Vertical Propagation of Default Risk Along the Supply Chain

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Abstract

This study investigates the propagation of default risk along the supply chain. We adopt a modified version of the firm-specific upstreamness measure used by Gofman, Segal, and Wu (2020) to determine the vertical distance for any firm to the final consumption products in a supply chain. We find that upstream firms are more exposed to default risk, and the upstream effect is more substantial for firms that belong to less prominent, more levered, and less diverse supply chains. We also find that a distressed firm only affects its upstream suppliers but not its downstream customers. Our results are robust across various empirical specifications.

JEL Classification Codes: G14, G33

Keywords: Bankruptcy Risk, Supply Chain Relationship, Bullwhip Effect, Financial Contagion

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Abstract

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1. Introduction

If firms were idiosyncratically isolated entities, subprime mortgage crises could be avoided. According to Lucas (1977), fluctuations are "averaged out" macroeconomically due to the Law of Large Numbers. Literature on contributing factors for bankruptcy risk often focus on firm-specific default risk (Altman, 1968; Altman and Hotchkiss, 2010; Merton 1974). However, after the subprime mortgage crisis, financiers have realized that idiosyncratically isolated firms may not prevent such crises.

As firms are connected through their business relationships and financial networks, small shocks can loop and lead to sizeable fluctuations. Gabaix (2011) argues that when the size of a firm is abnormally distributed, larger firms can be affected by shocks that cannot be balanced by the effects of smaller firms. Acemoglu et al. (2012) demonstrate the asymmetric effect of shocks on upstream suppliers versus downstream customers. Firm-specific shocks cannot be neutralized by the downstream customers; rather, shocks are amplified and directed toward supplier firms. The default risk of a firm, therefore, can generate spillover effects on upstream suppliers and downstream customer firms (Bernstein et al., 2019; Chakrabarty and Zhang, 2012; Schiller, 2017; Sautner and Vladimirov, 2018; Boone and Ivanov, 2012).

Motivated by this stream of literature, we explore how the upstreamness of a firm affects the firm's exposure to distress risks. When facing consumer demand shocks directly, the revenue of downstream retailers can be more volatile than upstream firms. Dhaliwal et al. (2016) find that firms who concentrate their sales on only a few customers have a higher equity cost due to higher risk exposures. Such characteristics can lead to a greater risk of distress for downstream firms in the supply chain because fundamental volatility plays an essential role in default risk evaluation. However, upper-stream firms require more time to transform their production into cash, making them more vulnerable to economic shocks (Gofman, Segal, and Wu, 2020; Osadchiy, Schmidt, and Wu, 2021). As customer firms provide more trade credits to downstream firms, both customer firms and downstream counterparties are exposed to both economic shocks, resulting in a potentially greater exposure to default risk.

Our results show that firms further away from the final consumer product are associated with a higher default risk, which are determined using the dynamic logit model of Campbell, Hilscher, and Szilagyi (2008) and the expected default frequency of Merton (1974) (Bharath and Shumway, 2008). The results are robust after controlling for common firm characteristics that may affect an individual firm's default risk and the selected upstream measures. Gofman and Wu (2022) apply recursive moral hazard theory and find that firms higher in the supply chain provide more trade credit to their downstream customers and have higher incentives against shirking than do firms closer to final consumer product (Kim and Shin, 2012). We control for accounts payable and receivable in our regression and find that the upstreamness effect on default risk cannot be explained by trade credit from upstream suppliers.

Our findings suggest the occurrence of the bullwhip effect often discussed in operations management literature. Lee, Padmanabhan, and Whang (1997) first argue that the demand variation from ultimate customers can be mishandled by their upstream suppliers As a retailer infers customer demands and places orders with suppliers, information from downstream is imperfectly conveyed to the decision sets of upstream firms. Subsequently, upstream firms might overestimate or underestimate the needs of downstream firms and ultimate customers and introduce significantly greater risks for upstream firms compared with similar downstream firms (Osadchiy et al., 2021; Fransoo and Wouters, 2000; Bray and Mendelson, 2012; Metters, 1997).

To further investigate the sources of the bullwhip effect, we study the asymmetric effect of bankruptcy risk propagation both upstream and downstream by analyzing 723 million lines of quarterly supply-chain data. We first identify distressed firms and then compute the upstream or downstream distance between other members in the supply chain and the distressed firm. We then determine whether the bankruptcy risk of counterparties is related to the upstream or downstream distance to distressed firms. Our results reveal that the default risk only increases when the distance from the distressed downstream counterparties increases. Consistent with the economic intuition that default risk propagation is more severe in a bear market, our results reveal that the effect is more significant when consumer sentiments are low. Our findings support the moral hazard model of Kim and Shin (2012) and the empirical findings of Gofman et al. (2020) and Osadchiy et al. (2021).

Finally, we study how chain characteristics interact with the upstreamness effect on default risk. The literature reveals that the counterparty features in the supply chain network play a role in the propagation of financial distress, such as the industry leverage suggested by Lang and Stulz (1992) and the financial healthiness of suppliers indicated by Itzkowitz (2015). Overall, our empirical results indicate that the upstreamness effect is more substantial for firms in supply chains that are less prominent, with higher leverage, and lower industry diversification.

The contribution of our study is twofold. First, our study adds to the literature on how economic relationships shape financial outcomes. By drawing from informational transmission, Cohen and Frazzini (2008) study the delayed propagation of information through the supply chain, which results in predictable patterns in returns. Guan, Wong, and Zhang (2015) demonstrate that analysts who follow both customers and suppliers benefit from the information gathered from both firms. Customer–supplier relationships also shape corporate financial decisions. Banerjee, Dasgupta, and Kim (2008) demonstrate that customer–supplier relationships affect capital structure decisions. Amiram, Li, and Owens (2020) examine loan contracts and find that supplier–customer relationships are beneficial in the loan-granting process. Our results reveal how customer–supplier relationships affect the default risk exposure of firms and demonstrate the vertical propagation of default risk through supply chains.

