoing* links. This helps to visually identify the industries with high *spc* in the graphs. From the graphs, one can see the similarity of the networks for the different forecast horizons of $H = 1, \ldots, 4$ quarters.

From the empirical network matrix, we compute the shock propagation capacity spc^H_j for industry j and horizon H analogous to Equation (3) from the main text as

$$spc^H_j = \sum_{\substack{i=1 \\ i \neq j}}^{N} d^H_{i,j}. \tag{C.1}$$

Diebold and Yilmaz (2014) call this measure *total directional connectedness to others from* j.

Table C.1 provides the *spc*'s of the 14 industries. Most importantly, one can see that there is a significant cross-sectional dispersion in *spc* at all horizons, so that this variable indeed has the potential to explain cross-sectional variation in asset pricing moments. In terms of important industries with high values for *spc*, manufacturing, wholesale trade, and utilities are at the top of the list for $H = 1$, and this ranking is stable across the four horizons. In contrast, cash flow shocks to construction and agriculture, forestry, fishing, and hunting seem to be less important for the rest of the economy.

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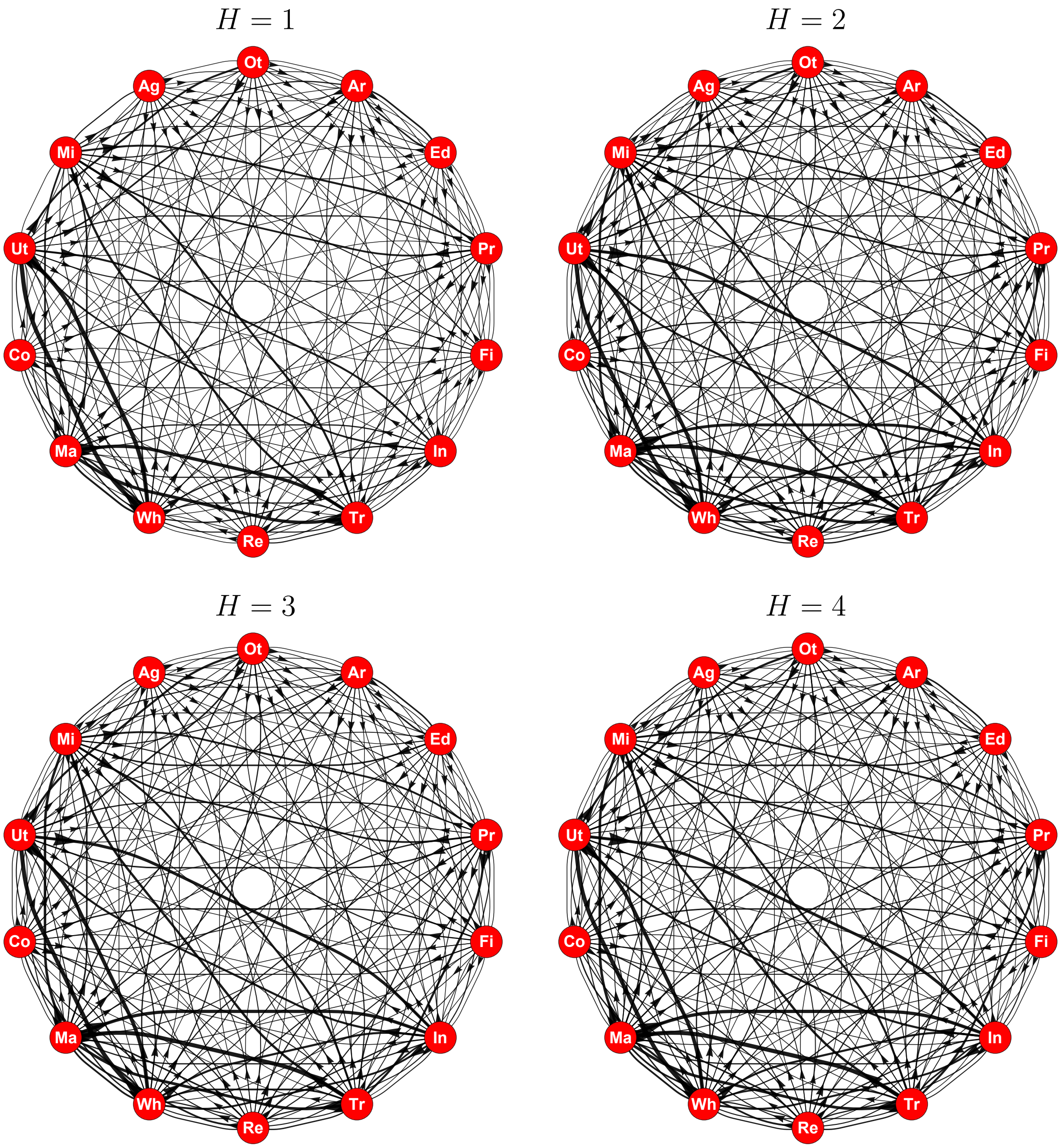

Figure C.1
Empirical cash flow networks for different forecast horizons H

The pictures show the empirical cash flow networks obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, \ldots, 4$, applied to quarterly log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. Arrowheads mark *outgoing* links. The thickness of a link corresponds to the size of the respective entry. Diagonal entries of the connectivity matrix are disregarded. The industries are listed in Online Appendix D.

