NETWORK CENTRALITY AND THE CROSS SECTION OF STOCK RETURNS

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ABSTRACT

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ABSTRACT

Industries that are more central in the network of intersectoral trade earn higher stock returns than industries that are less central. To explain this finding, I argue that stocks in more central industries have greater market risk because they have greater exposure to sectoral shocks that transmit from one industry to another through intersectoral trade. Consistent with this argument, stock returns of central industries covary more closely with market returns and future consumption growth. In addition, the empirical evidence suggests that sectoral shocks that contribute to aggregate risk are more likely to pass through central industries than peripheral industries.

In the 2011 Presidential Address to the American Finance Association, John Cochrane proposes an ambitious agenda to advance asset pricing research. Central to the agenda is a better understanding of the causes of systematic risk. In particular, why do some stocks have high betas and others have low betas? Some answers have already been proposed. One line of research decomposes betas into discount rate betas and cash flow betas (Campbell and Mei, 1993; Campbell and Vuolteenaho, 2004). Another line of research connects betas to corporate policy in production-based models of investment (e.g., Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004). Although these papers make important connections between systematic risk and economic primitives, most of this prior research assumes that market betas are exogenous. Given that exposure to market risk is at the heart of much of financial economics, it is imperative that we continue to investigate its root causes.

I propose a new explanation for market risk that is based on an industry's intersectoral trading relations. In the recent theory of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), intersectoral trade relations are a conduit through which sector-level shocks transmit across the economy. The key insight of their model is that if the linkages in the intersectoral trade network are sufficiently asymmetric, then sectoral shocks might not cancel out through diversification, but instead may aggregate into macroeconomic fluctuations. Take an oil embargo for example. First, refineries produce less gasoline, then shipping companies have higher costs, and later, internet retailers are less profitable. The shock originates at the sector-level, then spreads through customer-supplier relations to form an aggregate shock at the economy-level.

If sectoral shocks drive aggregate volatility, then a firm that is more exposed to sectoral shocks will have greater exposure to economy-wide market risk. Modeling the economy as a network of intersectoral relations, exposure to sectoral shocks is determined by a sector's relative position in the network. In particular, shocks are more likely to pass through central sectors than peripheral sectors. This argument provides a microfoundation to understand the causes of market risk.

Based on these arguments, I investigate three main questions in this paper: 1) Do central sectors earn higher stock returns than peripheral sectors? 2) Does centrality help explain why some stocks have greater market risk than others? And 3) do stock returns reflect the transmission of economic shocks over the network through time?

To address these questions, I construct an empirical network model of trade flows between all sectors of the economy, including industries, households, government, capital, and a foreign sector. First, following Ahern and Harford (2012), I construct the network of inter-industry trade flows using the Input-Output tables from the U.S. Bureau of Economic Analysis (BEA) from 1982 to 2002. I then append households, government, capital, and the foreign sector using data from the National Income and Product Account (NIPA) tables. This empirical model provides a complete network of all economic transactions between roughly 500 disaggregated sectors over a 20-year span. To my knowledge, this is the first network representation of the entire U.S. economy.

Using techniques from graph theory, I then calculate the centrality of each sector in the economy. By measuring an industry's economic connections to all sectors of the economy, including public, private, and government entities, centrality may provide additional information to estimate true market risk beyond betas estimated using only ex post stock returns of publicly-traded firms.

I find that industries in the highest quintile of centrality have average equal weighted monthly stock returns over 1983 to 2007 that are 27 basis points higher than industries in the lowest quintile of centrality. This result is statistically significant and economically meaningful. The same pattern is present in unlevered returns too, which suggests that the higher returns earned by central industries are compensation for operating risk, not financial risk.

The positive relationship between centrality and returns could be influenced by other industry characteristics. In particular, central industries have larger firms and greater concentrations of customer and supplier industries. In double-sorted portfolios that control for industrial concentration and firm size, stock returns remain positively and significantly related to centrality, with a positive interaction between centrality and supplier concentration. Industries that are central and have concentrated suppliers earn the highest average stock returns of all double-sorted portfolios. This result is consistent with the idea that greater concentration magnifies the higher returns earned by more central industries.

Next, I investigate whether centrality proxies for market risk. To test the relationship between industry centrality and aggregate risk, I form a Central Minus Peripheral (CMP) portfolio, by subtracting the returns of the industries in the lowest tercile of centrality from those in the highest tercile. CMP is positively correlated with the market risk premium and SMB, the size-mimicking portfolio of Fama and French (1993). In contrast, it is negatively correlated with Fama and French's value factor, HML, and uncorrelated with the momentum factor of Carhart (1997). The positive correlation with the market return is consistent with the hypothesis that central industries contribute more to aggregate risk and have larger market betas than do peripheral industries.

In two-stage cross-sectional regressions, I find that CMP is positively and significantly related to the returns of three-digit NAICS industry portfolios and firm-level returns. This relationship holds after controlling for the Fama-French and momentum factors. In addition, the inclusion of CMP in the cross-sectional tests increases the coefficient on the market beta and substantially reduces the magnitude and significance of average mispricing. In contrast, CMP has no power to explain cross-sectional variation in the Fama-French 25 size and book-to-market portfolios. In further industry-level cross-sectional tests, I also control for other variables that could relate to centrality, including within-industry sales concentration, the scope of industry activities, the fraction of input costs paid to labor, and the number of firms in an industry. After controlling for all of these alternative explanations, I still find a strong positive relation between an industry's average stock returns and its centrality in the economy.

I next show that centrality is related to macroeconomic outcomes. Controlling for a recession indicator, macroeconomic uncertainty, and a linear time trend, CMP has a significant correlation with future real nondurable consumption growth. These results persist if I also control for the Fama-French and momentum factors. These findings suggest that central industries in the intersectoral network have greater exposure to real aggregate risks, not just financial risk.

In the final set of cross-sectional tests, I show that the adjusted R^2s in time-series factor regressions on portfolios sorted by centrality increase almost monotonically as centrality increases. This is consistent with the idea that risk factors that explain average returns explain more of the variation in returns of industries that are more closely tied to the overall economy. These results also imply that shocks that pass through peripheral industries are less likely to contribute to market risk than are shocks that pass through central industries.

I acknowledge that the cross-sectional evidence in this paper is consistent with multiple interpretations. First, the evidence is consistent with the idea that centrality in the network of intersectoral trade helps determine exposure to market risk. In this interpretation, centrality provides a micro-foundation for market betas. Alternatively, if the four factor model is incomplete, the positive and significant coefficient on centrality in the two-stage regression test is consistent with the idea that centrality captures exposure to an omitted factor. Thus, in the spirit of Daniel and Titman (1997), centrality could proxy for an unknown risk factor, or alternatively, it could be a characteristic for market beta. A third alternative is that the significant coefficients in these tests could be caused by poorly measured ex post market betas (Blume, 1971; Elton and Gruber, 1973), regardless of the accuracy of the four factor model. Centrality may simply be a better proxy for the true ex ante beta. Without knowing the true model of returns and the true betas, it is impossible to disprove any of these different interpretations.

To address the third question of the paper, I investigate the diffusion of shocks across the network. In particular, if shocks diffuse in a wave-like pattern across the topology of the network, then an initial shock will affect distantly connected industries with a delay, and closely connected industries more immediately. While real economic shocks could travel slowly across the economy, if investors are rational, stock prices should account for the effects of spillovers to other industries immediately. However, recent evidence shows that investors have limited attention and do not immediately account for spillovers to even the most directly connected firms (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Thus, the timing of stock price reactions to shocks in distantly connected sectors may mirror the delay of the real economic effects.

To test for a positive relationship between the effect of network distance and time lags on returns, I use Dijkstra's (1959) algorithm to calculate the number of steps in the shortest path between every industry-pair. Then, for every industry, I use this calculation to separate close and distant industries in network space. I regress an industry's stock returns on the returns of close and distant industries for a series of time lags, while controlling for autocorrelation and monthly calendar-time fixed effects. Consistent with the diffusion of shocks across the network, I find two results: *i*) there is a positive correlation between an industry's returns and the returns of close industries in months $t-1$ to $t-3$; and *ii*) there is a positive correlation between an industry's returns and the returns of distant industries in months $t-10$ to $t-12$. Thus, shocks to distant industries have delayed effects compared to close industries. These results provide evidence that product market links are one conduit through which sector-level shocks diffuse across the economy. This evidence is consistent with the idea that centrality helps to determine market betas because centrality captures exposure to aggregate volatility formed through sectoral shocks.

The primary contribution of this paper is a new microfoundation to understand market risk based on real economic relations. In this vein, this paper contributes to research that connects stock returns to economic fundamentals (Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003; Carlson, Fisher, and Giammarino, 2004; Zhang, 2005; Hou and Robinson, 2006). Whereas these papers study within-industry characteristics, my paper emphasizes the importance of connections between industries to explain systematic risk. I believe this is an important advance because it more closely matches the idea that an asset's risk is driven by its covariance with the entire economy, not just its own individual characteristics. Second, this paper provides new insight into the evidence presented in Hong, Torous, and Valkanov (2007). They find that a subset of industries' returns lead the overall market return. Consistent with my results, the leading industries they identify are those that are the most central, such as real estate and finance. Centrality provides an explanation for this result based on economic fundamentals.

This paper also relates to recent work that studies networks in finance. Most closely related, Kelly, Lusting, and Van Nieuwerburgh (2013) study how firm-level product market connections influence the firm size distribution and the volatility of firm-level growth rates. While they focus on the effect of diversification on volatility at the firm-level, my study focuses on the role of centrality for average returns at the industry-level. In addition to industry networks, information and banking networks have also been studied both theoretically and empirically in prior research (Allen and Gale, 2000; Ozsoylev and Walden, 2011; Billio, Getmansky, Lo, and Pelizzon, 2012).

I. Hypothesis

The central hypothesis of this paper is that an industry's true market beta is determined, in part, by its centrality in the network of intersectoral trade. There are three important assumptions that underlie this hypothesis. First, it assumes that sector-level shocks can aggregate to form economy-wide shocks. Second, it assumes that sector-level shocks transmit across the economy through intersectoral trade links. And third, it assumes that sectoral shocks do not cancel out through diversification. I discuss each of these assumptions below.

First, systematic shocks are likely to originate in multiple ways. One way that a shock could originate is through an unexpected macroeconomic event, like a policy change at the central bank. This type of shock could have immediate and direct effects on most sectors of the economy simultaneously.

Another way that a systematic shock could originate is from a sector-level shock. A shock to technology, preferences, or natural resources often impacts just one or two sectors at a time. For example, the invention of interchangeable parts had a profound impact on productivity in manufacturing, but little direct impact on service sectors, such as lodging and bookkeeping. Another example is the passage of the North American Free Trade Agreement (NAFTA), which caused meaningful changes in supply and demand for automobiles, textiles, and agriculture and relatively small changes for energy and education (Villarreal and Fergusson, 2013). Even macroeconomic policy events, such as changes in monetary policy, have a more immediate effect on certain industries, such as banking, compared to others, such as legal services and car repair shops, for example.

For a sector-level shock to generate a systematic shock, it must spread to the entire economy. The second assumption of the hypothesis is that sectoral shocks spread across the economy through intersectoral trade relations. A shock to the economic fundamentals of an industry, such as a technology shock, can affect the industry's output, as well as its demand for inputs. In a circular flow diagram of an economy, all outputs are also inputs in another sector of the economy. Thus, an initial shock to one sector is likely to spill over to other industries through customer-supplier relations. Since all sectors are connected to some degree, a shock to any sector has the potential to influence at least one other sector.

To be clear, I do not claim that product market links are the only way in which shocks could be transmitted across an economy. Shocks could also transmit through common ownership links or geographic proximity, for example. I only make the weak assumption that product market links are one way in which sectoral shocks could travel through an economy.

The third underlying assumption of this paper is that random sectoral shocks do not cancel out. If a positive shock in one industry is balanced by a negative shock in another industry, on average, the economy would be unaffected. In the macroeconomics literature, diversification has long been the counter-argument to the importance of sectoral shocks for aggregate volatility. However, recent theoretical research by Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) overturns this view. The diversification argument assumes that trade connections between sectors are uniform and random. In a simple network model, Acemoglu et al. (2012) relax this assumption and show that when the intersectoral trade network is characterized by asymmetric sectors with non-uniform connections, randomly occurring sectoral shocks do not cancel each other out through diversification. Instead, sectoral shocks can aggregate to form economy-wide volatility. Intuitively, diversification across input-output linkages is based on the law of large numbers. When the intersectoral linkages are not symmetric, the law of large numbers does not hold.

Acemoglu et al. (2012) and Ahern and Harford (2012) present empirical evidence consistent with this theory. They show that the intersectoral trade network in the U.S. is asymmetric: there are large numbers of industries with few connections and few industries with many connections. Ahern and Harford also show that the asymmetric network structure has important consequences for the diffusion of economic shocks. In particular, their evidence suggests that economy-wide merger waves are formed by the aggregation of industry-level merger waves that spill over through product market connections. The asymmetry in the network creates a cascade of merger activity, similar to the volatility cascades in the theory of Acemoglu et al. (2012).

If local shocks aggregate to form economy-wide volatility, this volatility will affect asset prices. Appealing to the first two assumptions discussed above, if shocks originate sectorally and flow through trade relations, those industries that are more connected to the overall economy through input-output linkages have greater exposure to shocks. Appealing to the third assumption, the exposure to these shocks cannot be avoided through diversification. This leads to the hypothesis that industries that are more connected to the overall economy through input-output linkages earn higher returns as compensation for greater exposure to systematic market risk.

Using a network of economic connections to understand systematic risk is appealing because it mirrors the intuition of most asset pricing models. In most models, systematic risk is not driven by an asset's own idiosyncratic volatility. Instead, an asset's exposure to systematic risk is based on its relationship with the entire economy. Following this logic, the underlying source of systematic risk should also reflect the relationship between an asset's economic fundamentals and the overall economy's fundamentals. This relationship is precisely what the economic network captures.

The hypothesis of this paper also depends on the meaning of network centrality. So far, I have only loosely described this concept as intersectoral connections. In the next section, I provide specific formulas to calculate centrality such that an industry's centrality is directly related to its exposure to random shocks that propagate through the network.

II. The Network of Intersectoral Trade

To understand potential sources and transmission mechanisms of market risk, I construct a network of all economic transactions within the economy. This network is based on a modified social accounting matrix (SAM). A SAM presents an account of the circular flow of transactions between a complete set of economic agents, including production activities (industries), factors of production (capital and labor), and institutions (households, foreign sector, and government). Each row of the SAM provides the receipts of an agent and each column provides the expenditures, with total receipts equal to total expenditures for each agent in the economy. A SAM can be thought of as an expanded input-output (IO) table, that includes flows between government, a capital account, and a foreign sector.

A. Social Accounting Matrix

Though SAMs are commonly used in other countries, to my knowledge, there is no published SAM matrix for the U.S. Therefore, I construct the SAM using data from the Input-Output (IO) tables and the National Income and Product Account (NIPA) tables provided by the Bureau of Economic Analysis (BEA). The IO tables provide transaction values between suppliers and customers for all sectors of the economy, including manufacturing, service sectors, and government purchases at a disaggregated industry-level.

The BEA provides IO tables dating back to 1947 with updates every five years. While the updates help to maintain consistency in industry homogeneity, accounting for technological advance, the industry definitions change in each report. This makes it impossible to analyze the same set of industries over time, while accounting for changing trade patterns. In addition, before 1982, the reports do not contain enough information about employee compensation to account for all flows in the economy. Therefore, I create five separate SAMs using the data reported by the BEA in 1982, 1987, 1992, 1997, and 2002, the most recent report available. In this section, I provide details of the construction of the SAM using 1997 data, though the other years are constructed with only minor differences. The Internet Appendix provides more details for the other years.

