Financial Distress and Customer-supplier Relationships

Yili Lian*

Abstract

Using a customer-supplier matched sample from 1980 to 2009, I study the role of customer-supplier relationships on suppliers' financial distress. If a significant amount of a supplier's sales is tied to a major customer, the supplier's financial health is influenced by the major customer's financial conditions. I find that a supplier's financial distress probability is positively related to its major customer's financial distress. This relationship persists up to two years after a major customer is in financial distress. Further, I show that the relationship is more pronounced when customer-supplier relationships are stronger, when its major customer is more likely to fail in the future, and when the supplier makes unique products. The results highlight the importance of understanding customer-supplier relationships when analyzing a firm's probability of financial distress.

Keywords: Customer-Supplier Relationships; Financial Distress
JEL Classification: G30; G33

* Pennsylvania State University, Worthington Scranton. 120 Ridge View Drive, Dunmore, PA 18512. Phone: +1 570 963 2662. Fax: +1 570 963 2524. E-mail: yxl50@psu.edu.

1. Introduction

Researchers have focused on the customer-supplier relationship and its financial implication on suppliers. Existing evidence shows that major customers' financial conditions influence the performance of suppliers in the capital market, because a large portion of the suppliers' earnings are from major customers. For instance, Cohen and Frazzini (2008) show that customers' returns are positively correlated with the suppliers' returns. Hertzel et al. (2008) document a negative valuation effect of a customer's bankruptcy filings on its suppliers and the rivals in the suppliers' industries. Moreover, Jarrow and Yu (2001) and Gencay et al. (2015) show that the counterparty risk plays a role in determining the price of public debts. However, prior studies focus on the price effect of customer-supplier relationships on suppliers, e.g. stock returns and credit spreads, rather than the risk effect of customer-supplier relationships on suppliers. So far, we have limited evidence on whether and how risks transfer along the supply chain. This paper aims to fill the void by examining the impact of distressed major customers on the probability of suppliers' financial distress in the future.

This paper is motivated by several papers. Using a theoretical model, Jarrow and Yu (2001) argue that firm default risk arises not only from exposure to common risk factors but also from firm-specific counterparty risk. Major customers, as big counterparties of suppliers, influence their suppliers' default risk when the major customers are in financial distress. Using stock return data, Hartzel et al. (2008) find that the suppliers and their rivals have negative stock returns during customers' bankruptcy filing and pre-filing distress periods. Instead of focusing on the valuation effect, this paper investigates whether and how distress risks transfer along the supply chain.

Using the Compustat Customer Segment data from 1980 to 2009, I show that distressed major customers positively impact the future distress risk of suppliers. The effect is persistent up to two years after major customers are distressed. Further, I find that the effect is more pronounced when the customer-supplier relationships are stronger, when customers are more likely to fail in the future, and when suppliers make specialized or unique products.

One may argue that rather than a customer transfers distress risk to its suppliers, instead a risky customer may pick a risky supplier to do business together, and it may explain the positive relation of financial distress between customers and suppliers. However, this alternative explanation is less likely to be true. First, I lag one year between suppliers and customers. It is less likely that my research is suffered from the simultaneous bias because one year lag allows time effect to show up. Second, the effect of distressed customers on suppliers deteriorates over time, which counters the self-selection explanation of customers. Third, I match treatment and control firms using propensity score matching method that include a vector of customers' characteristics from previous year, a vector of suppliers' characteristics, year and industry fixed effects. I find that the main results are not changed. In addition, from an untabulated instrumental variable regression, I use customer Z-score in previous year as an instrumental variable for customers' financial distress indicator and find that the main results are consistent in the instrumental variable regressions.

This paper contributes to the supply chain literature. Previous studies have examined the effect of customer-supplier relationships on information transfer (Cohen and Frazzini, 2008), distress cost (Hartzel et al. 2008), bargaining power (Fee and Thomas, 2004), debt contracting (Kim et al., 2015), investment-cash flow sensitivity (Itzkowitz, 2012), cash holdings (Itzkowitz, 2013) and leverage (Titman and Wessels, 1988). In this paper, I study the transfer of distress risk along the supply chain. The probability of suppliers' financial distress is more pronounced when the inter-firm relationships are stronger, when customers are more likely to fail, and when suppliers make specialized or unique products. The findings shed lights on the risk contagion along supply chain. The findings explain the negative valuation effect of suppliers when their customers file bankruptcy in Hertzel et al. (2008) and the increase of suppliers' cost of debt when their customers' performance deteriorates in Kim et al. (2015).

