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Abstract

Using a panel of Credit Default Swap (CDS) spreads and supply chain links, we observe that both favorable and unfavorable credit shocks propagate through supply chains in the CDS market. Particularly, the three-day cumulative abnormal CDS spread change ($CASC$) is 63 basis points for firms whose customers experienced a CDS up-jump event (an adverse credit shock). The value is 74 basis points if their suppliers experienced a CDS up-jump event. The corresponding three-day $CASC$ values are -36 and -38 basis points, respectively, for firms whose customers and suppliers, respectively, experienced an extreme CDS down-jump event (a favorable credit shock). These effects are approximately twice as large for adverse credit shocks originating from natural disasters. Credit shock propagation is absent in inactive supply chains, and is amplified if supply-chain partners are followed by the same analysts. Industry competition and financial linkages between supply chain partners, such as trade credit and large sales exposure, amplify the shock propagation along supply chains. Strong shock propagation persists through second and third supply-chain tiers for adverse shocks but attenuates for favorable shocks.

JEL classification: E43, E51, G12, G14, G23, G24, G32, L11, L22.

Keywords: supply chains, credit risk, CDS, propagation, supply networks.

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1. Introduction

The propagation of financial shocks significantly affects the economy, as documented in the literature and witnessed during the recent financial crisis (Hertzel, Li, Officer, and Rodgers, 2008; Longstaff, 2010; Campello, Giambona, Graham, and Harvey, 2011; Yellen, 2013; Glasserman and Young, 2016; and Azizpour, Giesecke, and Schwenkler, 2018). Supply chains are a likely channel through which financial shocks spread. Supply chains enable flows of physical products and services downstream towards customers, and financial flows upstream towards manufacturers and the producers of raw materials. Alongside physical and financial flows are informational flows, which reflect demand forecasts, production capabilities, and the financial strength of companies.

Information is exchanged not only between supply chain partners, but also among their investors. For example, if the financial health of a supplier firm improves, its credit default swap (CDS) spread decreases, which signals the holders of a customer's CDS that it is less likely that the supplier will go bankrupt, leading to a decrease in the customer's CDS spread. Figure 1 illustrates how supply chains connect securities in the CDS market. It displays the 5-year CDS spreads for American Axle & Manufacturing Inc. (AXL), the Ford Motor Company (F), and the Advanced Micro Devices, Inc. (AMD), between October 1, 2008 and December 31, 2008. American Axle is a supplier of Ford; however, Advanced Micro Devices, a semiconductor manufacturer, has no buyer-supplier relationship with either American Axle or Ford. On November 21, 2008, Ford reported a $3 billion operating loss, and announced layoffs and a reduction in capital spending.[1] Ford's CDS spread increased sharply between November 18th and November 24th, 2008. American Axle likewise experienced a large increase in its CDS spread at about the same time (between November 19th and November 25th, 2008), but AMD's CDS spread did not show any significant change.

[Insert Figure 1 near here]

In this paper, we (1) investigate supply chains as a channel for credit shock propagation in the CDS market, and (2) examine which characteristics of credit shocks, firms, and supply chains influence this propagation.

[1]See http://money.cnn.com/2008/11/07/news/companies/automakers_3q_results/index.htm.

We define credit shock propagation as the CDS market reaction to credit events observed in the CDS market. We focus on the CDS market reaction for two reasons. First, the CDS market is important for corporate decision-making, investments, and overall economic stability. As indicated in Subrahmanyam, Tang, and Wang (2017), chief financial officers consider CDS market developments in their decision-making process. Stulz (2010) points out that the shock propagation in the CDS market was one of the drivers of the recent financial crisis. Second, although previous studies have linked supply chains with the stock market (Cohen and Frazzini, 2008; and Hertzel et al., 2008) and the bond market (Giesecke, 2004; Cen, Dasgupta, Elkamhi, and Pungaliya, 2015; Gençay, Signori, Xue, Yu, and Zhang, 2015; and Houston, Lin, and Zhu, 2016), little is known about the role of supply chains in the context of the CDS market.

We use the CDS market to identify credit events. More specifically, we calculate daily cumulative abnormal CDS spread changes (adjusting for the spreads of industry-rating-matched portfolios) and define extreme CDS jump events based on the high and low percentiles of these values (similar to Jorion and Zhang, 2007; and Hertzel et al., 2008). Using the CDS market to define credit events has three advantages. First, cumulative abnormal CDS spread changes reflect a multitude of credit events.[2] Second, we can study both favorable and adverse credit shocks, whereas in the literature on bankruptcy announcements, the shocks can only be adverse. Third, the CDS market is more liquid than bond markets and CDS spreads incorporate news faster than credit ratings, bond yields, or bankruptcy filings (Lee, Naranjo, and Velioglu, 2017; Blanco, Brennan, and Marsh, 2005; Stulz, 2010; Jorion and Zhang, 2007; and Lee et al., 2017). Therefore, extreme cumulative abnormal CDS spread changes are more likely to reflect unanticipated events in a timely manner.

We build a panel of daily CDS spreads observations for the period April 2003 through December 2014, by merging CDS and supply-chain-links data (the details regarding which are in §3). In the following, a supply chain link (also known as a dyad) is defined as a pair of companies, where one of the companies supplies products or services to the other.

[2] Table A1 presents the commonly observed firm events around the CDS jump events. This list is compiled using a LexisNexis search for news stories that happened during a period of 20 days around the first CDS jump event in a three-month window. Examples of firm events include defaults on debt payments, debt refinancing or restructuring, job cuts and layoffs, lawsuits or lawsuit settlements, factory or store closings, expansions into new products or markets, mergers and acquisitions, changes in earnings, and management turnovers.

Using this panel, we answer the first research question by observing that credit shocks propagate in the CDS market along supply chains (see §4). We find that the three-day cumulative abnormal CDS spread change ($CASC$) is 74 basis points for firms whose suppliers had an extreme CDS up-jump event. The three-day $CASC$ is 63 basis points if customers had an extreme CDS up-jump event. Similarly, the three-day $CASC$ is -38 basis points if suppliers had a CDS down-jump event and is -36 basis points if customers had a CDS down-jump event.

The shock propagation is economically significant. In particular, for comparison, the sample average $CASC$ is zero, and the sample average CDS spread (not-adjusted for industry-rating-matched CDS portfolios) is 157 basis points. Relative to the latter, the cumulative abnormal CDS spread changes in response to suppliers' and customers' extreme CDS up-jump events are 47% and 40%, respectively. The cumulative abnormal CDS spread changes in response to suppliers' and customers' extreme CDS down-jump events are -24% and -23%, respectively.

Next, we use natural disasters as a source for idiosyncratic, firm-level shocks following the frameworks in Barrot and Sauvagnat (2016) and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020). We collected data for natural disasters and for locations of firms' establishments to identify CDS jumps originating from natural disasters. We took measures as in Barrot and Sauvagnat (2016) and Carvalho et al. (2020) to ensure that these CDS jumps do not reflect any information common to product networks but are caused by idiosyncratic firm-level shocks. Consistent with our main results, there is significant credit shock propagation both upstream and downstream along supply chains (three-day cumulative abnormal CDS spread changes are between 167 basis points and 215 basis points). The propagation of credit shocks is economically significant. The three-day cumulative abnormal CDS spread changes at supply chain partners are at least 70% of the sample average CDS spread of 157 basis points. That is, the reaction to CDS jumps originating from disasters is approximately twice as strong as the reaction reported in our main analysis.

To further confirm that credit shock propagation through active supply chains is not driven by latent factors, which would be present regardless of the status of the supply chain relationship, we conduct several tests with supply chain links that are not active at the time of the CDS jump event. First, we run a placebo test using all inactive supply chains in the sample. Second, we select a subset of inactive links by matching simultaneously supplier and customer attributes of inactive and active links. The attributes are: size, leverage, Tobin's q, and Fama-French 12 industries, which reflect business model and product market characteristics (Chevalier, 1995; MacKay and Phillips, 2005; Hoberg and Maksimovic, 2021, and the references therein). This analysis mitigates the potential concern that the lack of shock propagation along inactive supply chain links may be due to different industry or product-market environments faced by firms in active and inactive links. Third, we analyze a subsample of links that became inactive following natural disasters. Such links are inactive due to firm level, exogenous shocks. Fourth, we study propagation of credit shocks originating from natural disasters through inactive supply chain links.

In all four versions of the inactive link analyses, we observe no credit shock propagation through inactive supply chains. These tests, combined with results for the active supply chain links, point out that credit shocks transmit through active supply chain links and the shock transmission is causal, not driven by latent factors.

To explore the informational channel of shock propagation, we augment our specification with indicator variables for when stock analysts are following both supply-chain partners, and find that this factor has a substantial effect. The shock propagation is at least 31% stronger if both supply-chain partners are being followed by the same analysts. Thus, credit shock propagation through supply chains becomes more pronounced when information about supply chains improves.

Further exploring the second research question, we find that trade-credit and customer-sales-percentage attributes have the largest economic effect on the credit shock propagation—both attributes proxy for close financial ties between supplier and customer firms. Industry competition is another important consideration. Product-similarity and low industry-concentration attributes amplify credit shock propagation through supply chains. We identify other attributes, in addition to those reflecting financial ties and industry competition, that affect the propagation intensity.

We estimate credit shock propagation to not only immediate supply chain partners, but also to second- and third-tier customers and suppliers. We find that the credit shock propagation is not purely mechanical, thus expected to diminish as one moves further away from the source of the shock along supply-chain tiers. Instead, for adverse shocks, the propagation is equally strong for all tiers, while for favorable credit shocks, the propagation attenuates for higher tiers.

We consider several alternative specifications (§5). We control for the correlation between supplier and customer daily changes in CDS spreads,[3] in order to consider transitory factors that are more frequent than the annual ones that are captured by supplier-customer-year fixed effects. In another specification, we apply Lewbel's (2012) instrumental variables approach for identification in order to address causality concerns. This approach allows for the existence of unobserved common shocks, and constructs instruments from the data based on the heteroscedastic error restrictions. We further test our findings using a model-free, event-study setup, a firm-level panel estimation, and a triad-level panel estimation.[4] We observe credit shock propagation for all of these alternative specifications. We perform numerous robustness checks (§6), such as examining sub-periods before, during, and after the financial crisis; limiting credit shock events to credit rating changes; using alternative definitions for credit-shock events, and alternative active supply chains link sample. Our findings are robust for all checks. We summarize the main takeaways in §7.

2. Literature

We contribute to the literature on supply chains as channels for information in financial markets. This literature has focused on adverse events, such as bankruptcies, defaults, credit rating downgrades, and natural disasters (e.g., Hertzel et al., 2008; Houston et al., 2016; Jacobson and Schedvin, 2015; Chang, Hung, and Tsai, 2015; Chen, Zhang, and Zhang, 2016; Kolay, Lemmon, and Tashjian, 2016; Barrot and Sauvagnat, 2016; Hendricks, Jacobs, and Singhal, 2017; and Carvalho et al., 2020). Here, we investigate both favorable shocks and adverse shocks, and find that adverse shocks propagate persistently, while favorable shocks attenuate, through higher supply-chain tiers.

We observe that the CDS market pays close attention to supply chains, contrary to Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Wu and Birge (2014), who found that limited attention was paid to supply chains in the equity market. Our study is thus consistent with the argument that the CDS market is more efficient than equity markets, particularly with respect to

[3]This is similar to Lang and Stulz (1992), who include correlation in order to capture similarities in cash flows.

[4]The unit of baseline analysis is a dyad, i.e., a supplier-customer pair. A triad is a triple: a supplier of a firm, the firm, and a customer of the firm.

credit events (Acharya and Johnson, 2007; Blanco et al., 2005; Lee et al., 2017; Zhang, 2009; and Zhang and Zhang, 2013). For example, Zhang (2009) reports that, relative to CDS prices, stock prices overreact to news of SEC probes, but underreact to financial-distress news. Zhang and Zhang (2013) show that earnings-surprise reactions result in post-announcement drifts in stock prices, but not in CDS prices. Our findings also align with the literature on the importance of analyst coverage for information diffusion (Guan, Wong, and Zhang, 2015; and Cen, Hertzel, and Schiller, 2017a).

Our paper adds to the literature on the role of input-output links during natural disasters. Among papers in this literature, Barrot and Sauvagnat (2016) and Carvalho et al. (2020) study the effect of natural disaster shocks on sales growth of supply chain partners, and the effect of these spillovers on aggregate GDP growth. While using a similar setting, we focus on credit shocks originating from natural disasters and study how such shocks propagate along supply chains in the CDS market through multiple supply chain tiers. Additionally, we use locations of firms' establishments instead of just headquarters as in Barrot (2016) to identify shocks' origins, which allows us to examine the role of disruptions to production and distribution facilities in credit shock propagation.

Researchers have studied how network characteristics, such as network centrality (Wu and Birge, 2014; and Yang and Zhang, 2016), customer concentration (Cen, Maydew, Zhang, and Zuo, 2017b; and Campello and Gao, 2017), customer relationships (Cen et al., 2015), leverage and implied volatilities of customers and suppliers (Gençay et al., 2015), and network distances from event firms (Wu, 2015) affect the revenues, valuation, and creditworthiness of firms. We also consider various supply-chain-network, firm, and shock characteristics, though we study a different market (the CDS market) and use forward-looking metrics (CDS spreads).

Finally, this paper contributes to the credit-risk contagion literature. In this literature, Lang and Stulz (1992) demonstrate the effect of bankruptcy announcements on the stocks of firms that are in the same industry as the firm that went bankrupt. Hertzel and Officer (2012) find higher spreads on loans in industries that are going through bankruptcy waves. Das, Duffie, Kapadia, and Saita (2007), Collin-Dufresne, Goldstein, and Helwege (2010), and Duffie, Eckner, Horel, and Saita (2009) provide empirical evidence for contagion in corporate bond defaults. Jorion and Zhang

(2007) show that bankruptcy announcements affect the CDS spreads of firms in the same industry.

Several studies have investigated trade credit relationships as constituting a credit risk shock propagation channel. Jorion and Zhang (2009) show that the bankruptcy event experienced by a customer has a significant contemporaneous effect on the abnormal stock return and cumulative adjusted CDS spread change of the customer's trade creditors. Boissay and Gropp (2013) show that firms facing payment defaults from their trade credit partners are more likely to default themselves if they are credit constrained. Costello (2018) reports liquidity spillovers from suppliers to trade-credit borrowers during the financial crisis period. Our paper contributes to this literature by examining CDS shock propagation through supply chains, across multiple tiers, and for both favorable and adverse credit shocks.

3. Data, variable definitions, and sample construction

We use the Markit CDS data from April 2003 to December 2014 to define abnormal spreads and cumulative abnormal CDS spread changes ($CASC$), as well as to introduce CDS jump events (see §3.1). We construct our sample as a panel of daily $CASC$ observations merged with FactSet Revere supplier-customer-links data (see §3.2). This panel consists of approximately 2 million observations, with the unique identifier being a supplier-customer-date triple (s, c, t). The panel contains 3,222 unique supplier-customer links (s, c), formed from 653 unique firms f (where a firm appears either as a supplier, $f = s$, or a customer, $f = c$). We augment this panel with information about firm and industry attributes, as well as supply-chain network characteristics (see §3.3).

3.1. The Credit Default Swap dataset

The Markit dataset provides daily (end-of-day) quotes of CDS spreads for US corporate obligators and other entities that issue or guarantee obligations. In this paper, we use 5-year spreads because these contracts are considered to be the most liquid, and they constitute the majority of the CDS market (Jorion and Zhang, 2007; Berndt, 2015; and Lee et al., 2017). The Markit CDS dataset describes 830 obligators for our sample period. Our sample of 653 firms then covers approximately 80% of the obligators in Markit. The sample period April 2003 - December 2014 contains approximately 985,000 daily observations of CDS spreads.

Panel A in Table 1 shows sample statistics for the daily CDS spreads by year. The sample average daily CDS spread is 157 basis points, with significant cross-sectional and time variations.[5]

[Insert Table 1 near here]

The main variable in our analysis is the cumulative abnormal CDS spread change ($CASC$), which reflects CDS spread changes after controlling for systematic market conditions. We compute this variable as follows: Let variable S_{ft} denote the CDS spread of firm f at the end of day t. We define the implied-industry-rating-adjusted, abnormal CDS spread of firm f on day t as $AS_{ft} = S_{ft} - I_{rt}$, where I_{rt} is the value on day t of the equally-weighted CDS index of a portfolio of firms with the same Markit-provided, implied rating r, as the rating for firm f on day $t-1$.[6] In the following, for brevity, we shall refer to the implied-industry-rating-adjusted, abnormal CDS spread as the abnormal spread (AS). We define cumulative abnormal spread change ($CASC$) for firm f over the time interval $[t+a, t+b]$ as $CASC_{ft}[a,b] = AS_{ft+b} - AS_{ft+a}$. For example, the one-day cumulative abnormal CDS spread change for firm f on date t is $CASC_{ft}[-1,0]$, which captures the change from the end-of-day for date $t-1$ to the end-of-day for date t. It is important to emphasize that large $CASC$ values over short time windows represent significant and rapid changes in the CDS levels, and therefore are economically important.

Panel B of Table 1 presents the summary of the daily, cumulative abnormal CDS spread changes,

[5] The Markit dataset reports a maximum spread of 194,800 basis points for the Financial Guarantee Insurance Co (FGIC) in March of 2010. The FGIC Co declared bankruptcy on August 4th of 2010. Because spreads are reported in annualized terms, it is possible for spread values to exceed 10,000 basis points. As a hypothetical example, imagine that a bond default is imminent within one day and that the recovery rate is zero. The CDS protection over this time then should be 100% of the par value, or 10,000 basis points. This translates into an annualized value of 3,600,000 basis points, using 360-business-days convention. In our sample, the average CDS spread of AAA- and AA-rated reference entities is approximately 60 basis points. The average CDS spread of B- or below-rated reference entities is approximately 638 basis points. The mean CDS spread peaked at 341 basis points in 2009. The nadir of the mean CDS spread was 85 basis points, as observed in 2007.

