White Paper

Centrality of the Supply Chain Network

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FACTSET

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Contents

Abstract

With the increasing availability of supply chain information, researchers are paying increasing attention to information flows and interactions between suppliers and customers; however, shocks to a supplier not only impact its immediate customers, but also generate ripple effects on the whole economy through the supply chain network. This paper strives to define the relative importance, or centrality, of a supplier in the whole supply chain network, and understand how the most central suppliers to the economy behave differently, and how they interact with the aggregate economy and the business cycle. Based on information from the FactSet Supply Chain Relationships database, the paper builds a supplier-customer network matrix at the beginning of each year from 2004 to 2014, and computes the supplier centralities of each company based on a list of centrality definitions. The paper then forms supplier central stock portfolios based on the centrality estimates, and perform historical analysis on their behaviors. Historical analysis shows that supplier central portfolios tend to be more volatile than average, and the stock performance of supplier central portfolios tends to predict the movements of the overall stock market.

JEL Classification: G10, G14.

Keywords: Supply chain, directed network, degree centrality, eigenvector centrality, PageRank, Kleinberg centrality

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Introduction

Researchers increasingly appreciate the important role structural relations and connections play in understanding the statistical relations of financial securities from different companies. Such structural relations include, for example, similarities in the underlying business, as often captured by industry classification and peer group identification. Stock returns from the same industry/peer group tend to move more closely together.[1] Similarly, when analyzing the behavior of a particular company, financial analysts[2] and investors tend to pay close attention to the company's major suppliers and customers, from which they strive to infer the potential risks and opportunities for the company. The closure or production delay of a major supplier can cause significant issues for the company's production, whereas the changing demand of the customer base poses challenges for the company's sales projection. Menzly and Ozbas (2010) argue that fully digesting the implication of the information from structurally connected firms can take time. As evidence, they show that stocks that are in economically related supplier and customer industries cross-predict each other's returns. Chen, Zhang, and Zhang (2014) show that the return predictability across supplier-customer industries can be even stronger for the corporate bond market. Shahrur, Becker, and Rosenfeld (2010) use a sample of equities listed on the exchanges of 22 developed countries to show that equity returns on customer industries lead the returns of supplier industries. At the firm level, Cohen and Frazzini (2008) use a data set of firms' principal customers to identify a set of economically related firms, and show that the stock price of a firm does not fully incorporate news involving its related firms, thus generating predictable subsequent price moves. These studies highlight the importance of understanding the structural connections across companies and the implications of these connections for cross relations.

In this paper, I argue that understanding the structural connections is important not only for enhancing the identification of pair-wise statistical relations (both contemporaneous and across different leads and lags), but also for identifying the key drivers of the business cycle and aggregate market fluctuations. For this purpose, I propose to examine the supplier-customer relation not in terms of pair-wise connections, but from the perspective of an economic supply chain network, with each relation serving as a directed node of the network. I explore the potentials of a list of centrality measures in capturing the major determinants of the supply chain network. Of these measures, the supplier-customer centrality pair defined based on Kleinberg (1999)'s algorithm looks particularly promising. The supplier centrality of a company is defined as the sum of the customer centralities of all its customers and the customer centrality of a company is defined as the sum of the supplier centrality of all its suppliers. The centralities can be solved as the leading eigenvector of the products of the supplier-customer network matrix.

Based on information from the FactSet supply chain relationship database, I build a supplier-customer network matrix at the beginning of each year from 2004 to 2014, compute the supplier and customer centralities of each company, and construct supplier and customer central stock portfolio based on the centrality estimates. I find that supplier central portfolios tend to be more volatile than customer central portfolios. Furthermore, the stock performance of supplier central portfolios tends to predict the movements of the overall stock market.

In related work, Ahern and Harford (69) represent the economy as a network of industries connected through customer and supplier trade flows and analyze how merger waves propagate through the network. Aobdia, Caskey, and Ozel (2014) define centrality of industries based on cross-industry trade flows and find that stock returns on central industries depend more on aggregate risks, and shocks to central industries propagate more strongly than shocks to other industries. Ahern (2013) show that industries that are more central in the network of intersectoral trade earn higher stock returns than industries that are less central.

1 Largely because of this observation, commonly-used risk models in the industry such as BARRA treat each industry as a stand-alone risk factor.
2 Luo and Nagarajan (2014) examine the antecedents and consequences of analysts choosing to become supply chain analysts, i.e., analysts following both a supplier and its major customer. Guan, Wong, and Zhang (2015) find that the likelihood of an analyst following a supplier-customer firm pair increases with the strength of the economic ties along the supply chain, as measured by the percentage of the supplier's sales to the customer.