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Industry	Forecast horizon			
	$H = 1$	$H = 2$	$H = 3$	$H = 4$
Agriculture, forestry, fishing, hunting	0.0560	0.1012	0.1061	0.1068
Mining	0.2895	0.3147	0.3237	0.3247
Utilities	0.3637	0.4185	0.4189	0.4186
Construction	0.0599	0.1548	0.1679	0.1720
Manufacturing	0.3584	0.5740	0.6330	0.6482
Wholesale trade	0.4326	0.5272	0.5273	0.5271
Retail trade	0.0782	0.2277	0.2450	0.2497
Transportation and warehousing	0.3175	0.3679	0.3744	0.3753
Information	0.1560	0.2300	0.2517	0.2554
Finance, insurance, real estate, ...	0.0448	0.0906	0.0998	0.1027
Professional and business services	0.1584	0.2861	0.3003	0.3022
Educational services, health care, ...	0.0780	0.1384	0.1445	0.1452
Arts, entertainment, accommodation, ...	0.1473	0.1388	0.1383	0.1382
Other services	0.0980	0.1375	0.1414	0.1415
Mean	0.1884	0.2648	0.2766	0.2791
Standard deviation	0.1350	0.1573	0.1643	0.1663

Table C.1
Shock propagation capacities

The table shows the shock propagation capacity (*spc*) for 14 industries. *spc* is obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *spc* is calculated according to Equation (C.1). Graphical representations of the networks are shown in Figure C.1.

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3. *Cross-sectional performance of shock propagation capacity*

Having estimated the network of cash flow linkages, we now illustrate the performance of *spc* in a cross-sectional asset pricing exercise. The data is from the CRSP securities monthly database and covers exactly the sample used for the cash flow network estimation. We assign firms to industry portfolios based on their NAICS code and form value-weighted industry portfolios accordingly.

For each industry portfolio, we calculate three variables over the whole sample, which serve as dependent variables in our regressions. The average excess return of an industry portfolio is the mean of the difference between its log return and the log three-month Treasury bill return. Return volatilities are calculated as the standard deviations of log returns. Sharpe ratios are computed as average excess returns divided by return volatilities. The numbers are shown in Table C.2.

The Sharpe ratio of an industry serves as a proxy for the market price of risk for cash flow shocks of the respective industry, MPJR, because these market prices of risk are not observable empirically. Recall from Equation (9) of the main text that the expected excess return on asset i is given as

$$\frac{1}{dt}\,\mathbb{E}\left[dR_i\right] - r \quad = \quad \sum_{j=1}^{n} \ell_j \,\mathrm{JEXP}_{i,j}\,\mathrm{MPJR}_j.$$

The i-th summand is by the far the largest on the right-hand side, since $\mathrm{JEXP}_{i,i}$ is the only exposure containing the direct cash flow effect represented by the jump size L. The expected excess return of an asset is thus mostly driven by the response of its price and of the pricing kernel to *its own cash flow shocks*. Therefore we use the Sharpe ratio of asset i as a proxy for MPJR_i and the return volatility as a proxy for $\mathrm{JEXP}_{i,i}$.

Table C.3 reports the main results from this empirical exercise. Each of the three panels shows four univariate cross-sectional regressions, where the explanatory variables are the industry shock propagation capacities, determined using the empirical procedure outlined above, with forecast horizons of $H = 1, 2, 3, 4$ quarters. The dependent variables are return volatilities, Sharpe ratios, and average excess returns.[6]

First, the coefficients in the Sharpe ratio regressions are positive and significant for $H = 2, 3, 4$, and the R^2's are large. This is also in line with Proposition 1, that shocks to the cash flows of high *spc* industries carry a large market price of risk, which manifests itself in high Sharpe ratios for these industries.

Second, the coefficients in the return volatility regressions are all negative and significant at the 1% level, and the adjusted R^2's are high for all forecasting horizons. This negative connection is in line with Proposition 2 which states that high *spc* assets have smaller jump exposures that translate into lower return volatilities.

[6] Although one of the three regressions is redundant, we report all three for the sake of completeness.

