ECONOMIC LINKS AND CREDIT SPREADS

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Abstract

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Keywords: NARMA, network autoregression, counterparty risk, corporate credit spreads, supply networks.

JEL Classification Numbers: C21, C31 (Cross-Sectional Models), C51 (Model Construction and Estimation), C58 (Financial Econometrics), G12 (Asset Pricing).

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Is counterparty risk an important determinant of corporate risk? In times of distress, credit contagion is well documented; bankruptcy announcements are followed by a widening in CDS spreads for creditors (Jorion and Zhang, 2009). At the same time, little is known about its impact on corporate risk under general market conditions. We examine whether counterparty risk in supplier-customer relationships matters in describing the cross-sectional and time-series variation in corporate credit spreads. Along the supply chain, counterparty risk arises from two primary mechanisms, trade credit exposure and future cash flow risk. Trade credits are extended whenever payment is not made upon delivery. When payment is delayed, the supplier acts as a lender, and vice-versa, when payment is anticipated, it is the buyer that acts as a lender.[1] In both circumstances, the lender takes on a risk exposure, whose magnitude depends on the size of the trade and the credit standing of the borrower. In turn, such exposure affects the credit standing of the lender. The second propagation mechanism, cash flow risk, hinges on the strength of the economic link between buyer and seller. Strong ties along the supply chain arise for several reasons. For example, a customer might share his technical knowledge for the engineering of custom-built parts, while a supplier might invest in customer-specific equipment. Such economic links are, indeed, a form of business partnership in which customers and suppliers are co-invested and therefore exposed to the uncertainties in each others' businesses.

What emerges from these mechanisms is that the impact of these economic links rests heavily on the degree of financial commitment they imply. Normally strong commitment is

[1]For a summary of the theoretical literature and a study of the determinants of credit terms, see Ng et al. (1999).

difficult to observe, but the dataset we use allows for its identification. Since 1998, Regulation SFAS No. 131 requires firms to disclose those customers that account for more than 10% of their total yearly sales.[2] Clearly, these relationships point to strong ties and are potential channels for the propagation of counterparty risk.

Our results establish counterparty risk, as identified by network factors, as an important determinant of credit spreads for corporate bonds. The magnitude of network effects is substantial: for a given firm, an increase of one standard deviation in the leverage of its main customers leads to a widening of its credit spread of 25 basis points on average. This figure is particularly compelling when compared to the effect of a firm's own leverage: an increase of a standard deviation in a firm's own leverage widens its credit spread by 50 basis points. Our result is consistent with the theoretical work of Merton (1974), in which leverage plays a key role in the pricing of corporate debt. A customer with higher leverage has on average wider spreads and, hence, a higher implied probability of default. This, in turn, reflects negatively on the supplier's prospects (trade credits are riskier and future demand uncertain), and it eventually leads to a higher spread.

In this paper, we describe an econometric model of network effects that is appropriate for the analysis of counterparty risk. In our context, nodes represent firms, while links between them represent supplier-customer relations. The essence of our approach is best described through an analogy. Just like in time series models the basic building blocks are constructed with the help of the time lag operator, we use a network lag operator which plays a similar role, only along a different dimension. The time lag operator shifts a variable by one period and its powers refer to events more distant in the time. Instead, a network lag of a variable is the average, possibly weighted, of values from neighboring nodes. Higher powers of the network lag operator refer, intuitively, to more distant firms along the supply chain. The network lag operator allows us to define processes that include moving averages

[2]Regulation SFAS 131 is established in FASB Statement No. 131, *Disclosures about Segments of an Enterprise and Related Information* (FASB, 1997). SFAS 131 is designed to increase information disaggregation, providing financial analysts with additional data about diversification strategies and exposures.

and are autoregressive along the network directions. We refer to these processes as Network Autoregressive Moving Average (NARMA).

Typically, each node in a financial network is observed through time and the data sample is structured as a panel. Although this type of data is the natural domain of panel data econometrics, modeling explicitly the network structure—when available—offers important complementarities, as well as some distinct advantages, over standard panel data models. First, the standard assumption of cross-sectional independence for the disturbances for panel models often does not hold in practice. While several panel techniques are available to tackle this issue,[3] they do not exploit the rich information about the links between the units, when available. In a network model, on the contrary, cross-sectional dependence is explicitly described in terms of a parsimonious model. Second, network models provide the ability to estimate the effects that neighboring units have on each other. While in principle allowing for individual effects can mitigate the bias introduced when ignoring these dependencies, the panel approach provides minimal information about their structural underpinnings.

The paper is organized as follows. Section **I** provides some background and reviews the literature. Section **II** is an introduction to the NARMA model. We define several basic notions from graph theory, describe the workings of the network lag operator and the general specification of the model. Section **III** contains the main empirical result of the paper. We describe application of our modeling framework to the analysis of counterparty risk in supplier-customer networks. Section **IV** considers three robustness checks: we consider the issue of bi-directionality of economic links, we discuss alternative specifications, and we explore the hypothesis that network effects proxy for cross-industry covariates rather than measuring counterparty risk. We reject this hypothesis. Section **V** concludes.

[3] A textbook example is the seemingly unrelated regressions method (SURE) introduced by Zellner (1962) which can account for cross-sectional correlations in long, narrow panels; asymptotically correct inference can be achieved using the method of Driscoll and Kraay (1998) to consistently estimate standard errors. Driscoll-Kraay standard errors are robust to heteroskedasticity, cross-sectional and temporal dependence.

I. Background and Literature Review

Recently, networks have risen to the foreground of empirical finance. Several studies document the importance of social ties in portfolio choices of retail investors and mutual fund managers, in contracting decisions and as drivers of return predictability.[4] Other works focus on the structural properties of financial networks and one of the most salient examples is the analysis of interbank loan markets.[5] By examining the dynamic properties of the network structure and through the use of simulations, these studies try to assess how the network topology determines market liquidity and systemic risk.

Our research combines the recent literature on the econometrics of networks and the broad topic of credit risk. The origin of our modeling framework can be traced back to the field of spatial econometrics and to the literature concerned with the identification of social interactions. The monographs on spatial econometrics by Anselin (1988), LeSage and Pace (2009) and Lee and Yu (2011), and the chapter on social interactions by Blume et al. (2010) provide recent overviews of these areas. Despite many formal similarities, there are a few differences that are worth noting.

An essential ingredient in spatial models is the weight matrix, an analogue of the network lag operator that encodes information about the relative locations and distances of the spatial units. Two common critiques directed at spatial models involve the arbitrariness in the determination of the spatial units and the, sometimes, tenuous economic relevance of the weights. In contrast, nodes in a network model are identified with specific entities and

[4]Hong et al. (2004) document that socially engaged households are more likely to participate in the stock market, and Cohen et al. (2008) find that portfolio managers place larger bets on firms to which they have social ties. Kuhnen (2009) shows that the contracting decisions made by mutual funds, such as selecting the board of directors and fund advisors, are influenced by past business relationships. Cohen and Frazzini (2008) suggest that investors fail to promptly take into account supplier-customer links and construct a customer momentum strategy that yield abnormal returns.