[6] The purpose of using date $t-1$ instead of date t is to avoid an endogenous change in the implied rating. We use Markit's implied rating because it is recomputed more frequently than the credit ratings provided by rating agencies. Markit's implied credit-rating is derived based on single-name, 5-year, daily CDS spreads and the associated CDS sector curve spreads. The description of Markit's implied-rating variable in WRDS is as follows: "[the implied rating is] calculated on a weekly basis by comparing the issuer's 5Y senior standard trading convention spread to the 5Y spreads of our sector curves and applying the rating of the logarithmically nearest rating curve specific to that sector." According to Markit, the sectors are: Basic Materials, Consumer Goods, Consumer Services Energy, Financials, Government, Healthcare, Industrials, Technology, Telecommunications Services, and Utilities (see https://www.markit.com/Product/File?CMSID=368ae091505d401a80660456ba504930)). Hence, the industry effect is reflected in this variable.

$CASC_{ft}[-1,0]$, for all firms f and dates t in the sample. The mean and the median of this variable are around zero (as one would expect, given the definition of $CASC$). The 25th and 75th percentiles for the sample are -0.75 and 0.78 basis points, respectively. The 0.1th and 99.9th percentiles are -92.49 and 90.02 basis points, respectively.

We define extreme *up-jump events* as $CASC_{ft}[-1,0]$ values above the 99.9th percentile of all daily $CASC$ values in the Markit CDS dataset over the sample period. Similarly, we define extreme *down-jump events* as $CASC_{ft}[-1,0]$ values below the 0.1th percentile of all daily $CASC$ values in the Markit CDS dataset over the sample period. We use the entire Markit dataset, rather than just our sample, so as to avoid tying the definition of events to the source of supply chain data.[7] Our definition is similar to that used in Jorion and Zhang (2007), who defined events using daily cumulative CDS spread changes (CSC),[8] and used 0.1th and 99.9th percentiles. Our approach is more conservative, because, by considering the $CASC$ instead of the CSC, we account for deviations from an industry-rating-adjusted benchmark.

Panel C of Table 1 presents the summary of the CDS jump events. There are $1,038$ up-jump events, and $1,063$ down-jump events in our sample. The means for the cumulative abnormal CDS spread change values corresponding to jump-up and down-jump events are $1,477$ and $-1,294$ basis points, respectively, with significant variation.[9]

Panel D of Table 1 presents the frequencies of CDS jump events per year. There are few CDS jump events for 2005-2006, and relatively many for 2008-2009 (i.e., during the financial crisis) and for 2010. In our robustness checks (§6.1), we investigate whether clustering of credit events may affect our results, and find that our results are general, and are not driven by the crisis period.

[7] We repeat the analysis after defining jumps from the sample data, i.e., the intersection of CDS data with supply-chain-links data. The results are comparable to those presented here.

[8] Jorion and Zhang (2007) define the cumulative CDS spread change (CSC) for firm f for the time interval $[t+a, t+b]$ as $CSC_{ft}[a,b] = S_{ft+b} - S_{ft+a}$. We repeat our analysis using the same jump definitions as introduced by Jorion and Zhang (2007). Our findings are even stronger when using their definitions.

[9] The smallest $CASC_{ft}[-1,0]$ value, corresponding to a up-jump event, is 402 basis points. The largest $CASC_{ft}[-1,0]$ value, corresponding to a up-jump event, is $158,706$ bps. It was recorded for the Financial Guarantee Insurance Co (FGIC) on March 4, 2010. The smallest absolute $CASC_{ft}[-1,0]$ value, corresponding to a down-jump event, is 364 basis points. The largest absolute $CASC_{ft}[-1,0]$ value, corresponding to a down-jump event, is $141,177$ bps. It was also recorded for the FGIC Co in July of 2010. The FGIC Co suffered significant losses on mortgage insurance contracts during the financial crisis, and had to declare bankruptcy on August 4, 2010. During the reorganization, the FGIC Co conducted a debt-to-equity swap, whereby the FGIC Co paid debt holders all of the company's cash and shares in the reorganized company (Fung, 2010). The unsecured debt holders were thus made whole, which resulted in the extreme drop in the CDS spread on FGIC's bonds.

3.2. *The supply chain datasets*

We use two supply chain datasets: the FactSet Revere and the Compustat Segment. The FactSet Revere is our main dataset because it offers better coverage of supply chains over time, compared with the Compustat Segment, which has been traditionally used in the literature. We use the Compustat Segment dataset as the sales data source and for robustness tests.

FactSet Revere hand-collects and verifies supply chain relationship information using various sources: 10-K filings, conference call transcripts, presentations to investors, company press releases, company websites, and major news-media reports. In contrast, the Compustat Segment relies on self-reporting by companies, in compliance with SEC regulation SFAS 131 (which superseded SFAS 14), to report customers that account for more than 10% of the revenues. All supply-chain links in the Compustat Segment dataset are also present in the FactSet Revere dataset. The FactSet Revere dataset contains approximately 20,000 supply-chain links per year (because links form and dissolve over time, we report these statistics per year). For comparison, the Compustat Segment dataset has only approximately 2,000 links per year. The number of firms in the FactSet Revere dataset varies between 5,500 and 8,000 per year, whereas the number of firms in the Compustat Segment dataset varies between 1,400 and 2,000 per year (Table 1, panel E).

Compared with FactSet Revere, the Compustat Segment dataset is biased towards links between smaller suppliers and larger customers. As shown in Panel F of Table 1, in the Compustat Segment dataset, the average number of customers (2.02) is much smaller than the average number of suppliers (11.08). In the FactSet Revere dataset, the average number of customers (21.20) is approximately the same as the average number of suppliers (29.76).[10]

One advantage of the Compustat Segment dataset is that it contains sales information. Due to the data collection process of FactSet Revere, sales information is not universally available for that dataset. Therefore, we use the Compustat Segment sales data when needed.

The Compustat Segment dataset has been used in a number of prior studies. Our work adds to the literature by introducing a more extensive supply chain network dataset—FactSet Revere.

[10]More details on the FactSet Revere dataset coverage and its strength and weaknesses, relative to the Compustat Segment dataset can be found in Deutsche Bank Markets Research Paper "The Logistics of Supply Chain Alpha," available at `https://www.longfinance.net/media/documents/DB_TheLogisticsofSupplyChainAlpha_2015.pdf`.

3.3. *Firm and supply chain attributes*

We consider a number of firm and supply chain attributes that may affect the response in the CDS market to credit shocks in supply chains. The definitions of variables capturing these attributes are in Table A2 (Appendix), while the summary statistics are in Table 1, panel G. The sample consists of firms with different characteristics. We have both low and high growth firms, as well as firms with different levels of leverage, size, working capital, inventory, and product differentiation. The supply-chain networks comprising the sample differ in the duration of supplier-buyer relationships and with regard to node centrality.

4. Credit shock propagation through supply chains

For the initial analysis, we begin with a model-free, event-study setup. For each extreme CDS jump event (defined in §3), we compute the one-day cumulative abnormal CDS spread changes (as discussed in §3) of the equally-weighted portfolios of the customers and suppliers of the event firm.[11] Figure 2 illustrates the CDS market reaction to extreme CDS jumps in supply chains, with panel A displaying reactions to up-jump events, and panel B to down-jump events. This figure shows a strong response from customers and suppliers of the event firm in the same direction as the jump events on the event day (Table A3 in the Appendix presents additional event study results, for up to 20 days after the event).

[Insert Figure 2 near here]

These event study results invite further analyses using a panel-estimation approach, which allows us to control for supplier-customer-year effects, and which facilitates the investigation of the firm and supply-chain-link attributes that may affect credit shock propagation. We discuss our findings from the panel estimations as follows: Section 4.1 contains our baseline results. Section 4.2 presents a natural disaster setting. Section 4.3 provides the analysis with supply chains that are no longer active. Section 4.4 highlights the informational channel by investigating the effect of

[11] That is, if the event is date t, then for a portfolio P_t of either suppliers or customers of the event firm (as of date t), we compute $CASC_{P_t t+\tau}[-1,0] = \frac{1}{|P_t|}\sum_{f\in P_t} CASC_{ft+\tau}[-1,0]$, for $\tau \in \{-5,...,5\}$, where $|P_t|$ is the number of firms in portfolio P_t.

analysts following supply-chain links. Section 4.5 explores how firm and supply-chain attributes affect credit shock propagation. Section 4.6 presents the results related to credit shock propagation through higher supply-chain tiers.

4.1. Baseline panel estimation results

Our main specification is based on a supply-chain-links panel.[12] Our unit of analysis is a supplier-customer-date triple (s, c, t), where s is the supplier of customer c on date t during the sample period April 2003 - December 2014. Equation (1a) below models the suppliers' reaction to customers' CDS jumps, while equation (1b) models the customers' reaction to suppliers' CDS jumps.

$$\begin{aligned} CASC_{st}[-1, a] =& \beta_0 + \beta_1 General\ Up\ (Down)\ Jump_t \\ & + \beta_2 Customer\ Up\ (Down)\ Jump_{ct} + \gamma_{scy(t)} + \varepsilon_{sct} \end{aligned} \tag{1a}$$

$$\begin{aligned} CASC_{ct}[-1, a] =& \beta_0 + \beta_1 General\ Up\ (Down)\ Jump_t \\ & + \beta_2 Supplier\ Up\ (Down)\ Jump_{st} + \gamma_{scy(t)} + \varepsilon_{sct} \end{aligned} \tag{1b}$$

The dependent variables are the cumulative abnormal CDS spread changes $CASC_{ft}[-1, a]$ (defined in §3) of either the customer or the supplier firm $f \in \{s, c\}$ in the supply-chain link (s, c). We consider specifications with $a = 0$, 1, and 2, corresponding to 1-day, 2-day, and 3-day cumulative abnormal CDS spread changes, respectively. Variable $Customer\ Up\ (Down)\ Jump_{ct}$ for customer firm c in the link (s, c) is an indicator of the customer's extreme CDS up-(down-) jump event on date t. Variable $Supplier\ Up\ (Down)\ Jump_{st}$ is defined similarly for the supplier's jump events. Variable $General\ Up\ (Down)\ Jump_t$ is an indicator of an extreme up-(down-) CDS jump on date t for any firm in Markit dataset. In addition, we have considered lagged indicator variables for general and supply-chain-partner jumps (not reflected in equations (1a) and (1b)). Each panel estimation controls for customer-supplier-year fixed effects ($\gamma_{scy(t)}$), which should alleviate the concern that CDS jump events may capture latent factors in the annually-varying supply-chain-

[12] As we argue in §5.3, this is a natural specification for studying supply chains. We have also considered firm-level and triad-level panel setups, which generated similar insights.

link or firm characteristics. In $\gamma_{scy(t)}$, function $y(t)$ computes the year that contains date t. All panel estimations are carried out using robust standard errors, clustered at the supply-chain-year level. Table 2 presents the results.

[Insert Table 2 near here]

As panels A and B in Table 2 show, the abnormal CDS spreads of reference firms increase when there is a CDS up-jump event in their supply chains, whether upstream or downstream. Similarly, as panels C and D show, the abnormal CDS spreads of reference firms decrease when there is a CDS down-jump event in their supply chains. For all specifications, the coefficients for the supply-chain-jump indicators are substantially larger than those for general-jump indicators. For example, in column (1) of panel A, the supplier's cumulative abnormal CDS spread change from day -1 to day 0 is 1.34 basis points (bps), in response to the general up-jump event, and is 59 bps in response to the customer's up-jump event. Recall that the sample average cumulative abnormal CDS spread change is zero bps, and that the sample average level of CDS spreads (i.e., not adjusted by the industry-rating portfolio) is 157 bps. Relative to the latter, the effect of a general jump event is 1%, and the effect of a customer's jump event is 38%. Similarly, as indicated in column (1) of panel B, while the effect of a general up-jump event is negligible, a supplier's up-jump event increases the customer's abnormal CDS spread by 71 bps, i.e., by 45% relative to the sample average CDS spread level. Credit shock propagation in the supply chain is similarly strong for favorable credit events (i.e., down-jumps). As indicated in column (1) of panel C, the supplier's cumulative abnormal CDS spread change is -1.54 bps, in response to a general down-jump event, and is -44.3 bps, in response to a customer's down-jump event. Relative to the sample average CDS spread level, these reactions are -1% and -27%, respectively. In column (1) of panel D, the customer's cumulative abnormal CDS spread change is -58.9 bps, in response to a supplier's down-jump event, i.e., -37% of the sample average CDS spread level. Together, these results indicate substantial credit shock propagation through supply chains in the CDS market.[13]

[13]In the panel estimations, R-squared turns out to be small. This is to be expected, because there is little variation in the independent variables,—i.e., the jump event indicators, relative to the dependent variables ($CASC$)—after controlling for customer-supplier-year effects. The statistical significance tests indicate that even these small variations in independent variables are of critical importance.

4.2. Firm-level idiosyncratic shocks: natural disasters

We use idiosyncratic firm-level credit shocks originating from natural disasters to examine the propagation of these adverse shocks through supply chains in the CDS market. Our setting is similar to those by Barrot and Sauvagnat (2016) and Carvalho et al. (2020). Barrot and Sauvagnat (2016) study the propagation of shocks, caused by natural disasters in the U.S., from suppliers to customers. Carvalho et al. (2020) study how economic shocks caused by 2011 Great East Japan Earthquake propagate upstream and downstream in value chains. These studies investigate the effect of natural disaster shocks on sales growth and macroeconomic outcomes, whereas we focus on credit markets.

We retrieve county-level, natural disaster data from the Federal Emergency Management Agency (FEMA) and firms' establishment locations data from the Environmental Protection Agency (EPA). We identify CDS jumps originating from natural disasters using two levels of spatial dimension: at the county and at the state level. To define shocks at the county level, for each disaster event, we determine which establishments are in the disaster-affected counties, identify firms with these establishments, and use as credit events CDS up-jumps of these firms that occurred up to 15 days following the natural disaster event. The definition at the state level is similar, except that we determine which establishments are in the disaster-affected states instead of counties.[14] There are 166 CDS jumps defined at the county-level. When we determine these jumps at the state-level, there are 344 CDS jumps. These CDS jumps are a subset of the jumps considered in our baseline estimations. We then perform the analysis using these CDS jumps.

To control for the possibility that natural disasters may affect both supply chain partners of a given supply chain link at the same time, we apply two approaches: one used by Barrot and Sauvagnat (2016), and another one used by Carvalho et al. (2020). In the first approach, similar to Barrot and Sauvagnat (2016), we add an indicator variable in equations (1a) and (1b) that takes a value of one if the firm whose $CASC$ reaction we are measuring is affected by a natural disaster during the month that contains date t. This is the variable $Affected\ by\ Disaster_{fm(t)}$

[14] Barrot and Sauvagnat (2016) use company headquarters only; we consider firms' facility locations in addition to headquarters to capture effects of disruption at production and distribution facilities.

with $f \in \{s, c\}$ and $m(t)$ representing the month containing date t in the following equations.

$$\begin{aligned} CASC_{st}[-1,a] = &\beta_0 + \beta_1 General\ Up\ (Down)\ Jump_t \\ &+ \beta_2 Customer\ Up\ (Down)\ Jump_{ct} \\ &+ \beta_3 Affected\ by\ Disaster_{sm(t)} + \gamma_{scy(t)} + \varepsilon_{sct} \end{aligned} \tag{2a}$$

$$\begin{aligned} CASC_{ct}[-1,a] = &\beta_0 + \beta_1 General\ Up\ (Down)\ Jump_t \\ &+ \beta_2 Supplier\ Up\ (Down)\ Jump_{st} \\ &+ \beta_3 Affected\ by\ Disaster_{cm(t)} + \gamma_{scy(t)} + \varepsilon_{sct} \end{aligned} \tag{2b}$$

In the second approach, similar to Carvalho et al. (2020), we exclude from the sample supply chain links for which both partners are in the state affected by a natural disaster for a period of the disaster month and one month after that. Both approaches are incorporated in our analyses to ensure that CDS jumps are due to exogenous firm-level shocks originating from natural disasters, and thus we are measuring the propagation of idiosyncratic firm-level credit shocks.

Table 3, Panels A and B present the results of this analysis. For panel A, we used the county-level definition of CDS jumps originating from disasters (see the explanation above). For panel B, we used the state-level definition. In each panel, Columns (1)-(3) provide estimation results using approach with an indicator variable (equation (2)). Columns (4)-(6) present estimation results using the approach that excludes supply chain links for which both partners are in the state affected by a natural disaster.

[Insert Table 3 near here]

Consistent with our main results, there is significant credit shock propagation both upstream and downstream along supply chains. For example, as reported in panel A, column (3), the three-day cumulative abnormal CDS spread change is 121 basis points for firms whose customers had a CDS up-jump event and 167 basis points for firms whose suppliers had a CDS up-jump event, when using an indicator. These values are 215 basis points and 209 basis points, when excluding links that are in the same state as the firm establishment affected by a disaster (column (6)).[15]

[15] 215 basis points are significant at 5 percent and 210 basis point finding is significant at 12 percent.