The remainder of the paper is organized as follows. The next section describes the FactSet supply chain relationship database. Section 3 discusses different centrality measures and their economic meanings within the context of the supply-chain network. Section 4 analyzes the supplier centralities of the U.S. economy. Section 5 concludes.

Data Source and Sample Construction

The firm-level supplier-customer relationship information is from FactSet, which maps the historical supplier/customer relationship for each company based on information from the company's regulatory disclosure reports, annual reports, and other primary sources. I confine the analysis to constituents of the S&P Composite 1500 index, which covers about 90% of the U.S. market capitalization and includes three leading indices: the S&P 500 index, the S&P MidCap 400 index, and the S&P SmallCap 600 Index. From January 2004 to January 2014, I take snapshots of the database at the beginning of each year, and merge the information with price and accounting data from Bloomberg. Over the 11-year period, each year I identify from 1214 to 1340 companies, and from 4169 to 6061 supplier-customer pairs, averaging 3-5 suppliers per customer.

The FactSet database indicates the applicable time period for each relationship, from which one can in principle extract the relational mapping at any time; nevertheless, I decide to take the snapshots at a relatively low frequency because of our concern that it may take time for the applicable relationship to become fully known to the average investor. By taking a snapshot once a year, I assume that the structural relation is relatively stable and will hold over the coming year, while avoiding to chase the intra-year variations that one may not be able to capture in practice.

The U.S. Securities and Exchange Commission (SEC) has a mandate (rule SFAS 131) that calls for companies to disclose their customers if their revenue exposure to them is 10% or greater. In addition, some companies choose to disclose more customer and supplier information if they believe the information will help improve their attractiveness and draw more attention from investors. FactSet expands and consolidates such information through cross validation and a reverse linkage methodology. For example, if company A identifies company B as a supplier, company A becomes the customer of company B. In practices, the relationships are not always symmetric due to size differences (among other things). For example, if company A is much smaller than company B, it is possible that although company B is a significant supplier for company A, company A is not a significant customer for B. In this case, the cross validation approach may bring a certain degree of bias to the data. Furthermore, in performing the analysis, I am conscious of the fact that a company can have supplier/customer relationships, possibly with lesser significance, with many more companies than reported in the database.

Finally, important questions arise on how to define the relative significance of a relationship. When highlighting the significance of a supplier to a company, the company may cite how much it spends on this supplier, maybe in percentage of its total cost of goods sold. On the other hand, when highlighting the significance of a customer to a company, the company can cite how much percentage of its sales come from this customer. While companies sometimes report these numbers and the FactSet database captures them, the information is still far too incomplete for systematic analysis. Absent from more detailed information, I treat each identified supplier as equally significant to its customer, and vice versa. Depending on the specific applications, one can also consider altering the significance of each relationship according to factors such as industry proximity, direction of disclosure, and size of firms. Furthermore, measures that capture the irreplaceability and/or value-added of a supplier can also be used as importance metrics.

Supply Chain Centrality Measures

Instead of focusing on the pair-wise relationship between a company and its suppliers, I examine the relationship from the perspective of the aggregate economy and the economy-wide network of the supply chain. I analyze the relative importance of each supplier in terms of its contribution to the networked economy.

Formally, I represent the supplier network at a given point in time via the supplier matrix $\{A_{i,j}\}_{i,j=1}^{N}$, where N denotes the number of companies, and $A_{i,j} = 1$ if company i is the supplier of company j. Thus, each column j represents an index of the suppliers for company j, and each row i lists the customers that the supplier i has.

In the language of networks, the supply chain network is a directed network, where one can imagine drawing an arrow from each customer to each of its suppliers. The literature on networks, e.g., Newman (2010), has proposed a long list of centrality measures to represent the relative importance of a vertex in 4 the network. I adapt these concepts to the supply chain network and explore their economic meaning and relevance in capturing the relative importance of a supplier in the supply chain network.