[5]Boss et al. (2004) and Soramaki et al. (2007) analyze the Austrian interbank market and the Fedwire Funds Service, respectively, and they both find these networks have a low average path length and low connectivity. Applying methods of network theory, Müller (2006) uses simulations to assess the risk of contagion in the Swiss interbank market.

the normalization of the network lag operator follows either an equal weighting scheme or is suggested by the economic setting.[6]

Our work expands on a long series of studies of corporate credit spreads by analyzing their network determinants. At the firm level, the most important factors are leverage, volatility, and jump risk (see, among others, Cremers et al., 2008). Campbell and Taksler (2003) find that equity volatility accounts for as much variation in corporate spreads as do credit ratings. Cremers et al. (2008) calibrate a jump-diffusion firm value process from equity and option data and confirm the importance of including jump risk with an out-of-sample test. Besides risk determinants, market frictions are priced in the spreads. An example is the liquidity premium that investors demand for their inability to trade large quantities over a short horizon without incurring into negative price effects. Chen et al. (2007) find that liquidity is priced in both levels and changes in the yield spread, while Bao et al. (2011) quantify implicit illiquidity costs as the (negative) autocorrelation of price reversals in high frequency transaction data and reach similar conclusions.

Another area related to our paper is the literature exploring the nature of default correlations. Several authors document the clustering of corporate default in time.[7] The practical repercussions are significant both from both asset pricing and risk management perspective. For example, Das et al. (2007) show that default correlations cannot be explained by the widely used doubly stochastic model of defaults.[8] A possible explanation for default clustering is the dependence of default intensities on a dynamic common factor. From this viewpoint, default clustering is puzzling only to the extent that such factor is unobserved. Duffie et al. (2009) discuss a model in which the posterior distribution of the latent factor is updated at the occurrence of defaults arriving with an anomalous timing (i.e. overly clustered). A second, independent explanation for default clustering is counterparty risk.

[6]For example, in the supplier-customer network that we consider, the sales associated to each edge (each supplier-customer pair) provide relevant economic weights.

[7]See Lucas (1995), and more recently Akhavein et al. (2005), Das et al. (2006), and de Servigny and Renault (2002).

[8]According to the doubly stochastic model, defaults are independent Poisson arrivals, conditional on past determinants of default intensities.

A common limitation of many studies is the abstraction from the economic links that connect the firms under consideration. In the absence of a suitable empirical framework and readily available data, such a limitation is both technical and practical. As a by-product, counterparty risk cannot be identified.

One of the few papers that is successful in isolating counterparty risk from generic credit contagion is the work of Jorion and Zhang (2009). In their study, they consider a sample of 250 bankruptcies between 1999 and 2005 and collect information about counterparty exposures as detailed in bankruptcy filings. Within this sample, equity value decreases and credit default swap spreads widen for those firms whose debtors undergo bankruptcy. Our analysis corroborates these findings but differs in that our approach not only provides evidence of counterparty risk, but it also includes a study of its determinants and of their impacts on credit spreads. Moreover, we are not restricted to events of particular gravity, such as bankruptcies, but instead examine interactions under general market conditions.

II. The NARMA Model

A. Networks and graphs

Networks can be represented by graphs. A graph g is a pair of sets (V, E) containing the vertices and the edges of the graph. These correspond to nodes and links in the network. In what follows, the terms network and graph are used interchangeably.

Edges can be uni-directional or bi-directional. Accordingly, the graph is called directed or undirected, respectively. A precise mathematical definition can be given as follows. An edge is identified by an ordered pair of vertices, its source and its target. Thus, the set E of all edges is a subset of $V \times V$ and, consequently, any edge e in E can be thought of as a pair (i, j), meaning that there is a edge between the node i and the node j. Therefore specifying E is the same as specifying a map

$$G : V \times V \to \{0, 1\} ,$$

such that $G(i,j) = 1$ if and only if there is an edge between (i,j). A graph is undirected (all edges are bi-directional) is the map G is symmetric, that is if $G(i,j) = G(j,i)$, for all the pairs of vertices (i,j). We assume that there are no selfloops, which is equivalent to condition $G(i,i) = 0$ for all i.

In some applications, it is useful to introduce the concept of *strength* of a link. A simple way of doing this is to attach a number to every edge, its *weight*. In practice this corresponds to extending the edge map G to the real numbers:

$$G : V \times V \to \mathbb{R} \; .$$

Given that the number of vertices V is finite, the map G can be interpreted as a square matrix with dimension the number of vertices, the *adjacency matrix*. More explicitly:

$$(G)_{ij} = G(i,j) \; .$$

When the graph is undirected, the matrix G is symmetric. In particular the sum of the entries of the i-th row is equal to the sum of the entries of the i-th column. Intuitively, this means that the vertex i influences the same number of nodes by which it is influenced. A typical weighting scheme is a simple uniform normalization where each non-zero row is divided by the sum of its entries.

The successive powers of the adjacency matrix capture the topology of the graph. A walk from node i to node j of length k is a succession of k edges starting at i and ending at j.[9] More precisely, the matrix entry $(G^k)_{ij}$ is equal to the number of walks from node i to node j of length k. [10]

[9]Generally, a *walk* is is not *path*. A path on a graph is to a succession of edges that does not visit the same vertex more than once, i.e. a path is a walk in which all vertices are different.

[10]See Van Mieghem (2010, pag. 26, Lemma 3).

B. Basic properties of NARMA models

The next step is to recognize that the adjacency matrix is a linear operator on vectors of vertex characteristics. We refer to this operator as the *Network Lag Operator* (NLO). Indeed, let x be an n-dimensional vector of vertex characteristics (i.e. x_i is some property of node i). Since the matrix G is an $n \times n$ matrix, x can be right multiplied by G. A *NARMA* process of order (p, q) is a stochastic process y on a network g (i.e. indexed by the nodes of the network g) that follows the data generating process

$$y = \sum_{i=1}^{p} \alpha_i G^i y + \sum_{j=0}^{q} \beta_j G^j x + \epsilon \; , \tag{1}$$

where x is an $(n \times 1)$-dimensional vector, $\{\alpha_i\}$ and $\{\beta_j\}$ are families of real parameters, G is the adjacency matrix (weighted or unweighted) of the network g, and ϵ is an $(n \times 1)$-dimensional vector of disturbances. More generally x can be an $n \times k$ matrix of exogenous characteristics and each β_j is a $1 \times k$ vector.