Panel B shows comparable results for CDS jumps from natural disasters defined at the state level. The three-day cumulative abnormal CDS spread change is 113 basis points for firms whose customers had a CDS up-jump event and 155 basis points for firms whose suppliers had a CDS up-jump event, when using an indicator (column (3)). These values are 193 basis points and 230 basis points, when excluding links that are in the same state as the firm establishment affected by a disaster (column (6)).

The propagation of credit shocks is economically significant. The three-day cumulative abnormal CDS spread changes at supply chain partners are at least 70% of the sample average CDS spread of 157 basis points. That is, the reaction to CDS jumps originating from disasters is approximately twice as strong as the reaction reported in our main analysis (Table 2).

4.3. Inactive supply chains

4.3.1. Baseline setting

To explore whether credit shock propagation in the CDS market is explained by active supply chain relationships, and not by latent attributes of the supply chain partners, we run a placebo test with inactive supply chain links in equation (1). We follow the definition of Barrot and Sauvagnat (2016) in determining inactive supply chains. Formally, a supply chain link (s, c) is considered to be inactive on date t if: (i) it has been active any time during window $[t-\min(L, t-t_0), t-\min(l, t-t_0))$, and (ii) it has not been active during $[t-\min(l, t-t_0), t]$, where $L > l \geq 0$ are time intervals, t_0 is the earliest date in our sample, and $t > t_0$. For example, if $L = 5 \times 365$ and $l = 365$ days, a supply chains link is considered inactive if it had been active any time between 1 and 5 years in the past relative to date t and has not been active for the entire year before date t, if time interval $t - t_0$ is longer than 5 years. If the time interval $t - t_0$ is shorter than 5 years, the definition accounts for this by adjusting the interval over which active and inactive periods are observed. In the main tables of the paper we present the results when $l = 0$ and $L = \infty$, i.e., a link is defined as inactive if it has been active any time during window $[t_0, t)$ but is not active at date t.[16,17]

Table 4, Panel A, columns (1)-(3) present the results for the analysis with the full sample of inactive links.

[Insert Table 4 near here]

This analysis shows no credit shock propagation through inactive supply chains. Comparing these results with those for active supply chains (Table 2), we observe that both the statistical and the economic significance disappear. Our placebo setup is conservative because some links might still be active, even though they are not reported as such in the data.

To address possible concerns that lack of propagation along inactive links can be attributed to changes in the business environment, and changes in firm or product characteristics that make inactive links different from active ones, we perform further analysis on a sample of inactive links that are matched with active ones. We use the Coarsened Exact Matching method, which matches exactly on coarsened values of chosen covariates (Iacus, King, and Porro, 2012), and match simultaneously supplier and customer characteristics of a link, using the following variables: size, leverage, Tobin's q, and Fama-French 12 industries. These characteristics reflect business model and product market characteristics (Chevalier, 1995; MacKay and Phillips, 2005; Hoberg and Maksimovic, 2021 and the references therein). The coarsened sets are computed using a binning algorithm with Sturge's rule (Blackwell, Iacus, King, and Porro, 2009). Unmatched observations are not included in the analysis. Panel B of Appendix Table A5 reports mean difference tests between matched active and inactive supply chain partners, and shows that the matching process generates a subset of inactive links in which supplier and customer firms are similar to supplier and customers of active links, not only in matching covariates, but also in other firm attributes.

Table 4, Panel A, columns (4)-(6) present the results for the analysis with the matched sample of inactive links. Similar to the results for the full sample, there is no credit shock propagation along inactive links in the matched sample.

[16]Panel C of Table A5 presents the statistics for how long a supply chain partner has been inactive for the full sample used in Panel A of the same table. The average time that a partner has been inactive is approximately 3 years.

[17]Table A4 in the Appendix presents the results for $L = 5 \times 365$ and $l = 365$. The results for the other values for thresholds L and l are similar, and are not reported for the sake of brevity.

As an alternative approach to address the issue that links may have become inactive due to firms changing business models, we identified firms in our sample that changed industries, as indicated by the SIC4 industry code. In our sample, 34 out of 653 firms (around 5 percent) changed industries. Removing these firms and the corresponding links from our sample does not affect the results.[18]

4.3.2. Natural disaster setting

To further ensure that supply chain links became inactive due to exogenous factors, not due to potential endogenous supply chain dynamics or changing business models, we identified supply chain links that became inactive within a month following the natural disasters, using establishment location data. There are 170 unique inactive links due to natural disasters when natural disaster shock is defined at the state level. As reported in Table 4, Panel B, Columns (1)-(3), credit shock propagation is not observed for these links.[19]

To verify that supply chains are the channel of shock propagation, we carried out our analysis using firm-level CDS shocks originating from natural disasters (§4.2), but using the full sample of inactive supply chain links. The results, reported in Table 4, Panel B, Columns (4)-(6), show that there is no credit shock transmission through inactive supply chain links in response to firm-level, idiosyncratic credit shocks originating from natural disasters. This finding, combined with the propagation of such shocks through active links, is evidence in support of causal propagation of credit shocks through active supply chain links.

4.4. Analyst coverage of supply chain partners

Analysts may have private information about firms (Chen and Jiang, 2005). If the same analyst follows multiple firms, this creates an opportunity for information diffusion (Cohen and Frazzini, 2008; Guan et al., 2015; Agarwal, Leung, Konana, and Kumar, 2017; and Cen et al., 2017a). Motivated by this possibility, we study whether analysts following supply chain partners affect the propagation of credit shocks through supply chains. We use information about equity analysts

[18]These results are not reported for brevity and are available upon request.

[19]We also find no propagation in inactive links when natural disasters are determined at the county level instead of state level. These results are available upon request.

as reported in the I/B/E/S dataset. In our sample, analysts follow 88% of firms and 10% of supply-chain links.

We define three indicator variables for this analysis: *Analyst following supplier*, *Analyst following customer*, and *Analyst following link*, which equal 1 if analysts are following the supplier firm, the customer firm, or both simultaneously, respectively. We have these variables interact with the CDS jump indicators defined in §3.1. The results are in Table 5.

[Insert Table 5 near here]

Table 5 shows that the propagation of credit shocks through supply chains is stronger when supply chain partners are followed by the same analysts, even after controlling for analyst coverage in general. For example, in column (9) of Table 5, while a customer's up-jump event results in a supplier's cumulative abnormal CDS spread change of 84 bps, the value is 207 bps larger (making the overall response 3.5 times larger) if the same analysts are following both supply chain partners. Similarly, while the cumulative abnormal spread change is −46 bps for a customer's down-jump event, there is a further −180 bps effect (making the overall response 4.9 times stronger) if the same analysts are following both supply chain partners. The effect is present for shocks to supplier firms as well. The customer's cumulative abnormal CDS spread change in response to a supplier's down-jump event is −57 bps, with a further −75 bps effect if analysts are following both supply chain partners. The corresponding numbers for supplier's up-jump events are 27 bps and 47 bps, respectively, though these are not statistically significant. To summarize, the credit shock propagation is at least two times stronger than the average when analysts are following both supply chain partners.

The amplified reaction when supply chain partners are followed by the same analysts points towards the informational channel of shock propagation in the CDS market through supply chains. This indicates that our results are not a byproduct of a common shock, but rather reflect the propagation of firm level shocks through information flows along supply chains.

4.5. Firm and supply-chain attributes affecting credit shock propagation through supply chains

Firm characteristics, industrial organization and supply network attributes play an important role in the propagation of shocks in the product networks (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Baqaee, 2018; Bigio and La'o, 2020 and the references therein). In this subsection, we investigate how firm, industry and supply-chain attributes affect credit shock propagation through supply chains. Variable definitions are in Table A2 (Appendix). We begin by discussing the expected effects of these attributes.

At the firm level, the variables *network centrality* and *size* proxy for a firm's importance in a supply chain. One expects that important firms should be less sensitive to economic shocks originating in their supply chains. At the same time, any shocks occurring at these important firms should have a substantial effect on their supply chain partners.

Variable *Tobin's Q* proxies for growth opportunities. Firms with high *Tobin's Q* values are important supply chain partners with high growth potential. However, these firms may have low asset-replacement values, making them more sensitive to adverse credit shocks. Therefore, the expected effect of the *Tobin's Q* variable is ambiguous.

Credit risk is an important determinant of CDS spreads. To measure credit risk, we use the variables *investment grade*, *leverage*, and *expected default frequency*.[20] CDS spreads of investment-grade firms, low-leverage firms, or firms with lower expected default frequencies should be less sensitive to shocks. These variables reflect the likelihood of a credit event. We also consider uncertainty about a firm's ability to withstand a shock, as measured by the *StDev(CASC)*. Our expectation is that greater uncertainty should amplify the propagation of credit shocks.

Variable *operating leverage* proxies for operational risk. Variables *cash and marketable securities*, *inventory*, *accounts receivable*, and *accounts payable* describe a firm's operating cycle and liquidity. From these variables, *inventory*, *accounts receivable*, and *accounts payable* are related to a firm's exposure to supply chains. The effect of these variables on credit shock propagation in supply chains is an open empirical question. For example, while accounts receivable can be sold

[20] Definitions of these variables are standard with the *expected default frequency* calculated based on the distance to default, as in Bharath and Shumway (2008).

if liquidity is needed, high accounts receivable also expose a firm to defaults of its customers and indicate that it has a weak bargaining position (and hence must finance its customers). While high account payables add to a firm's liabilities, they also indicate a strong bargaining position.

Similarly, at the industry level, predictions for several variables are ambiguous. Higher *product similarity* in an industry makes it easier for a firm to find alternative customers or suppliers, thus increasing the firm's resilience to supply chain shocks. However, firms in higher *product similarity* industries are also easier to replace in the event of financial distress, making it less likely that supply chain partners will rescue them. We calculate variable *product similarity* following Hoberg and Phillips (2016), as the aggregate similarity score between a firm and its rivals, using Hoberg and Phillips's text-based network industries analysis. Higher product similarity in an industry can indicate greater competition. An additional metric for industry competition is the *industry concentration* variable, which is the Herfindahl-Hirschman Index for industries as defined by Hoberg and Phillips (2016). Similar to *product similarity*, the effect of the *industry concentration* variable is ambiguous.

At the supply-chain-link level, variable *customer sales %* is the percentage of total supplier sales to a customer. Variable *trade credit* is the percentage of a supplier's accounts receivable from sales to a customer.[21] Variable *supply chain duration* is defined as the duration of a supplier-customer link. All three variables indicate the strength of financial links between supply chain partners and the importance of supply chain relationships. Therefore, we expect that the greater the values of these variables, the stronger the credit shock propagation.

Next, we estimate the effects of these attributes by augmenting the baseline model (1) with an interaction term between an attribute and a customer (or supplier) CDS jump indicator variable. Not all attributes turn out to be significant. For the sake of brevity, in Table 6, we present only the statistically significant results.

[Insert Table 6 near here]

Panel A of Table 6 reports the regression coefficients. In our discussion, we focus on the results that are robust for multiple specifications (i.e., for different time windows). We observe that all

[21] Because we do not have actual trade credit numbers, we use this proxy.

three supply chain attributes, *trade credit*, *customer sales %*, and *supply chain duration*, amplify credit shock propagation through supply chains, as predicted. *Trade credit* measures the immediate financial exposure of the supplier to trade-credit default risk. *Customer sales %* measures both the immediate exposure and the long-term importance of a customer. *Supply chain duration* proxies for the amount of mutual investment by the supply-chain partners, the integration between their systems, and thus the replacement cost.

Among firm attributes relevant to a firm's credit risk, empirically, customer's *expected default frequency* and *leverage* amplify the CDS market's reaction to suppliers' CDS jump events. The *investment grade* variable is not robustly significant.

Uncertainty about a firm's ability to withstand shocks amplifies credit shock propagation. A customer's *StDev(CASC)* increases that customer's reaction to suppliers' credit shocks. A supplier's *StDev(CASC)* increases that supplier's reaction to customers' credit shocks.

Among customer attributes, *inventory* attenuates the propagation of shocks from suppliers' down-jump events. This attribute also reduces credit shock propagation to the supplier. A possible interpretation is that inventory can be used as collateral, allowing firms to borrow. Another possibility is that a customer with high inventory is not likely to place a large order with the supplier in the near future, thereby insulating the supplier from the customer's credit shock. A customer's *accounts payable* appears to reduce shock propagation as well. Higher *accounts payable* may proxy for a stronger bargaining position, which attenuates credit risk.

Among supplier attributes, *network centrality* dampens shock propagation. If a supplier has many customers (i.e., it has higher *network centrality*), then it is less exposed to any one customer.

With respect to industry and product characteristics, *industry concentration* attenuates and *product similarity* amplifies shock propagation. This finding suggests that industry competition intensifies the propagation of credit shocks through supply chains.

Panel B of Table 6 reports the economic significance of attributes, calculated as the increase in the cumulative abnormal CDS spread change, when an attribute increases from its median value to the 75th percentile (for non-indicator variables), or from 0 to 1 (for indicator variables). The attributes with the greatest economic significance are *trade credit* and *customer sales %*. For example, for supply chain links with a *trade credit* value in the 75th percentile, the supplier's response in $CASC[-1,2]$ to a customer's up-jump event is 102 bps higher than for supply chain links with a *trade credit* at the median value. For supply chain links with a *customer sales %* value at the 75th percentile, the customer's response in $CASC[-1,2]$ to a supplier's down-jump event is 122 basis points lower than that observed for supply chains links with *customer sales %* at the medium value. These findings highlight the importance of financial links between supply chain partners for credit shock propagation along supply chains.

4.6. Higher-tier supply chain partners panel estimations

We extend the baseline analysis (§4.1) to the second and third tiers of supply chains. There are several reasons to expect a small to no reaction to extreme CDS jumps in the higher tiers of supply chains. First, many firms do not have full visibility vis-a-vis higher supply chain tiers (Leonard, 2019), and neither is it obvious that CDS market investors are aware of the composition of the higher tiers. Second, even if investors can map higher supply-chain tiers, the effects of extreme jumps are expected to be small, if the reaction to credit shocks is mechanical (i.e., the second-tier reaction experiences the same relative magnitude to changes in the first-tier $CASC$ values as the first-tier's reaction to $CASC$ jump events). The mean $CASC_{ft}[-1,0]$ value corresponding to jump-up (down) events is $1,477$ $(-1,294)$ basis points (see Panel C of Table 1). From Table 2, the supplier's $CASC_{st}[-1,0]$ reaction to a customer's up-jump event is 59 basis points, or approximately 4% of the mean jump-up $CASC_{ft}[-1,0]$ value. The supplier's $CASC_{st}[-1,0]$ reaction to a customer's down-jump event is -44.3 basis points, or approximately 3% of the mean down-jump $CASC_{ft}[-1,0]$ value. If the CDS market were to react mechanically, we would expect to see a $4\% \times 59 = 2.36$ basis points reaction to up-jump events and a $3\% \times (-44.3) = -1.33$ basis points reaction to down-jump events for tier-2 customers. Similar effects are expected for tier-2 supplier shocks. These predictions do not hold empirically.

To conduct the analysis, we use the specification in equation (1), except that instead of the immediate supply-chain partners, we use second- and third-tier customers and suppliers. For example, for the tier-2 analysis, we consider a pair of firms (s,c) where s is a supplier of another firm, which is a supplier of firm c. In forming our sample, we eliminate feedback loops so as to prevent a firm from being its own second- or third-tier supplier.[22] The results are presented in Table 7.

[Insert Table 7 near here]

Panel A of Table 7 reports the panel estimations for higher tiers. Panel B combines the results from the panel estimations for tier-1 (Table 2) with those for tiers 2 and 3 (Panel A of Table 7) to show how all tiers respond to a shock experienced by the event firm (tier-0 firm). Statistically significant values in Panel B are indicated in bold font.

As Table 7 shows, there is a significant response to extreme CDS jump events in the higher supply-chain tiers. CDS investors pay more attention to adverse shocks (up jumps), than to favorable shocks (down jumps). For up jumps, the one-day (i.e., $CASC_{ft}[-1, 0]$) reactions of suppliers and customers are comparable for all tiers. For tier-1, 2, and 3 suppliers, these values are 59, 59, and 54 basis points, respectively, while for tier-1, 2, and 3 customers, they are 71, 66, and 67 basis points, respectively. In contrast, for down jumps, the one-day reaction of tier-2 suppliers is only 66% of that for tier-1 suppliers (-29 versus -44 basis points, respectively). Over longer time windows, the pattern is similar: the reaction to down jumps is less pronounced than the reaction to up jumps as one moves up and down the supply chain away from the event firm. The reaction of suppliers to down jumps decreases along supply-chain tiers the fastest.

The magnitude of the CDS market reaction to credit shocks in higher supply chain tiers exceeds predictions based on a purely mechanical transmission of shocks. Our results indicate that CDS investors are aware of credit risk developments in all supply-chain tiers, and, moreover, that investors pay more attention to adverse shocks than to favorable shocks happening in higher tiers.

5. Alternative specifications

In this section, we discuss several alternative specifications: using the supplier-customer CDS correlation as a control; applying Lewbel's generalized method of moments; and using firm-level

[22]For the discussion of effects of feedback loops in the context of financial systems, such as banks, see Eisenberg and Noe (2001).

and triad-level panels. The corresponding results are summarized in Table 8, and are discussed in the following subsections.

[Insert Table 8 near here]

5.1. Using the supplier-customer CDS spreads' correlation as controls

A common shock to a supply-chain network should increase the comovement of CDS spreads for the firms in that particular network. To control for the effect of common shocks that occur at the annual or slower than the annual frequency, our baseline specification includes customer-supplier-year effects. To capture potential transient common shocks that may occur faster than an annual pace, we add controls for Pearson correlations in daily CDS spreads of supply-chain partners.[23] In addition, we consider strongly correlated supplier-customer pairs separately, by interacting CDS spread correlations with an indicator variable that takes a value of 1 for correlations above the 75th percentile of the sample. The results are presented in columns (1) and (6) of Table 8.