Second, our study contributes to the literature on financial contagion. Several studies focus on the role of financial intermediaries in financial contagion (Slovin, Sushka, and Polonchek, 1999 ; Kang and Stulz, 2000; Brunnermeier, 2009; Stulz, 2010; Aragon and Strahan, 2012; Chakrabarty and Zhang, 2012; Fernando, May, and Megginson, 2012; Dumontaux and Pop, 2013). Other studies emphasize the intra-industry financial contagion (Lang and Stulz, 1992; Hertzel and Smith, 1993; Ferris, Jayaraman, and Makhija 1997) or the exposure to counterparty risks (Jarrow and Yu, 2001; Jorion and Zhang, 2009; Boone and Ivanov, 2012; Houston, Lin, and Zhu, 2016). Our study emphasizes the vertical contagion of default risk along the supply chain. Our findings support the counterparty exposure channel because the customer–supplier relationship provides information about financial contagion. Further, we demonstrate that even without a direct connection, firms within the same supply chain are affected by shocks to the financial condition of other downstream firms.

To the best of our knowledge, our work is conceptually similar to two existing studies. Hertzel et al. (2008) examine the effects of pricing on the customers and suppliers of distressed firms after bankruptcy. Moreover, they investigate the abnormal returns of linked supplier and customer portfolios around a 5-day window by using a sample of 250 firms that filed for bankruptcy. Lian (2017) uses logistic regression to examine whether the future default risk of the direct supplier is positively correlated with distressed major customers. Our study explores the propagation of default risk beyond the direct-linked business partners. We use the FactSet database to construct a supply network containing 723 million lines of quarterly supply-chain data to explore the customer–supplier relationship. We also consider the vertical propagation of distress risk both upstream and downstream. Finally, our study finds that the vertical position in the supply chain is a crucial factor in the study of a firm's default risk.

The rest of the study is organized as follows. Section 2 details how we construct our upstreamness measures and the default risk measures. Section 3 presents summary statistics of our key variables. Section 4 presents our key empirical findings, that is, a firm's vertical position in the supply chain affects its default risk exposure. Section 5 examines how the upstreamness effect is interacted with supply chain characteristics. Finally, section 6 provides some concluding remarks.

2. Data Construction

We construct our measures for upstreamness by modifying the one of Gofman et al. (2020). At the end of each quarter, firms with no supplier are identified as the top producers in the supply chain. Firms in the consumer discretionary and consumer staples sectors (GICS = 25 and 30, respectively) are identified as the bottom producers. We then determine the shortest path from the top producers to the bottom producers for all possible top–bottom combinations to identify unique supply chains.

To measure the position of a firm in the supply network, Gofman et al. (2020) compute the shortest path to the bottom consumers among all supply chains the firm belongs to and argue that the chain with the shortest distance to the final customer is the most direct link. Although the shortest path is the most direct path from the downstream distressed customer to any supplier, a firm can belong to multiple supply chains at any point in time, and the shortest path does not always trigger the most significant effect. The magnitude of a supplier's counterparty risk can then be associated with the relative importance of all customers.

To account for the complicated nature of a firm's position in a supply network, we make two modifications to upstreamness measures of Gofman et al. (2020). First, we follow and extend the studies of Osadchiy et al. (2021) and Herskovic et al. (2020), which derive upstreamness by using industry-wide data from the U.S. Bureau of Economic Analysis to calculate the simple average upstreamness of all possible supply chains, which is denoted as $UPST_{ew.}$ This measurement uses all supply chain data and provides a more comprehensive description of the production network.

Second, because the effects from all customers are not equal, we aggregate the distances to all customers across supply chains by weighting the distances based on their relative importance. However, for most of the samples, the FactSet database does not report the exact amount of sales revenue from the relationship because supplier firms are only required by regulation to report customer names when customers contribute more than 10% of the total sales. Therefore, we use customer sales to capture the relative importance among supply chains. We assume that customers with more sales order more inputs from their upstream suppliers. The sales-weighted distance to the bottom layer avoids overstating the importance of supply chains that accounts for a marginal portion of supplier sales. In addition to the sales-weighted upstreamness ($UPST_{sw}$), we include the median distance to the bottom layer ($UPST_{med}$) as an alternative upstreamness measurement for robustness.

The data that we use to construct the supply chain network come from the FactSet Revere relationships database, which contains the start and the end date of customer–supplier relationships. Our sample covers the period from 2003 when the FactSet database is initiated and ends in 2019 when our subscription ends. Our data have a particular advantage over the traditional Compustat Segment data, which are the standard source for the supplier–customer relationship. Compustat Segment relies on U.S. Securities and Exchange Commission reporting requirements: firms must report a customer relationship only when the customer accounts for over 10% of the sales of a firm. Thus, the coverage is limited by nature. By contrast, FactSet employs a proprietary algorithm that sifts out supplier–customer relationships within a range of primary sources of information, including company filings, investor presentations, company websites and press releases, and corporate actions. Schiller (2017) notices that Compustat Segment file only covers a small sample (less than 15%) of the FactSet universe.

We merge multiple relationships for the same pair of customers and suppliers if the gap between two consecutive contracts is no larger than 6 months, following the method of Gofman et al. (2020). We use CUSIP to match firms in the FactSet and Compustat databases for the largest sample coverage. We exclude financial and utility firms (i.e., SIC codes from 4800 to 4999 and 6000 to 6999) from our sample due to their unique business properties. Ultimately, we include 9,339 unique US firms in our sample.

[Insert Table 1 Here]

Table 1 provides the summary statistics of our supply chain data. For example, we include 2,164 firms in 2003, generating 934,302 unique supply chains. The minimum supply chain length is three, and the longest supply chain contains 19 firms from top to bottom. The number of firms peaks in 2007 and decreases thereafter. However, the number of supply chains increases almost exponentially from 934,302 in 2003 to 30,841,910 in 2019, suggesting that a more integrated production network has arisen in recent years. The lengths of the supply chains are quite stable over time, which suggests that the structure of vertical separation might not have varied significantly in the past 2 decades.