Degree Centrality: The Number of Companies that the Supplier Serves

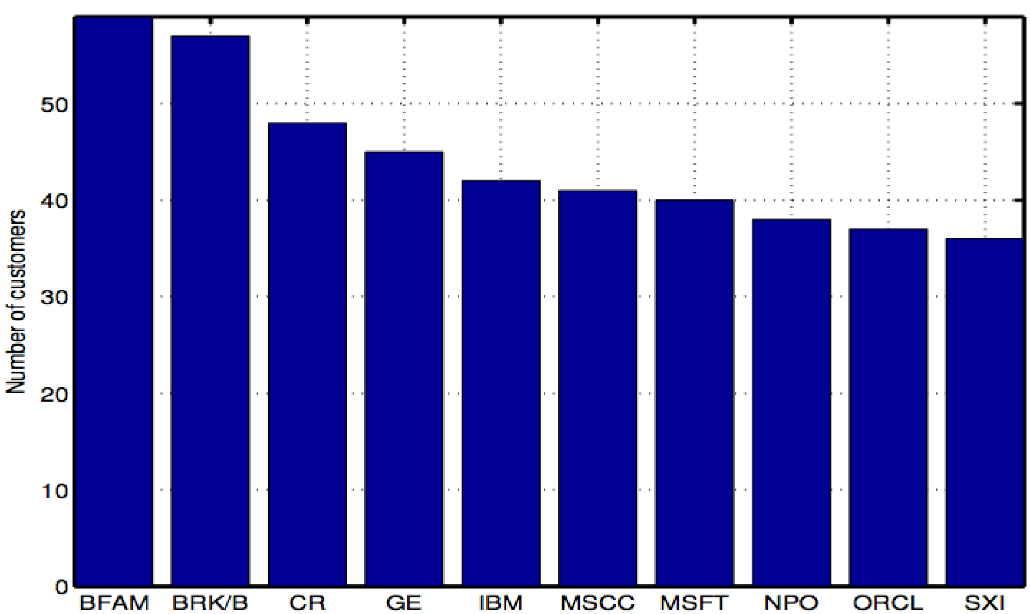
Intuitively, a supplier company is more important to the economy if it is the supplier of many companies instead of just one company. Thus, a simple measure of centrality for a supplier, often referred to as the **degree centrality**, can be defined as the number of companies that this supplier serves. From the perspective of the network topology, if one draws an arrow from a company to each of its suppliers, the degree centrality simply measures the degree of a vertex, or the number of arrows pointed to a particular supplier. From the supplier matrix A, one can compute the degree centrality vector, c, as the simple sum of each row, where e denotes a vector of ones.

(1)

$$c = Ae$$

Figure 1 plots the top ten suppliers as of January 2014 with the most number of customers. The top two on the list BFAM and BRK/B have more than 50 identified customers and the next five suppliers have 40 or more customers. The top list spans across different industries from child-care provider (BFAM), multinational conglomerate (BRK/B), manufacturers of industrial goods (CR, GE), to large technology companies (IBM, MSFT).

Fig. 1. Top Ten Suppliers with the Most Number of Customers.



Eigenvector Centrality: The importance of Customers as Suppliers Themselves

A natural extension of the simple degree centrality is eigenvector centrality. One can think of degree centrality as awarding one "centrality point" for each customer a vertex (supplier) has; however, not all customers 5 are equivalent. Each customer can be a supplier to other companies, and its importance to the economy increases if the customer itself is an important supplier to many other companies. Instead of awarding suppliers just one point for each customer, eigenvector centrality gives each supplier a score proportional to the sum of the scores of its customers.

Let c_i be the centrality measure for each company i. The eigenvector centrality of company i is proportional to the sum of the centralities of all its customers,

(2)

$$c_i = \left({}^{1}/_{\lambda}\right) \sum_j A_{i,j} c_j$$

In matrix notation, we have,

(3)

$$\lambda c = Ac$$

It can be shown that the thus-defined eigenvector centrality is proportional to the right leading eigenvector of the supplier matrix A (Bonacich (1987)). Furthermore, since all elements of the supplier matrix A are nonnegative, the Perron-Frobenius theorem states that the leading eigenvector has strictly positive components.

The eigenvector centrality has the nice property that it can be large either because a supplier has many customers or because it has important customers, or both. Equation (3) does not fix the normalization of the eigenvector centrality. Normalization is not essential to the analysis as I mostly focus on the relative ranking of the measure. One way to normalize the metric is, for example, to require that the centrality measures of all firms sum to $N, e \perp c = N$, where N is the number of companies in the network. With this normalization, the average centrality does not vary with the size of the economy.

PageRank: Discounting the Importance of Customers with Many Suppliers

The eigenvector centrality has one feature that can be undesirable. If a company with high eigenvector centrality is the customer of many suppliers, all these suppliers also get high centrality. This assignment is not always appropriate. In many cases it means less if a company is only one of the many suppliers. The 6 centrality gained by virtue of receiving an edge from a prestigious customer is diluted by being shared with so many suppliers. Being the sole supplier to an important company can be important, but being one of the hundreds of suppliers to the same company, especially if these suppliers are substitutes, may not be as valuable to the economy.

