The Globalization of Economic Shocks: Financial Contagion along International Supply-Chains

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Abstract

Using novel, hand-collected data on U.S. suppliers and their international principal customers, we show that firm-level supply chain links are an important channel for the propagation of financial contagion around the world. Following large country-level shocks, such as extreme market-index jumps or natural disasters like the 2011 earthquake and tsunami in Japan, dynamic conditional correlation (DCC) between U.S. suppliers and their customers increases significantly, above and beyond country-level and industry effects. Consistent with a trade-credit based explanation of contagion-propagation along the supply-chain, we find asymmetric effects for positive and negative shocks, larger increases in return correlation for supply-chain pairs with a closer relationship, and a positive relationship of DCC correlation with the use of trade credit by both supplier and customer firms. Our findings highlight the importance of studying global financial contagion at the firm level.

Keywords: Financial Contagion; Supply Chains; Shock Propagation; International Product Market

JEL classification: F30, F36, G14.

1 Introduction

Ever since the Asian Crisis in 1997 spread to other parts of the world and contributed to Russia's debt default and LTCM's bankruptcy in 1998, financial contagion has been a primary concern of managers, economists and policy makers. Today, with even more integrated financial markets and the increasing relevance of emerging markets for the global economy, understanding how country-level shocks propagate around the world is more important than ever.

Theory suggests a number of channels for the transmission of financial contagion.[1] They range from "fundamentals-based" mechanisms such as trade links or common creditors to "investor-behavior" channels based on herding or attention. However, there is widespread disagreement in the literature on both "the fundamentals that determine contagion" and "the mechanisms that link the fundamentals to asset correlation" (Bekaert, Harvey, and Ng, 2005).

Surprisingly, empirical research up to now has focused almost exclusively on financial contagion at the country and index level. For example, Longin and Solnik (2001) and Cuadro-Sáez, Fratzscher, and Thimann (2009) study the propagation of economic shocks using equity indices. Similarly, Chiang, Jeon, and Li (2007) and Bae, Karolyi, and Stulz (2003) focus on stock market indices using Dynamic Conditional Correlation models and Extreme Value Theory respectively. The global transmission of shocks at the firm level on the other hand has been widely ignored. In this paper we provide a new perspective on the mechanism that links fundamentals and asset correlation: We document that trade links between suppliers and customers are an important fundamentals-based, firm-level channel for the propagation of country-level shocks and show how these economic links contribute to international financial contagion.

A burgeoning literature on supply chains shows that small supplier firms regularly grant large amounts of trade credit to important customers, often at favorable terms.[2] It is not rare for a company to have "one large trade credit vis-a-vis one main client on its books, which may represent the entire profit of the year" (Boissay, 2006). Hence, as first suggested by Kiyotaki and Moore (1997), supplier firms are exposed to negative shocks affecting their customers, as the risk

[1]See for example Dornbusch, Park, and Claessens (2000), Van Rijckeghem and Weder (2001) and Pritsker (2001) for a summary of the theoretical literature.

[2]See Klapper, Laeven, and Rajan (2012). Rajan and Zingales (1995) estimate that trade credit in U.S. non-financial firms amounts to 15% of firm's total assets, Antràs and Foley (2015) find that accounts receivables support 39.2% of sales in general and 78.2% of sales focusing on common law countries.

of a major customer defaulting on outstanding trade credit obligations increases. This is especially critical if a significant proportion of the supplier's sales depend on a single, large customer.[3]

We therefore focus specifically on international supply-chain relationships using a novel, hand-collected dataset of dependent U.S. suppliers and international principal customers who represent a large proportion of total sales to the suppliers. Our main contribution is to show empirically that such links between closely connected firms are an important channel for the propagation of financial contagion around the world. Following large country-level shocks, such as extreme stock market jumps, as well as natural disasters such as the 2011 earthquake and tsunami in Japan, the dynamic conditional correlation (DCC) between U.S. suppliers and their international customers increases significantly, above and beyond the contagion at the country and index level.[4] We present evidence consistent with the idea that contagion along firm-level links is indeed partially driven by the trade-credit channel between the two companies: Shock propagation is asymmetric for positive and negative shocks, stronger for supplier-customer pairs with a closer economic relationship, and firm-level DCC correlation increases with the use of trade credit by the supplier and customer firms. These findings are in line with the recent theoretical model on predictable cross-border returns and trade credit in Albuquerque, Ramadorai, and Watugala (2015) and the credit-chain results documented in Jacobson and Schedvin (2015) based on Swedish data.

Without any contagion one would mechanically expect increased return correlations in periods of high volatility, as shown by Forbes and Rigobon (2001) and Forbes and Rigobon (2002). They hence define *financial shift contagion* as a 'dynamic change in the level of co-movement' after accounting for volatility in tranquil times and volatility clustering around important events. For this reason we start by estimating residuals of the customer and supplier returns using an ARMA-NAGARCH model with Hansen distributed residuals following Engle and Ng (1993) and Hansen (1994). Next, we apply a Dynamic Conditional Correlation (DCC) model following e.g. Chiang et al. (2007) and Christoffersen, Errunza, Jacobs, and Jin (2014) to generate a time-series of dynamic correlations for each customer-supplier pair. This DCC-GARCH approach allows us to simultaneously correct for heteroscedasticity in a direct way and study dynamic increments in correlations, which are

[3]For example, in 2004 the Financial Times reported that the "exposure of Electronic Data Systems (EDS) to U.S. Airways was such that it could slice almost a third from its earnings [...] following the airline's bankruptcy filing". When electronics retailer Circuit City filed for bankruptcy in November 2008, 48 out of its 50 largest unsecured creditors were trade creditors (Yang and Birge, 2013).

[4]Forbes (2004) first suggested firm-level trade links as a major channel for financial contagion.

necessary to disentangle *contagion* from *interdependence* following the definition of Forbes and Rigobon (2002). Using this measure of cross-market linkages, we analyze the impact of country-level shocks on shifts in correlation, the longevity of shock-induced changes in return correlation and the cross-sectional differences with regards to shock-, firm- and firm-pair characteristics.

In our baseline estimations we follow the Extreme Value Theory (EVT) approach of Bae et al. (2003) relying on extreme country-level stock index returns to identify country-level shocks. We then conduct event study tests on the average abnormal change in DCC correlation around country-index shocks and find a significant, economically large increase in dynamic correlation of customer- and supplier returns in the event window.[5] Our results show an average total *abnormal* DCC correlation of 0.2525 in the 21 weeks $[0, 20]$ around the country-index shock events. Approximately two thirds of this effect (0.1593) occur in the first 10 weeks after the shock. Compared to the average weekly DCC of 0.219, this implies that return correlation of economically connected firms more than doubles around country-index shocks. On the other hand, our results show no evidence of abnormal increases in DCC correlation *before* country-index shock events. The effect disappears after approximately 15 to 20 weeks and average abnormal DCC correlation goes back to zero.[6]

Stock markets in developed countries often lead smaller, less developed stock markets[7], making it difficult to study contagion relying solely on country-index shocks. A large shock to the U.S. market might propagate to other countries and result in a foreign country-index shock, while at the same time causing spurious DCC correlation between firms along the supply chain. To alleviate such endogeneity concerns we hand-collect a sample of large country-level disasters using data from the Emergency Events Database EM-DAT[8] as well as large-scale political events and crises. Our sample includes for example the 2011 earthquake and tsunami in Japan and the collapse of the Argentinian Peso in 2001.

Repeating our event study exercise with these country-level shocks, we find a statistically significant, economically large increase in dynamic conditional correlation (DCC) between customer- and supplier returns in the event window. Importantly, the results vary considerably when looking at different events of shocks individually. For natural disasters, such as the earthquake and tsunami

[5] In robustness tests we use several benchmarks including the index-level DCC correlation and find similar results.

[6] Consistent with the idea that larger shocks lead to higher financial shift contagion, robustness checks using the 0.5% and 0.1% percentile threshold for country-index shocks produce significantly larger abnormal DCC.

[7] See for example Marques, Gelos, and Melgar (2013) and Marshall, Nguyen, Visaltanachoti, et al. (2015).

[8] The database is frequently used in disaster research (compare e.g. Cavallo and Noy (2009)).

in Japan, we find no evidence of increased abnormal correlation prior to the event, a sharp increase in abnormal DCC in weeks 0 to 5 following the disaster, and a return to normal levels soon after that. In contrast, focusing on political events like the Eurozone bailouts, the majority of the increase in return correlation occurs in the ten weeks prior to the event, consistent with the notion that markets anticipated these events beforehand. Additionally, we obtain data on sovereign debt ratings changes from the Fitch Rating Agency and find similar results for negative ratings changes (downgrades), but no evidence of financial contagion for positive ratings changes (upgrades).