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Industry	Sharpe ratio	Return volatility	Average excess return
Agriculture, forestry, fishing, hunting	0.1609	0.0635	0.0102
Mining	0.1351	0.0665	0.0090
Utilities	0.1459	0.0409	0.0060
Construction	0.1559	0.0773	0.0121
Manufacturing	0.2236	0.0470	0.0105
Wholesale trade	0.2070	0.0509	0.0105
Retail trade	0.1853	0.0557	0.0103
Transportation and warehousing	0.1784	0.0565	0.0101
Information	0.1888	0.0507	0.0096
Finance, insurance, real estate, ...	0.1699	0.0557	0.0095
Professional and business services	0.1563	0.0546	0.0085
Educational services, health care, ...	0.1693	0.0765	0.0130
Arts, entertainment, accomodation,...	0.1842	0.0679	0.0125
Other services	0.1362	0.0691	0.0094

Table C.2
Descriptive statistics for industry portfolio returns

The table presents descriptive statistics for the returns of 14 value-weighted industry portfolios. The average excess return of an industry portfolio is the mean of the difference between its log return and the log three-month Treasury bill return. Return volatilities are calculated as the standard deviations of log returns. Sharpe ratios are computed as average excess returns divided by return volatilities. The data is from the CRSP securities monthly database and covers the sample from April 1966 to December 2014.

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const.	$H=1$	$H=2$	$H=3$	$H=4$	$\bar{R}^2$
		Sharpe ratios			
15.9158***	6.3940				0.0404
[20.46]	[1.24]				
14.9951***		8.0267**			0.1811
[15.78]		[2.10]			
14.8668***			8.1489**		0.2143
[15.91]			[2.37]		
14.8382***				8.1778**	0.2236
[16.03]				[2.46]	
		Return volatilities			
6.8792***	-4.9428***				0.3208
[16.73]	[-3.16]				
7.1838***		-4.6676***			0.4057
[16.87]		[-4.05]			
7.1831***			-4.4660***		0.4055
[17.30]			[-4.13]		
7.1776***				-4.4060***	0.4039
[17.44]				[-4.14]	
		Average excess returns			
1.0999***	-0.4888				0.0695
[16.06]	[-1.38]				
1.1052***		-0.3677			0.0340
[13.64]		[-1.22]			
1.0994***			-0.3311		0.0206
[13.59]			[-1.17]		
1.0972***				-0.3203	0.0162
[13.59]				[-1.15]	

Table C.3
Cross-sectional regressions on *spc*

The table reports the results of cross-sectional regressions of Sharpe ratios, return volatilities, and average excess returns of the 14 industry portfolios on their shock propagation capacity (*spc*). Returns within a portfolio are value-weighted. To obtain *spc*, we perform Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ and calculate *spc* as given in Equation (C.1). Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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Third, the coefficients in the average excess return regressions are insignificant for all horizons. These results are also in line with our theoretical findings. The effects of *spc* on the market price of jump risk and on price exposures have opposite signs, so that the overall effect of *spc* on expected excess returns cannot be uniquely determined in general within the model. Hence, the role of directedness in equilibrium can only be assessed appropriately when the two opposing effects described above are disentangled.

Finally, the coefficients in the Sharpe ratio and return volatility regressions are not only statistically, but also economically significant. For $H = 2$, the standard deviation of *spc* is around 0.16. Thus, with a coefficient for *spc* in the Sharpe ratio regression of around 8.03, a one-standard-deviation difference in *spc* leads to a difference in Sharpe ratios of roughly $8.03 \cdot 0.16 \approx 1.27$ percentage points monthly. Similarly, a one-standard-deviation difference in *spc* gives rise to a difference in return volatilities of about $-4.67 \cdot 0.16 \approx -0.74$ percentage points per month.

4. Empirical *spc* versus model-generated *spc*

The empirics above rely on generalized variance decompositions of cash flows to estimate the structure of the underlying network, whereas the model features connectivity in a network at the jump intensity level. We now show that the connectivity and directedness information from the empirically estimated cash flow network is indeed a close representation of the underlying intensity network.

To this end, we perform the following simulation exercise for each forecast horizon $H = 1, 2, 3, 4$. We plug the empirically estimated connectivity matrix (for the cash flows) as the beta matrix (for the jump intensities) into our model which we then multiply with $\frac{1}{2}$ to make sure that the stationarity condition (A.7) from the Appendix of the main text holds. The remaining model parameters are taken from Table C.4. Then we simulate 10,000 years of cash flows with monthly increments and run the procedure suggested by Diebold and Yilmaz (2014) on simulated log cash flow growth rates, exactly as we do with the empirical data, resulting in an estimate for the network matrix based on simulated data cash flows. From this, we compute the *spc* values for the different industries and compare them to the corresponding values based on the empirical network matrix that we had plugged into the model initially.