To further understand the action of the network lag operator, consider the following three alternative uses of the adjacency matrix. First, G can taken to be the (unweighted) adjacency matrix of a given graph g. Then the entries of Gx are the sums of neighbors' characteristics. More specifically,[11]

$$(Gx)_i = \sum_{j \in V} G_{ij} x_j = \sum_{j|i \to j} x_j \; ,$$

where the notation $j|i \to j$ means "(node) j such that i connects to j". A second option is for G be a row normalized adjacency matrix. Then

$$(Gx)_i = \sum_{j \in V} G_{ij} x_j = \sum_{j|i \to j} \frac{1}{n_i} x_j = \frac{1}{n_i} \sum_{j|i \to j} x_j \; ,$$

[11]The sums are written as sums over all the vertices in V. This is equivalent to summing over j that ranges from 1 to n.

$g \quad =$

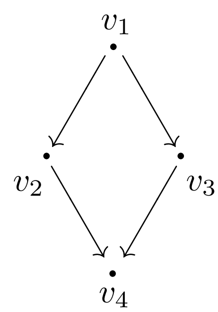

FIGURE 1. A simple example of a directed network.

where n_i is the number of neighbors of i, that is the number of nodes j such that i connects to j. Thirdly, G can be an stochastic weighted adjacency matrix.[12] Then

$$(Gx)_i = \sum_{j \in V} G_{ij} x_j = \sum_{j | i \to j} G_{ij} x_j$$

is the weighted average of the neighbors of nodes i.

First- and second-order network effects can be easily interpreted in a simple network and the arguments that follow can be easily extended to higher-order effects. Consider the directed network g depicted in Figure 1. For this network the adjacency matrix G and the matrix G^2 of walks of length 2 are

$$G = \begin{pmatrix} 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \quad G^2 = \begin{pmatrix} 0 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}$$

In a NARMA model, v_2 and v_3 affect v_1 and these are first order effects.[13] The effect of v_4 on v_1 is a second order effect. According to the matrix G^2, shocks from v_4 have weight 2 because there are two walks from v_4 to v_1. Walks accounting becomes important when there

[12] A square matrix of nonnegative real numbers is stochastic if the sum of the elements of each row is equal to one. This concept of stochasticity is not related to the concept of random networks.

[13] Note that it is the target vertex influencing the source vertex and not vice versa. This convention, which might seem counterintuitive, stems from the way the adjacency matrix is constructed and from the fact that it acts from the left. One could transpose the adjacency matrix and gain a more intuitive picture, but this would mean breaking away from the common practice adopted in graph theory.

is a need to discriminate between the relative impacts of different nodes, as it is the case for the second order effects of the network depicted Figure 2.

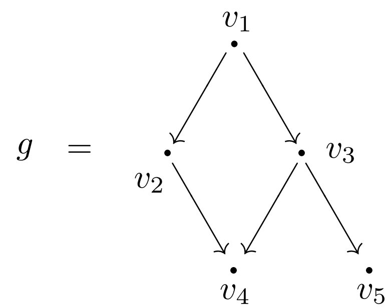

FIGURE 2. In this network, the second order effect of v_4 on v_1 has weight 2, while the second order effect of v_5 on v_1 has weight 1.

A similar line of reasoning can be applied to weighted adjacency matrices. In a NARMA model, when the adjacency matrix G is weighted, the product Gx is the local weighted sum of vertex characteristics, where local refers to the fact that, at each node, the sum is taken over neighboring nodes. To understand higher powers of the network lag operator, define the weight of a walk as the product of the weights of its segments. Then, the entry (i, j) of the k-th power of the adjacency matrix is the sum of the weights of the paths from i to j of length k.

III. The Network Determinants of Credit Spreads

A. The model: network spillovers

We focus our analysis on a model of network spillovers. Network spillovers occur when the characteristics of a node's neighbors have a direct impact on its outcomes. The NARMA(0,1) model is a simple approach that accounts for neighbors' characteristics by way of the network lags of the covariates:

$$CS_{i,t} = \alpha + \beta \; Firm_{i,t} + \gamma \; Customers_{i,t} + \delta_1 \; S\&P_t + \delta_2 \; YieldCurve_t + \epsilon_{i,t} \; , \tag{2}$$

where,

1. $CS_{i,t}$ is the credit spread for of firm i at time t.
2. $Firm_{i,t}$ is a vector of the firm's characteristics: leverage, volatility, and a measure of jump-to-default risk.

$$Firm_{i,t} = \{\ lev_{i,t},\ ivol_{i,t},\ jump_{i,t}\ \}\ .$$

   Alongside their theoretical underpinnings (Merton, 1974), leverage (*lev*), idiosyncratic volatility (*ivol*), and jump-to-default risk (*jump*) have been documented as determinants of credit spreads in several studies (for example Campbell and Taksler, 2003; Cremers et al., 2008).
3. $Customers_{i,t}$ is a vector of the characteristics of the firm's customers constructed using the supplier-customer network G:

$$Customers_{i,t} = \{\ (G_t \cdot lev_t)_i,\ (G_t \cdot ivol_t)_i,\ (G_t \cdot jump_t)_i\ \}\ .$$

4. $S\&P_t$ is a vector of the market's characteristics:

$$S\&P_t = \{\ ret_{S\&P,t},\ ivol_{S\&P,t},\ jump_{S\&P,t}\ \}\ .$$

5. $YieldCurve_t$ is a vector with two components,

$$YieldCurve_t = \{r_t^{10}, slope_t^{(2,10)}\ \}\ ,$$

   the 10-year Benchmark Treasury rate r_t^{10} and the slope of the yield curve, defined as the difference between the 10-year and the 2-year Benchmark Treasury rates, $slope_t^{(2,10)} = r_t^{10} - r_t^2$.
6. $\epsilon_{i,t}$ is a vector of white noise disturbances.

B. Sources

The data in this study is combined from several sources. In this section, we describe in detail how each variable is constructed. The analysis is carried out on weekly data for the 2004-2009 period.

1. *Credit Spreads.* Corporate bonds transactions come from the Trade Reporting and Compliance Engine (TRACE), a platform operated by the Financial Industry Regulatory Authority (FINRA) that covers the majority of US corporate bonds. The TRACE facility has been operating since 2002 and, by February 2005, its coverage reached approximately 99% of all public transactions. Our sample covers the years from 2004 to 2009. For each Friday in the sample and for each bond issue, we compute the volume weighted average yield from transaction data.[14] We obtain detailed information on corporate bond issues from Thompson Reuters DataStream and only select issues with fixed rate coupons and no embedded optionality. From Thompson Reuters DataStream we also obtain benchmark treasury interest rates and compute maturity matched credit spreads from a linear interpolation of the yield curve.[15] Finally, for each firm in the sample we select the most traded issue as measured by the average number of trades over the number of days the issue was traded.[16]

2. *Firm leverage.* Following Collin-Dufresne et al. (2001), for each firm i, we define firm leverage $lev_{i,t}$ as

$$\frac{Book\ Value\ of\ Debt}{Market\ Value\ of\ Equity + Book\ Value\ of\ Debt}.$$[17]

[14]In our calculations we consider only regular trades (trades executed between 8:00 a.m. to 6:29:59 p.m., Eastern Time, and reported within 15 minutes of trade execution) which are not flagged as having a "special price". Moreover, we impute large trades to their minimum possible size. Indeed, for investment grade bonds (junk bonds) when the par value of a transaction is greater than $5 million ($1 million), the quantity field in the TRACE dataset contains the value "5MM+" ("1MM+").