In our next set of tests, we estimate difference-in-difference models to tease out the causal impact of large country-level shocks on financial shift contagion in supply-chain networks controlling for time-, firm-, and relationship characteristics. The results are very similar to our event study findings. Weekly DCC correlation is strongly positively associated with the occurrence of index return shocks with a lag of up to 4 weeks. The estimates are significant at the 1% level, decrease monotonically from week 1 to week 4 after the event, and in aggregate indicate an increase of DCC correlation following the shock events of around 36%. Conversely, we find no evidence of shifts in correlation for positive shocks. This asymmetry is consistent for example with Longin and Solnik (2001), who find that equity index returns are more correlated in down-markets.

To rule out mechanical effects, we further match our sample of supplier firms with placebo suppliers from the same Fama-French 48 industry according to firm size. Univariate tests show that the DCC correlation is significantly higher for "true" firm-pairs than for pairs with placebo suppliers across our sample. In triple difference estimations we further show that the effect of country-index shocks on real firm-pairs is stronger than on placebo pairs.

To gauge the economic importance of our shock events and further address concerns about mechanical effects we estimate the value implications of disaster and country-index shocks using standard event studies on the daily returns of our suppliers and customers. We find daily cumulative average abnormal returns (CAAR) of -3.7% to -5.6% in the event window ($[-10, 40]$) around country-index shocks for our U.S. suppliers relative to a three-factor Fama-French model and -4.4% around the 2011 earthquake and tsunami in Japan.

Our results indicate that relying on foreign customers can expose U.S. supplier firms to political, economic and other shocks abroad and highlight the importance of studying firm-level economic links across countries, an issue that has been largely ignored by finance researchers so far. The direction of contagion from foreign countries to U.S. firms is especially interesting considering that most prior literature has documented a lead-lag relationship in the opposite direction in tranquil times (see e.g. Rapach, Strauss, and Zhou, 2013).

With this paper we contribute to the literature on international financial contagion by demonstrating an important channel for the propagation of economic shocks: supply-chain links between customers and suppliers. To the best of our knowledge this paper is the first to provide evidence on the transmission of country-level shocks in firm networks and study financial contagion focusing on economically connected firms. Our results lend support to the strand of literature on financial contagion that focuses on fundamentals-based mechanisms started by Forbes (2004) as opposed to investor-behavior based explanations and channels.

We also contribute to the fast growing literature on economic networks and the propagation of shocks started by Hertzel, Li, Officer, and Rodgers (2008) and Jorion and Zhang (2009) as well as Hertzel and Officer (2012) and Barrot and Sauvagnat (2016) more recently. These papers examine the effect of firm-level shocks on supplier and customer returns, and sales respectively. We extend this literature by focusing on two aspects that have previously been ignored: country-level shocks and the trade credit channel.

The rest of this paper is organized as follows. Section 2 summarizes our sample construction. In Section 3 we introduce the dynamic conditional correlation model used to estimate correlation between customer and supplier return residuals over time. In Sections 4 and 5 we present our findings for the event study and difference-in-difference tests, the relationship between dynamic conditional correlation and the use of trade credit, and a number of robustness checks. We summarize the main findings and discuss implications for future research in Section 6. All variable definitions and data sources are listed in Tables A.I and A.II in the Appendix.

2 Data and Descriptive Statistics

2.1 International Customer and U.S. Supplier Pairs

To identify a network of U.S. supplier firms and their international principal customers we rely on regulation SFAS No. 14 (before 1998) and SFAS No. 131 (after 1998) which require U.S. firms to disclose the existence of both domestic and foreign principal customer firms representing more than 10% of their total reported sales.

We organize this dataset of relationship pairs between U.S. suppliers and their foreign customers in the following steps based on information reported in the Compustat segment customer files and a complete list of international listed companies from Datastream. Since the Compustat segment customer file does not provide common identifiers (e.g., GVKEY) for reported customer firms and the reported customer names are often in abbreviation, we first use a language based text-matching algorithm to match the customer names with the names of international public firms provided by Datastream, keeping only sufficiently close text-matches. Second, we manually inspect the matches and drop obviously incorrect links from our sample based on the reported firm names.[9]

Third, all countries with fewer than five supplier-customer links are dropped from the sample to mitigate the effect of noisy international data. Fourth, we require that stock return information and accounting data must be available for both international customers and U.S. suppliers in our sample. Daily returns for the U.S. suppliers are from CRSP, daily returns for the international customers are computed from Datastream's daily total return index (RI).

Fifth, following Lee (2011), we apply a number of standard data screens to the daily international returns data. Non-trading days are excluded by removing observations for which 95% or more of the stocks on a given exchange have zero returns. A stock's monthly observations are dropped if more than 80% are zero-returns, or if a stock had fewer than 10 trading days per month. In line with Ince and Porter (2006) we set a daily return to missing if the current or previous day return index (RI) is below 0.01. Following again Lee (2011), we set both day t and $t-1$ returns to missing if any daily return above 100% is reversed the following day, i.e. if $(1+R_{it})*(1+R_{it}-1)-1 <= 0.5$ and ($R_{it} > 2$ or $R_{it} - 1 > 2$) and drop stock-day observations in which daily returns are in the top or bottom 0.1% of the stock's country in a given year.

After generating weekly returns from Wednesday to Wednesday from the daily data, we further drop supplier-customer pair-years if either the supplier or customer has less than 40 non-zero weekly return observations in a given year or more than 50% of return observations are zero.

The supplier-customer dataset and the CRSP/Datastream returns are matched with annual

[9]Many of the reported international customers are very large, well-known firms. Naturally, the phonetic language matching algorithm will suggest a few incorrect links due to ambiguous or inconclusive firm names or firms with foreign subsidiaries, among other things. Based on the estimates from the DCC specified in Section 3, remaining incorrect firm-links are eliminated.

firm-level accounting data from Compustat and Datastream/Worldscope. To obtain a measure of the intensity of the relationship between customer and supplier we divide the annual sales reported in the Compustat segment files by the total annual sales of the supplier in the given year. We further exclude customers and suppliers with fewer than 100 weekly returns during our sample period.

The sample selection criteria above yield a final sample of 2317 firm-pairs of U.S. suppliers and international customers (1465 unique suppliers and 619 unique customers) from 35 countries from 1985 to 2014, providing in total 7174 pair-year observations. The sample starts in 1985 since Datastream coverage is not available prior. Based on the classification provided by the International Financial Corporation (IFC) of the World Bank, the final sample includes customer firms from 17 developed-market countriesand 23 emerging-market countries. The average firm-relationship in the sample has a duration of 7.24 years, 75.8% of relationships last at least three years.

[Insert Table 1 about here.]

Annual summary statistics of the sample firms and firm-pairs as well as placebo firms are reported in Panel B of Table 1. The summary statistics confirm that the international customer firms in our sample are typically much larger than their U.S. suppliers. The median international customer firm is about 100 times larger than the median U.S. supplier in terms of book value of assets and about 50 times larger in terms of market capitalization (both in USD). The ratio of sales to the principal customer over total sales reported by U.S. suppliers (sales intensity) is around 18% on average with an interquartile range of 9% to 22%. This ratio is relatively constant over time from 1985 to 2014. Trade credit is widely used by both the suppliers and customers in our sample. The average supplier has a ratio of accounts receivables to sales (AR/Sales) of 19%, the average customer has a ratio of accounts payable to cost of goods sold (AP/COGS) of 20%. Taken together the summary statistics indicate a strong dependency of the suppliers on their international customers. Table 1 also shows that our placebo supplier matching procedure, described in detail in Section 4, is successful at matching our sample supplier firms with placebo firms of similar characteristics regarding size (assets and market capitalization), the use of trade credit, financial constraints, and default risk.

Table 2 reports descriptive statistics for weekly customer-, supplier- and country-index returns.

Panel A summarizes the first four sample moments of the annualized weekly returns at the firm level for every customer-year observation by country of the customer firm. Consistent with the literature we find higher average annualized returns for customer firms in emerging markets of 27.66%, compared to 14.37% in developed markets. This emerging markets premium corresponds to a higher annualized standard deviation of 1.0063 on average compared to an average of 0.6261 for customer firms in developed markets. Firm-level annualized skewness and excess kurtosis are approximately similar across firms in emerging and developed countries in our sample. These results are similar when focusing on the annualized weekly returns on the country-index level for each country with at least one customer firm in our sample as reported in Panel B. The average annualized index return in emerging countries is 24.43% with a mean standard deviation of 0.4813 compared to 13.41% with a mean standard deviation of 0.2659 in developed countries. Returns, standard deviation and excess kurtosis are higher for emerging market indices, skewness is mostly negative across developed markets and mostly positive and close to zero for emerging market indices.