To construct the SAM, I start by creating an IO table using the 'Make' and 'Use' tables reported by the BEA, as in Ahern and Harford (2012). These tables report the flow of close to 500 commodity outputs by a similar number of producing industries or final users. The number of industries and commodities change in each IO report year. A commodity, as defined by the BEA, is any good or service that is produced, including all sectors of the economy, not just manufacturing. The 'Make' table records the dollar value of each commodity produced by the producing industry. The 'Use' table defines the dollar value of each commodity that is purchased by each industry or final user. I create a matrix that records industry-to-industry trade flows, rather than commodity-to-industry flows, accounting for each industry's fraction of the total production of each commodity. See Ahern and Harford for a detailed description of the inter-industry matrix.

I make a few changes to the procedure in Ahern and Harford, because I wish to capture a complete representation of all trade flows, not just inter-industry flows. Therefore, I include imports and exports, used and secondhand goods, government enterprise, and other taxes and adjustment costs. Using the 1997 data, this produces a matrix of 478 producing industries, plus an industry that accounts for scrap, inventory adjustments, and used goods.

I append four additional large sectors to complete the economy: government, households, capital, and the foreign sector, for a total of 483 economic sectors in the 1997 SAM. From the IO tables, I aggregate government expenditures (consumption and investment) for both Federal and local governments. I use data from the NIPA tables to record government receipts from industry, households, capital, and foreign sectors. Household expenditures across all industries is recorded from the 'Personal consumption expenditures' item of the IO tables. Household taxes are from the NIPA tables, as is household income from government transfers and the capital account. Flows to the capital and foreign sectors are computed using IO and NIPA data. See the Internet Appendix for more details.

Table I presents the aggregated SAM for 1997, where for the sake of brevity, the economic activity of all 479 producing industries is compressed into one entry for firms. In the analysis, I use the disaggregated industries as the unit of observation.

Panel A of Table I shows that in 1997 firms spent \$6.5 trillion on intermediate inputs, \$4.7 trillion on labor, invested \$2.6 billion in capital, and paid \$1.3 trillion to the government. Of the \$16 trillion in total firm output, \$6.5 trillion was purchased by other firms, \$5.6 trillion was consumed by households, and \$1.6 trillion was transferred from government. The majority of household income was from labor (\$4.7 trillion), followed by capital (\$1.4 trillion), and government transfers (\$0.9 trillion). Finally, the foreign sector purchased \$822 billion from firms, \$44 billion from households, and paid tax of \$5 billion to government. Foreign receipts include \$944 billion from firms in the form of imports, \$998 million in capital gains, and \$24.9 billion in government spending. The trade deficit is \$98.7 billion, recorded as foreign spending towards the capital account.

Panel B of Table I normalizes the dollar flows by total expenditures. Thus, 40.7% of firm expenditures went towards intermediate goods sold by other firms and 29% went to labor. Of total household expenditures, 80.1% went to firms and 18% went to the government. In Panel C, I normalize by total receipts. Firms received 40.7% of total receipts from other firms and 35% from households. Households received 66.4% of their income from firms, in the form of labor compensation, and 13.3% from government transfers. These representations of the SAM serve to normalize the large differences in sector size.

The sector-to-sector flows are highly persistent over the 20 years from 1982 to 2002. Figure 2 illustrates the persistence in intersectoral relations. The fraction of firms' expenditures received by households is roughly 30% in every year. Likewise, the fraction of firms' expenditures that go to the capital account and to the government are highly persistent. The most notable change from 1982 to 2002 is the decline in the savings rate of households. In 1982, 9% of households' expenditures is received by the capital account. By 2002, the savings rate is 0.3%. The decline in savings is offset by a corresponding increase in households' purchases from firms. These results confirm the widely documented decline in the savings rate in the U.S. For complete details, Internet Appendix Table I presents the same information for all IO report years from 1982 to 2002.

Because the SAM is based on complete data from all economic sectors, not just industries, and not just publicly-traded firms recorded in Compustat and CRSP, this network is an empirical snapshot of a closed-economy model. In contrast to focusing on only inter-industry connections, the SAM provides a complete picture of the economy where all sectors' outputs and inputs balance. This provides an important benefit over the partial equilibrium approach in Ahern and Harford (2012) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), because it allows for the identification of the full effect of a shock to any particular sector.

B. Network Representation of Intersectoral Transactions

The trade flows of a SAM can be interpreted as connections in a network of economic sectors. In general, a network is defined by a set of nodes that are connected through edges. A network is represented by a square 'adjacency' matrix, denoted A, where each entry a_{ij} for row i and column j indicates the connection between node i and j. The matrix can be asymmetric, which allows directional relations, and the edges can be weighted to measure the strengths of the connections. Thus, to translate a SAM to a network setting is straightforward. The nodes in the network are the industries, plus the household, government, capital, and foreign sectors. The trade flows recorded in the SAM represent the strength and direction of the connection between agents. Considering the SAM as a network, rather than simply a matrix of expenditures and receipts affords the use of a wide range of techniques developed in graph theory and social network literatures.[1]

To illustrate how the SAM network can be used to trace sector specific shocks, consider a \$1 exogenous increase in household income. Using the network of suppliers in Panel B of Table I, of this \$1.00, \$0.80 will be used to purchase goods from firms, \$0.02 will be spent on the capital sector, and \$0.18 will be transferred to the government. If we continue to trace the effect of the shock, of the \$0.80 received by firms, $40.7\% \times \$0.80 = \$0.33$ will be retained by firms through spending on intermediate goods, $29.0\% \times \$0.80 = \$0.23$ will be spent on labor compensation, $16.3\% \times \$0.80 = \$0.13$ will be invested in capital, $8.2\% \times \$0.80 = \$0.07$ will be paid to the government, and $5.9\% \times \$0.80 = \$0.05$ will be sent to the foreign sector. The same calculations

[1]This insight was first made in Ahern and Harford (2012) using inter-industry IO relations. For a detailed introduction to networks in finance, see the Internet Appendix of their paper.

will show where the \$0.02 received by the capital sector and the \$0.18 received by the government will be spent.

Alternatively, the SAM network can be thought of as a Markov matrix, where each entry represents the transition probability that a shock moves from one sector to another. For instance, a shock to household income will be followed by a shock to industries 80% of the time, a shock to the capital sector 2% of the time, and a shock to the government 18% of the time. The Markov matrix interpretation highlights the importance of accounting for a closed-economy where no sectors are omitted and there are no sink sectors where shocks get completely absorbed.

As the exogenous shock transmits across the SAM network, a stable outcome emerges. This outcome is calculated as A^{∞}, which shows that for a \$1 exogenous shock anywhere in the economy, firms receive \$0.54, households receive \$0.24, the capital sector receives \$0.10, the government receives \$0.09, and the foreign sector receives \$0.03. Because this is a closed economy, tracing shocks through customer relations, as in Panel C of Table I, provides an identical result. This stable equilibrium concept is directly related to network centrality, discussed next.

C. Network Centrality

A number of measures have been developed to quantify centrality in networks. These include degree, closeness, betweenness, and eigenvector centrality. To use the correct measure for the flow of economic shocks in the intersectoral trade network, we must consider the assumptions that underlie each measure. Borgatti (2005) reviews these measures and classifies them based on assumptions about how traffic flows in a network. Network traffic could be assumed to follow a walk (an unrestricted sequence of nodes and links), a trail (a sequence in which no link is repeated), a path (a sequence in which no link or node is repeated), or a geodesic path (the shortest path between two nodes). Second, network traffic can be assumed to spread in serial (through only one path at a time), or in parallel (through multiple paths at the same time).

Though making generalizations about sectoral shocks is problematic, one can make a few reasonable assumptions about how shocks may flow from one sector to another. First, regardless of how an economic shock is defined, it is unlikely to follow a geodesic path. Only traffic that has a known destination follows a geodesic path through the shortest distance (e.g., a courier delivering a package). In contrast, economic shocks that transmit across an economy do not have final recipients and are unlikely to follow the shortest path between industries. According to Borgatti (2005), this means that closeness and betweenness centrality are inappropriate for economic shocks since they implicitly assume that traffic follows geodesic paths.

Second, economic shocks are likely to have feedback effects. A supply shock in one industry could affect the supply of downstream industries, which eventually could flow back to the original industry. For instance, an oil shock could affect the cost of gasoline, which affects transportation costs, which could then affect the oil industry. Just because a shock originated in the oil industry does not imply that it is immune from a subsequent transportation shock. Thus, economic shocks are unlikely to be restricted to follow paths or trails, in which nodes and links are not repeated. This rules out degree centrality.

Based on these assumptions, eigenvector centrality is the most appropriate measure for inter-sectoral trade networks. Eigenvector centrality is calculated as the principal eigenvector of the network's adjacency matrix (Bonacich, 1972). Nodes are more central if they are connected to other nodes that are themselves more central. As presented in Ahern and Harford, if we define the eigenvector centrality of node i as c_i, then c_i is proportional to the sum of the c_j's for all other nodes $j \neq i$: $c_i = \frac{1}{\lambda} \sum_{j \in M(i)} c_j = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} c_j$, where $M(i)$ is the set of nodes that are connected to node i and λ is a constant. In matrix notation, this is $\mathbf{A}\mathbf{c} = \lambda \mathbf{c}$. Thus, $\mathbf{c}$ is the principal eigenvector of the adjacency matrix.

The intuition behind eigenvector centrality can be seen in two different settings. First, eigenvector centrality is related to principal components analysis (PCA). PCA is designed to describe the covariance structure of a set of variables by identifying the primary directions in which the data vary. By identifying the directions, PCA seeks to reduce the dimensionality of the covariance to common factors. To identify these factors, PCA computes the eigenvalues and eigenvectors of the covariance matrix of the variables. The largest eigenvalue corresponds to the principal component and its associated eigenvector describes the direction (in a spatial representation) that accounts for the greatest variation in the data. The variable loadings on the principal component represents how the correlation of each variable contributes to the component's explanatory power.

Eigenvector centrality is calculated analogously, but instead of using statistical correlation as a measure of connectedness, eigenvector centrality uses the adjacency matrix, which in this case is based on intersectoral trade flows. Just as the variable loadings in PCA indicate the contribution of each variable's correlation to the largest source of variation in the data, eigenvector centrality calculates each industry's contribution to the most important source of connectivity in the network.

A recent paper highlights the similarity between PCA and eigenvector centrality. Billio, Getmansky, Lo, and Pelizzon (2012) perform a PCA on the returns of financial intermediaries to analyze systemic risk in the financial sector. They interpret each intermediary's loadings on the principal component as a measure of connectedness. Another way to view their results is that they have calculated eigenvector centrality using the variance covariance matrix of asset returns as a measure of connectedness.

The second setting that might provide greater intuition behind eigenvector centrality is Markov transition matrices, as mentioned above. According to the Perron-Frobenius theorem, every Markov matrix has an eigenvector corresponding to the largest eigenvalue of the matrix. This vector represents the stable stationary state. Equivalently, this vector can be found by multiplying the transition matrix by itself an infinite number of times, as discussed above. As long as the matrix has no sink states, then a non-trivial stationary distribution will arise in the limit. If we consider the normalized SAM matrix as a Markov matrix, eigenvector centrality represents the stationary distribution that would arise as a shock transitioned from one sector to another an infinite number of times. In the Markov matrix interpretation, eigenvector centrality represents the long-run proportion of time that a transitory shock is in a particular sector.

In sum, eigenvector centrality provides a measure of how important a node is in a network. In the case of the SAM network, it directly measures the strength of trade flows of a sector, considering the importance of the sectors to which it is connected. Equivalently, by tracing out all paths of a random shock in a network, eigenvector centrality also measures the likelihood that a sector will receive a random shock that transmits across the network.

III. The Empirical Relationship Between Centrality and Returns

To test the hypothesis that more central industries earn higher returns, I compare industry-level centrality using the SAM network and industry-level stock returns over 1983 to 2007. First, I compute eigenvector centrality using the fully disaggregated SAM network of roughly 500 sectors normalized by sector size, as described above. Because the SAM is balanced, with the row sums equal to column sums, eigenvector centrality computed using either the supplier network or customer network is identical.

Second, I collect stock price information from the Center for Research in Securities Prices (CRSP) Monthly Stocks data set for stocks with share codes 10 or 11 from January 1983 to December 2007. Following prior research, I omit observations where the stock price is less than five dollars to avoid liquidity effects (e.g., Jegadeesh and Titman, 2001; Diether, Malloy, and Scherbina, 2002). For each firm in the data set, I match the firm's 6-digit historical NAICS code or 4-digit SIC code (depending on the IO report year) to the IO industry codes based on the concordance tables provided by the BEA, following Ahern and Harford (2012). I then form equal-weighted industry-level portfolios, rebalanced monthly, using industry definitions from the most recent IO report year. The availability of stock price information limits the sample to a subset of the entire SAM network. For example, in 1997 out of 483 sectors, 385 have stock price data over the following five years.

A. Summary Statistics of Centrality

In Table II, I present a wide-range of summary statistics for eigenvector centrality for all sectors in the complete 1997 network and for the 385 sectors with publicly-tradable stocks. Since the centrality measure is skewed, I take the log of centrality in these statistics and in later tests. Figure 1 presents a histogram of the empirical distribution of log(centrality). As shown in the figure and statistics, log(centrality) is slightly skewed positively and has excess kurtosis of about 0.5. Comparing sectors in the entire network to those in the tradable network, the centrality of an average sector is slightly higher and the variance slightly lower in the tradable network. The largest difference between the complete set of sectors and the tradable set is that though a number of peripheral industries do not contain tradable stocks, the omission of the large aggregated sectors of household, capital, and government, substantially reduce the positive skewness of centrality.

This can be seen by comparing the 99th percentile to the maximum in both distributions. In the complete set of sectors, the maximum of log(centrality) is -0.182 and the 99th percentile is -2.234. In the tradable sectors, the maximum is -2.342, compared to the 99th percentile of -2.821.

To put these numbers in economic magnitudes, the mean of centrality is about 0.15%, and the most central sector, Retail Trade, has a centrality of about 10%. Following the Markov transition matrix intuition, this means that a random shock that propagates through the network is likely to hit an average sector about 0.15% of the time. For comparison, if sectors were all equally central, and a Markov shock was equally-likely to pass through all sectors, a shock would hit the average sector more often: about $100\%/483 = 0.21\%$ of the time. The skewness in the centrality of industries reflects the asymmetric nature of the network. As Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) show, this asymmetry is what allows volatility cascades to form, rather than to be canceled by diversification.

Internet Appendix Table II presents summary statistics of centrality for the complete networks in all IO report years 1982 to 2002. The distributions are nearly identical in all years.

B. Univariate Results

Figure 3 compares industry-level average monthly returns to log(centrality). Each circle represents one of the 385 industries in 1997. The industries are grouped according to large sectoral divisions, such as Fabricated Metal Manufacturing, Electrical Equipment, and Services. Each large division's fraction of the total circle is proportional to the division's fraction of the total number of industries. The distance of each industry from the center of the circle is based on its log(centrality), normalized by subtracting the maximum log(centrality) to avoid emptiness in the center of the figure. Industry average monthly returns from 1998 through 2002 are indicated by the darkness of each circle, where lighter colors indicate higher returns.

This figure reveals a number of relationships. First, the industries with the lowest returns are the least central industries, represented by the dark circles near the outside edge of the figure. Industries that are more central, and closer to the center of the figure, have higher average returns. Second, the centrality of industries varies by the large sectoral divisions. In particular, the Service industries are all relatively central in the economy, compared to industries in the Machinery Manufacturing division. Similarly, industries in the Wholesale, Retail, and Transportation division are all relatively central, with retail and wholesale being the most central industries. The Miscellaneous Manufacturing division is characterized by periphery industries, which is intuitive, given that the industries are not important enough to be classified in any large division.

In Table III, I sort industries into five quintiles based on centrality. Quintile portfolios are formed using the centrality of a sector in the most recent IO report year. Panel A of Table III presents the average time-series monthly returns from 1983 to 2007 for four portfolios of equal or value-weighted and levered or unlevered returns. Levered returns are the raw industry returns. Unlevered returns are calculated following Bernardo, Chowdhry, and Goyal (2007).[2] Because the shocks that are likely to pass through the economic network are shocks to operations, rather than financing, unlevered returns are perhaps a better estimate. Levered and unlevered returns are aggregated to the quintile portfolio using either equal or value-weights, in which value-weighted portfolios are based on an industry's average firm market equity, rebalanced monthly.