Table C.5 presents correlations between the two *spc* vectors. One can see that the two network matrices are very similar with respect to the *spc* values they generate, with correlations of 0.75 or higher. Furthermore, it is especially relevant in the context of our empirical analysis that sorting industries on *spc* delivers roughly the same ordering for cash flow-based and intensity-based network matrices.

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Investors		
Relative risk aversion	γ	10
Intertemporal elasticity of substitution	ψ	1.5
Subjective discount rate	δ	0.02
Aggregate consumption		
Expected growth rate of log aggregate consumption	μ	0.02
Jump size of log aggregate consumption	$K_1 = \ldots = K_{14}$	-0.004
Industry cash flows		
Expected growth rates of log cash flows	$\mu_1 = \ldots = \mu_{14}$	0.02
Jump sizes of log cash flows	$L_1 = \ldots = L_{14}$	-0.04
Stochastic jump intensities		
Mean reversion speeds	$\kappa_1 = \ldots = \kappa_{14}$	0.85
Mean reversion levels	$\bar{\ell}_1 = \ldots = \bar{\ell}_{14}$	0.05

Table C.4
Model Parameters

The table reports the parametrization of our model. The beta matrix is determined empirically using the approach described in Section C.2 of the Online Appendix.

5. Regressions in model-generated data

In Section 4 of the Online Appendix, we show that applying the Diebold and Yilmaz (2014) estimation method to simulated data, preserves the ordering of industries with respect to *spc*. As a final step and to further corroborate that the empirical procedure is in line with the intuition behind the theoretical model, we now analyze whether the regression results from Section 3 also carry over to model-generated data.

We start from the simulated path for $H = 3$ over a period of 10,000 years with monthly increments from the previous section.[7] Using these 14 industry cash flow time series, we compute *spc* by applying the Diebold and Yilmaz (2014) methodology exactly as in the data. Again the forecast horizons are $H = 1, 2, 3, 4$ quarters. Unconditional Sharpe ratios, return volatilities, and average excess returns are computed from the simulated monthly return time series exactly like their empirical counterparts in Section 3 of the Online Appendix. Table C.6 reports these results. As one can see, the analyses based on simulated and empirical data produce qualitatively similar results for Sharpe ratios (positive coefficients) and for return volatilities (negative coefficients for *spc*).

[7]For the sake of brevity, we report the results for this sample path only. The results using the paths for

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	Forecast horizon			
	$H=1$	$H=2$	$H=3$	$H=4$
correlation	0.85	0.81	0.87	0.66
rank correlation	0.82	0.85	0.90	0.75

Table C.5
Empirical *spc* versus model-generated *spc*

The table reports correlations and rank correlations between empirically estimated and model-generated shock propagation capacities. The model-generated values are obtained from simulated data using the empirically estimated network matrix as an input. The procedure is described in detail in Section C.4 of the Online Appendix. We calculate *spc* as given in Equation (C.1).

The coefficients for all regressions are much larger in Table C.6 than in Table C.3. The reason is that the values for *spc* are smaller in model-generated than in empirical data. The diagonal entries of the beta matrix are by definition not included when we compute *spc* according to Equation (3) from the main text. So a comparably smaller value for *spc* in the model-generated data shows that self excitation, represented by the diagonal elements of the beta matrix, is more pronounced in model-generated than in empirical data. In the real world, shocks are also spread via potentially diffusive channels (which are not present in our model for the sake of parsimony) and this can increase the relative size of the shocks passed on to other industries, making the diagonal elements of the empirical network matrix smaller and the off-diagonal elements, and thus also *spc*, larger.

With the given parameters, the model produces only weakly significant coefficients in the regressions for unconditional average excess returns for $H = 2, 3, 4$, whereas in our empirical analysis we basically found no impact of *spc* on risk premia. However, given our discussion concerning the two opposing directions in which *spc* impacts exposures (negatively) and market prices of risk (positively) in the model, the results for average excess returns in Table C.6 could simply mean that the positive effect of *spc* on the market prices of risk weakly dominates in the simulated economy, whereas the two effects more or less seem to offset each other in the empirical data.

In summary, the analysis generates results which are overall in line with our results from Propositions 1 and 2. Hardly surprising, however, our very stylized model does not match the unconditional volatility of the U.S. stock market (reflecting the well-documented excess volatility puzzle), as indicated by the low values for the constants in the return volatility regressions in Table C.6. In principle, it would be possible to include additional features, but this would unnecessarily complicate the solution of the model and shift the focus away from the clear theoretical results derived above.[8]

$H = 1, 2, 4$ are qualitatively similar.