This paper also contributes to the financial distress literature. First, I show that customers' distress indicator plays an important role when predicting the probability of suppliers' financial distress. Shumway (2001) proposes a model that combines a vector of accounting and market variables and shows that his model well predict the bankruptcy risk than Altman's (1968) and Zmijewski's (1984) models. Chava and Jarrow (2004) confirm the better performance of Shunway's (2001) model. But they point out that including industry effect in predicating distress risk is important. Besides those variables mentioned above, I show that customers' distress status is positively and significantly associated with the probability of suppliers' financial distress in the future. I also show that the effect of customers' distress is persistent up to two years. Second, I support the contagion effect of financial distress along supply chain. Lang and Stulz (1992) show that financial distress affect its rivals in the same industry. Hartzel et al. (2008) argue that financial distress not only affect the rivals in the same industry but also the suppliers along the supply chain. Beside the valuation effect found in the existing literature, I provide direct evidence on the transfer of distress risk from customers to suppliers.

The remainder of this paper is organized as follows. Section 2 discusses the development of hypotheses and the empirical strategy. Section 3 describes the data, variables and summary statistics. Section 4 reports the empirical results and Section 5 provides concluding remarks.

2. Hypotheses Development and Empirical Strategy

My main hypothesis is that financial distress transfers from customers to suppliers along the supply chain. First, major customers in financial distress may fail to fulfill their obligations to supplier firms, which increases the cash flow risks and default risks of their suppliers (Jarrow and Yu, 2001; Giesecke and Weber, 2004). Second, distressed customers may decrease the future demand on the products or services from suppliers, which deteriorates the suppliers' future earnings and cash flows (Olsen and Dietrich, 1985; Pandit et al., 2011). So the existence of distressed customers increases the supplier's default risk. Third, prior literature suggests that customer-supplier relationship is established via long-term contracts, strategic alliance or relationship-specific investments (Titman, 1984; Banerjee et al. 2008; Raman and Shahrur, 2008; Johnson et al., 2010). The switching cost of finding a new customer is very high for a supplier. Therefore, the failure of major customers will negatively impact the future earnings of suppliers, thereby increasing the default risk of suppliers.

Hypothesis I: financial distress transfers along the supply chain.

In cross-section, customer-supplier relationships vary by different characteristics suppliers and customers. When customer-supplier relationships are stronger, I expect that the effect of distressed customers on their suppliers is much higher. As suggested by prior literature, a strong business relationship can be formed by large stake on the suppliers' sales or by concentrated customers. Therefore, a larger stake customers hold on a supplier, a higher chance the supplier is likely to suffer when its major customers are in distress.

Hypothesis II: all else being equal, the effect of distressed customers on suppliers is more pronounced when the customer-supplier relationship is stronger.

As I argue above, because suppliers' earnings are tied to the major customers' demand, the risks of earnings and cash flows of suppliers increase if major customers fail in the future. So the effect of distressed customers on suppliers is more pronounced when the customers are more likely to fail in the future. I use customers' financial constraint and customers' market competition to measure the likelihood of failure of a distressed customer in the future. First, financial constraint literature shows that financial constraint firms are difficult to raise money from external market, and the frictions prevent firms from funding all desired investment. As argued in Livdan et al. (2009), the risk of firms increases with the inflexibility in adjusting capital investment to absorb the impact of positive shocks. Therefore, financial constraint firms are riskier. Compared with customers that are not financially constrained, financial constrained customers are more likely to fail and lead to distressed suppliers in the future due to missing obligations or decrease of demand, all else being equal. Following prior literature, I use KZ index to measure financial constrain (Kaplan and Zingales, 1997). Second, distressed customers operating in competitive markets are more likely to fail in the future than those operating in concentrated markets because of the pronounced market competition. As shown above that finding a new customer is very costly for a supplier, I expect that the effect of distressed customers on suppliers are more pronounced when distressed customers are operating in competitive markets.

Hypothesis III: all else being equal, the effect of distressed customers on suppliers is more pronounced when distressed customers are more likely to fail in the future.

As argued by Titman and Wessels (1988), suppliers that producing unique or specialized products are likely to suffer relative high costs when the customers are bankrupt. The switching cost is high when the products are unique. Therefore, the distress risk of suppliers is high when they producing specialized or unique products.