The equal weighted portfolio of the lowest quintile of centrality has an average levered stock return of 1.69% per month, compared to 1.96% per month for industries in the highest quintile, a statistically significant difference. For unlevered returns, the lowest centrality quintile has an average return of 1.49% and the highest has an average return of 1.70%, also statistically significant. For portfolios of value weighted returns, there is no statistically significant difference across the quintiles of centrality. This suggests that firm size may affect the relationship between centrality and stock returns.[3]

The economic magnitude of the relation between centrality and equal weighted stock returns is meaningful. For levered returns, the difference is roughly 27 basis points per month between the highest and lowest quintiles of centrality. This translates into a difference between the extreme

[2]The calculation is $r_U = \frac{r_E}{1+(1-\tau)D/E}$, where r_U is the unlevered return, r_E is the unadjusted equity return, τ is the marginal tax rate, and D/E is the firm's debt-to-equity ratio. The D/E ratio is computed from Compustat data. I use firm-level marginal tax rates generously provided by John Graham.

[3]Value-weighted portfolios could display smaller spreads because they are dominated by multi-divisional firms. The industry centrality of these firms is likely to be less precisely estimated.

quintiles of approximately 3.2 percentage points per year. The increase in returns from low centrality to high centrality portfolios is roughly monotonic and spread across the quintiles, though there is a greater jump in returns at lower quintiles. This probably reflects the skewness in centrality.

Other variables may explain the relation between centrality and stock returns. First, diversification may be important. From a corporate decision-making point of view, diversification provides a co-insurance effect for firms that operate in different industries (Lewellen, 1971). In contrast, I consider diversification from an industrial organization point of view, where an industry's production function determines diversification exogenously. In particular, some industries are characterized by using a few, but relatively important inputs in production. Others use a wide variety of inputs, none of which is relatively large. Likewise, some industries have a wide customer base, whereas others sell primarily to a few large customer sectors. A shock that reaches an industry that has few, but important, customer or suppliers may have a greater impact than a shock that reaches an industry with many small customers or suppliers, where the industry is diversified (Kelly, Lusting, and Van Nieuwerburgh, 2013)

To measure industrial concentration, I compute the Herfindahl concentration ratio for customer and supplier industries. These ratios are based on the fraction of an industry's total receipts that are received by the industry's customer sectors, and the fraction of an industry's total expenditures that are sent to the industry's suppliers. All sectors, including government, households, industry, capital and foreign sectors are included in the calculations.

Panel B of Table III shows that more central industries have more concentrated customers and suppliers. Using eigenvector centrality allows for more central industries to have more concentrated connections because it accounts for higher order connections. If an industry has concentrated links to few industries, but those industries are also central, the first industry can be central itself. Second, centrality is related to average firm size. More central industries also have larger firms, increasing monotonically from the first to the fifth centrality quintile.

C. Double-Sorted Portfolios

To account for a possible interaction between industrial concentration, firm size, and centrality, I double sort industries into nine portfolios. I first sort industries into terciles by either an industry's average market equity, its concentration of customers, or its concentration of suppliers. Within each of these terciles, I sort industries into five terciles of network centrality. This two-stage sorting ensures that there are enough observations in each tercile-pair.

Table IV lists a sample of five industries in the extremes of these double sorts for the 1997 data, omitting non-industrial sectors such as households and government. Panel A presents the extreme size-centrality pairs. Industries with the lowest centrality and also the lowest average firm size include household vacuum cleaners, musical instruments, and explosives. These industries do not have strong connections to other industries and also are dominated by small firms. Industries such as mattress manufacturing, elevators, and industrial gases are dominated by large firms, but are not central in the intersectoral network. More central industries include frozen food, ready-mix concrete, hospitals, and petroleum refineries. Frozen food and ready-mix concrete industries are characterized by small firms on average, compared to hospitals and refineries, which are characterized by large firms.

Panels B and C present sorts on concentration of customers and suppliers. The industries with the least concentrated customers and lowest centrality include iron forging, nonwoven fabric mills, and stationary manufacturing. The industries with the greatest centrality, but least concentrated customers include truck transportation, semiconductors manufacturing, and nondepository credit intermediaries, which includes pension funds and credit card companies. However, fabric mills and stationary are not centrally located in the economy, whereas truck transportation and semiconductors are. These samples of industries provide a sense of which industries are more central and how centrality interacts with firm size and industrial concentration.

Table V presents average monthly returns from 1983 to 2007 for the nine double-sorted portfolios, for both equal and value weighted returns. Panel A shows that the positive univariate relation between centrality and average stock returns is primarily present among industries with smaller firms. In the first tercile of size, more central industries earn significantly higher stock returns. In the second tercile of size, there is a positive, but insignificant relationship. In addition, among the least central industries, the industries with larger firms earn higher stock returns. Both of these results are present in both equal and value weighted portfolios.

Sorting by customer concentration in Panel B, I find that though stock returns increase with centrality in the equal weighted portfolios, there is no statistically significant difference between the highest and lowest terciles. In Panel C, sorting by the concentration of suppliers, I find a positive relation between centrality and stock returns driven by the industries with the most concentrated suppliers, in both equal and value weighted portfolios.

These results suggest that there is a positive relationship between centrality and stock returns, though the relationship is influenced by firm size and concentration of suppliers and customers. In particular, Table V shows that when centrality is high, greater concentration of suppliers and customers is associated with significantly higher stock returns. Industries that are more central and prone to receive a shock through product market relations and that also have less diversified suppliers and customers experience the highest average stock returns of all of the nine double-sorted portfolios. These results are consistent with the importance of diversification in inter-firm networks, as argued by Kelly, Lusting, and Van Nieuwerburgh (2013).

IV. Centrality and Market Risk

In this section, I test whether centrality provides an economic microfoundation for understanding exposure to market risk. Assuming that some aggregate shocks are formed by sector-level shocks, more central industries should have greater exposure to market-wide risk. To understand whether exposure to market risk is characterized by centrality, I create a portfolio of central minus peripheral (CMP) monthly returns over January 1983 to December 2007. CMP is formed by subtracting the monthly returns of the lowest centrality tercile from the returns of the highest centrality tercile. Returns are the equally-weighted industry returns, value-weighted across industries in each tercile. Though the BEA data are updated every five years, this portfolio allows me to generate a continuous time series of returns.

A. Correlation Between Market Returns and Centrality Returns

Table VI presents summary statistics of the Fama-French and momentum factors, plus the CMP portfolio. Panel A shows that the CMP portfolio has average and median monthly returns of 17 basis points (bps), with a standard deviation of 2.75%. This compares to average returns of 65 bps for $R_M - R_F$, 4 bps for SMB, 40 bps for HML and 76 bps for UMD. Panel B presents correlation coefficients between the factors. CMP is significantly positively related to the market excess return and SMB, and negatively related to HML.

These results are consistent with the hypothesis that centrality is related to market risk. Central industries covary more with market returns than peripheral industries. The positive correlation between CMP and SMB and the negative correlation with HML are consistent with this interpretation as well since small stocks and stocks with low book-to-market ratios tend to have higher market betas.

B. Two-Stage Cross-Sectional Regressions

Following standard practice in the literature, I run cross-sectional regressions on the 25 size and book-to-market (B/M) portfolios used by Fama and French (1993). However, as argued by Lewellen, Nagel, and Shanken (2010) and Daniel and Titman (2012), the inherent factor structure of the size-B/M portfolios means that many additional factors are likely to correlate with these portfolios. At the same time, these portfolios do not capture cross-sectional variation in other, unspecified dimensions of variation. As recommended by Lewellen et al. (2010), I use two additional sets of portfolios to test the cross-sectional properties of the factors: 1) 74 portfolios of NAICS three-digit industries, and 2) firm-level returns.

As is convention, in the first stage of the cross-sectional tests, I estimate within-portfolio contemporaneous correlations between the factors and the CMP portfolio returns in the following time-series regressions:

$$R_{i,t} - R_{F,t} = b_0 + b_{i,R_M-R_F}(R_{M,t} - R_{F,t}) + b_{i,SMB}SMB_t + b_{i,HML}HML_t + b_{i,CMP}CMP_t + \varepsilon_{i,t}. \quad (1)$$

In the second stage, I estimate monthly cross-sectional regressions of excess factor returns on the factor betas estimated in Equation 1, as follows:

$$R_i - R_F = \lambda_0 + \lambda_{R_M-R_F}b_{i,R_M-R_F} + \lambda_{SMB}b_{i,SMB} + \lambda_{HML}b_{i,HML} + \lambda_{CMP}b_{i,CMP} + \nu_i. \quad (2)$$

Standard errors of the coefficients in the second stage are calculated using the Shanken (1992) correction.

Panel A of Table VII provides results consistent with prior research using the 25 size-B/M portfolios. The market beta is negative and there is a positive alpha. When the CMP portfolio is included in the second specification, its coefficient is insignificant. Thus CMP does not help explain variation in these portfolios.

In contrast, in Panel B, when I use the industry portfolios as test assets, I find a positive and significant effect of CMP. In the standard model without CMP, I find a positive and significant coefficient for the market beta, a positive coefficient for SMB, and a negative coefficient for HML. When the CMP portfolio is included in the second specification, it is positive and significant. In addition, once the CMP factor is included, the magnitude and statistical significance of the market factor increases and the coefficient and significance on average mispricing (alpha) decreases, while HML becomes insignificant. In the most conservative test, using firm-level returns in Panel C, CMP is positive and statistically significant, while the factors are little changed.

These cross-sectional factor regression results are consistent with more than one hypothesis. On the one hand, the positive loading on CMP could represent that CMP accounts for a dimension of systematic risk not captured by the standard factors. Alternatively, a more likely explanation is that the ex post beta coefficient is poorly measured and the CMP portfolio provides a better measure of ex ante exposure to market risk. The measured market beta may remain significant after controlling for the CMP portfolio because CMP is only partially correlated with market returns. As mentioned above, centrality is only expected to account for market risk that is formed by the aggregation of sectoral shocks that transmit through customer-supplier links. Macroeconomic news announcements and shocks that flow through alternative links, such as common ownership, will not be picked up by the centrality portfolio.

C. Additional Cross-Sectional Regression Tests

In this section, I run additional cross-sectional tests at the IO-industry-level. This allows me to exploit the full variation in centrality across all tradable sectors, accounting for industry characteristics. However, since industry definitions change every five years, I use the industries in the 1997 SAM network as the unit of observation and extend the time-series of returns to ten years.

Because the underlying variable of interest, centrality, does not vary over time, two-stage cross-sectional regressions are not appropriate in this case. Instead, I run cross-sectional regressions on value-weighted industry-level average monthly returns from 1993 to 2002 controlling for a host of exogenous explanatory variables recorded in December 1997. The results are robust to just using the five years following 1997 to control for possible reverse causation, or the twenty years surrounding 1997 to include a longer time sample.

Consistent with the prior results, in column 1 of Table VIII, I find that log(centrality) is positively and significantly related to average stock returns. In column 2, I regress average returns on the Fama-French and momentum coefficients. I find that an industry's market beta and SMB coefficient are positively related to returns, and HML is negatively related to an industry's average returns, as shown in the prior results.

In column 3, I include industry-level concentration ratios calculated as the eight-firm concentration ratio of sales, using data from the Economic Census of the U.S. Census Bureau in 1997.[4] I find a negative, but insignificant relation. The negative sign is consistent with Hou and Robinson (2006), who find that firms in more concentrated industries have statistically lower returns.

In column 4, I find no direct effect of an industry's concentration of customer sectors on average stock returns. In column 5, I find a positive and significant effect of supplier concentration, consistent with my prior results. This indicates that industries with a greater concentration of suppliers have higher average returns, even in a disaggregated industry-level analysis. In column 6, I find no direct effect of the average size of firms in an industry on its average returns. This provides more evidence that centrality is not simply a proxy related to firm size.

In column 7, I include the variable 'Industry Scope' as calculated in Ahern and Harford (2012). This variable records the percent of all NAICS codes that map to a particular IO industry. This variable provides a measure of the variation of business activities of each IO industry (Economic Classification Policy Committee, 1993; Gollop, 1994). I find a positive and weakly significant relation between industry scope and stock returns. This indicates that industries that are more heterogeneous have higher stock returns. Following the centrality hypothesis, this could occur

[4]With the exception of agriculture and public administration, concentration measures are reported for all industries. Since these data cover firms of all sizes and the vast majority of industries, they provide the most comprehensive concentration ratios available.

because more heterogeneous industries are more likely to receive a sectoral shock that is transmitting across the network.

In column 8, I include the fraction of each industry's total input that is accounted for by compensation of employees. This variable is designed to test whether the higher returns of service sector industries, as shown in Figure 3, is based on their greater centrality, or on the importance of human capital. I find that industries with higher relative labor expenditures have higher returns, consistent with this hypothesis.

In column 9, I include a measure of the total number of firms in each industry, as provided by the Statistics of U.S. Businesses from the Census Bureau. This accounts for the possibility that in industries with more firms, a sectoral shock can be avoided by switching suppliers or customers. The results show that industries with more firms have higher average stock returns.

Finally, in column 10, I create an alternative measure of centrality for robustness based on the text-based similarity measure developed in Hoberg and Phillips (2010a) and Hoberg and Phillips (2010b). Hoberg and Phillips create a firm-level network of Compustat firms based on the similarity of product descriptions in their 10-K filings. I aggregate the 1997 data, provided on Jerry Hoberg's website, to IO industry-levels by recording the total number of firms in the Hoberg-Phillips database that are in each IO-industry-pair. This provides a measure of the connection between IO industries based on asset complementarity, rather than economic transactions. Using these inter-industry connections, I calculate the eigenvector centrality for each IO industry.

This measure has important differences from SAM network centrality. In particular, sectors without Compustat firms in 1997 are omitted from the Hoberg-Phillips network, in contrast to the complete picture of the entire economy that the SAM network provides. Second, the Hoberg-Phillips network is not directional, as industry connections are based on product similarity, rather than the directional flow of real money between sectors. Nevertheless, the two centrality measures are positively correlated and present alternative industry network relations. In Table VIII, I find that the Hoberg-Phillips centrality is also strongly related to stock returns. Thus, centrality in the network of product similarity and centrality in the network of trade flows are both positively related to average stock returns.

In column 11, I include all the variables, excluding Hoberg-Phillips centrality. The level and statistical significance of the SAM network centrality is virtually unchanged after including all of the additional variables. This reinforces the evidence that centrality is an exogenous and powerful predictor of stock returns. The market model beta remains significant and the concentration of customer sectors is marginally significant. Average firm size and industry scope are both negatively related to stock returns in the full model, and labor's fraction of inputs remains positive and significant. In column 12, I run the same tests, but include the Hoberg-Phillips measure of centrality and find the SAM network centrality measure remains positive and significant.

In sum, even after accounting for a wide range of possible alternative explanations, including firm size, industry concentration, industry size, I find a strong positive cross-sectional relation between centrality in the intersectoral network and average stock returns.

D. Macroeconomic Risk Exposure

To assess whether centrality relates to underlying economic risks, I test the relationship between the CMP portfolio and three measures of macroeconomic activity: consumption growth, recessions, and macroeconomic uncertainty. Consumption growth is the growth in real nondurable consumption per capita over the future 12 months, using data from the NIPA tables. Recessions are based on NBER recession dates with business cycle peaks equal to zero and troughs equal to one, and linear interpolation in the intervening months. Macroeconomic uncertainty is based on the uncertainty factor of Jurado, Ludvigson, and Ng (2013) using a 12-month future horizon. This variable is designed to capture the unexpected variation in forecasts of a large number of macroeconomic indicators, such as real output and income, employment, capacity utilization, and housing starts. These data are provided on Sydney Ludvigson's website.