2. Measuring Default Risk

Several studies use a logit model to measure the financial healthiness or bankruptcy risk of firms based on accounting information, such as the Altman (1968) Z-score and the Ohlson (1980) O-score. Both models are commonly used in the bankruptcy literature and exhibit high predictability for firm bankruptcy (Altman and Hotchkiss, 2010; Begley, Ming, and Watts, 1996). Although accounting-based methods, such as O-score and Z-score, describe the financial robustness of a firm, scholars argue that financial statements, which are based on historical information, may not provide timely information about a firm's operation condition (Hillegeist et al., 2004; Vassalou and Apedjinou, 2004). Moreover, accounting-based methods do not consider firm volatility when evaluating a firm's distress risk.

Campbell et al. (2008) improves the precision of the logit models by including equity market information, which is a greater indicator of a firm's future prospect. We construct our first default risk measure following their approach. Specifically, at the end of each quarter, we run a logistic regression of a firm-failure indicator on all available historical variables. Such variables include net income to market-valued total assets, total liabilities to market-valued total assets, the ratio of a company's cash and short-term assets to the market value of total assets, monthly excess returns over the S&P 500 index, daily stock return volatility in the last 3 months, the relative market capital to the S&P 500 index, and the market-to-book ratio. We then estimate the probability of default for each firm by using the estimated coefficients and the quarterly financial data as our default risk measure, *Camp*.

An alternative popular approach incorporates the market prices of firms into the estimated default probability, which is based on the Merton (1976) model. In this study, we adopt the expected default frequency (EDF) measure used by Bharath and Shumway (2008). Based on Merton's model, the value of equity can be expressed as follows:

$$V_{\mathrm{E}} = V_{\mathrm{A}} N(d_1) - X e^{-rT} N(d_2), \tag{1}$$

where V_{E} and V_{A} are the value of equity and assets, $d_1 = \frac{\ln(V_{\mathrm{A}}/X) + \left(r + \frac{1}{2}\sigma_{\mathrm{A}}^2\right)T}{\sigma_{\mathrm{A}}\sqrt{T}}$, $d_2 = d_1 - \sigma_{\mathrm{A}}\sqrt{T}$, X is the face value of a firm's debt, r is the risk-free rate, σ_{A} is the standard deviation of the asset value, and $N(.)$ is the cumulative distribution function of a normal distribution.

A firm's default probability increases as the firm value decreases toward the debt value. Therefore, the EDF can be expressed as follows:

$$EDF_{\mathrm{t}} = N\left(-\frac{\ln\left(V_{\mathrm{A,t}}/X_{\mathrm{t}}\right) + \left(\mu - \frac{1}{2}\sigma_{\mathrm{A}}^2\right)T}{\sigma_{\mathrm{A}}\sqrt{T}}\right). \tag{2}$$

We construct our two distress risk measures, *Camp* and *EDF*, and firm characteristics on a quarterly basis by using the CRSP and Compustat databases. To ensure that all variables are available in our estimation, we leave at least a 3-month gap before the accounting data in Compustat are used. The two distress risk measures and the firm characteristics are then merged with our supply chain data for regression analysis.

3. Data and Summary Statistics

[Insert Table 2 and Table 3 Here]

Table 2 and Table 3 present the summary statistics and the Pearson correlation coefficients of our two default risk measures and the upstreamness measures. *EDF* ranges from 0 to 1 with a mean of 0.065 and a standard deviation of 0.176. *Camp* ranges from −7.481 to −2.340 with a mean of −6.412 and a standard deviation of 0.634. The equal-weighted upstreamness measure, $UPST_{ew}$, indicates that the average distance to the bottom producer is approximately 3.48, with a standard deviation of 2.33 across individual firms. The minimum value of $UPST_{ew}$ is 1, which denotes firms in short supply chains that consist of only two firms; a maximum value of 18.32 indicates that the most upstream firms of the longest supply chain has 18 downstream layers on average. The maximum values of $UPST_{ew}$ and $UPST_{sw}$ are the same because the firm only has one directly connected downstream customer.

The Pearson correlation coefficients in Table 3 show that *EDF* and *Camp* are highly correlated with a coefficient of 0.512. The upstreamness measures, $UPST_{ew}$, $UPST_{sw}$, and $UPST_{med}$, are also highly correlated. For example, the correlation coefficient between $UPST_{ew}$ and $UPST_{sw}$ is 0.901 and that between $UPST_{ew}$ and $UPST_{med}$ is almost 0.985. The results suggest that the choice of weighting scheme does not significantly bias our empirical analysis.

4. Propagation of Default Risk Along Supply Chain

In this section, we present empirical evidence on how a firm's vertical position in the supply chain influences its default risk.

4.1 Effect of Upstreamness on Default Risk

To study how the upstreamness of a firm is associated with its default risk, we run a regression with the following specifications:

$$DEF_{\mathrm{i,q}} = \alpha + \beta \times UPST_{\mathrm{i,q}} + \delta \times X_{\mathrm{i,q}} + F_{\{\mathrm{ind,qtr}\}} + \varepsilon_{\mathrm{i,q}}, \tag{3}$$

where $DEF_{i,q}$ is the default measure of *EDF* or *Camp* for firm *i* estimated at the end of each quarter q. We standardize the default risk measures to have a mean of 0 and a standard deviation of 1 for comparisons across models. $UPST_{i,}$ is the measure of upstreamness in $UPST_{\mathrm{ew}}$, $UPST_{\mathrm{sw}}$, or $UPST_{\mathrm{med}}$. Because firms in the same industry can be affected by industry-wide economic shocks that increase the default risk of all firms in the industry, we add $F_{ind,tr}$ to control for the time and industry-fixed effects by using the Fama and French 49 industry classifications. $X_{i,}$ denotes a set of firm characteristics that can influence the distress risk of a firm. Because firm size is a common component for constructing distress risk measures, we use the log value of sales rather than total assets or market equity as a control variable. The market-to-book ratio is included to control for firm growth opportunities. We include the ratio of accounts payable and receivable to sales, which controls for the trade-credit effect of Gofman and Wu (2022). We also include other firm characteristics such as firm age and return on assets.