One can allow for this by defining a variation on the eigenvector centrality in which the centrality a company derives from a customer is proportional to the centrality of the customer divided by the number of suppliers the customer has. A customer that has many suppliers passes only a small amount of its centrality on to each of these suppliers, even if its own centrality is high. In mathematical terms, this centrality is defined by

(4)

$$c_i = \left({}^{1}/_{\lambda}\right) \sum_j A_{i,j} \frac{c_j}{k_j}, \qquad k_j = max\left(1, \sum_i A_{i,j}\right)$$

Since $A_{i,j}$ is one if company i is the supplier of company j, the sum of the j th column, $\sum_i A_{i,j}$, captures the number of suppliers of company j. If company j has no suppliers, it will not have any contribution to any supplier's centrality. Therefore, one can simply set k_j to one without affecting the calculation.

Let K denote the diagonal matrix with the ith diagonal element bing k_i, one can write the relation (4) in matrix form,

(5)

$$\lambda c = AK^{-1}c$$

and thus solve the centrality as the leading eigenvector of the scaled supplier matrix $\tilde{A} = (AK^{-1})$. Essentially, the scaled matrix $\tilde{A}$ normalizes each column by its sum so that each column sums to one. Brin and Page (1998) propose a similar scaling idea in their modeling and ranking of the internet hyperlinks. The measure, with some variation, is commonly known as PageRank, the trade name given it by the Google web search corporation, which uses it as a central part of their web ranking technology.

For an undirected network, where the matrix A is symmetric, equation (5) leads to a trivial solution: It is easy to see that it gives simply $c_i = k_i$ and therefore is just the same as ordinary degree centrality. For a directed network as is the case for the supply chain network or intent hyperlinks, it does not reduce to any equivalent simple value and thus may have its own value.

Kleinberg Centrality: Distinguish Supplier Centrality from Customer Centrality

The above discussion focuses on the relative importance of a supplier to the supply chain, and considers measures that accord a company high centrality if its customers have high centrality. On the flip side of this discussion, customers also play important roles in the economy and thus it may also be appropriate to accord high customer centrality to a company if it is the customer of many other highly important customers.

From the perspective of a directed network, Kleinberg (1999) proposes to construct two types of centralities, labeled as the authority centrality and the hub centrality, to quantify each vertex's prominence in the two roles, with authorities corresponding to important suppliers and hubs corresponding to important customers in our application. Kleinberg develops a centrality algorithm called hyperlink-induced topic search or HITS, which, for our particular application, can be interpreted as giving each company i a supplier centrality s_i and a customer centrality c_i. The defining characteristic of a company with high supplier centrality is that it is the supplier of many customers with high customer centrality. The defining characteristic of a company with high customer centrality is that it is the customer of many suppliers with high supplier centrality. Thus, the importance of customers defines the importance of the supplier and the importance of suppliers defines the importance of the customer. Mathematically, this can be written as

(6)

$$s_i = \alpha \sum_j A_{i,j} c_j, \qquad c_i = \beta \sum_j A_{j,i} s_j$$

In matrix notation,

(7)

$$s = \alpha A c, \quad c = \beta A^{\mathsf{T}} s$$

Combining the two,

(8)

$$AA^{\intercal}s = \lambda s, \quad A^{\intercal}Ac = \lambda c$$

with $\lambda = (\alpha\beta)^{-1}$. Thus the supplier and customer centralities are respectively given by eigenvectors of $AA^{\intercal}$ and $A^{\intercal}A$ with the same eigenvalue. By an argument similar to the one we have used for the standard eigenvector centrality, one can show that we should in each case take the eigenvector corresponding to the leading eigenvalue.

A crucial condition for this approach to work, is that $AA^{\intercal}$ and $A^{\intercal}A$ have the same leading eigenvalue λ; otherwise, we cannot satisfy both conditions in equation (8). This is indeed the case, and in fact that all eigenvalues are the same for the two matrices. To see this, one can start with $AA^{\intercal}s = \lambda s$, and multiply both sides by $A^{\intercal}$ to give

$$A^{\intercal}A(A^{\intercal}s) = \lambda(A^{\intercal}s)$$

and hence $A^{\intercal}c$ is the eigenvector of $A^{\intercal}A$ with the same eigenvalue λ. Comparing to (8), this means that

(9)

$$A^{\intercal}s = c$$

which gives us a fast way of calculating the customer centrality once we have the supplier centrality.

It is possible that a company is not the supplier to any other company. This will lead to a row of zeros in the supplier matrix. Both the degree centrality and eigenvector centrality for this company will be zero. A zero centrality measure for this company sounds intuitive as a company that supplies to nobody should be ranked low in the supply chain. However, imagine another company, which is a supplier to thousands of such companies. The fact that it is a supplier of many companies should make it "important" and this importance shows up in the degree centrality measure. However, since its customers all have zero eigenvector centrality, this company will also end up having zero eigenvector centrality. Taking this argument further, a company may be pointed to by others that themselves are pointed to by many more, and so on through many generations, but if the progression ends up at a company or companies that supply to no other companies, it is all for nothing — the final value of the eigenvector centrality will still be zero. Such a chain effect does not sound quite as intuitive.