[8]One way to generate stock return volatilities in the model that are closer to their empirical counterparts

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const.	$H=1$	$H=2$	$H=3$	$H=4$	$\bar{R}^2$
		Unconditional Sharpe ratios			
0.0026***	4.9670				-0.0705
[1.45]	[0.45]				
0.0010***		6.6106***			0.0522
[0.73]		[2.97]			
0.0010***			6.6073***		0.0527
[0.72]			[2.98]		
0.0010***				6.6073***	0.0527
[0.72]				[2.98]	
		Unconditional return volatilities			
0.9091***	-904.7605***				0.2432
[17.98]	[-2.84]				
0.9629***		-533.6300***			0.5922
[25.64]		[-4.96]			
0.9631***			-532.1669***		0.5917
[25.59]			[-4.95]		
0.9631***				-532.1604***	0.5917
[25.59]				[-4.95]	
		Unconditional average excess returns			
0.0023***	0.7408				-0.0828
[1.68]	[0.09]				
0.0012***		3.2697*			-0.0183
[1.14]		[1.78]			
0.0012***			3.2711*		-0.0179
[1.13]			[1.78]		
0.0012***				3.2712*	-0.0179
[1.13]				[1.78]	

Table C.6
Cross-sectional regressions on *spc* in model-generated data

The table reports the results from cross-sectional regressions of model-generated Sharpe ratios, return volatilities, and average excess returns of 14 assets on their shock propagation capacity (*spc*). As beta matrix, we use the empirical network determined in Online Appendix C.2 for a forecast horizon of $H = 3$ quarters. The remaining parameters are given in Table C.4. Given the model solution, we run a Monte Carlo simulation over 10,000 years with monthly time increments. From the simulated data, we compute Sharpe ratios, return volatilities, and average excess returns. To obtain *spc*, we apply Diebold and Yilmaz (2014) H-quarter generalized variance decompositions to simulated log cash flow growth rates for $H = 1, 2, 3, 4$ and calculate *spc* as in Equation (C.1). Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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6. Eigenvector centrality

We start by providing some technical details on eigenvector centrality in the context of our model. First, we derive the eigenvector centralities from the empirical network matrix with the diagonal elements set to zero. The reason is that the entries of the network matrix resulting from the Diebold and Yilmaz (2014) generalized variance decomposition method represent percentage shares, so that the row sums are all equal to 1. The principal eigenvalue of such a matrix is equal to 1, and the associated eigenvector is a (multiple of a) vector of ones. Hence all the nodes in the network would be assigned the same eigenvector centrality if we used the full matrix with diagonal elements.

Second, even with diagonal elements set to zero, *evc* is well-defined. According to the Perron-Frobenius theorem, to guarantee that there exists a positive principal eigenvalue with an associated positive principal eigenvector, the matrix has to be positive, i.e., has to have only positive elements. An extension of the Perron-Frobenius Theorem states that any nonnegative matrix (i.e., a matrix with all entries ≥ 0) has a positive principal eigenvalue and a positive principal eigenvector if it is an irreducible matrix. A matrix is called irreducible if it cannot be rearranged as a block upper triangular matrix by permutations of rows and columns. In network terms, this means that the network must be strongly connected, i.e., every node is reachable from every other node. Since our empirical approach yields such an irreducible network matrix with only positive entries (except for the diagonal entries which we set to 0), the extended Perron-Frobenius theorem applies, and *evc* is well-defined.

Table C.7 reports the values of *evc* for the 14 industries. The cross-sectional dispersion in *evc* is similar to *spc*. Tables C.9, C.8, and C.10 present the results of regressions analogous to those shown in Table C.3, but now with *evc* as additional regressor. For the bivariate regressions, we orthogonalize *evc* with respect to *spc* to quantify the *additional* explanatory power of this measure beyond *spc*.[9]

The new regressions yield several interesting findings. The univariate regressions for Sharpe ratios in Table C.8 show that *evc* has no explanatory power, while *spc* remains robustly significant across all horizons. In the return volatility regressions in Table C.9, *evc* can explain the cross-section of return volatilities for industry portfolios. When combined with *spc*, however, the orthogonalized version of *evc* is insignificant for $H = 1$, but it seems to have explanatory power beyond *spc* for $H = 2, 3, 4$. In the bivariate regressions, the coefficient for *spc* is significant for all horizons. Finally, in the regressions for average excess returns in Table C.10, *evc* yields negative and significant coefficients at the 10% level, while *spc* is not significant both in the univariate and in the bivariate regressions. Overall, we conclude that our theoretically motivated measure of directedness *spc*

would be to introduce persistent diffusion processes representing, e.g., stochastic volatility of consumption growth.

[9] In Section C.7 of the Online Appendix, we also compare *spc* to a symmetrified version of eigenvector centrality that has been proposed in the literature recently.

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indeed contains additional information above and beyond the information captured by centrality measures like *evc*.