[Insert Table 2 about here.]

In Panel C of Table 2 we focus on U.S. supplier firms and report the sample moments of the annualized weekly returns on the firm-level for every supplier- and placebo-supplier-year observation by year as well as the U.S. value-weighted market return. Annualized firm returns are roughly consistent with U.S. market returns per year and have similar higher moments as firm and index returns in other developed countries.

2.2 Country-index shocks and disaster events

In the spirit of the extreme value theory (EVT) approach of Bae, Karolyi, and Stulz (2003) (BKS), we identify country-level shocks as large (negative) jumps in country-index returns. We obtain weekly stock market index returns based on daily return data from Datastream for each country with a customer firm in our sample and standardize returns by the 20 week moving average of return standard deviation, lagged by one week, to account for volatility clustering as in Lee and Mykland (2008).[10] Next, we identify the 2.5% percentile of the most positive and negative weekly returns for each index over the full length of the sample period and define these events as country-index (BKS)

[10] In untabulated tests we also use a number of other configurations and obtain similar results.

shocks. For further robustness tests we also use the 0.5% and 0.1% percentile of weekly return shocks. Country-index shocks that are followed by a reversal in the following week are excluded from the sample. Furthermore, if a shock was followed by another shock, either positive or negative, within the next 30 weeks, only the first shock observation was included. After applying these filters we keep 1355, 946 and 364 “BKS” events using the bottom 2.5%, 0.5% and 0.1% negative country-index return shocks. This approach has the obvious advantage of providing us with a wide range of shocks across all customer countries and time periods due to its construction.

Of course, using negative country-index return shocks does not allow us to identify which country-level event in particular is driving the index price-jump. Large and developed economies and stock markets often lead smaller, less developed economies (see for example Marques et al. (2013) and Marshall et al. (2015)) making it difficult to establish causality or even the direction of financial contagion relying solely on country-index shocks. Causality might for example be reversed if a large shock in the U.S. propagates to foreign countries and is picked up as a country-index shock, leading to a spurious increase in return correlation and “contagion”. To alleviate endogeneity concerns we hand-collect a sample of large country-level disasters as well as large-scale political events and crises, using data from the Emergency Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED) among other sources. The database is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutions, and press agencies (compare e.g. Cavallo and Noy (2009)).[11]

Table A.II in the Appendix summarizes the natural and political shocks in our sample including the 2011 earthquake and tsunami in Japan, the 2004 earthquake and tsunami in the South East Asia region as well as the Taiwan Straits crisis, the collapse of the Argentinian currency and the two Eurozone bailout deals in 2010. In total our sample includes 25 major events affecting 27 countries and 430 firm-pairs of international customers and their U.S. suppliers. The largest group of observations within our disaster sample, 135 firm-pairs, stems from Japanese customers affected by the 2011 tsunami and earthquake.

For further robustness checks we also follow Chiang et al. (2007) and collect sovereign ratings changes from the Fitch Ratings Agency. We split the sample in ratings up- and downgrades of a

[11]EM-DAT defines a disaster as a natural situation or event which overwhelms local capacity and/or necessitates a request for external assistance.

customer country's sovereign debt to study negative and positive shocks. As shown in Section 4, the effects of truly exogenous, natural disasters on financial contagion are distinctly different from the impact of political events and sovereign ratings changes.

3 Modeling Firm-Level Return and Correlation Dynamics

Forbes and Rigobon (2002) define contagion as a *"significant increase in cross-market linkages after a shock to a country, as measured by asset price co-movement relative to tranquil times"*. Following this definition, our objective is to study the dynamic changes in return correlations between customer and supplier firms in the cross-section and time-series. As Bekaert et al. (2005) point out, we would mechanically expect a higher level of correlation during times of increased volatility without any contagion effects. Further, it is well known (e.g. Engle and Ng (1993) and Bekaert and Wu (2000)) that asset returns and volatility are negatively related (the so-called "leverage effect") and that equity index returns are more correlated in down markets (e.g. Longin and Solnik (2001)). To accommodate volatility persistence, heteroscedasticity and the leverage effect as well as asymmetric correlation responses to return innovations for each customer-supplier pair, we rely on the asymmetric DCC-GARCH model introduced by Engle (2002) and Tse and Tsui (2002). This type of model generates comparatively realistic threshold correlations while being analytically tractable and easy to implement using the techniques developed in Engle, Shephard, and Shepphard (2008).

Our dynamic model development proceeds in three steps. In the first step, we model the mean dynamics on the univariate time series of each firm's stock return. In the second step, we model the variance dynamics and the distribution of the time-series residual for each firm. In the third step, we develop a dynamic conditional correlation (DCC) model for equity returns using the firm pairs in our sample.

3.1 Modeling the return and volatility process

As is common in the international finance literature we rely on log returns at the weekly frequency to avoid issues with overlapping time-zones and local market opening hours. In order to obtain white-noise innovations required for consistent modeling of correlation dynamics, we fit univariate

ARMA-NAGARCH models to the weekly return time series of each customer and supplier firm to correct for short-term dynamics in returns. To maximize the precision of the estimation we use the longest available time-series of weekly firm-level returns between January 1985 and December 2014 for each firm. Following Christoffersen, Jacobs, Jin, and Langlois (2016), we start by fitting each of the possible $ARMA$ specifications with AR and MA orders up to two. The optimal $ARMA$ order for each time series is then chosen using the finite sample corrected AIC criterion. In particular, we first estimate the following nine possible models, nested within an $ARMA(2,2)$ model, on the weekly log-differences in equity prices for each firm at time t:

$$R_t = \mu + \phi_1 R_{t-1} + \phi_2 R_{t-2} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \epsilon_t, \tag{1}$$

where ϵ_t is assumed to be uncorrelated with R_s for $s < t$. Next, we fit the Engle and Ng (1993) Nonlinear Asymmetric GARCH ($NAGARCH(1,1)$) model to the ARMA filtered residuals ϵ_t:

$$\begin{aligned} \epsilon_t &= \sigma_t z_t \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + \alpha(\epsilon_{t-1} - \gamma\sigma_{t-1})^2 \\ z_t &\sim i.i.d.\ ast(z;\lambda,\nu). \end{aligned} \tag{2}$$

We constrain $\omega > 0$, $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$ to ensure that the conditional variance is positive in every week. The well-known inability of the normal distribution to match skewness and kurtosis in residuals leads us to consider the skewed t distribution of Hansen (1994). The i.i.d. return residuals z_t are assumed to follow the asymmetric standardized t distribution of Hansen (1994) which we denote as $ast(z;\lambda,\nu)$. The skewness and kurtosis of the distribution are nonlinear functions governed by the parameters λ and ν. When $\lambda = 0$ we obtain the symmetric standardized t distribution, when $\lambda = 0$ and $1/\nu = 0$, the return residuals follow the normal distribution. The corresponding cumulative return probabilities are then as follows:

$$\eta_t \equiv Pr_{t-1}(R < R_t) = \sigma_t^{-1} \int_{-\infty}^{\sigma_t^{-1}(R_t - \mu_t)} ast(z;\lambda,\nu) dz. \tag{3}$$

In this model the individual return shock distributions are constant through time but the individual return distributions vary through time because the return mean and variance are dynamic.

Using weekly firm-level observations of ϵ_t, the parameters $\alpha, \beta, \gamma, \omega, \lambda$ and ν are estimated using a likelihood function based on equation (2) and $ast(z; \lambda, \nu)$.

3.2 Mean and Variance Estimates

Panel A of Table 3 reports the proportion of respective (p,q) combinations for our $ARMA$ model chosen across all firms following the AIC criterion. The most commonly selected model is the $ARMA(2, 2)$, used in about 40% of cases for both customer and supplier firms. Although this might be taken as evidence that higher lag orders should be considered we refrain from adding an $AR(3)$ term since the purpose of this model is to ensure consistent estimation of second and higher-order moments and not to replace an economic model of expected returns. The percentages across all other models are relatively similar.

[Insert Table 3 about here.]