[15]The yield curve is linearly interpolated using maturities of 1, 3, 6 months and of 2, 3, 5, 7, 10, 30 years.

[16]There is no substantial difference when we select issues based on the average quantity traded.

[17]*Book Value of Debt* is the the sum of long term debt (Compustat item DLTTQ) and debt in liabilities (Compustat item DLCQ), while *Market Value of Equity* is the product of the number of share outstanding (CRSP item SHROUT) and the price or bid/ask average (CRSP item PRC).

3. *Implied Volatility.* Weekly implied volatilities are constructed using the OptionMetrics dataset. OptionMetrics contains quotes and analytics for US equity option markets and, in particular, it reports the volatility surface constructed via kernel smoothing on a fixed grid of maturities and deltas.[18] We estimate future volatility as the average of the implied volatilities of near-the-money call and put options:

$$ivol = 0.5 \left(\sigma^{\text{imp}}_{i,\text{put}}(-0.5) + \sigma^{\text{imp}}_{i,\text{call}}(0.5) \right) ,$$

where $\sigma^{\text{imp}}_{i,\text{put}}$ is the implied volatility of the call option with 60 days to expiry on the underlying stock of firm i as a function of delta.

4. *Jump Measure.* To quantify the probability of negative jumps we use a formula developed by Yan (2010) as a formalization of the intuitive measure defined by Collin-Dufresne et al. (2001). The basic idea is to exploit the stylized fact, known as the volatility smile, that, as the strike value of an option varies, implied volatility follows approximately a concave parabola — volatility smiles. This pattern is attributed to the probability of extreme moves in firm value, with such probability being higher the more the smile is accentuated. Practically, one can use near- and out-of-the money puts and near and in-the-money calls to interpolate the implied volatility $\sigma(K)$ as a quadratic polynomial in the strike K and quantify jump risk as $\sigma(0.9\ S) - \sigma(S)$, where S is the stock closing price. This is the approach of Collin-Dufresne et al. (2001). Instead, we use the formula by Yan (2010), who provides a formal argument in support of the following estimate of the slope of the volatility smile:

$$jump = \sigma^{\text{imp}}_{i,\text{put}}(-0.5) - \sigma^{\text{imp}}_{i,\text{call}}(0.5) , \tag{3}$$

where $\sigma^{\text{imp}}_{i,\text{call}}$ is defined as above.

[18] The OptionMetrics volatility surface contains information on standardized options, both calls and puts, with expirations of 30, 60, 91, 122, 152, 182, 273, 365, 547, and 730 calendar days, at deltas from 0.20 to 0.80 in steps of 0.05 units for calls and at negative deltas for puts. For European options, the implied volatility is calculated inverting numerically the Black-Scholes model. For American options, the implied volatility is estimated by evaluating iteratively a binomial tree model until the model price converges to the market price.

5. *Market returns.* Weekly S&P index returns, $S\&P_{i,t}$, are obtained by aggregating daily data from the Center for Research on Security Prices (CRSP).

C. Supplier-customer network

According to Regulation SFAS no.131, suppliers are required to report those customers that account for at least 10% of their total yearly sales. This information is contained in the Compustat Customer Segment files. For each supplier, the key items in each entry of the customers segments are the customer's name and the customer's total amount of sales. As major customers are self-reported and, in particular, names are manually entered, the matching of a reported customer's name with a standard identifier is not a straightforward matter. For example, the same company can be reported with different names (IBM vs. International Business Machines), acronyms are sometimes included and sometimes omitted (ADR, LLC, INC, etc.), or the company's name can be outright misspelled. We take a very conservative approach. After filtering common acronyms, we only consider those links for which there is an exact match between a word in the reported name and an entry in the Compustat datafile of names. In the case of multiple matches, a link is manually identified by inspecting additional information, such as TIC symbols and CUSIP codes, and by querying the online matching engine available through the WRDS servers.[19]

Following this procedure, we identify 4,462 companies and 21,400 links, between the years 2003 and 2009. For each supplier, links are weighted by the total amount of sales corresponding to the target customer, normalized by the observed total amount of sales. With such weighting, more importance is given to those customer that account for a larger shares of trades. There are two aspects that dictate the network dynamics. First, when a link is identified, it is considered active for one year prior to the reported date. In the case of multiple links between two vertices for a given date, these are aggregated into one link and the sales counts associated with different links summed. Second, as fiscal years vary between

[19]This procedure allows us to match a major customer firm to its unique identifier in Compustat (GVKEY field). In turn, this allows us to merge data from Compustat with CRSP and TRACE data.

businesses, new links are established and existing links are dropped throughout the year. Overwhelmingly, links are updated in the month of December (2887 links reported, on average), followed by end-of-quarter-months (March, June, and September; 279 links reported, on average), and the rest (68 links, on average). Overall, the supplier-customer network so constructed, although dynamic, is slowly varying.

Of the 4,462 companies in the supplies-customer network, 3,521 are covered in CRSP, 2,133 are reported in the OptionMetrics dataset, and only 564 firms are active in the credit markets. For each time unit t, let lev_t, $ivol_t$, and $jump_t$ be the vectors of vertex (firms) characteristics, and let G_t be the adjacency matrix of the supplier-customer network. Using the formalism of the network lag operator, we compute the weighted average of customers' characteristics as $G_t \cdot lev_t$, $G_t \cdot ivol_t$ and $G_t \cdot jump_t$.

Table 1 contains the summary statistics for the final sample. The time period is January 2004 to December 2009 and the sample frequency is weekly. The sample includes bonds that have a spread of less than 30% and more than 0.1%, maturities that are between 5 and 35 years, and with a minimum of 20 observations. After matching the firms in the supplier-customer network with the corporate bond trades in TRACE, with the bond characteristics from DataStream, and dropping incomplete observations, our final sample consists of 154 firms,[20] and 12,128 weekly observations. Our panel is unbalanced: the number of observations for each firm varies between 20 to 294, with a median value of 74. The median maturity of the sample is December 2016.

[Insert Table 1 about here.]