First, Panel B of Table VI shows that future consumption growth is positively correlated with the market premium, SMB, and CMP. The recession variable and macroeconomic uncertainty are uncorrelated with all of the factors and with centrality. Next, Panel A of Table IX shows that consumption growth is positively related to the market premium and to CMP in a multivariate setting. Controlling for the recession indicator, macroeconomic uncertainty, and a linear time trend, the market premium and CMP have significant correlations with future consumption growth of roughly equal magnitudes. Panel B of Table IX tests whether CMP is related to macroeconomic outcomes after controlling for risk factors. In all specifications, CMP is positively and significantly related to future consumption growth. In addition, the market premium is positively related to the CMP portfolio when no other risk factors are included. Including SMB and HML eliminates the statistical significance on the market premium.

These results suggest that central industries face greater economic risk than peripheral industries. When central industries have high returns relative to peripheral industries, future consumption growth rises. In addition, these results provide further evidence that CMP shares similarities with the market risk premium, suggesting that centrality may help to understand what drives market risk. However, no relation is found between CMP and recessions and macroeconomic uncertainty. The limited number of recessions and aggregate fluctuations in macroeconomic outcomes during the sample period is likely to reduce the power of these tests.

E. Idiosyncratic Volatility

In the final set of cross-sectional tests, I investigate whether centrality is related to idiosyncratic volatility. If centrality is important for understanding the underlying source of systematic risk, known pricing factors are likely to have greater explanatory power for more central industries, compared to peripheral industries. Risk factors that explain average returns should be more precise for industries that are more closely tied to the overall economy.

Internet Appendix Table III presents estimates of time-series factor regressions on ten portfolios of value-weighted returns sorted by centrality using the four-factor model of Fama and French and Carhart. The explanatory power of the standard factors is higher for more central industries than for less central industries. The adjusted R^2 of the time-series regressions increases almost monotonically with centrality. In the 3rd decile, the adjusted R^2 is 72.12%. In the 10th decile, the R^2 is 93.67%. This implies that standard factor models have poor explanatory power for peripheral industries, as conjectured.

The monotonic increase in adjusted R^2 with centrality sheds new light on idiosyncratic volatility (Campbell, Lettau, Malkiel, and Xu, 2001; Ang, Hodrick, Xing, and Zhang, 2006). This is consistent with the idea that shocks that pass through industries on the periphery are less likely to be aggregate shocks, compared to shocks that pass through central industries. This means that the variation in the returns of these peripheral industries remain unexplained by systematic risk factors. In general, these results provide additional evidence that exposure to market-wide systematic risk is based on an industry's position in the economy-wide network.

V. The Diffusion of Shocks Across Industries Over Time

The evidence presented above suggests that centrality in the intersectoral trade network is related to exposure to market risk in the cross-section. If this relationship is driven by the transmission of sectoral shocks across product market links, as I have argued, returns could follow predictable patterns in both time and network space. In particular, if economic shocks diffuse in a wave-like pattern, we could observe a positive relationship between time and distance for the return correlations of two industries. A shock to one industry will affect the returns in closely-connected industries sooner than it will affect returns in more distantly-connected industries.

Consistent with a wave-like diffusion of shocks, Ahern and Harford (2012) observe a positive relationship between time and distance for the transmission of merger activity across the IO network. They show that distant merger activity has a delayed impact on a subject industry's merger activity, while close industries' merger activity has a more immediate impact. Since mergers are complex and time-consuming corporate actions, it is reasonable to expect a delay for merger shocks to arise. For stock returns, this does not need to be the case. Rational investors can trace the effect of economic shocks through the network to predict the effect on stock prices almost immediately, even in distant industries.

However, the empirical evidence suggests that investors do not immediately account for shocks that flow through product market relations, even for closely connected firms and industries. In particular, the evidence in Cohen and Frazzini (2008) and Menzly and Ozbas (2010) suggests that stock prices respond with a delay of at least a month, on average, following direct customer or supplier shocks. Given the complexity of the intersectoral network, it is reasonable to assume that investors could respond with a considerable delay for shocks that originate in distant industries. Empirically, the more rational and forward-looking are investors, the less likely I am to observe the transmission of shocks in returns.

To test the relationship between time and distance in the network, I first calculate the shortest path between an industry and all other industries in the intersectoral supplier network using Dijkstra's (1959) algorithm. Because these tests are at the industry-level, which change every five years as discussed above, I use the 1997 IO report and stock return data from 1993 to 2002. The main results are robust to using only ex-post returns (to address any look ahead bias) and a longer time series. Distance between two industries is defined to be the inverse of the strength of the supplier relations, such as those illustrated in Panel B of Table I. Industries that provide a greater fractions of another industry's inputs have a shorter distance between them. The Dijkstra algorithm calculates the distance between two industries, as well as the number of steps between intermediate sectors in the shortest path between two industries. The shortest path is the one that minimizes the total distance, based on the inverse of the product market strength. I then relate this measure of distance in the product market space to distance in time in the following model:

$$r_{i,t} = \alpha + \sum_{s=1}^{T} \rho_s r_{i,t-s} + \sum_{s=1}^{T} \theta_s r_{Close,t-s} + \sum_{s=1}^{T} \phi_s r_{Distant,t-s} + \gamma_t + \varepsilon_{i,t} \tag{3}$$

where $r_{i,t}$ denotes the returns of industry i in month t, $r_{Close,t}$ are the cross-sectional average returns in month t of industries that are close to industry i in the intersectoral network, $r_{Distant,t}$ are the returns of distant industries, and γ_t are calendar-time fixed effects.

Close and distant industries are defined at the sector-level by first calculating the 25th and 75th percentiles of an industry's number of steps to every other sector. Close sectors are defined to be those that are fewer steps away than an industry's 25th percentile of steps to all other industries. Distant industries are at a distance greater than the 75th percentile of steps.

The ρ coefficients in Equation 3 account for autocorrelation in monthly returns up to T months. This helps to control for heterogeneity in momentum. The γ coefficients account for all macro factors that do not vary in the cross-section, such as asset pricing factors and economy-wide variables, whether observed or unobserved. Thus, this model identifies the lead-lag relationship between an industry's returns and the returns of close and distant industries, while controlling for within-industry persistence in returns and system-wide time-series variation.

Table X presents a summary of the results. Columns 1 through 3 use value-weighted industry returns. Columns 4 through 6 use equal-weighted industry returns. Columns 1 and 4 only include a one month lag, columns 2 and 5 include six months of lags, and columns 3 and 6 include 12 months of lags. For brevity, I aggregate the coefficients on the lags into recent and old lags by summing the coefficient estimates. Recent returns include the most recent three months. Old returns include the returns from $t-4$ to $t-6$ in columns 2 and 5, and the returns from $t-10$ to $t-12$ in columns 3 and 6. I aggregate the recent and old return coefficients from close and distant industries separately. The full results with all monthly coefficient estimates are reported in Internet Appendix Table V.

First, there is a positive and significant relationship between an industry's returns and the one-month lagged returns of its close industries. A one percentage point increase in the average close industry's monthly value-weighted return is associated with a 15 basis point increase in a subject industry's returns next month. This is consistent with the results in Cohen and Frazzini (2008) and Menzly and Ozbas (2010). In contrast, distant industries' one-month and six-month lagged returns do not affect a subject industry's current returns.

In columns 3 and 6, I include 12 months of lags and a new pattern emerges. The old returns of distant industries in months $t-10$ to $t-12$ are positively and significantly related to the subject industry's current returns. A one percentage point increase in the value-weighted monthly returns in $t-10$ to $t-12$ for distant industries is associated with an increase of 17 basis points in the current returns of the subject industry. At the same time, returns for close industries in $t-1$ to $t-3$ are associated with an increase of 21 basis points in the subject industry. It is important to note that these regressions include controls for autocorrelation and month fixed effects, which accounts for any pattern of system-wide time-series effects.

In Panel B of Table X, I calculate the differences in coefficient estimates for recent and old time periods and close and distant industries. In all specifications, the marginal impact of recent returns are greater for close industries than for distant industries. In the months $t-1$ to $t-3$, the marginal effect of a one percentage point increase in the returns of close industries is 34 basis points larger than the impact of returns in distant industries. In contrast, in months $t-10$ to $t-12$, the returns of distant industries have an impact that is 25 basis points larger than the impact of close industries. Finally, the difference-in-difference of recent versus old and close versus distant is positive and significant in both the 6-month and the 12-month lag specifications, for both equal-weighted and value-weighted returns. The difference between recent and old returns is 60 basis points higher in close industries than in distant industries.

These results provide empirical support to the idea that shocks transmit across the economy through the network of customer-supplier links. Shocks in close industries have almost immediate effects, while shocks in distant industries have delayed effects.

VI. Conclusion

This paper provides new evidence that an industry's position in the network of intersectoral trade flows helps to explain its exposure to market risk. Industries that are more central in the network have greater exposure to sectoral shocks that transmit from one sector to another through trade relations. Central industries, such as automakers, paper mills, and hospitals, are at greater risk of exposure to sectoral shocks, because they are embedded in the center of the economy. In comparison, peripheral industries, such as sugarcane farms, musical instruments, and mattress manufacturers have less exposure to a sectoral shocks that are transmitted through customer-supplier links. This leads more central industries to earn higher stock returns as compensation for bearing more economic risk. Controlling for a host of alternative explanations, the empirical results in this paper support this view. In addition, the results suggest stock returns reflect shocks that travel through customer-supplier links in a wave-like pattern over time.

More broadly, this paper contributes new evidence on the underlying microeconomic sources of market risk. Though empirical tests using ex post measures of market betas do not support the CAPM (Fama and French, 1992), the theoretical arguments for the importance of market risk in explaining the cross-section of stock returns remains compelling. My results suggest that the predicted relation between market risk and stock returns is supported in the data using arguably more informative estimates of exposure to systematic risk based on economic primitives. In particular, just as the theory argues that asset prices are based on the covariance of an asset's returns with macroeconomic outcomes, this paper shows that asset prices are based, in part, on the real product market connections between an industry and the rest of the economy.

This line of research has important implications. First, by understanding the ex ante economic sources of systematic risk, we may be better able to understand the value of non-tradable assets, such as private firms and internal divisions. Second, this research identifies which sectors are more important for the overall economy, allowing policy makers to consider the aggregate implications of government intervention in a particular industry (e.g., the bailouts of the financial sector and automakers). Finally, as more detailed data become available, future research may be able to exploit economy-wide firm-level networks to identify how micro-level events can have macro-level implications.

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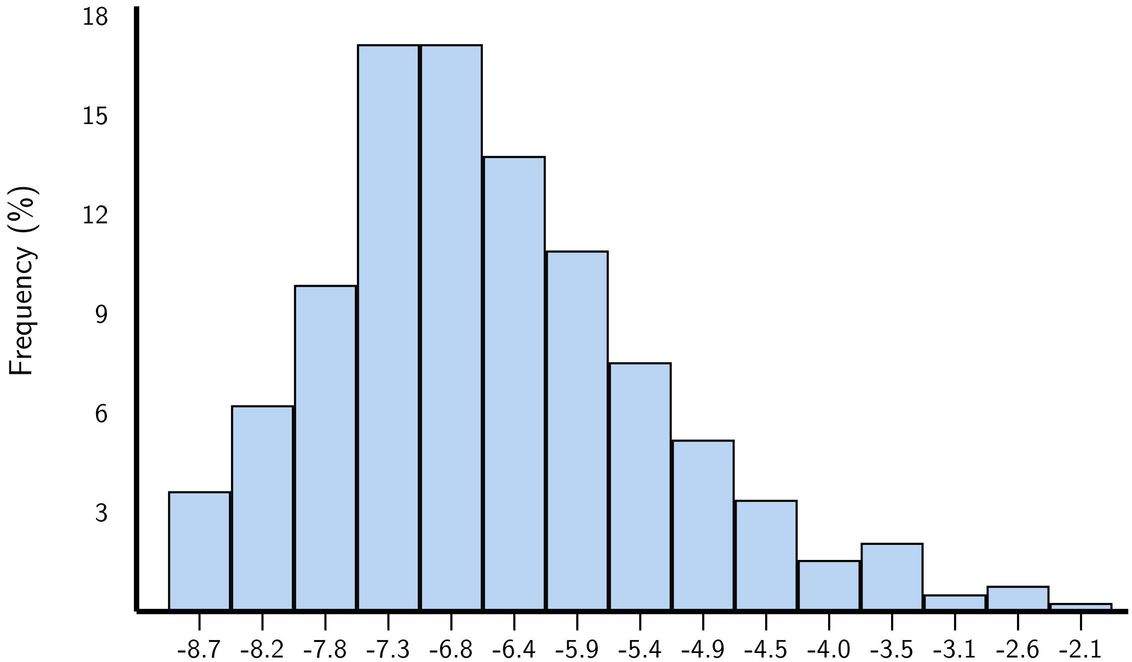
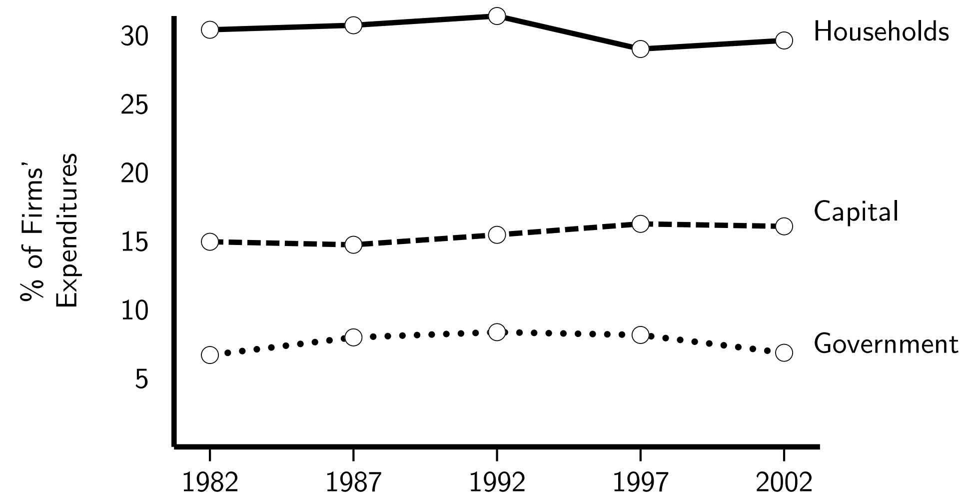
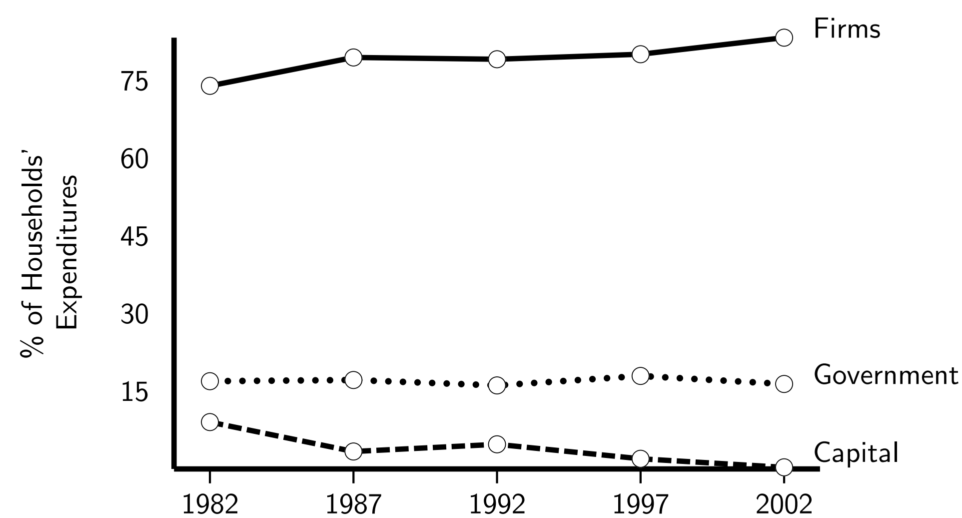


Figure 1
Distribution of Centrality
This figure shows a histogram of log(Centrality) from 385 industries that have tradable stocks in 1997. Industry definitions are from the 1997 detailed-level industries from the Bureau of Economic Analysis Input-Output and National Income and Product Account data.