The results when controlling for CDS spread correlations are comparable to those reported for the baseline specification (Table 2). While the coefficients on the correlations are mostly insignificant,[24] the coefficients for the CDS jump-events continue to be substantial. The evidence that the coefficients for the correlations are mostly insignificant suggests that customer-supplier-year effects capture the majority of the comovement across CDS spreads within a network, and that the main findings are not driven by transient common shocks.[25]

5.2. Lewbel's Method

To further address causality, we employ an instrumental variables specification and apply the generalized method of moments from Lewbel (2012). Lewbel constructs instruments from the data, which is useful when external instruments are not readily available. According to this method, one

[23] Correlations are calculated over a rolling 90-day window. Our approach is similar to that in Lang and Stulz (1992), who control for correlations in order to capture cash flow similarities when examining benign contagion.

[24] We have considered other specifications as well: using changes in correlations, using percentiles values other than the 75th, and excluding the interaction term. The results are similar to those reported.

[25] We have run estimations with correlations as controls for inactive supply chains, as in §4.3. The results are comparable with those that do not include correlations, as reported in §4.3.

identifies a model with a mismeasured variable using a heteroscedastic covariance restriction. As discussed in Lewbel (2012), this approach applies to many models for which errors are correlated because of an unobserved common shock. It is thus useful in our setting to allow for the possibility of common shocks. The description of Lewbel's method in our specification is as follows: For the effect of a customer's up (down) jumps on a supplier's $CASC$ in the supply chain link (s, c),

$$CASC_{st}[-1, a] = \beta_0 + X'b + \beta_1 Customer\ Up\ (Down)\ Jump_{ct} + \varepsilon_{sct}, \tag{3a}$$

$$Customer\ Up\ (Down)\ Jump_{ct} = \alpha_0 + Z'a + u_{sct}, \tag{3b}$$

where X is a vector of exogenous variables (discussed below) and Z is a vector based on the subset of variables in X. Variable $Customer\ Up\ (Down)\ Jump_{ct}$ is treated as endogenous, and as possibly affected by unobserved common shocks driving variable $CASC_{st}[-1, a]$. Similarly, for the effect of a supplier's up (down) jumps on a customer's $CASC$ in the supply chain link (s, c),

$$CASC_{ct}[-1, a] = \beta_0 + X'b + \beta_1 Supplier\ Up\ (Down)\ Jump_{st} + \varepsilon_{sct}, \tag{4a}$$

$$Supplier\ Up\ (Down)\ Jump_{st} = \alpha_0 + Z'a + u_{sct}. \tag{4b}$$

The standard assumptions for the above specifications are that $E[X\varepsilon] = E[Xu] = 0$. Lewbel's approach can use all exogenous variables, X, or a subset of them, Z. For Lewbel's estimation to be identified, the assumptions are that $cov(Z, \varepsilon u) = 0$ and $cov(Z, u^2) \neq 0$. The assumption that $cov(Z, \varepsilon u) = 0$ assures that Zu is uncorrelated with ε. The assumption that $cov(Z, u^2) \neq 0$ indicates that the data structure in equations (3b) and (4b) is heteroscedastic. This latter assumption assures that Zu is correlated with u, and thus with $Customer$ or $Supplier\ Up\ (Down)\ Jump_{ct}$. As a result, $(Z - \bar{Z})u$ can be used as an instrument, where $\bar{Z}$ is the sample mean. The validity of the condition that $cov(Z, \varepsilon u) = 0$ can be tested with the Hansen J test. The strength of the instruments can be tested by the Kleibergen-Paap test.

We employ Lewbel's method by augmenting our baseline specification (1) with two additional variables: the focal firm's daily CDS volatility; and the focal firm's one-day lagged $CASC$—that is, $CASC_{ft-1}[-1, a]$, where the focal firm is the firm whose reaction to CDS jump events is being examined. The volatility is calculated using a 90-day rolling window. These two variables are chosen because they are available in high frequency. The results of Lewbel's analysis are presented in columns (2) and (7) of Table 8.

The Kleibergen-Paap F-test statistics, reported in this table, indicate that our instruments are sufficiently strong, with p-values less than 0.1. Based on the Hansen J Statistics, the over-identification restrictions are satisfied (with p-values above 0.1). The results are similar to our baseline specification. The coefficients for the customers' and the suppliers' CDS jump indicators are significant and substantially larger than those for general jumps. Thus, Lewbel's method estimations support our argument that CDS jumps propagate through the supply chain, and that our results are not an artifact of unobserved common shocks.

5.3. Firm-level and triad-level panel specifications

As discussed in §4.1, our primary specification is the link-level one, also referred to as the dyad-level specification. Here, we consider several alternative panel specifications: firm-level and triad-level. The following are their relative strengths and weaknesses, the results based on these alternative specifications, and our reasons for focusing on the link-level one in our main analysis.

All specifications can be characterized using the index in the panel estimation analysis, as follows. For the firm-level specification, the index is (f, t), where f is the firm whose $CASC$ we observe on date t. For the dyad-level specification, the index is (f_1, f_0, t), where firm f_1 is a supplier of firm f_0. For the triad-level specification, the index is (f_2, f_1, f_0, t), where firms with higher sub-indices sell to firms with lower ones by 1 (i.e., firm f_2 sells to f_1, but not f_0, while firm f_1 sells to f_0). More generally, one can analyze the entire value chain. Such general specifications would be indexed as $(f_n, ..., f_0, t)$, where firms with higher sub-indices sell to firms with lower ones by 1 (i.e., firm f_k sells to f_{k-1}, but not to any firm f_j, where $j < k-1$). In our main specification, for mnemonic convenience, we use index (s, c, t), where firm s is a supplier to firm c. Similarly, for mnemonic convenience, for the triad-level specification below, we use index (s, f, c, t), where firm s is a supplier to firm f, and firm c is a customer of firm f.

There are trade-offs when using these specifications. The firm-level specification cannot control for link-level and triad-level effects. Conversely, while the triad and value-chain specifications allow for these effects, they present implementation challenges. First, the lengths of value chains (measured by the number of tiers) vary. Discarding chains shorter or longer than some cutoff value limits which firms and chains are included in the analysis. Second, once we extend the analysis beyond dyads, the structures of supply chain networks become intricate. Firms belonging to the same tier can be selling to each other: for example, firms f_1 and f_2 can be selling to firm f_0, and f_2 can also be selling to f_1. There can be loops, where firm f_0 sells to firm f_2. There can be multiple suppliers, customers, and intermediary firms. Identifying triads (and, generally, value chains of a given length) is a complex computational task. There is an exponential explosion in the replication of $CASC$ values. For example, consider a relatively simple supply chain, where a firm has five suppliers, and five customers. This would generate 25 triads containing the firm, and 25 identical CASC values for the firm on date t. While being mindful of these limitations and computational challenges, we analyze credit shock propagation using firm- and triad-level specifications.

The model based on the firm-level specification is described (in condensed form) by equation (5).

$$\begin{aligned} CASC_{ft}[-1,a] =& \beta_0 + \beta_1 General\ Up(Down)\ Jump_t \\ & + \beta_2\, X\ of\ Customer/Supplier\ Up(Down)\ Jumps_{ft} + \gamma_{fy(t)} + \varepsilon_{ft} \end{aligned} \tag{5}$$

When applying this model, we select either Up or $Down$ for the direction of jumps consistently for all variables in equation (5) with $Up(Down)$ expressions. We consider either customers or suppliers of firm f as of date t. Label X takes three values: "Indicator," "Number," and "Percentage." For example, the $Indicator\ of\ Customer\ Up\ Jump_{ft}$ variable equals 1 if any of the customers of firm f on date t experience an extreme CDS jump on that date. The variable $Number\ of\ Customer\ Up\ Jumps_{ft}$ equals the number of customers of firm f as of date t that experience CDS up-jump events on that date. The variable $Percentage\ of\ Customer\ Up\ Jumps_{ft}$ equals the number of extreme CDS up-jumps on date t of the customers of firm f, divided by the total number of customers of firm f. We use equal weights for contributions from $Customers/Suppliers$ of a firm, because the sales data usually used for computing weights are sparse. The results are presented in columns (3)-(5) and (8)-(10) of Table 8. These results indicate substantial credit shock propagation along supply chains in the CDS market, which is consistent with the results from our main specification based on dyads.

The model, based on the triad-level specification, is described by equation (6):

$$\begin{aligned} CASC_{ft}[-1,a] = \beta_0 &+ \beta_1 General\ Up\ (Down)\ Jump_t \\ &+ \beta_2 Supplier\ Up\ (Down)\ Jump_{st} + \beta_3 Customer\ Up\ (Down)\ Jump_{ct} \\ &+ \beta_4 Supplier\ Up\ (Down)\ Jump_{st} \times Customer\ Up\ (Down)\ Jump_{ct} \\ &+ \gamma_{sfcy(t)} + \varepsilon_{sfct} \end{aligned} \tag{6}$$

This model contains both supplier and customer jumps, and includes triad-level and year effects (i.e., $(supplier, firm, customer, year)$ effects). The model controls for the jump events of the suppliers and customers of a firm at the same time, but it is computationally intensive because there are approximately 360 million observations in the triad-level panel.[26] The results are presented in column (11) of Table 8. We observe that both customers' and suppliers' CDS jump events significantly affect a firm's $CASC$, which is consistent with our baseline findings (Table 2). The coefficient on the interaction term between suppliers' and customers' CDS jump events is not significant, suggesting that joint jumps do not lead to an additional reaction for the firm in the CDS market. Overall, these results support our findings that credit shocks propagate in the CDS market for both adverse and favorable events, and in both the upstream and downstream directions of supply chains.

We used a dyad-level specification for our main analyses because it allows for the best compromise between the goals of reducing complexity and controlling for fixed effects relevant to supply-chain links. Moreover, we posit that the dyad-level specification is the most natural one to use, when studying supply chains. Supply chains comprise not just firms (i.e., nodes in a network), but also the relationships between them. A dyad is an atom in a supply chain system—the smallest indivisible element. Thus, although it is possible to consider only the nodes of a supply chain network (i.e., firms), looking at dyads provides richer information about the supply chain network, while avoiding further computational complexity of triad level specifications.

[26] These estimations were carried out on a 16-core, 32 GB RAM cloud computer.

6. Robustness checks

In this section, we discuss the results from a series of robustness checks. The specification is given by equation (1), but events and the sample are modified as discussed in the following subsections. Table 9 presents the results.

[Insert Table 9 near here]

Robustness checks support the baseline findings (§4.1) that credit shocks propagate through supply chains in the CDS market.

6.1. Effects of the financial crisis

During the financial crisis, there was high systemic risk and a clustering of credit events (as presented in Panel D of Table 1). Credit risk propagation may have been more pronounced during this period and, therefore, may be driving our baseline findings. Furthermore, the definition of CDS jump events using the full sample may have been influenced by the credit events clustering during the financial crisis.

To understand the effect of the financial crisis period on our findings, we consider three sub-periods: before, during, and after the crisis. The results are presented in Panel A of Table 9. Following Demirguc-Kunt, Detragiache, and Merrouche (2013), we define the financial crisis period as August 2007 - April 2009. In order to differentiate between the potential effects of the financial crisis on the definition of credit events and on the reaction to credit events, we perform two versions of the analysis.

In the first version, we use events defined for the baseline analysis, but study reactions in the three time sub-periods separately. As columns (1)-(3) of panel A in Table 9 show, there is credit shock propagation in all sub-periods.

In the second version of the analysis, we define credit shock events separately for each time sub-period, as those above 99.9th percentile and below 0.1th percentile of $CASC_{ft}[-1, 0]$ values during the respective sub-period. The results support the findings from the baseline panel estimations (Table 2). As columns (4)-(6) of Panel A in Table 9 show, supply chain links are significant in transmitting credit shocks in all time sub-periods, except for down-jump events following the financial crisis. As expected, the shock propagation was amplified during the financial crisis.

Overall, these results indicate that credit shock propagation through supply chains is a general phenomenon, and not driven by the clustering of credit events and systemic risk that was observed during the financial crisis.

6.2. Jumps preceding credit rating changes

In our baseline estimations (§4.1), we study extreme CDS jump events, defined as percentiles of $CASC_{ft}[-1, 0]$, similar to Jorion and Zhang (2007) and Hertzel et al. (2008). These extreme CDS jumps reflect a variety of events affecting firms (see Table A1 in Appendix). To consider firm events more specifically, we look at extreme CDS jump events that precede credit-rating-change announcements by up to 90 days. Considering CDS jumps preceding rating-change announcements builds on the results of Lee et al. (2017), who report that CDS spread changes precede upcoming rating changes by up to 90 days. Similarly, Chang et al. (2015) report that CDS spreads do not reflect the contemporaneous credit rating downgrades within a production network. We consider both rating upgrades and downgrades. Data on credit rating changes are from S&P Capital IQ. The intersection of the supply chain, CDS jumps, and rating change datasets contain 233 supplier's and 352 customer's up-jump events, as well as 104 supplier's and 228 customer's down-jump events. Most of these events are from the high-yield sub-sample of firms. The results using these events are in column (1) of Panel B in Table 9.

For the CDS up-jump events preceding credit rating downgrades, the results are comparable to those in the baseline estimation (Table 2). Specifically, adverse credit shocks propagate through supply chains in the CDS market. These findings are different from those in Chang et al. (2015), who did not find a CDS market reaction to rating downgrades of supply chain partners.

For the extreme CDS down-jump events preceding credit rating upgrades, the results are not significant. These weaker effects are consistent with Lee et al. (2017), who found that CDS spreads change primarily for rating downgrades. Overall, this evidence supports our findings about the direction of the effect of extreme CDS jumps on supply chain partners.

6.3. *First in n-months jumps*

While we consider extreme CDS jumps as unexpected credit events, it is possible that some jumps are corrections, and do not correspond to new information. To address this concern, we redefine events as the first extreme CDS jumps in an n-month time window, with $n \in \{1, 3\}$. The motivation is that the first jump is more likely to contain new information about credit risk compared with subsequent jumps. Columns (2) and (3) of Panel B in Table 9 present the results.

The findings are comparable to the baseline (Table 2). In all specifications, the coefficients for the supply chain jump indicator variables are substantially larger than those for general jumps, and most are statistically significant. Some weakening in the statistical significance is expected because extreme CDS jumps that occur after the first jumps in 1- or 3-month window are now a part of the control group.

6.4. *Annually-redefined jump events*

In our baseline analysis, we defined extreme CDS jumps using percentiles of $CASC_{ft}[-1, 0]$ values over the entire sample period. As shown in Panels B and D of Table 1, there is significant variability in the CASC values, and in the frequency of CDS jump events over time. To ascertain that the clustering of jumps in some periods does not drive the results, we recalculate $CASC$ percentiles for the extreme CDS jump definition separately every year. The results are in column (4) of Panel B in Table 9, and are consistent with the baseline results (Table 2).

6.5. *Eliminating highly connected firms*

As shown in Panel F of Table 1, the median number of suppliers (customers) for a firm in our dataset is 14 (15), but the maximum number of suppliers (customers) for a firm is 226 (122). To verify that our results are not driven by highly connected firms, we run a test on a sub-sample constructed by removing the top 10% of firms, by the number of customers or suppliers. Column (5) of Panel B in Table 9 presents the results, which are again consistent with the baseline results (Table 2).

6.6. *CDS data errors and stale prices*

According to Markit,[27] their data undergoes a thorough validation process: "Rules-based cleaning algorithms are applied to inputs to remove stale data and anomalies. Audits by our experienced valuations team help ensure customers receive trusted and reliable pricing data." Therefore, it is unlikely that many of the extreme CDS spread values are erroneous records. Nevertheless, we rerun our analysis after removing records with CDS jumps that are above 10,000 basis points. The results are presented in column (6) of Panel B in Table 9, and are consistent with those in the baseline (Table 2).

We also consider the possibility that some of the CDS prices are stale, and that this may be driving the results. To control for stale prices, we use Wojtowicz's (2014) findings, that price volatility is highly correlated with liquidity, as measured by the bid-ask spread. We remove the top 5% of CDS observations by volatility and repeat our analysis. The results are in column (7) of Panel B in Table 9, and the significance and the direction of the results are similar to those in the baseline (Table 2).

6.7. *Alternative definitions of $CASC$ variables*

For our main analysis, we defined the abnormal CDS spread changes (i.e., $CASC$) similar to Jorion and Zhang (2007). To ensure that the shock propagation through supply chains reported in our paper is not driven by factors that are found to drive market risk premiums in credit markets—such as liquidity, stock market volatility, intermediary capital ratios (He, Kelly, and Manela, 2017), among other factors—we define an alternative $CASC$ variable using a linear factor decomposition, similar to Collin-Dufresne, Goldstein, and Martin (2001), and Anderson (2017). Specifically, for the reference entity f at date t, we decompose $CASC$ as follows:

$$\begin{aligned} CASC_{ft}[-1,0] = \alpha + \beta_1 \Delta r10_t + \beta_2 \Delta Term_t + \beta_3 \Delta VIX_t + \beta_4 SP500_t \\ + \beta_5 \gamma_{ft} + \beta_6 \Delta AggDef_t + \beta_7 \Delta ICR_t + \varepsilon_{ft}, \end{aligned} \tag{7}$$

[27] https://www.markit.com/Product/File?CMSID=b239787a32924f52a57e08b3e1f0a8a0.

where symbol Δ indicates the change in a variable over time; $r10_t$ is the 10-year Treasury yield; $Term_t$ is the term premium (i.e., the slope of the yield curve) calculated as the difference between the 10-year and the 2-year Treasury yields; VIX_t is the S&P500 volatility index; $SP500_t$ is the S&P500 index return; γ_{ft} is the proxy for illiquidity, following Roll (1984), and Bao, Pan, and Wang (2011); $AggDef_t$ is the aggregate default premium in the market measured as the difference between the Aaa and Baa bond yields; and ICR_t is the intermediary capital ratio.[28]

We use residuals from the estimation of equation (7) to redefine the $CASC$ variable (denoted as $altCASC$). We use these $altCASC$ values, instead of the original $CASC$ values, to define jump events and to measure the credit shock propagation through supply chains. Column (8) of Panel B in Table 9 contains the results, which support our baseline findings (Table 2).