I use two approaches to measure specialized or unique products of suppliers. First, as suggested by Titman and Wessels (1988), research and development expenses is a good candidate to measure product uniqueness, because firms sell products with close substitutes are likely to do less research and development and because successful research and development projects lead to new unique products. Second, Titman and Wessels (1988) suggest that durable goods firms depend more on relationship-specific assets than non-durable goods firms. Prior research suggests that firms in durable goods industry produce more unique goods than those in non-durable goods (e.g. Kale and Shahrur, 2007; Banerjee et al., 2008). So I compare the effect of customers' financial distress on suppliers in between durable goods industries and non-durable goods industries.

Hypothesis IV: all else being equal, the effect of distressed customers on suppliers producing specialized or unique products is more pronounced.

To test the above hypotheses, I specify the following logistic regression model:

$$sdistress_{i,t+1} = \beta_0 + \beta_1 cdistress_{i,t} + \beta_2 Supplier\ Characteristics_{i,t-1} + \beta_3 Year + \beta_4 Indutry + \varepsilon_{i,t} \quad (1)$$

The dependent variable is an indicator variable that equals one if a supplier is in financial distress at year t+1. The key independent variable, cdistress, is an indicator variable that equals one if a customer is in financial distress at year t. Financial distress status of a firm is identified using the option pricing model development by Merton (1974) that is widely used in prior studies on distress risk. For each firm in each month, I calculate the expected default frequency (EDF) using the option pricing model. I sort the unconditional distribution of EDF for all firms in the sample into quintiles. Firms that appear in the highest quintile of EDF for more than six times in a calendar year are identified as in financial distress in that year. Alternatively, I test different cutoffs of the EDF distribution and use Altman's (1968) Z-score as an alternative benchmark to identify firms in financial distress. The main results are robust under different measures.

Supplier characteristics includes accounting and market based variables. Firms with lower profitability and higher debt ratio are more likely to be in financial distress. So I control for the ratio of net income to total assets and the ratio of total liabilities to total assets. Firms that are discounted by traders in the market are more likely to be in financial distress. Therefore, I control for the logarithm of firm market capitalization to the total size of NYSE/AMEX market and the excess stock returns of suppliers. Firms with high idiosyncratic volatility is more likely to be in financial distress as well. So I control for idiosyncratic volatility for suppliers. Shumway (2001) argues that those variables above well predict the distress risk than other variables. Chava and Jarrow (2004) suggest to include industry effects in Shumway's model, so I include year and industry fixed effects in all regressions to control for potential differences of distress risks across industries and years.

3. Data, Variables and Summary Statistics

3.1. Data

The data for the paper comes from the Standard & Poor's Compustat database and the Center for Research in Security Prices (CRSP) database. I begin with all firms in Compustat with non-missing value of total assets from 1980 to 2009. I delete financial and utilities firms from the initial sample because these industries are highly regulated. I then collect customer-supplier data from Compustat Segment data. According to the Statement of Financial Accounting Standards (SFAS) No. 14, firms are required to report information for segments including major customers that represent 10% or more of consolidated sales for fiscal years after 1977. In 1997, the SFAS No. 131 was issued to revise the SFAS No. 14, and it permitted firms to optionally report the customer's name if it was considered important but below the 10% threshold.

The major customers are generally reported with abbreviated names in the segment data. Using a method similar to that of Fee and Thomas (2004), I match customer names with their corresponding unique identifiers (GVKEY) in Compustat. I first exclude the customers that are reported as governments, regions, or militaries. Then, I run a text matching program to match the reported customer names and the Compustat firm names. Finally, I manually identify matched customers using information from company website, SEC filings, and internet resources.

3.2. Measure of financial distress

I use the option pricing model developed by Merton (1974) to measure financial distress. The model is being used by the KMV Corporation that is now a subsidy of Moody's. According to Shumway (2001), market based measures of financial distress provide better prediction of bankruptcy than accounting based measures, e.g. Altman's (1968) Z-score. This approach has been used widely in the financial distress literature, e.g. Bharath and Shumway (2008) and Chava and Jarrow (2004). I compute the expected default frequency (EDF) from the option pricing model for all firms in my sample. For each calendar year, I sum up months where the EDF of each firm in the top quintile of the distribution of the entire sample. If the sum of the months in the top quintile equals to or exceeds six times, I classify that firm is in financial distress in that calendar year. I apply this approach to identify customers and suppliers in financial distress in the sample. Specifically, I start with pairs of customers and suppliers at year t, and I focus on the relation between customer distress at year t and supplier distress at year t+1.