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Industry	Forecast horizon			
	$H = 1$	$H = 2$	$H = 3$	$H = 4$
Agriculture, forestry, fishing, hunting	0.0581	0.0689	0.0707	0.0713
Mining	0.2680	0.2869	0.2877	0.2870
Utilities	0.4577	0.3808	0.3773	0.3769
Construction	0.0847	0.0888	0.0928	0.0938
Manufacturing	0.4083	0.3425	0.3311	0.3297
Wholesale trade	0.4859	0.4038	0.4089	0.4097
Retail trade	0.0774	0.1680	0.1688	0.1687
Transportation and warehousing	0.3575	0.4039	0.3989	0.3981
Information	0.2623	0.4355	0.4365	0.4366
Finance, insurance, real estate, ...	0.0415	0.0629	0.0652	0.0655
Professional and business services	0.1878	0.1950	0.2102	0.2126
Educational services, health care, ...	0.0757	0.0802	0.0788	0.0784
Arts, entertainment, accommodation, ...	0.1583	0.1341	0.1316	0.1310
Other services	0.1870	0.1796	0.1852	0.1863
Mean	0.2222	0.2308	0.2317	0.2318
Standard deviation	0.1542	0.1399	0.1382	0.1380

Table C.7
Eigenvector centrality

The table reports eigenvector centrality (*evc*) for the 14 industries in our sample. The network measure is obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *evc* is calculated according to Equation (C.1) from the Appendix of the main paper. Graphical representations of the networks are shown in Figure C.1.

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$H=1$				$H=2$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
15.9409***		5.3110	0.0280	15.7070***		6.1260	0.0385
[19.64]		[1.17]		[22.02]		[1.64]	
15.9158***	6.3940	-1.9904	-0.0459	14.9951***	8.0267**	-2.8222	0.1171
[20.85]	[1.25]	[-0.09]		[16.40]	[2.25]	[-0.37]	
$H=3$				$H=4$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
15.7510***		5.9117	0.0275	15.7557***		5.8880	0.0262
[22.07]		[1.61]		[22.04]		[1.60]	
14.8668***	8.1489***	-3.9154	0.1642	14.8382***	8.1778***	-4.0006	0.1759
[17.16]	[2.70]	[-0.54]		[17.38]	[2.83]	[-0.57]	

Table C.8
Cross-sectional regressions of Sharpe ratios on *spc* and *evc*

The table reports the results from cross-sectional regressions of the Sharpe ratios of the 14 industry portfolios on their shock propagation capacity (*spc*) and eigenvector centrality (*evc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *evc* is calculated according to Equation (C.1) from the Appendix of the main paper, *spc* in Equation (C.1). In bivariate regressions, we orthogonalize *evc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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$H=1$				$H=2$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
6.9909***		-4.6955***	0.3923	7.1819***		-5.3478***	0.4246
[15.87]		[-3.46]		[16.03]		[-3.59]	
6.8792***	-4.9428***	-8.3586	0.3571	7.1838***	-4.6676***	-3.1963*	0.4247
[15.68]	[-3.32]	[-1.52]		[17.32]	[-4.12]	[-1.95]	
$H=3$				$H=4$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
7.2001***		-5.4049***	0.4233	7.2033***		-5.4157***	0.4235
[15.98]		[-3.60]		[15.97]		[-3.60]	
7.1831***	-4.4660***	-3.2327**	0.4310	7.1776***	-4.4060***	-3.2633**	0.4328
[17.77]	[-4.33]	[-2.01]		[17.96]	[-4.40]	[-2.03]	

Table C.9

Cross-sectional regressions of return volatilities on *spc* and *evc*

The table reports the results from cross-sectional regressions of the return volatilities of the 14 industry portfolios on their shock propagation capacity (*spc*) and eigenvector centrality (*evc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *evc* is calculated according to Equation (C.1) from the Appendix of the main paper, *spc* in Equation (C.1). In bivariate regressions, we orthogonalize *evc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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$H = 1$				$H = 2$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
1.1202***		-0.5057	0.1300	1.1394***		-0.5702*	0.1399
[15.25]		[-1.55]		[14.80]		[-1.86]	
1.0999***	-0.4888	-1.5207	0.1103	1.1052***	-0.3677	-0.6554*	0.0649
[16.84]	[-1.51]	[-1.62]		[14.98]	[-1.41]	[-1.81]	
$H = 3$				$H = 4$			
const.	*spc*	*evc*	$\bar{R}^2$	const.	*spc*	*evc*	$\bar{R}^2$
1.1450***		-0.5919*	0.1516	1.1458***		-0.5951*	0.1533
[14.76]		[-1.90]		[14.75]		[-1.91]	
1.0994***	-0.3311	-0.7147*	0.0819	1.0972***	-0.3203	-0.7237**	0.0848
[15.43]	[-1.43]	[-1.94]		[15.57]	[-1.42]	[-1.96]	