6.8. Alternative Supply Chain Link Sample

The number of observations in the inactive-links sample used for the placebo analysis (§4.3) is smaller than the number of observations in the active-links sample used for baseline estimations (§4.1). It is conceivable that an explanation for not finding significant results with inactive links while finding significant coefficients with active links, is the lower statistical power of estimations with the inactive-links sample. To address this issue, we randomly choose an active-links observation for each inactive-links observation, and conduct the analysis on this active-links subsample. If our results were due to the difference in the statistical power, then we should not observe shock propagation in such analysis. However, Table 9, Panel B, Column (9) shows that there is credit shock propagation with this random subsample from active-links observations.

For comparison, from Table 4, Panel A, Column (3), an estimation with the sample that has the same number of inactive-links observations shows no propagation.[29] In fact, as observed in this Table, the reactions in abnormal CDS spreads are in the opposite direction from the CDS jumps of their supply chain partners in most cases, and none are significant. For those reactions that are in the same direction as jumps, the t-statistics are less than 1 (p values are above 0.3).

[28]He et al., 2017 find that the capital ratios of financial intermediaries have a significant effect on the cross-section of asset returns.

[29]In the estimation, customer-supplier-year fixed effects remove invariant observations, which are different in both samples. Thus, reported number of observations in the estimations are slightly different between these tables.

Therefore, significant CDS jump propagation along active supply chains is robust to sample size, pointing out that the results are not driven by the difference between active and inactive link sample sizes that may affect the statistical power.

7. Conclusion

CDS spreads provide measures of credit risk. They respond to news faster than credit ratings and bond yields. CDS market movements are considered in corporate decision-making, and moreover, were one of the drivers of the recent financial crisis. It is therefore important to understand credit-shock propagation channels in this market. We demonstrate that supply chains are one such channel, and identify firm and supply chain attributes that amplify or attenuate shock propagation. Using the CDS market as the source of credit shocks allows us to investigate both adverse and favorable credit events, and to provide the first evidence of a favorable credit shock propagation in the CDS market through supply chains.

Specifically, we find that the CDS jump events in supply chains result in substantial abnormal CDS spread changes for the supply chain partners of the event firm, in the same direction as the jumps. A supplier's 3-day cumulative abnormal CDS spread change ($CASC$) is 63 basis points in response to a customer's up-jump event, and a customer's 3-day $CASC$ is 74 basis points in response to a supplier's up-jump event. These values are -36 and -38 basis points in response to a down-jump event at a customer and a supplier, respectively. These effects are economically significant relative to the sample CDS spread level average of 157 basis points. Our results show that CDS spreads change rapidly in response to shocks in supply chains, and that the new levels of CDS spreads persist.

Credit shock propagation through the supply chain is more prominent for CDS jumps that are caused by natural disasters. The increase in three-day cumulative abnormal CDS spreads is substantial: between 113 and 215 basis points in response to customer up-jumps, and between 155 to 230 basis points in response to supplier up-jumps. These values are around twice as large as those observed for the baseline results. Thus, natural-disaster-originated credit shocks transmit through supply chains, and considerably increase the credit risk of supply chain partners as reflected in the

CDS market.

Credit shock transmission is not observed in supply chain links that are no longer active. These results hold with inactive links that have similar product market characteristics as active ones, as well as for supply chain links that become inactive due to idiosyncratic natural disaster shocks. These findings underscore the notion that active supply chains serve as the shock propagation channel in the CDS market.

The intensity of shock propagation is substantially stronger for supply chain partners followed by the same analysts. This points to information diffusion as an important mechanism driving shock propagation.

Several supply-chain and firm attributes affect credit shock propagation. In particular, stronger supply chain relationships amplify propagation. The strength of relationships is measured by the duration of the supply chain links, trade credit, and customer sales percentage. Industry competition amplifies credit shock propagation as well, with competition measured by high product similarity and low industry concentration. Both higher bankruptcy risk (measured by the expected default frequency) and uncertainty about a firm's ability to withstand shocks (measured by the standard deviation of abnormal CDS spread changes) amplify propagation. In contrast, higher customer's inventory, higher supplier's network centrality, and higher account payables for either firm attenuate shock propagation.

The propagation of shocks in the CDS market through supply chains is not confined to the immediate customers and suppliers of the event firm, but extends to higher supply chain tiers. The magnitude of this propagation is greater than one would predict based on mechanical reasons alone. The propagation towards higher tiers is stronger for adverse shocks than for favorable shocks.

To summarize, we identify an important channel—supply chains—for credit shock propagation in the CDS market, for both adverse and favorable credit shocks and via both upstream and downstream supply chain partners through multiple tiers. Our findings suggest that the CDS market is aware of the physical, informational, and financial links among companies in the immediate and extended supply chains, and that analyst coverage improves information diffusion. We further pinpoint the operational and financial attributes of firms and supply chains that affect shock propagation, and that credit shocks originating from natural disasters have large effects on supply chain partners. Moreover, we find evidence that the CDS market pays more attention to adverse events than favorable ones in higher tiers of supply chains.

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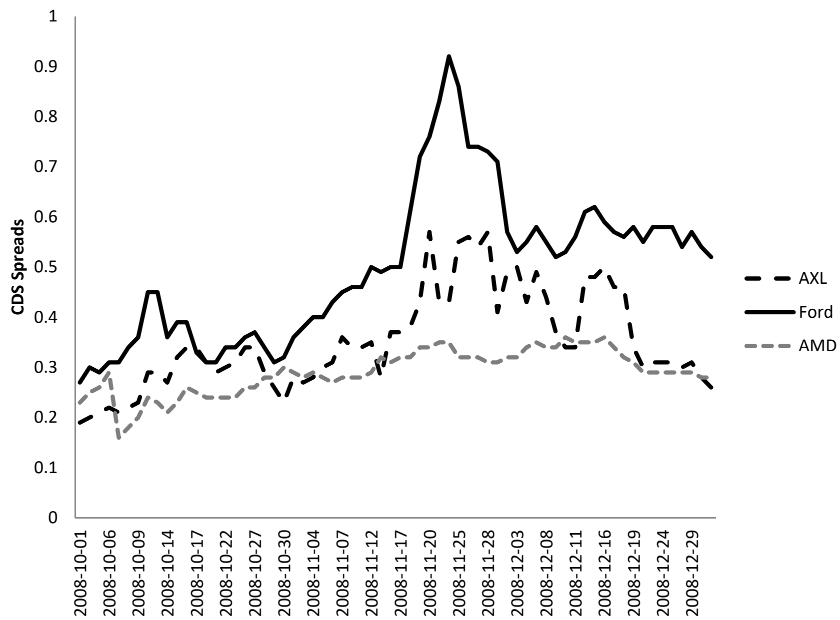

Fig. 1. 5-year CDS spreads of American Axle & Manufacturing Inc. (AXL), Ford Motor Company (F), and Advanced Micro Devices, Inc. (AMD) between October 1, 2008 and November 30, 2008.

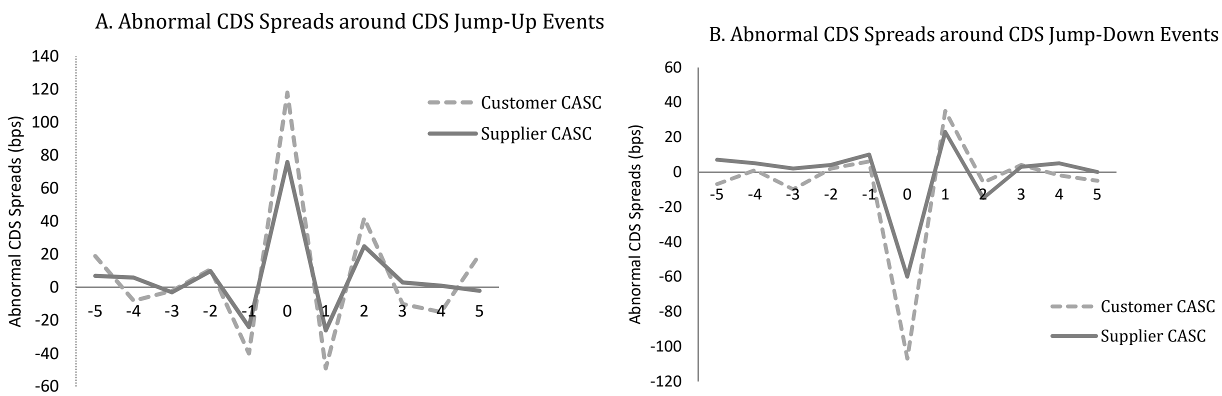

Fig. 2. One-day cumulative abnormal CDS spread changes ($CASC$) of supply chain partners of the firm that experienced an extreme CDS jump event.

These figures show one-day cumulative abnormal CDS spread changes ($CASC_{P_t t+\tau}[-1, 0]$) before and after the event ($\tau \in \{-5, ..., 5\}$) of equally-weighted portfolios (P_t) of customers and suppliers of the firm that experienced an extreme CDS jump event (event date is t, marked by $\tau = 0$ in these figures). Sub-figures A and B show reactions to jump-up and down-jump events, respectively.

Table 1: Sample description

These tables present descriptive statistics. All CDS contracts in the sample have a 5-year maturity and all CDS statistics are reported in basis points. Sample period is April 2003 - December 2014. Panel A presents summary statistics for daily CDS spreads. Panel B presents summary statistics for cumulative abnormal CDS spread changes ($CASC$). Abnormal spreads are adjusted for industry and rating. Panel C contains summary statistics of up- and down-jump events. The up-jump event is defined based on the 99.9th percentile of daily $CASC$ values in the entire Markit CDS dataset over the sample period. The down-jump event is defined based on the 0.1th percentile of daily $CASC$ values in the entire Markit CDS dataset over the sample period. Panel D reports the frequency of CDS jump events by year, including frequency of jumps defined as the first in 1 month and the first in 3 months events. Panel E reports the number of supply chain links by year in FactSet and Compustat datasets. Panel F reports degree distribution (the number of suppliers and customers of a firm) in the sample for both FactSet Revere and Compustat Segment datasets. Panel G reports summary statistics for the firm and supply chain characteristics of the sample. Variable definitions are in Table A2 (Appendix). Size is the natural log of the total assets in millions of dollars. Supply chain duration is in months. For each variable, the number of observations, mean, standard deviation and 25th and 75th percentiles are reported. Firm-level variables are winsorized at the 1st and 99th percentile.

Panel A: Daily CDS spreads by year (bps)

Year	Obs	Mean	Std Dev	Median	Max	Min	p25	p75
2003	44,282	122	182	52	1,800	8	31	100
2004	78,814	98	170	48	2,500	5	28	100
2005	91,266	100	205	44	2,900	2	28	100
2006	92,738	88	170	40	2,800	3	23	100
2007	96,968	85	126	43	2,600	2	25	100
2008	95,616	249	500	100	15,200	5	63	200
2009	90,953	341	1,224	100	58,400	72	65	300
2010	86,025	169	365	100	26,900	10	62	200
2011	81,877	167	396	100	10,400	11	68	100
2012	85,377	178	370	100	12,500	10	67	200
2013	83,931	126	179	91	4,300	12	54	100
2014	57,359	117	343	71	12,700	11	43	100
Total	*985,206*	*157*	*476*	*81*	*58,400*	*2*	*41*	*100*

Panel B: Daily cumulative abnormal spread changes (CASC) by year (bps)

Year	Obs	Mean	Std Dev	Median	p0.1	p99.9	p25	p75
2003	44,235	-0.03	18.47	0.12	.91.93	42.85	-0.91	1.38
2004	78,763	-0.06	20.41	0.04	-27.37	26.78	-0.73	0.80
2005	91,247	-0.03	13.42	0.01	-12.51	14.75	-0.57	0.55
2006	92,716	0.02	16.01	0.02	-6.81	8.33	-0.31	0.36
2007	96,953	-0.03	12.46	-0.03	-15.36	14.34	-0.65	0.41
2008	95,612	-0.11	63.56	-0.24	-99.98	99.83	-2.07	1.15
2009	90,952	0.71	206.32	0.26	-158.97	146.50	-1.37	2.35
2010	86,022	0.49	141.36	0.02	-96.77	93.70	-0.92	1.05
2011	81,872	-0.40	63.54	0.00	-88.00	89.83	-0.80	0.76
2012	85,372	0.15	73.49	0.01	-90.62	85.71	-0.56	0.73
2013	83,927	-0.04	27.98	0.01	-33.94	26.84	-0.47	0.51
2014	57,359	0.08	34.69	0.00	-28.27	26.01	-0.36	0.38
Total	*985,030*	*0.07*	*84.34*	*0.01*	*-92.49*	*90.02*	*-0.75*	*0.78*

Panel C: Jumps based on cumulative abnormal spreads change (CASC) (bps)

	Obs	Mean	Std Dev	Median	Max	Min
Jump-up	1,038	1,477	5,162	800	158,706	402
Jump-down	1,063	-1,294	4,626	-623	-364	-141,177

Panel D: Frequency of CDS jump events by year

	All Jumps		1st Jump in 1-month		1st Jump in 3-months	
Year	Up	Down	Up	Down	Up	Down
2003	3	6	3	5	3	3
2004	10	13	4	8	3	6
2005	2	3	0	3	0	3
2006	1	5	1	4	1	3
2007	7	7	5	2	4	2
2008	187	182	70	39	44	23
2009	446	458	94	108	44	65
2010	226	252	67	64	43	23
2011	20	24	7	13	3	9
2012	54	38	29	23	27	14
2013	42	40	22	22	15	15
2014	40	35	12	8	9	4
Total	*1,038*	*1,063*	*314*	*299*	*196*	*170*

Panel E: Supply chain data summary

Year	FactSet (without quantified sales)				Compustat (with ≥ 10% sales)			
	All firms	Suppliers	Customers	Links	All firms	Suppliers	Customers	Links
2003	5,514	3,155	3,200	22,133	1,404	998	527	1,504
2004	5,854	3,338	3,447	23,905	1,602	1,172	588	1,830
2005	5,950	3,406	3,513	23,983	1,601	1,157	610	1,848
2006	5,826	3,356	3,363	21,158	1,723	1,277	616	1,809
2007	5,939	3,368	3,459	20,569	1,878	1,415	690	2,103
2008	6,088	3,437	3,576	21,051	1,953	1,438	747	2,210
2009	5,933	3,292	3,472	19,436	1,883	1,368	724	2,056
2010	6,007	3,346	3,483	18,074	1,754	1,249	683	1,850
2011	6,453	3,580	3,778	18,504	1,677	1,178	669	1,859
2012	5,406	2,810	3,201	13,586	1,415	922	603	1,618
2013	7,215	4,042	4,356	24,723	1,802	1,219	751	2,285
2014	7,974	4,585	4,795	27,464	1,837	1,269	748	2,326
Total	*18,338*	*16,493*	*17,962*	*159,878*	*4,540*	*3,190*	*1,836*	*7,753*

Panel F: Degree distribution (number of suppliers and customers)

	Mean	Std Dev	Median	Max	Min	p1	p25	p75	p99
# Suppliers (FactSet)	29.76	40.18	14	226	1	1	5	37	210
# Customers (FactSet)	21.2	21.52	15	122	1	1	6	30	117
# Suppliers (Compustat)	11.8	17.27	5	72	1	1	2	15	72
# Customers (Compustat)	2.02	0.99	2	4	1	1	2	3	4

Panel G: Summary statistics for firm and supply chain variables

Variable	Obs	Mean	Std Dev	Median	p25	p75
Size	985,165	9.22	1.95	9.04	7.96	10.24
Leverage	985,165	0.31	0.21	0.27	0.16	0.41
Inventory	985,165	0.12	0.13	0.07	0.01	0.18
Cash and marketables	985,165	0.16	0.19	0.08	0.03	0.21
Accounts receivable	985,165	0.17	0.16	0.12	0.06	0.21
Accounts payable	985,165	0.12	0.13	0.07	0.03	0.12
R&D expense	985,165	0.03	0.05	0.00	0.00	0.03
Tobin's Q	985,165	1.72	1.30	1.22	0.84	2.03
Operating leverage	985,165	0.37	0.31	0.24	0.10	0.76
Industry concentration	985,165	0.29	0.29	0.16	0.09	0.35
Product similarity	864,492	3.91	5.66	2.07	1.34	4.02
Investment grade	804,860	0.11	0.31	0.00	0.00	0.00
Expected default frequency	827,093	0.12	0.28	0.00	0.00	0.03
Customer network centrality	301,263	1.80	0.82	1.69	1.00	2.39
Supplier network centrality	683,902	1.73	0.79	1.69	1.00	2.10
Customer sales %	84,607	17.15	9.19	14.00	11.00	20.30
Trade credit	73,471	1.99	2.08	1.48	0.84	2.47
Supply chain duration (months)	985,165	28.08	26.40	18.96	8.04	39.96
Ind. of analysts following firm	985,206	0.81	0.39	1.00	1.00	1.00
Ind. of analysts following link	985,206	0.10	0.30	0.00	0.00	1.00
StDev(CASC) (basis points)	963,978	11.64	24.12	2.39	1.14	11.87

Table 2: Panel estimations for the credit shock propagation through supply chains.