(a) Who Receives Firm's Expenditures



(b) Who Receives Households' Expenditures

Figure 2
The Recipients of Expenditures by Firms and Households
Panel A presents the fraction of total expenditures by firms that are received by households, government, and the capital sectors. Panel B presents the fraction of total expenditures by households that are received by firms, government, and the capital sectors. Data are from BEA Input-Output Tables and NIPA Tables for each report year 1982, 1987, 1992, 1997, and 2002. Fractions do not sum to one because the foreign sector is not included in either panel and because the firm sector is not included in Panel A.

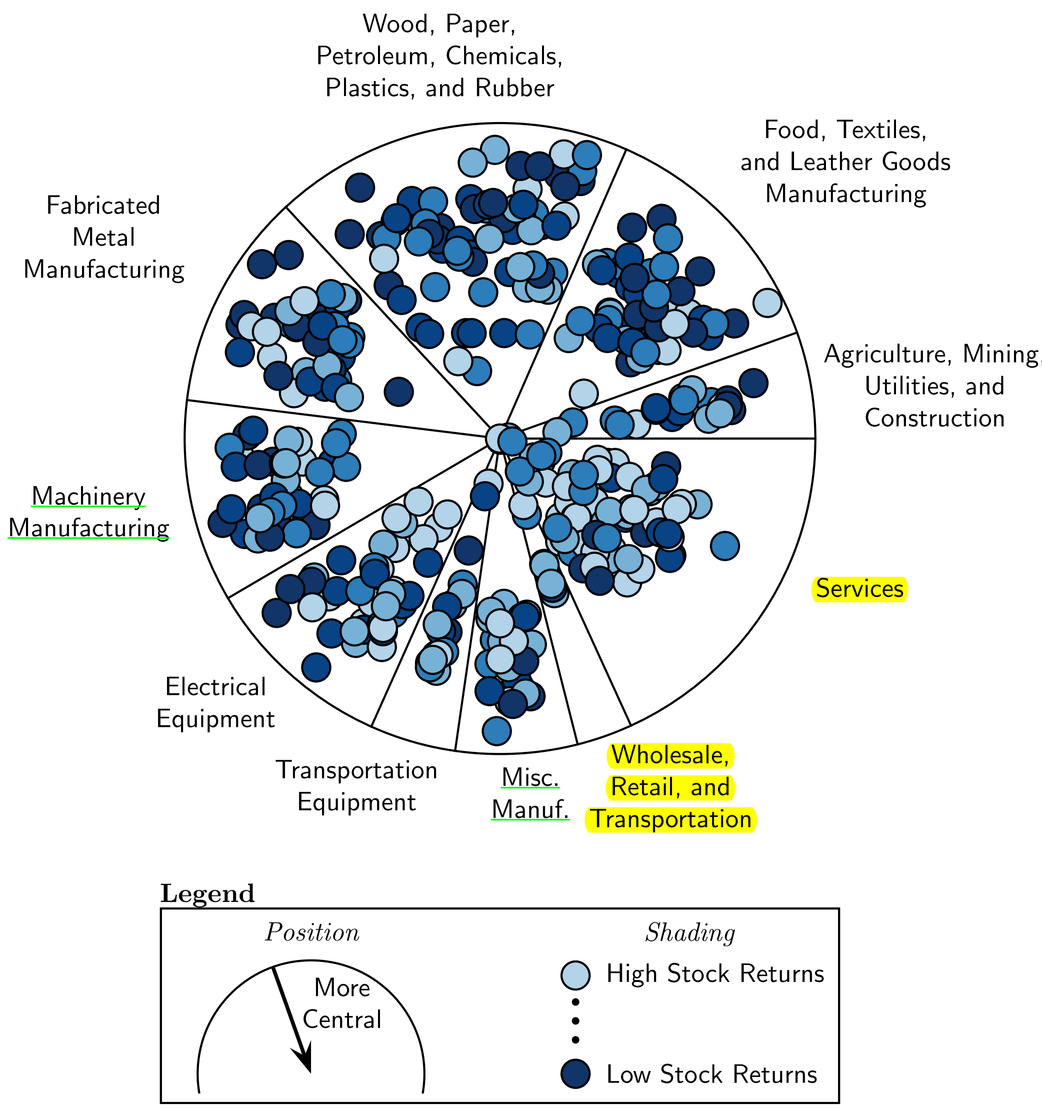


Figure 3
Network Centrality and Average Stock Market Returns by Industry
Each circle represents an industry using industry definitions from the 1997 detail-level Input-Output tables of the Bureau of Economic Analysis. Industries are categorized according to aggregate production groupings. The size of each grouping's slice of the total circle is the ratio of the number of industries contained in the grouping to the total number of industries. Within each grouping, the distance from each industry's placement in the circle to the center of the circle is proportional to log(Centrality). Centrality is the eigenvector centrality in the inter-sector network of trade flows, based on all 483 sectors in the complete network. Only sectors with stock return data are presented in the figure and the distance to the center of the circle is normalized to be zero for the most central industry with stock price data. The lighter is the shading of an industry circle, the higher is its time-series average value-weighted stock returns, where firm-level returns are aggregated based on firm market equity, over January 1998 to December 2002.

Table I
Social Accounting Matrix of the U.S. Economy in 1997
This table presents the economic transactions between five aggregate sectors of the economy. Panel A reports dollar transactions in millions of 1997 dollars. Panel B reports the fraction of total expenditures by column sectors that are received by row sectors. Panel C reports the fraction of the total receipts of row sectors that are contributed by column sectors. Data are from the 1997 detail-level Input-Output and National Income and Product Account tables of the Bureau of Economic Analysis. The 'Firms' sector is an aggregate of 479 separate industries. 'Government' does not include government enterprises, such as local transit and electric utilities, which are included under 'Firms.' The government sector in this table includes tax collections and consumption and investment expenditures for Federal and local governments.

Panel A: Dollar Flows

	Expenditures				
Receipts	Firms	Households	Capital	Government	Foreign
Firms	6,530,867	5,616,840	1,472,776	1,609,666	822,163
Households	4,656,650	0	1,382,900	929,800	44,753
Capital	2,610,103	137,712	0	113,724	98,735
Government	1,309,840	1,259,550	103,600	0	5,100
Foreign	944,853	0	998	24,900	0
Total	16,052,313	7,014,102	2,960,274	2,678,090	970,750

Panel B: Supplier Network
(% of Column Expenditures Received by Row)

	Expenditures				
Receipts	Firms	Households	Capital	Government	Foreign
Firms	40.7	80.1	49.8	60.1	84.7
Households	29.0	0.0	46.7	34.7	4.6
Capital	16.3	2.0	0.0	4.2	10.2
Government	8.2	18.0	3.5	0.0	0.5
Foreign	5.9	0.0	0.0	0.9	0.0

Panel C: Customer Network
(% of Row Receipts Spent by Column)

	Expenditures				
Receipts	Firms	Households	Capital	Government	Foreign
Firms	40.7	35.0	9.2	10.0	5.1
Households	66.4	0.0	19.7	13.3	0.6
Capital	88.2	4.7	0.0	3.8	3.3
Government	48.9	47.0	3.9	0.0	0.2
Foreign	97.3	0.0	0.1	2.6	0.0

Table II
Centrality Summary Statistics in 1997
This table reports summary statistics for log(centrality) across sectors. All sectors include the 478 industry sectors in the 1997 Detailed Input-Output Tables from the Bureau of Economic Analysis, plus five aggregate sectors: Households, Government, Foreign, Capital, and Used Goods/Scrap, calculated using the 1997 National Income and Product Account tables. Sectors with stock returns only include those industries with stock price data in 1997. Centrality is the eigenvector centrality in the inter-sector network of trade flows, based on all 483 sectors.

	All Sectors	Sectors with Stock Returns
Observations	483	385
Mean	−6.623	−6.536
Standard Deviation	1.402	1.261
Skewness	1.059	0.713
Kurtosis	4.817	3.470
Minimum	−9.424	−8.954
1st Percentile	−8.910	−8.804
25th	−7.524	−7.435
Median	−6.871	−6.753
75th	−5.880	−5.814
99th Percentile	−2.234	−2.821
Maximum	−0.182	−2.342

Table III

Industry Returns and Characteristics Sorted by Centrality

This table presents industry-level averages across five quintiles of centrality from January 1983 to December 2007. Centrality is the eigenvector centrality in the inter-sector network of trade flows. Sectors are defined using the detail-level Input-Output (IO) and National Income and Product Account tables of the Bureau of Economic Analysis from 1982 to 2002. Sector returns and characteristics are formed by equal-weighting firms and are rebalanced monthly. Centrality quintiles are formed using all sectors in the most recent IO report, but only sectors with stock return data are presented in the table. 'Levered returns' are the raw returns reported on CRSP. 'Unlevered returns' are unlevered using debt-to-equity ratios and marginal tax rates. 'Value weighted' returns are value-weighted monthly across sectors using the sector's average firm-level market-equity. 'Equal weighted' portfolios are formed monthly using equal weights across sectors. 'Customer HHI' is the Herfindahl index of sales outputs per industry. 'Supplier HHI' is the Herfindahl index for purchases per industry. 'Log(Market Equity)' is the cross-sectional average log market equity of all sectors in a quintile. Statistical significance of the difference between the highest and lowest centrality quintiles is reported by t-tests from Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Centrality						
	Low 1	2	3	4	High 5	5−1	t-statistic
Panel A: Monthly Returns (%)							
Levered							
Value weighted	2.01	2.22	1.96	2.01	2.08	0.07	(0.35)
Equal weighted	1.69	1.84	1.78	1.90	1.96	0.27**	(2.24)
Unlevered							
Value weighted	1.84	2.03	1.73	1.84	1.80	−0.04	(−0.23)
Equal weighted	1.49	1.60	1.56	1.64	1.70	0.21**	(2.07)
Panel B: Industry Characteristics							
Log(Centrality)	−7.86	−7.23	−6.67	−5.93	−3.92	3.94***	(415.99)
Customer HHI	0.26	0.28	0.34	0.28	0.32	0.06***	(10.04)
Supplier HHI	0.17	0.13	0.20	0.16	0.22	0.05***	(42.92)
Log(Market Equity)	8.70	9.09	9.69	10.04	11.81	3.11***	(51.82)

Table IV

Industry Lists by Centrality, Firm Size, and Concentration of Customers and Suppliers

This table presents a sample of the five largest industries grouped into either the first or fifth quintile of centrality, average market equity, concentration of customers, or concentration of suppliers. In Panel A, industries are first sorted into five quintiles based on the average market equity of firms in each industry. Within each quintile, firms are then sorted into five quintiles of centrality. Centrality is the eigenvector centrality in the inter-sector network of trade flows, based on 483 sectors. Sectors are defined using the 1997 detail-level Input-Output and National Income and Product Account tables of the Bureau of Economic Analysis. Centrality quintiles are formed using all 483 sectors, but only industries with stock return data are presented in the table. In Panel B, industries are first sorted into five quintiles of the concentration of customer industries. Within each of these sectors, five quintiles are formed based on centrality. In Panel C, the first sort is based on the concentration of supplier sectors.

Panel A: Average Market Equity

	Smallest Average Market Equity	Largest Average Market Equity
Lowest Centrality	Household vacuum cleaner manufacturing	Industrial gas manufacturing
	Fabric coating mills	Gold, silver, and other metal ore mining
	Musical instrument manufacturing	Mattress manufacturing
	Laboratory apparatus and furniture manufacturing	Copper, nickel, lead, and zinc mining
	Explosives manufacturing	Elevator and moving stairway manufacturing
Highest Centrality	Automotive repair, except car washes	Hospitals
	Travel arrangement and reservation services	Automobile and light truck manufacturing
	Frozen food manufacturing	Insurance carriers
	Ready-mix concrete manufacturing	Petroleum refineries
	Textile and fabric finishing mills	Pharmaceutical and medicine manufacturing

Panel B: Concentration of Customers

	Lowest Concentration	Highest Concentration
Lowest Centrality	Iron and steel forging	Sugarcane and sugar beet farming
	Nonwoven fabric mills	Sawmill and woodworking machinery
	Stationery and related product manufacturing	Small arms manufacturing
	Flexible packaging foil manufacturing	Burial casket manufacturing
	Software reproducing	Tortilla manufacturing

Highest Centrality	Truck transportation	Hospitals
	Semiconductors and related device manufacturing	Automobile and light truck manufacturing
	Nondepository credit intermediation	Insurance agencies, brokerages, and related
	Accounting and bookkeeping services	Aircraft manufacturing
	Commercial printing	Cigarette manufacturing
	Panel C: Concentration of Suppliers	
	Lowest Concentration	Highest Concentration
Lowest Centrality	Household laundry equipment manufacturing	Water, sewage and other systems
	Prefabricated wood building manufacturing	Ophthalmic goods manufacturing
	Ammunition manufacturing	Tobacco stemming and redrying
	Sugarcane and sugar beet farming	Musical instrument manufacturing
	Elevator and moving stairway manufacturing	Software reproducing
Highest Centrality	Motor vehicle parts manufacturing	Hospitals
	Paper and paperboard mills	Monetary authorities and depository credit
	Electronic computer manufacturing	Insurance carriers
	Aircraft manufacturing	Automobile and light truck manufacturing
	Frozen food manufacturing	Petroleum refineries

Table V

Mean Portfolio Returns by Centrality, Size, and Product Market Concentration

This table reports average monthly portfolio returns, where portfolios are formed based on sorts into three terciles of the average market equity of firms in the industry (Panel A), the concentration of customers (Panel B), or the concentration of suppliers (Panel C). Market equity sorts are rebalanced monthly. Customer and supplier sorts are rebalanced every five years to reflect the most recent data from the BEA. Within each of these terciles, industries are sorted into three terciles of centrality. Equal weighted tercile returns are based on sector returns, where sectors are defined by the BEA. Value weighted returns are weighted by the average market equity in each sector. Returns are from January 1983 to December 2007. Stocks with a price less than five dollars are excluded. t-statistics in parentheses are adjusted for autocorrelation following Newey-West procedure. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Sorting by Size and Centrality

	Equal Weighted					Value Weighted				
	Market Equity Tercile					Market Equity Tercile				
Centrality Tercile	Low 1	2	High 3	High-Low	t-stat	Low 1	2	High 3	High-Low	t-stat
1 Low	1.61	1.79	1.98	0.37**	(1.99)	1.59	1.80	2.12	0.53*	(1.95)
2	1.78	1.74	1.88	0.10	(0.72)	1.78	1.79	1.99	0.20	(0.87)
3 High	1.97	1.84	1.97	0.00	(−0.01)	1.95	1.81	2.10	0.14	(0.72)
High-Low	0.36**	0.05	−0.01			0.37**	0.02	−0.02		
t-statistic	(2.37)	(0.49)	(−0.09)			(2.36)	(0.18)	(−0.15)		

Panel B: Sorting by Concentration of Customers and Centrality

	Equal Weighted					Value Weighted				
	Concentration Tercile					Concentration Tercile				
Centrality Tercile	Low 1	2	High 3	High-Low	t-stat	Low 1	2	High 3	High-Low	t-stat
1 Low	1.67	1.87	1.80	0.13	(0.96)	2.11	2.13	1.93	−0.18	(−0.57)
2	1.85	1.84	1.73	−0.12	(−1.02)	2.03	1.93	2.02	−0.02	(−0.09)
3 High	1.83	1.96	2.00	0.17	(1.46)	1.69	2.10	2.19	0.50**	(2.27)
High-Low	0.16	0.10	0.20			−0.42	−0.03	0.26		
t-statistic	(1.40)	(0.72)	(1.57)			(−1.48)	(−0.13)	(1.25)		

Panel C: Sorting by Concentration of Suppliers and Centrality

	Equal Weighted					Value Weighted				
	Concentration Tercile					Concentration Tercile				
Centrality Tercile	Low 1	2	High 3	High-Low	t-stat	Low 1	2	High 3	High-Low	t-stat
1 Low	1.78	1.73	1.72	−0.06	(−0.51)	1.88	1.95	1.65	−0.24	(−1.43)
2	1.79	1.86	2.00	0.21	(1.49)	2.29	2.02	2.19	−0.10	(−0.43)
3 High	1.73	1.83	2.11	0.38**	(2.23)	1.78	2.03	2.11	0.33*	(1.85)
High-Low	−0.05	0.10	0.39***			−0.11	0.09	0.46**		
t-statistic	(−0.43)	(0.87)	(2.80)			(−0.76)	(0.38)	(2.28)		