[Insert Table 4 Here]

Table 4 presents the regression results of our baseline model by using the sales-weighted upstreamness measure, $UPST_{\mathrm{sw}}$, as the key independent variable. We find that the further away a firm is from the final consumption products, the higher the default risk. For example, the regression results in the first column indicate that one layer away from the bottom producer results in a 0.0037 standard-deviation-increase in EDF when firm size and growth opportunity are controlled for. Moreover, smaller firms and firms with higher growth opportunities tend to be associated with a higher default risk. The coefficient of market-to-book ratio is 0.628 and that of *Sale* is −0.053. Both effects are significant at the 1% confidence level. The upstreamness effect is stronger and more significant after additional firm characteristics are controlled for and yields a coefficient of 0.0045. The positive relationship between upstreamness and default risk is robust when default risk is measured.

Gofman and Wu (2022) find that firms that are more upstream in the supply chain both provide and receive more trade credit. Based on the recursive moral hazard theory from Kim and Shin (2012), Gofman and Wu argue that upstream suppliers have higher incentives against shirking, providing trade credit credits to downstream firms. In this case, the provision of trade credit could lead to higher financial risks of upstream firms.

To account for the alternative explanation that the upstreamness effect on bankruptcy risk is merely an artifact of increased trade credits, we control for two variables that capture the trade-credit effect in our regression: the ratio of accounts payable to sales (AP2S) and the ratio of accounts receivable to sales (AR2S). When all firm characteristics are controlled for, the coefficients for $UPST_{sw}$ stay positive and significant for both default risk measures.

[Insert Table 5 Here]

The regression results from the equal-weighted shortest path and the median of the shortest path are reported in Table 5. The results in Table 5 present the same findings as in Table 4 and support that a firm's default risk is positively associated with its upstreamness. For instance, the regression coefficients in the first column demonstrate that when using $UPST_{ew}$ as the upstreamness measure, one layer away from the bottom producer results in a 0.0067 standard deviation increase in EDF, and a one-step increase in the $UPST_{med}$ leads to a 0.0064 standard deviation increase in EDF. The coefficients are positive and significant at a 1% confidence level.

4.2 Direction of Propagation of Default Risk

The empirical evidence in the previous section reveals that the distance to the ultimate customers is associated with a firm's exposure to default risk. This section presents further evidence to support the vertical propagation of financial distress risk within supply chains. Specifically, we study how the vertical distance to a financially distressed firm influences the default risk of an upstream supplier or a downstream customer. Default risk can propagate along the supply chain in two directions: from downstream customers to upstream suppliers and vice versa. Most literature cites evidence that financial contagion spreads from consumers to suppliers. For example, Hertzel et al. (2008) find that a portfolio on suppliers whose customers are experiencing financial distress generates significantly negative returns, but a portfolio on the customers of distressed suppliers does not produce abnormal returns. Lian (2017) demonstrates that financial distress significantly transforms from customers to suppliers. These studies explore vertical propagation along the supply chain by investigating directly linked supplier–customer relationships. However, whether financial distress transfers in the opposite direction is unknown.

We obtain evidence that the upstreamness of a firm is positively associated with its default risk. Although upstream suppliers are associated with a higher default risk, default risk may not be transferred from downstream customers to upstream counterparties. Thus, we explore how the distance to distressed firms influences propagation and whether the effect of the distance is asymmetrical for upstream and downstream firms.

We construct a firm-level measure to capture the vertical distance to distressed firms in the supply chain. At the end of each quarter, we define a firm as distressed if its default risk falls into the top decile. For each firm in the supply chain of the distressed firm, we compute the vertical distances to the distressed firm. We then aggregate the distance to the distressed firm into firm-level measures by calculating the sales-weighted average distance across supply chains. For firms upstream of distressed firms, we use the sales of directly linked customers as the weight to compute the sales-weighted distance to distressed firms (*DistUp*). For firms downstream of distressed firms, we use the sales of the directly linked suppliers as the weight to compute the sales-weighted distance to distressed firms (*DistDn*). A firm can be downstream of a distressed firm in one supply chain and upstream of a distressed firm in another supply chain at one point in time. Moreover, if all the supply chains of a given firm do not have any distressed firms, the firm is excluded from our analysis because the distance to distressed firms is missing. The baseline model in the regression analysis is as follows:

$$DEF_{i,q} = \alpha + \beta \times DistUp_{i,q} + \gamma \times DistDn_{i,q} + \delta \times X_{i,q} + F_{\{ind,qtr\}} + \varepsilon_{i,q}, \quad (4)$$

where $DistUp_{i,q}$ denotes the sales-weighted average distance to downstream distressed firms of an upstream firm i, and $DistDn_{i,q}$ is the sales-weighted average distance to upstream distressed firms of that firm i. The other variables are the same as Eq. (3).

[Insert Table 6 Here]

We run a firm-level regression and control for time and industry-fixed effects. The results are reported in Table 6. The coefficients of *DistUp* are positively significant for predicting both default risk measures. The coefficient of *DistUp* for predicting EDF indicates that, on average, one layer away from the downstream distressed firms leads to an increase of 0.0070 in the standard deviation of the expected default frequency, which was significant at a 99% level. The distance to upstream distressed firms does not influence a downstream customer's default risk because the coefficients for *DistDn* are not significant for either measure. These results suggest an asymmetrical propagation of default risk along the supply chain.

We determine that the default risk of downstream customers tends to spill over to upstream customers, but not vice versa. Moreover, our results suggest that the effect of propagation can aggregate further upstream. A directly connected supplier of a distressed customer may not be affected the most from the customer's distress. Instead, the magnitude is amplified as the distress risk spreads to upstream firms. The results reveal that the data in Table 6 remain the same after the upstreamness of individual firms is controlled for.