This table reports the panel estimations of reactions of supplier's ($CASC_{st}[-1,a]$) and customer's ($CASC_{ct}[-1,a]$) cumulative abnormal CDS spread changes over $a+1$ days to extreme CDS jumps at their supply chain partners. The model is given by equation (1), where the dependent variable is the cumulative abnormal CDS spread change $CASC_{ft}[-1,a]$ for $a \in \{0,1,2\}$ for the supplier ($f = s$) or customer ($f = c$) firm in the supply chain link (s,c) and independent variables are indicators of jump events. Specifically, variable *Customer Up* (*Down*) $Jump_{ct}$ is an indicator that the customer firm c in the link (s,c) has an extreme CDS up- (respectively, down-) jump event on date t. Similarly, variable *Supplier Up* (*Down*) $Jump_{st}$ is an indicator that the supplier firm s in the link (s,c) has an extreme CDS up- (respectively, down-) jump event on date t. Variable *General Up* (*Down*) $Jump_t$ is an indicator that there is an extreme CDS up-(down-) jump event at any firm in Markit dataset on date t. Extreme CDS up- (down-) jump events are based on 99.9th (for up-jumps) and 0.1th (for down-jumps) percentiles of $CASC_{ft}[-1,0]$ values from Markit dataset for the sample period April 2003 - December 2014. Estimations except for (1), (4), and (7) include lagged indicator variables for the general, customers', or suppliers' jump events. For all estimations, we control for customer-supplier-year fixed effects. Panel A reports the supplier's cumulative abnormal CDS spread changes in response to the customers' extreme CDS up-jump events. Panel B reports the customer's cumulative abnormal CDS spread changes in response to the suppliers' extreme CDS up-jump events. Panels C and D report results for down-jump events. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Customer Up-Jump Event

	Supplier CASC[-1,0] in bps			Supplier CASC[-1,1] in bps			Supplier CASC[-1,2] in bps		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
General up jump	1.34***	0.80**	0.65**	1.32***	0.81***	0.88***	1.41***	0.78***	0.74***
	[2.992]	[2.412]	[1.973]	[3.438]	[2.942]	[3.012]	[4.294]	[3.190]	[2.971]
Customer up jump	59.00***	60.80***	60.10***	38.90***	39.50***	37.80***	63.20***	63.80***	63.20***
	[2.651]	[2.658]	[2.708]	[2.870]	[2.855]	[2.765]	[2.856]	[2.827]	[2.859]
General up jump, lagged		-0.17	-0.11		0.22	0.08		0.31	0.32
		[-0.917]	[-0.609]		[1.296]	[0.499]		[1.532]	[1.601]
Customer up jump, lagged		-21.60*	-22.70*		3.67	2.67		5.73	4.55
		[-1.675]	[-1.710]		[0.867]	[0.636]		[0.843]	[0.665]
General up jump, lagged twice			0.29*			0.15			-0.04
			[1.885]			[0.937]			[-0.230]
Customer up jump, lagged twice			17.60*			23.50**			16.60*
			[1.655]			[1.970]			[1.682]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,056,183	2,038,028	2,069,481	2,051,191	2,033,366	2,064,458	2,046,491	2,028,986

Panel B: Supplier Up-Jump Event

	Customer CASC[-1,0] in bps			Customer CASC[-1,1] in bps			Customer CASC[-1,2] in bps		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
General up jump	-0.31	-0.67***	-0.71***	0.46	0.13	0.03	0.52*	0.19	0.15
	[-0.994]	[-2.998]	[-3.139]	[1.519]	[0.566]	[0.132]	[1.935]	[0.872]	[0.640]
Supplier up jump	71.00***	74.20***	73.90***	43.30***	45.10***	43.90**	73.50***	76.50***	76.90***
	[2.696]	[2.707]	[2.710]	[2.623]	[2.629]	[2.549]	[2.777]	[2.785]	[2.780]
General up jump, lagged		0.85***	0.86***		0.87***	0.89***		1.15***	1.17***
		[6.685]	[6.961]		[5.689]	[6.203]		[6.821]	[7.283]
Supplier up jump, lagged		-28.60**	-29.80**		2.26	2.26		-2.43	-2.81
		[-2.111]	[-2.121]		[0.527]	[0.508]		[-0.477]	[-0.528]
General up jump, lagged twice			0.10			0.26*			-0.09
			[0.998]			[1.778]			[-0.503]
Supplier up jump, lagged twice			23.80*			22.50			13.60
			[1.872]			[1.561]			[1.318]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,056,183	2,038,028	2,052,392	2,034,437	2,067,115	2,048,780	2,031,040	2,075,153

Panel C: Customer Down-Jump Event

	Supplier CASC[-1,0] in bps			Supplier CASC[-1,1] in bps			Supplier CASC[-1,2] in bps		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
General down jump	-1.54***	-0.94***	-0.77***	-1.02**	-0.38	-0.27	-1.71***	-0.95***	-0.93***
	[-3.480]	[-3.167]	[-2.722]	[-2.352]	[-1.413]	[-1.059]	[-3.665]	[-3.019]	[-3.030]
Customer down jump	-44.30**	-46.90**	-46.80**	-22.90**	-24.20**	-24.20**	-35.80**	-38.10**	-38.20**
	[-2.473]	[-2.508]	[-2.503]	[-2.220]	[-2.282]	[-2.293]	[-2.247]	[-2.322]	[-2.325]
General down jump, lagged		0.59***	0.60***		-0.34**	-0.08		0.26	0.23
		[3.856]	[3.583]		[-2.076]	[-0.633]		[1.467]	[1.351]
Customer down jump, lagged		23.20*	24.00*		10.50	10.60		14.50	14.70
		[1.941]	[1.960]		[0.858]	[0.857]		[1.129]	[1.121]
General down jump, lagged twice			-0.84***			-0.44**			-0.13
			[-4.300]			[-2.172]			[-0.767]
Customer down jump, lagged twice			-10.60			-6.62			-6.80
			[-1.556]			[-1.175]			[-1.189]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,056,183	2,038,028	2,069,481	2,051,191	2,033,366	2,064,458	2,046,491	2,028,986

Panel D: Supplier Down-Jump Event

	Customer CASC[-1,0] in bps			Customer CASC[-1,1] in bps			Customer CASC[-1,2] in bps		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
General down jump	-1.54***	-1.29***	-1.21***	-1.01***	-0.62**	-0.53**	-1.81***	-1.50***	-1.53***
	[-4.109]	[-4.216]	[-4.108]	[-2.799]	[-2.255]	[-1.997]	[-4.028]	[-3.967]	[-4.121]
Supplier down jump	-58.90***	-61.80***	-63.60***	-36.50***	-38.70***	-40.20***	-38.10***	-40.70***	-42.10***
	[-2.598]	[-2.616]	[-2.645]	[-2.739]	[-2.789]	[-2.825]	[-2.756]	[-2.817]	[-2.838]
General down jump, lagged		0.71***	0.81***		-0.22*	-0.19*		0.03	0.01
		[4.667]	[4.725]		[-1.775]	[-1.733]		[0.189]	[0.0734]
Supplier down jump, lagged		23.70	24.50		21.70*	22.20*		27.90*	28.50*
		[1.628]	[1.620]		[1.681]	[1.655]		[1.835]	[1.812]
General down jump, lagged twice			-0.78***			-0.60**			0.02
			[-4.454]			[-2.568]			[0.0923]
Supplier down jump, lagged twice			2.40			6.86			5.56
			[0.820]			[1.425]			[1.441]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,056,183	2,038,028	2,067,817	2,052,193	2,034,437	2,067,115	2,048,780	2,031,040

Table 3: Panel estimations under the natural disaster setting.

This table reports the panel estimations of reactions of supplier's ($CASC_{st}[-1,a]$) and customer's ($CASC_{ct}[-1,a]$) cumulative abnormal CDS spread changes over $a+1$ days to extreme CDS jumps originating from natural disasters. The details of the estimation are the same as in Table 2, except that CDS jumps are due to natural disasters. Panel A and Panel B provide the results where natural disasters are determined at the county level and state level, respectively. In columns (1)-(3), Indicator "if affected by disaster" is an indicator variable that takes the value of 1 if the firm whose CASC is measured is affected by a natural disaster in the same month as its supplier/customer that experience CDS jumps originating from natural disasters. In columns (4)-(6), the sample excludes supply chain links for which both partners are in the state affected by a natural disaster. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, %, and 1% level, respectively.

Panel A: Natural disaster location at county-level

	Jumps after natural disasters (Indicator if affected by disaster)			Jumps after natural disasters (Excluding supply chains in same states)		
	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)	(4)	(5)	(6)
Customer Up Jumps on Supplier CASC						
General up jump	1.46***	1.40***	1.54***	2.05***	1.82***	1.94***
	[2.802]	[3.499]	[4.159]	[2.757]	[3.186]	[3.694]
Customer up jump	115.00*	81.60*	121.00*	205.00*	150.00*	215.00*
	[1.900]	[1.695]	[1.940]	[1.954]	[1.766]	[1.970]
Indicator if supplier affected by disaster	0.01	0.03	0.04			
	[0.0807]	[0.224]	[0.218]			
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,069,481	2,064,458	1,355,463	1,351,832	1,348,543
Supplier Up Jumps on Customer CASC						
General up jump	-0.16	0.54*	0.67***	0.12	0.75**	0.89***
	[-0.489]	[1.806]	[2.589]	[0.282]	[1.990]	[2.712]
Supplier up jump	145.00	170.00*	167.00*	198.00	207.00	209.00
	[1.470]	[1.684]	[1.652]	[1.483]	[1.547]	[1.542]
Indicator if customer affected by disaster	0.05	0.06	0.05			
	[0.571]	[0.384]	[0.203]			
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,070,929	2,067,115	1,355,548	1,352,472	1,349,700

Panel B: Natural disaster location at state-level

	Jumps after natural disasters (Indicator if affected by disaster)			Jumps after natural disasters (Excluding supply chains in same states)		
	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)	(4)	(5)	(6)
Customer Up Jumps on Supplier CASC						
General up jump	1.45***	1.40***	1.52***	2.02***	1.81***	1.91***
	[2.761]	[3.484]	[4.088]	[2.710]	[3.168]	[3.615]
Customer up jump	108.00*	63.40*	113.00*	185.00*	111.00*	193.00*
	[1.768]	[1.691]	[1.809]	[1.822]	[1.772]	[1.847]
Indicator if supplier affected by disaster	-0.02	0.09	0.14			
	[-0.207]	[0.642]	[0.658]			
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,069,481	2,064,458	1,355,463	1,351,832	1,348,543
Supplier Up Jumps on Customer CASC						
General up jump	-0.18	0.53*	0.65**	0.09	0.74**	0.86***
	[-0.543]	[1.788]	[2.505]	[0.216]	[1.966]	[2.610]
Supplier up jump	144.00*	107.00*	155.00*	223.00*	153.00*	230.00*
	[1.765]	[1.935]	[1.851]	[1.841]	[1.884]	[1.857]
Indicator if customer affected by disaster	0.09	0.16	0.29			
	[1.085]	[1.060]	[1.307]			
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,070,929	2,067,115	1,355,548	1,352,472	1,349,700

Table 4: Analysis with inactive supply chains.

This table reports the panel estimations of reactions of supplier's ($CASC_{st}[-1,a]$) and customer's ($CASC_{ct}[-1,a]$) cumulative abnormal CDS spread changes over $a+1$ days (for $a \in \{0,1,2\}$) to extreme CDS jumps at inactive supply chain partners. The details of the estimation are the same as in Table 2, except that the active supply chain partners are replaced with the inactive (placebo) ones. To identify placebo partners, we consider supply-chain links that are not active on date t, but that have been active prior to that date (during our sample period). Panel A reports the results for the full sample (columns (1)-(3)) and for the matched sample (columns (4)-(6)). Matching is done between active and inactive supply chain partners based on the propensity score in firm size, leverage, Tobin's q, and Fama-French 12 industries. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. Panel B reports the results for the natural disaster setting. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Inactive supply chains placebo test

	Full sample			Matched sample		
	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)	(4)	(5)	(6)
Customer Up Jumps on Supplier CASC						
General up jump	1.10	0.97	1.27	-2.262**	-1.553**	-1.759**
	[0.809]	[0.824]	[1.299]	(-2.541)	(-2.055)	(-2.139)
Customer up jump	2.46	-0.16	-4.62	-9.210	16.794	31.478
	[0.437]	[-0.0144]	[-0.207]	(-1.501)	(1.441)	(1.514)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	185,763	185,380	185,023	26,153	26,119	26,086
Customer Down Jumps on Supplier CASC						
General down jump	-2.72*	-1.69	-2.66	1.344**	1.634**	1.501*
	[-1.723]	[-1.136]	[-1.490]	(2.442)	(1.992)	(1.735)
Customer down jump	12.10	22.80	-26.80	13.724	20.327	12.254
	[1.417]	[1.217]	[-0.953]	(1.259)	(1.238)	(1.185)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	185,763	185,380	185,023	26,153	26,119	26,086
Supplier Up Jumps on Customer CASC						
General up jump	1.13	1.29	1.09	0.005	1.237	1.901
	[0.900]	[1.194]	[1.303]	(0.019)	(1.194)	(1.482)
Supplier up jump	-3.32	-6.61	-13.50	0.516	0.827	1.124
	[-0.675]	[-1.037]	[-1.070]	(0.550)	(0.348)	(0.433)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	185,770	185,564	185,364	26,154	26,122	26,090
Supplier Down Jumps on Customer CASC						
General down jump	-1.66	-1.56	-2.06	0.513**	-2.021	-4.005
	[-1.257]	[-1.179]	[-1.470]	(2.438)	(-1.068)	(-1.095)
Supplier down jump	3.02	-5.81	0.41	2.523	6.657	7.224
	[1.239]	[-0.829]	[0.124]	(1.513)	(1.569)	(1.403)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	185,770	185,564	185,364	26,154	26,122	26,090

Panel B: Inactive supply chains - natural disasters

	Natural Disaster Caused Inactivity			Natural Disaster CDS Shocks		
	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)	(4)	(5)	(6)
Customer Up Jumps on Supplier CASC						
General up jump	0.55	0.46	1.01	1.11	1.25	1.02
	[0.473]	[0.667]	[1.057]	[0.883]	[1.160]	[1.212]
Customer up jump	21.80	27.40	20.20	16.1	11.4	8.93
	[0.917]	[1.116]	[0.825]	[0.661]	[0.750]	[0.592]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	55,769	55,646	55,525	185,770	185,564	185,364
Supplier Up Jumps on Customer CASC						
General up jump	6.45e-06	4.37e-05	3.30e-05	1.1	0.97	1.26
	[0.179]	[0.787]	[0.489]	[0.811]	[0.825]	[1.294]
Supplier up jump	12.40	4.78	0.21	10.3	-2.89	-5.18
	[1.026]	[0.646]	[0.0264]	[0.964]	[-0.202]	[-0.393]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	55,781	55,728	55,675	185,763	185,380	185,023

Table 5: Analysts following supply chain partners.