Table VI
Summary Statistics of Risk Factors and Centrality
This table reports summary statistics for the three Fama-French (1993) factors, the Carhart (1997) momentum factor (UMD), and the centrality portfolio, Central Minus Peripheral (CMP) over the 300 months from January 1983 to December 2007. CMP is computed as the monthly returns of the industries in the top tercile of centrality minus returns of industries in the bottom tercile of centrality. Centrality is eigenvector centrality over all sectors formed from the BEA Input-Output and NIPA tables using the most recent table from 1982, 1987, 1992, 1997, or 2002. Panel A reports summary statistics and Panel B reports pairwise correlations. Panel B also includes *Consumption Growth*, the 12-month future growth in real per capita nondurable consumption, *Recession*, a linearly interpolated value between 0 and 1 between peak and troughs (0 = peak, 1 = trough), and *Macroeconomic Uncertainty*, the uncertainty over macroeconomic variables over the following 12 months, as calculated in Jurado, Ludvigson, and Ng (2013). $p-$values are in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Summary Statistics

	Observations	Mean	Standard Deviation	Minimum	Median	Maximum	t-statistic
$R_M - R_F$	300	0.65	4.24	−23.14	1.05	12.43	2.67
SMB	300	0.04	3.28	−16.83	−0.14	21.99	0.21
HML	300	0.40	3.09	−12.41	0.34	13.84	2.21
UMD	300	0.76	4.23	−25.01	0.88	18.40	3.12
CMP	300	0.17	2.75	−9.30	0.11	15.98	1.09

Panel B: Correlation Coefficients

	$R_M - R_F$	SMB	HML	UMD	CMP
SMB	0.205***				
	(< 0.001)				
HML	−0.492***	−0.417***			
	(< 0.001)	(< 0.001)			
UMD	−0.087	0.106*	−0.080		
	(0.133)	(0.066)	(0.169)		
CMP	0.206***	0.403***	−0.432***	0.067	
	(< 0.001)	(< 0.001)	(< 0.001)	(0.248)	
Consumption Growth	0.103*	0.098*	−0.118**	−0.010	0.127**
	(0.075)	(0.089)	(0.041)	(0.862)	(0.028)
Recession	0.045	0.112	0.072	−0.073	0.002
	(0.442)	(0.052)	(0.217)	(0.205)	(0.973)
Macroeconomic Uncertainty	−0.067	0.051	−0.002	−0.004	−0.056
	(0.246)	(0.379)	(0.977)	(0.943)	(0.335)

Table VII
Two-Stage Cross-Sectional Regressions
This table presents results of two-stage monthly cross-sectional regressions over January 1983 to December 2007 of average excess portfolio returns on full-period factor betas for the 25 size and book to market portfolios (Panel A), 74 3-digit NAICS industry portfolios (Panel B), and 4,508 firm-level returns in an average month (Panel C). Full period betas are estimated from time-series regressions of portfolio returns on factors. T-statistics are computed as in Shanken (1992). Adjusted R^2 are based on OLS regressions. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Intercept	b_{RM-RF}	b_{SMB}	b_{HML}	b_{UMD}	b_{CMP}	Adj. R^2
Panel A: Size and Book-to-Market Portfolios							
Coef.	0.900	−0.153	0.007	0.439*	2.726**		0.482
t-stat.	(1.406)	(−0.211)	(0.030)	(1.969)	(2.780)		
Coef.	1.141*	−0.411	0.021	0.405*	2.363***	−0.337	0.534
t-stat.	(2.087)	(−0.659)	(0.093)	(1.920)	(3.030)	(−1.005)	
Panel B: Industry Portfolios							
Coef.	0.365	0.972**	0.626**	−0.486*	1.165*		0.139
t-stat.	(1.513)	(2.571)	(2.262)	(−1.862)	(1.954)		
Coef.	0.236	1.057***	0.679**	−0.300	1.254**	0.507**	0.157
t-stat.	(0.947)	(2.705)	(2.407)	(−1.060)	(2.104)	(2.093)	
Panel C: Firm-Level Returns							
Coef.	0.666***	0.598**	0.525***	−0.357*	0.336		0.086
t-stat.	(7.975)	(2.303)	(2.599)	(−1.847)	(1.225)		
Coef.	0.664***	0.612**	0.518**	−0.361*	0.345	0.302*	0.099
t-stat.	(7.953)	(2.349)	(2.577)	(−1.883)	(1.245)	(1.746)	

Table VIII

Cross Sectional Regressions of Industry-Level Average Monthly Returns

This table presents regression coefficients and robust standard errors in parentheses. The dependent variable is average monthly value-weighted industry returns from January 1993 to December 2002. Industries are based on BEA Input-Output (IO) definitions from 1997. 'Centrality' is the eigenvector centrality of the industry in the economy-wide sector network. 'Industry Concentration' is the four-sector concentration ratio of sales in an industry. 'Concentration of Customers' is the four-sector concentration ratio of sales outputs per industry. 'Concentration of Suppliers' is for purchases per industry. 'Log(Industry Average Market Equity)' is the cross-sectional average market equity of all firms listed on CRSP in each industry, averaged over 1/1993 to 12/1997. 'Log(Industry Scope)' is the fraction of all NAICS codes that map to the IO industry code. 'Labor's Fraction of Inputs' is the total dollars spent on labor compensation divided by total input costs per industry. 'Log(Number of Firms)' is the number of firms by industry from the Statistics of U.S. Businesses (SUSB), 'Log(Hoberg Phillips Centrality)' is the eigenvector centrality of industries in an inter-industry network based on the text-based similarity measures of Hoberg and Phillips (2010a) and Hoberg and Phillips (2010b). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(Centrality)	0.218***										0.193***	0.187***
	(< 0.001)										(< 0.001)	(0.001)
$R_M - R_F$		0.753***									0.896***	0.895***
		(< 0.001)									(< 0.001)	(< 0.001)
SMB		0.651***									0.316**	0.313**
		(< 0.001)									(0.043)	(0.046)
HML		−0.833***									−0.811***	−0.809***
		(< 0.001)									(< 0.001)	(< 0.001)
UMD		0.364									0.169	0.162
		(0.106)									(0.437)	(0.456)
Industry			−0.003								0.002	0.002
Concentration			(0.460)								(0.388)	(0.375)
Concentration of				0.359							0.374**	0.365**
Customers				(0.243)							(0.021)	(0.031)
Concentration of					1.054*						0.082	0.067
Suppliers					(0.050)						(0.846)	(0.877)
Log(Industry Average						−0.029					−0.139***	−0.139***
Market Equity)						(0.543)					(< 0.001)	(< 0.001)
Log(Industry Scope)							0.065				−0.228***	−0.230***
							(0.359)				(< 0.001)	(< 0.001)
Labor's Fraction								1.170**			0.776**	0.766**
of Inputs								(0.011)			(0.024)	(0.027)
Log(Number of Firms)									0.156***		0.015	0.017
									(< 0.001)		(0.612)	(0.583)
Log(Hoberg Phillips										0.406***		0.021

Centrality)										(< 0.001)		(0.763)
Constant	2.918***	1.084***	1.623***	1.243***	0.841***	1.900***	1.925***	1.137***	0.472**	3.262***	1.875***	1.929***
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(0.010)	(0.003)	(< 0.001)	(< 0.001)	(0.049)	(< 0.001)	(0.008)	(0.009)
Observations	385	310	357	385	385	377	385	385	379	385	286	286
Adjusted R^2	0.043	0.327	−0.001	0.001	0.005	−0.001	−0.001	0.013	0.039	0.030	0.411	0.409

Table IX
Consumption and Macroeconomic Risk Exposure

This table reports time-series regression coefficients from regressions on the three Fama-French (1993) factors, the Carhart (1997) momentum factor (UMD), and the centrality portfolio, Central Minus Peripheral (CMP) over the 300 months from January 1983 to December 2007. CMP is computed as the monthly returns of the industries in the top tercile of centrality minus returns of industries in the bottom tercile of centrality. Each regression includes *Consumption Growth*, the 12-month future growth in real per capita nondurable consumption, *Recession*, a linearly interpolated value between 0 and 1 between peak and troughs (0 = peak, 1 = trough), *Macroeconomic Uncertainty*, the uncertainty over macroeconomic variables over the following 12 months, as calculated in Jurado, Ludvigson, and Ng (2013), a constant, and a time trend. Panel A reports regressions on each of the factors. Panel B reports regressions on the CMP factor. $p-$values from Newey-West standard errors are in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Panel A: Regressions on Risk Factors and Centrality

	$R_M - R_F$	SMB	HML	UMD	CMP
Consumption Growth	0.271*	0.167	−0.229	−0.033	0.213*
	(0.054)	(0.230)	(0.136)	(0.843)	(0.057)
Recession	0.002	0.018***	0.009	−0.012	−0.003
	(0.814)	(0.005)	(0.250)	(0.249)	(0.710)
Macroeconomic Uncertainty	−0.075	0.116**	0.009	−0.044	−0.047
	(0.334)	(0.037)	(0.888)	(0.563)	(0.391)
Time trend	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	300
Adjusted R^2	0.004	0.021	0.008	−0.007	0.007

Panel B: Regressions on CMP Portfolio

Consumption Growth	0.180*	0.156*	0.127*	0.215*	0.114*	0.114*
	(0.092)	(0.064)	(0.087)	(0.057)	(0.089)	(0.094)
Recession	−0.003	−0.009	0.001	−0.002	−0.004	−0.004
	(0.660)	(0.216)	(0.841)	(0.749)	(0.463)	(0.442)
Macroeconomic Uncertainty	−0.038	−0.087*	−0.044	−0.045	−0.073	−0.072
	(0.492)	(0.079)	(0.437)	(0.424)	(0.166)	(0.173)
$R_M - R_F$	0.124**				−0.012	−0.011
	(0.013)				(0.791)	(0.805)

SMB		0.345***			0.234***	0.234***
		(0.003)			(0.008)	(0.005)
HML			−0.377***		−0.279***	−0.278***
			(0.001)		(< 0.001)	(< 0.001)
UMD				0.044		0.006
				(0.729)		(0.920)
Time trend	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300	300	300	300	300	300
Adjusted R^2	0.040	0.170	0.183	0.008	0.241	0.238

Table X

The Diffusion of Return Shocks Across Close and Distant Industries

Observations are sector-months from January 1993 to December 2002 for sectors from the BEA Input-Output Detailed Industry Table in 1997. The dependent variable is the sector-month value-weighted return at time t. 'Own Industry Lagged Returns' are the lagged own-sector monthly returns for $t-1$ in columns 1 and 4, $t-1$ to $t-6$ in columns 2 and 5, and $t-1$ to $t-12$ months in columns 3 and 6. 'Close (Distant) Returns' are the average returns from industries that are close (distant) in the inter-sector network. Close (distant) industries are those that are fewer (more) steps from the subject industry than the 25th (75th) percentile in the industry's distribution of steps between all other industries, computed using the Dijkstra (1959) algorithm. 'Month Fixed Effects' are fixed effects for the calendar month. Columns 1 and 4 (2 and 5, 3 and 6) includes lags of $t-1$ ($t-1$ to $t-6$, $t-1$ to $t-12$). These estimates are not shown for brevity. The lags are aggregated and reported as 'Recent' and 'Old'. 'Recent' indicates the sum of coefficients on lags 1, 2, and 3. 'Old' indicates the sum of coefficients on lags 4, 5, and 6 in columns 2 and 5, and lags 10, 11, and 12 in columns 3 and 6. 'Close−Distant' is the difference between the close coefficients and the distant coefficients. 'Difference-in-Difference' is the difference of close and distant industries for recent and the old periods. Numbers in parentheses are p-values based on standard errors that are clustered at the industry level. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Value-Weighted Returns			Equal-Weighted Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Coefficient Estimates						
Close Industries						
Recent	0.153***	0.217**	0.210**	0.138***	0.092	0.111
	(0.003)	(0.021)	(0.034)	(0.008)	(0.297)	(0.224)
Old		−0.011	−0.079		−0.012	−0.023
		(0.885)	(0.370)		(0.873)	(0.784)
Distant Industries						
Recent	0.017	−0.138	−0.134	−0.080	−0.188*	−0.157
	(0.741)	(0.191)	(0.216)	(0.138)	(0.073)	(0.145)
Old		0.024	0.174*		0.042	0.263**
		(0.800)	(0.090)		(0.631)	(0.014)
Own-Industry Lagged Returns	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.150	0.154	0.158	0.181	0.186	0.190
Observations	43,041	41,101	38,776	42,992	41,057	38,740
Panel B: Difference-In-Differences						
Close−Distant Industries						
Recent	0.136*	0.355***	0.344**	0.218***	0.280**	0.268**
	(0.077)	(0.010)	(0.015)	(0.004)	(0.031)	(0.047)
Old		−0.035	−0.252**		−0.054	−0.286**
		(0.790)	(0.047)		(0.630)	(0.025)
Difference-In-Difference		0.391*	0.596***		0.334*	0.554***
		(0.056)	(0.005)		(0.082)	(0.007)

Internet Appendix for

"Network Centrality and the Cross Section of Stock Returns"

This Internet Appendix provides more details on the data used in the paper. To construct the social account matrix (SAM) I combine data from the Input-Output (IO) tables and the National Income and Product Account (NIPA) tables, both provided by the Bureau of Economic Analysis. The IO tables record real economic trade flows between commodity producers and industry and final users, including government and foreign sectors. Commodities are defined as goods and services, not just manufacturing goods. Thus the IO tables provide a picture of inter-industry trade flows, final uses, and all production inputs including labor. A SAM extends the IO tables to include complete expenditures and receipts for government, a foreign sector, and a capital sector. A typical SAM separates purchasing agents into producing agents (industries), factors of production (labor and capital), institutions (households and government), capital account, and a foreign sector, each with various degrees of aggregation (e.g., high income and low income households, local and federal governments). I modify the standard SAM to combine labor and households into one agent, since I will use the SAM to form a network. Having two nodes for the same agent would distort the network analysis.

The IO tables are published by the BEA every five years, for years ending in two and seven. The tables go as far back as 1947, however, the tables before 1982 do not include employee compensation. Given the importance of households in the economy, the omission of compensation makes these tables unusable for the purposes of this paper. The most recent report published by the BEA is 2002. Therefore, in the paper I use IO reports for years 1982, 1987, 1992, 1997, and 2002. Since each report redefines industry definitions to better reflect the economy and intersectoral trade flows, a constant set of industries is unavailable. Instead, I construct a SAM network using each of the five IO reports from 1982 to 2002.

I. Input-Output Tables

To construct the IO matrix, I follow the procedure in Ahern and Harford (2012) (AH), with a few minor exceptions. See AH and the Internet Appendix of AH for a complete and detailed description of the IO tables.

Like in AH, I account for the fact that some commodities are produced by multiple industries, and some industries do not have a corresponding commodity that can be identified with an industry, by recording each industry's output as a fraction of the total production of a commodity. I also combine the construction industries in the IO tables because they all match to the same SIC or NAICS codes (depending on the IO report year).

Also, like in AH, I modify the 'Make' table to include employee compensation as an industry. Though the IO tables record the compensation of employees as a commodity input in production, there is no corresponding industry that produces compensation. Because of this, employee compensation gets dropped from the industry matrices. Therefore, I create an artificial labor industry to make sure that I account for labor as an input in the industry matrices. The same problem also occurs for 1) *Noncomparable imports*; 2) *Used and secondhand goods* (*Used goods* in 1982); 3) *Rest of world adjustment to final uses* (*Rest of the world industry* in 1982); 4) *Indirect business tax and nontax liability* (*Taxes on production and imports, less subsidies* in 2002); 5) *Other value added* (*Profit-type income, net interest, and CCA* in 1982 and *Gross operating surplus* in 2002); and 6) *Commodity Credit Corporation*, which is only included in the 1982 data. Therefore, I alter the Make table to make sure these elements of the IO matrix are not lost when converting from industry-by-commodity accounts to a directed industry-by-industry matrix.