In Panels B and C of Table 3 we present estimates, summary statistics and model diagnostics for each of the four NAGARCH(1,1) parameters (ω, α, β, γ) and the two parameters of the asymmetric t distribution. Firstly, the results show that the $ARMA$ model performs well at removing short-term noise, the residual mean and standard deviation of both suppliers and customers is very close to 0 and 1 respectively, with a median of -0.01 and 0.00, and 0.99 and 1.00. Secondly, consistent with previous literature (e.g. Christoffersen et al. (2016)), we find a high degree of volatility persistence. The volatility persistence implied by our median estimates, defined by $(\alpha(1 + \gamma^2) + \beta)$ is 0.955 for suppliers and 0.962 for customer firms. Next, our results show a strong negative relation of return residuals and volatility with an average asymmetry parameter γ of 0.539 for suppliers and 0.427 for customers. In both cases the interquartile range is entirely positive, in line with the "leverage effect".[12]

Looking at the parameters of the t distribution we find median values of 4.10 and 5.13 for ν indicating fat tails consistent with previous results in the literature. Our estimates for the skewness parameter λ are relatively close to zero and range from positive to negative values with medians of 0.11 and 0.09 for suppliers and customers.

[12]Observations with $\beta < 0.4$ were excluded in the following event study tests and regressions to reduce noise.

3.3 Modeling dynamic conditional correlations

Traditional dynamic dependence models such as the scalar BEKK model of Engle and Kroner (1995) impose rigid restrictions on the variance and covariance dynamics. For example, Cappiello, Engle, and Sheppard (2006) have found that the persistence in correlation differs from the persistence in variance in stock as well as bond markets. We therefore model the dynamic correlation of customer and supplier returns using the more flexible dynamic conditional correlation (DCC) model of Engle (2002) and Tse and Tsui (2002).

The variance-covariance matrix is given by the product of correlation and standard deviation, so we can write $\Sigma_t = D_t \Gamma_t D_t$. D_t has the standard deviations $\sigma_{i,t}$ of firms i at time t from equation (2) on the diagonal and zeros elsewhere. Γ_t has ones on the diagonal and our main variable of interest, firm-pair level dynamic conditional correlations of return residuals, off the diagonal. The correlation dynamics in our model are driven by the cross-products of the return shocks z_t from equation (2):

$$\tilde{\Gamma}_t = (1 - \alpha_\Gamma - \beta_\Gamma)\tilde{\Gamma} + \alpha_\Gamma (z_{t-1} z'_{t-1}) + \beta_\Gamma \tilde{\Gamma}_{t-1}. \tag{4}$$

α and β are set to be non-negative scalar parameters satisfying $(\alpha + \beta) < 1$). We normalize the conditional correlation between firm i and firm j in week t by setting $\Gamma_{ij,t} = \tilde{\Gamma}_{ij,t} / \sqrt{\tilde{\Gamma}_{ii,t} \tilde{\Gamma}_{jj,t}}$ to ensure that all DCC correlations are between -1 and 1. The DCC model accounts for volatility clustering and the leverage effect directly in the definition of the conditional variance process. We use $1/T \sum_{t=1}^{T} z_t z'_t$ to estimate $\tilde{\Gamma}$ so that only two correlation parameters, α_Γ and β_Γ need to be estimated simultaneously, using numerical optimization. We follow Christoffersen et al. (2014) and rely on composite likelihood (CL) estimation using

$$CL(\alpha_\Gamma, \beta_\Gamma) = \sum_{t=1}^{T} ln\ f(\alpha_\Gamma, \beta_\Gamma; z_{it}, z_{jt}) \tag{5}$$

for each pair of firms i and j in our sample. $f(\alpha_\Gamma, \beta_\Gamma; z_{it}, z_{jt})$ denotes the bivariate normal distribution of return residuals of i and j and covariance targeting is imposed. To increase precision in our estimations we make a simplifying assumption and use the first year in which a supplier discloses a close relationship with a customer firm as the starting year of the firm-pair link and use the full time-series of return residuals until the last reported year of the customer-supplier relationship.

3.4 Correlation dynamics estimates

Consistent with prior literature (e.g. Chiang et al. (2007) and Christoffersen et al. (2014)) we find that the correlation persistence defined as $(\alpha + \beta)$ is very close to one when focusing on DCC models on country-level index returns as shown in Table 4, implying very slow mean-reversion in correlations. Looking at α and β estimates for the firm-level return pairs however, the results are very different. The average α for customer-supplier pair returns is roughly three times larger than the corresponding parameter for country-level pairs. On the other hand, β is much lower with a median estimate around 0.3 for firm-level return correlations. These results indicate that firm-level correlations both react much more strongly to recent return shocks $(z_{t-1}z'_{t-1})$ and mean-revert at a much faster rate. To exclude noisy estimates, supplier-customer pairs for which the DCC model estimation did not converge or produced very low estimates of β were excluded in the following event study tests and regressions, reducing the sample by about 10%.

[Insert Table 4 about here.]

We present time-series plots of weekly average dynamic conditional correlations (DCC) across all firm-pairs of U.S. suppliers and international customers in our sample, as well as the average DCC correlation between the market index return of the customers' home country and the U.S. value-weighted market index in Figure (1). Panel A shows the aggregate values across all firms, Panel B summarizes the 11 countries with the largest number of customers in our sample individually. The results are consistent with Christoffersen, Errunza, Jacobs, and Langlois (2012) and Christoffersen et al. (2014) and show that while pairwise correlations fluctuate considerably from week to week, they show a clear upward trend since the mid-1990s. Panel A in Figure 1 highlights that, focusing on country-level indices, DCC correlation increased from roughly 0.3 in the mid-1990s to values around 0.6 in 2012 and has slightly decreased since then. Focusing on the aggregate firm level correlations we find a similar upward trend with average DCC correlation increasing roughly threefold since the mid-1990s.

4 The Effect of Country-Level Shocks on Contagion

4.1 Event study tests

In the majority of our event study tests we follow the approach used for example in Da, Engelberg, and Gao (2011) and define “abnormal DCC” ($ADCC_t$) as the difference between DCC correlation in week t minus the firm-pair's average DCC correlation ($\frac{1}{(T-k)}\sum_{j=k}^{T} DCC_j$) over an estimation window from 70 to 20 weeks prior to the week of the event. We drop firm-event observations with fewer than 35 DCC correlation estimates in the estimation window and any firm-event observation with missing DCC_t in the event window.

We then aggregate $ADCC_t$ over the weeks of the event window to obtain a measure of “cumulative abnormal DCC”. Given the nature of our country-level shocks affecting a large number of firm-pairs at the same time, cross-sectional dependence (Kolari and Pynnönen, 2010) and event induced volatility (Boehmer, Masumeci, and Poulsen, 1991) might produce misleading test statistics in our event study tests. For each abnormal correlation estimate we therefore report t statistics following a battery of parametric- and non-parametric significance tests, including the standard cross-sectional t-statistic using robust standard errors and the Crude Dependence Adjustment (CDA) test following Brown and Warner (1980) and Brown and Warner (1985) as well as the non-parametric Rank Test (Corrado and Zivney, 1992) and the Sign Test and Generalized Sign Test introduced in Cowan (1992). We conservatively use the maximum of the p-values corresponding to the “weakest” t-statistic across all significance tests to determine the reported level of statistical significance.

4.1.1 Country-index shocks. Table 5 presents event study estimates of the weekly cumulative average abnormal DCC correlation between U.S. suppliers and their international customers around country-index return shocks as defined in Section 2.2.

[Insert Table 5 about here.]

Our main results using the 2.5% country-index shocks are summarized in Panel A and show an economically large, statistically significant average abnormal DCC correlation between U.S. supplier- and customer returns of 0.0925 in the 6 weeks ($t = [0, 5]$) and 0.1593 in the 11 weeks ($t = [0, 10]$) following the country-index shock to the customer country. Compared to the average weekly DCC correlation DCC_t of 0.219 across all observations in our sample this implies an increase in return correlation by more than 40% following negative country-index shocks. In other words, in *each* of the 6 weeks after the initial shock we observe an upward shift in return correlation − after directly controlling for volatility clustering and asymmetric return distribution − of 1.54 percentage points, or roughly 8% compared to the weekly DCC correlation in normal times.

Figure (2) provides further graphical evidence showing the weekly average abnormal DCC correlation for negative and positive country-index shocks for the supplier-customer pairs in our sample as well as the matched "placebo" suppliers from our placebo tests (see Section 4.3). Consistent with our event study estimates the graph shows a sharp increase in return correlation following negative index shocks and a slow return to normal correlation levels after about 20 weeks. Furthermore, the graph shows no impact of positive shocks on correlation levels and a distinctly larger impact on our sample supplier firms compared to matched placebo suppliers.