This table reports the effect of analysts following supply chain partners on the intensity of credit shock propagation in the CDS market through supply chains. *Analyst following supplier/customer* is an indicator variable that takes the value of 1 if the supplier or the customer, respectively, is being followed by analysts. *Analyst following link* is an indicator variable that takes the value of 1 if both supply chain partners are being followed by the same analysts. Other variable definitions are as in Table 2. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

	CASC[-1,0]			CASC[-1,1]			CASC[-1,2]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Customer Up Jumps on Supplier CASC									
General up jump	1.34***	1.35***	1.35***	1.32***	1.33***	1.33***	1.41***	1.41***	1.41***
	[2.995]	[3.000]	[3.007]	[3.440]	[3.444]	[3.450]	[4.299]	[4.301]	[4.311]
Customer up jump	84.80	39.50**	84.50	54.50	21.00**	54.30	83.90	42.10**	83.60
	[1.592]	[2.229]	[1.587]	[1.641]	[2.343]	[1.634]	[1.563]	[2.282]	[1.557]
Customer up jump*Analyst following supplier	-31.90		-57.30	-19.30		-42.30	-25.50		-52.90
	[-0.577]		[-1.037]	[-0.597]		[-1.261]	[-0.453]		[-0.944]
Customer up jump*Analyst following link		180.00	192.00		164.00**	173.00**		195.00*	207.00*
		[1.543]	[1.630]		[2.293]	[2.361]		[1.812]	[1.903]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,075,006	2,075,006	2,069,481	2,069,481	2,069,481	2,064,458	2,064,458	2,064,458
Customer Down Jumps on Supplier CASC									
General down jump	-1.54***	-1.55***	-1.55***	-1.02**	-1.02**	-1.03**	-1.71***	-1.72***	-1.72***
	[-3.481]	[-3.487]	[-3.489]	[-2.353]	[-2.356]	[-2.358]	[-3.666]	[-3.673]	[-3.675]
Customer down jump	-65.50	-33.40**	-65.40	-40.80	-16.00**	-40.70	-46.00	-17.00**	-45.80
	[-1.527]	[-2.260]	[-1.525]	[-1.491]	[-2.172]	[-1.489]	[-1.644]	[-2.083]	[-1.638]
Customer down jump*Analyst following supplier	26.70		41.80	22.50		32.20	12.90		37.70
	[0.598]		[0.944]	[0.842]		[1.182]	[0.457]		[1.346]
Customer down jump*Analyst following link		-99.00	-109.00		-62.20	-69.60		-172.00*	-180.00*
		[-1.081]	[-1.180]		[-1.178]	[-1.296]		[-1.757]	[-1.817]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,006	2,075,006	2,075,006	2,069,481	2,069,481	2,069,481	2,064,458	2,064,458	2,064,458
Supplier Up Jumps on Customer CASC									
General up jump	-0.31	-0.31	-0.31	0.46	0.45	0.45	0.52*	0.52*	0.52*
	[-0.993]	[-0.998]	[-0.997]	[1.520]	[1.516]	[1.516]	[1.936]	[1.929]	[1.931]
Supplier up jump	38.90	58.60**	39.00	26.40	34.60**	26.40	26.60	61.40**	26.70
	[1.210]	[2.352]	[1.208]	[0.854]	[2.539]	[0.854]	[0.977]	[2.323]	[0.976]
Supplier up jump*Analyst following customer	34.90		22.00	18.40		9.16	51.10*		39.00
	[1.215]		[0.525]	[0.780]		[0.270]	[1.821]		[0.984]
Supplier up jump*Analyst following link		51.80	49.40		36.50	35.50		51.00	46.70
		[0.758]	[0.688]		[0.839]	[0.760]		[0.780]	[0.682]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,075,153	2,075,153	2,070,929	2,070,929	2,070,929	2,067,115	2,067,115	2,067,115
Supplier Down Jumps on Customer CASC									
General down jump	-1.54***	-1.54***	-1.54***	-1.01***	-1.01***	-1.01***	-1.81***	-1.81***	-1.81***
	[-4.110]	[-4.103]	[-4.103]	[-2.798]	[-2.792]	[-2.790]	[-4.028]	[-4.022]	[-4.021]
Supplier down jump	-52.50*	-46.00**	-52.70*	-65.50*	-23.40**	-65.70*	-56.80	-23.30**	-57.00
	[-1.701]	[-2.207]	[-1.695]	[-1.868]	[-2.209]	[-1.866]	[-1.581]	[-2.159]	[-1.579]
Supplier down jump*Analyst following customer	-6.98		7.54	32.00		47.90	20.60		38.30
	[-0.305]		[0.212]	[0.997]		[1.331]	[0.663]		[1.024]
Supplier down jump*Analyst following link		-60.70	-61.60		-62.00	-67.70*		-70.30*	-74.90*
		[-0.982]	[-0.940]		[-1.641]	[-1.697]		[-1.907]	[-1.872]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,075,153	2,075,153	2,075,153	2,070,929	2,070,929	2,070,929	2,067,115	2,067,115	2,067,115

Table 6: Significant firm and supply-chain attributes affecting propagation of credit shocks in the CDS market through supply chains.

This table summarizes the significant coefficients on the interactions of CDS jump event indicators with customer, supplier, and supply-chain attributes. Only significant coefficients are reported. Panel A presents these coefficients' values. Panel B reports the economic significance, calculated by increasing a variable's value from the sample median to the 75th percentile (for non-indicator variables), or from 0 to 1 (for indicator variables). Change in $CASC$ is given in basis points. Panel estimations are as described in Table 2. Variable definitions are in Table A2 (Appendix). *, ** and *** represent 10%, 5% and 1%.

Panel A. Statistically significant attributes

	Customer CDS up jump		Customer CDS down jump		Supplier CDS up jump		Supplier CDS down jump	
	Supplier CASC[-1,1]	Supplier CASC[-1,2]	Supplier CASC[-1,1]	Supplier CASC[-1,2]	Customer CASC[-1,1]	Customer CASC[-1,2]	Customer CASC[-1,1]	Customer CASC[-1,2]
Supply Chain Attributes								
Trade Credit	102.00**	103.00*	-21.00**	-70.90**	37.10***	22.60**	-84.60***	-109.00**
Customer Sales %	33.20**		-8.78**	-52.50**	9.82***	6.99**	-17.60**	-19.40*
Supply Chain Duration	1.12**			-1.19*			-1.07**	-1.17**
Firm Attributes								
Customer								
Expected default frequency		216.00*			252.00**	461.00***	-159.00**	-175.00**
Leverage					145.00*	244.00*	-158.00***	-158.00***
Inventory	-192.00**	-260.00**	122.00*	208.00**			193.00**	198.00**
Cash and Marketable Securities						419.00*		
Accounts Payable	-158.00**	-215.00*	102.00*	171.00**			165.00**	177.00**
Operating Leverage						178.00*		
Industry Concentration	-73.30**	-145.00**	43.00*	61.10*	-68.20**	-139.00**		51.10*
Product Similarity	10.80*	33.90*	-7.93*					
StDev(CASC)	0.48**	0.89**			1.75***	3.01***	-1.62***	-1.73***
Supplier								
Investment Grade					73.10*		-66.50*	-69.10*
Network Centrality	-58.30**	-89.10**		67.90*			53.60**	56.60**
Size		-19.80*						
Leverage	-108.00*	-172.00*						
Accounts Payable		-311.00**	134.00*			-428.00**		
Cash and Marketable Securi					282.00*	396.00*		
Product Similarity	20.30**	41.10***	-16.60*		12.70*	24.50**	-12.40*	-13.90**
StDev(CASC)	2.95***	4.82***	-1.93***	-3.05***		1.29*	-0.66*	

Panel B. Economic significance of supply-chain-dyad and firm-level variables

	Change in variable, (75th-median) or 0 to 1	Change in CASC[-1,2] (in bps)			
		Supplier CASC, Customer Jump		Customer CASC, Supplier Jump	
		Up	Down	Up	Down
Supply Chain Attributes					
Trade Credit	0.99	102	-70	22	-108
Customer Sales %	6.3		-331	44	-122
Supply Chain Duration	21		-25		-25
Firm Attributes					
Customer					
Expected default frequency	0.03	6		14	-5
Leverage	0.14			34	-22
Inventory	0.11	-29	23		22
Cash and Marketable Securities	0.13			54	
Accounts Payable	0.05	-11	9		9
Operating Leverage	0.52			93	
Industry Concentration	0.19	-28	12	-26	10
Product Similarity	1.95	66			
StDev(CASC), bps	9.47	8		29	-16
Supplier					
Investment Grade	1				-69
Network Centrality	0.41	-37	28		23
Size	1.2	-24			
Leverage	0.14	-24			
Accounts Payable	0.05	-16		-21	
Cash and Marketable Securities	0.13			51	
Product Similarity	1.95	80		48	-27
StDev(CASC), bps	9.47	0.5	-0.3	0.2	

Table 7: Panel estimations for propagation of credit shocks to higher supply-chain tiers.

This table reports the panel estimations for propagation of credit shocks to second and third supply-chain tiers. The specification is the same as for Table 2, except that instead of the immediate supply chain partners, partners from higher tiers are used. Second- and third-tier suppliers (customers) are defined recursively. For example, a second-tier supplier s of customer c is a supplier of a supplier of customer c. Loops, where a firm is its own higher-tier supplier or customer, are eliminated. Panel A reports reaction in $CASC_{ft}[-1, a]$ of higher-tier supplier (customer) firms. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively. Panel B combines results from the panel estimations for tier 1 (Table 2) with those for tiers 2 and 3 (Panel A of this table) and summarizes how all tiers in supply chain respond a CDS jump event at tier-0 firm. Statistically significant numbers in Panel B are in bold.

Panel A: Panel estimation for higher tiers

	Tier 2			Tier 3		
	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)	(1)	(2)	(3)
Customer Up Jump on Supplier CASC						
General up jump	0.70**	0.91***	1.61***	-0.30**	0.13	0.94***
	[2.424]	[3.623]	[6.708]	[-2.014]	[0.940]	[6.920]
Customer up jump	58.90***	40.70***	56.70***	54.10***	38.20**	52.60***
	[3.478]	[2.947]	[3.497]	[3.652]	[2.573]	[3.224]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	4,919,817	4,904,136	4,889,908	10,360,190	10,324,372	10,291,787
Customer Down Jump on Supplier CASC						
General down jump	-1.70***	-0.46	-1.93***	-0.83***	0.44***	-0.89***
	[-5.675]	[-1.495]	[-5.623]	[-4.788]	[3.703]	[-4.871]
Customer down jump	-29.20	-11.10	-25.00*	-28.3*	6.23	-2.67
	[-1.392]	[-0.587]	[-1.862]	[-1.758]	[0.445]	[-0.262]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	4,919,817	4,904,136	4,889,908	10,360,190	10,324,372	10,291,787
Supplier Up Jump on Customer CASC						
General up jump	-0.44**	0.73***	0.86***	-0.46***	0.70***	0.91***
	[-2.292]	[3.224]	[4.088]	[-3.881]	[4.191]	[5.657]
Supplier up jump	66.30***	46.00***	63.90***	66.70***	47.50***	63.00***
	[4.320]	[3.705]	[4.356]	[4.379]	[3.062]	[3.731]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	4,920,072	4,907,965	4,896,994	10,360,879	10,332,889	10,308,016
Supplier Down Jump on Customer CASC						
General down jump	-1.84***	-1.36***	-2.35***	-1.64***	-1.17***	-1.98***
	[-7.413]	[-5.264]	[-7.569]	[-10.23]	[-6.592]	[-9.720]
Supplier down jump	-60.00***	-39.30***	-39.50***	-51.30***	-27.30**	-32.70***
	[-4.358]	[-3.723]	[-3.857]	[-3.559]	[-2.530]	[-3.343]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	4,920,072	4,907,965	4,896,994	10,360,879	10,332,889	10,308,016

Panel B: Effect of the CASC jump of the event firm on multiple supplier and customer tiers

		CASC[-1,0]		CASC[-1,1]		CASC[-1,2]	
	Tier	Up Jump	Down Jump	Up Jump	Down Jump	Up Jump	Down Jump
Supplier	3	**54**	**-28**	**38**	6	**53**	-3
	2	**59**	-29	**41**	-11	**57**	**-25**
	1	**59**	**-44**	**39**	**-23**	**63**	**-36**
Event Firm	0						
Customer	1	**71**	**-59**	**43**	**-37**	**74**	**-38**
	2	**66**	**-60**	**46**	**-39**	**64**	**-40**
	3	**67**	**-51**	**48**	**-27**	**63**	**-33**

Table 8: Alternative specifications.

This table reports the panel estimations for several alternative specifications. Columns (1) and (6) contain estimations for equation (1) with 90-day Pearson correlation between supplier and customer CDS spreads as an additional control. In this specification, variable *Correlation in 75 percentile* is an indicator that equals 1 if the CDS spreads correlation is above 75th percentile. Columns (2) and (7) contain estimations using Lewbel's instrumental variables method, described by equations (4) and (3), respectively. The instruments are the product of heteroscedastic errors from the first stage estimation with the focal firm's daily CDS volatility (calculated over 90-day rolling window) and its one-day lagged $CASC[-1, 0]$. Columns (3)-(5) and (8)-(10) present results for firm-level panel estimations, described by equation (5). Column (3) shows results for variables *indicator of supplier up/down jumps.* These indicator variables equal 1 if any of the suppliers of the firm f have a CDS up-jump event or, respectively, a down-jump event on date t. Column (4) shows results for variables *number of supplier up/down jumps.* These variables equal the number of suppliers of the firm f with CDS up-jump events or, respectively, down-jump events on date t. Column (5) shows results for variables *percentage of supplier up/down jumps.* These variables equal the number of suppliers with CDS up-jump events or, respectively, down-jump events on date t, out of the total number of suppliers of the firm f on the same date. Firm-year fixed effects are included in these estimations. Variables in columns (8)-(10) are defined similarly, but for customers of firm f. Column (11) presents results for triad-level panel estimation, described by equation (6). A triad comprises a supplier, a firm, and a customer, where the firm buyers from the supplier and the customer buys from the firm. Other variables are as discussed for Table 2. Supplier-firm-customer-year (triad-year) effects are included in this specification. Standard errors are clustered at the supply-chain-year level for CDS correlation and Lewbel's method results (Columns (1)-(2) and (6)-(7)), at firm-year level for firm-level results (Columns (3)-(5) and (8)-(10)), and at triad-year level for triad results (Column (11)). Robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

	Supplier CASC [-1,2]					Customer CASC[-1,2]					Firm CASC [-1,2]
	CDS	Lewbel	Firm-level panel			CDS	Lewbel	Firm-level panel			Triad-level panel
	Correlation	method	Indicator	No. Jumps	% Jumps	Correlation	method	Indicator	No. Jumps	% Jumps	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Effects of Up Jumps											
General up jump	1.40***	1.36***	0.98*	0.87	0.73	0.51*	0.56*	0.72	0.52	0.62	0.209***
	[4.266]	[4.953]	[1.748]	[1.529]	[1.230]	[1.901]	[1.809]	[1.404]	[0.975]	[1.171]	[14.27]
Customer up jump	63.40***	81.30***	151.00***	51.00***	244.00***						29.53***
	[2.857]	[2.973]	[2.635]	[2.762]	[2.659]						[17.93]
Supplier up jump						74.80***	55.80**	104.00**	65.4**	139.00**	34.57***
						[2.781]	[2.099]	[2.211]	[2.411]	[2.112]	[14.01]
Correlation	0.001					0.001					
	[-1.401]					[0.438]					
Correlation*Correlation in 75 percentile	0.001					0.001					
	[0.499]					[1.219]					
Supplier up jump*Customer up jump											12.72
											[0.32]
Customer-supplier-year FE	Yes	Yes				Yes	Yes				
Firm FE			Yes	Yes	Yes			Yes	Yes	Yes	
Triad-year FE											Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.006
Kleibergen-Paap P-Value		0.01					0.01				
Hansen J Test P-Value		0.182					0.116				
Observations	2,060,865	2,040,379	652,960	652,960	652,960	2,063,359	2,029,539	680,506	680,506	680,506	362,248,666
Effects of Down Jumps											
General down jump	-1.69***	-1.81***	-0.48	-0.79	-0.64	-1.74***	-1.89***	-0.84	-2.06**	-2.14**	-0.88***
	[-3.606]	[-7.042]	[-0.876]	[-1.213]	[-0.990]	[-3.897]	[-6.795]	[-1.284]	[-2.479]	[-2.573]	[-68.87]
Customer down jump	-36.30**	-21.60**	-73.30**	-29.40**	-168.00**						-15.72***
	[-2.262]	[-2.337]	[-2.019]	[-2.220]	[-2.036]						[-16.69]
Supplier down jump						-38.70***	-16.90	-86.70*	-34.50**	-65.60*	-22.78***
						[-2.781]	[-1.538]	[-1.823]	[-2.517]	[-1.704]	[-12.20]
Correlation	0.001					0.001					
	[-1.418]					[0.331]					
Correlation*Correlation in 75 perc.	0.001					0.001					
	[0.522]					[1.290]					
Supplier down jump*Customer down jump											18.54
											[1.44]
Customer-supplier-year FE	Yes	Yes				Yes	Yes				
Firm FE			Yes	Yes	Yes			Yes	Yes	Yes	
Triad-Year FE											Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.006
Kleibergen-Paap P-Value		0.01					0.01				
Hansen J Test P-Value		0.111					0.192				
Observations	2,060,865	2,040,379	652,960	652,960	652,960	2,063,359	2,029,539	680,506	680,506	680,506	362,248,666

Table 9: Robustness tests.