A second difference with AH, is that I include all industries and final users from the IO tables, including government enterprise, exports and imports, scrap, and various adjustments. Including the following sectors: households, capital, government, foreign, and used/inventory adjustments, the total number of unique economic sectors in the economy by year is 493 (1982), 479 (1987), 488 (1992), 483 (1997), and 425 (2002).

II. Social Accounting Matrix

I account for government receipts and expenditures by creating a government agent that collects taxes and makes consumption and investment expenditures. From the IO matrix, I aggregate government expenditures by summing the IO column entries associated with federal, state, and local government spending as listed in Internet Appendix Table VI. Industries classified in the IO tables as *Government industry*, *General Federal defense government services*, *General Federal* *nondefense government services*, *General state and local government services*, *Other Federal Government enterprises*, *Other state and local government enterprises*, *Federal electric utilities*, *State and local electric utilities*, and *State and local government passenger transit* remain disaggregated in the analysis. These industries are represented in the IO tables as completely separate and balanced industries, with total receipts equal to total expenditures, just as are private industries. Therefore, the government agents listed in Internet Appendix Table VI can be thought of as the redistributive aspect of government, whereas government enterprise is grouped with other industrial production.

To record household expenditures and consumption from the IO tables, I record expenditures as *Personal consumption expenditures* and income receipts as *Compensation of employees.* The calculation of taxes and capital investment are recorded from the NIPA tables, described below.

The expenditures of the capital account are composed of the IO entry for *Private fixed investment*, and the income receipts for capital are composed of the IO entry for *Other value added,* which is the residual claim or profit after accounting for all other input costs.

I adjust the IO values of imports and exports to create a balanced foreign sector. The IO tables record a column *Imports of goods and services* as negative values of final use. I transpose these entries to be positive flows to the row entries for the foreign sector. I then calculate the receipts of the foreign sector by summing this row with the IO input rows 1) *Noncomparable imports,* and 2) *Rest of the world adjustment to final uses.* The expenditures column for the foreign sector is recorded as the IO column entry for *Exports of goods and services.*

Next, I aggregate a few industry categories that record small adjustments in usage and consumption. These include 1) *Change in private inventories,* 2) *Scrap,* 3) *Used and secondhand goods,* and 4) *Inventory valuation adjustment.*

I also aggregate a few industries that are all assigned to the same SIC or NAICS codes. Since firms must be matched to the IO industries, I collapse these industries into one industry with a unique SIC/NAICS match. In 1982, these include two forest and greenhouse industries; 21 residential construction industries, 20 utilities construction industries, six farm construction industries, two petroleum and gas well industries; and two private electric and gas utilities. In 1987, aggregated industries include two forest and greenhouse industries; two petroleum and gas well industries; and two private electric and gas utilities. In 1992, these are two forest and greenhouse industries;

two residential construction industries; five commercial construction industries; two highway construction industries; two petroleum and gas well industries; two other construction industries; and two occupied dwellings and royalties industries. In 1997, these include 13 construction industries. Finally, in 2002 these include seven construction industries.

Finally, I transpose all negative dollar flows from industry i to j recorded in the IO tables to positive flows from industry j to i. This allows the dollar flows in the SAM to be interpreted as the strength of the connection between two agents in a network setting.

A. Government

To incorporate taxes paid to the government, I use the NIPA tables provided by the BEA. First, from NIPA Table 3.1 on Government Current Receipts and Expenditures, I calculate the total flows from industry to the government as the sum of *Taxes on production and imports*, *Taxes on corporate income*, 50 percent of the *Contribution to government social insurance* (assuming households and firms split this evenly), and *Current (net) transfer receipts from business*. To use the data from 1997 as an illustrative example, this equals \$1.174 trillion. The IO tables only record total indirect taxes paid by business to government. I take the difference between total government receipts from businesses in the NIPA table and the total indirect taxes from the IO table to calculate the additional taxes not recorded in the IO table. I then allocate this extra tax across all production industries by subtracting it from each industry's value added, in proportion to each industry's total value added.

I next record taxes paid by households as the sum of Personal current taxes, 50% of *Contribution to government social insurance*, and *Current transfer receipts from persons*, as recorded on NIPA Table 3.1 Government Current Receipts. This is \$1.259 trillion in 1997. Taxes paid by the capital sector are \$103.6 billion in 1997, as recorded as *Income receipts on assets* from NIPA Table 3.1. Finally, taxes paid by the foreign sector are \$5.1 billion, from NIPA 3.1 entry for *Taxes from the rest of the world*. Since I have kept government enterprises as separate entities, I do not include their surplus as part of the redistributive government agent.

Government expenditures for production output are as recorded in the IO tables. Government expenditures (transfers) to households are taken from NIPA Table 3.1, *Government social benefits* *paid to persons* for a value of \$929.8 billion. Transfers to the foreign sector are recorded as the sum of *Government social benefits to the rest of the world* and *Other current transfer payments to the rest of the world*, for a total of \$24.9 billion in 1997. The difference of \$113 billion between government receipts and expenditures, is recorded as government expenditure paid to the capital account.

B. Households

Household income from firms is provided as *Compensation of employees* in the IO tables, which is equal to \$4.656 trillion in 1997. Household receipts from government are as recorded above, \$929.8 billion. Household receipts from capital is from NIPA Table 2.1, and is recorded as *Total personal income* minus *Compensation of employees* minus *Personal current transfer receipts*. This total of \$1.382 trillion represents all non-wage and non-government transfer income, including the NIPA items, 1) *Proprietors' income with inventory valuation*, 2) *Rental income of persons with capital consumption adjustment*, and 3) *Personal income receipts on assets*. Household income from the foreign sector is recorded from employee compensation in the IO tables.

C. Capital

Receipts to the capital account from firms is taken from *Private fixed investment* in the IO tables. Capital receipts from households is recorded as the difference in household receipts and household expenditures. Thus this represents the saving of households of \$137 billion in 1997. The contribution of the foreign sector to the capital account, or foreign savings, is the difference between foreign receipts and foreign expenditures, or, in other words, the trade deficit. Using the data from the IO tables and the other NIPA accounts, I calculate this as \$98.7 billion in 1997. According to NIPA Table 4.1 Foreign Transactions in the NIPA, it was \$101.4 billion. Thus, these estimates are very similar.

III. Time-Series of Industry Centrality

As mentioned above, one limitation of using the BEA input-output data is that industry definitions are updated every five years. At each update, the number of industries changes and there is not a direct mapping between report years. Moreover, in 1997, the BEA switched from using SIC codes as a basis for the input-output industry definitions to using NAICS codes. This change led to a substantial revamping of the structure of industry definitions.

At the same time, the updates in industry definitions are essential for the input-output linkages to be relevant. Take the sectors related to computers, for instance. In the 1982 BEA reports there are two sectors related to computers: 1) Computer and data processing services, and 2) Electronic computing equipment. In the 2002 report, there are 10 sectors related to computers: 1) Electronic computer manufacturing, 2) Computer, storage device manufacturing, 3) Computer terminals and other computer peripheral equipment, 4) Software publishers, 5) Internet publishing and broadcasting, 6) Data processing, hosting, and related services, 7) Other information services, 8) Custom computer programming services, 9) Computer systems design services, and 10) Other computer related services, including facilities management. Clearly, computers have become more important and diverse in the economy since 1982. On the other hand, other industries have vanished or have been collapsed into related industries. This suggests that using 1982 industry codes to explain the economy in 2002 would provide a distorted picture. Given the challenges presented by these data limitations, understanding the evolution of the intersectoral network over time is beyond the scope of this paper. Instead, to detail the changes in industrial structure over time in a robust way requires a full-length treatment, as in Ahern (2013).

Internet Appendix Table I
Social Accounting Matrix of the U.S. Economy, 1982–2002

This table presents the economic transactions between five aggregate sectors of the economy in 1982, 1987, 1992, 1997, and 2002. Entries represent expenditures by the sectors listed on the column heading and receipts by the sectors listed on the rows. Dollar transactions in millions of current dollars are presented in columns under 'Dollar Flows.' The fraction of total expenditures by column sectors that are received by row sectors is presented in columns under 'Supplier Network.' The fraction of the total receipts of row sectors that are contributed by column sectors is presented in columns under 'Customer Network.' Data are from the detail-level Input-Output and National Income and Product Account tables of the Bureau of Economic Analysis. The 'Firms' sector is an aggregate of separate industries. 'Government' does not include government enterprises, such as local transit and electric utilities, which are included under 'Firms.' The government sector in this table includes tax collections and consumption and investment expenditures for Federal and local governments. See the first section of the Internet Appendix for a complete description of each sector.

	Dollar Flows					Supplier Network (% of Column Expenditures Received by Row)					Customer Network (% of Row Receipts Spent by Column)				
	Firms	HHs	Capital	Govt	Foreign	Firms	HHs	Capital	Govt	Foreign	Firms	HHs	Capital	Govt	Foreign
Panel A: 1982															
Firms	2,746,742	2,035,661	614,872	646,595	259,670	43.6	74.0	50.4	64.6	90.1	43.6	32.3	9.8	10.3	4.1
Households	1,917,005	0	492,400	342,400	0	30.4	0.0	40.4	34.2	0.0	69.7	0.0	17.9	12.4	0.0
Capital	942,712	249,016	0	0	27,053	15.0	9.0	0.0	0.0	9.4	77.3	20.4	0.0	0.0	2.2
Government	422,152	466,250	111,394	0	1,400	6.7	16.9	9.1	0.0	0.5	42.2	46.6	11.1	0.0	0.1
Foreign	274,930	877	116	12,200	0	4.4	0.0	0.0	1.2	0.0	95.4	0.3	0.0	4.2	0.0
Total	6,303,540	2,751,805	1,218,782	1,001,195	288,123	100.0	100.0	100.0	100.0	100.0	54.5	23.8	10.5	8.7	2.5
Panel B: 1987															
Firms	3,623,838	3,074,849	830,130	922,203	330,106	41.3	79.5	50.7	63.5	68.8	41.3	35.0	9.5	10.5	3.8
Households	2,699,413	0	721,200	447,400	1,841	30.7	0.0	44.1	30.8	0.4	69.8	0.0	18.6	11.6	0.0
Capital	1,293,906	130,405	0	66,629	145,990	14.7	3.4	0.0	4.6	30.4	79.0	8.0	0.0	4.1	8.9
Government	701,032	664,600	85,600	0	2,000	8.0	17.2	5.2	0.0	0.4	48.2	45.7	5.9	0.0	0.1
Foreign	462,936	0	0	17,000	0	5.3	0.0	0.0	1.2	0.0	96.5	0.0	0.0	3.5	0.0
Total	8,781,125	3,869,854	1,636,930	1,453,232	479,936	100.0	100.0	100.0	100.0	100.0	54.1	23.9	10.1	9.0	3.0
Panel C: 1992															
Firms	4,591,961	4,242,631	879,464	1,337,600	552,612	39.6	79.1	42.1	63.9	87.9	39.6	36.6	7.6	11.5	4.8
Households	3,645,483	0	954,300	729,500	33,472	31.4	0.0	45.7	34.8	5.3	68.0	0.0	17.8	13.6	0.6
Capital	1,793,989	255,074	0	0	40,302	15.5	4.8	0.0	0.0	6.4	85.9	12.2	0.0	0.0	1.9
Government	970,649	865,050	255,601	0	2,600	8.4	16.1	12.2	0.0	0.4	46.4	41.3	12.2	0.0	0.1
Foreign	602,186	0	0	26,800	0	5.2	0.0	0.0	1.3	0.0	95.7	0.0	0.0	4.3	0.0
Total	11,604,268	5,362,755	2,089,365	2,093,900	628,986	100.0	100.0	100.0	100.0	100.0	53.3	24.6	9.6	9.6	2.9

	Dollar Flows					Supplier Network (% of Column Expenditures Received by Row)					Customer Network (% of Row Receipts Spent by Column)				
	Firms	HHs	Capital	Govt	Foreign	Firms	HHs	Capital	Govt	Foreign	Firms	HHs	Capital	Govt	Foreign
Panel D: 1997															
Firms	6,530,867	5,616,840	1,472,776	1,609,666	822,163	40.7	80.1	49.8	60.1	84.7	40.7	35.0	9.2	10.0	5.1
Households	4,656,650	0	1,382,900	929,800	44,753	29.0	0.0	46.7	34.7	4.6	66.4	0.0	19.7	13.3	0.6
Capital	2,610,103	137,712	0	113,724	98,735	16.3	2.0	0.0	4.2	10.2	88.2	4.7	0.0	3.8	3.3
Government	1,309,840	1,259,550	103,600	0	5,100	8.2	18.0	3.5	0.0	0.5	48.9	47.0	3.9	0.0	0.2
Foreign	944,853	0	998	24,900	0	5.9	0.0	0.0	0.9	0.0	97.3	0.0	0.1	2.6	0.0
Total	16,052,313	7,014,102	2,960,274	2,678,090	970,750	100.0	100.0	100.0	100.0	100.0	54.1	23.6	10.0	9.0	3.3
Panel E: 2002															
Firms	8,472,868	7,534,793	1,716,201	2,018,412	832,881	41.2	83.3	45.4	61.2	63.0	41.2	36.6	8.3	9.8	4.0
Households	6,096,928	0	1,667,200	1,247,900	35,665	29.6	0.0	44.1	37.8	2.7	67.4	0.0	18.4	13.8	0.4
Capital	3,308,476	28,500	0	0	445,019	16.1	0.3	0.0	0.0	33.7	87.5	0.8	0.0	0.0	11.8
Government	1,411,477	1,484,400	395,836	0	7,600	6.9	16.4	10.5	0.0	0.6	42.8	45.0	12.0	0.0	0.2
Foreign	1,285,408	0	2,758	33,000	0	6.2	0.0	0.1	1.0	0.0	97.3	0.0	0.2	2.5	0.0
Total	20,575,157	9,047,693	3,781,995	3,299,312	1,321,166	100.0	100.0	100.0	100.0	100.0	54.1	23.8	9.9	8.7	3.5

Internet Appendix Table II
Centrality Summary Statistics, 1982–2002

This table reports summary statistics for log(centrality) across sectors. Data are from the Detailed Input-Output Tables from the Bureau of Economic Analysis, plus five aggregate sectors: Households, Government, Foreign, Capital, and Used Goods/Scrap, calculated using the National Income and Product Account tables. Centrality is the eigenvector centrality in the inter-sector network of trade flows, based on all sectors.