Alternatively, I use top decile instead of top quintile or Altman Z-score below 1.8 to identify financial distress of customer and supplier firms. I find that the main regression results are consistent under these alternative measurements.

3.3. Control variables

I follow the existing literature to control for a vector of firm characteristics that may affect a firm's financial distress status. I control for the ratio of net income to total assets (ni_ta). I expect that the ratio of net income to total assets is positively related to financial distress because profitable firms are less likely to have financial distress in the future. I control for the ratio of total liabilities to total assts (tl_ta). Firms with higher debt ratio are expected to have a higher probability of financial distress. I control for the logarithm of each supplier's size to the total size of the NYSE and AMEX market (log_resize). Market equity is typically discounted by traders when a firm is close to financial distress. I scale market equity by the total size of NYSE and AMEX market to make size stationary. I control for the past excess return measured by suppliers' annual returns subtracted by the value-weighted CRSP NYSE/AMEX index annual returns (exret). The past excess return is an alternative to measure how traders discount the market equity and should predict the supplier's financial distress as well. I control for the idiosyncratic standard deviation of each supplier's stock returns (ivol). Idiosyncratic risk is highly related to financial distress because it measures the firm specific risks, e.g. cash flow risk. All variable definitions are in Appendix. To eliminate the influence of outliers, all variables lower than first percentile or higher than ninety-ninth percentile are winsorized. The variables that I control for are widely accepted in the bankruptcy prediction models. Shumway (2001) uses those market-driven variables and accounting ratios and shows that those variables are quite accurate in out-of-sample tests.

3.4. Summary Statistics

Table 1 provides summary statistics of the variables used in this paper. The sample contains 20,847 supplier firm-year observations, with average distressed customers of 8.17% at year t and average distressed suppliers of 17.02% at year t+1. The sample consists of supplier firms with average ratio of net income to total assets of -3.99%, but median of 3.06%, with average ratio of total liabilities to total assets of 46.2%, with past excess stock return of 1.27% , with idiosyncratic volatility of 52.7%, and with average logarithm of market equity to total size of the NYSE/AMEX market of -11.02. The summary statistics is similar to the one in Shumway (2001) and Chava and Jarrow (2004).

Table 2 provides time series of suppliers' distress surrounding the customer distress year. Average suppliers in distress increases from 11.9% at year t-1 to 14.8% at year t and to 17.0% at year t+1, and decreases gradually to 16.1% at year t+2 and 13.9% at year t+3. The difference of the number of distressed suppliers after year t-1 and the number of distressed suppliers at year t-1 is all statistically significant at better than 1% level.

4. Results

4.1. Baseline Results: Test of Hypothesis I

Table 3 reports the results of the relationship between distressed customers and its impact on the probability of suppliers' financial distress. Column 1 shows that distressed customers at year t are positively significantly associated with the probability of suppliers' financial distress at year t+1. The coefficient of distressed customer indicator is significant at better than the 1% level. Column 2 includes the suppliers' accounting and market variables, industry and year fixed effects to control for suppliers' characteristics that is associated with suppliers' distress risk, and cross-industry and cross-year variation of distress risk. The coefficient of distressed customer indicator is positive and significant at better than the 1% level after controlling those variables. Column 3 reports the Fama-MacBeth results for OLS regression to ensure that the unknown error correlation structure does not overstate the precision of the results. I show that the main results are consistent under the Fama-MacBeth approach. The base results are in line with Hypothesis I.

The other results of Table 3 are consistent with those in prior papers. Profitable firms with low leverage are less likely to be distressed in the future. Firms with less discounted market capitalization and with low idiosyncratic volatility are less likely to be distressed in the future.

Table 4 reports the results of effect of customers' distress on suppliers from year t-1 to year t+3. The coefficient of customers' distress is positive and statistically significant at better than the 1% level at year t and t+1 and better than the 10% level at year t+2. The size of the coefficient reduces gradually as time goes by. The results show that the effect of distressed customers on suppliers are up to two years after year t.