The panel estimations are as described in Table 2. Panel A presents the results for the effect of the financial crisis. The financial crisis period is August 2007 - April 2009. We divide the sample period into three sub-periods: before, during, and after the financial crisis. For columns (1), (2), and (3) of Panel A, the same events as in the baseline estimations (Table 2), defined based on the entire sample period, are used, but estimations are run for each sub-period separately. For columns (4), (5), and (6) jump events are defined within each sub-period separately first, and then estimations are run for each sub-period. Panel B presents the results for sub-samples and alternative definitions. For column (1), extreme CDS jump events are limited to those that precede credit-rating-change announcements by up to 90 days. For columns (2) and (3), extreme CDS jump events are redefined as the first jumps in 1 and 3 month time windows, respectively. For column (4), extreme CDS jumps percentiles are calculated for each year separately. Column (5) reports the results for a subsample of firms at 90th percentile or below by the number of supply chain partners. For column (6), CDS jumps that are above 10,000 basis points are excluded. For column (7), top 5% of credit default swaps by spread volatility are excluded. For column (8), an alternative $CASC$ definition is used based on residuals of the estimation of equation (7). Factors used in this equation are the yield curve, VIX, S&P index return, default premium, and the intermediary capital ratio. For column (9), an alternative supply chain link sample is used. In both panels, standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A. Financial Crisis

	CDS Jump Events Defined for Overall Period			CDS Jump Events Defined Each Period		
	Before Crisis	During Crisis	After Crisis	Before Crisis	During Crisis	After Crisis
	(1)	(2)	(3)	(4)	(5)	(6)
Supplier Up Jumps on Customer CASC[-1,2]						
General up jump	-0.24	-0.32	0.93**	-0.25	-0.23	0.09**
	[-1.043]	[-0.733]	[2.445]	[-1.056]	[-0.510]	[2.469]
Supplier up jump	3.76*	67.9***	40.50**	5.95**	155.00**	50.30*
	[1.665]	[3.076]	[2.224]	[2.213]	[2.291]	[1.739]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	754,299	324,012	988,804	754,299	324,012	988,804
Supplier Down Jumps on Customer CASC[-1,2]						
General down jump	0.79	0.45	-0.33***	0.08	0.28	-3.26***
	[0.408]	[1.041]	[-4.517]	[0.417]	[0.666]	[-4.523]
Supplier down jump	-9.45	-61.40***	-20.90*	-16.20***	-47.80**	-28.30
	[-1.216]	[-3.555]	[-1.801]	[-3.065]	[-2.224]	[-1.316]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	754,299	324,012	988,804	754,299	324,012	988,804
Customer Up Jumps on Supplier CASC[-1,2]						
General up jump	-0.94***	0.1.11**	1.71***	-0.9***	1.26***	1.73***
	[-6.923]	[2.501]	[3.613]	[-6.919]	[2.858]	[3.651]
Customer up jump	7.40**	64.10***	33.30**	7.61**	125.00**	48.20**
	[2.311]	[3.117]	[2.317]	[2.441]	[2.249]	[1.981]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	769,700	324,103	988,613	769,700	324,103	988,613
Customer Down Jumps on Supplier CASC[-1,2]						
General down jump	1.53***	4.55e-05	-3.68***	0.15***	0.35	-3.69***
	[11.14]	[0.964]	[-4.882]	[11.15]	[0.729]	[-4.896]
Customer down jump	-7.79	-45.60***	-22.4*	-16.30***	-51.40*	-28.50
	[-1.347]	[-2.968]	[-1.843]	[-3.289]	[-1.874]	[-1.440]
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001
Observations	769,700	324,103	988,613	769,700	324,103	988,613

	Credit Rating Changes	Alternative Jump Definitions: First 1 month	Alternative Jump Definitions: First in 3 months	Alternative Jump Definitions: Annually redefined	No highly connected firms	No jumps above 10,000 bps	No exterme volatility	Alt. CASC definition	Alternative Supply Chain Link Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Supplier Up Jumps on Customer CASC[-1,2]									
General up jump	4.75***	2.95***	1.79***	0.44*	0.42	1.79***	0.26	2.93***	0.98
	[5.558]	[6.009]	[3.051]	[1.832]	[1.466]	[4.450]	[0.976]	[5.587]	(1.248)
Supplier up jump	102.00*	72.50***	73.30***	38.00***	76.50***	72.80***	77.00***	121.00**	65.73**
	[1.820]	[2.742]	[2.773]	[2.803]	[2.793]	[2.751]	[2.648]	[2.160]	(2.074)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Observations	2,067,115	2,067,115	2,067,115	2,067,115	1,672,720	2,067,115	1,990,191	1,190,689	185,169
Supplier Down Jumps on Customer CASC[-1,2]									
General down jump	-17.30***	-3.24***	-1.44***	-0.83***	-1.69***	-1.81***	-1.70***	-5.90***	-1.08
	[-7.809]	[-7.527]	[-3.659]	[-3.965]	[-3.420]	[-4.028]	[-3.687]	[-7.320]	(-1.237)
Supplier down jump	8.48	-37.90***	-38.70***	-14.20*	-39.80***	-38.10***	-31.50**	-59.20*	-47.72**
	[1.158]	[-2.741]	[-2.799]	[-1.698]	[-2.772]	[-2.756]	[-2.174]	[-1.749]	(-2.190)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Observations	2,067,115	2,067,115	2,067,115	2,067,115	1,672,720	2,067,115	1,990,191	1,190,689	185,169
Customer Up Jumps on Supplier CASC[-1,2]									
General up jump	3.93***	3.36***	2.49***	1.05***	1.84***	2.12***	1.27***	2.35***	2.41***
	[5.358]	[7.377]	[4.849]	[4.526]	[4.618]	[5.441]	[4.065]	[5.097]	(2.589)
Customer up jump	106.00**	35.60***	32.50***	44.20***	73.50***	62.80***	70.10***	71.90*	79.64**
	[2.070]	[2.909]	[2.701]	[2.991]	[2.862]	[2.838]	[2.656]	[1.761]	(2.478)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Observations	2,064,458	2,064,458	2,064,458	2,064,458	1,670,866	2,064,458	1,987,752	1,324,286	184,953
Customer Down Jumps on Supplier CASC[-1,2]									
General down jump	-7.44***	-1.90***	-1.03**	-0.80***	-2.20***	-1.71***	-1.63***	-3.62***	-1.35*
	[-3.771]	[-5.168]	[-2.453]	[-3.253]	[-3.837]	[-3.665]	[-3.428]	[-5.655]	(-1.667)
Customer down jump	-52.40	-24.50**	-19.60	-17.10**	-41.80**	-35.80**	-35.40*	-64.00**	-56.19**
	[-1.251]	[-2.336]	[-1.588]	[-2.106]	[-2.251]	[-2.247]	[-1.884]	[-2.088]	(-2.346)
Customer-supplier-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000
Observations	2,064,458	2,064,458	2,064,458	2,064,458	1,670,866	2,064,458	1,987,752	1,324,286	184,953

Appendix A. Appendix

Table A1: Common CDS Jump Events.

This table reports news categories associated with extreme CDS jumps for a subsample that covers 20 days (-10,10) around CDS jump events that are the first extreme jumps in a three-month window, as described in §6.3. News events are screened using the LexisNexis newspaper news search. News categories that are in italics appear more frequently.

Common CDS Jump Events	
Up Jump	Down Jump
Negative outlook	*New product/new market*
Credit rating downgrade	*Credit rating upgrade*
Bankruptcy possibility announcement/bankruptcy filing	*Debt financing/refinancing*
Management change	*Lawsuit settlement*
Lawsuit	*Management change*
Debt restructuring	*Positive earnings*
Debt refinancing	*Positive growth*
Negative earnings	*M&A*
Job cuts and layoffs	Federal aid
Lack of liquidity	
Closing factory/store	
Missing interest payments	
Exit from product	
Change of default definition	
Demand for federal aid	
Business restructuring	

Table A2: Definitions of Variables.

Variable Name	Definition	Source
Credit default swap (CDS) spread	5 year credit default swap spread	Markit
StDev(CASC)	90-day rolling window Standard Deviation of CASC[-1,0]	Markit
Customer network centrality	natural log of 1 + number of suppliers	Factset
Supplier network centrality	natural log of 1 + number of customers	Factset
Duration of supply chain	Supplier-customer relationship length in months	Factset
Size	Natural log of total assets = log(AT).	Compustat
Leverage	(Long term debt + Short term debt)/ Total Assets = (DLTT+DLC)/AT	Compustat
Inventory	Inventory/Total Assets = INVT/AT	Compustat
Cash and marketable secutirities	Cash and Marketable Securities/ Total Assets = CHE/AT	Compustat
Accounts receivable	Accounts Receivable/ Total Assets = RECT/AT	Compustat
Accounts payable	Accounts Payable/Total Assets = AP/AT	Compustat
R&D	R&D/Assets = XRD/AT	Compustat
Tobin's Q	Tobin's Q = ((CSHO*PRCC)+(DLTT+DLC))/AT	Compustat
Operating leverage	SG&A/Assets = XSGA/AT	Compustat
Investment grade	Indicator that takes a value of one for investment grade long term issue rating or a value of zero otherwise	Compustat
Customer sales %	Percentage of sales contributed by the customer	Compustat
Expected default frequency	Calculated based on the distance to default from Bhararth and Shumway (2008)	Compustat
Trade credit	Calculated as supplier sales to a customer ∗ supplier accounts receivable/total supplier sales	Compustat
Industry concetration	HHI index for Text-based Network Industries = TNIC3HHI variable in Hoberg and Phillips (2016)	Hoberg and Phillips (2016)
Product similarity	Similarity score between the firm and its rivals = TNIC3TSIMM variable in Hoberg and Phillips (2016)	Hoberg and Phillips (2016)

Table A3: Event study: propagation of shocks in the CDS market through supply chains.

This table reports $CASC$ (cumulative abnormal CDS spread change) reaction to CDS jump events of the customers or suppliers. Event definitions are as described for Table 2. For each event firm, an equally-weighted portfolio of this firm's customers and an equally-weighted portfolio of this firm's suppliers at the time of the event t are constructed. We compute daily $CASC_{Pt}[a, a+1]$ of these portfolios (P) for daily time windows shifted by $a = -6, ..., 19$. We also compute $CASC_{pt}[-1, b]$ of these portfolios for $b = 1, 2, 5, 10, 20$. All $CASC$ values are reported in basis points. Colored bars indicate the size of the reaction within a particular column. Green-colored bars corresponds to the increase in $CASC$. Red-colored bars correspond to the decrease in $CASC$. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

	CASC reaction to CDS jump up event				CASC reaction to CDS jump down event			
	Customers' CASC		Suppliers' CASC		Customers' CASC		Suppliers' CASC	
Window	Mean (bps)	t-stat.	Mean (bps)	t-stat.	Mean (bps)	t-stat.	Mean (bps)	t-stat.
[-6,-5]	19.36	2.68***	7.28	1.28	-6.86	-0.89	6.83	1.56
[-5,-4]	-8.04	-1.19	5.91	1.37	1.31	0.15	4.98	1.03
[-4,-3]	-1.89	-0.23	-2.95	-0.64	-10.25	-1.28	2.32	0.46
[-3,-2]	10.53	1.14	9.85	1.73*	1.65	0.18	3.71	0.77
[-2,-1]	-39.89	-1.77*	-24.23	-1.76*	5.69	0.46	9.51	1.49
[-1,0]	118.21	4.33***	76.41	3.94***	-106.86	-3.66***	-59.98	-3.26***
[0,1]	-48.53	-2.18**	-26.24	-1.89*	34.75	1.47	23.11	1.85*
[1,2]	41.91	1.92*	25.47	1.91*	-5.61	-0.76	-15.34	-1.20
[2,3]	-10.45	-0.98	3.08	0.64	4.29	0.61	3.27	0.71
[3,4]	-15.07	-0.92	0.86	0.18	-1.95	-0.27	5.24	0.98
[4,5]	20.43	1.32	-2.40	-0.33	-4.74	-0.65	0.18	0.04
[5,6]	-2.28	-0.23	2.13	0.40	-8.83	-1.12	-1.51	-0.29
[6,7]	-49.28	-1.76*	-28.20	-1.42	-7.72	-0.76	2.93	0.59
[7,8]	23.10	1.06	14.65	1.14	-17.09	-0.96	-25.07	-2.01**
[8,9]	0.88	0.12	-2.04	-0.60	5.25	0.32	7.32	0.62
[9,10]	-2.42	-0.50	-3.14	-0.78	-7.59	-0.93	-0.26	-0.06
[10,11]	7.60	0.95	-3.29	-0.81	9.86	0.65	13.25	1.11
[11,12]	-32.74	-1.41	-15.54	-1.10	-4.33	-1.15	-2.18	-0.64
[12,13]	31.41	1.52	13.24	1.00	-0.90	-0.17	14.98	1.31
[13,14]	-1.01	-0.18	-3.09	-0.97	-9.83	-1.58	-7.91	-1.75*
[14,15]	2.26	0.29	5.61	1.49	-3.48	-0.47	-0.63	-0.15
[15,16]	-13.99	-0.90	-0.44	-0.14	-11.60	-1.74*	-0.04	-0.01
[16,17]	13.44	0.86	-0.82	-0.18	-2.30	-0.27	5.95	1.44
[17,18]	2.24	0.15	23.85	1.83*	-30.38	-1.33	-11.78	-0.91
[18,19]	-6.69	-1.09	-12.27	-0.96	23.67	1.07	18.74	1.53
[19,20]	-0.29	-0.04	12.64	1.02	-8.80	-1.38	-3.57	-0.83
[-1,1]	69.69	2.18**	50.18	2.32**	-72.51	-3.41***	-37.00	-2.70***
[-1,2]	111.60	3.81***	75.72	3.74***	-78.13	-3.77***	-52.56	-2.87***
[-1,5]	106.90	3.51***	77.52	3.44***	-80.03	-3.35***	-44.51	-2.18**
[-1,10]	76.91	2.01**	60.94	2.48**	-115.95	-3.81***	-61.55	-2.78***
[-1,20]	79.35	1.65	79.71	2.71***	-155.06	-4.44***	-35.17	-2.07**
Number of events	411		394		394		516	

Table A4: Inactive supply chains analysis with links from the time window 1 to 5 years in the past.

This table reports the panel estimations of reactions of supplier's ($CASC_{st}[-1,a]$) and customer's ($CASC_{ct}[-1,a]$) cumulative abnormal CDS spread changes over $a+1$ days (for $a \in \{0,1,2\}$) to extreme CDS jumps at inactive (placebo) supply chain partners. Abnormal spreads are adjusted for rating and industry. Extreme CDS jumps are 0.1th and 99.9th percentile $CASC$ values. We consider supply-chain links that are not active during time window $[t-365,t]$, but that have existed some time during time window $[t-5*365,t-365]$ and carry out analyses with these inactive links as if they were active ones. Standard errors are clustered at the supply-chain-year level and robust t-statistics are reported in brackets. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

	CASC[-1,0]	CASC[-1,1]	CASC[-1,2]
	(1)	(2)	(3)
Customer Up Jumps on Supplier CDS Spreads			
General up jump	1.36	1.65	1.38
	[0.567]	[0.804]	[0.870]
Customer up jump	4.72	-3.25	-12.20
	[0.388]	[-0.138]	[-0.253]
Customer-supplier-year FE	Yes	Yes	Yes
R-squared	0.001	0.001	0.001
Observations	102,743	102,548	102,371
Customer Down Jumps on Supplier CDS Spreads			
General down jump	-4.21	-3.03	-4.72
	[-1.538]	[-1.164]	[-1.516]
Customer down jump	26.40*	48.80	-53.50
	[1.841]	[1.522]	[-1.028]
Customer-supplier-year FE	Yes	Yes	Yes
R-squared	0.001	0.001	0.001
Observations	102,743	102,548	102,371
Supplier Up Jumps on Customer CDS Spreads			
General up jump	0.10	0.48	0.41
	[0.350]	[1.294]	[0.840]
Supplier up jump	-5.61	-13.20	-25.30
	[-0.642]	[-1.174]	[-1.111]
Customer-supplier-year FE	Yes	Yes	Yes
R-squared	0.001	0.001	0.001
Observations	102,747	102,663	102,580
Supplier Down Jumps on Customer CDS Spreads			
General down jump	-0.50	-0.16	-0.60
	[-1.078]	[-0.391]	[-1.041]
Supplier down jump	4.89	-9.61	-1.45
	[1.354]	[-0.772]	[-0.256]
Customer-supplier-year FE	Yes	Yes	Yes
R-squared	0.001	0.001	0.001
Observations	102,747	102,663	102,580

Table A5: Sample information for analysis with inactive supply chains.

This table reports the sample information for Panel A in Table 4. Panel A reports the results of the mean difference test on firm characteristics between active and inactive supply chain partners for the full sample used in Panel A. Panel B reports the results of the mean difference test for the matched sample used. Panel C reports statistics for how long a supply chain partner has been inactive for the full sample used in Panel A. *, **, *** indicate significance at 10%, 5%, and 1% level, respectively.

Panel A: Mean difference test between active and inactive supply chain partners(Full)

	Customers			Suppliers		
	Inactive customer	Active customer	p-value	Inactive supplier	Active supplier	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
Size	10.65	10.08	0.00	8.17	9.01	0.00
Leverage	0.24	0.27	0.01	0.33	0.31	0.06
Tobin's Q	1.20	1.38	0.00	1.69	1.48	0.00
Industry concentration	0.19	0.20	0.12	0.18	0.21	0.00
Inventory	0.15	0.11	0.00	0.07	0.08	0.08
Firm centrality	3.84	3.38	0.00	1.87	2.76	0.00
Cash and marketable secutirities	0.09	0.11	0.00	0.19	0.13	0.00
Accounts receivable	0.16	0.14	0.01	0.11	0.14	0.00
Accounts payable	0.18	0.12	0.00	0.08	0.08	0.24
R&D	0.02	0.02	0.06	0.05	0.03	0.00
Operating leverage	0.21	0.23	0.04	0.20	0.19	0.05
Product similarity	3.26	3.63	0.18	6.71	3.35	0.00
Expected default frequency	0.04	0.08	0.00	0.10	0.11	0.76
Investment grade	0.93	0.88	0.01	0.62	0.74	0.00
StDev(CASC)	13.74	13.03	0.84	46.60	22.85	0.03

Panel B: Mean difference test between active and inactive supply chain partners(Matched)

	Customers			Suppliers		
	Inactive customer	Active customer	p-value	Inactive supplier	Active supplier	p-value
	(1)	(2)	(3)	(4)	(5)	(6)
Size	10.69	10.64	0.74	8.49	8.44	0.80
Leverage	0.25	0.24	0.63	0.28	0.27	0.82
Tobin's Q	1.18	1.19	0.91	1.37	1.39	0.81
Industry concentration	0.17	0.18	0.59	0.18	0.16	0.22
Inventory	0.13	0.13	0.96	0.09	0.09	0.74
Firm centrality	3.93	3.94	0.92	2.05	2.17	0.23
Cash and marketable secutirities	0.09	0.08	0.41	0.17	0.16	0.72
Accounts receivable	0.17	0.18	0.72	0.12	0.12	0.96
Accounts payable	0.16	0.16	0.74	0.08	0.08	0.75
R&D	0.02	0.02	0.72	0.05	0.05	0.68
Operating leverage	0.21	0.21	0.75	0.17	0.17	0.79
Product similarity	3.37	2.84	0.37	5.13	5.18	0.95
Expected default frequency	0.02	0.05	0.06	0.08	0.10	0.48
Investment grade	0.96	0.96	0.98	0.59	0.66	0.32
StDev(CASC)	15.63	9.92	0.39	42.61	35.23	0.74

Panel C: Statistics of time intervals (in months) since a supply chain link for a jump event has been active

Jump Event	N	Mean	Min	Max	p25	p50	p75
Supplier jump up	239	44	5	128	22	36	67
Supplier jump down	249	44	6	128	23	34	68
Customer jump up	95	32	1	76	8	43	48
Customer jump down	111	34	1	71	10	44	49