In a strict sense, a company must have customers, even though these customers may not take the form of a company. Furthermore, companies do not report all their customers. By regulation, they only need to report customer companies that generate over 10% of their revenue. Some companies may choose to report more. Even so, it is unlikely the database lists all possible customers. For many retail companies, their customers are simply the consumers. Thus, one common solution to this issue is to give each company a small amount of centrality "for free," regardless of its position in the network. This modification was first proposed by Katz (1953) and was also adopted in the actual application of PageRank.

The customer and supplier centralities circumvent this problem from an alternative angle. Companies not cited by any others as a supplier (that is, companies with no customers) have supplier centrality zero, which is reasonable, but they can still have non-zero customer centrality. Thus, their suppliers can have non-zero supplier centrality by virtue of being a supplier. This is perhaps a more elegant solution to the problems of eigenvector centrality in directed networks than the more ad hoc method of introducing an additive constant term in Katz (1953). Defining the importance of a supplier based on the importance of its customers as a customer also sounds more economically intuitive than based on the importance of its customers as a supplier.

Similarities and Differences

The four supplier centrality measures are all defined based on the number of customers a supplier has and the relative importance of its customers. The difference lines in the definition of the customer importance. Degree centrality assumes that all customers are equally important and one can thus use an equally weighted sum of the customers to measure the degree centrality. Eigenvector centrality assumes that customer importance is the same as the supplier importance, thus leading to a recursive equation: The eigenvector centrality of a supplier is proportional to the sum of the eigenvector centrality of its customers. PageRank also uses the supplier importance as the starting point, but discount the importance of each customer by its number of suppliers. By contract, the customer importance in Kleinberg centrality definition increases with the number and importance of its suppliers as it is defined as the sum of it supplier centrality. Therefore, while all measures agree that the importance of a supplier depends on its number of customers, they differ on how to adjust for the importance of each customer. The appropriate choice of adjustment is likely to be dependent on the particular application and can be an interesting subject for further research in the future.

Central Suppliers of the U.S. Economy

I analyze the historical behaviors of the different centrality measures constructed on the U.S. economy. To do so, I map the FactSet supply-chain data to the universe of the S&P composite 1500 companies and construct the supply-chain matrix A at the beginning of each year from 2004 to 2014. From the supply chain matrix, I construct the five centrality measures: Degree centrality, Eigenvector centrality, PageRank centrality, Supplier centrality, and Customer centrality.

To gauge their similarities and differences of these measures, I estimate the Spearman rank correlation of the five centrality measures each year. Table 1 reports the historical average of the cross correlation estimates. The first four centrality measures are all about the relative importance as a supplier. They show positive correlations of different degrees. The highest correlation is between eigenvector and PageRank centrality at 0.965. The lowest is between PageRank and Supplier centrality at 0.75. One potential driver for this low correlation is their somewhat opposite assumption on customer importance.

The customer centrality measure, on the other hand, measures the relative importance of a company as a customer and shows negative correlations with all four supplier centrality measures. The most negative correlation is between the customer centrality and its counterpart suppler centrality at –0.111.

The Top Ten List

I rank the companies based on each centrality measure and analyze the behavior of the top ten companies with the highest centrality estimates. Table 2 provides the ticker of the top ten suppliers with the most customers (and hence the highest degree centrality) at the beginning of each year. Technology companies are the most prominent top suppliers during the earlier period of the sample, but the list becomes more diverse in the more recent years with some companies from the industrial goods and services sectors.

Table 3 provides the top ten suppliers with the highest eigenvector centrality in panel A. Once we consider the feedback effect of the network, technology companies dominate the top ten lists for most years. In particular, Atmel, which designs, develops, and manufactures semiconductor integrated circuit products, becomes the top supplier from 2006 to 2012.

Panel B of Table 3 provides the top ten list based on the PageRank centrality measure. Scaling the centrality by number of suppliers generates further shuffling. Technology companies remain prominent on the list during the early years, but 2014 shows a more diverse picture with two companies from healthcare, two from financials and one from the service sector.

Table 4 provides the top ten list of supplier centrality in panel A. By changing the definition of customer importance, the top ten supplier list has a completely new makeover in recent years. In particular, the 2014 top ten list includes six REIT companies, but none from the technology sector. The reasoning behind this shift needs further exploration.

Panel B of Table 4 provides the top ten list of customer centrality. The list is quite distinctive and includes many large retail stores. In 2014, this list includes BestBuy, Costco, Home Depot, Lowe's, Sears, Target, and Walmart.

