Three Essays on Customer-Supplier Networks and Financial Markets

by

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Abstract

This thesis is composed of three independent essays on customer-supplier networks and financial markets. The first chapter, entitled "Economic Links and Return Volatility", is co-authored with Keyi Zhang and Ramazan Gençay. This study investigates the propagation of stock return volatility along supply chains. Our results show that the effect of customer volatility is approximately 10 times as large as trading volume on supplier's volatility. Our findings are robust to controlling for variables capturing the time-series properties of volatility and a set of idiosyncratic, industry and market factors; tested under various assumptions regarding the activeness of customer-supplier linkages; and to different estimation methods. Our out-of-sample tests provide consistent evidence that incorporating customer channel improves volatility forecasting. Furthermore, the transfer of volatility is more pronounced when investors are more aware of customer-supplier linkages.

The second chapter, entitled "Resilience to the Financial Crisis in Customer-Supplier Networks" is also co-authored with Ramazan Gençay and Keyi Zhang. Inspired by the Capital Asset Pricing Model (CAPM) beta, we construct customer and supplier betas to separately investigate potentially different properties of downstream and upstream linkages. With the adjacency matrix acting as a "filter" to extract each company's return covariances with its trading partners, the cross-sectional dependence contained in the customer-supplier network is summarized by our betas. We explore how these two betas are related to a company's resilience to the financial crisis of 2008-2009. We observe that a higher customer beta is generally associated with more resilience during the crisis.

The third chapter, entitled "Economic Links and Credit Spreads", is co-authored with Ramazan Gençay, Daniele Signori, Yi Xue and Keyi Zhang. This paper has been published in the Journal of Banking & Finance. This study describes a model of financial networks that is suitable for the construction of proxies for counterparty risk. We find that, for each supplier, counterparties' leverage and option implied volatilities are significant determinants of corporate credit spreads in the period after the 2008-2009 U.S. recession. Our findings are robust after controlling for several idiosyncratic, industry, and market factors.

Keywords: Network analysis; Customer-supplier links; Financial market; Financial risk

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Chapter 1

Economic Links and Return Volatility

1.1 Introduction

Equity market volatility is broadly understood as the degree of variation in stock prices or returns. Compared to the fairly large econometric literature focusing on pure time-series modeling and forecasting of volatility (Andersen, Bollerslev, Christoffersen, and Diebold (2006) provide a survey on these topics), research on economic channels of volatility is relatively scarce. As a seminal paper on the drivers of equity market volatility, Schwert (1989) investigates the relationship of stock volatility with macroeconomic volatility, economic activity, financial leverage and stock trading activity. More recently, adopting a comprehensive approach, Paye (2012) and Christiansen, Schmeling, and Schrimpf (2012) model volatility in a predictive regression setting. Motivated by existing theoretical literature, Paye (2012) identifies a set of candidate predictors and tests the ability of these variables to improve volatility forecasts. Christiansen et al. (2012) perform an even more comprehensive examination of financial volatility in the sense that they investigate a larger set of potential predictors and study not only equity market but also volatility in other asset classes (i.e., bonds, foreign exchange and commodities).

Note that the majority of the existing literature has focused exclusively on aggregate equity market volatility. In contrast, the present paper investigates stock return volatility from the perspective of individual firms. More important, we focus on one particular channel of volatility—the transfer of volatility along supply chains.

Today, no firm is an isolated island—firms are connected to one another through different types of linkages. Some of these links are direct and explicit, while others are relatively obscure. Allen and Babus (2008) provide a survey of possible sources of connections between financial institutions and how these connections are modeled and explored to answer important economic questions. In this study, we focus on the customer-supplier links between firms—these links are clearly defined, contractual, and founded on real trading activities.

There are interesting studies investigating customer-supplier relationships. For example, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) study the systemic risks originating from intersectoral input-output linkages and argue that sizable aggregate fluctuations may originate from microeconomic idiosyncratic shocks only if there are significant asymmetries in the roles that sectors play as suppliers to others. In another examination of the linkages along the supply chain, Hertzel, Li, Officer, and Rodgers (2008) study the wealth effects of distress and bankruptcy filing for the suppliers and customers of filing firms and find that significant contagion effects extend to suppliers of the filing firms but not the customers. In a recent paper, Gençay, Signori, Xue, Yu, and Zhang (2015) introduce an econometric network model to appropriately analyze counterparty risks and find that for each supplier, customers' leverage and option implied volatilities are significant determinants of corporate credit spreads in the period after the 2008 to 2009 U.S. recession.

Shocks can propagate through supply chains. Customers are crucial to suppliers because they play an indispensable role in fulfilling most firms' ultimate goal—selling goods and/or services for a profit. Cohen and Frazzini (2008b) show that firms' real operations, measured by sales and operating income, are significantly more correlated when they are linked through customer-supplier relationships, which affirms the intuition that there are significant comovements in the underlying cash flows of the linked firms. Furthermore, as documented in Hertzel et al. (2008), when a firm experiences financial distress, which largely reflects a shift in demand away from the firm, this may also reduce the derived demand for its suppliers' output—this is a typical example of how shocks propagate through supply chains. As firms are stakeholders in their customers' operations—the financial health of their major customers affects their own profitability, and shocks to the customers have resulting effects on the supplier firm—it is natural to hypothesize that the customer-supplier link is an important channel for the propagation of stock return volatility. Specifically, customers' return volatility predicts that of suppliers.

This paper tests and examines this hypothesis in a predictive regression setting. As a seminal paper on the drivers of equity market volatility, Schwert (1989) provides evidence that there is a strong association between stock return volatility and stock trading activity. Our analysis shows that the effect of customer volatility is approximately 10 times as large as trading value on supplier's volatility. Our findings are robust to controlling for variables capturing the time-series properties of stock return volatility and a set of idiosyncratic, industry and market factors. Further, they are tested under various assumptions regarding the activeness of customer-supplier linkages and using different estimation methods. In particular, we explicitly address the potential concern of endogeneity and confirm our results through estimations with instrumental variables (IVs) using the two-step efficient Generalized Method of Moments (GMM).

Moreover, using various benchmark models and rolling estimation windows, our out-of-sample tests show that incorporating the customer channel improves forecasts of a supplier's volatility. In particular, even in the most aggressive case, namely, using a benchmark model with a large set of forecasting variables that are documented to be important predictors of volatility, our results still provide evidence of improvements in forecasting when the customer channel is included.

In addition to demonstrating the predictive power of customer volatility, we test how the public's awareness of customer-supplier linkages affects the intensity of volatility transfer. Specifically, we investigate the interaction between customer volatility and analyst coverage. As the research activities and recommendations of financial analysts reveal a firm's information to the market, higher analyst coverage implies that the public has better access to information regarding a firm's operations and financial conditions and is more likely to be aware of the identities of its major customers. As expected, our results show that the transfer of volatility from customers to suppliers is more pronounced for firms with higher analyst coverage (after controlling for the size of the firm, measured by market capitalization and trading value). Our interpretation is that when investors are more aware of a firm's principal customers, they anticipate the propagation of shocks through these related firms and respond more actively to news on firm's customers; that is, they incorporate such news into their investment and asset allocation decisions regarding the supplier companies. This trend contributes to the stronger association between customer and supplier volatility.

We would like to emphasize that our analysis is based on a large sample over a long period in the equity market. We employ panel data spanning approximately forty years, from 1977 to 2015. After matching with data on the control variables we consider, our final sample contains 2,738 unique suppliers with a total of 134,007 monthly observations.

The remainder of the paper is organized as follows. Section 1.2 introduces the construction of customer-supplier networks and how we model stock return volatility in a predictive regression setting. Section 1.3 describes the data. Section 1.4 reports the estimation results. Section 1.5 considers five robustness checks: we control for industry effects; examine alternative assumptions regarding the activeness of customer-supplier linkages; address the potential correlation between individual fixed effects and the autoregressive term; address the potential concern of endogeneity using IV estimation; and for comparison, show that while customers' return volatility predicts that of suppliers, return volatilities of randomly selected firms are not significant determinants of a firms's volatility. The out-of-sample analysis is performed in Section 1.6. Section 1.7 examines the interaction between customer volatility and analyst coverage. Section 1.8 concludes.

1.2 Methodology

1.2.1 Customer-Supplier Networks and Adjacency Matrices

In a survey paper, Allen and Babus (2008) report that networks, which are generally understood as collections of nodes and links between nodes, can be useful representations of economic or financial systems. Nodes represent entities in the system; links describe certain relationships between the entities.

In this paper, we examine customer-supplier networks, where each firm is a "node", and a customer-supplier relationship is a "link" between two firms. The structure of the network can be characterized by an adjacency matrix, G, which is a square matrix with dimension of the number of nodes (i.e., firms) in the network. The entry in the ith row and jth column of G, $(G)_{ij}$, is one if and only if i (j) is the supplier (customer) of j (i), zero otherwise.

Consider the simple network depicted in Figure 1.1, v_i, $i = 1, ..., 5$, denotes the firm; the arrow indicates the flow of output. For example, the arrow between v_1 and v_2 indicates that firm 1 (2) is the supplier (customer) of firm 2 (1). Matrix G characterizing the structure of this network is therefore

$$G = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

The second row of G, for example, refers to firm 2, which indicates that firm 2 has only one customer, which is firm 4, as only the fourth entry is one. More generally, the ith row of G captures firm i's first-order (i.e., immediate) customer linkages.

The adjacency matrix G we have referred to thus far is unweighted, in the sense that it has entries of either one or zero. In some applications, it is useful to introduce the concept of the *strength* of a link. In this paper, we use a sales-weighted matrix G to capture the relative importance of customers.[1] First, we construct an unweighted G. Next, for each supplier (i.e., each row) in G, links (i.e., entries that have a value of one) are weighted by the amount of sales made to the target customer, normalized by the observed total amount of sales (i.e., the sum of all sales to customers) of this supplier in this period. The sum of the entries in each row of the sales-weighted G is equal to one. Using this weighting, from a supplier's perspective, greater importance is assigned to customers that account for a larger shares of trades.[2]

1.2.2 Stock Return Volatility

Realized stock return volatility is often measured by the realized variance or the square root of the realized variance of the (excess) stock returns. (For example, see Schwert (1989), Andersen et al. (2006), Corsi (2009), Paye (2012), Christiansen et al. (2012) and Cao and Han (2013).) Following the same approach, we focus on modeling and forecasting the sample standard deviation of daily stock returns over one month. Specifically, the realized stock return volatility of firm i in month t, $RV_{i,t}$, is characterized by

$$RV_{i,t} = \sqrt{\frac{1}{T_{i,t}-1}\sum_{\tau=1}^{T_{i,t}}(DailyRet_{i,t,\tau} - \overline{DailyRet_{i,t}})^2}, \tag{1.1}$$

where, for firm i, $T_{i,t}$ is the number of trading days observed in month t; $DailyRet_{i,t,\tau}$ is the daily return on the τth trading day of month t (i.e., $DailyRet_{i,t,\tau} = \frac{P_{i,t,\tau}-P_{i,t,\tau-1}}{P_{i,t,\tau-1}}$, where $P_{i,t,\tau}$ is the closing stock price on the τth trading day of month t); and $\overline{DailyRet_{i,t}}$ is the sample average of daily returns in month t.

For each firm i, its customers' stock return volatility in month t is measured and denoted by $(G\cdot RV)_{i,t} = (G_t \cdot RV_t)_i$. Suppose that there are n firms in the customer-supplier network in month t, G_t is the $n \times n$ sales-weighted adjacency matrix in month t, RV_t is the $n \times 1$ vector containing each firm's return volatility in month t, and $(G_t \cdot RV_t)$ is therefore a vector capturing the return volatility of each firm's customers in month t. Specifically, the ith entry in $(G_t \cdot RV_t)$ is the sales-weighted average of the return volatilities of firm i's customers in month t.

We model volatility in a predictive regression setting—all of the right-hand-side variables are one month prior to the dependent variable, especially focusing on the channel from customer volatility to that of the supplier:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t} \tag{1.2}$$

where $ControlVariables$ is a row vector containing a set of time-series, market and idiosyncratic factors that are introduced in the next section, and Γ is a column vector of coefficients.[3]

As also noted by Cohen and Frazzini (2008b), current U.S. financial accounting regulation requires public firms to report the customers that account for at least 10% of their total yearly sales (but not their suppliers); thus, our data source provides more information about firms' major customers (but not major suppliers).[4] Therefore, we focus our investigation on the effects of customers, that is, the transfer of volatility from customers to suppliers.

1.2.3 Control Variables

Motivated by the existing theoretical and empirical literature, we incorporate a set of control variables into our analysis. First, to capture the time-series properties of stock return volatility, we include an autoregressive term, the one-month-lagged return volatility (RV^m), in our model. In addition, we apply the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) from Corsi (2009) and Andersen, Bollerslev, and Diebold (2007), including return volatilities over different time horizons other than one month: one quarter (RV^q), one-half year (RV^{hy}), and one year (RV^y). They are defined and calculated using daily stock returns in the same way as RV in Equation 1.1, except that they are over longer time horizons.

To control for market-level volatility, we include the sample standard deviation of daily returns on the Standard & Poor's 500 Composite Index over one month, $RV_{S\&P}$. In addition, we include *yield curve slope* and *Baa-Aaa spread.* The slope of the yield curve is measured as the difference between the 10-year and 2-year Treasury Constant Maturity rates, $r^{10} - r^2$; the Baa-Aaa spread is the difference between BAA- and AAA-rated corporate bond yields, $r^{BAA} - r^{AAA}$, which is a measure of market credit risk.

A set of firm characteristics that are related to stock return volatility is considered. First, we account for a firm's *market capitalization*, MV, measured as the product of the closing price on the last trading day of a month and the number of shares outstanding. Moreover, it has been well-documented that an increase in the proportion of debt to equity leads to an increase in return volatility (see Merton (1974) and Schwert (1989), for example), and hence, we include *leverage* as the ratio of total liabilities to total assets. In addition, the *earnings-price ratio* (*EPS/P*) and *dividend-price ratio* (*D/P*) are shown to be closely associated with return volatility (see Mele (2007) and Christiansen et al. (2012), for example). Furthermore, Schwert (1989) provides evidence that there is a strong association between stock return volatility and stock trading activity. To capture this effect, we include monthly *trading value*, measured as the product of the closing price on the last trading day of a month and the total number of shares sold during the month.

1.3 Data

1.3.1 Customer-Supplier Relationships

According to the U.S. Statement of Financial Accounting Standards (SFAS) No.131, public enterprises are required, once each year, to report the 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 customer segment files are the customer's name and the total amount of annual sales from this supplier to this customer.

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 included in some instances and omitted in others, or the company's name can be outright misspelled. We adopt a very conservative approach—we only consider those customer-supplier relations (i.e., links) for which there is an exact match (case-insensitive) between the reported name and an entry, which can be the company name or the company's legal name, or ticker, in the Compustat datafile of names.

Following this procedure, in the period from June 1976 to October 2015, 7,459 unique firms with a total of 40,279 reported links are identified. That is, during this period, there are, in total, 7,459 unique firms that have ever appeared in the customer-supplier networks identified from the customer segment files. Among them, 5,078 firms reported their customers, 3,264 firms were reported as customers by other companies, and 883 firms took the role of both a supplier and a reported customer.

Public companies are required to report their major customers once every fiscal year. As fiscal years vary across businesses, they report in different months. When a link is reported, we consider it active for a one-year period.[5] Specifically, it is considered active for up to one year prior to the reporting date.[6]

1.3.2 Other Data

To calculate realized stock return volatilities, we collect daily closing stock prices from the Center for Research in Security Prices (CRSP) U.S. Stock database for the period from January 1977 to December 1982 and from the Compustat-North America database for the period from January 1983 to December 2015. As our customer-supplier links are identified from the customer segment files of the Compustat-North America database, it is natural to collect stock prices from the same source; however, because daily data prior to January 1983 are not available there, we collect daily prices from the CRSP U.S. Stock database for the earlier period. We focus our analysis on common stocks and American depositary receipts (ADR) only, which together account for approximately 90% of the daily closing stock price observations in the sample. For firms that have multiple issues, we use that with the highest average daily trading volume throughout the sample period as the representative issue.[7] Dividends are reinvested. We exclude the observations with a stock price that is less than $1 and those for which the number of outstanding shares differs from the previous trading day. If there is a suspension longer than 7 days, the daily price observation on the day immediately after the suspension is also excluded.

Monthly interest rates on Treasury constant maturities and corporate bonds are collected from the Federal Reserve Bank database. Daily returns on the Standard & Poor's 500 Composite Index and monthly data on closing stock price, number of shares outstanding and number of shares traded are from the CRSP. Quarterly data on a firm's total assets, total liabilities, earnings per share (excluding extraordinary items), and monthly dividends per share are collected from the Compustat-North America database. Daily value-weighted returns on industry portfolios are obtained from Kenneth French's website.[8]

Table 1.1 contains the summary statistics for our final sample. Our data have a panel structure covering the period from February 1977 to October 2015. After matching with data on the entire set of variables listed in Section 1.2 - 1.2.3, there are 2,738 unique suppliers with a total of 134,007 monthly observations. The panel is unbalanced: the number of monthly observations for each supplier varies between 1 and 316, with a median of 34.

1.4 Estimation Results

With various sets of control variables, Equation 1.2 is estimated by pooled ordinary least squares (OLS) with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (Driscoll and Kraay (1998)). Except for four of the variables, which are the yield curve slope, Baa-Aaa spread, earnings-price ratio (EPS/P) and dividend-price ratio (D/P), all variables in Equation 1.2 are natural-logarithm transformed prior to estimation.[9] The results are presented in Table 1.2. Motivated by the existing theoretical and empirical literature, after controlling for the variables capturing the time-series properties of stock return volatility and a set of market and idiosyncratic factors, customer volatility is a statistically significant determinant of a supplier's volatility—the estimated coefficient is significant at the 0.1% level in all specifications. In addition, according to Model (4), the estimated effect of customer volatility is approximately 10 times as large as trading value on supplier's volatility. Further, the effect of customer volatility is approximately one-third and one-fifth of the effect of RV^m in Model (4) and (5), respectively.[10] The predictive power of customer volatility is to be further examined in the out-of-sample analysis in Section 1.6.

1.5 Robustness

1.5.1 Industry Effects

In addition to originating from customer-supplier linkages, an alternative explanation for the presence of a customer effect in our framework is an industry effect. Averaging over customers' stock return volatilities, the argument holds, builds proxies for return volatility of the industry in which this firm operates. To address this concern, we introduce industry volatility as an additional control variable.

We obtain daily value-weighted stock returns on industry portfolios from Kenneth French's website.[11] These returns are constructed by assigning each AMEX, NYSE and NASDAQ stock to an industry portfolio according to its Standard Industrial Classification (SIC) code. For robustness, we consider various classifications, resulting in 12, 17, 30, 38 and 48 industry portfolios. For each classification scheme and each industry portfolio, first, we compute industry volatility as the sample standard deviation of daily returns in a month. Second, given a classification scheme, each firm in our dataset is matched to its industry portfolio according to its Compustat SIC code. Let $indRV_i$ denote the return volatility of the industry portfolio to which firm i is matched. Controlling for industry volatility, partial effects are estimated for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + \beta_2 \; indRV_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t}, \qquad (1.3)$$

where *ControlVariables* includes the entire set of variables listed in Section 1.2 - 1.2.3.

As presented in Table 1.3, the effects of industry volatility are positive and statistically significant. Compared to the results presented in Table 1.2, the estimated coefficient on customer volatility decreases very marginally (with respect to Model (5) in Table 1.2 which contains the entire set of control variables other than industry volatility), and it is statistically significant at the 0.1% level for all of the industry classification schemes considered.

1.5.2 Activeness of Customer-Supplier Linkages

As required by SFAS no.131, public companies report their major customers once every fiscal year. As fiscal years vary across businesses, they report in different months during the year. We consider a customer-supplier linkage active for up to a one-year period once a supplier company reports the name of and the yearly sales to the customer company. In this section, we compare three windows for the activeness of customer-supplier linkages and thus for the construction of sales-weighted G: (1) one year prior to the reporting date; (2) one year centered on the reporting date; and (3) one year after the reporting date.[12] For each of the three windows, Equation 1.2 is estimated by pooled OLS with the Driscoll-Kraay standard error. The estimated effects of customer volatility, as reported in Table 1.4, are quite stable across different choices of windows.

1.5.3 Estimation with the Hausman-Taylor Approach

When including an autoregressive term (RV^m), Equation 1.2 is a dynamic panel model, and a traditional fixed effects (de-meaned) regression would cause endogeneity by design; correlation between the lagged dependent variable and the unobserved individual fixed effect is non-zero. In other words, if one believes that an unobserved individual time-invariant effect (u_i) exists, it must be the case that $Cov(y_{t-1}, u_i) \neq 0$, which would certainly cause inconsistency. Therefore, in this section, we estimate Equation 1.2 by the Hausman-Taylor approach, which controls for the potential correlation between the individual fixed effect and the autoregressive term (Hausman and Taylor (1981)).[13]

As reported in Table 1.5, estimated coefficients on customer volatility under various specifications are generally larger than those obtained above using pooled OLS and are all statistically significant at the 0.1% level. In particular, the magnitude of the effect from customer volatility is still about 10 times as large as that from trading value on supplier's volatility in Model (4), (5) and (6).

1.5.4 Estimation with Instrumental Variables

There might be concerns that the variable of interest, customers' return volatility, is endogenous (i.e, not orthogonal to the error term). For example, one concern is that the regression equation is simultaneous in the sense that the transfer of volatility also goes from suppliers to customers. First, we argue that this simultaneity is unlikely because our investigation is undertaken in a predictive regression setting—supplier's volatility, the dependent variable, is one-period later in time than the customer volatility. However, regardless of the source of endogeneity, we explicitly address this concern by estimating Equation 1.2 by constructing and utilizing instrumental variables (IVs) in this section.

First, we construct $G_{i,t}^{new,k}$ to capture firm i's newly established customers in month t. Specifically, $G_{i,t}^{new,k}$ captures those customers of firm i in month t that were not firm i's customers k months ago, that is, firms that while they are firm i's customers in month t are not customers of firm i in month $t-k$. Next, RV_{t-k}, the $n \times 1$ vector containing each firm's return volatility in month $t-k$, is multiplied by $G_t^{new,k}$, to produce the IV. That is, the k-month-lagged return volatility of these "newly established customers", $(G_t^{new,k} \cdot RV_{t-k})_i$, is utilized as an IV. As these firms are not firm i's customers k months ago by construction, their k-month-lagged volatilities are *unlikely* to be correlated with the current disturbance term. Hence, we claim this IV to be exogenous. However, as return volatility is in general a persistent process, k-month-lagged volatilities of these newly established customers should be correlated with their own more recent volatilities; hence, this IV is correlated with the variable of interest.