Table C.10
Cross-sectional regressions of average excess returns on *spc* and *evc*

The table reports the results from cross-sectional regressions of the average excess returns of the 14 industry portfolios on their shock propagation capacity (*spc*) and eigenvector centrality (*evc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *evc* is calculated according to Equation (C.1) from the Appendix of the main paper, *spc* in Equation (C.1). In bivariate regressions, we orthogonalize *evc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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7. Symmetrified eigenvector centrality

In this section, we compare our theoretically motivated measure *spc* to a symmetrified version of eigenvector centrality proposed by Ahern (2013), which we label *symevc*. To compute it in the context of our model, we construct a new network matrix β^{sym} by setting $\beta^{\text{sym}}_{i,j} = \beta^{\text{sym}}_{j,i} = \max\{\beta_{i,j}, \beta_{j,i}\}$. From this new matrix, obviously representing an undirected network, we then again compute the eigenvector centralities of the n nodes.

Ahern (2013) works with data from the BEA input-output tables, and these tables contain many zero entries. Symmetrifying these sparse network matrices makes them irreducible so that the extended Perron-Frobenius theorem applies, and *symevc* is well-defined. In our empirical procedure, we do not face this irreducibility problem because our empirical network matrix does not contain zeros, but we document the results for *symevc* to link our paper to the existing literature. For the same reason, we compute *symevc* based on the network matrix with diagonal entries, in particular since the problem pointed out above (that the row sums are all equal to 1) does not apply to the symmetrified matrix.

Table C.11 reports the values of *symevc* for the 14 industries. The cross-sectional dispersion in *symevc* is smaller relative to *evc* and *spc*. Tables C.13, C.12, and C.14 then present the results of regressions analogous to those shown in Table C.3, but now with *symevc* as additional regressors. For the bivariate regressions, we orthogonalize *symevc* with respect to *spc* to quantify the *additional* explanatory power of these measures beyond *spc*.

The univariate regressions for return volatilities in Table C.13 show that *symevc* yields negative and significant coefficients for all horizons, albeit the results are weaker than for *evc*. When combined with *spc*, however, the orthogonalized version of *symevc* does not have additional explanatory power beyond *spc*, which itself remains significant for all horizons. In the Sharpe ratio regressions (Table C.12), *symevc* is significant as a single regressor (except for $H = 1$) but the parts of this measure not already captured by *spc* fail to deliver additional explanatory power. At the same time, *spc* remains robustly significant across all horizons. Finally, in the regressions for average excess returns (Table C.14), *symevc* has no explanatory power. Both in the univariate and in the bivariate regressions, *spc* is not significant.

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Industry	Forecast horizon			
	$H = 1$	$H = 2$	$H = 3$	$H = 4$
Agriculture, forestry, fishing, hunting	0.2183	0.1807	0.1796	0.1790
Mining	0.2778	0.2631	0.2645	0.2642
Utilities	0.3191	0.2995	0.2874	0.2850
Construction	0.2354	0.2502	0.2525	0.2529
Manufacturing	0.2989	0.3752	0.3999	0.4056
Wholesale trade	0.3264	0.3099	0.3006	0.2991
Retail trade	0.2299	0.2585	0.2633	0.2651
Transportation and warehousing	0.2876	0.3006	0.3014	0.3019
Information	0.2813	0.2777	0.2814	0.2821
Finance, insurance, real estate, ...	0.2068	0.1713	0.1753	0.1767
Professional and business services	0.2642	0.3058	0.2976	0.2944
Educational services, health care, ...	0.2307	0.2293	0.2200	0.2178
Arts, entertainment, accommodation, ...	0.2562	0.2063	0.2024	0.2011
Other services	0.2755	0.2379	0.2305	0.2285
Mean	0.2649	0.2619	0.2612	0.2610
Standard deviation	0.0370	0.0554	0.0589	0.0599

Table C.11
Symmetrified eigenvector centrality

The table reports symmetrified eigenvector centrality (*symevc*) for the 14 industries in our sample. The network measure is obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *symevc* is calculated as described in Section C.7 of the Online Appendix.