4.2. Propensity Score Matching

I compare the probability of suppliers' financial distress of a sample of treatment firms with customers' financial distress to the probability of suppliers' financial distress of control firms without customers' financial distress. This approach rules out omitted treads that are correlated with customers' financial distress and suppliers' financial distress in both groups. For instance, customers' profitability may simultaneously influence the likelihood of customers' and suppliers' financial distress. Propensity score matching rules out the possibility that a change of customers' profitability drives the changes of suppliers' distress. This approach controls for constant unobserved differences between the treatment and the control group.

I report the probit model results in Panel A of Table 5. The dependent variable is customers' distress indicator at year t, and the independent variables are all control variables in equation (1) and the customers' ratio of net income to total assets, ratio of total liabilities to total assets, excess stock returns, logarithm of market value of equity to the total size of NYSE/AMEX market, and idiosyncratic risk at year t-1. The results suggest that the specification captures a significant amount of variation of customers' financial distress, as indicated by a psedo-R^2 of 41.4%. I use the predicted probabilities from the probit model and perform a one-to-one propensity score matching procedure. I end up with 1628 unique pairs of matched firms.As indicated in Panel B of Table 5, the average treatment effect on the treated is 2.83% in the matched sample, compared to 7.32% in the unmatched sample.

4.3. The Effect of Strong Customer-Supplier Relationship: Test of Hypothesis II

Hypothesis II predicts that the effect of customers' distress is more pronounced when the customer-supplier relationships are stronger. To test hypothesis II, I estimate equation (1) in subsamples of low and high sales concentration to major customers and of low and high percent of sales to major customers.

As shown in Table 6, the coefficient of distressed customer indicator is significantly at better than the 1% level and the magnitude of the coefficient is higher for suppliers with high percent of sales to major customers and high sales concentration to major customers. All control variables have the expected signs as I discussed above. The results support hypothesis II that suppliers with strong customer-supplier relationship tend to have higher distress risk in the future.

4.4. The Effect of Likely-to-Fail Distressed Customers: Test of Hypothesis III

Hypothesis III predicts that the effect of distressed customers is more pronounced when the distressed customers are more likely to fail in the future because searching a new customer is costly for an existing supplier. I use KZ index (Kaplan and Zingales, 1997) and customers' product market concentration to measure the likelihood of failure customers. The results in Table 7 show that suppliers with customers who are financially constrained or who operate in competitive product markets tend to have higher financial distress risk in year t+1. The results are in line with Hypothesis III.

4.5. The Effect of Product Uniqueness: Test of Hypothesis IV

Hypothesis IV predicts that the effect of distressed customers is more pronounced when suppliers' product is unique or specialized due to the high switching cost and relationship-specific investments. According to Titman and Wessels (1988), I use research and development expenses and durable goods manufactures to proxy for product uniqueness. The results of Table 8 show that the coefficient of distressed customer indicator is significantly positive at better than the 1% level for suppliers with positive research and development expenses and suppliers operating in the durable goods industries. Compared to the results in positive research and development firms, the coefficient of distressed customer indicator in no research and development expenses firms is smaller and marginally significant. The coefficient of distressed customer indicator is insignificant among non-durable goods manufacturers. The results support Hypothesis IV.

4.6. Alternative Measure of Financial Distress

I identify distressed firms using Altman's (1968) Z-score below 1.8 or EDF in top of 90^{th} percentile of the unconditional distribution. I re-estimate equation (1) using those two alternative measures. Table 9 shows that the main results are robust to alternative measures of financial distress.

5. Conclusion

The paper shows that distress risk transfers along the supply chain. I show that the effect of distressed customers on suppliers is persistent up to two years. I also show that the effect of distressed customers is more pronounced on suppliers who have stronger customer-supplier relationships, who have more likely-to-fail distressed customers in the future, and who produce specialized or unique products.

The paper contributes to the financial distress literature by showing that the major customers play an important role in determining the distress risk of a suppler besides the accounting and market based firm characteristics (Shumway, 2001; Chava and Jarrow, 2004). The paper also contributes to the supply chain literature by showing that the distress risks of customers do transfer to suppliers. The findings complement the existing evidence on valuation effect of the customer-supplier relationships.