The estimation results are presented in Table 1.6. Specifically, we use different combinations of the following IVs: $(G_{t-2}^{new,2} \cdot RV_{t-4})_i$, $(G_{t-2}^{new,6} \cdot RV_{t-8})_i$ and $(G_{t-2}^{new,12} \cdot RV_{t-14})_i$. They capture the corresponding lagged return volatilities of firm i's newly established customers that are not a customer of firm i, 2 months, 6 months and 12 months ago, respectively. The coefficients are estimated by the two-step efficient Generalized Method of Moments (GMM) procedure, with the estimated asymptotic variance of the GMM estimator being heteroskedasticity and autocorrelation consistent (HAC). The asymptotic variance of the sample analogue of the orthogonality or moment conditions (specifying that all of the instruments in the equation are uncorrelated with the error term) is estimated using a Bartlett kernel with bandwidth $q(n) = 13$ (Newey and West (1987)). The inverse of the estimated asymptotic variance is then used as the weighting matrix in the second stage of the GMM estimation to obtain the efficient GMM estimator[14].

We report the Kleibergen-Paap Wald rk F statistic (Kleibergen and Paap (2006) and Kleibergen and Schaffer (2015)) as a weak-instruments test. With every combination of IVs, the F statistic is above 700—it well exceeds the "rule of thumb" requirement of Staiger and Stock (1997), which states that the F statistic should be greater than 10 for weak identification not to be considered a problem. We also report the p-value that is associated with Hansen's test of overidentifying restrictions (Hansen (1982)). The large p-values, ranging from approximately 0.33 to 0.56, indicate in our favor that we *fail to reject* the null that *all the regularity assumptions of the model (including the assumption that the IVs are orthogonal to the error term) are satisfied.* Most important, the estimated coefficients on customer volatility are comparable to the previous results, in terms of sign, magnitude and level of statistical significance. That is, our previous results are further confirmed by the estimation with IVs.

1.5.5 Stock Return Volatility and Randomized Linkages

To further demonstrate the robustness of our results, in this section, we construct $(G^R \cdot RV)$, where G^R is the randomized sales-weighted G: columns of sales-weighted G are shuffled randomly[15]. That is, rather than capturing firm i's customers, the ith row of G^R contains randomly selected firms which may or may not be firm i's customers. So the ith entry in $(G_t^R \cdot RV_t)$ is the weighted average of the return volatilities of randomly selected firms in month t.

With various sets of control variables, the following equation is estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G^R \cdot RV\right)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t}, \tag{1.4}$$

Estimation results are reported in columns (2) and (4) of Table 1.7. For comparison, benchmark results from Table 1.2 are presented in columns (1) and (3), where customer volatility $(G \cdot RV)$ is constructed using sales-weighted G. Comparing to the estimated coefficients on the customer volatility, the coefficients on $(G^R \cdot RV)$ are smaller in magnitude, and more importantly, do not have statistical significance. That is, results in Table 1.7 indicate that, while customers' return volatility predicts that of suppliers, return volatilities of randomly selected firms are not significant determinants of a firms's volatility.

1.6 Out-of-Sample Analysis

1.6.1 Out-of-Sample Forecasting Tests

In this section, we test whether incorporating customer volatility improves volatility forecasts from an out-of-sample perspective. Let model 1 be the benchmark model; model 2, which nests model 1 and includes customer volatility as an additional forecasting variable, is the augmented model.

$$\text{Model 1: } RV_{i,t} = \beta_0 + X_{i,t-1}\boldsymbol{\beta}_1 + \epsilon_{i,t}, \tag{1.5}$$

$$\text{Model 2: } RV_{i,t} = \beta_0 + X_{i,t-1}\boldsymbol{\beta}_1 + \beta_2 \left(G \cdot RV\right)_{i,t-1} + \epsilon_{i,t}, \tag{1.6}$$

where $X_{i,t-1}$ is a row vector of forecasting variables of firm i in month $t-1$, which does not include customer volatility, $(G \cdot RV)_{i,t-1}$; $\boldsymbol{\beta}_1$ is a column vector of parameters.

Mean squared prediction error (MSPE) has been one of the most commonly used statistics for comparing forecasts of an augmented model to the nested benchmark model (see, for example, Lettau and Ludvigson (2001), Stock and Watson (2002), Stock and Watson (2003), Stock and Watson (2004) and Orphanides and van Norden (2005)). We apply the test for equal MSPE proposed by Clark and West (2007). Specifically, Clark and West (2007)'s approach centers on the idea that, under the null that the benchmark model generates the data, the augmented model introduces noise into the forecasting process by estimating parameters with population values of zero; hence, the MSPE of the augmented model is expected to be larger than that of the benchmark model. The MSPE of the augmented model should therefore be adjusted to account for this noise. In our context, the sample MSPE for model 1 and model 2 are, respectively,

$$\hat{\sigma}_1^2 = P^{-1} \sum_i \sum_t (RV_{i,t+1} - \hat{RV}_{1,i,t+1})^2, \tag{1.7}$$

$$\hat{\sigma}_2^2 = P^{-1} \sum_i \sum_t (RV_{i,t+1} - \hat{RV}_{2,i,t+1})^2, \tag{1.8}$$

where $\hat{RV}_{1,i,t+1}$ and $\hat{RV}_{2,i,t+1}$ denote one-step-ahead predictions of $RV_{i,t+1}$ from model 1 and 2, respectively; P denotes the number of out-of-sample predictions used in computing these averages. The adjustment, which is subtracted from $\hat{\sigma}_2^2$ to account for the additional noise associated with the augmented model's forecasts, is

$$adj. = P^{-1} \sum_i \sum_t (\hat{RV}_{1,i,t+1} - \hat{RV}_{2,i,t+1})^2. \tag{1.9}$$

Clark and West (2007) propose testing the null hypothesis of equal MSPE by examining the "MSPE-adjusted" statistic:

$$MSPE\text{-}adjusted \equiv \hat{\sigma}_1^2 - (\hat{\sigma}_2^2 - adj.). \tag{1.10}$$

This is a one-sided test with the alternative hypothesis that model 1 has a greater MSPE than model 2. Clark and West (2007) argue that, although the MSPE-adjusted statistic is not asymptotically normal, standard normal critical values result in actual sizes close to, but slightly smaller than, nominal size for sufficiently large samples.

For the out-of-sample analysis, the entire sample is divided into two parts: the observations in the first T_1 time periods are for estimating the parameters in the forecasting models (estimation sample), and the observations in the final T_2 time periods are used to estimate the MSPE associated with each model (forecasting sample). We use 24-, 36-, 48- and 60-month rolling estimation windows to estimate the parameters in the forecasting models.

We select seven benchmark models (i.e., model 1) for forecast evaluation. First, following Paye (2012), an AR(6) specification is used:

$$RV_{i,t} = \beta_0 + \sum_{k=1}^{6} \beta_k RV_{i,t-k} + \epsilon_{i,t}. \tag{1.11}$$

The next four benchmark models each contains one set of the following forecasting variables: heterogeneous autoregressive terms (RV^m, RV^q, RV^{hy}, and RV^y); market factors ($RV_{S\&P}$, yield curve slope and Baa-Aaa spread); firm characteristics (MV, leverage, EPS/P, D/P and trading value); and industry volatility under the 30-industry classification scheme. The sixth benchmark model contains heterogeneous autoregressive terms, market factors and industry volatility that are as specified above. The last benchmark model includes the entire set of variables introduced in Section 1.2 - 1.2.3 and industry volatility as forecasting variables.

In Table 1.8, the Clark and West MSPE-adjusted statistic and corresponding p-value are reported for each benchmark and estimation scheme combination. For the first six benchmark models, the null of equal MSPE is rejected for all estimation schemes used, most of which at the 0.1% significance level. Even with the most aggressive choice, namely, using a benchmark model containing the entire set of variables introduced in Section 1.2 - 1.2.3 and industry volatility as forecasting variables (*All-But-No-CRV*), the null of equal MSPE is rejected at the 5% level when using the 60-month rolling estimation window. These results provide consistent evidence that incorporating customer volatility improves forecasts of supplier volatility.

1.6.2 Application: Density Forecasts

Density forecasting plays an important role in financial risk management, for example, in measuring and monitoring asset or portfolio Value-at-Risk. Coupled with the assumption that a firm's daily stock returns are normally distributed, the customer-channel-based volatility forecast can be used to forecast stock return density. Following Andersen, Bollerslev, Diebold, and Labys (2003), we assess our density forecasts using the methods of Diebold, Gunther, and Tay (1998). Suppose that the daily stock returns, r_τ, in month t follows conditional density, $f(r_\tau \mid \mathcal{F}_{t-1})$, where $\mathcal{F}_{t-1}$ denotes the full information set available in month $t-1$. If the forecasted density, $f_{t|t-1}(r_\tau)$, is equal to the true density, $f(r_\tau \mid \mathcal{F}_{t-1})$, the sequence of probability integral transforms of daily returns with respect to $f_{t|t-1}(\cdot)$[16] should be uniformly distributed on $(0, 1)$. Thus, the performance of the density forecasts and, thus, also the customer-channel-based volatility forecasts, can be investigated by checking whether the distributions of the probability integral transforms are $U(0, 1)$.

In Table 1.9, we report six selected quantiles of the probability integral transforms of observed daily returns using the sequence of one-month-ahead predicted volatilities. Again, we use 24-, 36-, 48- and 60-month rolling windows to estimate the parameters in the forecasting models. For all schemes, the first estimation sample starts in December 1984. As reported, for each estimation scheme, the percentages are approximately consistent with the corresponding selected quantiles, which indicates that, when coupled with the assumption that a firm's daily stock returns are normally distributed, our customer-volatility model generally performs well at forecasting stock return density.

1.7 Stock Return Volatility and Analyst Coverage

In addition to demonstrating the predictive power of customer return volatility, we find the following question quite intriguing: when investors are more aware of the identity of a firm's principal customers, will we observe more pronounced volatility transferring through the customer channel? To gain insights into this question, we investigate the interaction between customer volatility and analyst coverage. Intuitively, the research activities and recommendations of financial analysts reveal a firm's information to the market. Ceteris paribus, a higher number of analysts covering a firm entails a higher level of information transparency for this firm; that is, the public has better access to information regarding its operations and financial conditions and is more likely to be aware of its major customer-supplier relationships.

Specifically, we estimate the following model:

$$\begin{aligned} RV_{i,t} = \beta_0 &+ \beta_1 \left(G \cdot RV\right)_{i,t-1} \\ &+ \beta_2 \left(G \cdot RV\right)_{i,t-1} \times N^{Analysts}_{i,t-1} + \beta_3 N^{Analysts}_{i,t-1} \\ &+ ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t}, \end{aligned} \tag{1.12}$$

where $N^{Analysts}_{i,t}$ is the number of analysts who issue recommendations (which can be buy, hold, or sell) for firm i in month t. We also use $Ave.\ N^{Analysts}$ as an alternative measure of analyst coverage, which is the monthly average number of analysts who issue recommendations for a firm over the sample period. The numbers of recommendations are collected from the Institutional Brokers' Estimate System (I/B/E/S) database. Given the availability of data, our sample covers the period from December 1993 to October 2015.

Equation 1.12 is estimated by pooled OLS with the Driscoll-Kraay standard error. The results are reported in Tables 1.10 and 1.11. In Table 1.10, MV and trading value are included to control for the fact that larger companies tend to have higher analyst coverage, and an industry dummy variable under the 12-industry classification scheme is included to capture the various industry properties. In Table 1.11, the entire set of variables listed in Section 1.2 - 1.2.3 and industry volatility under the 30-industry classification scheme are included as controls. Variables other than the industry dummy, yield curve slope, Baa-Aaa spread, EPS/P, D/P, $N^{Analysts}$ and $Ave.\ N^{Analysts}$ are log-transformed prior to estimation.

For robustness, Equation 1.12 is also estimated by the Hausman-Taylor approach—the results are reported in columns (5) and (6) of Table 1.11.

In most cases, the estimated coefficient on the interaction term is positive and statistically significant at the 0.1% level. These results show that a higher number of analysts who follow a firm is generally associated with larger customer effect on suppliers, which indicates that the transfer of volatility from customers to suppliers is more pronounced when investors are more aware of the linkages. Our interpretation is that for a firm with higher analyst coverage, investors are likely to be more aware of its principal customers; as they anticipate the propagation of shocks through customer-supplier linkages, they respond more actively to news regarding firm's customers. That is, they incorporate such news into their investment and asset allocation decisions related to the supplier companies. This trend contributes to the stronger association between customer and supplier volatility. Our observation and interpretation shed light on one of the mechanisms of shocks propagation via customer-supplier linkages; and indicate that customer-supplier relationship is a channel for news to be incorporated into stock prices.

1.8 Conclusions

The majority of the existing literature has focused exclusively on aggregate equity market volatility, or pure time-series modeling and forecasting of volatility. In contrast, this paper investigates stock return volatility from the perspective of individual firms and examines one particular channel—the transfer of volatility along supply chains, in a predictive regression setting.

Existing literature documents that there is a strong association between stock return volatility and trading activity. Our analysis shows that the effect of customer volatility is approximately 10 times as large as trading value on supplier's volatility. Our findings are robust to controlling for variables capturing the time-series properties of stock return volatility and a set of idiosyncratic, industry, and market factors. Further, they are tested under various assumptions regarding the activeness of customer-supplier linkages and using different estimation methods, including estimations with instrumental variables using GMM. Moreover, using various benchmarks and rolling estimation windows, our out-of-sample tests produce consistent evidence of improvements in volatility forecasting when the customer channel is included.

In addition, we demonstrate that the transfer of volatility through the customer channel is more pronounced for firms with higher financial analyst coverage, after controlling for the size of firm, measured by market capitalization and trading value. This result is consistent with our expectation that with greater awareness of the identity of a firm's major customers, investors tend to respond more actively to news regarding these customers by incorporating such news into their investment decisions related to the supplier company. This trend contributes to the stronger association between customer and supplier volatility.

1.9 Notes

[1]Details regarding the data and the matching procedure that we use to identify the customer-supplier relations and to construct the sales-weighted G are provided in Section 1.3 - 1.3.1.

[2]The adjacency matrices that characterize customer-supplier networks are constructed as in Gençay et al. (2015).

[3]We also construct $RV_{i,t}$ without subtracting the sample average of daily returns—this version of stock return volatility produces quite similar estimation results to those obtained using the de-meaned version, for all specifications in this paper.

[4]Further information about this data source can be found in Section 1.3 - 1.3.1.

[5]We may have a different sales-weighted G in every month, as there are some firms reporting in different months, but each row of the sales-weighted G (i.e., each firm's customer linkages) is fixed for a 12-month period.

[6]In Section 1.5 - 1.5.2, we consider alternative window periods for the activeness of customer-supplier linkages, that is, for up to one year centered on the reporting date and one year after the reporting date.

[7]For each issue, average daily trading volume is measured as its total number of shares traded divided by its total number of trading days in the entire sample. Hence, by construction, each issue has an unchanged average daily trading volume throughout the entire period.

[8]Industry variables and data are explained in greater detail in Section 1.5 - 1.5.1.

[9]To preserve the sample size, the yield curve slope, Baa-Aaa spread, EPS/P and D/P are not log-transformed, as they have some non-positive observations.

[10]We also use total assets instead of MV to measure a firm's size and the total number of shares traded instead of trading value in a month to measure a stock's trading activity; the estimation results for customer volatility are quite similar with these different choices of control variables.

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

[12]In the results presented previously, we used the first type of window "one year prior to the reporting date" for the activeness of customer relations.

[13]It should be noted that the Hausman-Taylor estimator does not remove the individual fixed effect. For the estimator to be consistent, we need to assume that there is no correlation between the individual fixed effect and any variables other than the dependent variable.

[14]See Hayashi (2000), Sections 3.5 and 6.6, for further details.

[15]Columns of sales-weighted G are shuffled randomly by the MATLAB fucntion "randperm" with the seed of randomization set to 100.

[16]In particular, this is the cumulative density function with respect to $f_{t|t-1}(\cdot)$ evaluated at the observed daily return, r_τ: i.e., $\int_{-\infty}^{r_\tau} f_{t|t-1}(u)du$.

1.10 Tables and Figures

Table 1.1: **Summary Statistics**

This table contains summary statistics for the main variables in our final sample (without log-transformation). The data have a panel structure covering the period from February 1977 to October 2015. There are 2,738 unique suppliers with a total of 134,007 monthly observations. The panel is unbalanced: the number of monthly observations for each supplier varies between 1 and 316, with a median of 34. RV, realized return volatility, is the sample standard deviation of daily returns over one month; $(G \cdot RV)$, customer volatility, is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). RV^q, RV^{hy}, and RV^y are realized return volatilities over one quarter, one-half year and one year, respectively. MV, market capitalization, is the product of the closing price on the last trading day of a month and the number of shares outstanding. *Leverage* is the ratio of total liabilities to total assets. EPS/P and D/P are the earnings-price ratio and dividend-price ratio, respectively. *Trading value* is the product of the closing price on the last trading day of a month and the total number of shares sold during the month. MV and trading value are reported in millions and thousands of dollars, respectively. For comparison, we also report statistics for the entire sample (the "universe"), spanning the same period as ours, from which data on each variable are collected. These statistics are presented in square brackets underneath the corresponding variables.

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
$(G \cdot RV)$	0.020	0.016	0	1.891	134,007
RV	0.034	0.025	0	2.437	134,007
	[0.037]	[0.047]	[0]	[27.997]	[2,634,700]
RV^q	0.035	0.023	0.003	1.623	134,007
	[0.036]	[0.035]	[0]	[16.213]	[2,542,397]
RV^{hy}	0.036	0.023	0.005	1.623	134,007
	[0.035]	[0.031]	[0]	[11.182]	[2,407,074]
RV^y	0.035	0.020	0.001	0.773	134,007
	[0.034]	[0.023]	[0]	[1.829]	[2,198,866]
MV ($ million)	2,863	12,837	0.322	501,512	134,007
	[2,153]	[11,816]	[0.005]	[750,709]	[1,993,997]
Leverage	0.455	0.347	0.010	22	134,007
	[1.972]	[65.663]	[-4,927]	[25,968]	[3,060,729]
EPS/P	-0.030	3.074	-647.498	6.234	134,007
	[-7.943]	[3,551.363]	[-2,762,672.750]	[258,979.359]	[3,026,240]
D/P	0.001	0.010	0	1.846	134,007
	[0.009]	[13.230]	[0]	[27,375]	[4,307,487]
Trading Value ($ 1,000)	546,592	2,174,322	3.487	113,449,435	134,007
	[312,754]	[1,945,809]	[0.021]	[344,843,943]	[1,993,838]

Table 1.2: **Stock Return Volatility and Customer-Supplier Linkages**

Partial effects are estimated with various sets of control variables for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). An autoregressive term (RV^m) and the heterogeneous autoregressive terms—volatilities over different time horizons—quarter (RV^q), half year (RV^{hy}) and year (RV^y), are included. Market factors include the market volatility ($RV_{S\&P}$), yield curve slope ($r^{10} - r^2$) and Baa-Aaa spread ($r^{BAA} - r^{AAA}$). Firm characteristics include market capitalization (MV), leverage (total liabilities/total assets), earnings-price ratio (EPS/P), dividend-price ratio (D/P), and trading value. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed. The data have a panel structure covering the period from February 1977 to October 2015. There are 2,738 unique suppliers with a total of 134,007 monthly observations according to model (5). The models are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (number in parentheses).

	(1)	(2)	(3)	(4)	(5)
$(G \cdot RV)$	0.3368***	0.0481***	0.0266***	0.0618***	0.0345***
	(0.0311)	(0.0128)	(0.0056)	(0.0126)	(0.0054)
RV^m		0.2119***	0.1985***	0.1922***	0.1726***
		(0.0168)	(0.0144)	(0.0170)	(0.0137)
RV^q		0.2581***	0.2509***	0.2531***	0.2443***
		(0.0252)	(0.0230)	(0.0226)	(0.0205)
RV^{hy}		0.3026***	0.3098***	0.2610***	0.2688***
		(0.0372)	(0.0331)	(0.0346)	(0.0303)
RV^y		0.0886***	0.0933***	0.0806***	0.0853***
		(0.0232)	(0.0206)	(0.0223)	(0.0202)
$RV_{S\&P}$			0.0702*		0.0875**
			(0.0307)		(0.0309)
YieldCurve Slope			−0.0212*		−0.0178
			(0.0104)		(0.0101)
BaaAaa Spread			−0.0390		−0.0349
			(0.0270)		(0.0236)
MV				−0.0336***	−0.0391***
				(0.0050)	(0.0052)
Leverage				−0.0022	−0.0037
				(0.0035)	(0.0032)
EPS/P				−0.0005	−0.0005
				(0.0003)	(0.0003)
D/P				−0.2604	−0.2827
				(0.1584)	(0.1595)
Trading Value				0.0061	0.0097**
				(0.0032)	(0.0035)
$\bar{R}^2$	0.10	0.60	0.60	0.58	0.59
N	181,004	160,932	160,932	134,007	134,007

$*\ p < 0.05$; $**\ p < 0.01$; $***\ p < 0.001$

Table 1.3: **Controlling for Industry Effects**

Controlling for industry stock return volatility, partial effects are estimated for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + \beta_2 \; indRV_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). Industry volatility ($indRV$) is the return volatility of the industry portfolio that the firm is matched to, which is based on one of the five classification schemes (12, 17, 30, 38, and 48 industry portfolios). Heterogeneous autoregressive terms include RV^m RV^q, RV^{hy}, and RV^y. Market factors include $RV_{S\&P}$, the yield curve slope and the Baa-Aaa spread. Firm characteristics include MV, leverage, EPS/P, D/P, and trading value. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed. The data have a panel structure covering the period from December 1984 to October 2015, given the availability of SIC codes that are used to match a firm to its industry portfolio. The models are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (number in parentheses).