The country-level shocks have a relatively long lasting impact on return correlation. Over the five weeks $t = [6, 10]$ and $t = [11, 15]$ relative to the shock event, we find statistically significant average abnormal DCC correlation of 0.0670 and 0.0676, equivalent to roughly a 6% increase in return correlation in *each* of the five weeks compared to the sample average. Only after 25 weeks abnormal return correlation returns back to zero. In line with our expectation that country-level shocks induce contagion across firm-level links we find no evidence of abnormal return correlation in the weeks before the shock events. This result is robust to using different shock thresholds or test specifications in Panels A to C.

The results using country-index shocks based on a 0.5% and 0.1% percentile threshold are summarized in Panels B and C of Table 5. Consistent with the idea that larger country-index shocks affect customer firms more strongly and cause larger financial contagion along the supply-chain, we find cumulative average abnormal correlation of 0.2831 and 0.3464 respectively in the 11 weeks $[0, 10]$ following the country-index shock. Although most of this effect can be attributed to the first six weeks $[0, 5]$ ($CAADCC$ of 0.1938 and 0.2448 respectively) we find that even in weeks $[16, 20]$ and $[21, 25]$ return correlation is abnormally high at a statistically significant level, indicating that extreme country-index shocks have a long lasting impact. In line with our findings using the 2.5% threshold we find no evidence of abnormal correlation before the country-index shocks as well as 25 weeks afterwards.

For further robustness we also use the difference between DCC_t and the DCC correlation at the index level between the U.S. and the customer country market index ($DCC_t - DCC_t^{indices}$) compared its historical average during the estimation window as a benchmark. The results, summarized in Panel D of Table 5, are very similar to our main tests.

4.1.2 Country-level (disaster) events. In Table 6 we conduct a similar event study focusing on the sample of country-level disasters and large scale political events outlined in Section 2.2. (Cumulative) abnormal correlation is defined in the same way as before. Panel A of Table 6 summarizes the results for the full sample of events, Panels B and C focus on two of the shocks affecting the largest number of firms in our sample, the earthquake and flood in Japan in 2011 and the Eurozone bailout decisions in 2010.

[Insert Table 6 about here.]

In general, the results from our country-event sample corroborate our previous findings based on country-index shocks. The results for the pooled sample of country-level events in Panel A show an abnormal increase in DCC correlation of 0.0651 in the eleven weeks $[0, 10]$ following the initial event shock. Most of this abnormal DCC correlation (0.0500) is concentrated in weeks $[0, 3]$ around the event, indicating an increase of 5.71% compared to the sample average DCC correlation in *each* of the four weeks of the event window (22.83% in total). Before the event, as well as ten weeks after, we find no evidence of abnormally high or low DCC correlation, consistent with the idea that large scale country events induce temporary financial contagion.

Focusing on individual events in our sample in Panels B and C, we observe a striking difference between 'natural' shocks (e.g. the earthquake and tsunami in Japan 2011) and political events such as the Eurozone bailouts of 2010. Similar to our full event sample, DCC correlation increases significantly by about 0.05, or about 22.83%, in the weeks $[0, 5]$ after the tsunami shock event in Japan. Focusing on the Eurozone bailout events, the picture looks quite different. We find no evidence of abnormally high DCC correlation after each of the bailout announcements. However, in the ten weeks $[-10, -1]$ *before* the events, we find a statistically significant abnormal DCC of 0.1591, consistent with the notion that these events were partially anticipated by market participants. Taken together, these results indicate that large country-level events, similar to our results from market-index shocks, generate a large upward shift in return co-movement lasting about ten to twenty weeks after the initial shock. Figures (4) and (5) provide graphical evidence for both the Japanese earthquake and Eurozone bailout events.

4.1.3 Sovereign debt ratings changes. To shed further light on the asymmetry of positive and negative shocks and the importance of truly exogenous events we collect sovereign credit rating changes for the countries of our customer firms from the Fitch Ratings Agency and repeat the event studies shown above. This approach follows Chiang et al. (2007) who suggests that credit ratings changes are associated with international contagion. Table 7 presents our results.

[Insert Table 7 about here.]

Looking first at the impact of negative ratings changes (downgrades) in Panel A, we find evidence of abnormal DCC correlation in the five weeks $[-5, -1]$ before the announcement of the ratings downgrade consistent with the findings of Chiang et al. (2007). However, the magnitude is relatively small at 0.0382 compared to our sample of country-level events and market-index shocks and statistically insignificant for 2 out of 5 test statistics. Turning to positive ratings changes (upgrades) we obtain abnormal correlation ($ADCC$) estimates very close to zero in magnitude and generally find no evidence of financial "contagion". These results confirm our previous findings that positive and negative shocks have a distinctly different impact on financial contagion along economically linked firms in the supply-chain, consistent with asymmetry in the trade credit channel hypothesis of Kiyotaki and Moore (1997) and Jacobson and Schedvin (2015). Furthermore, the results indicate that sovereign credit ratings changes are anticipated by financial markets and do not result in economically large shifts in return co-movement in our sample of international supplier-customer firms, as illustrated by the graphs in Figure (7).

4.2 Multivariate tests and difference-in-difference estimations

4.2.1 Country-index return shocks. The impact of country-level shocks on firm-level financial contagion likely varies across time and firm pairs. Therefore, we next extend our analysis to multivariate panel regressions. To capture the causal effect of country-level shocks on DCC correlation we define a dummy variable $BKSEvent_{i,t}$, which takes the value of one if the customer firm in relationship i was affected by a BKS-type country-index shock in week t, and zero otherwise and estimate a series of regressions of the form:

$$DCC_{i,t} = \alpha + \beta * BKSEvent_{i,t-k} + \delta' X_{i,t} + \omega_i + \gamma_t + \epsilon_{i,t}, \tag{6}$$

where $X_{i,t}$ denotes a vector of supplier firm-, customer firm-, and firm-pair characteristics listed in Table A.I in the Appendix. Identification in this setting comes from examining differences *within firm-pairs affected by a customer-country shock* relative to differences *across firm-pairs not affected by such shocks.* Since we simultaneously include both firm-pair fixed effects (ω_i) and weekly time fixed effects (γ_t) this specification is equivalent to a quasi difference-in-difference approach with index-return shocks as country-week level treatment effects. For robustness we estimate this specification using different event lags, $k = 0, ...4$.

[Insert Table 8 about here.]

Panel A of Table 8 reports our results regarding the impact of negative as well as positive 2.5% country-index return shocks on DCC correlation as specified in equation (6). Looking at negative shocks first, we obtain positive, economically large coefficient estimates for each of the country-index shock indicators with lags of 1 to 4 weeks individually, as well as when include all four lags together in one regression. The results show that country-index shocks increase DCC correlation by 0.012, or 5.5%, in the first two weeks and 0.006 in weeks three and four following the index shock. All estimates are statistically significant at the 1% level. The coefficients on lags 1 through 4 decrease monotonically indicating a slowly decreasing impact of country-level shocks on financial contagion over time. In contrast, the coefficient estimates on positive country-index shocks are very close to zero and statistically insignificant. The results show that positive country shocks are not related to an upward shift in return correlation in the following weeks, consistent with our event study results.

In Panel B of Table 8 we present a number of alternative specifications and sub-sample tests. The estimates show that our results are robust to including monthly instead of weekly firm fixed effects or excluding firm-pair fixed effects. Further, we split the sample into firm-pairs with relatively strong and weak relationships according to the percentage of total sales the supplier represents to the customer. If supply-chain links between customers and suppliers are an important channel for the transmission of financial contagion, we would expect a stronger effect of country-level shocks on DCC correlation for firm-pairs with a tighter economic link. The results indeed show that coefficient estimates are larger than our base estimates for all weekly lags from 0 to 5 and statistically highly significant when focusing on firm-pairs with a strong relationship. Focusing on firm-pairs with low relationship strength on the other hand, the coefficient estimates are roughly half in size on aggregate and statistically not significant at standard levels for lags 0, 1 and 3.

As shown for example in Christoffersen et al. (2014), DCC correlations of market indices around the world have changed significantly over time. For this reason, we next split our sample into subsamples before and after the year 2000. The results indicate that our findings are largely concentrated in the more recent half of our sample period from 2000 to 2014. We find statistically highly significant, slightly larger coefficient estimates for all four weekly lags compared to our base estimations. In contrast, focusing on the early half our sample, we find weaker results and statistically insignificant coefficient estimates on lags 1, 3 and 4. For further robustness we estimate similar panel regressions with firm-pair and weekly time fixed effects using the alternative country-index shock cutoffs of 0.5% and 0.1% percentiles. The results are summarized in Panel D and confirm our previous findings. Large negative country-index shocks lead to higher DCC correlation in the following weeks after controlling for firm-pair average DCC correlation as well as firm- and time specific characteristics.