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Appendix: definitions of variables

Variables	Definition
sdistress	The variable equals one when a supplier is in distress at year t+1. Using Merton (1974)'s distance to default model, I identify the probability of default for each supplier each month. If the default probability is in the top quintile of the distribution for more than six months in a year, the value of sdistress equals one in that year.
cdistress	The variable equals one when a customer firm is in distress at year t. Using Merton (1974)'s distance to default model, I identify the probability of default for each customer each month. If the default probability is in the top quintile of the distribution for more than six months in a year, the value of cdistress equals one in that year.
ni_ta	The ratio of net income to total assets of a supplier
tl_ta	The ratio of total liabilities to total assets of a supplier
exret	The supplier's past excess returns measured by the annual return of a supplier firm minus the annual return of value-weighted CRSP NYSE/AMEX index return in the past year.
ivol	The idiosyncratic volatility measured by the standard deviation of the residual of a market model regression using past twelve-month returns of a supplier.
log_resize	The natural logarithm of supplier firm's size relative to the total size of the NYSE and AMEX market.

Table 1: Summary Statistics

This table presents the summary statistics of key variables used in the paper. Accounting information and customer-suppler data are obtained from Compustat database. Stock return and market capitalization data are obtained from CRSP databse. sdistress is an indicator that equals one if a supplier firm is in financial distress at year t+1. cdistress is an indicator that equals one if a customer firm is in financial distress at year t. ni_ta is the ratio of net income/total assets of a supplier. tl_ta is the ratio of total liabilities/total assets of a supplier. exret is the excess return of a supplier measured by the annual return of that firm minus the annual return of the value-weighted CRSP NYSE/AMEX index return. ivol is the idiosyncratic volatility of a supplier measured by the standard deviation of the residuals from a market model using the past twelve month returns. log_resize is the natural logarithm of a supplier's size relative to the total size of the NYSE and AMEX market. To eliminate the influence of outliers, all variables are winsorized at 1% and 99%.

	N	Mean	Std	Min	p25	Median	p75	Max
sdistress	20847	0.1702	0.376	0	0	0	0	1
cdistress	20847	0.0816	0.274	0	0	0	0	1
ni_ta	20847	-0.0399	0.254	-1.918	-0.0575	0.0306	0.0759	0.306
tl_ta	20847	0.462	0.258	0.0199	0.262	0.449	0.619	1.918
exret	20847	0.0127	0.655	-0.960	-0.405	-0.110	0.241	2.532
ivol	20847	0.527	0.311	0.0921	0.312	0.454	0.654	1.715
log_resize	20847	-11.02	1.836	-15.08	-12.31	-11.13	-9.866	-5.745

Table 2: Supplier Distress before and after Customer Distress

This table presents the time series of supplier distress surrounding customer distress at year t. The difference is the mean of supplier distress at year t, t+1, t+2 and t+3 minus the mean of supplier distress at year t-1.

	N	Mean	Difference	t-stat
sdistress at year t-1	20847	0.119		
sdistress at year t	20847	0.148	0.0296	12.06
sdistress at year t+1	20847	0.170	0.0514	17.73
sdistress at year t+2	20847	0.161	0.0420	13.84
sdistress at year t+3	20847	0.139	0.0201	6.57

Table 3: Financial Distress along Supply Chain

This table presents the logistic regression results of supplier distress at year t+1 on customer distress at year t. Specification (1) and (2) use logistic regression model, and specification (3) uses Fama-MacBeth OLS regression model. The z-statistics or t-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1)	(2)	(3)
	Logististic	Logististic	Fama-MacBeth
cdistress	0.479***	0.293***	0.0361**
	(7.98)	(3.90)	(2.58)
ni_ta		0.382***	0.0610**
		(4.20)	(2.14)
tl_ta		2.539***	0.364***
		(28.49)	(14.33)
exret		-1.538***	-0.154***
		(-31.90)	(-10.98)
ivol		1.587***	0.202***
		(19.83)	(8.46)
log_resize		-0.377***	-0.0353***
		(-25.31)	(-11.23)
Constant	-1.629***	-9.733***	-0.502***
	(-83.45)	(-15.70)	(-14.70)
Industry FE	No	Yes	No
Year FE	No	Yes	No
Observations	20847	20520	20847
Pseudo/Adjusted R-squared	0.003	0.271	0.196