	(1)	(2)	(3)	(4)	(5)
$(G \cdot RV)$	0.0285***	0.0296***	0.0307***	0.0299***	0.0277***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0045)
indRV					
12-Industry	0.0740***				
	(0.0123)				
17-Industry		0.0555***			
		(0.0123)			
30-Industry			0.0454***		
			(0.0120)		
38-Industry				0.0508***	
				(0.0120)	
48-Industry					0.0636***
					(0.0110)
Other Control Variables					
Hetero. AR	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Market Factors	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm Charact.	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Robustness					
Heteroskedasticity	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Serial Correlation	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Cross-Sectional Dep.	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
$\bar{R}^2$	0.55	0.55	0.55	0.55	0.55
N	102,823	102,823	102,823	102,823	102,823

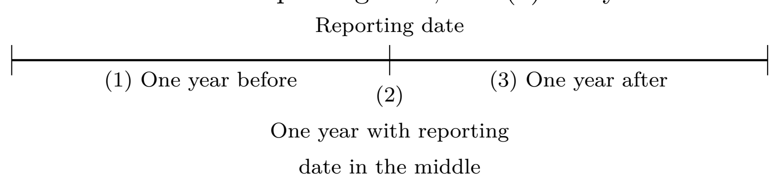
$*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Table 1.4: **Activeness of Customer-Supplier Linkages**

Partial effects are estimated for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G. A customer-supplier linkage is considered active for up to (1) one year prior to the reporting date; (2) one year centered on the reporting date; and (3) one year after the reporting date.



The entire set of control variables listed in Section 1.2 - 1.2.3 and industry volatility under the 30-industry classification scheme are included. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed. The data have a panel structure covering the period from 1984 to 2015 (given the availability of SIC codes that are used to match a firm to its industry portfolio). The models are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (number in parentheses).

		(1)	(2)	(3)
$(G \cdot RV)$		0.0307***	0.0308***	0.0310***
		(0.0047)	(0.0046)	(0.0045)
Control Variables				
	Hetero. AR	*Yes*	*Yes*	*Yes*
	Market Factors	*Yes*	*Yes*	*Yes*
	Firm Charact.	*Yes*	*Yes*	*Yes*
	Industry Vol.	*Yes*	*Yes*	*Yes*
Robustness				
	Heteroskedasticity	*Yes*	*Yes*	*Yes*
	Serial Correlation	*Yes*	*Yes*	*Yes*
	Cross-Sectional Dep.	*Yes*	*Yes*	*Yes*
$\bar{R}^2$		0.55	0.55	0.53
N		102,823	104,548	102,904

$*\quad p < 0.05;\quad **\quad p < 0.01;\quad ***\quad p < 0.001$

Table 1.5: **Estimation with the Hausman-Taylor Approach**

Partial effects are estimated with various sets of control variables for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 (G \cdot RV)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). An autoregressive term (RV^m) and the heterogeneous autoregressive terms—volatilities over different time horizons—quarter (RV^q), half year (RV^{hy}) and year (RV^y), are included. Market factors include the market volatility ($RV_{S\&P}$), yield curve slope ($r^{10} - r^2$) and Baa-Aaa spread ($r^{BAA} - r^{AAA}$). Firm characteristics include market capitalization (MV), leverage (total liabilities/total assets), earnings-price ratio (EPS/P), dividend-price ratio (D/P), and trading value. *indRV* is the return volatility of the industry portfolio that the firm is matched to, which is based on the 30-industry classification scheme. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed. The data have a panel structure covering the period from 1984 to 2015. The models are estimated by the Hausman-Taylor approach which controls for the potential correlation between the individual fixed effect and the autoregressive term. The numbers in parentheses are standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
$(G \cdot RV)$	0.1519***	0.0978***	0.0512***	0.1041***	0.0557***	0.0458***
	(0.0025)	(0.0025)	(0.0028)	(0.0027)	(0.0030)	(0.0030)
RV^m		0.1713***	0.1500***	0.1615***	0.1339***	0.1280***
		(0.0038)	(0.0038)	(0.0043)	(0.0044)	(0.0044)
RV^q		0.2275***	0.2122***	0.2243***	0.2092***	0.2060***
		(0.0072)	(0.0071)	(0.0079)	(0.0078)	(0.0078)
RV^{hy}		0.2187***	0.2135***	0.1986***	0.1966***	0.1901***
		(0.0077)	(0.0077)	(0.0086)	(0.0085)	(0.0085)
RV^y		0.0521***	0.0597***	0.0477***	0.0535***	0.0497***
		(0.0048)	(0.0048)	(0.0053)	(0.0053)	(0.0053)
$RV_{S\&P}$			0.1146***		0.1223***	0.0538***
			(0.0035)		(0.0037)	(0.0054)
YieldCurve Slope			−0.0197***		−0.0214***	−0.0211***
			(0.0015)		(0.0016)	(0.0016)
BaaAaa Spread			0.0062		−0.0097**	−0.0076*
			(0.0035)		(0.0036)	(0.0036)
MV				−0.0320***	−0.0404***	−0.0455***
				(0.0034)	(0.0033)	(0.0033)
Leverage				0.0019	0.0022	0.0046
				(0.0030)	(0.0031)	(0.0031)
EPS/P				−0.0435***	−0.0418***	−0.0400***
				(0.0044)	(0.0044)	(0.0044)
D/P				0.0180	−0.0017	−0.0021
				(0.1156)	(0.1148)	(0.1146)
Trading Value				−0.0110***	−0.0052**	−0.0042*
				(0.0019)	(0.0019)	(0.0019)
indRV						0.0972***
						(0.0056)
N	142,958	127,084	127,084	102,823	102,823	102,823

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 1.6: **Estimation with Instrumental Variables**

Partial effects are estimated for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 (G \cdot RV)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). *ControlVariables* includes the entire set of variables listed in Section 1.2 - 1.2.3. We use different combinations of the following IVs: $(G^{new,2}_{t-2} \cdot RV_{t-4})_i$, $(G^{new,6}_{t-2} \cdot RV_{t-8})_i$ and $(G^{new,12}_{t-2} \cdot RV_{t-14})_i$. They capture the corresponding lagged return volatilities of firm i's newly established customers that are not a customer of firm i, 2 months, 6 months and 12 months ago, respectively. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed.
Column (1) is estimated by pooled OLS with the Driscoll-Kraay standard error (in parentheses). Columns (2) - (4) are estimated using the two-step efficient GMM procedure, with HAC estimated asymptotic variance. The asymptotic variance of the sample analogue of the orthogonality conditions is estimated using a Bartlett kernel with bandwidth $q(n) = 13$. The inverse of the estimated asymptotic variance is then used as the weighting matrix in the second stage of the GMM estimation to obtain an efficient GMM estimator. The numbers in parentheses are HAC standard errors. We report the Kleibergen-Paap Wald rk F statistic as a weak identification test, with the null that the IVs and customer volatility are weakly correlated. We also report the p-value that is associated with Hansen's test of overidentifying restrictions, with the null that all of the regularity assumptions of the model (including the assumption that the IVs are orthogonal to the error term) are satisfied. The sample covers the period from 1977 to 2015.

	(1)	(2)	(3)	(4)
$(G \cdot RV)_{i,t-1}$	0.0345***	0.0534**	0.0518**	0.0497**
	(0.0054)	(0.0171)	(0.0176)	(0.0171)
Control Variables				
Hetero. AR	*Yes*	*Yes*	*Yes*	*Yes*
Market Factors	*Yes*	*Yes*	*Yes*	*Yes*
Firm Charact.	*Yes*	*Yes*	*Yes*	*Yes*
Instrumental Variables				
$(G^{new,2}_{t-2} \cdot RV_{t-4})$		*Yes*	*Yes*	*Yes*
$(G^{new,6}_{t-2} \cdot RV_{t-8})$		*Yes*		*Yes*
$(G^{new,12}_{t-2} \cdot RV_{t-14})$			*Yes*	*Yes*
Weak Identification Test, F statistic		719.714	723.429	733.803
Overidentifying Restrictions Test, p-value		0.3906	0.3266	0.5564
$\bar{R}^2$	0.59	0.61	0.61	0.61
N	134,007	7,238	7,155	7,151

$*$ $p < 0.05$; $**$ $p < 0.01$; $***$ $p < 0.001$

Table 1.7: **Stock Return Volatility and Randomized Linkages**

Partial effects are estimated with various sets of control variables for the following model:

$$RV_{i,t} = \beta_0 + \beta_1 (G \cdot RV)_{i,t-1} + ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month. In columns (1) and (3), customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). In columns (2) and (4), ($G \cdot RV$) is constructed using randomized sales-weighted G: columns of sales-weighted G are shuffled randomly. An autoregressive term (RV^m) and the heterogeneous autoregressive terms—volatilities over different time horizons—quarter (RV^q), half year (RV^{hy}) and year (RV^y), are included. Market factors include the market volatility ($RV_{S\&P}$), yield curve slope ($r^{10} - r^2$) and Baa-Aaa spread ($r^{BAA} - r^{AAA}$). Firm characteristics include market capitalization (MV), leverage (total liabilities/total assets), earnings-price ratio (EPS/P), dividend-price ratio (D/P), and trading value. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed. The data have a panel structure covering the period from February 1977 to October 2015. The models are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (number in parentheses). Columns (1) and (3) contain the benchmark results as in Table 1.2.

	(1)	(2)	(3)	(4)
$(G \cdot RV)$	0.0266***	0.0062	0.0345***	0.0040
	(0.0056)	(0.0035)	(0.0054)	(0.0033)
RV^m	0.1985***	0.1942***	0.1726***	0.1747***
	(0.0144)	(0.0152)	(0.0137)	(0.0149)
RV^q	0.2509***	0.2548***	0.2443***	0.2428***
	(0.0230)	(0.0251)	(0.0205)	(0.0231)
RV^{hy}	0.3098***	0.2990***	0.2688***	0.2636***
	(0.0331)	(0.0358)	(0.0303)	(0.0324)
RV^y	0.0933***	0.1044***	0.0853***	0.1004***
	(0.0206)	(0.0208)	(0.0202)	(0.0202)
$RV_{S\&P}$	0.0702*	0.0926**	0.0875**	0.1120***
	(0.0307)	(0.0324)	(0.0309)	(0.0327)
YieldCurve Slope	−0.0212*	−0.0265*	−0.0178	−0.0246*
	(0.0104)	(0.0109)	(0.0101)	(0.0108)
BaaAaa Spread	−0.0390	−0.0410	−0.0349	−0.0368
	(0.0270)	(0.0294)	(0.0236)	(0.0259)
MV			−0.0391***	0.0024
			(0.0052)	(0.0039)
Leverage			−0.0037	−0.0351***
			(0.0032)	(0.0054)
EPS/P			−0.0005	−0.0003
			(0.0003)	(0.0002)
D/P			−0.2827	−0.1078
			(0.1595)	(0.2896)
Trading Value			0.0097**	0.0093*
			(0.0035)	(0.0039)
$\bar{R}^2$	0.60	0.60	0.59	0.58
N	160,932	94,291	134,007	77,343

$*\ p < 0.05$; $**\ p < 0.01$; $***\ p < 0.001$

Table 1.8: **Out-of-Sample Forecasting Tests**

This table reports the Clark and West MSPE-adjusted statistic and corresponding p-value (in parentheses) for testing the following hypothesis: $H_0 : MSPE_1 - MSPE_2 = 0; H_1 : MSPE_1 - MSPE_2 > 0$. $MSPE_1$ and $MSPE_2$ are the MSPE from model 1 (benchmark model) and 2 (augmented model), respectively:

$$\text{Model 1: } RV_{i,t} = \beta_0 + X_{i,t-1}\boldsymbol{\beta_1} + \epsilon_{i,t},$$
$$\text{Model 2: } RV_{i,t} = \beta_0 + X_{i,t-1}\boldsymbol{\beta_1} + \beta_2 \left(G \cdot RV\right)_{i,t-1} + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date), and X is a row vector of forecasting variables that does not include customer volatility. We select seven benchmarks: AR(6); heterogeneous autoregressive terms (RV^m, RV^q, RV^{hy}, and RV^y); market factors ($RV_{S\&P}$, yield curve slope and Baa-Aaa spread); firm characteristics (MV, leverage, EPS/P, D/P and trading value); industry volatility under the 30-industry classification scheme; a combination of heterogeneous AR, market factors and industry volatility; and, finally, a model includes the entire set of variables introduced in Section 1.2 - 1.2.3 and industry volatility as forecasting variables (*All-But-No-CRV*). All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed; 24-, 36-, 48- and 60-month rolling windows are used to estimate parameters in the forecasting models. For the first four benchmarks, the first estimation sample starts in February 1977; for the last three benchmarks that contain industry volatility, the first estimation sample starts in December 1984. The whole sample period is from February 1977 to October 2015.

	Rolling Estimation Window			
Benchmark Model	24-Month	36-Month	48-Month	60-Month
AR(6)	0.0169***	0.0138***	0.0142***	0.0090***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hetero. AR	0.0161***	0.0136***	0.0137***	0.0136***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Market Factors	0.0023***	0.0022***	0.0038***	0.0060***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm Charact.	0.0844*	0.0365*	0.0582***	0.0560***
	(0.0428)	(0.0450)	(0.0000)	(0.0001)
Industry Vol.	0.0060***	0.0072***	0.0096***	0.0107***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
HAR-Market-Industry	0.0031***	0.0017**	0.0016***	0.0016***
	(0.0009)	(0.0018)	(0.0001)	(0.0000)
All-But-No-CRV	0.2184	−0.0278	0.0063	0.0062*
	(0.1286)	(0.3787)	(0.1828)	(0.0114)

One-sided test: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 1.9: **Distributions of Probability Integral Transforms**

This table reports the selected quantiles of the probability integral transform of returns with respect to the density forecasts from the following customer-volatility model:

$$RV_{i,t} = \beta_0 + \beta_1 \left(G \cdot RV\right)_{i,t-1} + X_{i,t-1}\Gamma + \epsilon_{i,t},$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date), and X is a row vector containing the entire set of variables listed in Section 1.2 - 1.2.3 and industry volatility under the 30-industry classification scheme. All variables, except for the yield curve slope, Baa-Aaa spread, EPS/P and D/P, are log-transformed; 24-, 36-, 48- and 60-month rolling windows are used to estimate parameters in the forecasting models. For all schemes, the first estimation sample starts in December 1984. The whole sample period is from December 1984 to October 2015.

	Rolling Estimation Window			
Quantile	24 Months	36 Months	48 Months	60 Months
5%	0.0256	0.0382	0.0437	0.0465
10%	0.0977	0.1089	0.1136	0.1158
25%	0.2914	0.2887	0.2888	0.2878
75%	0.7149	0.7184	0.7206	0.7226
90%	0.9156	0.9046	0.9008	0.8989
95%	0.9823	0.9717	0.9669	0.9646

Table 1.10: **Stock Return Volatility and Analyst Coverage I**

Partial effects are estimated for the following model:

$$\begin{aligned} RV_{i,t} = \beta_0 &+ \beta_1 \left(G \cdot RV\right)_{i,t-1} \\ &+ \beta_2 \left(G \cdot RV\right)_{i,t-1} \times N^{Analysts}_{i,t-1} + \beta_3 N^{Analysts}_{i,t-1} \\ &+ ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t}, \end{aligned}$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). $N^{Analysts}$ is the number of analysts who issue recommendations (buy, hold, or sell) for a firm in a month (from the I/B/E/S database). We also use *Ave.* $N^{Analysts}$ as an alternative measure of analyst coverage, which is the monthly average number of analysts who issue recommendations for a firm over the sample period. MV and trading value are included to control for the fact that larger companies tend to have higher analyst coverage. An industry dummy variable under the 12-industry classification scheme is included to capture the various industry properties. All variables, except for the dummy, $N^{Analysts}$ and *Ave.* $N^{Analysts}$, are log-transformed. The sample covers the period from December 1993 to October 2015. The models are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence (number in parentheses).

	(1)	(2)	(3)	(4)	(5)	(6)
$(G \cdot RV)$	0.3043***	0.2401***	0.2432***	0.2948***	0.2292***	0.2353***
	(0.0325)	(0.0291)	(0.0296)	(0.0325)	(0.0295)	(0.0294)
$(G \cdot RV) \times N^{Analysts}$	0.0044**	0.0056***	0.0044**			
	(0.0014)	(0.0014)	(0.0015)			
$N^{Analysts}$	−0.0005	0.0291***	0.0184**			
	(0.0060)	(0.0056)	(0.0061)			
$(G \cdot RV) \times$ *Ave.* $N^{Analysts}$				0.0065***	0.0064***	0.0052***
				(0.0013)	(0.0011)	(0.0012)
Ave. $N^{Analysts}$				0.0068	0.0390***	0.0282***
				(0.0055)	(0.0045)	(0.0050)
Control Variables						
MV and Trading Value		*Yes*	*Yes*		*Yes*	*Yes*
Industry Dummy			*Yes*			*Yes*
$\bar{R}^2$	0.18	0.33	0.30	0.17	0.34	0.30
N	104,577	94,106	76,564	104,577	94,106	76,564

$*\ p < 0.05$; $**\ p < 0.01$; $***\ p < 0.001$

Table 1.11: **Stock Return Volatility and Analyst Coverage II**

Partial effects are estimated for the following model:

$$\begin{aligned} RV_{i,t} = &\beta_0 + \beta_1 (G \cdot RV)_{i,t-1} \\ &+ \beta_2 (G \cdot RV)_{i,t-1} \times N^{Analysts}_{i,t-1} + \beta_3 N^{Analysts}_{i,t-1} \\ &+ ControlVariables_{i,t-1}\Gamma + \epsilon_{i,t}, \end{aligned}$$

where realized return volatility (RV) is the sample standard deviation of daily returns over one month, and customer volatility ($G \cdot RV$) is constructed using sales-weighted G (a customer-supplier linkage is considered active for up to one year prior to the reporting date). $N^{Analysts}$ is the number of analysts who issue recommendations (buy, hold, or sell) for a firm in a month (from the I/B/E/S database). We also use $Ave.\ N^{Analysts}$ as an alternative measure of analyst coverage, which is the monthly average number of analysts who issue recommendations for a firm over the sample period. Heterogeneous autoregressive terms include RV^m, RV^q, RV^{hy}, and RV^y. Market factors include $RV_{S\&P}$, yield curve slope and Baa-Aaa spread. Firm characteristics include MV, leverage, EPS/P, D/P and trading value. $indRV$ is the industry volatility under the 30-industry classification scheme. Variables other than the yield curve slope, Baa-Aaa spread, EPS/P, D/P, $N^{Analysts}$ and $Ave.\ N^{Analysts}$ are log-transformed. The sample covers the period from December 1993 to October 2015. Columns (1) to (4) are estimated by pooled OLS with the Driscoll-Kraay standard error that is robust to heteroskedasticity and cross-sectional and temporal dependence; columns (5) and (6) are estimated by the Hausman-Taylor approach which controls for the potential correlation between the individual fixed effect and the autoregressive term. The numbers in parentheses are standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)
$(G \cdot RV)$	0.1308***	0.0225***	0.1206***	0.0200**	0.0349**	0.0299***
	(0.0164)	(0.0063)	(0.0165)	(0.0063)	(0.0049)	(0.0052)
$(G \cdot RV) \times N^{Analysts}$	0.0040**	0.0007			0.0011*	
	(0.0014)	(0.0007)			(0.0004)	
$N^{Analysts}$	0.0221***	0.0044			0.0030	
	(0.0055)	(0.0027)			(0.0019)	
$(G \cdot RV) \times Ave.\ N^{Analysts}$			0.0050***	0.0010		0.0018***
			(0.0012)	(0.0006)		(0.0005)
$Ave.\ N^{Analysts}$			0.0319***	0.0067**		0.0095***
			(0.0047)	(0.0025)		(0.0024)
Control Variables						
Hetero. AR		*Yes*		*Yes*	*Yes*	*Yes*
Market Factors	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Firm Charact.	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Industry Vol.	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
$\bar{R}^2$	0.37	0.54	0.38	0.54		
N	93,058	70,509	93,058	70,509	70,509	70,509

$*\ p < 0.05$; $**\ p < 0.01$; $***\ p < 0.001$

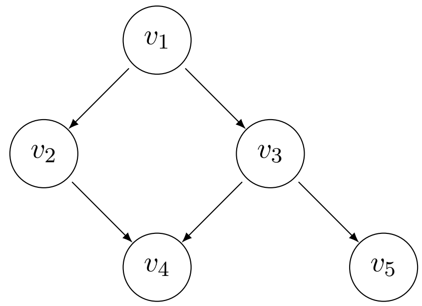


Figure 1.1: **A simple example of a customer-supplier network.**
In this figure, v_i, $i = 1, ..., 5$, denotes the firm; the arrow indicates the flow of output. For example, the arrow between v_1 and v_2 indicates that firm 1 (2) is the supplier (customer) of firm 2 (1).

Chapter 2

Resilience to the Financial Crisis in Customer-Supplier Networks

2.1 Introduction

As summarized by Allen and Babus (2008), networks which are generally understood as collections of nodes, and links between nodes can be useful representations of economic or financial systems. The nodes represent the entities in the system; the links describe direct or indirect relationships between the entities. Allen and Babus (2008) emphasize that network theories can provide conceptual frameworks within which the various patterns of connections and interdependencies can be described and analyzed in a meaningful way. In particular, by modeling the economic interactions, network analysis can better explain certain economic phenomena.

In a customer-supplier network, each company is represented by a node, and a customer-supplier relationship between two companies is described by a link connecting them. Acemoglu et al. (2012) offer a typical example that utilizes customer-supplier networks to explain the systemic risk that originate from the intersectoral input-output linkages. Specifically, the authors argue that sizable aggregate fluctuations may originate from microeconomic idiosyncratic shocks only if there are significant asymmetries in the roles that sectors play as suppliers to others. They also note that first-order interconnections provide only partial information on customer-supplier relations. A shock in one sector may lead to reduced production not only for its immediate downstream sectors but also for a sequence of sectors interconnected to one another, creating a cascade effect that leads to systemic risk.

In another examination of the linkages along the supply chain, Hertzel et al. (2008) investigate the wealth effects of distress and bankruptcy filing for the suppliers and customers of filing firms. Most interestingly, they find the contagion effects on the suppliers and customers of the filing firms to be asymmetric. Significant contagion effects extend beyond industry competitors along the supply chain to suppliers of the filing firms, but the customers of filing firms generally do not experience contagion effects. One explanation for the asymmetry offered by the authors is that financial distress largely reflects a shift in demand away from the filing firm; hence contagion due to distress spreads upstream, such that suppliers are harmed by a reduction in the derived demand for their output, but customers are not affected by the distress to an equal extent because they are the source of the distress.