	1982	1987	1992	1997	2002
Observations	493	479	488	483	425
Mean	−6.751	−6.761	−6.833	−6.623	−6.475
Standard Deviation	1.540	1.525	1.563	1.402	1.388
Skewness	0.681	0.792	0.712	1.059	1.135
Kurtosis	4.105	4.281	4.101	4.817	4.974
Minimum	−10.783	−10.248	−10.787	−9.424	−9.814
1st Percentile	−9.848	−9.693	−9.819	−8.910	−8.708
25th	−7.830	−7.813	−7.969	−7.524	−7.449
Median	−6.806	−6.900	−6.958	−6.871	−6.716
75th	−5.868	−5.941	−6.004	−5.880	−5.811
99th	−2.424	−2.278	−2.349	−2.234	−2.113
Maximum	−0.179	−0.183	−0.171	−0.182	−0.180

Internet Appendix Table III
Factor Sensitivities by Centrality

This table reports estimates of time series regressions of monthly returns from January 1983 to December 2007 on a four factor model including the three Fama-French factors plus the momentum factor, $E(R_{it} - R_{ft}) = \alpha_i + b_i(R_{mt} - R_{ft}) + s_i SML_t + h_i HML_t + u_i UMD_t + \varepsilon_{it}$. Portfolio returns are value-weighted industry returns formed for ten deciles of network centrality, where industries and centrality are defined using the most recent BEA IO and NIPA tables from 1982, 1987, 1992, 1997, and 2002. Stocks with a price less than five dollars are excluded. Newey-West adjusted t-statistics are reported in parentheses. 'High−Low' is the portfolio long in the 10th decile and short the 1st decile. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

Portfolio	Alpha (%)	Factor Loadings				Adj. R^2 (%)
		$R_M - R_F$	SMB	HML	UMD	
Low Centrality	0.680	0.898	0.597	0.532	0.095	30.71
	(2.197)	(10.941)	(5.070)	(4.168)	(0.878)	
2	0.730	1.072	0.511	0.261	−0.087	80.92
	(5.742)	(25.373)	(7.973)	(3.511)	(−2.012)	
3	0.640	0.985	0.424	0.307	−0.080	72.12
	(3.885)	(16.515)	(4.232)	(2.492)	(−1.263)	
4	1.340	0.915	0.978	−0.358	0.124	76.91
	(5.597)	(13.632)	(5.248)	(−3.989)	(1.477)	
5	1.090	1.056	0.938	0.040	−0.086	83.17
	(5.714)	(28.131)	(13.388)	(0.618)	(−2.085)	
6	0.750	0.977	0.326	0.030	−0.001	81.64
	(5.273)	(28.839)	(7.045)	(0.570)	(−0.022)	
7	0.740	1.038	0.590	0.437	−0.081	85.16
	(6.236)	(30.910)	(9.018)	(5.285)	(−1.619)	
8	1.100	0.933	0.864	−0.338	−0.039	89.31
	(6.931)	(31.036)	(13.397)	(−4.721)	(−0.638)	
9	1.150	1.029	0.710	−0.223	−0.095	90.00
	(7.087)	(28.760)	(12.110)	(−3.780)	(−1.687)	
High Centrality	0.910	0.993	0.665	0.199	−0.025	93.67
	(8.644)	(49.531)	(19.417)	(5.174)	(−1.563)	
High-Low	0.230	0.096	0.068	−0.333	−0.120	4.64
	(0.728)	(1.182)	(0.639)	(−2.481)	(−1.160)	

Internet Appendix Table IV

Cross Sectional Regressions of Industry-Level Average Monthly Returns: Unlevered Returns

This table presents regression coefficients and robust standard errors in parentheses. The dependent variable is the average monthly value-weighted unlevered industry returns from January 1993 to December 2002. Industries are based on BEA Input-Output (IO) definitions from 1997. 'Centrality' is the eigenvector centrality of the industry in the economy-wide sector network. 'Industry Concentration' is the four-sector concentration ratio of sales in an industry. 'Concentration of Customers' is the four-sector concentration ratio of sales outputs per industry. 'Concentration of Suppliers' is for purchases per industry. 'Log(Industry Average Market Equity)' is the cross-sectional average market equity of all firms listed on CRSP in each industry, averaged over 1/1993 to 12/1997. 'Log(Industry Scope)' is the fraction of all NAICS codes that map to the IO industry code. 'Labor's Fraction of Inputs' is the total dollars spent on labor compensation divided by total input costs per industry. 'Log(Number of Firms)' is the number of firms by industry from the Statistics of U.S. Businesses (SUSB), 'Log(Hoberg Phillips Centrality)' is the eigenvector centrality of industries in an inter-industry network based on the text-based similarity measures of Hoberg and Phillips (2010a) and Hoberg and Phillips (2010b). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
Log(Centrality)	0.156***										0.129***	0.146***
	(< 0.001)										(0.004)	(0.003)
$R_M - R_F$		0.717***									0.881***	0.884***
		(< 0.001)									(< 0.001)	(< 0.001)
SMB		0.529***									0.245*	0.254*
		(< 0.001)									(0.097)	(0.084)
HML		−0.928***									−0.935***	−0.943***
		(< 0.001)									(< 0.001)	(< 0.001)
UMD		0.215									0.095	0.115
		(0.318)									(0.658)	(0.596)
Industry			−0.002								0.000	0.000
Concentration			(0.602)								(0.877)	(0.931)
Concentration				0.376							0.366**	0.393**
of Customers				(0.156)							(0.026)	(0.019)
Concentration					0.799						−0.054	−0.008
of Suppliers					(0.105)						(0.897)	(0.985)
Log(Industry Average						−0.017					−0.102***	−0.102***
Market Equity)						(0.654)					(0.007)	(0.007)
Log(Industry Scope)							0.026				−0.212***	−0.208***
							(0.678)				(0.001)	(0.001)
Labor's Fraction								0.977**			0.729**	0.761**
of Inputs								(0.017)			(0.044)	(0.034)
Log(Number of Firms)									0.127***		−0.002	−0.006
									(< 0.001)		(0.944)	(0.837)
Log(Hoberg Phillips										0.277***		−0.063

Centrality)										(0.006)		(0.302)
Constant	2.297***	0.955***	1.355***	1.013***	0.781***	1.528***	1.447***	0.978***	0.443**	2.484***	1.268*	1.103
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(0.009)	(0.003)	(< 0.001)	(< 0.001)	(0.033)	(< 0.001)	(0.069)	(0.120)
Observations	385	310	357	385	385	377	385	385	379	385	286	286
Adjusted R^2	0.028***	0.366***	−0.002***	0.003***	0.003***	−0.002***	−0.002***	0.011***	0.033***	0.017***	0.417***	0.416***

Internet Appendix Table V
The Diffusion of Return Shocks Across Close and Distant Industries
This table reports results from regressions to estimate the effect of returns that occur in industries connected through customer-supplier links. Observations are sector-months from January 1993 to December 2002 for sectors from the BEA Input-Output Detailed Industry Table in 1997. The dependent variable is the sector-monthly value-weighted return at time t. 'Own Returns' are the lagged own-sector monthly returns. 'Close (Distant) Returns' are the average returns from industries that are close (distant) in the inter-sector network. Close and distant industries are defined by steps between industries following the shortest path. Shortest paths are computed using the Dijkstra (1959) algorithm on the weighted and directed supplier network. Close industries are those that are fewer steps from the subject industry than the 25th percentile in the industry's distribution of steps between all other industries. Distant industries are greater than the 75th percentile of an industry's steps. 'Month Fixed Effects' are fixed effects for the calendar month. Columns 1 and 4 includes lags of $t-1$ only. Columns 2 and 5 include lags from $t-1$ to $t-6$. Columns 3 and 6 include lags from $t-1$ to $t-12$. Panel A reports all coefficient values. Panel B sums coefficients by lag length. 'Recent' indicates the sum of coefficients on lags 1, 2, and 3. 'Old' indicates the sum of coefficients on lags 4, 5, and 6 in columns 2 and 5, and lags 10, 11, and 12 in columns 3 and 6. 'Close−Distant' is the difference between the close coefficients and the distant coefficients. 'Difference-in-Difference' is the difference of close and distant industries for recent and the old periods. Numbers in parentheses are p-values based on standard errors that are clustered at the industry level. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***.

	Dependent Variable: Monthly Industry Returns					
	Value-Weighted Returns			Equal-Weighted Returns		
	(1)	(2	(3)	(4)	(5)	(6)
Panel A: All Coefficients						
Own Returns						
Lag 1	−0.020**	−0.025***	−0.027***	−0.015*	−0.020**	−0.021**
	(0.012)	(0.003)	(0.002)	(0.074)	(0.031)	(0.024)
Lag 2		−0.006	−0.006		−0.011	−0.011
		(0.497)	(0.494)		(0.205)	(0.225)
Lag 3		0.010	0.009		0.005	0.003
		(0.306)	(0.409)		(0.599)	(0.738)
Lag 4		0.021**	0.022**		0.014	0.015*
		(0.020)	(0.015)		(0.109)	(0.069)
Lag 5		0.004	0.005		0.006	0.008
		(0.570)	(0.474)		(0.430)	(0.342)
Lag 6		0.041***	0.044***		0.034***	0.036***
		(< 0.001)	(< 0.001)		(< 0.001)	(< 0.001)
Lag 7			0.019***			0.019**
			(0.009)			(0.013)
Lag 8			0.005			0.008
			(0.527)			(0.331)
Lag 9			0.018**			0.017**
			(0.030)			(0.025)
Lag 10			0.000			−0.008
			(0.998)			(0.370)

Lag 11			−0.006			−0.004
			(0.431)			(0.595)
Lag 12			0.008			0.009
			(0.238)			(0.237)
Close Returns						
Lag 1	0.153***	0.140***	0.149***	0.138***	0.144***	0.146***
	(0.003)	(0.006)	(0.004)	(0.008)	(0.005)	(0.005)
Lag 2		0.067	0.042		0.019	0.004
		(0.212)	(0.454)		(0.701)	(0.936)
Lag 3		0.010	0.019		−0.072	−0.039
		(0.851)	(0.734)		(0.184)	(0.481)
Lag 4		−0.060	−0.040		−0.009	−0.003
		(0.236)	(0.442)		(0.867)	(0.960)
Lag 5		0.093**	0.093*		0.083*	0.083*
		(0.042)	(0.052)		(0.075)	(0.086)
Lag 6		−0.044	−0.031		−0.086*	−0.066
		(0.386)	(0.571)		(0.081)	(0.239)
Lag 7			−0.054			−0.043
			(0.287)			(0.407)
Lag 8			0.102*			0.036
			(0.062)			(0.504)
Lag 9			0.048			0.026
			(0.361)			(0.628)
Lag 10			−0.160***			−0.113*
			(0.004)			(0.064)
Lag 11			0.088			0.117**
			(0.121)			(0.035)
Lag 12			−0.007			−0.027
			(0.893)			(0.602)
Distant Returns						
Lag 1	0.017	0.020	0.005	−0.080	−0.062	−0.076
	(0.741)	(0.712)	(0.924)	(0.138)	(0.261)	(0.183)
Lag 2		−0.110*	−0.112*		−0.044	−0.019
		(0.073)	(0.083)		(0.476)	(0.783)
Lag 3		−0.049	−0.028		−0.081	−0.062
		(0.495)	(0.709)		(0.254)	(0.401)
Lag 4		0.009	−0.018		0.053	0.057
		(0.890)	(0.800)		(0.390)	(0.395)
Lag 5		−0.057	−0.032		−0.145***	−0.123**
		(0.306)	(0.593)		(0.010)	(0.045)
Lag 6		0.072	0.070		0.134**	0.136**
		(0.167)	(0.216)		(0.014)	(0.022)
Lag 7			0.091			0.061
			(0.255)			(0.421)
Lag 8			−0.138**			−0.102
			(0.040)			(0.118)
Lag 9			−0.028			0.004

			(0.678)			(0.957)
Lag 10			0.057			0.137**
			(0.279)			(0.024)
Lag 11			0.007			−0.011
			(0.911)			(0.873)
Lag 12			0.109*			0.137**
			(0.093)			(0.030)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.150	0.154	0.158	0.181	0.186	0.190
Observations	43,041	41,101	38,776	42,992	41,057	38,740
Panel B: Combined Coefficients						
Close						
Recent	0.153***	0.217**	0.210**	0.138***	0.092	0.111
	(0.003)	(0.021)	(0.034)	(0.008)	(0.297)	(0.224)
Old		−0.011	−0.079		−0.012	−0.023
		(0.885)	(0.370)		(0.873)	(0.784)
Distant						
Recent	0.017	−0.138	−0.134	−0.080	−0.188*	−0.157
	(0.741)	(0.191)	(0.216)	(0.138)	(0.073)	(0.145)
Old		0.024	0.174*		0.042	0.263**
		(0.800)	(0.090)		(0.631)	(0.014)
Close−Distant						
Recent	0.136*	0.355***	0.344**	0.218***	0.280**	0.268**
	(0.077)	(0.010)	(0.015)	(0.004)	(0.031)	(0.047)
Old		−0.035	−0.252**		−0.054	−0.286**
		(0.790)	(0.047)		(0.630)	(0.025)
Difference-In-Difference						
		0.391*	0.596***		0.334*	0.554***
		(0.056)	(0.005)		(0.082)	(0.007)

Internet Appendix Table VI
Government Entities Aggregated into Government Sector
This table presents the government entities recorded in the IO tables that are included in the government sector by IO report year.

1982
Federal Government purchases, national defense
Federal Government purchases, nondefense
Elementary and secondary public school systems
Public educational facilities beyond high school
S&L gov't purchases, other education and libraries
S&L gov't hospitals and categorical health programs
S&L gov't public welfare institutions and activities
Public sewerage systems, capital account purchases only
S&L gov't purchases, sanitation
S&L gov't police
S&L gov't fire fighting organizations and auxiliary services
S&L gov't correctional institutions
Public highways (excl. non-capital expenditures of toll roads)
S&L gov't waterports and airports, capital account only
S&L gov't-operated transit systems, capital account only
S&L gov't other commerce activities n.e.c., capital account only
S&L gov't gas and electric utilities, capital account only
S&L gov't-operated water supply facilities, capital account only
S&L gov't redevelopment projects, capital account only
S&L gov't natural & agric. resources & recreation facilities
S&L gov't other general government activities n.e.c.

1987
Federal Government purchases, national defense
Federal Government purchases, nondefense
State and local government purchases, elementary and secondary public school systems
State and local government purchases, public educational facilities beyond high school
State and local government purchases, other education and libraries
State and local government purchases, hospitals and categorical health programs
State and local government purchases, public welfare institutions and activities

State and local government purchases, public sewerage systems, capital account only
State and local government purchases, sanitation
State and local government purchases, police
State and local government purchases, fire fighting organizations and auxiliary services
State and local government purchases, correctional institutions
State and local government purchases, public highways (excluding non-capital expenditures of toll roads)
State and local government purchases, waterports and airports, capital account only
State and local government purchases, government-operated transit systems, capital account only
State and local government purchases, other commerce activities n.e.c., capital account only
State and local government purchases, gas and electric utilities, capital account only
State and local government purchases, government-operated water supply facilities, capital account only
State and local government purchases, redevelopment projects, capital account only
State and local government purchases, natural and agricultural resources and recreation facilities
State and local government purchases, other general government activities, n.e.c.

1992

Federal Government gross investment, national defense
Federal Government consumption expenditures, national defense
Federal Government gross investment, nondefense
Federal Government consumption expenditures, nondefense
State and local government gross investment, elementary and secondary public school systems
State and local government gross investment, public educational facilities beyond high school
State and local government gross investment, other education and libraries
State and local government consumption expenditures, elementary and secondary public school systems
State and local government consumption expenditures, public educational facilities beyond high school
State and local government consumption expenditures, other education and libraries
State and local government gross investment, hospitals and categorical health programs
State and local government gross investment, public welfare institutions and activities
State and local government gross investment, public sewerage systems
State and local government gross investment, sanitation
State and local government consumption expenditures, hospitals and categorical health programs
State and local government consumption expenditures, public welfare institutions and activities
State and local government consumption expenditures, sanitation
State and local government gross investment, police
State and local government gross investment, fire fighting organizations and auxiliary services

State and local government gross investment, correctional institutions
State and local government consumption expenditures, police
State and local government consumption expenditures, fire fighting organizations and auxiliary services
State and local government consumption expenditures, correctional institutions
State and local government gross investment, public highways
State and local government gross investment, waterports and airports
State and local government gross investment, government-operated transit systems
State and local government gross investment, other commerce activities n.e.c.
State and local government gross investment, gas and electric utilities
State and local government gross investment, government-operated water supply facilities
State and local government gross investment, redevelopment projects
State and local government gross investment, natural and agricultural resources and recreation facilities
State and local government gross investment, other general government activities, n.e.c, gross investment
State and local government consumption expenditures, public highways (non-capital expenditures of toll roads)
State and local government consumption expenditures, natural and agricultural resources and recreation facilities
State and local government consumption expenditures, other general government activities, n.e.c.

1997

Federal Government consumption expenditures, national defense
Federal Government gross investment, national defense
Federal Government consumption expenditures, nondefense
Federal Government gross investment, nondefense
State and local government consumption expenditures, education
State and local government gross investment, education
State and local government consumption expenditures, other
State and local government gross investment, other

2002

Federal Government defense: Consumption expenditures
Federal Government defense: Gross investment
Federal Government nondefense: Consumption expenditures
Federal Government nondefense: Gross investment
State and local government education: Consumption expenditures
State and local government education: Gross investment
State and local government other: Consumption expenditures

State and local government other: Gross investment