As with all variables in corporate finance, upstreamness and default risk can be endogenously determined. That said, we argue that our setting is less prone to the reverse causality problem since the vertical distance to the bottom producer is a result of production processes rather than defaults. It is also possible that the observed propagation is the result of an unknown factor associated with both the firm's vertical position and its distress risk. Given that the structure of vertical separation has not changed significantly in the past two decades as shown in Table 1, we test an intuitive implication of propagation effect instead of using a DID approach to further support our arguments.

Intuitively, the propagation of default risk is more severe when investors are more pessimistic about the market condition. Unfavorable news of a firm can convey information that causes investors to reassess the creditworthiness of the entire supply chain and produces a fall in demand (Lang and Stulz, 1992). We include an indicator variable (*LowCSI*) in our regression, which indicates that the number of years in which Consumer Sentiment Index scores (collected by the Surveys of Consumers at the University of Michigan) are lower than the timeseries median in our sample period. The interaction between *DistUp* and *LowCSI* demonstrates that the upstream propagation effect is stronger during the years where consumer sentiments are lower. When consumers are more reluctant to spend, upstream firms are more likely to be associated with a higher default risk.

4.3 Influence of Chain Characteristics on the Upstreamness Effect

In addition to the relative importance of a firm's customers, other supply chain characteristics can affect the propagation of bankruptcy risk. The literature indicates that the effect of propagation through economic links can be related to the prominence, capital structure, and the diversity of associated firms.[2] One advantage of our approach is that we can analyze features that are related with each of the supply chains that a given firm belongs to. We then study how the upstreamness effect addressed in the previous sections interacts with supply chain characteristics by running a regression (Eq. [5]) to explore the influence of chain characteristics on the upstreamness effect, where $ChainChar_{i,}$ is one of the chain characteristics variables. The rest of the variables are the same as those in Eq. (3).

$$DEF_{i,q} = \alpha + \beta \times UPST_{i,q} + \gamma \times ChainChar_{i,q} + \theta \times UPST_{i,q} \times ChainChar_{i,q} + \delta \times X_{i,q} + F_{\{ind,qtr\}} + \varepsilon_{i,q} \quad (5)$$

[2] For example, Lang and Stulz (1992) find that the negative announcement return of portfolio on the competitors of bankrupt firms is more significant for highly levered industries. Itzkowitz (2015) argues that the ratio of investment to cash sensitivity is lower for firms with principal buyers, who act as monitors. The effect is especially strong for financially distressed suppliers. Lian (2017) finds that the financial contagion of distress from customer to supplier is stronger for customers who are more likely to default in the future.

First, we investigate how the prominence of a supply chain affects the transmission of bankruptcy risk. Larger firms are often in the center of supply networks and consist of more customers and producers. Therefore, more prominent supply chains are less vulnerable with fewer possible exposures to counterparty risk. We expect that the upstreamness effect is smaller for firms in more prominent supply chains. We proxy the prominence of supply chains by first averaging the market equity for all the firms in each supply chain as a chain-level size. Then we compute the simple average of chain size across all chains a firm belongs to as our firm-level chain prominence measure.

[Insert Table 7 Here]

Our results in Table 7 demonstrate that the upstreamness effect is more substantial for firms in less prominent chains. For example, the coefficient of the interaction between $UPST_{\mathrm{ew}}$ and *Chain_ME* in the first column is −0.0212 with a *t* value of −8.38. Thus, for firms in larger supply chains, an increase in upstreamness has significantly less influence on the distress risk than for firms in smaller supply chains. This result is robust across all default risk measures and the two different weighting schemes for upstreamness.

We evaluate how the upstream effect interacts with the capital structures of other firms on the supply chain. The leverage of a chain is associated with the chain's financial vulnerability. Intuitively, the propagation of financial distress is more severe in more leveraged chains. For example, Lang and Stulz (1992) find that the financial contagion effect on competitors in the same industry increases with the leverage of competitors. However, studies addressing the default risk puzzle, such as George and Hwang (2010), reveal that financial and investment decisions are inseparable. Firms that are more exposed to distressed risks choose to have lower leverage. In this case, high leverage chains do not have a stronger upstreamness effect because the firm chooses to have high leverage are those who can handle high exposure to default risk.

[Insert Table 8 Here]

We use a simple average of the book-debt-to-asset ratio across all firms in the supply chain that a firm belongs to as our chain-leverage measure (*Chain_Lev*) and run a regression (Eq. [5]). Overall, the marginal effect of chain leverage on the upstreamness effect is positive, as presented in Table 8. The coefficient of the interaction between *UPST* and *Chain_Lev* is

0.0102 (0.0140), with a *t* value of 4.18 (4.74) in the second (fourth) column. The finding that the upstreamness effect is stronger for firms in supply chains with higher leverage is consistent with that of Lang and Stulz (1992), who argue that bankruptcy conveys poor information that causes counterparties to reassess creditworthiness, leading to a fall in demand.

Finally, we consider how the diversity of a supply chain affects the propagation of bankruptcy risk. As a supply chain spreads into more industries, the transmission of risk can be slowed or affected by diversification. We proxy the extent of chain diversification by taking the number of industries of each supply chain and aggregating the number of the firm level by using the simple average.

[Insert Table 9Here]

The empirical results are presented in Table 9. The marginal effects of industry diversification are negative for both default risk measures, which suggests that the effect of vertical propagation of default risk is weaker when a firm belongs to more diverse supply chains. The results are consistent with our conjecture because more supply chains spread across multiple industries reduce the risk of industry-wide economic shocks. The results are also consistent with the literature that shows customer concentration increases with firm risk. (Dhaliwal et al., 2016; Irvine, Park, and Yıldızhan, 2015; Campello and Gao, 2017; Mihov and Naranjo, 2017; Hui, Liang, and Yeung, 2019; Itzkowitz, 2013))

The effect of industry diversification may be a side effect of the length of supply chains. However, untabulated results indicate that the supply chain length has a marginal influence on the upstreamness effect. Specifically, adding chain length as a control variable does not prevent the marginal effect of industry diversification.

6. Conclusion

In this study, we explore the effects of a firm's vertical position in the supply chain on the exposure to default risk. Our empirical design uses a modified version of the upstreamness measure of Gofman and Wu (2022) to provide a more comprehensive description of the production network. We find that the further away a firm is from the final consumption product, the more the firm is exposed to default risk. This confirms the bullwhip effect that is often discussed in operations management literature.