Using data on the North American customer-supplier network of public companies, we explore how the properties of a company's downstream (i.e., customer) and upstream (i.e., supplier) linkages in the pre-crisis period are related to its resilience during the financial crisis of 2008-2009 in terms of stock returns. Specifically, inspired by the Sharpe (1964) - Lintner (1965) Capital Asset Pricing Model (CAPM) beta, two measures or "indices" are being constructed: customer and supplier betas. With the adjacency matrix, which captures the structure of the network, acting as a "filter" to extract each company's return covariances with its trading partners, the cross-sectional dependence contained in the customer-supplier network is summarized by our betas.

We would like to emphasize the major difference between our betas and the CAPM beta. The CAPM beta indicates an asset's return covariance with the entire market, regardless of whether there are direct connections between this asset and other assets in the market, whereas our betas are supported by real customer-supplier relations – they summarize each company's return covariances with its trading partners only. We show that under certain assumptions, the CAPM beta can be decomposed into several components, including the customer and supplier betas, which helps us to identify the different sources of the return covariance between a company and the market portfolio.

The contribution of our work is threefold. First, customer and supplier relations could have different characteristics and thus lead to different implications and consequences. For example, as documented in Hertzel et al. (2008), which we mentioned above, the contagion effects on the suppliers and customers of the filing firms are asymmetric. Hence, decomposing them into two different measures helps us to separately analyze their characteristics and implications. We indeed observe asymmetric effects from the customer and supplier sides, which suggests that downstream linkages are more influential than upstream ones. One explanation is that it becomes difficult to retain customers during a financial crisis, hence having "robust" downstream linkages in the pre-crisis period is crucial for a company to survive the crisis. However, it is relatively easy to retain or to find new suppliers, because "willingness to buy" is always welcomed. Hence upstream linkages in the pre-crisis period is not that crucial. Our results provide firms with useful guidelines for managing relationships with trading partners. That is, more attention should be devoted to downstream customers.

Second, as the regression results indicate that the customer beta could capture a company's resilience during the financial crisis of 2008-2009 measured by stock returns, it is useful for an investor or portfolio manager to construct it when conducting risk or stress analysis to gain insights into the relative negative impact of a potential crisis on a stock's performance. This is an innovative approach to conducting stress analysis in the sense that it utilizes information contained in the customer-supplier network. Moreover, the application of the customer beta can be incorporated into existing approaches to portfolio selection as an additional dimension or perspective.

Third, by using powers of adjacency matrices, effects of higher-order linkages, as emphasized in Acemoglu et al. (2012), can be captured and studied. Our results indicate that a company's weighted sum of return covariances with its higher-order trading partners is not important in explaining the company's resilience during the financial crisis of 2008-2009, which suggests that greater attention should be devoted to immediate customers than to other higher-order trading partners.

It should be noted that the applications of the customer and supplier betas are not limited to studying resilience during a financial crisis. As measures or "indices" summarizing the cross-sectional dependence contained in customer-supplier network, they can potentially be explored and applied in other areas, such as portfolio allocation and risk management.

The remainder of the paper is organized as follows. Section 2.2 introduces the methodology, that is, how the customer and supplier betas are defined and constructed. Section 2.3 presents the main cross-sectional regression we use to investigate a company's resilience during the financial crisis. Section 2.4 describes the data sources and summary statistics. Section 2.5 reports the regression results. Section 2.6 considers some robustness checks. Some potential applications of the customer beta are discussed in Section 2.7. Section 2.8 concludes.

2.2 Methodology

The customer and supplier betas we propose are inspired by the CAPM beta. In this section, we introduce how the betas are defined and their relationship with the CAPM beta. We begin by recalling the structure of the CAPM beta.

2.2.1 The CAPM Beta

The CAPM beta of an asset (or portfolio) captures the linear association of this asset's return with the return of the market portfolio, which is understood as this asset's sensitivity to the market portfolio. Specifically, the CAPM beta of an asset i is

$$\beta_i = \frac{cov(r_i, r_m)}{\sigma_m^2} \tag{2.1}$$

where $cov(r_i, r_m)$ is the covariance of the return on asset i with the return on the market portfolio, and σ_m^2 is the variance of the return on the market portfolio.

Suppose that there are n assets in the market, an $n \times 1$ vector $\boldsymbol{\beta}$, where β_i, $i = 1, ..., n$, is the ith element of $\boldsymbol{\beta}$, can be expressed as

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} = \frac{\Sigma_m X_m}{\sigma_m^2} \tag{2.2}$$

where Σ_m is the $n \times n$ return variance-covariance matrix; X_m is the $n \times 1$ vector containing the market portfolio weights, that is, the relative weight of market capitalization for each asset, and the sum of the entries in X_m is one.[17] The derivation of Equation 2.2 is provided in Appendix 2.9.1.

2.2.2 Customer-Supplier Networks and Adjacency Matrices

In a survey paper, Allen and Babus (2008) report that networks, which are generally understood as collections of nodes and links between nodes, can be useful representations of economic or financial systems. Nodes represent entities in the system; links describe certain direct or indirect relationships between the entities.[18]

In the customer-supplier network that we investigate in this paper, each company i is represented by a node i. A customer-supplier relationship between companies i and j is described by the link between them, where the supplier is the source and the customer is the target. The structure of the network can be characterized by an adjacency matrix, G, which is a square matrix with dimension of the number of nodes (i.e., companies) in the network. The entry in the ith row and jth column of G, $(G)_{ij}$, is one if and only if i (j) is the supplier (customer) of j (i) and zero otherwise. Accordingly, in matrix G^T, which is the transpose of G, $(G^T)_{ij}$ is one if and only if i (j) is the customer (supplier) of j (i) and zero otherwise.

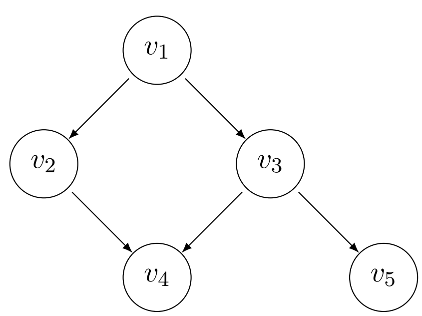


Figure 2.1: **A simple example of a customer-supplier network.**
In this figure, v_i, $i = 1, ..., 5$ denotes the company; the arrow indicates the flow of output. For example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1).

Consider the simple network depicted in Figure 2.1; v_i, $i = 1, ..., 5$ denotes the company; the arrow indicates the flow of output. For example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1). Matrix G characterizing the structure of this network is therefore

$$G = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

The second row of G, for example, refers to company 2, which indicates that company 2 has only one customer, which is company 4, as only the fourth entry is one. More generally, the ith row of G captures company i's first-order (i.e., immediate) customer linkages. Similarly, company i's first-order supplier linkages are characterized by the ith row of G^T.[19] [20]

It is worth noting that there can be two special cases: self-loop and bilateral linkage. Suppose $G = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$ and thus $G^T = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{n1} \\ a_{12} & a_{22} & \cdots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \cdots & a_{nn} \end{bmatrix}$,

where $a_{ij} = 1$ or 0 for any i and j. The two special cases are, first, $a_{ii} = 1$ for some i if company i is a customer (or supplier) of itself, that is, node i has a self-loop; and second, $a_{ij} = a_{ji} = 1$ for some i and j, where $i \neq j$ if company i is both a supplier and a customer of company j, that is, the link between nodes i and j is bilateral.

2.2.3 Customer and Supplier Betas

Suppose that there are n companies in the network. Define the customer and supplier beta, respectively, as

$$\boldsymbol{\beta_c} = (G \circ \Sigma)\, X \tag{2.3}$$

$$\boldsymbol{\beta_s} = \left(G^T \circ \Sigma\right) X \tag{2.4}$$

where

- $\circ$ denotes the element-wise product of two matrices;
- $\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & . & . & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & . & . & \sigma_{2n} \\ . & . & . & . & . \\ . & . & . & . & . \\ \sigma_{n1} & \sigma_{n2} & . & . & \sigma_{nn} \end{bmatrix}$ is the $n \times n$ return variance-covariance matrix,

where σ_{ii} is the return variance of company i; σ_{ij}, $i \neq j$, is the return covariance between companies i and j; and,

- $X = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix}$ is the $n \times 1$ vector, where x_i is the relative weight of market capitalization of company i, and the sum of the entries in X is one.

Hence, $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ are $n \times 1$ vectors.[21] The ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$, that is, β_{ci} and β_{si}, are the weighted sum of company i's return covariances with its customers and suppliers, respectively. The weights applied are the relative market capitalizations of its customers and suppliers, respectively. Return covariance, which represents the linear association between two companies' stock returns, can be considered a measure of the cross-sectional dependence between two companies. For the network in Figure 2.1, the customer and supplier betas are

$$\boldsymbol{\beta_c} = [G \circ \Sigma]\, X = \begin{bmatrix} \sigma_{12}x_2 + \sigma_{13}x_3 \\ \sigma_{24}x_4 \\ \sigma_{34}x_4 + \sigma_{35}x_5 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \beta_{c1} \\ \beta_{c2} \\ \beta_{c3} \\ \beta_{c4} \\ \beta_{c5} \end{bmatrix}$$

$$\boldsymbol{\beta_s} = \left[G^T \circ \Sigma\right] X = \begin{bmatrix} 0 \\ \sigma_{21}x_1 \\ \sigma_{31}x_1 \\ \sigma_{42}x_2 + \sigma_{43}x_3 \\ \sigma_{53}x_3 \end{bmatrix} = \begin{bmatrix} \beta_{s1} \\ \beta_{s2} \\ \beta_{s3} \\ \beta_{s4} \\ \beta_{s5} \end{bmatrix}$$

Other things being equal, company i has higher β_{ci} (or β_{si}) if: (a) it has larger return covariances with its customers (or suppliers); (b) it has larger number of customers (or suppliers) with which it has positive return covariances; and (c) the customers (or suppliers) with which it has positive return covariances have larger market capitalizations.[22] Hence, we consider customer and supplier betas the summary of a company's cross-sectional dependence with its customers and suppliers, respectively. A higher customer (or supplier) beta represents "stronger" cross-sectional dependence with the downstream (or upstream) trading partners; which we define specifically as having more customers (or suppliers) which are larger companies and with which the company has larger positive return covariances.

2.2.4 Customer and Supplier Betas versus CAPM Beta

We would like to emphasize the major difference between our betas and the CAPM beta: the CAPM beta indicates an asset's return covariance with the entire market regardless of whether there are connections between this asset and other assets or companies in the market, whereas our betas are supported by real customer-supplier relations which are based on bilateral contracts and agreements. That is, the customer and supplier betas capture a company's return covariances with its trading partners only.

Under two assumptions, the relationship between the CAPM beta and our betas can be demonstrated by a decomposition. First, let us assume that there are n companies in the customer-supplier network and that these companies constitute the entire population of companies. In principle, the return variance-covariance matrix Σ_m and vector X_m in the CAPM beta should contain all of the assets in the market; but in practice, when the customer and supplier betas are constructed, Σ and X contain only the companies in the customer-supplier network that we identify from the data. Hence, to make the CAPM beta and our betas comparable and thus to accomplish the decomposition, we need to assume that the stocks of the n companies in the customer-supplier network are the only assets in the market. Given this assumption, $\Sigma_m = \Sigma$ and $X_m = X$. Second, we assume that there is no self-loop or bilateral linkage in the network. As we illustrate in Section 2.2 - 2.2.2, $a_{ii} = 1$ if company i has a self-loop, and $a_{ij} = a_{ji} = 1$ where $i \neq j$ if the link between companies i and j is bilateral. Hence, if there is either a self-loop or a bilateral linkage, there are entries in $(G + G^T)$ that are greater than one such that we would not be able to accomplish the decomposition.[23] Under these two assumptions, the CAPM beta can be decomposed into four components, including the customer and supplier betas:

$$
\begin{aligned}
\boldsymbol{\beta} =& \Sigma X \frac{1}{\sigma_m^2} \\
=& \left(G^* \circ \Sigma\right) X \frac{1}{\sigma_m^2} \\
=& \left[\left(G + G^T + G_u + I_n\right) \circ \Sigma\right] X \frac{1}{\sigma_m^2} \\
=& \left[\left(G \circ \Sigma\right) X + \left(G^T \circ \Sigma\right) X + \left(G_u \circ \Sigma\right) X + \left(I_n \circ \Sigma\right) X\right] \frac{1}{\sigma_m^2} \\
=& \left[\boldsymbol{\beta_c} + \boldsymbol{\beta_s} + \boldsymbol{\beta_u} + \vec{Var}\right] \frac{1}{\sigma_m^2}
\end{aligned}
$$

where

- $G^* = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{bmatrix}$ is an $n \times n$ matrix of 1;

- I_n is the identity matrix of size n;
- $G_u = G^* - G - G^T - I_n$ captures the lack of a customer-supplier relationship between companies, that is, companies that are unconnected;
- $\boldsymbol{\beta_u}$'s ith entry, β_{ui}, is the weighted sum of company i's return covariances with companies that are neither its customers nor suppliers, and the weights applied are the relative market capitalizations of these unconnected companies; and,
- $\vec{Var}$ captures each company's weighted return variance, and the weight applied to each company is the relative market capitalization of that company.

It is worth noting that, implicitly, the CAPM beta contains an "adjacency matrix" with all of the entries being one. In this sense, the CAPM beta does not utilize the specific structure of the customer-supplier network. By performing this decomposition, we observe that the return covariance between a company and the market portfolio captured by the CAPM beta originates from several sources: a company's return covariances with its customers, suppliers, and unconnected companies and its own return variance. The decomposition of the CAPM beta in the network depicted in Figure 2.1 is presented in Appendix 2.9.2. Moreover, the application of CAPM beta is generally from the perspective of investors to understand a portfolio's systematic risk. This is in contrast with a company's customer and supplier betas considered here—which summarize a company's cross-sectional dependence with its customers and suppliers, respectively—could also be applied by this company's management team to understand relationships with their trading partners.

2.3 Resilience to the Financial Crisis in Customer-Supplier Networks

2.3.1 The Main Cross-Sectional Regression

Given that, as addressed in Section 2.2 - 2.2.3, β_{ci} and β_{si} are respectively considered the summary of company i's cross-sectional dependence with its customers and suppliers, we are interested in how these two betas are related to a company's resilience during financial crisis as measured by stock returns. We would like to emphasize that we construct betas using data from the *pre-crisis* period (rather than the crisis period). There are two reasons for this approach. First, one objective of our study is to gain insights into the relative negative impact of a potential crisis on a stock's performance; only data from before the crisis are obtainable and relevant for serving this purpose. Second, the asset that the companies possess to combat the crisis is their customer-supplier relations as they existed before the crisis emerged. We study the financial crisis of 2008-2009.

The main cross-sectional regression is

$$\begin{aligned}\bar{r}_i^{cr} - \bar{r}_i^{pr} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} \\ + \delta_3\hat{b}_{mi}^{pr} + \delta_4\hat{b}_{SMBi}^{pr} + \delta_5\hat{b}_{HMLi}^{pr} + \delta_6\hat{b}_{mi}^{cr} + \delta_7\hat{b}_{SMBi}^{cr} + \delta_8\hat{b}_{HMLi}^{cr} + \epsilon_i\end{aligned} \tag{2.5}$$

where $\bar{r}_i^{cr}$ and $\bar{r}_i^{pr}$ are the time-series average of company i's monthly excess returns[24] during the crisis and pre-crisis period, respectively. They measure stock i's *average performance* during the crisis and pre-crisis period, respectively. And thus $\bar{r}_i^{cr} - \bar{r}_i^{pr}$ captures the difference in performance between these two periods for company i. On average, a company's stock return is expected to be negatively affected by the financial crisis, that is, $\bar{r}_i^{cr}$ tends to be smaller than $\bar{r}_i^{pr}$; hence a relatively larger (either more positive or less negative) $\bar{r}_i^{cr} - \bar{r}_i^{pr}$ indicates that company i is more resilient to the financial crisis as measured by stock returns.

The variables of interest are β_{ci} and β_{si}. One $\boldsymbol{\beta_c}$ and one $\boldsymbol{\beta_s}$ are constructed using data from the pre-crisis period;[25] β_{ci} and β_{si} are the ith entry from the $n \times 1$ vector $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$, respectively. The control variables are interpreted in the next subsection.

2.3.2 Fama-French Three-Factor Model – Rationale for the Control Variables

The Fama-French three-factor model (Fama and French, 1992 and Fama and French, 1996) postulate that the expected return on an asset is explained by the sensitivity of its return to three factors: (i) the excess return on the market portfolio (m); (ii) the difference between the returns on a portfolio of small stocks and a portfolio of large stocks (SMB portfolio); and (iii) the difference between the returns on a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks (HML portfolio). Specifically, asset i's three factor sensitivities, b_{mi}, b_{SMBi}, and b_{HMLi}, are the slope coefficients in the time-series regression

$$r_{it} - r_{ft} = a_i + b_{mi}(r_{mt} - r_{ft}) + b_{SMBi}r_{SMBt} + b_{HMLi}r_{HMLt} + \epsilon_{it} \tag{2.6}$$

where r_{it} is the rate of return on asset i at time t; r_{ft} is the risk-free rate of return at time t; and r_{mt}, r_{SMBt} and r_{HMLt} are the rate of return on the market, SMB and HML portfolios at time t, respectively. Fama and French demonstrate that the sensitivity of an asset's return to the three factors provides a simple but powerful characterization of the cross-section of average stock returns for the 1963-1990 period.

The rationale for using $\hat{b}_m^{pr}$, $\hat{b}_{SMB}^{pr}$, $\hat{b}_{HML}^{pr}$, $\hat{b}_m^{cr}$, $\hat{b}_{SMB}^{cr}$, and $\hat{b}_{HML}^{cr}$ as control variables is thus based on the Fama-French three-factor model. Using monthly data from the pre-crisis period, $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$ and $\hat{b}_{HMLi}^{pr}$ for each company i are estimated from the time-series regression specified in Equation 2.6. According to the Fama-French three-factor model, $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$ and $\hat{b}_{HMLi}^{pr}$ can explain part of the cross-sectional variation in average stock returns during the pre-crisis period. $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ for each company i, capturing the cross-sectional variation in average stock returns in the crisis period, are obtained similarly using data from the crisis period.

2.4 Data

We use data on the North American customer-supplier network of public companies; our full sample is from January 2003 to December 2009. As the U.S. is the major economy in North America, and according to the U.S. National Bureau of Economic Research (NBER), the 2008-2009 U.S. recession began in December 2007 and ended in June 2009, we consider the years 2008 and 2009 as an approximation of the crisis period in our study. The period 2003 to 2007 is the pre-crisis period.[26]

2.4.1 Sources

According to the U.S. Statement of Financial Accounting Standards (SFAS) No.131, public enterprises are required, once each year, to report the 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 customer segment files are the customer's name and the total amount of annual sales from this supplier to this customer.[27]

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 included in some instances and omitted in others, or the company's name can be outright misspelled. We adopt a very conservative approach – we only consider those customer-supplier relations (i.e., links) for which there is an exact match (case-insensitive) between the reported name and an entry, which can be the company name or the company's legal name, or ticker, in the Compustat datafile of names.

Public companies are required to report their major customers once every fiscal year.[28] Whenever a customer-supplier relationship is reported at least once during the period 2003 to 2007 (i.e., the pre-crisis period), we consider the link to exist throughout this period.[29] Following the rules described in Section 2.2 - 2.2.2, *one* adjacency matrix G is then constructed for the entire period that captures the identified customer-supplier relationships. Table 2.1 summarizes the sample of customers and suppliers identified in each period from 2003 to 2007 and aggregated period (2003-2007). The property of the customer and supplier network is relatively stable across selected periods, in terms of the numbers of customers and suppliers identified.

Here, we describe the sources from which we obtain the data to construct X and Σ in Equations 2.3 and 2.4. We use company's annual total market value, the Compustat item mkvalt, to construct X – the vector containing the relative weight of market capitalization of each company. In particular, for each company i, the sum of its total market value from each year in the pre-crisis period is used to calculate its relative weight of market capitalization, x_i. Companies' monthly total returns, the Compustat item TRT1M, are then used to construct the variance-covariance matrix Σ. Thus, one $\boldsymbol{\beta_c}$ and one $\boldsymbol{\beta_s}$ are constructed for the pre-crisis period.

Companies' monthly total returns (the Compustat item TRT1M) are also used to construct the dependent variable, $\bar{r}_i^{cr} - \bar{r}_i^{pr}$, in Equation 2.5. The monthly returns on risk-free assets and the Fama-French three factors are obtained from Kenneth French's Data Library. The returns are all in percentages.

2.4.2 Summary Statistics

After matching with the market value and return data in Compustat, 719 companies exist throughout the entire sample period of 2003 to 2009.[30] Among them, five companies have either a self-loop or a bilateral linkage, which are reported in Appendix 2.9.3. For a company that has a self-loop or a bilateral linkage, there is overlap in its customer and supplier, which is reflected in G and G^T – this issue is addressed in detail in Appendix 2.9.4. To avoid this overlap, in other words, to preserve the distinction between a company's customer and supplier betas, we exclude these five companies. Our final sample consists of 714 companies. For each company, 60 monthly return observations (from 2003 to 2007) are used to calculate the pre-crisis period average return, $\bar{r}_i^{pr}$, and 24 monthly return observations (from 2008 to 2009) are used to calculate the crisis period average return, $\bar{r}_i^{cr}$. Then, those monthly return observations are used to estimate the CAPM beta and Fama-French three-factor betas in pre-crisis and crisis periods. Because customer beta and supplier beta are constructed based on the information in pre-crisis period, only the 60 monthly return observations (from 2003 to 2007) for each company are used to calculate the return variance-covariance matrix, Σ, in deriving $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ as in Equations 2.3 and 2.4. Table 2.2 contains the summary statistics for our sample.

The sample mean of $\bar{r}^{cr} - \bar{r}^{pr}$ is negative (-1.452%), and it can be shown that the population mean of $\bar{r}^{cr} - \bar{r}^{pr}$ is statistically significantly smaller than zero[31], which confirms our expectation that, on average, a company's stock return is negatively affected by the financial crisis. As presented in Figure 2.2, the histogram of $\bar{r}^{cr}$ moves to the left relative to that of $\bar{r}^{pr}$, which is also consistent with our expectation. Therefore, a relatively larger $\bar{r}_i^{cr} - \bar{r}_i^{pr}$ (either more positive or less negative) indicates that company i is more resilient to the crisis as measured by stock returns.