Table 4: Persistence of Financial Distress along the Supply Chain

This table presents the logistic regression results of supplier distress from year t-1 to year t+3 on customer distress indicator at year t. All regressions are estimated using logistic regression model with industry and year fixed effects. The industry fixed-effects are based on the Fama-French (1997) 48 industry classifications. The z-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1) sdistress year t-1	(2) sdistress year t	(3) sdistress year t+1	(4) sdistress year t+2	(5) sdistress year t+3
cdistress	0.106	0.513***	0.293***	0.141*	0.0104
	(1.20)	(6.65)	(3.90)	(1.85)	(0.12)
ni_ta	-0.0622	0.238**	0.382***	0.248***	0.230**
	(-0.64)	(2.51)	(4.20)	(2.76)	(2.41)
tl_ta	3.420***	3.296***	2.539***	1.776***	1.392***
	(32.57)	(33.03)	(28.49)	(21.67)	(16.51)
exret	-0.216***	-1.376***	-1.538***	-0.543***	-0.286***
	(-5.80)	(-29.04)	(-31.90)	(-15.26)	(-8.10)
ivol	1.070***	1.991***	1.587***	0.847***	0.427***
	(12.45)	(23.43)	(19.83)	(11.19)	(5.32)
log_resize	-0.642***	-0.512***	-0.377***	-0.296***	-0.277***
	(-32.79)	(-29.77)	(-25.31)	(-21.25)	(-19.02)
Constant	-12.31***	-9.192***	-9.733***	-8.039***	-6.596***
	(-16.32)	(-13.82)	(-15.70)	(-13.34)	(-11.24)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	20476	20520	20520	20520	20520
Pseudo R-squared	0.318	0.336	0.271	0.156	0.120

Table 5: Propensity Score Matching

This table presents the effect of distressed customers at year t on the probability of supplier distress at year t+1 using the propensity score matching method. I match firms using the one-to-one matching method with no replacement on a host of observable characteristics including ni_ta, tl_ta, exret, ivol, log_resize of both supplier and customer firms, industry and year fixed effects. The treatment group contains suppliers with distressed customers at year t, and the control group includes suppliers without distressed customers at year t.

Panel A: Propensity Score Matching Probit Regression

	(1)
	cdistress
ni_ta	0.0709
	(0.95)
tl_ta	0.0435
	(0.61)
exret	-0.0780***
	(-2.79)
ivol	0.143**
	(2.21)
log_resize	0.0478***
	(4.62)
cni_ta	-1.326***
	(-7.89)
ctl_ta	2.449***
	(25.48)
cexret	-0.935***
	(-21.78)
civol	1.254***
	(13.46)
clog_resize	-0.271***
	(-26.34)
Constant	-5.279***
	(-11.96)
Industry FE	Yes
Year FE	Yes
Observations	19834
Pseudo R-squared	0.414

Panel B: Average Treatment Effect on the Treated

	n. treat	n control	ATT	z stat
Unmatched	1628	18206	0.0732	7.56
One-to-one matching	1628	1628	0.0283	1.99

Table 6: Strong Customer-Supplier Relationship and Financial Distress along the Supply Chain

This table presents the logistic regression results of supplier distress at year t+1 on customer distress at year t. High Sale indicates that the customers' sales divided by total supplier's sales is above the sample median. High Customer Concentration indicates that the Herfindahl-Hirschman Index of sales determined by the sum of the squares of the share of sales of each reported customers to the total sales of a supplier is above the sample median. All regressions are estimated using logistic regression model with industry and year fixed effects. The industry fixed-effects are based on the Fama-French (1997) 48 industry classifications. The z-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1) High Sale	(2) Low Sale	(3) High Customer Concentration	(4) Low Customer Concentration
cdistress	0.306***	0.231*	0.361***	0.177
	(3.29)	(1.76)	(3.79)	(1.41)
ni_ta	0.371***	0.292*	0.368***	0.304**
	(3.23)	(1.91)	(3.24)	(1.97)
tl_ta	2.439***	2.686***	2.466***	2.643***
	(20.68)	(19.41)	(20.96)	(19.01)
exret	-1.487***	-1.612***	-1.498***	-1.595***
	(-23.40)	(-21.60)	(-23.40)	(-21.59)
ivol	1.455***	1.796***	1.469***	1.788***
	(13.80)	(14.31)	(13.94)	(14.29)
log_resize	-0.349***	-0.412***	-0.345***	-0.412***
	(-16.74)	(-18.59)	(-16.60)	(-18.69)
Constant	-9.694***	-10.65***	-9.370***	-10.71***
	(-11.40)	(-8.90)	(-11.72)	(-8.88)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	10706	9776	10701	9780
Pseudo R-squared	0.263	0.293	0.265	0.289

Table 7: Likely-to-Fail Distressed Customers and Financial Distress along the Supply Chain