We also analyze the vertical propagation of the default risk by investigating whether the distance of a firm to a distressed counterparty in the supply chain influences its exposure to default risk. We provide fresh evidence to the literature on financial contagion by demonstrating that the effects of financial distress are not just limited to direct counterparty firms, but can also be transmitted through a supply chain. We find that the contagion effect is asymmetrical: a firm's default risk is only positively related to downstream distressed customers but not to upstream distressed suppliers. Finally, we evaluate how supply chain characteristics influence the upstreamness effect. We discover that the upstreamness effect is more substantial for firms that belong to smaller supply chains with larger leverage ratios and less industry diversification.

Due to the growing concerns on regional political risk landscapes, supplier-customer links have become a focal of interest. Our analysis adds to the understanding of how such relationships in production networks have financial implications. The modified measure of supply chain upstreamness that contains 723 million lines of quarterly supply-chain data can also be useful in further research endeavors. The methodology can also be readily extended to a global network of supply chain that has become one of the weakest links in the global economy in a post-COVID world now.

Table 1

Summary Statistics for Supply Chains

This table presents the summary statistics for our supply chain sample from 2003 to 2019. The sample includes US firms with supplier–customer relationships present in the FactSet database and accounting data in the Compustat database. We exclude financial and utility firms (SIC codes between 4800 to 4999 and 6000 to 6999) due to their unique business properties. We identify the unique shortest path from top producers to bottom producers for all possible combinations of top producers and bottom producers. *#of firms* is the number of firms included in constructing the supply chain network. *#of chains* is the number of unique chains founded. *Min(length)*, *Med(length)*, and *Max(length)* are the minimum, median, and maximum length of supply chains, respectively, that are identified at the end of each year.

Year	#of firms	# of chains	Min(length)	Med(length)	Max(length)
2003	2164	934302	3	7	19
2004	3282	1835295	2	7	26
2005	3555	2125282	3	7	18
2006	3590	2270120	3	7	21
2007	3792	2621171	3	7	19
2008	3788	2478921	3	7	20
2009	3562	2423653	3	7	20
2010	3431	3654381	3	8	24
2011	3358	6431525	3	8	19
2012	3384	7439765	2	8	20
2013	3347	6964792	2	7	19
2014	3484	14258562	2	8	21
2015	3402	18718677	2	8	22
2016	3120	29027054	2	8	23
2017	2909	31860603	2	7	24
2018	2716	27378339	2	7	21
2019	2494	30841910	2	8	22

Table 2

Summary Statistics for Default Risk and Upstreamness Measures

This table presents the descriptive statistics of the measures for default risk and upstreamness. The measures for default risk includes the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure of Campbell et al. (2008) (Camp). We also calculate three versions of firm-level upstreamness measures: the equal-weighted ($UPST_{ew}$), sales-weighted ($UPST_{sw}$), and the median ($UPST_{med}$) distance to the bottom producer across all supply chains. The numbers in the table are the mean (Mean), median (Med), standard deviation (Std), minimum value (Min), and maximum value (Max) of the key variables. ME is the market-to-book ratio. Sale is the log of sales (in millions), Age denotes the firm age, ROA is the return on assets, AP2S is the ratio of accounts payable to sales, and AR2S is the ratio of accounts receivable to sales.

	Mean	Med	Std	Min	Max
EDF	0.065	0.000	0.176	0.000	1.000
Camp	-6.412	-6.624	0.634	-7.481	-2.340
$UPST_{ew}$	3.477	3.017	2.329	1.000	18.321
$UPST_{sw}$	4.157	4.063	2.135	1.000	18.321
$UPST_{med}$	3.411	3.000	2.422	1.000	18.000
MB	0.560	0.528	0.307	0.029	7.993
Sale	6.970	7.144	2.223	-1.332	12.316
Age	25.902	25.000	14.278	1.000	57.000
ROA	0.003	0.045	0.248	-7.670	3.606
AP2S	0.100	0.071	0.223	0.000	7.519
AR2S	0.150	0.145	0.086	0.000	0.624

Table 3

Correlation Coefficient Matrix for Default Risk and Upstreamness Measures

This table presents the Pearson correlation coefficients of our key variables. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure (Camp) of Campbell et al. (2008). $UPST_{ew}$ is the simple average distance to the downstream firms across all supply chains. $UPST_{sw}$ is the sales-weighted average distance to the downstream firms across all supply chains, which sues the sales of a firm's direct customer in each chain as weights. $UPST_{med}$ is the median distance to the bottom of the chain across all supply chains. The numbers in parentheses are the *p* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	EDF	Camp	$UPST_{ew}$	$UPST_{sw}$	$UPST_{med}$
EDF	1				
Camp	0.512	1			
	(<0.01)***				
$UPST_{ew}$	0.015	0.029	1		
	(<0.01)***	(<0.01)***			
$UPST_{sw}$	0.020	0.062	0.901	1	
	(<0.01)***	(<0.01)***	(<0.01)***		
$UPST_{med}$	0.015	0.029	0.985	0.872	1
	(<0.01)***	(<0.01)***	(<0.01)***	(<0.01)***	

Table 4

Default Risk and Firm Upstreamness

This table presents the estimated regression coefficients of two default risk measures for firm upstreamness. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure (*Camp*) of Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. The upstreamness measure, $UPST_{sw}$, is the sales-weighted average distance to the downstream firms across all supply chains, which uses the sales of a firm's direct customers in each chain as weights. We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). We use a regression model to estimate the coefficients by considering both time and industry-fixed effects. The numbers in parentheses are the *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	EDF	EDF	Camp	Camp
$UPST_{sw}$	0.0037	0.0045	0.0034	0.0050
	(1.90)*	(2.32)**	(1.86)*	(2.80)***
MB	0.6275	0.5060	1.1791	0.9348
	(43.08)***	(31.12)***	(89.12)***	(63.42)***
Sale	-0.0530	-0.0282	-0.1913	-0.1637
	(-24.98)***	(-12.20)***	(-97.27)***	(-76.73)***
AP2S		-0.0010		-0.0094
		(-1.38)		(-10.31)***
AR2S		0.0379		-0.0117
		(1.78)*		(-0.61)
Firm Age		-0.0071		-0.0026
		(-20.92)***		(-8.54)***
ROA		-0.3131		-0.7092
		(-14.84)***		(-35.98)***
Nobs	46951.0	46951.0	46951.0	46951.0
R-Squared	0.0712	0.0855	0.3147	0.3374