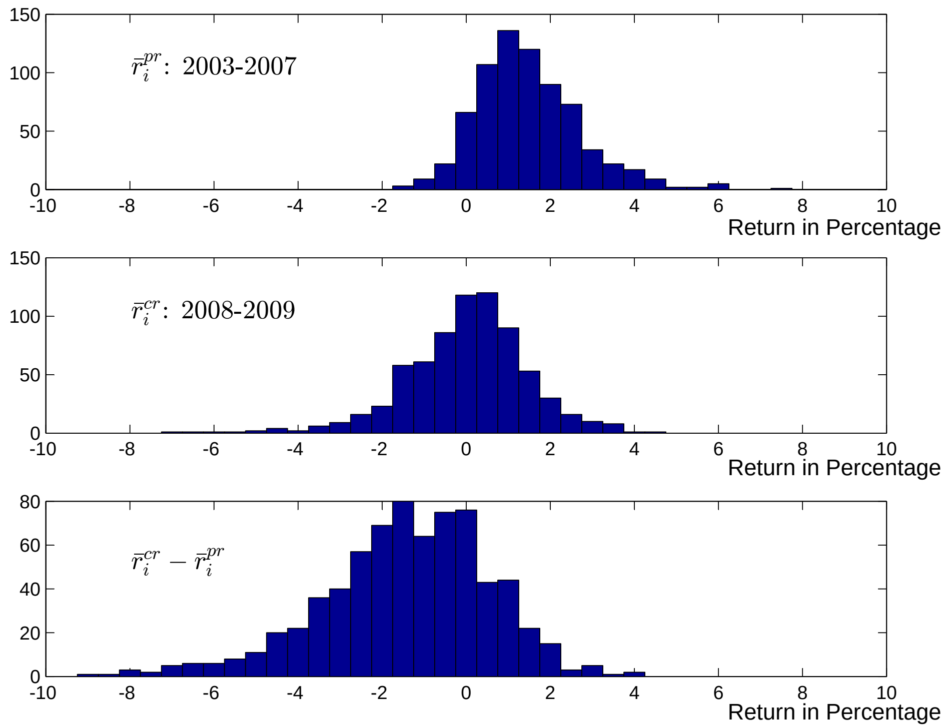


Figure 2.2: **Histogram of average monthly excess returns.**
In this figure, $\bar{r}_i^{pr}$ and $\bar{r}_i^{cr}$ are the time-series average of monthly excess returns for company i in the pre-crisis (2003-2007) and crisis period (2008-2009), respectively; $\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the regressand in the main cross-sectional regression specified in Equation 2.5. The returns are in percentages. The upper, middle and lower figures depict the histogram of $\bar{r}_i^{pr}$, $\bar{r}_i^{cr}$ and $\bar{r}_i^{cr} - \bar{r}_i^{pr}$, respectively. The sample size is 714 companies.

2.5 Estimation Results

As described in the introduction, Hertzel et al. (2008) find the contagion effects on suppliers and customers of filing firms to be asymmetric – significant contagion effects extend along the supply chain to suppliers of the filing firms but not to the customers. One explanation offered by the authors is that financial distress largely reflects a shift in demand away from the filing firm; hence contagion due to distress spreads upstream such that suppliers are harmed by a reduction in the derived demand for their output. However, customers are not affected by the distress to an equal extent because they are the source of the distress. That is, from a company's perspective, a negative shock affecting its downstream customers would lead to more adverse consequences for this company than a negative shock affecting its upstream suppliers.

Estimation results for the model specified in Equation 2.5 are reported in Table 2.3. We also obtain asymmetric effects between the customer and supplier sides, which is similar to the asymmetry found in Hertzel et al. (2008) – as presented in Table 2.3, the coefficient on β_c is positive and statistically significant, but the coefficient on β_s is not significant.[32] [33]

This result is generally robust to different choices of pre-crisis period, which are consecutive subsets of the years 2003 to 2007.

We offer two potential explanations for this asymmetry. One possibility is that, as also noted by Hertzel et al. (2008), Cohen and Frazzini (2008b) and Gençay et al. (2015), current U.S. financial accounting regulation requires public firms to report the customers that account for at least 10% of their total yearly sales (but not their suppliers); thus, our data source provides more information about firms' major customers (but not major suppliers).

Another possibility is that downstream (i.e., customer) linkages are essentially more important than upstream (i.e., supplier) ones. As addressed in Section 2.2 - 2.2.3, customer and supplier betas are considered a measure of a company's cross-sectional dependence with its customers and suppliers, respectively. "Stronger" cross-sectional dependence, measured by our betas, is specifically characterized by having more customers (or suppliers) which are larger companies and with which the company has larger positive return covariances. During a financial crisis, when most companies tend to perform poorly financially, it becomes difficult to retain customers established before the crisis. Hence having "robust" downstream linkages in the pre-crisis period – having more customers which are larger companies as captured by a higher β_c – is important for a company to survive the crisis, which explains the positive sign and the statistical significance of the coefficient on β_c. However, it is relatively easy to retain one's suppliers or to find new ones , because "willingness to buy" is always welcomed, especially when it is difficult to find someone to sell to during a crisis. Hence supplier linkages in the pre-crisis period are not crucial for a company to survive the crisis, which explains the statistical insignificance of the coefficient on β_s.

2.6 Robustness

2.6.1 Median Returns

To address the concern that extreme cases or events may be washed out in mean-type analysis, we use also the median rather than average returns to strengthen our results. Specifically, we estimate the following cross-sectional regression

$$\begin{aligned} r^{cr}_{median,i} - r^{pr}_{median,i} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} \\ + \delta_3\hat{b}^{pr}_{mi} + \delta_4\hat{b}^{pr}_{SMBi} + \delta_5\hat{b}^{pr}_{HMLi} + \delta_6\hat{b}^{cr}_{mi} + \delta_7\hat{b}^{cr}_{SMBi} + \delta_8\hat{b}^{cr}_{HMLi} + \epsilon_i \end{aligned} \tag{2.7}$$

where $r^{cr}_{median,i}$ and $r^{pr}_{median,i}$ are the time-series median of monthly excess returns for company i in the crisis and pre-crisis period, respectively; and $r^{cr}_{median,i} - r^{pr}_{median,i}$ is hence the difference between these two medians for company i. The returns are in percentages. All other variables are the same as described in Equation 2.5.

The estimation results are reported in Table 2.4. The estimated coefficients on the variables of interest are similar to what we obtained in Table 2.3. In particular, the coefficient on β_c is positive and statistically significant but the coefficient on β_s is not statistically significant.

2.6.2 Network Formation Period

To address the concern that the result in the main table may be sensitive to the approach that customer-supplier network is obtained by aggregating data between 2003 and 2007 (pre-crisis period), we examine the main regression using an alternative customer-supplier network that is obtained by aggregating data in 2007 only. The estimation results are reported in Table 2.5. The estimated coefficients on the variables of interest are similar to the main results as in Table 2.3. In particular, the coefficient on β_c is positive and statistically significant but the coefficient on β_s is not statistically significant.

2.6.3 Sales-Weighted Adjacency Matrix

The adjacency matrix G we have referred to thus far is unweighted, in the sense that it has entries of either one or zero. In some applications, it is useful to introduce the concept of the *strength* of a link – such a consideration assigns weights to customers or suppliers to capture their relative importance in our context. To serve this purpose, we further utilize the sales-weighted G and G^T to construct customer and supplier beta, respectively. First, we construct an unweighted G. Next, for each supplier (i.e., each row) in G, links (i.e., entries that have a value of one) are weighted by the amount of sales made to the target customer during the pre-crisis period, normalized by the observed total amount of sales (i.e., the sum of all sales to customers) of this supplier in this period. The sum of the entries in each row of the sales-weighted G is equal to one. Using this weighting, from a supplier's perspective, greater importance is assigned to those customers that account for larger shares of trades.[34] This weighted G is then used to construct customer beta. The sales-weighted G^T is constructed similarly and then used to construct supplier beta.[35]

Recall the example of the simple network depicted in Figure 2.1; using weighted G and G^T, the customer and supplier betas for this network now become

$$\boldsymbol{\beta_c} = [G \circ \Sigma]\, X = \begin{bmatrix} \sigma_{12}(\frac{S_{12}}{TS_1})x_2 + \sigma_{13}(\frac{S_{13}}{TS_1})x_3 \\ \sigma_{24}(\frac{S_{24}}{TS_2})x_4 \\ \sigma_{34}(\frac{S_{34}}{TS_3})x_4 + \sigma_{35}(\frac{S_{35}}{TS_3})x_5 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \beta_{c1} \\ \beta_{c2} \\ \beta_{c3} \\ \beta_{c4} \\ \beta_{c5} \end{bmatrix}$$

$$\boldsymbol{\beta_s} = \left[G^T \circ \Sigma\right] X = \begin{bmatrix} 0 \\ \sigma_{21}(\frac{S_{12}}{TS_2})x_1 \\ \sigma_{31}(\frac{S_{13}}{TS_3})x_1 \\ \sigma_{42}(\frac{S_{24}}{TS_4})x_2 + \sigma_{43}(\frac{S_{34}}{TS_4})x_3 \\ \sigma_{53}(\frac{S_{35}}{TS_5})x_3 \end{bmatrix} = \begin{bmatrix} \beta_{s1} \\ \beta_{s2} \\ \beta_{s3} \\ \beta_{s4} \\ \beta_{s5} \end{bmatrix}$$

where S_{ij} is the total sales that company i made to company j in the pre-crisis period, and TS_i is the observed total amount of sales that is either made by or made to company i in the same period.[36] Under this construction, in addition to relative market capitalization, in customer (supplier) beta, a company's return covariances with its customers (suppliers) are also weighted by the relative importance of the customers (suppliers) in terms of sales.

Using these $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$, we estimate Equation 2.5. As reported in Table 2.6, the estimation results are similar to those presented in Table 2.3 in terms of sign, magnitude and level of statistical significance of the coefficients on the variables of interest.

2.6.4 Size of Customer Market

To address the concern that results may be simply driven by the size or the number of customers, we explicitly include the size of customer market for each company, $CustomerMktSize_i$, into the main regression as one of the control variables. The size of customer market for company i is calculated as the total market share of company i's customers relative to the whole market, based on the observations in pre-cisis period, which is the same period used in constructing customer and supplier betas. The estimation results are reported in Table 2.7. The estimated coefficients on β_c and β_s are similar to the main result as in Table 2.3: the coefficient on β_c is positive and statistically significant with a similar level, while the coefficient on β_s is not statistically significant. It is worth mentioning that the coefficient on the size of customer market is not statistically significant, with a p value equal to 0.8189. The result suggests that the resilience characteristic is not simply driven by the size or the number of customers, and the aggregated cross-sectional dependence, measured by customer beta, has a robust association with the resilience measure.

2.6.5 Effects from Higher-Order Linkages

As described in Section 2.2 - 2.2.2, G (G^T) captures first-order customer (supplier) linkages. Higher-order linkages are characterized by powers of G (G^T). Consider the network depicted in Figure 2.1 again; the square of G,

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

indicates that company 1 has two second-order customers, which are companies 4 and 5, because its first row has two non-zero entries, which are the fourth and the fifth. The fourth entry contains the value "2" because there are *two* walks of length 2 from node 1 to 4: from v_1 to v_2 to v_4 and from v_1 to v_3 to v_4. Similarly, the fifth entry takes the value "1" because there is only *one* walk of length 2 from node 1 to 5: from v_1 to v_3 to v_5. More formally, the entry in the ith row and jth column of G^k, where k is some positive integer, is equal to the number of walks from node i to node j of length k, where a walk from node i to node j of length k is a succession of k links beginning at i and ending at j.[37] Hence, the ith row of G^k captures the kth-order customer linkages of company i, and the value of the entry indicates the number of walks of length k from company i to the corresponding customer. A similar interpretation applies to the transpose of G, that is, company i's kth-order supplier linkages are characterized by the ith row of $(G^T)^k$.

To investigate the effects of higher-order linkages, we construct $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that correspond to each order of linkages:

$$\boldsymbol{\beta_{ck}} = \left(G^k \circ \Sigma\right) X \tag{2.8}$$

$$\boldsymbol{\beta_{sk}} = \left((G^T)^k \circ \Sigma\right) X \tag{2.9}$$

where $k = 1,\ 2, ..., K$. When $k = 1$, $\boldsymbol{\beta_{c1}} = (G \circ \Sigma) X$ and $\boldsymbol{\beta_{s1}} = \left(G^T \circ \Sigma\right) X$ are equivalent to $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that are defined in Equations 2.3 and 2.4. When $k = 2, 3, ...,$ $\boldsymbol{\beta_{ck}}$, $(\boldsymbol{\beta_{sk}})$ summarizes companies' weighted sum of the return covariances with their second-order, third-order, and so fourth, customers (suppliers). The following cross-sectional regression is conducted:

$$\begin{aligned} \bar{r}_i^{cr} - \bar{r}_i^{pr} \quad = \quad & \delta_0 + \delta_1\beta_{c1i} + \delta_2\beta_{c2i} + \delta_3\beta_{c3i} + \delta_4\beta_{s1i} + \delta_5\beta_{s2i} + \delta_6\beta_{s3i} \\ & + \delta_7\hat{b}_{mi}^{pr} + \delta_8\hat{b}_{SMBi}^{pr} + \delta_9\hat{b}_{HMLi}^{pr} \\ & + \delta_{10}\hat{b}_{mi}^{cr} + \delta_{11}\hat{b}_{SMBi}^{cr} + \delta_{12}\hat{b}_{HMLi}^{cr} + \epsilon_i \end{aligned} \tag{2.10}$$

where β_{cki} and β_{ski}, $k = 1,\ 2$ and 3, are the variables of interest. The largest value of k taken is 3.[38] For the pre-crisis period, $\boldsymbol{\beta_{ck}}$ and $\boldsymbol{\beta_{sk}}$ are constructed; β_{cki} and β_{ski} are the ith entry from the $n \times 1$ vectors $\boldsymbol{\beta_{ck}}$ and $\boldsymbol{\beta_{sk}}$, respectively. The dependent and control variables are as defined in Equation 2.5.

The regression results are presented in Table 2.8. For different choices of a pre-crisis period that are consecutive subsets of 2003-2007[39], β_{c1}, which captures the first-order customer linkages, is the only one that is consistently positive and statistically significant. This implies that a company's weighted average return covariances with its higher-order or indirect trading partners are not important in explaining this company's resilience to the financial crisis of 2008-2009 as measured by stock returns, at least in the network we identify from the data.

2.7 Potential Applications

As customer beta can capture a company's resilience to the 2008-2009 financial crisis, as measured by stock returns, investors or portfolio managers could construct the customer beta when conducting risk or stress analysis to gain insights into the *relative* negative impact of a potential financial crisis on a stock's performance. Specifically, the customer betas of stocks of interest should be constructed and ranked from high to low by magnitude, with a higher rank indicating more resilience to a crisis as measured by stock returns. This is an innovative way of conducting stress analysis in the sense that it utilizes information contained in the customer-supplier network.

The application of customer beta can also be incorporated into existing approaches to portfolio selection as an additional dimension or perspective. For a specific example, consider the single-period mean-variance (MV) model of Markowitz (1952) with no risk-free asset; to find a portfolio on the MV-efficient frontier, solve

$$\min_{x_1, x_2, \cdots, x_N} \sum_{i=1}^{N} \sum_{j=1}^{N} x_i x_j \sigma_{ij}$$

subject to

$$\sum_{i=1}^{N} x_i \mu_i = a$$

$$\sum_{i=1}^{N} x_i = 1$$

where x_i is the percentage of wealth allocated to security i, σ_{ij} is the return covariance between security i and j (σ_{ii} is the return variance of security i), μ_i is the expected value of return on security i. That is, we minimize portfolio variance provided that the expected value of the return on the portfolio takes some value a. Then, the efficient frontier can be identified by allowing a to vary. As Markowitz (1952) suggests, we may use the time-series average of returns and sample covariance (variance) of returns for some period of the past as proxies for μ_i and σ_{ij} (σ_{ii}). Given the computed set of MV-efficient portfolios, the investor could select the preferred MV combination. The customer beta, which captures a stock's *relative* resilience to a crisis, can be incorporated into the above problem as an additional constraint; for instance, after stocks are ranked by the magnitude of customer beta, only stocks that are above a certain threshold (e.g., the 25-percent quantile) can be included in the portfolio. By enforcing such a constraint, only securities that are relatively more resilient to potential crisis are used to construct the MV-efficient frontier, whereas stocks that would potentially encounter substantial losses are excluded. This approach incorporates the dynamic feature into the static single-period model of portfolio selection.

2.8 Conclusions

Inspired by the CAPM beta, we construct two measures or "indices", customer and supplier beta, to separately investigate potentially different properties and implications of downstream and upstream linkages. With the adjacency matrix acting as a "filter" to extract each company's return covariances with its trading partners, the cross-sectional dependence contained in the customer-supplier network is summarized by our betas. Under certain assumptions, the CAPM beta can be decomposed into four components, including the customer and supplier beta, which helps to identify the different sources from which the return covariance between a company and the market portfolio originates.

Using data on the North American public companies, we find asymmetric effects on the customer and supplier sides that are similar to the asymmetry found in Hertzel et al. (2008). Our empirical study indicates that, a higher customer beta is generally associated with more resilience to the 2008-2009 financial crisis, as measured by stock returns; but the coefficient on the supplier beta lacks statistical significance. One explanation for the asymmetry is that customer linkages are essentially more important than supplier ones. During a financial crisis, it becomes difficult to retain customers as most companies perform poorly financially. Hence having "robust" downstream linkages in the pre-crisis period – having more customers which are larger companies as captured by a higher β_c – is important for a company to survive the crisis. However, it is relatively easy to retain or to find new suppliers, because "willingness to buy" is always welcomed, especially when it is difficult to find someone to sell to during a crisis. Hence supplier linkages in the pre-crisis period are not crucial for a company to survive the crisis.

As potential applications, investors or portfolio managers could construct customer beta when conducting risk or stress analysis to gain insights into the relative negative impact of a potential financial crisis on a stock's performance, which can be incorporated into existing approaches to portfolio selection as an additional dimension or perspective. As measures or "indices" summarizing the cross-sectional dependence contained in the customer-supplier network, our betas could potentially be applied in other areas, which should be explored in future studies.

2.9 Supplemental Materials

2.9.1 Derivation of Equation 2.2

Suppose that there are n assets in the market,

$$\Sigma_m X_m = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$
$$= \begin{bmatrix} \sigma_{11}x_1 + \sigma_{12}x_2 + \cdots + \sigma_{1n}x_n \\ \sigma_{21}x_1 + \sigma_{22}x_2 + \cdots + \sigma_{2n}x_n \\ \vdots \\ \sigma_{n1}x_1 + \sigma_{n2}x_2 + \cdots + \sigma_{nn}x_n \end{bmatrix} = \begin{bmatrix} \sum_j x_j\sigma_{1j} \\ \sum_j x_j\sigma_{2j} \\ \vdots \\ \sum_j x_j\sigma_{nj} \end{bmatrix}$$

For $\forall i = 1, \ldots, n$,

$$\begin{aligned} \sum_j x_j\sigma_{ij} &= \sum_j x_j cov(r_i, r_j) \\ &= \sum_j x_j \left[\sum_s p_s \left(r_{is} - E\left(r_i\right)\right) \left(r_{js} - E\left(r_j\right)\right) \right] \\ &= \sum_s p_s \left(r_{is} - E\left(r_i\right)\right) \left[\sum_j x_j \left(r_{js} - E\left(r_j\right)\right) \right] \\ &= \sum_s p_s \left(r_{is} - E\left(r_i\right)\right) \left[\sum_j x_j r_{js} - \sum_j x_j E\left(r_j\right) \right] \\ &= \sum_s p_s \left(r_{is} - E\left(r_i\right)\right) \left[r_{ms} - E\left(\sum_j x_j r_j \right) \right] \\ &= \sum_s p_s \left(r_{is} - E\left(r_i\right)\right) \left(r_{ms} - E\left(r_m\right)\right) \\ &= cov\left(r_i, r_m\right). \end{aligned}$$

Hence,

$$\frac{\Sigma_m X_m}{\sigma_m^2} = \begin{bmatrix} \frac{cov(r_1,r_m)}{\sigma_m^2} \\ \frac{cov(r_2,r_m)}{\sigma_m^2} \\ \vdots \\ \frac{cov(r_n,r_m)}{\sigma_m^2} \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} = \boldsymbol{\beta}.$$

2.9.2 The Decomposition of CAPM Beta in the Network Depicted in Figure 2.1

Given the simple customer-supplier network presented in Figure 2.1, assuming that there are only these five companies, such that their stocks are the only assets in the market, and as this simple network does not have any self-loop or bilateral linkage, the CAPM beta can be decomposed into four components, including the customer and supplier beta:

$$
\begin{aligned}
\boldsymbol{\beta} =& \Sigma X \frac{1}{\sigma_m^2} \\
=& \left(\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \circ \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} & \sigma_{35} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} & \sigma_{45} \\ \sigma_{51} & \sigma_{52} & \sigma_{53} & \sigma_{54} & \sigma_{55} \end{bmatrix} \right) \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \frac{1}{\sigma_m^2} \\
=& \left\{ \left(\begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 1 & 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \right) \right. \\
& \left. \circ \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} & \sigma_{14} & \sigma_{15} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} & \sigma_{24} & \sigma_{25} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} & \sigma_{35} \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_{44} & \sigma_{45} \\ \sigma_{51} & \sigma_{52} & \sigma_{53} & \sigma_{54} & \sigma_{55} \end{bmatrix} \right\} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} \frac{1}{\sigma_m^2} \\
=& \left(\begin{bmatrix} \sigma_{12}x_2 + \sigma_{13}x_3 \\ \sigma_{24}x_4 \\ \sigma_{34}x_4 + \sigma_{35}x_5 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \sigma_{21}x_1 \\ \sigma_{31}x_1 \\ \sigma_{42}x_2 + \sigma_{43}x_3 \\ \sigma_{53}x_3 \end{bmatrix} + \begin{bmatrix} \sigma_{14}x_4 + \sigma_{15}x_5 \\ \sigma_{23}x_3 + \sigma_{25}x_5 \\ \sigma_{32}x_2 \\ \sigma_{41}x_1 + \sigma_{45}x_5 \\ \sigma_{51}x_1 + \sigma_{52}x_2 + \sigma_{54}x_4 \end{bmatrix} + \begin{bmatrix} \sigma_{11}x_1 \\ \sigma_{22}x_2 \\ \sigma_{33}x_3 \\ \sigma_{44}x_4 \\ \sigma_{55}x_5 \end{bmatrix} \right) \frac{1}{\sigma_m^2} \\
=& \left[\boldsymbol{\beta_c} + \boldsymbol{\beta_s} + \boldsymbol{\beta_u} + \vec{Var} \right] \frac{1}{\sigma_m^2}
\end{aligned}
$$

2.9.3 Self-Loop and Bilateral Linkage

After matching the firms in the customer-supplier network with market value and return data in Compustat, 719 companies exist throughout the entire sample period of 2003 to 2009. Among them, five companies that have either a self-loop or a bilateral linkage are excluded from the final sample to preserve the distinction between customer and supplier beta. Information regarding these five companies is provided in Table 2.9. Zale Corporation has a self-loop, that is, it is a major customer of itself. There is a bilateral linkage between Xilinx, Inc. and Avnet, Inc and another bilateral linkage between Pfizer, Inc and Cardinal Health, Inc.; in other words, Xilinx, Inc. and Avnet, Inc. are major customers of one another, as are Pfizer, Inc and Cardinal Health, Inc.