This table presents the logistic regression results of supplier distress at year t+1 on customer distress at year t. High HHI indicates that the Herfindahl-Hirschman Index of the sum of the squared market shares of firms in the customer's industry is above the sample median. High KZ indicates that the Kaplan and Zingales (1997) Index of a customer is above the sample median. All regressions are estimated using logistic regression model with industry and year fixed effects. The industry fixed-effects are based on the Fama-French (1997) 48 industry classifications. The z-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1)	(2)	(3)	(4)
	High HHI	Low HHI	High KZ	Low KZ
cdistress	0.192*	0.348***	0.285***	0.279
	(1.81)	(3.16)	(3.33)	(1.53)
ni_ta	0.286**	0.479***	0.253**	0.553***
	(2.10)	(3.87)	(2.12)	(3.81)
tl_ta	2.558***	2.550***	2.544***	2.608***
	(19.77)	(20.28)	(21.55)	(18.48)
exret	-1.533***	-1.557***	-1.609***	-1.446***
	(-21.69)	(-23.36)	(-25.16)	(-19.44)
ivol	1.630***	1.582***	1.600***	1.560***
	(13.82)	(14.28)	(15.32)	(12.19)
log_resize	-0.332***	-0.427***	-0.386***	-0.372***
	(-15.11)	(-20.41)	(-19.65)	(-15.72)
Constant	-10.41***	-8.987***	-9.754***	-9.773***
	(-11.49)	(-7.62)	(-13.63)	(-12.86)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	10296	10188	10986	9504
Pseudo R-squared	0.262	0.287	0.277	0.270

Table 8: Suppliers with Unique Products and Financial Distress along the Supply Chain

This table presents the logistic regression results of supplier distress at year t+1 on customer distress at year t. RD is the research and development expenses of suppliers. Durable goods manufacturers are firms that have a primary SIC code from 3400 to 3990. Non-durable goods manufacturers are firms that have a primary SIC code from 2000 to 3390. All regressions are estimated using logistic regression model with industry and year fixed effects. The industry fixed-effects are based on the Fama-French (1997) 48 industry classifications. The z-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1)	(2)	(3)	(4)
	RD>0	RD=0	Durable Goods	Non-durable Goods
cdistress	0.317***	0.205*	0.620***	-0.0623
	(3.01)	(1.86)	(5.49)	(-0.33)
ni_ta	0.377***	-0.0389	0.492***	0.437**
	(3.45)	(-0.20)	(3.14)	(2.14)
tl_ta	2.397***	2.741***	2.951***	2.164***
	(20.46)	(18.60)	(19.03)	(12.75)
exret	-1.480***	-1.614***	-1.440***	-1.559***
	(-22.02)	(-22.85)	(-18.87)	(-14.81)
ivol	1.468***	1.728***	1.568***	1.782***
	(13.34)	(14.08)	(11.87)	(9.60)
log_resize	-0.363***	-0.377***	-0.392***	-0.471***
	(-17.41)	(-16.40)	(-16.20)	(-14.14)
Constant	-9.785***	-9.713***	-12.60***	-10.06***
	(-12.81)	(-13.08)	(-10.27)	(-12.28)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12068	8408	8696	4985
Pseudo R-squared	0.261	0.279	0.281	0.308

Table 9: Alternative Measure of Financial Distress

This table presents the logistic regression results of supplier distress at year t+1 on customer distress at year t. I use Z-score below 1.8 to identify distressed firms in Specification (1). I use EDF in top 10% of the unconditional distribution to identify distressed firms in Specification (2). All regressions are estimated using logistic regression model with industry and year fixed effects. The industry fixed-effects are based on the Fama-French (1997) 48 industry classifications. The z-statistics are reported in the parenthesis. ***, **, * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively. Definition of all variables is provided in the Appendix.

	(1)	(2)
	Z-score	EDF>90%
cdistress	0.205***	0.402***
	(4.41)	(3.13)
ni_ta	-3.905***	0.364***
	(-32.11)	(3.28)
tl_ta	5.472***	2.381***
	(49.91)	(22.10)
exret	-0.0981***	-1.878***
	(-2.94)	(-24.85)
ivol	0.645***	1.340***
	(7.87)	(13.70)
log_resize	-0.188***	-0.337***
	(-14.20)	(-17.01)
Constant	-5.376***	-10.05***
	(-18.04)	(-17.70)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	21609	21655
Pseudo R-squared	0.396	0.261