The Statistical Behavior of Central Stock Portfolios

While I define several centrality measures to identify the central suppliers and customers of an economy, it is unclear how the central vertices of the network behave and how their behaviors impact the aggregate economy. To explore the historical behavior of "central" companies, I form equal-weighted stock portfolios using the top ten companies[3] defined by each centrality measure and analyze their statistical behaviors in terms of their relations with the aggregate market, proxyed by the S&P 500 index. The compositions of the portfolios are updated at the beginning of each year based on the renewed centrality measure estimates. Table 5 summarizes these statistical behaviors.

First, I regress the daily returns on the central stock portfolios against the S&P 500 index return to estimate the beta of each central portfolio. The beta estimates on reported in Table 5 under the column titled "b." The customer central portfolio has a beta estimate slightly less than one at 0.984, whereas the supplier centrality portfolios all have beta estimates around 1.2 or higher, except the portfolio defined on degree centrality. Thus, top suppliers companies show larger market exposure than top customer companies. When I measure the correlation between the daily central portfolio returns and the S&P 500 index returns, the estimates are very high, all around 0.8 or higher, as reported in Table 5 under the column "r."

To examine whether the stock performance of top suppliers and customers provide any precursor for the overall market movements, I compute quarterly returns on the central portfolios, and measures their forecasting correlations with the S&P 500 index returns over three- and six-month horizons. When using total return on the central portfolios as the predictor, the forecasting correlations are all positive for all central portfolios at both horizons. The predictions are the most positive for the PageRank portfolio at three-month horizon, and the supplier central portfolio at six-month horizon.

Part of the positive correlation prediction is due to the momentum effect identified by, for example, Jegadeesh and Titman (2001). To control for this, I regress each stock return against the S&P 500 index return to generate excess stock returns, and then compute the excess returns on the central portfolios. Using the excess returns as a predictor of future index returns, I find that the forecasting correlation is virtually zero for the customer central portfolio, but remain positive for all other central portfolios. Excess return on the supplier central portfolio generates the strongest predictive correlation at both three and six month horizons. Thus, the evidence seems to suggest that the stock performance of central suppliers predict the following performance of the overall market, but the stock performance of central customers do not lead the market performance.

Comparing the relative forecasting power of the different centrality measures, we can also gain some basic understanding on the effectiveness of different measures. The quarterly forecasting correlation is 8.8% for the simple degree centrality portfolio. By contrast, the eigenvector centrality portfolio generates stronger forecasting correlations at 11.5%, highlighting the importance of the feedback effect. The forecasting power becomes even stronger for the

3 An alternative is to form stock portfolios with weights proportional to the centrality estimates. The results are qualitatively similar whether we use equal weighting or set weighting proportional to the centrality estimates. Varying the number of companies included in the portfolio does not alter the qualitative conclusion, either.

PageRank central portfolio, suggesting the potential importance of scaling by number of suppliers. Finally, defining the importance of the supplier based on the importance of the customer using Kleinberg (1999)'s algorithm generates the strongest and most persistent forecasting power for the supplier central portfolio. Thus, the algorithm is not only elegant theoretically and intuitive economically, it also identifies the most predictive central suppliers.

Concluding Remarks

With the increasing availability of supply chain information, researchers are paying increasing attention to information flows and interactions between suppliers and customers. In this paper, I examine the interactions from the perspective of an economy-wide supply-chain network, and propose a list of network centrality measures to capture the relative importance of each company within this network. Based on information from the FactSet Supply Chain Relationships database, I build a supplier network matrix at the beginning of each year from 2004 to 2014, and compute the supplier centralities of each company. I then construct supplier central stock portfolio based on the top ten companies with the highest centrality estimates and find that supplier central portfolios tend to be more volatile than customer central portfolios. Furthermore, the stock performance of supplier central portfolios tends to predict the movements of the overall stock market.

The idea of analyzing the centrality of the supply-chain network is relatively new. While my analysis shows some promising results, there is much to do for future research. First, this paper has explored several centrality definitions. A lot more research, both theoretical and empirical, is needed to fully understand which measure is the most relevant for what purpose. Furthermore, many more variations can be constructed both from the perspective of building the supplier network matrix and from the perspective of constructing new centrality measures. For the network matrix, one can explore different firm characteristics and data sources to enrich the network and differentiate the relative importance of each supplier to a customer. The importance metrics can be based on how much it supplies to the customer and/or how unique and irreplaceable the supply is. One can also explore different clustering of the network matrix to understand flows from a more aggregate level, for example, for one industry to another industry or from one economic or geographic region to another region. For centrality measures, much theoretical work can be done one the shock and response dynamics, from which one can motivate the definition of an appropriate centrality measure and better understand the flow of the shocks within the supply chain. Second, given the construction of the network matrix and centrality measures, much research can be done in understanding the statistical behavior of financial security prices and trading behaviors across different centrality levels and how they interact. Shocks to the supply chain can generate ripple effects, which can show up potentially as lead-lag predictive relations in security returns, earning surprises, default probabilities, and/or distinctive term structure patterns in realized and option implied volatilities and credit default swaps.