2.9.4 Directed Ring Structure

In a customer-supplier network that contains a directed ring structure, for a company that is involved in the directed ring, there are overlaps in its (higher-order) customers and (higher-order) suppliers. Specifically, there are three possible cases for a company in a directed ring: (1) its *first-order* customer is equivalent to its *first-order* supplier; (2) its *first-order* customer is equivalent to its *higher-order* supplier (or its *first-order* supplier is equivalent to its *higher-order* customer); (3) its *higher-order* customer is equivalent to its *higher-order* supplier.

(1) Case 1: *first-order* customer is equivalent to *first-order* supplier.

Self-loop and bilateral linkage are the simplest directed ring structure – a directed ring that only contains one or two nodes. Company i has a self-loop if it is a customer and supplier of itself. Company j and k have a link that is bilateral if company j is both a supplier and customer of company k (and thus k is also both a supplier and customer of j). From these companies' perspective, there are overlaps in their customers and suppliers.

(2) Case 2: *first-order* customer is equivalent to *higher-order* supplier (or *first-order* supplier is equivalent to *higher-order* customer).

For example, as presented in Figure 2.3, consider a simple network with three companies that is a directed ring.

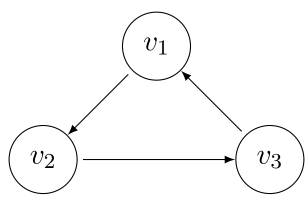


Figure 2.3: **A customer-supplier network with three companies that is a directed ring.**

In this figure, v_i, $i = 1, ..., 3$, denotes the company; the arrow indicates the flow of output, for example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1).

Matrix G, which captures first-order customer relations, is equal to $(G^T)^2$ that captures second-order supplier relations:

$$G = (G^T)^2 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \end{bmatrix}$$

That is, from any company's perspective, its first-order customer is equivalent to the second-order supplier. For instance, company 2 is both a first-order customer and a second-order supplier of company 1 (and company 3 is both a first-order supplier and a second-order customer of company 1).

(3) Case 3: *higher-order* customer is equivalent to *higher-order* supplier.

For example, as presented in Figure 2.4, consider a simple network with four companies that is a directed ring. In this network, G^2, which captures second-order customer relations,

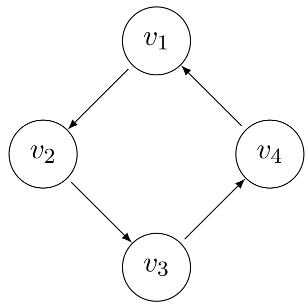


Figure 2.4: **A customer-supplier network with four companies that is a directed ring.**

In this figure, v_i, $i = 1, ..., 4$, denotes the company; the arrow indicates the flow of output, for example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1).

is equal to $(G^T)^2$, which captures second-order supplier relations:

$$G^2 = (G^T)^2 = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

That is, from any company's perspective, its second-order customer is equivalent to the second-order supplier. For instance, company 3 is both a second-order customer and a second-order supplier of company 1.

We wish to emphasize that there would be overlaps between customers and suppliers only for a company that is in a directed ring structure. In the network we constructed from the data, there is only one self-loop and two bilateral linkages, which have been reported in Appendix 2.9.3. We have excluded these five companies to preserve the distinction between customers and suppliers from every company's perspective in our final sample.

2.10 Notes

[17]In practice, the CAPM beta can also be estimated from the time-series regression $r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + \epsilon_{it}$, where r_{it} is the rate of return on asset i at time t, r_{ft} is the risk-free rate of return at time t, and r_{mt} is the rate of return on the market portfolio at time t.

[18]The literatures that introduce and review general network theory and its applications include Newman (2018); Newman, Barabasi, and Watts (2011); Caldarelli (2007). Other literatures on utilizing networks to represent economic and financial systems include Rossi, Blake, Timmermann, Tonks, and Wermers (2018); Diebold and Yılmaz (2015); Acemoglu, García-Jimeno, and Robinson (2015). The literatures that focus on customer-supplier networks include Oberfield Ezra (2018); Gençay et al. (2015); Alldredge and Cicero (2015); Acemoglu et al. (2012); Cohen and Frazzini (2008b); Banerjee, Dasgupta, and Kim (2008); Hertzel et al. (2008).

[19]For instance, the second row of

$$G^T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

indicates that company 2 has only one supplier, which is company 1, as only the first entry is one.

[20]The terms "customer linkages" and "supplier linkages" are specific in this application. They correspond to more general terms used in directed graph literatures as "out-degrees" and "in-degrees": the "out-degree" of a node (or "vertex") is the number of links (or "arcs") leading away from that node, and the "in-degree" of a node is the number of links leading to that node.

[21]$G = G^T$ if and only if all of the linkages are bilateral. In general, customer-supplier relations are not bilateral. Thus G is not symmetric although Σ is symmetric – G and G^T extract different information from Σ. Hence $\boldsymbol{\beta_c} \neq \boldsymbol{\beta_s}$ in general.

[22]In terms of mathematical expression, given that, $\beta_{ci} = \sum_j x_j \sigma_{ij} C_{ij}$ where $C_{ij} = 1$ if j is a customer of i, 0 otherwise, we have: (a) $\frac{\partial \beta_{ci}}{\partial \sigma_{ij}} = x_j C_{ij} > 0$ for $C_{ij} = 1$; (b) $\frac{\triangle \beta_{ci}}{\triangle C_{ij}} = x_j \sigma_{ij} > 0$ for $\sigma_{ij} > 0$; and (c) $\frac{\partial \beta_{ci}}{\partial x_j} = \sigma_{ij} C_{ij} > 0$ for $C_{ij} = 1$ and $\sigma_{ij} > 0$.

[23]The key to the decomposition, as presented, is to decompose the $n \times n$ matrix of *one* into G, G^T, G_u and I_n, *all of which have entries of either one or zero.* Hence, we would not be able to accomplish the decomposition if there are entries in $(G + G^T)$ that are greater than one.

[24]Monthly excess return is the difference between monthly return and the corresponding monthly risk-free rate of return.

[25]The construction of $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ is explained in greater detail in Section 2.4 after describing the sources from which we obtain the customer-supplier relations data.

[26]The results from our main regression analysis are robust to different choices of pre-crisis period that are consecutive subsets of the years 2003 to 2007.

[27]The amount of sales is used in the robustness section 2.6 - 2.6.3.

[28]As fiscal years vary across businesses, they report in different months.

[29]Results remain similar when a single year, instead of an aggregated period from 2003 to 2007, is used to identify the links, as illustrated in the robustness section 2.6 - 2.6.2.

[30]Companies with monthly excess returns that are greater than 50% are considered outliers and excluded from the final sample.

[31]Let μ_{cr-pr} be the population mean of $\bar{r}^{cr} - \bar{r}^{pr}$.
$H_0 : \mu_{cr-pr} \geq 0$ and $H_1 : \mu_{cr-pr} < 0$
$t = \frac{mean(\bar{r}^{cr} - \bar{r}^{pr})}{std(\bar{r}^{cr} - \bar{r}^{pr})/\sqrt{n}} = \frac{-1.452}{2.054/\sqrt{714}} = -18.89$; hence we reject the null at the 0.1% significance level.

[32]It is worth mentioning that the dependent variable of interest in current analysis is the resilience measure, i.e., the change in average returns over a specific crisis period. This is different from the equations used in studying cross-sectional returns in equilibrium. Including all Fama-French factors (in both periods) is necessary as control variables, while the statistic significance of those factors are not naturally implied.

[33]In addition to regression results, we calculate the correlation coefficients between resilience measure $(\bar{r}_i^{cr} - \bar{r}_i^{pr})$ and β_c. The Pearson's and Kendall's correlation coefficients are equal to 0.1480 ($p = 0.0067$) and 0.0704 ($p = 0.0551$) respectively, suggesting that the two variables are not independent.

[34]The sales-weighted adjacency matrix is constructed as in Gençay et al. (2015).

[35]To construct sales-weighted G^T, for each customer (i.e., each row), links are weighted by the amount of sales from the corresponding supplier during the pre-crisis period, normalized by the observed total amount of sales that are made to this customer in this period. The sum of the entries in each row of the sales-weighted G^T is also equal to one. Using this weighting, from a customer's perspective, its suppliers that account for larger shares of trades receive more importance.

[36]In $\boldsymbol{\beta_c}$, TS_i is the observed total amount of sales that is made *by* company i; whereas in $\boldsymbol{\beta_s}$, TS_i is the observed total amount of sales that is made *to* company i.

[37]See Van Mieghem (2010) [page 26, Lemma 3].

[38]The customer-supplier network that we identify from the data has four layers: there are 869 first-order linkages, 196 second-order linkages, 31 third-order linkages, but only 3 fourth-order linkages. Hence we investigate effects of higher-order linkages that are up to the third order.

[39]To save space, only regression results using 2003-2007 as the pre-crisis period are presented in Table 2.8.

2.11 Tables

Table 2.1: **Sample of Customers and Suppliers Identified**

This table reports the summary statistics of customers and suppliers identified in the sample. The results in the table are the numbers of companies having various numbers of customers and suppliers, average numbers of customers and suppliers per company, and the total number of companies included in the sample when different choices of pre-crisis period are used. In the main regression, the period 2003 to 2007 is considered the pre-crisis period.

	2003	**2004**	**2005**	**2006**	**2007**	**2003-2007**
Having 1 Customer	376	465	486	462	486	310
Having 2 Customers	101	130	130	139	162	112
Having > 2 Customers	45	58	77	79	86	78
Having 1 Supplier	151	183	203	197	210	159
Having 2 Suppliers	43	57	57	59	53	45
Having > 2 Suppliers	66	77	92	90	102	84
Ave. Num. of Customers	1.43	1.43	1.52	1.55	1.57	1.74
Ave. Num. of Suppliers	2.88	2.94	2.98	3.05	3.16	3.02
Num. of Companies	958	1,089	1,159	1,156	1,188	1,059

Table 2.2: **Summary Statistics**

This table reports the summary statistics for the regressand and regressors in the main regression

$$\begin{aligned}\bar{r}_i^{cr} - \bar{r}_i^{pr} &= \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} \\ &+ \delta_3\hat{b}_{mi}^{pr} + \delta_4\hat{b}_{SMBi}^{pr} + \delta_5\hat{b}_{HMLi}^{pr} + \delta_6\hat{b}_{mi}^{cr} + \delta_7\hat{b}_{SMBi}^{cr} + \delta_8\hat{b}_{HMLi}^{cr} + \epsilon_i\end{aligned}$$

$\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. The returns are in percentages. β_{ci} and β_{si} are the ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that are specified in Equations 2.3 and 2.4, respectively, constructed using data from the pre-crisis period. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period 2003 to 2007 is considered the pre-crisis period.

	Mean	**Std. Dev.**	**Min.**	**Max.**	**N**
$\bar{r}^{cr} - \bar{r}^{pr}$	-1.452	2.054	-11.011	3.882	714
β_c	0.057	0.156	-0.235	1.351	714
β_s	0.005	0.039	-0.013	0.817	714
$\hat{b}_m^{pr}$	0.965	0.579	-0.830	3.475	714
$\hat{b}_{SMB}^{pr}$	0.562	0.789	-1.955	5.138	714
$\hat{b}_{HML}^{pr}$	0.122	0.846	-4.72	2.647	714
$\hat{b}_m^{cr}$	1.022	0.566	-0.656	3.084	714
$\hat{b}_{SMB}^{cr}$	0.506	0.98	-2.691	4.755	714
$\hat{b}_{HML}^{cr}$	-0.104	0.905	-3.264	5.016	714

Table 2.3: **Resilience to the Financial Crisis as Measured by Average Stock Returns**

Regression estimates for various restrictions of the model

$$\bar{r}_i^{cr} - \bar{r}_i^{pr} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} + \delta_3\hat{b}_{mi}^{pr} + \delta_4\hat{b}_{SMBi}^{pr} + \delta_5\hat{b}_{HMLi}^{pr} + \delta_6\hat{b}_{mi}^{cr} + \delta_7\hat{b}_{SMBi}^{cr} + \delta_8\hat{b}_{HMLi}^{cr} + \epsilon_i$$

$\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. The returns are in percentages. β_{ci} and β_{si} are the ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that are specified in Equations 2.3 and 2.4, respectively, constructed using data from the pre-crisis period. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period 2003 to 2007 is considered the pre-crisis period. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_c	1.3774∗∗∗		1.8886∗∗∗
	(0.0014)		(0.0001)
β_s	0.4867		0.4504
	(0.3408)		(0.4097)
$\hat{b}_m^{pr}$		0.2378	0.1074
		(0.1685)	(0.5389)
$\hat{b}_{SMB}^{pr}$		−0.0055	−0.0838
		(0.9597)	(0.4474)
$\hat{b}_{HML}^{pr}$		−0.1789	−0.1730
		(0.1016)	(0.1084)
$\hat{b}_m^{cr}$		−0.4978∗∗∗	−0.5588∗∗∗
		(0.0027)	(0.0007)
$\hat{b}_{SMB}^{cr}$		0.0659	0.0770
		(0.5003)	(0.4277)
$\hat{b}_{HML}^{cr}$		0.2586∗∗	0.2664∗∗∗
		(0.0103)	(0.0089)
Intercept	−1.5326∗∗∗	−1.1543∗∗∗	−1.0371∗∗∗
	(0.0000)	(0.0000)	(0.0000)
$\bar{R}^2$	0.01	0.05	0.06
n	714	714	714

∗ $p < 0.1$; ∗∗ $p < 0.05$; ∗∗∗ $p < 0.01$

Table 2.4: **Resilience to the Financial Crisis as Measured by Median Returns**

Regression estimates for various restrictions of the model

$$r^{cr}_{median,i} - r^{pr}_{median,i} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} + \delta_3\hat{b}^{pr}_{mi} + \delta_4\hat{b}^{pr}_{SMBi} + \delta_5\hat{b}^{pr}_{HMLi} + \delta_6\hat{b}^{cr}_{mi} + \delta_7\hat{b}^{cr}_{SMBi} + \delta_8\hat{b}^{cr}_{HMLi} + \epsilon_i$$

$r^{cr}_{median,i} - r^{pr}_{median,i}$ is the difference between crisis and pre-crisis period time-series median of monthly excess returns for company i. The returns are in percentages. β_{ci} and β_{si} are the ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that are specified in Equations 2.3 and 2.4, respectively, constructed using data from the pre-crisis period. $\hat{b}^{pr}_{mi}$, $\hat{b}^{pr}_{SMBi}$, $\hat{b}^{pr}_{HMLi}$, $\hat{b}^{cr}_{mi}$, $\hat{b}^{cr}_{SMBi}$ and $\hat{b}^{cr}_{HMLi}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period 2003 to 2007 is considered the pre-crisis period. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_c	1.1685*		1.6148**
	(0.0645)		(0.0237)
β_s	0.3026		0.0083
	(0.8224)		(0.9947)
$\hat{b}^{pr}_{m}$		−0.0335	−0.1451
		(0.8837)	(0.5401)
$\hat{b}^{pr}_{SMB}$		−0.0801	−0.1480
		(0.5916)	(0.3427)
$\hat{b}^{pr}_{HML}$		−0.1996	−0.1957
		(0.1481)	(0.1544)
$\hat{b}^{cr}_{m}$		−0.2887	−0.3406
		(0.2048)	(0.1324)
$\hat{b}^{cr}_{SMB}$		−0.0257	−0.0161
		(0.8328)	(0.8945)
$\hat{b}^{cr}_{HML}$		−0.0918	−0.0855
		(0.4728)	(0.5045)
Intercept	−0.9073***	−0.4394*	−0.3369
	(0.0000)	(0.0899)	(0.1956)
$\bar{R}^2$	0.00	0.00	0.01
n	714	714	714

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.5: **Resilience to the Financial Crisis with the Network Formed in Single Year - 2007**

Regression estimates for various restrictions of the model

$$\bar{r}_i^{cr} - \bar{r}_i^{pr} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} + \delta_3\hat{b}_{mi}^{pr} + \delta_4\hat{b}_{SMBi}^{pr} + \delta_5\hat{b}_{HMLi}^{pr} + \delta_6\hat{b}_{mi}^{cr} + \delta_7\hat{b}_{SMBi}^{cr} + \delta_8\hat{b}_{HMLi}^{cr} + \epsilon_i$$

$\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. The returns are in percentages. β_{ci} and β_{si} are the ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ that are specified in Equations 2.3 and 2.4, respectively, constructed using data from the pre-crisis period. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period of 2007 is considered the pre-crisis period, which is used to form the customer and supplier network. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_c	2.1214***		2.1048***
	(0.0001)		(0.0001)
β_s	0.4246		1.4849
	(0.6551)		(0.2686)
$\hat{b}_m^{pr}$		−0.2913	−0.3777**
		(0.1209)	(0.0473)
$\hat{b}_{SMB}^{pr}$		0.2237**	0.2062**
		(0.0153)	(0.0261)
$\hat{b}_{HML}^{pr}$		0.1133	0.1089
		(0.1461)	(0.1603)
$\hat{b}_m^{cr}$		−0.2273	−0.2558
		(0.4069)	(0.3446)
$\hat{b}_{SMB}^{cr}$		0.6019***	0.5731***
		(0.0000)	(0.0001)
$\hat{b}_{HML}^{cr}$		0.8261***	0.8341***
		(0.0000)	(0.0000)
Intercept	−0.2238	0.1378	0.1584
	(0.1125)	(0.6853)	(0.6408)
$\bar{R}^2$	0.01	0.08	0.10
n	698	698	698

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.6: **Customer and Supplier Beta with Sales-Weighted Adjacency Matrix**

Regression estimates for various restrictions of the model

$$\bar{r}_i^{cr} - \bar{r}_i^{pr} = \delta_0 + \delta_1 \beta_{ci} + \delta_2 \beta_{si} + \delta_3 \hat{b}_{mi}^{pr} + \delta_4 \hat{b}_{SMBi}^{pr} + \delta_5 \hat{b}_{HMLi}^{pr} + \delta_6 \hat{b}_{mi}^{cr} + \delta_7 \hat{b}_{SMBi}^{cr} + \delta_8 \hat{b}_{HMLi}^{cr} + \epsilon_i$$

$\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. The returns are in percentages. β_{ci} and β_{si} are respectively the ith entry in $\boldsymbol{\beta_c}$ and $\boldsymbol{\beta_s}$ constructed using sales-weighted G and G^T, using data from the pre-crisis period. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period 2003 to 2007 is considered the pre-crisis period. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_c	1.4814**		1.9525**
	(0.0401)		(0.0116)
β_s	0.5127		0.7625
	(0.7886)		(0.7054)
$\hat{b}_m^{pr}$		0.2378	0.1831
		(0.1685)	(0.2934)
$\hat{b}_{SMB}^{pr}$		−0.0055	−0.0390
		(0.9597)	(0.7194)
$\hat{b}_{HML}^{pr}$		−0.1789	−0.1749
		(0.1016)	(0.1059)
$\hat{b}_m^{cr}$		−0.4978***	−0.5366***
		(0.0027)	(0.0010)
$\hat{b}_{SMB}^{cr}$		0.0659	0.0681
		(0.5003)	(0.4807)
$\hat{b}_{HML}^{cr}$		0.2586**	0.2613***
		(0.0103)	(0.0099)
Intercept	−1.5007***	−1.1543***	−1.1087***
	(0.0000)	(0.0000)	(0.0000)
$\bar{R}^2$	0.00	0.05	0.05
n	714	714	714

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2.7: **Resilience to the Financial Crisis Controlling for the Size of Customer Market**

Regression estimates for various restrictions of the model

$$\bar{r}_i^{cr} - \bar{r}_i^{pr} = \delta_0 + \delta_1\beta_{ci} + \delta_2\beta_{si} + \delta_3 CustomerMktSize_i \\ + \delta_4\hat{b}_{mi}^{pr} + \delta_5\hat{b}_{SMBi}^{pr} + \delta_6\hat{b}_{HMLi}^{pr} + \delta_7\hat{b}_{mi}^{cr} + \delta_8\hat{b}_{SMBi}^{cr} + \delta_9\hat{b}_{HMLi}^{cr} + \epsilon_i$$

$CustomerMktSize_i$ is the total market share of company i's customers relative to the whole market, based on the observations in pre-crisis period. The rest variables are same as in Table 2.3: $\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. β_{ci} and β_{si} are customer beta and supplier beta, respectively. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are Fama-French three-factor sensitivities in pre-crisis and crisis periods. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_c	1.3805**		1.9814***
	(0.0110)		(0.0015)
β_s	0.4863		0.4414
	(0.3422)		(0.4199)
Customer Mkt. Size	−0.0942		−2.5748
	(0.9929)		(0.8189)
$\hat{b}_m^{pr}$		0.2378	0.1013
		(0.1685)	(0.5678)
$\hat{b}_{SMB}^{pr}$		−0.0055	−0.0854
		(0.9597)	(0.4384)
$\hat{b}_{HML}^{pr}$		−0.1789	−0.1726
		(0.1016)	(0.1097)
$\hat{b}_m^{cr}$		−0.4978***	−0.5591***
		(0.0027)	(0.0007)
$\hat{b}_{SMB}^{cr}$		0.0659	0.0796
		(0.5003)	(0.4113)
$\hat{b}_{HML}^{cr}$		0.2586**	0.2668***
		(0.0103)	(0.0087)
Intercept	−1.5324***	−1.1543***	−1.0249***
	(0.0000)	(0.0000)	(0.0000)
$\bar{R}^2$	0.01	0.05	0.06
n	714	714	714

$*\ \ p < 0.1$; $**\ \ p < 0.05$; $***\ \ p < 0.01$

Table 2.8: **Effects from Higher-Order Linkages**

Regression estimates for various restrictions of the model

$$\begin{aligned}\bar{r}_i^{cr} - \bar{r}_i^{pr} = {} & \delta_0 + \delta_1\beta_{c1i} + \delta_2\beta_{c2i} + \delta_3\beta_{c3i} + \delta_4\beta_{s1i} + \delta_5\beta_{s2i} + \delta_6\beta_{s3i} \\ & + \delta_7\hat{b}_{mi}^{pr} + \delta_8\hat{b}_{SMBi}^{pr} + \delta_9\hat{b}_{HMLi}^{pr} \\ & + \delta_{10}\hat{b}_{mi}^{cr} + \delta_{11}\hat{b}_{SMBi}^{cr} + \delta_{12}\hat{b}_{HMLi}^{cr} + \epsilon_i\end{aligned}$$

$\bar{r}_i^{cr} - \bar{r}_i^{pr}$ is the difference between crisis and pre-crisis period time-series average of monthly excess returns for company i. The returns are in percentages. β_{cki} and β_{ski} are the ith entry in $\boldsymbol{\beta_{ck}}$ and $\boldsymbol{\beta_{sk}}$ that are specified in Equation 2.8 and 2.9, respectively, constructed using data from the pre-crisis period. $\hat{b}_{mi}^{pr}$, $\hat{b}_{SMBi}^{pr}$, $\hat{b}_{HMLi}^{pr}$, $\hat{b}_{mi}^{cr}$, $\hat{b}_{SMBi}^{cr}$ and $\hat{b}_{HMLi}^{cr}$ are company i's Fama-French three-factor sensitivities estimated from the time-series regression specified in Equation 2.6, using data from the pre-crisis and crisis period, respectively. We study the financial crisis of 2008-2009. The period 2003 to 2007 is considered the pre-crisis period. The numbers in parentheses are p-values calculated using heteroscedasticity-robust standard errors.