Table 5

Default Risk and Firm Upstreamness: Alternative Measures

This table displays the estimated regression coefficients of two default risk measures for firm upstreamness. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure (*Camp*) in Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. $UPST_{ew}$ is the simple average distance to the downstream firms across all supply chains. $UPST_{med}$ is the median distance to the bottom of the chain across all supply chains. We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). We use a regression model to estimate the coefficients by considering both time and industry-fixed effects. The numbers in parentheses are the *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	EDF	EDF	Camp	Camp
$UPST_{ew}$	0.0067		0.0112	
	(3.56)***		(6.56)***	
$UPST_{med}$		0.0064		0.0105
		(3.55)***		(6.37)***
MB	0.4676	0.4677	0.8830	0.8830
	(29.21)***	(29.21)***	(60.83)***	(60.83)***
Sale	-0.0265	-0.0265	-0.1626	-0.1626
	(-11.54)***	(-11.54)***	(-76.74)***	(-76.75)***
AP2S	-0.0001	-0.0001	-0.0026	-0.0026
	(-0.24)	(-0.23)	(-4.09)***	(-4.07)***
AR2S	0.0106	0.0106	-0.1062	-0.1062
	(0.87)	(0.87)	(-9.82)***	(-9.83)***
Firm Age	-0.0072	-0.0072	-0.0025	-0.0025
	(-21.81)***	(-21.81)***	(-8.43)***	(-8.42)***
ROA	-0.3524	-0.3525	-0.7271	-0.7272
	(-16.87)***	(-16.88)***	(-37.46)***	(-37.47)***
Nobs	46951.0	46951.0	46951.0	46951.0
R-Squared	0.0833	0.0833	0.3304	0.3303

Table 6

Upstream Propagation of Default Risk Along the Supply Chain

This table presents the estimated regression coefficients of two default risk measures for an individual firm's distance to its upstream distressed supplier and downstream customers. The measures of default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure of Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. *DistUp* denotes the sales-weighted average distance to the downstream distressed firms of an upstream firm, and the *DistDn* denotes the sales-weighted average distance to the upstream distressed firms of a downstream firm. A firm is considered distressed if it falls within the highest decile of the default risk measure. We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). LowCSI is an indicator variable that is equal to 1 in years where scores from the Consumer Sentiment Index (collected by the Surveys of Consumers at the University of Michigan) are lower than the timeseries median. We use a regression model to estimate the coefficients by considering both time and industry-fixed effects for the first two column. Only industry-fixed effects are considered in the interaction columns. The numbers in parentheses are the *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	Camp	EDF	Camp	EDF
DistUp	0.0070	0.0057	0.0012	0.0030
	(1.80)*	(3.85)***	(0.19)	(1.77)*
DistDn	0.0000	0.0015	0.0025	-0.0002
	(0.00)	(0.96)	(0.46)	(-0.12)
DistUp*LowCSI			0.0203	0.0065
			(1.99)**	(2.35)**
LowCSI			-0.0622	0.0318
			(-1.39)	(2.87)***
MB	0.7769	0.1138	1.0202	0.1137
	(27.52)***	(10.99)***	(26.64)***	(11.11)***
Sale	-0.0847	0.0001	-0.1219	-0.0012
	(-22.52)***	(0.11)	(-23.87)***	(-0.92)
AP2S	-0.0044	-0.0012	-0.0058	-0.0013
	(-4.97)***	(-3.70)***	(-4.83)***	(-3.77)***
AR2S	0.0243	0.0434	0.0744	0.0422
	(0.40)	(2.43)**	(0.91)	(2.39)**
Firm Age	-0.0021	-0.0015	-0.0019	-0.0017
	(-4.59)***	(-8.99)***	(-2.97)***	(-10.08)***
ROA	-0.0004	0.0115	-0.1009	0.0108
	(-0.01)	(0.78)	(-1.91)*	(0.74)
Nobs	6806.00	7213.00	6806.00	7213.00
R-Squared	0.3243	0.0901	0.3392	0.1127

Table 7

Influence of Chain Size on the Upstreamness Effect

This table presents the estimated regression coefficients of the two default risk measures for firm upstreamness with interaction effects on chain characteristics. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure of Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. $UPST_{ew}$ is the simple average distance to the downstream firms across all supply chains. $UPST_{sw}$ is the weighted average distance to the downstream firms across all supply chains, which uses the sales of a firm's direct customer in each chain as weights. To measure the size of chains, we calculate the average market equity of all firms within each chain. We then average all the calculated results across all chains that a firm belongs to as the measure for chain size of that firm (Chain_ME). We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). We use a regression model to estimate the coefficients by considering both time and industry-fixed effects. The numbers in parentheses are the *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	Camp	EDF	Camp	EDF
$UPST_{ew}$	0.1936	0.3002		
	(10.16)***	(13.66)***		
$UPST_{sw}$			0.1363	0.2093
			(5.79)***	(7.48)***
$UPST_{ew}$ *Chain_ME	-0.0212	-0.0353		
	(-8.38)***	(-12.11)***		
$UPST_{sw}$ *Chain_ME			-0.0153	-0.0234
			(-4.98)***	(-6.38)***
Chain_ME	-0.1112	-0.1024	-0.1342	-0.1931
	(-14.02)***	(-11.16)***	(-10.44)***	(-12.57)***
MB	0.8623	0.4820	0.8495	0.4910
	(42.71)***	(20.56)***	(37.59)***	(18.11)***
Sale	-0.1353	0.0379	-0.1256	0.0432
	(-35.94)***	(8.80)***	(-30.88)***	(9.02)***
AP2S	0.0002	-0.0016	-0.0081	-0.0077
	(0.24)	(-1.66)*	(-6.94)***	(-5.34)***
AR2S	-0.0768	0.0319	-0.0355	0.1220
	(-1.54)	(0.59)	(-0.62)	(1.96)*
Firm Age	-0.0047	-0.0094	-0.0039	-0.0089
	(-9.63)***	(-16.20)***	(-7.49)***	(-14.19)***
ROA	-0.5227	-0.2223	-0.7730	-0.2944
	(-20.65)***	(-7.77)***	(-22.88)***	(-7.25)***
Nobs	46943.0	46943.0	46943.0	46943.0
R-Squared	0.3736	0.1031	0.3700	0.1116