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$H=1$				$H=2$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
13.1127***		15.1323	-0.0313	11.9947***		19.5747*	0.1120
[3.09]		[0.86]		[4.21]		[1.72]	
15.9158***	6.3940	-37.1568	0.0100	14.9951***	8.0267**	-5.7534	0.1100
[23.44]	[1.32]	[-0.92]		[16.15]	[2.11]	[-0.29]	
$H=3$				$H=4$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
11.6226***		21.0519**	0.1716	11.5536***		21.3334**	0.1874
[4.75]		[2.21]		[4.94]		[2.37]	
14.8668***	8.1489**	1.3740	0.1431	14.8382***	8.1778**	2.9284	0.1539
[15.85]	[2.38]	[0.06]		[15.89]	[2.47]	[0.13]	

Table C.12
Cross-sectional regressions of Sharpe ratios on *spc* and *symevc*

The table reports the results from cross-sectional regressions of the Sharpe ratios of the 14 industry portfolios on their shock propagation capacity (*spc*) and symmetrified eigenvector centrality (*symevc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *symevc* is calculated as described in Section C.7 of the Online Appendix, *spc* as in Equation (C.1). In bivariate regressions, we orthogonalize *symevc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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$H=1$				$H=2$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
10.4057***		-16.8305**	0.2689	8.8483***		-11.0762***	0.2586
[5.54]		[-2.51]		[7.90]		[-2.89]	
6.8792***	-4.9428***	-2.2073	0.2602	7.1838***	-4.6676***	5.0411	0.3656
[16.49]	[-3.14]	[-0.14]		[18.21]	[-4.25]	[0.55]	
$H=3$				$H=4$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
8.6517***		-10.3533***	0.2539	8.6080***		-10.1939***	0.2546
[9.34]		[-3.32]		[9.73]		[-3.44]	
7.1831***	-4.4660***	6.5912	0.3755	7.1776***	-4.4060***	6.7958	0.3751
[18.97]	[-4.50]	[0.73]		[19.10]	[-4.54]	[0.74]	

Table C.13
Cross-sectional regressions of return volatilities on *spc* and *symevc*

The table reports the results from cross-sectional regressions of the return volatilities of the 14 industry portfolios on their shock propagation capacity (*spc*) and symmetrified eigenvector centrality (*symevc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *symevc* is calculated as described in Section C.7 of the Online Appendix, *spc* as in Equation (C.1). In bivariate regressions, we orthogonalize *symevc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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$H = 1$				$H = 2$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
1.5533***		-2.0594	0.1206	1.2404***		-0.8883	0.0017
[4.33]		[-1.50]		[6.31]		[-1.19]	
1.0999***	-0.4888	-2.5987	0.0437	1.1052***	-0.3677	0.3094	-0.0518
[15.60]	[-1.41]	[-1.30]		[13.76]	[-1.23]	[0.19]	
$H = 3$				$H = 4$			
const.	*spc*	*symevc*	$\bar{R}^2$	const.	*spc*	*symevc*	$\bar{R}^2$
1.1915***		-0.7033	-0.0232	1.1808***		-0.6629	-0.0281
[6.69]		[-1.06]		[6.78]		[-1.02]	
1.0994***	-0.3311	0.8877	-0.0516	1.0972***	-0.3203	0.9976	-0.0520
[13.92]	[-1.20]	[0.49]		[13.94]	[-1.19]	[0.54]	

Table C.14

Cross-sectional regressions of average excess returns on *spc* and *symevc*

The table reports the results from cross-sectional regressions of the average excess returns of the 14 industry portfolios on their shock propagation capacity (*spc*) and symmetrified eigenvector centrality (*symevc*). Within the portfolios, returns are value-weighted. Both network measures are obtained from Diebold and Yilmaz (2014) H-quarter generalized variance decompositions for $H = 1, 2, 3, 4$ (from upper left to lower right panel), applied to log industry earnings growth rates over the sample from 1966-Q2 to 2014-Q4, i.e., 686 observations in total. *symevc* is calculated as described in Section C.7 of the Online Appendix, *spc* as in Equation (C.1). In bivariate regressions, we orthogonalize *symevc* with respect to *spc*. Numbers in square brackets denote t-stats adjusted for cross-sectional heteroskedasticity. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

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D. Industries

We use the industry codes in the Industry Economic Accounts provided by the Bureau of Economic Analysis (BEA) at the sector level.[10] These are based on the North American Industry Classification System (NAICS) code structure and contain 15 groups of industries. Following Menzly and Ozbas (2010) and Aobdia, Caskey, and Ozel (2014), we exclude the government sector. We refer to the 14 industries in our network graphs in Figure C.1 as:

1. Ag: Agriculture, forestry, fishing, and hunting;
2. Mi: Mining;
3. Ut: Utilities;
4. Co: Construction;
5. Ma: Manufacturing;
6. Wh: Wholesale trade;
7. Re: Retail trade;
8. Tr: Transportation and warehousing;
9. In: Information;
10. Fi: Finance, insurance, real estate, rental, and leasing;
11. Pr: Professional and business services;
12. Ed: Educational services, health care, and social assistance;
13. Ar: Arts, entertainment, recreation, accommodation, and food services;
14. Ot: Other services, except government.

[10] Available at the BEA homepage (`https://bea.gov/industry/io_annual.htm`).

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