	(1)	(2)	(3)
β_{c1}	1.4507***		1.9737***
	(0.0046)		(0.0003)
β_{c2}	−1.0802		−1.1748
	(0.4588)		(0.3810)
β_{c3}	4.2334		4.4210
	(0.1832)		(0.1428)
β_{s1}	1.2020		1.7329
	(0.5828)		(0.4542)
β_{s2}	−4.4310		−5.8331
	(0.2677)		(0.1701)
β_{s3}	9.0509		5.0402
	(0.8595)		(0.9257)

(*continued*)

Table 2.8: (*continued*)

	(1)	(2)	(3)
$\hat{b}_{m}^{pr}$		0.2378	0.1102
		(0.1685)	(0.5305)
$\hat{b}_{SMB}^{pr}$		-0.0055	-0.0751
		(0.9597)	(0.5009)
$\hat{b}_{HML}^{pr}$		-0.1789	-0.1778
		(0.1016)	(0.1020)
$\hat{b}_{m}^{cr}$		-0.4978***	-0.5762***
		(0.0027)	(0.0005)
$\hat{b}_{SMB}^{cr}$		0.0659	0.0715
		(0.5003)	(0.4636)
$\hat{b}_{HML}^{cr}$		0.2586**	0.2597**
		(0.0103)	(0.0115)
Intercept	-1.5276***	-1.1543***	-1.0191***
	(0.0000)	(0.0000)	(0.0000)
$\bar{R}^2$	0.01	0.05	0.06
n	714	714	714

$*$ $p < 0.1$; $**$ $p < 0.05$; $***$ $p < 0.01$

Table 2.9: **Companies with Self-Loop or Bilateral-Linkage**

This table provides information about the five companies that have either a self-loop or a bilateral linkage, that are excluded from the final sample. Zale Corporation has a self-loop. There is a bilateral linkage between Xilinx, Inc. and Avnet, Inc, and another bilateral linkage between Pfizer, Inc, and Cardinal Health, Inc. The market value is the end-of fiscal-year value in 2007.

Company	Core Business	Headquarter	Market Value in 2007 ($ Millions)	Loop Type
Zale Corporation	jewelry retailer	Irving, Texas, USA	1,041.40	self-loop
Xilinx, Inc.	technology company	San Jose, California, USA	5,938.31	bilateral linkage
Avnet, Inc.	technology business-to-business distributor	Phoenix, Arizona, USA	7,613.56	bilateral linkage
Pfizer, Inc.	pharmaceutical company	New York City, New York, USA	26,002.58	bilateral linkage
Cardinal Health, Inc.	health care services company	Dublin, Ohio, USA	153,677.53	bilateral linkage

Chapter 3

Economic Links and Credit Spreads

3.1 Introduction

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.[40] 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 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.[41] 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. 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 9.6 basis points on average. In comparison, the credit spreads increase by 30.4 basis points when own leverage increases by one standard deviation. 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 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,[42] 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 3.2 provides some background and reviews the literature. Section 3.3 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 3.4 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 3.5 considers five robustness checks: we discuss alternative specifications, consider the issue of bi-directionality of economic links, explore and reject the hypothesis that network effects proxy for cross-industry covariates rather than measuring counterparty risk, investigate interactions between network effects and bond or firm characteristics, and lastly examine the robustness of our principal result by including other control variables. Section 3.6 concludes.

3.2 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.[43] Other works focus on the structural properties of financial networks and one of the most salient examples is the analysis of interbank loan markets.[44] 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, Brock, Durlauf, and Ioannides (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 the normalization of the network lag operator follows either an equal weighting scheme or is suggested by the economic setting.[45]

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, Driessen, Maenhout, and Weinbaum, 2008b). Campbell and Taksler (2003) find that equity volatility accounts for as much variation in corporate spreads as do credit ratings. Cremers, Driessen, and Maenhout (2008a) 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, Lesmond, and Wei (2007) find that liquidity is priced in both levels and changes in the yield spread, while Bao, Pan, and Wang (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.[46] The practical repercussions are significant from both asset pricing and risk management perspective. For example, Das, Duffie, Kapadia, and Saita (2007) show that default correlations cannot be explained by the widely used doubly stochastic model of defaults.[47] 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, Eckner, Horel, and Saita (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. 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.

3.3 The NARMA Model

3.3.1 Networks and Adjacency Matrices

As summarized by Allen and Babus (2008), networks which are generally understood as collections of nodes and links between nodes can be useful representations of economic or financial systems. The nodes represent the entities in the system; the links describe some direct or indirect relations between the entities.

In the supplier-customer network we investigate in this paper, each company i is represented by a node i. A supplier-customer relation between companies i and j is described by the link between them. The structure of the network can be characterized by adjacency matrix, G, which is a square matrix with dimension of the number of nodes (i.e. companies) in the network. The entry in the ith row and jth column of G, $(G)_{ij}$, is one if and only if i (j) is the supplier (customer) of j (i), and zero otherwise.

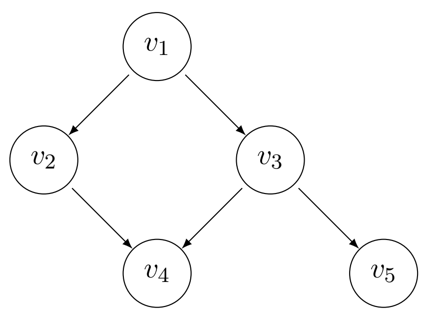


Figure 3.1: **A simple example of supplier-customer network.**
In this figure, v_i, $i = 1, ..., 5$, denotes the company; the arrow indicates the flow of output, for example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1).

Consider a simple network depicted in Figure 3.1, v_i, $i = 1, ..., 5$, denotes the company; the arrow indicates the flow of output, for example, the arrow between v_1 and v_2 indicates that company 1 (2) is the supplier (customer) of company 2 (1). The G matrix characterizing the structure of the network is therefore

$$G = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

The second row of G, for example, refers to company 2, which indicates that company 2 has only one customer that is company 4 since only the fourth entry is one. More generally, the ith row of G captures company i's first-order customer linkages.

Higher-order linkages are indicated by powers of G. Consider the network depicted in Figure 3.1 again, the square of G,

$$G^2 = \begin{bmatrix} 0 & 0 & 0 & 2 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

indicates that company 1 has two second-order customers that are company 4 and 5 because its first row has two non-zero entries which are the fourth and the fifth. The fourth entry has value "2" since there are two walks of length 2 from node 1 to 4: from v_1 to v_2 to v_4 and from v_1 to v_3 to v_4. Similarly, the fifth entry has value "1" as there is only one walk of length 2 from node 1 to 5: from v_1 to v_3 to v_5. More formally, the entry in the ith row and jth column of G^k, where k is some positive integer, is equal to the number of walks from node i to node j of length k, where a walk from node i to node j of length k is a succession of k links starting at i and ending at j.[48] Hence, the ith row of G^k captures the kth-order customer linkages of company i.

The adjacency matrix G we haven been referring to is unweighted, in the sense that it has entries of either one or zero. 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 link, its *weight*.

3.3.2 Basic Properties of NARMA Models

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

$$y = \sum_{i=1}^{p} \alpha_i G^i y + \sum_{j=0}^{q} \beta_j G^j x + \epsilon \ , \tag{3.1}$$

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, 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 be taken to be the unweighted adjacency matrix of a given network. Then the entries of Gx are the sums of neighbors' characteristics. More specifically,[49]

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

where the notation $j|i \rightarrow j$ means "(node) j such that i connects to j". In the context of supplier-customer network, the ith entry in Gx is the sum of characteristics of customers that belong to company i.

A second option is for G to be a row normalized adjacency matrix. Specifically,

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

where n_i is the number of neighbors of i, that is the number of nodes j such that i connects to j. In a supplier-customer network, $(Gx)_i$ is then the average of company i's customers characteristics.

We utilize the third option in this study - G can be a stochastic weighted adjacency matrix, that is, the sum of the elements of each row is equal to one.[50] Then

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

is the weighted average of the neighbors' (customers') characteristics of node i.

The arguments can be easily extended to higher-order effects. That is, $(G^k x)$ contains the sums, or averages, or weighted averages of the kth-order neighbors' (customers') characteristics of each company, depending on which option of G (unweighted, row normalized, or stochastic weighted) is used.

3.4 The Network Determinants of Credit Spreads

3.4.1 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:

$$CS_{i,t} = \alpha + \beta \ Firm_{i,t} + \gamma \ Customers_{i,t} + \delta_1 \ S\&P_t + \delta_2 \ YieldCurve_t + \epsilon_{i,t} \ , \qquad (3.2)$$

where,

1. $CS_{i,t}$ is the credit spread 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., 2008b).
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:

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

where $ret_{S\&P,t}$ is S&P index return at time 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 the white noise disturbance.

3.4.2 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 January 2004 to August 2013 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 period from January 2004 to August 2013. For each Friday in the sample and for each bond issue, we compute the volume weighted average yield from transaction data.[51] We obtain detailed information on corporate bond issues from Thomson Reuters DataStream and only select issues with fixed rate coupons and no embedded optionality. We obtain benchmark treasury interest rates from the Federal Reserve Board website and compute maturity matched credit spreads from a linear interpolation of the yield curve.[52] Finally, for each firm in the sample we select the most traded issue as measured by the number of trades over the number of days the issue was traded.

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

$$\frac{Book\ Value\ of\ Debt}{Market\ Value\ of\ Equity + Book\ Value\ of\ Debt}\ .$$ [53]

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.[54] We estimate future volatility as the average of the implied volatilities of near-the-money call and put options:

$$ivol = 0.5\left(\sigma_{i,\text{put}}^{\text{imp}}(-0.5) + \sigma_{i,\text{call}}^{\text{imp}}(0.5)\right)\ , \qquad (3.3)$$

where $\sigma_{i,\text{call}}^{\text{imp}}$ 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, and similar definition applies to $\sigma_{i,\text{put}}^{\text{imp}}$.

4. *Jump Measure.* To quantify the probability of negative jumps we use a formula developed by Yan (2011) 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 (2011), who provides a formal argument in support of the following estimate of the slope of the volatility smile:

$$jump = \sigma_{i,\text{put}}^{\text{imp}}(-0.5) - \sigma_{i,\text{call}}^{\text{imp}}(0.5)\ , \tag{3.4}$$

where $\sigma_{i,\text{call}}^{\text{imp}}$ and $\sigma_{i,\text{put}}^{\text{imp}}$ are defined as above.

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

3.4.3 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 - we only consider those links for which there is an exact match between the reported name (or ticker) and an entry in the Compustat datafile of names (or ticker).

Following this procedure, we identify 4,700 companies and 21,661 links, between the years 2004 and 2014. There are two aspects that dictate the network dynamics. First, when a link is identified, it is considered active for up to one year prior to the reported date. Second, as fiscal years vary between businesses, new links are established and existing links are dropped throughout the year. Overwhelmingly, links are updated in the month of December (15,728 links reported), followed by end-of-quarter-months (March, June, and September; 3,965 links reported), and the rest (1,968 links). Overall, the supplier-customer network so constructed, although dynamic, is slowly varying.

Of the 4,700 companies in the supplier-customer network, 2,767 are covered in CRSP, 1,949 are reported in the OptionMetrics dataset, and only 384 firms are active in the credit markets. For each time unit t, using the supplier-customer relations identified from the Compustat Customer Segment files, first we construct unweighted adjacency matrix G_t according to the rules described in Section

3.3. Then for each supplier (i.e. each row) in G_t, links (i.e. entries that have value of one) are weighted by the amount of sales made to the target customer, normalized by the observed total amount of sales of this supplier. That is, as described in Section 3.3, the sum of the entries in each row of G_t is equal to one. With such weighting, more importance is given to those customers that account for a larger shares of trades. Let lev_t, $ivol_t$, and $jump_t$ be the vectors of node (firm) characteristics at time t, then 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 3.1 contains the summary statistics for the final sample. The time period is January 2004 to August 2013 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. 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 254 firms, and 19,676 weekly observations. Our panel is unbalanced: the number of observations for each firm varies between 1 to 486, with a median value of 142. The median maturity of the sample is February 2022.

3.4.4 Estimation Results

The regression estimates in Table 3.2 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 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 3.2 below.[55]

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 (0.193) in the average leverage of the customers leads to a widening of the credit spread of up to 9.611 basis points ($\sim 0.193 \times 0.498 \times 100$ bp). In comparison, the credit spreads increase by 30.352 basis points ($\sim 0.226 \times 1.343 \times 100$ bp) when own leverage increases by one standard deviation (0.226).

And also, an increase in the average of the customers' option implied volatilities increases the credit spread as well: an increase of one standard deviation (0.216) in the average option implied volatilities of the customers leads to a widening of the credit spread of up to 8.942 basis points ($\sim 0.216 \times 0.414 \times 100$ bp).

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.

3.4.5 Network Determinants of Credit Spreads in Different Periods

To investigate the effects of network lags on corporate credit spreads over time, we decompose the full sample into separate periods. Specifically, as our data is on North American supplier-customer network of public companies and it spins over the 2008-2009 U.S. recession, we divide our sample into three periods: before recession (January 2004 - November 2007), recession (December 2007 - June 2009) and after recession (July 2009 - August 2013).[56] The main specification (see Equation 3.2) is estimated in each period to contrast the significance of network lags over time.

The regression results are presented in Table 3.3. Interestingly, we find that customers' characteristics are not statistically significant determinants of corporate credit spread before and during the recession; however, customers spillovers emerge afterwards, that is, after the recession, an increase in the average of the customers' leverage or option implied volatilities increases the credit spread. The estimated coefficients are comparable to what we obtained in the full sample period in terms of sign, size and level of statistical significance.

After undergoing the economic hardship during the recession, corporations that have customers with higher default risk are now perceived by the public to be more susceptible to default themselves. Moreover, after times of financial distress, investors who suffered from the economic hardship now become less tolerant towards the credit risk contained in their corporate bonds investments, and thus are more alert to the counterparty risk associated with the bond issuers, and require higher credit spreads accordingly for compensation. This explains why effect of counterparty risk becomes stronger after the recession.

3.5 Robustness

3.5.1 Higher Network Lags and Model Specification

To investigate spillovers from higher network lags, we perform the regression

$$CS_{i,t} = \alpha + \beta \ Firm_{i,t} + \gamma \ Customers_{i,t} + \delta_1 \ S\&P_t + \delta_2 \ YieldCurve_t + \epsilon_{i,t} \ , \tag{3.5}$$

where

$$Customers_{i,t} = \{ \ (G_t \cdot lev_t)_i, \ (G_t \cdot ivol_t)_i, \ (G_t \cdot jump_t)_i, \ (G_t^2 \cdot lev_t)_i, \ (G_t^2 \cdot ivol_t)_i, \ (G_t^2 \cdot jump_t)_i \ \} \ ,$$

$(G_t^2 \cdot lev_t)_i$, $(G_t^2 \cdot ivol_t)_i$ and $(G_t^2 \cdot jump_t)_i$ are weighted average of second-order customers' characteristics, and thus γ is 6-vector of parameters quantifying first-order and second-order customers spillovers.

As presented in Table 3.4, coefficients pertaining to the second-order customers' characteristics are generally insignificantly different from zero across time (while the main results are practically unchanged). This is mainly due to the fact that 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 316 at degree 2 - as the matrix entry $(G^2)_{ij}$ is equal to the number of walks from node i to node j of length 2, most of the entries in the square of our adjacency matrices are zero.

The sparseness of the higher powers of our network lag operators leads to another consequence: it is sufficient for us to focus on a model of network spillovers and ignore the autoregressive component. When the supplier-customer network does not contain many long walks, it is easy to show that a network autoregressive model is equivalent to a finite network moving average.

Under certain regularity conditions, a NARMA process admits 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 nodes in the network. Then, when the matrix $(\mathbb{I} - \alpha G)$ is invertible y admits a NMA(∞) representation,[57] indeed

$$\begin{aligned} y - \alpha G y &= \beta x + \epsilon \\ (\mathbb{I} - \alpha G) y &= \beta x + \epsilon \\ y &= (\mathbb{I} - \alpha G)^{-1}(\beta x + \epsilon) = \sum_{k=0}^{\infty} \alpha^k G^k (\beta x + \epsilon) \; . \end{aligned} \tag{3.6}$$

The general NARMA model can be represented as a NMA whenever the matrix $(\mathbb{I} - \sum \alpha_k G^k)$ is invertible.[58]

For the sake of argument, consider the extreme example of a network in which there are no walks of length greater than one. As the matrix entry $(G^k)_{ij}$ is equal to the number of walks from node i to node j of length k, entries in higher powers of adjacency matrix of such network are zero. Expanding (3.6),

$$\begin{aligned} y &= (\mathbb{I} + \alpha G + \alpha^2 G^2 + \dots)(\beta x + \epsilon) \\ &= \beta x + \alpha \beta G x + \tilde{\epsilon} \; , \end{aligned}$$

for an appropriate error process $\tilde{\epsilon}$.[59] As a result there is little difference between local averages and global effects, making the case for the need of an autoregressive component weak.

3.5.2 Bi-directionality of Supplier-Customer Relationships

The supplier-customer 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 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.[60] Earlier in the same year, the Japanese Earthquake similarly caused serious disruptions to the worldwide supply chain.[61] In this section, we estimate the influence of suppliers' characteristics on the credit worthiness of customers.

In order to account for suppliers' effects, consider again the simple network depicted in Figure 3.1 and recall that the arrow indicates the flow of output. The transpose of G capturing this network is

$$G^T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} .$$

The second row of G^T, for instance, indicates that company 2 has only one supplier which is company 1 since only the first entry is one. That is, company i's first-order supplier linkages are characterized by the ith row of G^T. The initial specification (see Equation 3.2) is augmented with the introduction of a term containing the characteristics of the firm's suppliers constructed using G^T

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

Table 3.5 reports estimates under various restrictions of the following model:

$$CS_{i,t} = \alpha + \beta\ Firm_{i,t} + \gamma^c\ Customers_{i,t} + \gamma^s\ Suppliers_{i,t} + \delta_1\ S\&P_t + \delta_2\ YieldCurve_t + \epsilon_{i,t}\ . \quad (3.7)$$

Before the recession, coefficients on suppliers' leverage and jump risk are significantly different from zero; during the recession, suppliers' implied volatilities have significant impact on firm's credit spread. It might be counterintuitive that their impacts are negative - this might be due to the nature of the supplier-customer network constructed from the Compustat Customer Segment files. As described in Section 3.4–3.4.3, according to Regulation SFAS no.131, supplier-customer relations are reported and thus identified from the data only when the customer contributes at least 10% to its supplier's total yearly sales. That is, in the network we construct, from a supplier's perspective, most of its important customers in terms of share of sales are included. However, for small company that is a customer, although some suppliers are important from the customer's own perspective, such supplier-customer relation is not reported if this small company does not contribute at least 10% to its supplier's total yearly sales. Hence the suppliers' characteristics summarized from our network are not as representative as the customers' ones, which may lead to biasness in estimated coefficients pertaining to suppliers' characteristics.

For our purposes, there are two lessons that emerge form Table 3.5. The first one is that the economic and statistical significance of customer's effects is robust to the introduction of supplier's covariates. The second is that the estimated coefficients on suppliers' characteristics become less negative in the after recession period, which is consistent with the argument we made in Section 3.4–3.4.5, that is, investors become more alert to counterparty risk after suffering economic hardship, and thus require higher credit spreads accordingly for compensation.

3.5.3 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.[62] 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 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 code. 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 and volatilities.[63] 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 $n \times 2$ 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.

Estimation results using 12-industry classification are presented in Table 3.6. Our principal results remain unchanged when adding the industry and cross-industry conditions: the estimates of the network effects are the same for all practical purposes. These results are robust when using other industry classification schemes (17, 30, 38 and 48 industries) as well.[64]

3.5.4 Interactions between Network Effects and Bond or Firm Characteristics

To investigate the interactions between customers spillovers and key bond features or firm characteristics, we divide our sample into groups according to bond grade (investment grade and high yield), bond days to maturity by quartile, and firm size (total asset) by quartile, respectively, and estimate the main specification (see Equation 3.2) in each group. As presented in Table 3.7, customers' implied volatility is significantly and positively correlated to firm's credit spread for investment grade bonds; whereas, for high yield bonds, network lags do not have significant impact on firm's credit spread. This could be due to the fact that high yield bonds are already perceived by the investors to have much higher default risk than investment grade bonds, which makes the marginal effect from counterparty risk on credit spread immaterial for them. No clear pattern is observed for interactions between customers spillovers and bond days to maturity or firm size.