4.2.2 Country-level (disaster) events. Relying on our sample of country events, we estimate similar difference-in-difference regressions as specified in equation (6) to determine the effect of major political or disaster event on firm-level DCC correlation with a lag of up to four weeks. The results, summarized in Table 9, show a similar impact of country events on DCC correlation as the previously discussed country-index shocks regarding the sign and magnitude of the obtained coefficient estimates. Aggregating the coefficient estimates of lags 0 to 4, DCC correlation increases by 0.04, or 18.26%, as a result of a country-level (disaster) events in our regressions when including weekly and firm-pair fixed effects as shown in Panel A. The results are statistically significant at the 1% and 5% level for lags 0 and 1.[13]

[13] When we estimate similar regressions including monthly instead of weekly time fixed effects, we find even larger, highly significant regression coefficients.

[Insert Table 9 about here.]

In Panel B we present the results of a number of sample splits and alternative specifications. First we explore the importance of firm-pair relationship strength for the transmission of financial contagion along supply-chain links. Consistent with our previous country-index shock results we find that the positive relationship between (lagged) country-level events and subsequent DCC correlation is almost completely concentrated in firm-pairs with above median relationship strength. Splitting our sample into three periods and we find again that our results are mostly due to the most recent observations since 2004. This is not surprising given that the majority of the country-level events occurred in the last part of the sample making it hard to find robust results for the beginning of the sample period from 1985 to 2003. Further, looking at two of the most significant events in the sample, the disaster in Japan in 2011 and the Eurozone bailout, the results support our previously reported event study findings. DCC correlation significantly increases by almost 50% (on aggregate) over the four weeks following the disaster event in Japan. In line with our event study findings, we obtain much weaker estimates for the Euro bailout events, likely due to markets anticipating these events in advance as previously shown.

4.3 Placebo tests

Our approach of focusing on global supplier-customer links as a channel for the transmission of contagion allows us to specifically test the importance of the trade link for international contagion while controlling for market- and industry level contagion. The literature on financial contagion has suggested a number of channels for the transmission of financial contagion as summarized in Dornbusch et al. (2000) and Chiang et al. (2007). Any channel for the transmission of financial contagion based on investor behavior such as the 'wake-up call hypothesis', 'liquidity channel' or 'wealth effect channel' summarized in Pritsker (2001) would affect all firms in the initially "sick" country as well the subsequently "infected" country in a similar way. Moreover, if financial contagion is due to industry shocks and business prospects for a certain sector in the affected country, we would expect firms in the same industry as our supplier firms to be affected similarly in response to a country-level shock. To disentangle the supply-chain channel of financial contagion from alternative mechanisms and explanations and rule out mechanical effects, we conduct placebo tests replacing the U.S. suppliers in our sample with matched placebo suppliers from the same Fama-French 48 industry.

Our firm-relationship approach and novel dataset enables us to directly compare the differential effect of customer-country shocks on the return co-movement of "real" pairs of U.S. suppliers and their customers and "placebo pairs" of matched U.S. suppliers from the same industry and the "original" customers. We match placebo suppliers to our actual U.S. supplier firm observations by identifying the most similar firm in terms of average size (book value of assets) over the duration of the firm-pair relationship within the same Fama-French 48 industry. The matching procedure relies on firm size for identification since it is a well-known proxy for attention, liquidity and the speed of information diffusion. We exclude potential placebo supplier matches with insufficient return observations during the period from the beginning to the end of the "real" supplier-customer relationship.

Panel A of Table 1 summarizes the DCC correlation between U.S. suppliers and their international customers as well as the DCC correlation between matched placebo suppliers and the international customers and the mean difference. The results show that on average the DCC correlation is about 15% higher for real suppliers compared to placebo suppliers, the difference is statistically significant at the 0.01% level. Extending the regression specification in equation (6) to a triple difference specification, we interact our $BKSEvent_{i,t}$ dummy variable with a dummy variable $Supl\_is\_real_i$ taking the value of one for all "real" supplier-customer relationships in our sample and zero for the matched placebo pairs to examine if country-level shocks have a distinct effect on the firms linked along the supply chain. We pool the observations of both the real and placebo supplier-customer pairs and estimate regressions of the form:

$$\begin{aligned} DCC_{i,t} &= \alpha + \beta_1 * BKSEvent_{i,t-k} + \beta_2 * Supl\_is\_real_i \\ &\quad + \beta_3 * (BKSEvent_{i,t-k} \times Supl\_is\_real_i) + \delta' X_{i,t} + \omega_i + \gamma_t + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where β_3 estimates the triple difference effect of country-level shocks on the "real" and matched placebo firm pairs. Firm- and pair-level controls $X_{i,t}$, weekly time fixed effects γ_t, and relationship fixed effects ω_i are defined similarly as before.

The estimation results for equation (7) are summarized in Panel C of Table 8. Firstly, the results show that that DCC correlation is significantly higher for real compared to placebo supplier-customer pairs in line with our univariate evidence from Panel A of Table 1. Secondly, negative country-index shocks with a lag of up to 4 weeks increase firm-level DCC correlation by 15% on aggregate, confirming the results from the event study approach and the graphical evidence from Figure (2). This effect is statistically significant at the 1% level for the first 3 weekly lags. However, the coefficient estimates are much smaller in magnitude than the estimates obtained from the original sample including only "real" supplier-customer pairs in Panels A and B of Table 8.

Thirdly, the interaction effect of the (lagged) country-index shock and the $Supl\_is\_real$ dummy variable shows that our shock events have a significantly stronger effect on economically linked pairs of suppliers and customers than our matched placebo pairs. Each regression includes both firm-pair and weekly time fixed effects in addition to a host of firm- and firm-pair controls listed in Table A.I in the Appendix. Taken together, these results support the notion that economic links between customers and suppliers are an important channel for the transmission of financial contagion across financial markets: DCC correlation on average is significantly higher for real vs. placebo supplier firms and international customers, coefficient estimates on country-index shocks are smaller compared to our base estimations as we include placebo firms which are not subject to the same exposure from international customers. Finally, country-index shocks have a stronger effect on real supplier-customer pairs compared to placebo pairs.

5 Firm Value Implications and the Trade Credit Channel

5.1 Value effects of country-level shocks

To further rule out mechanical effects and show that large country level shocks have a distinct effect on U.S. supplier firms exposed to these shocks through their supply-chain partners abroad, we estimate the value effects of country-level shocks for both real and placebo suppliers. As in Section 4.3, placebo suppliers were matched to the sample U.S. suppliers within the same Fama-French 48 industry classification according to average firm size over the length of the supplier-customer relationship period.

We start by calculating daily cumulative average abnormal returns ($CAAR$) for each U.S. supplier and placebo supplier around large daily (0.5% and 0.1% threshold) country-index return shocks in the customer's country. Abnormal returns are computed after estimating, for each (placebo) supplier, a three-factor Fama-French model over the interval from 271 to 21 trading days before the event date. We exclude firm-shock observations with missing returns in the estimation or event windows, or when the customer firm's country is affected by another index return shock within 40 trading days around the event.[14]

[Insert Table 10 about here.]

Table 10 summarizes the results regarding the daily average abnormal returns around country-index event. As shown in Panel A, in the daily event window $[-10, 40]$ around the 0.5% country-index shocks we find a cumulative average abnormal return of -3.73% for the U.S. suppliers in our sample, statistically significant at the 1% level for each test statistic. In contrast, we obtain a statistically insignificant abnormal average return of -1.16% for our sample of matched placebo suppliers over the same event window. Looking at the $CAAR$ around 0.1% (daily) country-index shocks in Panel B of Table 10 we find similar results. Our U.S. suppliers experience an average abnormal return of -5.62% over the $[-10, 40]$ event window, significant at the 1% level, the $CAAR$ for matched placebo suppliers over the same horizon is much smaller at -2.71% and statistically insignificant. These results are in line with our previous finding that more severe country level shocks have a larger spillover effect on connected U.S. supplier firms and support the notion that the transmission of country-level shocks is indeed due to the specific supply chain links on the firm-level.