D. Results

The regression estimates in Table 2 indicate that network lags are economically and statistically significant determinants of corporate credit spreads. Moreover, the signs of the coefficients, when significant, are consistent with theoretical predictions. Standard errors

[20]The total market capitalization of our sample is approximately $2.8 trillion (median value between 2004 and 2009). For comparison, the S&P 500 has a median market capitalization over the same period of $11.3 trillion.

are estimated following the procedure of Driscoll and Kraay (1998), which is robust to heteroskedasticity, cross-sectional and temporal dependence. Our most important findings are reported in Table 2 below.[21]

We find that an increase in the average of the customers' leverage increases the credit spread. Its economic impact is sizable: an increase of one standard deviation (0.23) in the average leverage of the customers leads to a widening of the credit spread of up to 25 basis points ($\sim 0.22 \times 1.13 \times 100$ bp). In comparison, the credit spreads increase by 50 basis points ($\sim 0.22 \times 2.3 \times 100$ bp) when own leverage increases by one standard deviation (0.22).

The slope of the volatility smile, as captured by the variable *jump*, is statistically significant and its economic significance is comparable to the firms' own jump risk measure. The average value of firm's *jump* (0.009) is twice as much than the corresponding customer variable (0.004, see Table 1), the factor loading on the latter (20.6) is almost twice as much as the former (13.4, see Table 2). As a result, the economic impact of the customer *jump* risk is comparable to that of the supplier specific *jump* risk.

S&P returns, volatility and jump risk are included in the model as control variables for general economic conditions. Across all models S&P returns have a positive impact on credit spreads and are statistically significant. Neither $S\&P$ implied volatility nor $S\&P$ jump risk are significant when yield curve covariates are included in the regression.

[Insert Table 2 about here.]

IV. Robustness

A. Bi-directionality of Supplier-Customer Relationships

The customer-supplier relationship is clearly bi-directional and, potentially, so is the possibility of risk transfer. Our analysis so far has been concerned solely with the risks flowing from customers to their suppliers and has disregarded the possibility that distressed suppliers affect their customers' financial standing. There are several counter-examples that

[21] All the numerical examples in this section refer to model 7 in Table 2. Since the estimated coefficients are stable across various models, the differences in the interpretation of the results are immaterial.

illustrate this possibility. For example, at the end of 2011, Western Digital had to shut down its Thai factories as a consequence of severe floods, cutting its hard drive production capacity by 60%. The incident influenced computer makers world-wide.[22] Earlier in the same year, the Japanese Earthquake similarly caused serious disruptions to the worldwide supply chain.[23] This section addresses two issues related to the bi-directionality of supplier-customer relationships. First, we estimate the influence of suppliers' characteristics on the credit worthiness of customers. Second, our findings provide evidence that the risk channel operating from customers to suppliers is distinct form the channel operating from suppliers to customers.

In order to account for suppliers' effects, consider again the supplier-customer network g and its adjacency matrix G. To the transposed matrix G^T, there corresponds another network g^T, whose links are reversed with respect to the original network g, that is, g^T is a network whose connections run from suppliers to customers. The initial specification (see Equation 2) is augmented with the introduction of a term containing the characteristics of the firm's suppliers constructed using the the adjacency matrix G^T

$$Customers_{i,t} = \{ \ (G_t^T \cdot lev_t)_i, \ (G_t^T \cdot ivol_t)_i, \ (G_t^T \cdot jump_t)_i \ \} \ .$$

Table 3 reports estimates under various restrictions of the following model:

$$CS_{i,t} = \alpha + \beta \ Firm_{i,t} + \gamma^c \ Customers_{i,t} + \gamma^s \ Suppliers_{i,t} + \delta_1 \ S\&P_t + \delta_2 \ YieldCurve_t + \epsilon_{i,t} \ .$$

Within our sample, the coefficients for suppliers' leverage and jump risk are not significantly different from zero. Instead, there is strong statistical evidence that suppliers' implied volatility has, perhaps counterintuitively, a negative impact on a firm's credit spread. This holds true across numerous different specifications (see also Tables 4 and 6). For our purposes, there are two important lessons that emerge form Table 3. The first one is that the economic and statistical significance of customer's effects is robust to the introduction

[22] *Counting the cost of calamities*, The Economist, Jan 14th, 2012.
[23] *Broken Links*, The Economist, Mar 31st, 2011.

of supplier's covariates. Indeed, the statistical significance of the customers' leverage and jump coefficients (γ_1^c and γ_3^c, respectively) is even stronger upon introducing suppliers into the model. The second is that customers' and suppliers' effects seem to operate through different channels, leverage and jump risk in the case of customers, implied volatility in the case of suppliers.

B. Model Specification and Higher Network Lags

We focus on a model of network spillovers and ignore the autoregressive component because the supplier-customer network resulting from our final sample does not contain many long walks. Indeed, the non-zero observations for higher lags are only 354 at degree 2 and 4 at degree 3. Under such circumstances, it is easy to show that the a network autoregressive model is equivalent to a finite network moving average.

A NARMA process admits, under certain regularity conditions, a Wold-type representation as a network moving average (NMA) of infinite order. For example, consider the following NARMA(1,1) process;

$$y = \alpha G y + \beta x + \epsilon$$

Let $\mathbb{I}_n$ be the identity matrix of dimension given by the number of vertices in the graph g. Then, when the matrix $(\mathbb{I} - \alpha G)$ is invertible y admits a NMA(∞) representation,[24] indeed

$$\begin{aligned} y - \alpha G y &= \beta x + \epsilon \\ (\mathbb{I} - \alpha G) y &= \beta x + \epsilon \end{aligned}$$

$$y = (\mathbb{I} - \alpha G)^{-1}(\beta x + \epsilon) = \sum_{k=0}^{\infty} \alpha^k G^k (\beta x + \epsilon) \ . \tag{4}$$

The general NARMA model can be represented as a NMA whenever the matrix $(\mathbb{I} - \sum \alpha_k G^k)$ is invertible.[25]

[24]The matrix $(\mathbb{I} - \alpha G)$ is invertible if (1) G is row normalized and $|\alpha| \leq 1$, or more generally (2) $\alpha^{-1} \in (\min \sigma(G), \max \sigma(G))$, where $\sigma(G)$ is the spectrum of G, i.e. the set of all eigenvalues of G.

[25]A condition for the invertibility of the matrix $(\mathbb{I} - \sum \alpha_k G^k)$ is that $\lim_{n \to \infty} (\sum \alpha_k G^k)^n$ exists. A sufficient condition is that $\sum |\alpha_k| \cdot ||G^k|| < 1$, where $|| \cdot ||$ is any matrix norm.