3.5.5 Customers Spillovers with Other Control Variables

In order to further examine the robustness of our principal result, besides the firm-level credit risk determinants and macroeconomic conditions that we have controlled for, in this section we also include several important empirically-motivated credit risk determinants into our main specification (see Equation 3.2): total assets, market to book ratio, return on asset ratio at the firm-level; Baa-Aaa spread (as a measure of market credit price) and swap-Treasury spread (as a measure of fixed income market liquidity) at the macro-level; and the bond feature days to maturity. As reported in Table 3.8, the statistical significance of customer's effects is robust to the introduction of various controls.

3.6 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 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.

3.7 Notes

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

[41]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.

[42]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.

[43]Hong, Kubik, and Stein (2004) document that socially engaged households are more likely to participate in the stock market, and Cohen, Frazzini, and Malloy (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 (2008a) suggest that investors fail to promptly take into account supplier-customer links and construct a customer momentum strategy that yield abnormal returns.

[44]Boss, Elsinger, Summer, and Thurner (2004) and Soramaki, Bech, Arnold, Glass, and Beyeler (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.

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

[46]See Lucas (1995), and more recently Akhavein, Kocagil, and Neugebauer (2005), Das, Freed, Geng, and Kapadia (2006), and de Servigny and Renault (2002).

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

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

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

[50]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.

[51]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+").

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

[53]*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).

[54]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.

[55]All the numerical examples in this section refer to model 6 in Table 3.2. Since the estimated coefficients are stable across various models, the differences in the interpretation of the results are immaterial.

[56]According to the U.S. National Bureau of Economic Research (NBER), the 2008-2009 U.S. recession began in December 2007 and ended in June 2009.

[57]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.

[58]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.

[59]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 $\epsilon + \alpha G \epsilon$.

[60]*Counting the cost of calamities*, The Economist, Jan 14th, 2012.

[61]*Broken Links*, The Economist, Mar 31st, 2011.

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

[63]As before, weights are normalized sales.

[64]For the sake of space, estimation results using 17-, 30-, 38- and 48-industry classification are omitted from Table 3.6. These results are available upon request.

3.8 Tables

Table 3.1: **Summary Statistics**

This table presents summary statistics for the regressors and regressand in our final sample. The data covers the time period from January 2004 to August 2013 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 volatilities 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 (3.4)). 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 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 (254 Firms)				
	Credit Spread	2.588	2.380	0.109	29.800	21861
Leverage	Firm	0.345	0.226	0.012	0.999	20293
	Customers	0.184	0.193	0.000	0.998	3746
	Customers (all)	0.031	0.106	0.000	0.998	21861
	Suppliers	0.136	0.174	0.000	0.996	16968
	Suppliers (all)	0.106	0.163	0.000	0.996	21861
Implied Volatility	Firm	0.309	0.166	0.021	2.489	20386
	Customers	0.286	0.216	0.006	1.833	3080
	Customers (all)	0.040	0.128	0.000	1.833	21861
	Suppliers	0.201	0.204	0.000	2.566	15618
	Suppliers (all)	0.143	0.195	0.000	2.566	21861
	S&P	0.193	0.084	0.095	0.608	21860
Implied Jump Measure	Firm	0.006	0.039	−0.679	1.446	20386
	Customers	0.007	0.047	−1.051	0.700	3080
	Customers (all)	0.001	0.018	−1.051	0.700	21861
	Suppliers	0.005	0.050	−1.038	1.430	15618
	Suppliers (all)	0.004	0.043	−1.038	1.430	21861
	S&P	0.001	0.008	−0.039	0.038	21860
Weekly Returns	S&P	0.001	0.026	−0.195	0.116	21860
Term Structure	r^{10}	3.428	1.015	1.470	5.220	21861
	slope	1.546	0.939	−0.170	2.870	21861

Table 3.2: **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 August 2013. The sample includes bonds that have a spread of less than 30% and higher than 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	1.386∗∗∗	1.326∗∗∗	1.308∗∗∗	1.416∗∗∗	1.353∗∗∗	1.343∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	ivol, β_2	7.931∗∗∗	7.835∗∗∗	7.930∗∗∗	7.854∗∗∗	7.771∗∗∗	7.820∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	jump, β_3	4.248∗	4.141∗	3.948∗	4.237∗	4.131∗	3.951∗
		(0.027)	(0.028)	(0.035)	(0.029)	(0.029)	(0.035)
Customers	*lev*, γ_1				0.597∗∗∗	0.513∗∗∗	0.498∗∗∗
					(0.000)	(0.000)	(0.001)
	ivol, γ_2				0.467∗∗∗	0.414∗∗∗	0.414∗∗∗
					(0.000)	(0.000)	(0.000)
	jump, γ_3				0.440	0.215	0.250
					(0.306)	(0.541)	(0.469)
S&P	*ret*, $\delta_{1,1}$			4.153∗∗∗			4.143∗∗∗
				(0.000)			(0.000)
	ivol, $\delta_{1,2}$			0.072			0.221
				(0.876)			(0.636)
	jump, $\delta_{1,3}$			−1.526			−1.521
				(0.501)			(0.503)
Yield Curve	r^{10}, $\delta_{2,1}$		−0.301∗∗∗	−0.298∗∗∗		−0.297∗∗∗	−0.294∗∗∗
			(0.000)	(0.000)		(0.000)	(0.000)
	slope, $\delta_{2,2}$		−0.077∗∗	−0.083∗∗		−0.078∗∗	−0.088∗∗
			(0.010)	(0.006)		(0.008)	(0.003)
Constant		−0.528∗∗∗	0.662∗∗∗	0.622∗∗∗	−0.550∗∗∗	0.630∗∗∗	0.577∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N		19676	19676	19676	19676	19676	19676
R^2		0.56	0.57	0.58	0.56	0.58	0.58

∗ $p < 0.05$; ∗∗ $p < 0.01$; ∗∗∗ $p < 0.001$

Table 3.3: **Network Determinants of Credit Spreads in Different Periods**

Regression estimates of the model in different time periods

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

The variables and notation are detailed in the caption of Table 3.2. The observation frequency is weekly. There are four time periods classified according to the 2008-2009 U.S. recession: before recession (January 2004 - November 2007), recession (December 2007 - June 2009), after recession (July 2009 - August 2013), and full period (January 2004 - August 2013). The sample includes bonds that have a spread of less than 30% and higher than 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).

		Before Recession	Recession	After Recession	Full Period
Firm	lev, β_1	1.743∗∗∗	1.424∗∗∗	1.098∗∗∗	1.343∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$ivol$, β_2	6.500∗∗∗	8.098∗∗∗	7.527∗∗∗	7.820∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$jump$, β_3	−1.927∗∗	5.301	4.163∗∗∗	3.951∗
		(0.004)	(0.126)	(0.000)	(0.035)
Customers	lev, γ_1	0.045	1.123	0.494∗∗∗	0.498∗∗∗
		(0.725)	(0.164)	(0.000)	(0.001)
	$ivol$, γ_2	0.125	0.419	0.510∗∗∗	0.414∗∗∗
		(0.276)	(0.271)	(0.000)	(0.000)
	$jump$, γ_3	0.569	0.703	−0.095	0.250
		(0.329)	(0.337)	(0.831)	(0.469)
S&P	ret, $\delta_{1,1}$	2.791∗∗	3.272∗∗∗	3.317∗∗∗	4.143∗∗∗
		(0.008)	(0.000)	(0.000)	(0.000)
	$ivol$, $\delta_{1,2}$	0.695	−2.450∗∗	−2.742∗∗∗	0.221
		(0.388)	(0.003)	(0.000)	(0.636)
	$jump$, $\delta_{1,3}$	−2.308	−2.660	−7.056∗∗∗	−1.521
		(0.069)	(0.335)	(0.001)	(0.503)
Yield Curve	r^{10}, $\delta_{2,1}$	0.047	−0.732∗∗∗	−0.096	−0.294∗∗∗
		(0.421)	(0.000)	(0.450)	(0.000)
	$slope$, $\delta_{2,2}$	−0.226∗∗∗	0.054	−0.281	−0.088∗∗
		(0.000)	(0.484)	(0.107)	(0.003)
Constant		−0.802∗∗	2.683∗∗∗	1.166∗∗∗	0.577∗∗∗
		(0.003)	(0.000)	(0.000)	(0.000)
N		6039	3425	10212	19676
R^2		0.49	0.56	0.46	0.58

∗ $p < 0.05$; ∗∗ $p < 0.01$; ∗∗∗ $p < 0.001$

Table 3.4: **Network Spillovers from Second Lag of Firm Characteristics**

Regression estimates of the model in different time periods

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

where γ is 6-vectors of parameters quantifying first-order and second-order customers spillovers, $Customers_{i,t}$ is vector of first-order and second-order customers' characteristics

$$Customers_{i,t} = \{ \; (G_t \cdot lev_t)_i, \; (G_t \cdot ivol_t)_i, \; (G_t \cdot jump_t)_i, \; (G_t^2 \cdot lev_t)_i, \; (G_t^2 \cdot ivol_t)_i, \; (G_t^2 \cdot jump_t)_i \; \} \; .$$

Further variables and notation are detailed in the caption of Table 3.2. The time period classification and sample selection are detailed in the caption of Table 3.3. The observation frequency is weekly. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		Before Recession	Recession	After Recession	Full Period
Firm	*lev*, β_1	1.743***	1.401***	1.089***	1.334***
		(0.000)	(0.000)	(0.000)	(0.000)
	ivol, β_2	6.501***	8.097***	7.530***	7.821***
		(0.000)	(0.000)	(0.000)	(0.000)
	jump, β_3	−1.930**	5.297	4.164***	3.950*
		(0.004)	(0.126)	(0.000)	(0.035)
Customers	*lev*, γ_1	0.043	1.141	0.505***	0.508***
		(0.738)	(0.158)	(0.000)	(0.001)
	ivol, γ_2	0.125	0.443	0.514***	0.420***
		(0.273)	(0.248)	(0.000)	(0.000)
	jump, γ_3	0.576	0.799	−0.106	0.251
		(0.319)	(0.298)	(0.811)	(0.466)
	second-lag *lev*, γ_4	0.360	−0.979	−0.646*	−0.436
		(0.391)	(0.270)	(0.034)	(0.105)
	second-lag *ivol*, γ_5	−0.350	−0.883	−0.566	−0.767**
		(0.094)	(0.312)	(0.156)	(0.003)
	second-lag *jump*, γ_6	4.063*	−14.184	2.288	2.592
		(0.042)	(0.417)	(0.434)	(0.278)
S&P	*ret*, $\delta_{1,1}$	2.797**	3.268***	3.308***	4.139***
		(0.008)	(0.000)	(0.000)	(0.000)
	ivol, $\delta_{1,2}$	0.702	−2.420**	−2.739***	0.224
		(0.381)	(0.003)	(0.000)	(0.630)
	jump, $\delta_{1,3}$	−2.296	−2.629	−7.037***	−1.488
		(0.070)	(0.337)	(0.001)	(0.512)
Yield Curve	r^{10}, $\delta_{2,1}$	0.047	−0.727***	−0.095	−0.294***
		(0.425)	(0.000)	(0.456)	(0.000)
	slope, $\delta_{2,2}$	−0.227***	0.054	−0.283	−0.087**
		(0.000)	(0.480)	(0.105)	(0.004)
Constant		−0.801**	2.670***	1.170***	0.579***
		(0.003)	(0.000)	(0.000)	(0.000)
N		6039	3425	10212	19676
R^2		0.49	0.56	0.46	0.58

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3.5: **Customers Spillovers and Suppliers Spillovers**

Regression estimates of the model in different time periods

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

where $Suppliers_{i,t}$ is vector of suppliers' characteristics, including leverage *lev*, option implied volatilities *ivol* and an implied jump risk measure *jump*. Further variables and notation are detailed in the caption of Table 3.2. The observation frequency is weekly. There are four time periods classified according to the 2008-2009 U.S. recession: before recession (January 2004 - November 2007), recession (December 2007 - June 2009), after recession (July 2009 - August 2013), and full period (January 2004 - August 2013). The sample includes bonds that have a spread of less than 30% and higher than 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).

		Before Recession	Recession	After Recession	Full Period
Firm	lev, β_1	1.753∗∗∗	1.406∗∗∗	1.102∗∗∗	1.348∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$ivol$, β_2	6.474∗∗∗	8.101∗∗∗	7.526∗∗∗	7.814∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$jump$, β_3	−1.917∗∗	5.292	4.171∗∗∗	3.954∗
		(0.004)	(0.127)	(0.000)	(0.035)
Customers	lev, γ_1^c	0.006	1.048	0.484∗∗∗	0.465∗∗
		(0.962)	(0.198)	(0.000)	(0.002)
	$ivol$, γ_2^c	0.093	0.368	0.502∗∗∗	0.387∗∗∗
		(0.412)	(0.322)	(0.000)	(0.000)
	$jump$, γ_3^c	0.540	0.649	−0.098	0.230
		(0.344)	(0.369)	(0.827)	(0.506)
Suppliers	lev, γ_1^s	−0.251∗∗∗	0.209	0.048	−0.015
		(0.000)	(0.358)	(0.524)	(0.805)
	$ivol$, γ_2^s	−0.040	−0.529∗	−0.078	−0.143∗
		(0.425)	(0.020)	(0.158)	(0.011)
	$jump$, γ_3^s	−0.542∗	−0.026	0.031	−0.175
		(0.030)	(0.967)	(0.856)	(0.216)
S&P	ret, $\delta_{1,1}$	2.771∗∗	3.320∗∗∗	3.316∗∗∗	4.153∗∗∗
		(0.008)	(0.000)	(0.000)	(0.000)
	$ivol$, $\delta_{1,2}$	0.703	−2.463∗∗	−2.740∗∗∗	0.230
		(0.380)	(0.003)	(0.000)	(0.623)
	$jump$, $\delta_{1,3}$	−2.300	−2.521	−7.051∗∗∗	−1.503
		(0.070)	(0.362)	(0.001)	(0.508)
Yield Curve	r^{10}, $\delta_{2,1}$	0.053	−0.736∗∗∗	−0.096	−0.294∗∗∗
		(0.369)	(0.000)	(0.450)	(0.000)
	$slope$, $\delta_{2,2}$	−0.223∗∗∗	0.053	−0.281	−0.087∗∗
		(0.000)	(0.481)	(0.108)	(0.004)
Constant		−0.788∗∗	2.763∗∗∗	1.171∗∗∗	0.599∗∗∗
		(0.003)	(0.000)	(0.000)	(0.000)
N		6039	3425	10212	19676
R^2		0.49	0.56	0.46	0.58

∗ $p < 0.05$; ∗∗ $p < 0.01$; ∗∗∗ $p < 0.001$

Table 3.6: **Industry Controls for Customers Spillovers**

Regression estimates for the model 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 variable definitions as in Table 3.2. The observation frequency is weekly. There are four time periods classified according to the 2008-2009 U.S. recession: before recession (January 2004 - November 2007), recession (December 2007 - June 2009), after recession (July 2009 - August 2013), and full period (January 2004 - August 2013). The sample includes bonds that have a spread of less than 30% and higher than 0.1%, and maturities between 5 and 35 years. 12-industry classification is used. The numbers in parenthesis are Driscoll-Kraay p-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		Before Recession	Recession	After Recession	Full Period
Firm	lev, β_1	1.689∗∗∗	1.518∗∗∗	1.096∗∗∗	1.353∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$ivol$, β_2	6.595∗∗∗	7.903∗∗∗	7.522∗∗∗	7.765∗∗∗
		(0.000)	(0.000)	(0.000)	(0.000)
	$jump$, β_3	−1.943∗∗	5.212	4.090∗∗∗	3.855∗
		(0.007)	(0.132)	(0.000)	(0.040)
Customers	lev, γ_1	0.171	0.439	0.385∗∗	0.343∗∗∗
		(0.176)	(0.368)	(0.001)	(0.001)
	$ivol$, γ_2	0.207	0.601	0.411∗∗∗	0.394∗∗∗
		(0.072)	(0.083)	(0.000)	(0.000)
	$jump$, γ_3	0.649	0.832	−0.103	0.244
		(0.268)	(0.231)	(0.832)	(0.491)

Table 3.6: (*continued*)

		Before Recession	Recession	After Recession	Full Period
S&P	*ret*, $\delta_{1,1}$	2.665	−0.818	2.159	0.102
		(0.084)	(0.710)	(0.082)	(0.941)
	ivol, $\delta_{1,2}$	1.459	−2.421**	−2.407***	0.398
		(0.060)	(0.008)	(0.000)	(0.377)
	jump, $\delta_{1,3}$	−1.738	−2.047	−6.240**	−1.614
		(0.136)	(0.453)	(0.003)	(0.439)
Yield Curve	r^{10}, $\delta_{2,1}$	0.057	−0.664***	−0.119	−0.290***
		(0.352)	(0.000)	(0.341)	(0.000)
	slope, $\delta_{2,2}$	−0.233***	0.063	−0.254	−0.087**
		(0.000)	(0.386)	(0.138)	(0.002)
Industry	*ret*, η_1	0.008	0.146*	0.045	0.155**
		(0.875)	(0.049)	(0.309)	(0.007)
	vol, η_2	−0.108*	0.026	−0.051	−0.031
		(0.017)	(0.522)	(0.060)	(0.202)
Cross-Industry	*ret*, ϕ_1	−0.016	0.046	0.031	0.059
		(0.795)	(0.480)	(0.422)	(0.127)
	vol, ϕ_2	−0.170***	0.061	0.110***	0.064*
		(0.000)	(0.122)	(0.000)	(0.019)
Constant		−0.852**	2.385***	1.152***	0.566***
		(0.002)	(0.000)	(0.000)	(0.000)
N		6039	3382	10212	19633
R^2		0.50	0.56	0.46	0.58

$*\ p < 0.05$; $**\ p < 0.01$; $***\ p < 0.001$

Table 3.7: **Interactions between Customers Spillovers and Bond or Firm Characteristics**

Regression estimates of the model according to bond or firm characteristics

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

The variables and notation are detailed in the caption of Table 3.2. The observation frequency is weekly. The time period is January 2004 to August 2013. The full sample includes bonds that have a spread of less than 30% and higher than 0.1%, and maturities between 5 and 35 years. The regressions are performed according to bond or firm characteristics: bond grade (upper panel), bond days to maturity by quartile (middle panel) and firm size by quartile (lower panel). For the sake of space, only results for the variables of interest (customers' leverage *lev*, option implied volatilities *ivol* and jump risk measure *jump*) are presented. The numbers in parenthesis are Driscoll-Kraay *p*-values (robust to heteroskedasticity, cross-sectional and temporal dependence).

		Bond Grade	
		Investment	High Yield
Customers	*lev*, γ_1	0.090	−0.283
		(0.479)	(0.415)
	ivol, γ_2	0.454***	−0.342
		(0.000)	(0.124)
	jump, γ_3	0.250	−0.675
		(0.537)	(0.382)
N		14890	2439
R^2		0.62	0.64

		Bond Days to Maturity by Quartile			
		1st	2nd	3rd	4th
Customers	*lev*, γ_1	0.772***	0.863***	0.151	0.035
		(0.000)	(0.000)	(0.790)	(0.855)
	ivol, γ_2	0.852***	0.273	0.317	0.043
		(0.000)	(0.097)	(0.337)	(0.769)
	jump, γ_3	0.695	1.580*	−1.354	1.811***
		(0.054)	(0.025)	(0.155)	(0.000)
N		4920	4911	4882	4963
R^2		0.61	0.70	0.51	0.59

		Firm Size by Quartile			
		1st	2nd	3rd	4th
Customers	*lev*, γ_1	0.543**	−0.000	−0.680***	−0.054
		(0.005)	(1.000)	(0.000)	(0.887)
	ivol, γ_2	0.280*	−0.095	0.015	−1.240***
		(0.035)	(0.439)	(0.939)	(0.001)
	jump, γ_3	−0.041	0.843	−1.677	−5.191
		(0.906)	(0.130)	(0.220)	(0.164)
N		4594	5022	4980	5080
R^2		0.70	0.74	0.52	0.48

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3.8: **Customers Spillovers with Other Control Variables**

Regression estimates for various restrictions of the model

$$\begin{aligned} CS_{i,t} = \alpha + \beta\ Firm_{i,t} + \gamma\ Customers_{i,t} + \delta_1\ S\&P_t + \delta_2\ YieldCurve_t \\ + \phi_1\ asset_{i,t} + \phi_2\ M/B_{i,t} + \phi_3\ ROA_{i,t} \\ + \phi_4\ BaaAaaSpread_t + \phi_5\ SwapTreaSpread_t + \phi_6\ daysToMaturity_{i,t} + \epsilon_{i,t}\ , \end{aligned}$$

where $asset_{i,t}$ is firm's asset, $M/B_{i,t}$ is firm's market to book ratio, $ROA_{i,t}$ is firm's return on asset ratio, $BaaAaaSpread_t$ is Baa-Aaa spread, $SwapTreaSpread_t$ is swap-Treasury spread, $daysToMaturity_{i,t}$ is bond's days to maturity. Other variables and notation are detailed in the caption of Table 3.2. The observation frequency is weekly. The time period is January 2004 to August 2013. The sample includes bonds that have a spread of less than 30% and higher than 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).

		(1)	(2)	(3)	(4)	(5)
Firm	*lev*, β_1	1.343***	2.433***	1.364***	1.330***	2.441***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	ivol, β_2	7.820***	7.368***	7.605***	7.792***	7.165***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	jump, β_3	3.951*	6.078*	3.784*	3.957*	5.950*
		(0.035)	(0.012)	(0.043)	(0.035)	(0.013)
Customers	*lev*, γ_1	0.498***	0.307*	0.534***	0.476**	0.335**
		(0.001)	(0.019)	(0.000)	(0.001)	(0.009)
	ivol, γ_2	0.414***	0.252**	0.406***	0.394***	0.244**
		(0.000)	(0.002)	(0.000)	(0.000)	(0.003)
	jump, γ_3	0.250	0.371	0.270	0.242	0.393
		(0.469)	(0.294)	(0.409)	(0.488)	(0.215)
Controls in Main Specification						
S&P	δ_1	Yes	Yes	Yes	Yes	Yes
Yield Curve	δ_2	Yes	Yes	Yes	Yes	Yes
Firm Characteristics						
assets	ϕ_1		Yes			Yes
M/B	ϕ_2		Yes			Yes
ROA	ϕ_3		Yes			Yes
Bond Market Characteristics						
BaaAaaSpread	ϕ_4			Yes		Yes
SwapTreaSpread	ϕ_5			Yes		Yes
daysToMaturity	ϕ_6				Yes	Yes
N		19676	18465	19676	19676	18465
R^2		0.58	0.61	0.59	0.58	0.62

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

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