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Tables

Table 1

Average rank correlation between different centrality measures Entries report the historical average of the Spearman rank correlation estimates between the different centrality measures estimated at the beginning of each year from 2004 to 2014 on U.S. S&P 1500 companies.

	Degree	Eigenvector	Page rank	Supplier	Customer
Degree	1.000	0.776	0.772	0.891	-0.086
Eigenvector	0.776	1.000	0.965	0.805	-0.045
PageRank	0.772	0.965	1.000	0.750	-0.046
Supplier	0.891	0.805	0.750	1.000	-0.111
Customer	-0.086	-0.045	-0.046	-0.111	1.000

Table 2

Top ten suppliers with the most number of customers Entries list the tickers of the top ten companies with the most customers and hence the highest degree centrality estimates at the beginning of each year from 2004 to 2014.

2004	GE	HPQ	IBM	INFA	INTC	IWOV	MSFT	ORCL	ROK	WBSN
2005	A	ACN	CNQR	GE	HPQ	IBM	INTC	IWOV	MSFT	ORCL
2006	ACN	GE	HPQ	IBM	INFA	IWOV	MANH	MSFT	ORCL	ROVI
2007	EMC	GE	HPQ	IBM	IWOV	MSFT	ORCL	PRGS	QTM	ROVI
2008	DDR	EMC	HPQ	IBM	IWOV	JDAS	MSFT	ORCL	PRGS	ROVI
2009	DDR	EMC	HPQ	IBM	JDAS	LXP	MSFT	ORCL	PRGS	ROVI
2010	DDR	EMC	HPQ	IBM	JDAS	LXP	MSFT	ORCL	PRGS	ROVI
2011	ACN	DIS	FRT	HPQ	IBM	INTC	JDSU	LXP	MSFT	PTC
2012	ADC	BFS	EP	FRT	HPQ	IBM	INTC	LFUS	MSFT	PWR
2013	BRK/B	CR	HON	HPQ	IBM	IRC	LFUS	MSFT	NPO	ORCL
2014	BFAM	BRK/B	CR	GE	IBM	MSCC	MSFT	NPO	ORCL	SXI

Table 3

Top ten suppliers with the highest eigenvector and PageRank centralities Entries list the tickers of the top ten companies with the highest eigenvector centrality estimates (panel A) and Katz centrality estimates (panel B) at the beginning of each year from 2004 to 2014.

Panel A. Eigenvector Centrality										
2004	CYMI	IBM	INTC	KEM	NTAP	ORCL	PSEM	SMTC	TTMI	XLNX
2005	A	AMCC	CYMI	IBM	IRF	KEM	NTAP	PSEM	SMTC	TTMI
2006	A	ATML	IBM	IRF	MSFT	ORCL	PSEM	ROVI	TTMI	XLNX
2007	ATML	BRKS	CA	IBM	JBL	JDSU	KEM	PSEM	QTM	SNIC
2008	ATML	AVT	COGT	CYMI	IBM	KEM	ORCL	PSEM	ROVI	SNIC
2009	ATML	CYMI	EMC	HPQ	IBM	JAVA	MSFT	QLGC	ROVI	SNIC
2010	ATML	EMC	HPQ	IBM	JAVA	MSFT	QLGC	QTM	ROVI	SNIC
2011	ADBE	ATML	CDNS	HPQ	IBM	INTC	KEM	MSFT	QTM	SNIC
2012	ATML	CDNS	HPQ	IBM	INTC	IRF	KEM	LFUS	XCRA	MSFT
2013	IBM	INTC	IRF	JBL	KEM	LFUS	LSI	NVDA	ORCL	XLNX
2014	AKAM	COHU	EXAR	IBM	INTC	LFUS	LSI	MMM	NVDA	XLNX
Panel B. PageRank Centrality										
2004	CTSH	EMC	FFIV	IBM	INTC	NTAP	ORCL	OSK	TIBX	TRMB
2005	AMCC	ANST	IBM	IRF	MCRS	MSFT	NTAP	ORCL	PCTI	SLAB