For the sake of argument, consider the extreme example of a network in which there are no walks of length greater than one. As an immediate consequence of Proposition **??**, the square of the adjacency matrix of such network is zero. Expanding (4)

$$y = (\mathbb{I} + \alpha G + \alpha^2 G^2 + \dots)(\beta x + \epsilon)$$

$$y = \beta x + \alpha\beta G x + \tilde{\epsilon}\ ,$$

for an appropriate error process $\tilde{\epsilon}$.[26] As a result there is little difference between local averages and global effects, making the case for the need of an autoregressive component weak.[27]

C. Counterparty Risk and Cross-Industry Effects

Beside originating from counterparty risk, an alternative explanation for the presence of network effects in our model of credit spreads is cross-industry spillover. Averaging over customers' characteristics, the argument goes, builds proxies for whole industrial sectors that are connected along the supply-chain. Therefore, according to this hypothesis, network effects should be interpreted as broad macroeconomic covariates and not as measures of idiosyncratic counterparty shocks. To address these concerns, we introduce control variables for both industry and cross-industry economic conditions.

We obtain value-weighted returns of industry portfolios from French's website.[28] These returns are constructed by assigning each AMEX, NYSE and NASDAQ stock to a portfolio according to its Standard Industrial Classification (SIC) code. For robustness, we consider various classifications, resulting in 12, 17, 30, 38 and 48 portfolios. For example the 12-industry classification consists of the following 12 categories: 1. consumer non-durables; 2. consumer durables; 3. manufacturing; 4. oil, gas, and goal extraction and products; 5. chemicals and

[26]In this case powers of the adjacency matrix of order two and higher are zero and the vector of disturbances $\tilde{\epsilon}$ is equal to $\epsilon + G\epsilon$.

[27]This is confirmed empirically: coefficients pertaining to the second lag of firm's characteristics are insignificantly different from zero, while the main results are practically unchanged. These results are available upon request.

[28]These data and definitions are available online at Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

allied products; 6. business equipment; 7. telephone and television transmission; 8. utilities; 9. shops (wholesale, retail and some services); 10. healthcare, medical equipment, and drugs; 11. finance; 12. other. Detailed definitions for the 12-industry classification, as well as the others, are available from French's website.

Industry variables are constructed as follows. First, for each classification scheme and each industry portfolio we compute weekly realized volatilities. Second, given a classification scheme, each firm in our dataset is assigned to a portfolio using its Compustat SIC codes. Third, each firm's neighboring industries are identified by the industries of the firm's customers, and neighboring industries returns and volatilities are computed as weighted averages of weekly returns.[29] This extension fits naturally within the modeling framework described thus far. Let $indret_k$ and $indvol_k$ denote the returns and volatility for industry k, and denote with $k(i)$ the industry of firm i. Define the $2 \times n$ matrix Ind of firm specific industry characteristics as the vector

$$Ind_i = (indret_{k(i)}, indvol_{k(i)}) \ ,$$

where n is the number of firms. With this notation, the model with industry and cross-industry effects is

$$y = \underbrace{\beta Firm + \gamma(G \cdot Firm)}_{\substack{\text{Firm and}\\ \text{Customers}\\ \text{effects}}} + \underbrace{\delta(S\&P, \, YieldCurve)}_{\substack{\text{Market}\\ \text{effects}}} + \underbrace{\eta Ind + \phi(G \cdot Ind)}_{\substack{\text{Industry and}\\ \text{Cross-industry}\\ \text{effects}}} + \epsilon \ ,$$

where η and ϕ are 2-vectors of parameters quantifying industry and cross-industry effects, respectively.

[Insert Table 4 about here.]

Our principal result remains unchanged. Cross-industry effects are generally insignificant across the classification considered models, and moreover the economic significance of their contribution to the corporate credit spreads is minimal. The estimates of the network effects

[29] As before, weights are normalized sales.

are the same for all practical purposes. Tables 5 and 6 extend these robustness results to include upstream (suppliers) industries.

V. Conclusions

The main objective of this paper is to evaluate the market assessment of counterparty risk in supplier-customer relationships. To this end, we study the network determinants of corporate credit spreads and use network effects as an instrument for counterparty risk. Using an econometric framework that allows us to estimate network effects, we show that along the supply chain, network effects are economically and statistically significant determinants of credit spreads.

Besides the empirical analysis of counterparty risk, an important contribution of this paper is the introduction of a powerful modeling framework for financial networks. Its major strengths are the ability to model parsimoniously cross-sectional dependence and the possibility to quantify the impact that neighboring units have on each other. In our application of the NARMA model we showed the importance of network effects in asset pricing. There are several possible directions for future research in this area. The interbank loans market and fragmentation that characterizes equity trading are only two of many interesting topics where we believe that the application of our modeling framework can lead to new insights.

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Table 1
Summary Statistics

This table presents summary statistics for the regressors and regressand in our final sample. The data covers the years 2004 to 2009 with weekly frequency. Credit spreads are computed using transaction data as differences between volume weighted average yields and a linear interpolation of benchmark treasury bond yields. Leverage is defined as the ratio between book value of debt and total capital. Volatility is estimated as the average of the implied volatilites of near-the-money call and put options with 60 days to expiry. The jump measure quantifies the risk of negative jumps using an estimate of the slope of the volatility smile (see Equation (3)). The slope of the yield curve is defined as the difference between the 10-year, r^{10}, and the 2-year, r^2, Benchmark Treasury rates. Firm, Customers, Suppliers, and S&P refer to individual, downstream neighbors (customers), upstream neighbors (suppliers), and market characteristics, respectively. In particular, for a each firm, customers' characteristics are averages of leverage, volatility and jump measure, weighted on sales shares, of their customers. Suppliers' characteristics are defined similarly. Several firms in our supplier-customer network have no customers. In this case, customers' characteristics are zero. Summary statistics including these observation are also reported (under "Customers (all)"). The same considerations apply to the definition of "Suppliers (all)".

		Mean	SD	Min	Max	Obs
All Maturities (154 Firms)						
	Credit Spread	2.927	3.117	.115	29.261	12133
Implied Volatility	Firm	.3619	.2285	.085	2.363	12133
	Customers	.2555	.1288	.107	2.012	2695
	Customers (all)	.0606	.1255	0	2.012	11357
	Suppliers	.3999	.2010	.020	1.353	1296
	Suppliers (all)	.1006	.2007	0	1.353	5150
	S&P	.1860	.0959	.095	.607	12133
Implied Jump Measure	Firm	.0089	.0419	-.602	.881	12133
	Customers	.0039	.0148	-.264	.281	2695
	Customers (all)	.0009	.0074	-.264	.281	11357
	Suppliers	.0103	.0951	-1.016	1.824	1295
	Suppliers (all)	.0025	.047	-1.016	1.824	5150
	S&P	.0016	.0090	-.039	.035	12133
Leverage	Firm	.3387	.2158	.0123	.979	12133
	Customers	.2440	.2275	.0008	.9992	2668
	Customers (all)	.0570	.1508	0	.9992	11422
	Suppliers	.278	.2254	0	.9347	1923
	Suppliers (all)	.1217	.2032	0	.9347	4406
Weekly Returns	S&P	.0010	.026	-.195	.116	12133
Term Structure	r^{10}	4.140	.6341	2.130	5.226	12133
	slope	1.003	.9498	-.190	2.749	12133