Panels C and D present cumulative average abnormal returns and cumulative average raw returns ($CARR$) for U.S. suppliers connected to Japanese customers and Japanese customer firms respectively around the earthquake and tsunami in Japan. Consistent with the evidence from the country-index shocks we find a $CAAR$ of -4.40% for U.S. suppliers with Japanese customers (significant at the 5% level) and a very small, insignificant $CAAR$ of +0.35% for our sample of matched placebo suppliers over the $[-10, 40]$ event window. Unsurprisingly, we also find a very large, negative cumulative raw return for the Japanese customers directly affected by the disaster in 2011. Interestingly, the negative impact of the disaster shock appears to be fully incorporated

[14] For each estimate we report ADJ-BMP t-statistics computed with the parametric, standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010). We also report Corrado-Zivney t-statistics computed with the non-parametric rank test of Corrado and Zivney (1992) and Kolari and Pynnonen (2011).

into stock prices of the Japanese customers after about 5 days, for each of the daily horizons $[5, 10]$, $[11, 20]$, $[21, 30]$ and $[31, 40]$ the cumulative return is slightly positive, albeit statistically insignificant.

Figures (7), (8) and (9) provide graphical evidence regarding the value effects of country-level shocks and events: They show that (a) country-index shocks have strong, negative value implications for U.S. suppliers linked to the affected customers and the same effects cannot be found for matched placebo suppliers (Fig. 7), (b) the disaster in Japan had a very large effect on the Japanese market index as well as local customer companies (Fig. 8) and (c) U.S. suppliers connected to Japanese customers were strongly negatively affected by the disaster and the effects were much weaker and statistically insignificant for placebo suppliers (Fig. 9).

5.2 Trade credit and DCC correlation

As formally shown by Kiyotaki and Moore (1997) and recently empirically confirmed for a proprietary sample of Swedish trade relationships and bankruptcies by Jacobson and Schedvin (2015), suppliers who extend trade credit to customers are exposed to negative shocks to their customer firms as their potential default on trade credit obligations can propagate along the supply-chain link. Kiyotaki and Moore (1997) dub this mechanism the credit-chain channel. Correspondingly, if the trade-credit channel is an important mechanism for the cross-country propagation of financial contagion we would expect DCC correlation on the firm-level to be related to the use of trade credit by U.S. suppliers and international customers in our sample.

[Insert Table 11 about here.]

In Table 11 we therefore estimate cross-sectional regressions of annual average DCC correlation by firm-pair year on the use of trade credit by U.S. suppliers and international customers. Following e.g. Shenoy and Williams (2015) we use the ratio of "accounts receivables to sales" as a proxy for the trade credit extended by the supplier and the ratio of "accounts payable to cost of goods sold" as a proxy for trade credit used by the customer as is common in the trade credit literature (e.g. Demirgüç-Kunt and Maksimovic, 2001). We include country-year fixed effects in each specification to control for cross-sectional and time-series variation in the characteristics of the customer countries and control for the intensity and strength of the supply-chain relationships using measures based both on the relative proportion of sales to the customer and the proportion of cost of goods sold represented by the supplier. Our results show that both contemporaneous as well as lagged measures of the trade credit extended by the supplier is positively related to the firm-pair level DCC correlation of supplier and customer. The coefficient estimates are statistically significant at the 5% and 1% level and indicate that a one standard deviation increase in AR/Sales of the supplier firm is associated with a 5.3% increase in DCC correlation in the current year and a 7.8% increase in DCC correlation in the following year. Our results further indicate that the use of trade credit by customer firms ("AP/COGS") is positively related to firm-level DCC correlation both for the current year and with a one-year lag. The estimates are significant at the 1% and 5% level respectively and represent a roughly 5% increase in return correlation for a one standard deviation increase in AP/COGS.

These results are consistent with the literature and recent evidence presented by Jacobson and Schedvin (2015) and support the notion that the trade-credit channel is an important mechanism for the propagation of financial contagion on the firm-level. In the cross-section, supplier firms using more trade credit are associated with a higher level of return DCC correlation with their international principal customers, even when controlling for the intensity and strength of the supply-chain relationship.

Taken together our results show that country-level shocks and events abroad have a distinct spillover effect for U.S. supplier firms linked to international customers in the affected countries along the supply chain with regards to return co-movement, i.e. financial contagion, and firm value. The same shock propagation and induced contagion cannot be found for matched placebo firms that are likely to be subject to similar industry- and market forces and factors as our sample suppliers. Further, the use of trade credit by both supplier and customer firm is an important determinant of DCC correlation, supporting the idea of trade-credit chains raised in Kiyotaki and Moore (1997).

6 Conclusion and Discussion

Despite the long-time interest of policy makers and managers in the fundamentals that determine international contagion and the channels that help transmit contagion, there is very little empirical evidence at the firm-level on the role of economic networks and trade links for cross-country contagion. We fill this gap in the literature by using novel, hand-collected data on U.S. suppliers and their international principal customers to study the transmission of country-level shocks and their impact on financial contagion.

Following large country-level shocks such as extreme stock market jumps studied for example in Bae et al. (2003) as well as natural disasters such as the 2011 earthquake and tsunami in Japan, the dynamic conditional correlation (DCC) between U.S. suppliers and their principal customers increases significantly, in some cases up to twofold, above normal levels. Further, these shocks have a relatively long lasting impact on return correlation of up to 25 weeks. Our findings are robust to a difference-in-difference estimation strategy using natural disasters and political events as exogenous country-level shocks.

In placebo tests, using matched 'fake' supplier firms, we cannot find similar evidence suggesting that firm-level supply-chain links are indeed an important mechanism for the propagation of financial contagion. Event study tests around country-level shocks and disaster events further indicate large value implications for our sample of U.S. suppliers, but not for the matched placebo firms. Consistent with the notion of a 'trade-credit mechanism' underlying this transmission channel, we find that financial contagion is stronger for supply-chain pairs with a close relationship and further document a positive relationship between firm-level DCC correlation and the use of trade credit by both supplier and customer firms.

Our findings indicate that U.S. firms potentially incur a severe cost as a result of globalized supply-chains as they become exposed to large country level shocks such as natural disasters or political events abroad. This 'dark side of globalization' has previously been ignored in the international finance literature. Our results also have important implications for investors and risk-managers as they affect the benefits of international diversification. If asset returns are more correlated following large country shocks, the benefits from internationally diversified portfolios are low in the most critical states of nature.