FACTSET

2006	A	ADCT	AMAT	BRKS	HPQ	IBM	MSFT	ORCL	ROVI	SNPS
2007	AFFX	BEC	BRCM	IIVI	INTC	LIFE	LSI	RSYS	TIBX	TXN
2008	AMCC	BTU	CTSH	HRC	IBM	JDSU	ORCL	PCXCQ	ROVI	SCI
2009	AVT	BTU	CDNS	COGT	CTSH	EMC	IBM	MSFT	PCXCQ	ROVI
2010	BTU	CTSH	EMC	FTI	IBM	JBL	JDSU	OSIS	PCXCQ	FN
2011	BTU	DD	IBM	INTC	JBL	JDSU	MSFT	OSIS	PCXCQ	FN
2012	CDNS	CERN	DD	EQIX	HPQ	IBM	MSFT	PKE	UHS	UHT
2013	CUZ	DD	IBM	JBL	XCRA	MSFT	ORCL	PKE	PRGS	PRU
2014	A	COHU	COR	CSX	IBM	INTC	JBL	XCRA	UHS	UHT

Table 4

Top ten companies with the highest supplier and customer centralities Entries list the tickers of the top ten companies with the highest supplier centrality (panel A) and customer centrality (panel B) estimated based on the Kleinberg (1999) algorithm at the beginning of each year from 2004 to 2014.

Panel A. Supplier Centrality										
2004	IBM	INFA	INTC	IRF	KEM	MSFT	ORCL	SANM	WBSN	XLNX
2005	A	EMC	GE	HPQ	IBM	IRF	KEM	MSFT	ORCL	SANM
2006	A	HPQ	IBM	INFA	IRF	IWOV	MSFT	ORCL	PRGS	ROVI
2007	BSCI	EQIX	IBM	IRF	IWOV	JCI	MSFT	PRGS	QTM	ROVI
2008	DDR	DDR	EQY	FICO	FRT	IWOV	MAC	PEI	PRGS	ROVI
2009	DDR	EMC	EQY	HPQ	IBM	MAC	MSFT	PEI	PTC	PRGS
2010	DDR	EMC	EQY	HPQ	IBM	KRG	MAC	MSFT	P PEI	PRGS
2011	ADC	FRT	HPQ	IBM	JAH	KRG	MAC	MSFT	PEI	SPG
2012	ADC	AKR	DDR	EQY	FRT	KIM	KRG	MAC	PEI	SPG
2013	ADC	CR	DDR	FRT	HON	IRC	KIM	KRG	LEG	MAC
2014	ADC	CR	DDR	FRT	IRC	KRG	LEG	MAC	MMM	SXI
Panel B. Customer Centrality										
2004	AVT	BA	CSCO	DELL	GE	HPQ	IBM	INTC	LMT	WMT
2005	BA	CSCO	DELL	F	GE	HPQ	IBM	INTC	LMT	WMT
2006	BA	CSCO	F	GE	HPQ	IBM	INTC	LMT	MSFT	WMT
2007	BA	CSCO	F	GE	HPQ	IBM	LMT	SHLD	T	WMT
2008	BA	CSCO	HD	HPQ	IBM	LMT	SHLD	T	TGT	WMT
2009	BA	HD	HPQ	IBM	KSS	MSFT	SHLD	T	TGT	WMT
2010	BA	BBY	HD	HPQ	IBM	KSS	SHLD	T	TGT	WMT
2011	BBY	HD	HPQ	IBM	JCP	KSS	M	SHLD	TGT	WMT

2012	BBY	COST	HD	JCP	KSS	LOW	M	SHLD	TGT	WMT
2013	BA	GE	HD	KSS	LMT	LOW	NOC	SHLD	TGT	WMT
2014	BA	BBY	COST	HD	LMT	LOW	NOC	XCRA	TGT	WMT

Table 5

Statistical behaviors of central company stock portfolios I form equal weighted stock portfolios using the top ten companies with the highest centrality measures. The compositions of the portfolios are updated at the beginning of each year based on the renewed centrality measure estimates. Entries report the relations between these portfolios and the S&P 500 index. β measures the contemporaneous daily return regression slope against the index, ρ measures the contemporaneous daily return correlation with the S&P 500 index. The remaining columns reports the predictive correlation of quarterly total portfolio returns and quarterly excess portfolio returns on future index returns over three and six month horizons.

			Quarterly Total Return		Quarterly Excess Return	
Year	β	ρ	3-Month	6-Month	3-Month	6-Month
Degree	1.075	0.879	0.177	0.043	0.088	0.015
Eigenvector	1.245	0.795	0.185	0.079	0.115	0.093
PageRank	1.269	0.860	0.237	0.076	0.207	0.096
Supplier	1.208	0.840	0.232	0.103	0.232	0.177
Customer	0.984	0.872	0.122	0.016	0.010	-0.002