Table 2
Network Determinants of Credit Spreads

Regression estimates for various restrictions of the model

$$CS_{i,t} = \alpha + \beta\ Firm_{i,t} + \gamma\ Customers_{i,t} + \delta_1\ S\&P_t + \delta_2\ YieldCurve_t + \epsilon_{i,t}\ ,$$

where $Firm_{i,t}$, $Customers_{i,t}$ and $S\&P_t$ are vectors of firm's, customers', and market's characteristics, including leverage *lev* (for firms and customers) and returns *ret* (for the S&P), option implied volatilities *ivol* and an implied jump risk measure *jump*. The vector $YieldCurve_t$ has two components, the 10-year Benchmark Treasury rate r_t^{10} and the slope of the yield curve, defined as the difference between the 10-year and the 2-year Benchmark Treasury rates, $slope_t^{(2,10)} = r_t^{10} - r_t^2$. The index i refers to the i-th observation at time t. The observation frequency is weekly. The time period is January 2004 to December 2009. The sample includes bonds with at least 20 observations which have a spread of less that 30% and higher that 0.1%, and maturities between 5 and 35 years. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		Classical Models			Customers Spillovers		
		(1)	(2)	(3)	(4)	(5)	(6)
Firm	lev, β_1	2.020***	2.243***	2.231***	2.131***	2.314***	2.282***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	ivol, β_2	9.298***	8.502***	8.536***	9.100***	8.374***	8.474***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	jump, β_3	12.44***	12.97***	12.84***	13.02***	13.53***	13.35***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customers	lev, γ_1				0.802	1.196*	1.135*
					(0.104)	(0.015)	(0.030)
	ivol, γ_2				0.670	0.255	0.337
					(0.142)	(0.542)	(0.458)
	jump, γ_3				22.54***	21.34***	20.63**
					(0.000)	(0.001)	(0.001)
S&P	ret, $\delta_{1,1}$			3.961***			3.660***
				(0.000)			(0.000)
	ivol, $\delta_{1,2}$			0.159			-0.300
				(0.823)			(0.686)
	jump, $\delta_{1,3}$			-1.463			-0.880
				(0.538)			(0.727)
Yield Curve	r^{10}, $\delta_{2,1}$		-0.680***	-0.684***		-0.639***	-0.673***
			(0.000)	(0.000)		(0.000)	(0.000)
	slope, $\delta_{2,2}$		-0.128*	-0.140**		-0.126*	-0.129**
			(0.012)	(0.003)		(0.014)	(0.007)
Constant		-1.233***	1.920***	1.906***	-1.324***	1.645***	1.818***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
N		12133	12133	12133	11186	11186	11186
R^2		0.684	0.694	0.695	0.691	0.699	0.700

Table 3
Customers Spillovers versus Suppliers Spillovers

Regression estimates for various restrictions of the model

$$CS_{i,t} = \alpha + \beta\ Firm_{i,t} + \gamma^c\ Customers_{i,t} + \gamma^s\ Suppliers_{i,t} + \delta_1\ S\&P_t + \delta_2\ YieldCurve_t + \epsilon_{i,t}\ ,$$

where $Firm_{i,t}$, $Customers_{i,t}$, $Suppliers_{i,t}$, and $S\&P_t$ are vectors of firm's, customers', suppliers', and market's characteristics, including leverage *lev* (for firms and customers) and returns *ret* (for the S&P), option implied volatilities *ivol* and an implied jump risk measure *jump*. Notation, sample selection, and further control variables are detailed in the caption of Table 2. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		Network Spillovers		
		Customers	Suppliers	Both
Firm	lev, β_1	2.282***	2.057***	2.087***
		(0.000)	(0.000)	(0.000)
	ivol, β_2	8.474***	7.320***	7.328***
		(0.000)	(0.000)	(0.000)
	jump, β_3	13.35***	4.945**	5.014***
		(0.000)	(0.001)	(0.001)
Customers	lev, γ_1^c	1.135*		2.011***
		(0.030)		(0.001)
	ivol, γ_2^c	0.337		−0.817
		(0.458)		(0.129)
	jump, γ_3^c	20.63**		12.77***
		(0.001)		(0.000)
Suppliers	lev, γ_1^s		−1.260	−1.151
			(0.101)	(0.135)
	ivol, γ_2^s		−1.296***	−1.166***
			(0.000)	(0.000)
	jump, γ_3^s		0.283	−0.225
			(0.655)	(0.681)
S&P	ret, $\delta_{1,1}$	3.660***	6.011***	5.916***
		(0.000)	(0.000)	(0.000)
	ivol, $\delta_{1,2}$	−0.300	1.442	1.712
		(0.686)	(0.250)	(0.194)
	jump, $\delta_{1,3}$	−0.880	−2.966	−2.851
		(0.727)	(0.482)	(0.501)
Yield Curve	r^{10}, $\delta_{2,1}$	−0.673***	−0.874***	−0.858***
		(0.000)	(0.000)	(0.000)
	slope, $\delta_{2,2}$	−0.129**	−0.160	−0.185
		(0.007)	(0.090)	(0.063)
Constant		1.818***	3.275***	3.022***
		(0.000)	(0.000)	(0.000)
N		11186	3849	3530
R^2		0.700	0.702	0.710

Table 4
Industry Controls for Customers Spillovers

Regression estimates for various models with industry and cross-industry effects.

$$y = \beta Firm + \gamma(G \cdot Firm) + \delta(S\&P,\, YieldCurve) + \eta Ind + \phi(G \cdot Ind) + \epsilon\ ,$$

where η and ϕ are 2-vectors of parameters quantifying industry and cross-industry effects, respectively. Let $indret_k$ and $indvol_k$ denote the returns and volatility for industry k, and denote with $k(i)$ the industry of firm i. Then Ind is the matrix of firm specific industry characteristics

$$Ind_i = (indret_{k(i)}, indvol_{k(i)})\ ,$$

and the vector $G \cdot Ind$ involves characteristics of downstream industries (customers' industries). We use the same sample selection and variable definitions as in Table 2. We consider various classifications, resulting in 12, 17, 30, 38 and 48 portfolios. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		No Industries	Industry Portfolios				
		0	12	17	30	38	48
Firm	lev, β_1	2.282***	2.222***	2.237***	2.240***	2.276***	2.252***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	ivol, β_2	8.474***	8.494***	8.521***	8.512***	8.479***	8.484***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	jump, β_3	13.35***	13.48***	13.51***	13.49***	13.33***	13.38***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Customers	lev, γ_1^c	1.135*	1.202*	1.161*	1.126*	1.204*	1.257*
		(0.030)	(0.021)	(0.030)	(0.037)	(0.022)	(0.013)