Table 8

Influence of Chain Leverage on Upstreamness Effect

This table presents the estimated regression coefficients of the two default risk measures for firm upstreamness and the interaction effects on chain characteristics. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure of Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. $UPST_{ew}$ is the simple average distance to the downstream firms across all supply chains. $UPST_{sw}$ is the weighted average distance to the downstream firms across all supply chains, which uses the sales of a firm's direct customer in each chain as weights. To measure chain leverage, we calculate the average debt-to-asset ratio of all firms within each chain. We then average all the calculated results across all chains that a firm belongs to as the chain-leverage measure for that firm (Chain_Lev). We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). We use a regression model to estimate the coefficients by considering both time and industry-fixed effects. The numbers in parentheses are the *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	Camp	EDF	Camp	EDF
$UPST_{ew}$	0.0201	0.0036		
	(10.10)***	(1.69)*		
$UPST_{sw}$			0.0290	0.0073
			(12.95)***	(2.92)***
$UPST_{ew}$ *Chain_Lev	-0.0031	0.0102		
	(-1.36)	(4.18)***		
$UPST_{sw}$ *Chain_Lev			0.0009	0.0140
			(0.35)	(4.74)***
Chain_Lev	-0.0310	-0.0070	-0.0207	-0.0295
	(-4.32)***	(-0.91)	(-1.97)**	(-2.56)**
MB	0.8168	0.4084	0.7675	0.4472
	(43.21)***	(19.99)***	(38.72)***	(20.20)***
Sale	-0.0770	-0.0183	-0.0598	-0.0136
	(-17.25)***	(-3.73)***	(-14.03)***	(-2.81)***
AP2S	-0.0036	-0.0049	-0.0127	-0.0099
	(-4.22)***	(-5.12)***	(-12.00)***	(-8.22)***
AR2S	0.0227	0.0257	0.0552	0.0556
	(1.32)	(1.37)	(2.63)***	(2.37)**
Firm Age	-0.0090	-0.0082	-0.0076	-0.0078
	(-27.34)***	(-23.03)***	(-22.69)***	(-20.88)***
ROA	-1.1388	-0.4629	-1.4126	-0.5084
	(-54.23)***	(-20.93)***	(-55.46)***	(-17.89)***
Nobs	47302.0	47302.0	47302.0	47302.0
R-Squared	0.2447	0.0779	0.2565	0.0796

Table 9

Influence of Chain Diversification on Upstreamness Effect

This table presents the estimated regression coefficients of the two default risk measures for firm upstreamness and the interaction effects on chain characteristics. The measures for default risk are the expected default frequency (EDF) of Bharath and Shumway (2008) and the default risk measure of Campbell et al. (2008). Both default risk measures are standardized to have a mean of 0 and a standard deviation of 1. $UPST_{ew}$ is the simple average distance to the downstream firms across all supply chains. $UPST_{sw}$ is the weighted average distance to the downstream firms across all supply chains, which uses the sales of a firm's direct customer in each chain as weights. To measure chain diversification, we calculate the number of industries within each chain. We then average all the calculated results across all chains that a firm belongs to as the chain diversification measure for that firm (Chain_indN). We include common firm characteristics that influence firm default risk as control variables, including the log of sales, market-to-book ratio (MB), firm age, return on assets (ROA), the ratio of accounts payable to sales (AP2S), and the ratio of accounts receivable to sales (AR2S). We use a regression model to estimate the coefficients by considering both time and industry-fixed effects. The numbers in parentheses are *t* values. *, **, and *** indicate statistical significance at 10%, 5%, and 1% confidence levels, respectively.

	Camp	EDF	Camp	EDF
$UPST_{ew}$	0.0197	0.0319		
	(2.62)***	(3.66)***		
$UPST_{sw}$			0.0027	0.0428
			(0.29)	(3.88)***
$UPST_{ew}$ *Chain_indN	-0.0037	-0.0079		
	(-1.95)*	(-3.60)***		
$UPST_{sw}$ *Chain_indN			-0.0004	-0.0093
			(-0.18)	(-3.52)***
Chain_indN	0.0305	0.0466	0.0210	0.0494
	(3.81)***	(5.02)***	(1.99)**	(3.91)***
MB	0.8660	0.4880	0.8538	0.5028
	(42.18)***	(20.48)***	(37.22)***	(18.18)***
Sale	-0.1923	-0.0279	-0.1710	-0.0212
	(-58.39)***	(-7.36)***	(-46.80)***	(-4.88)***
AP2S	-0.0006	-0.0026	-0.0089	-0.0088
	(-0.80)	(-2.69)***	(-7.49)***	(-6.00)***
AR2S	-0.0618	0.0444	-0.0350	0.1206
	(-1.22)	(0.81)	(-0.60)	(1.89)*
Firm Age	-0.0047	-0.0094	-0.0041	-0.0094
	(-9.44)***	(-16.11)***	(-7.90)***	(-14.75)***
ROA	-0.5364	-0.2390	-0.7953	-0.3212
	(-20.86)***	(-8.23)***	(-23.20)***	(-7.76)***
Nobs	46943.0	46943.0	46943.0	46943.0
R-Squared	0.3544	0.0766	0.3526	0.0778

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