(Continued)

	ivol, γ_2^c	0.337	0.0966	0.235	0.337	0.141	-0.0494
		(0.458)	(0.835)	(0.647)	(0.512)	(0.787)	(0.914)
	jump, γ_3^c	20.63**	20.90***	21.60***	21.33**	20.55***	19.53***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
S&P	ret, $\delta_{1,1}$	3.660***	3.491***	3.142***	2.681**	4.399***	4.201***
		(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)
	ivol, $\delta_{1,2}$	-0.300	0.642	0.863	0.740	-0.452	-0.285
		(0.686)	(0.376)	(0.248)	(0.287)	(0.623)	(0.690)
	jump, $\delta_{1,3}$	-0.880	-2.157	-2.799	-1.397	-1.413	-1.101
		(0.727)	(0.363)	(0.224)	(0.577)	(0.599)	(0.658)
Yield Curve	r^{10}, $\delta_{2,1}$	-0.673***	-0.632***	-0.599***	-0.634***	-0.687***	-0.673***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	slope, $\delta_{2,2}$	-0.129**	-0.132**	-0.127**	-0.135**	-0.133**	-0.129**
		(0.007)	(0.003)	(0.003)	(0.002)	(0.004)	(0.007)
Industry	ret, η_1		0.00288	0.00186	0.00795	-0.0143*	-0.00336
			(0.671)	(0.863)	(0.248)	(0.011)	(0.553)
	vol, η_2		-0.00936***	-0.0104***	-0.00634***	0.000221	-0.000822
			(0.000)	(0.000)	(0.000)	(0.855)	(0.432)
Cross-Industry	ret, ϕ_1		-0.0481**	-0.0385***	-0.0343**	-0.00939	-0.0220

(Continued)

		(0.004)	(0.001)	(0.001)	(0.241)	(0.077)
vol, ϕ_2		0.0166***	0.00229	−0.00057	0.00174	0.00530*
		(0.000)	(0.643)	(0.799)	(0.133)	(0.032)
Constant	1.818***	1.540***	1.351***	1.521***	1.910***	1.834***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
N	11186	11186	11186	11186	11186	11186
R^2	0.700	0.702	0.702	0.702	0.700	0.701

Table 5
Industry Controls for Suppliers Spillovers

Regression estimates for various models with industry and cross-industry effects.

$$y = \beta Firm + \gamma^s(G \cdot Firm) + \delta(S\&P, YieldCurve) + \eta Ind + \phi^s(G^T \cdot Ind) + \epsilon \ ,$$

where η and ϕ are 2-vectors of parameters quantifying industry and cross-industry effects, respectively. Let $indret_k$ and $indvol_k$ denote the returns and volatility for industry k, and denote with $k(i)$ the industry of firm i. Then Ind is the matrix of firm specific industry characteristics

$$Ind_i = (indret_{k(i)}, indvol_{k(i)}) \ ,$$

and the vector $G^T \cdot Ind$ involves characteristics of upstream industries (suppliers' industries). We use the same sample selection, variable definitions and controls (omitted for the sake of space) as in Table 2. We consider various industry classifications, resulting in 12, 17, 30, 38 and 48 portfolios. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		No Industries	Industry Portfolios				
		0	12	17	30	38	48
Suppliers	lev, γ_1^s	-1.26	-1.54^{*}	-1.37^{*}	-1.41^{*}	-1.18	-1.27
		(0.101)	(0.036)	(0.047)	(0.043)	(0.097)	(0.082)
	ivol, γ_2^s	-1.3^{***}	-1.39^{***}	-1.36^{***}	-1.37^{***}	-1.23^{***}	-1.32^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	jump, γ_3^s	.283	.287	.206	.192	.31	.324
		(0.655)	(0.698)	(0.791)	(0.801)	(0.628)	(0.636)
Supplier Industries	ret, ϕ_1^s		$-.0225$	$-.0132$	$-.0206$	$-.0228$	$-.0192$
			(0.240)	(0.652)	(0.380)	(0.204)	(0.245)
	vol, ϕ_2^s		$.0119^{***}$	.00882	.00641	$-.00211$	.00106
			(0.000)	(0.310)	(0.186)	(0.436)	(0.714)
N		3849	3791	3791	3791	3791	3791

Table 6
Industry Controls for Suppliers and Customers Spillovers

Regression estimates for various models with industry and cross-industry effects.

$$y = \beta Firm + \gamma^c (G \cdot Firm) + \gamma^s (G^T \cdot Firm) + \delta(S\&P, YieldCurve) + \eta Ind + \phi^c (G \cdot Ind) + \phi^s (G^T \cdot Ind) + \epsilon \ ,$$

where η and ϕ are 2-vectors of parameters quantifying industry and cross-industry effects, respectively. Let $indret_k$ and $indvol_k$ denote the returns and volatility for industry k, and denote with $k(i)$ the industry of firm i. The vectors Ind, $G \cdot Ind$, and $G \cdot Ind$ are defined as in Tables 4 and 5. We use the same sample selection and variable definitions as in Table 2. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		No Industries	Industry Portfolios				
		0	12	17	30	38	48
Customers	lev, γ_1^c	2.01***	1.83**	2.01**	1.93**	2.04**	2.08**
		(0.001)	(0.006)	(0.002)	(0.004)	(0.002)	(0.002)
	ivol, γ_2^c	−.817	−.772	−.817	−.687	−.74	−.81
		(0.129)	(0.189)	(0.161)	(0.258)	(0.266)	(0.188)
	jump, γ_3^c	12.8***	14.2***	13.9***	13.8***	13.4***	13.4***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Suppliers	lev, γ_1^s	−1.15	−1.5*	−1.33	−1.34	−1.12	−1.19
		(0.135)	(0.042)	(0.054)	(0.055)	(0.119)	(0.104)
	ivol, γ_2^s	−1.17***	−1.26***	−1.25***	−1.24***	−1.12***	−1.19***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
	jump, γ_3^s	−.225	−.539	−.444	−.261	−.0612	−.0621
		(0.681)	(0.431)	(0.604)	(0.735)	(0.918)	(0.918)
Customer Industries	ret, ϕ_1^c		−.0337	−.0521	−.0385*	−.00665	−.0264
			(0.216)	(0.057)	(0.041)	(0.577)	(0.082)
	vol, ϕ_2^c		.0192***	.0038	0	−.00162	−.00117
			(0.000)	(0.408)	(1.000)	(0.317)	(0.504)
Supplier Industries	ret, ϕ_1^s		−.0174	−.0157	−.0236	−.0174	−.0196
			(0.371)	(0.643)	(0.343)	(0.375)	(0.224)
	vol, ϕ_2^s		.0141***	.0121	.00703	−.00137	.00106
			(0.000)	(0.174)	(0.179)	(0.573)	(0.686)
N		3530	3506	3506	3506	3506	3506