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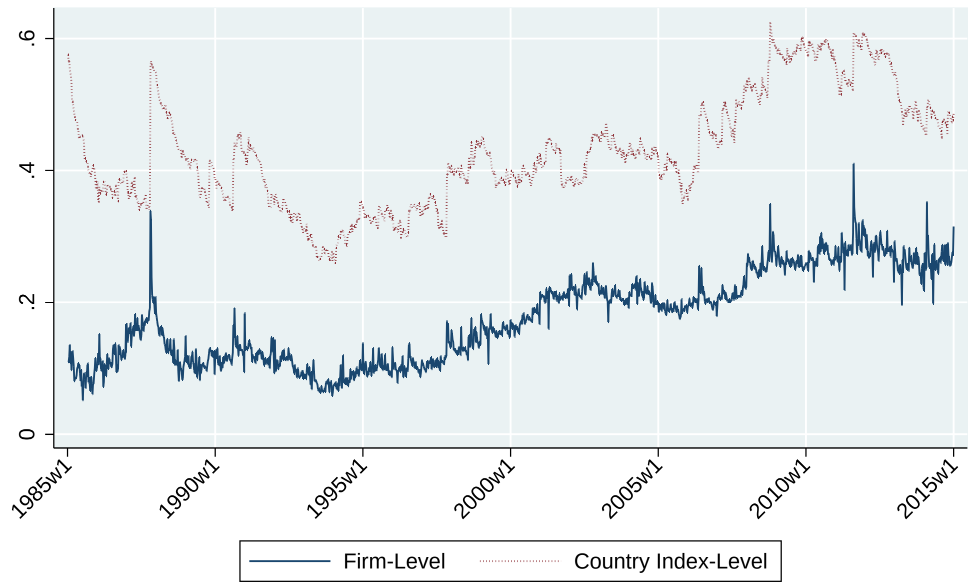
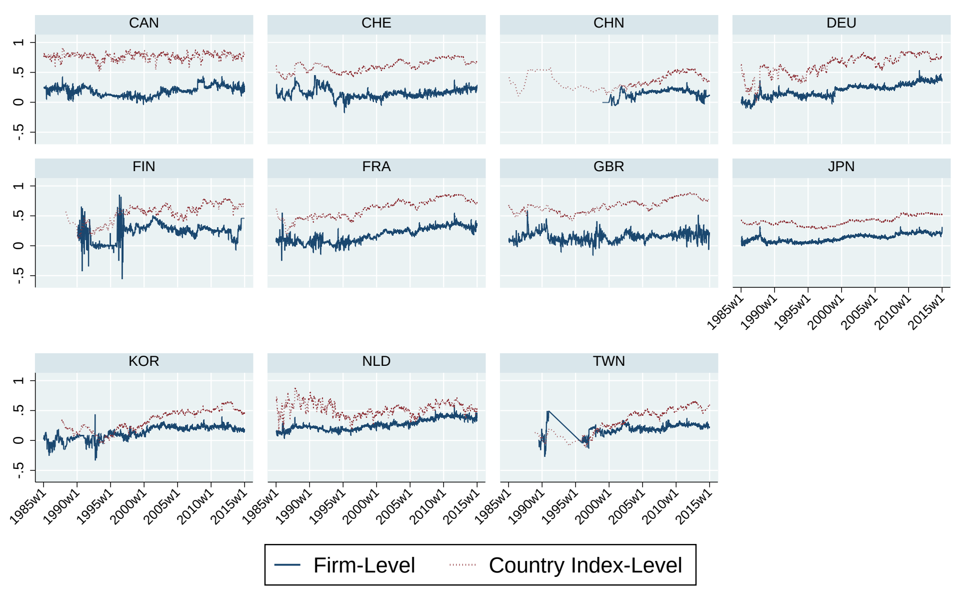
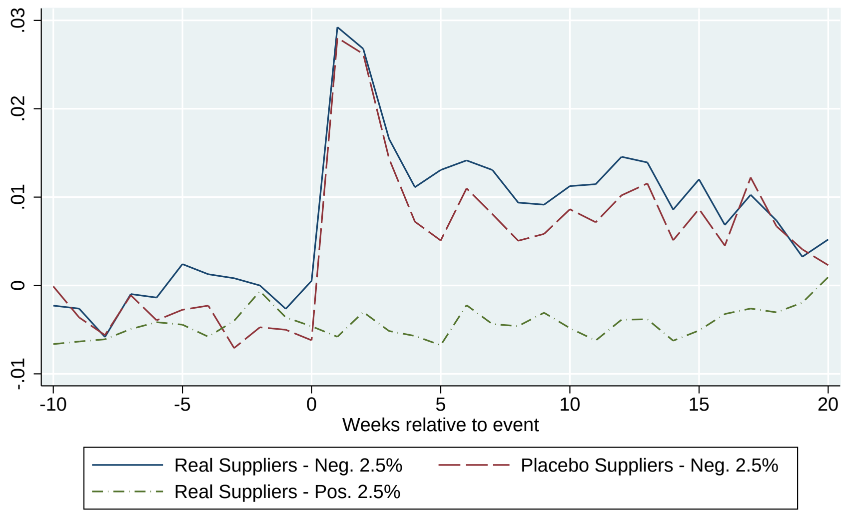


(a) Average weekly DCC correlation across all countries.

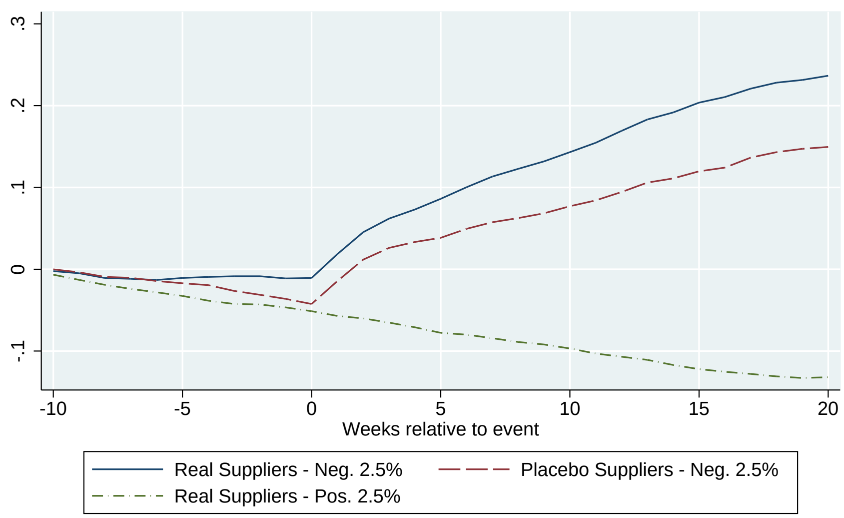


(b) Average weekly DCC correlation country-by-country.

Figure 1. *Notes.* In figure (a) the solid line shows the average weekly DCC correlation across all firm-pairs of US suppliers and international customers in our sample, the dotted line shows the average DCC correlation between the market index return of the customers' home country (Source: Datastream) and the US value-weighted market index. Figure (b) also shows the average weekly DCC correlation on firm- and country-index level by country focusing on the 11 countries with the largest number of customers in our sample. Our sample covers the time from January 1985 to December 2014 and has 2317 firm-pairs across 35 countries.



(a) Average Abnormal DCC ($AADCC_t$) correlation.



(b) Cumulative Average Abnormal DCC ($CAADCC$) correlation.

Figure 2. *Notes.* This figure presents the weekly average abnormal DCC correlation ($AADCC_t$) in figure (a) and the cumulative average abnormal DCC correlation ($CAADCC$) in figure (b) between the real U.S. suppliers and their customers around the negative 2.5% BKS-style country-index shocks (solid line), the 2.5% positive BKS shocks (short-dashed line) and the matched placebo suppliers around the negative 2.5% BKS country-index shocks (long-dashed line) from 10 weeks before the BKS shock to 20 weeks after the event. Average abnormal DCC correlation for each customer-supplier-week is estimated as the difference between the weekly DCC correlation of the firm-pair minus the firm pair's average DCC correlation over the interval from 70 to 20 weeks before the event week. If the firm-pair had fewer than 35 weekly DCC correlation estimates during the estimation window or missing weekly DCC estimates during the event window the firm-shock observation was excluded. If a country-index shock was followed by another shock within the next 20 weeks, only the first shock observation was included. Over our sample period from 1985 to 2014 we find 1355 negative 2.5% firm-pair shock observations satisfying these requirements.

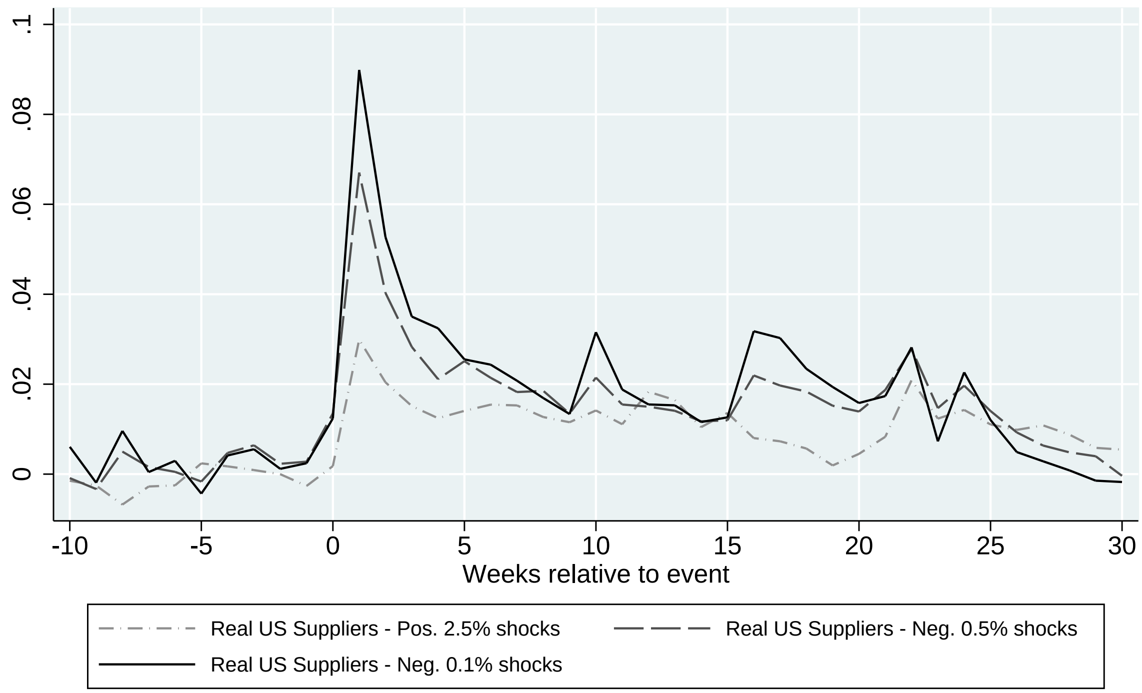
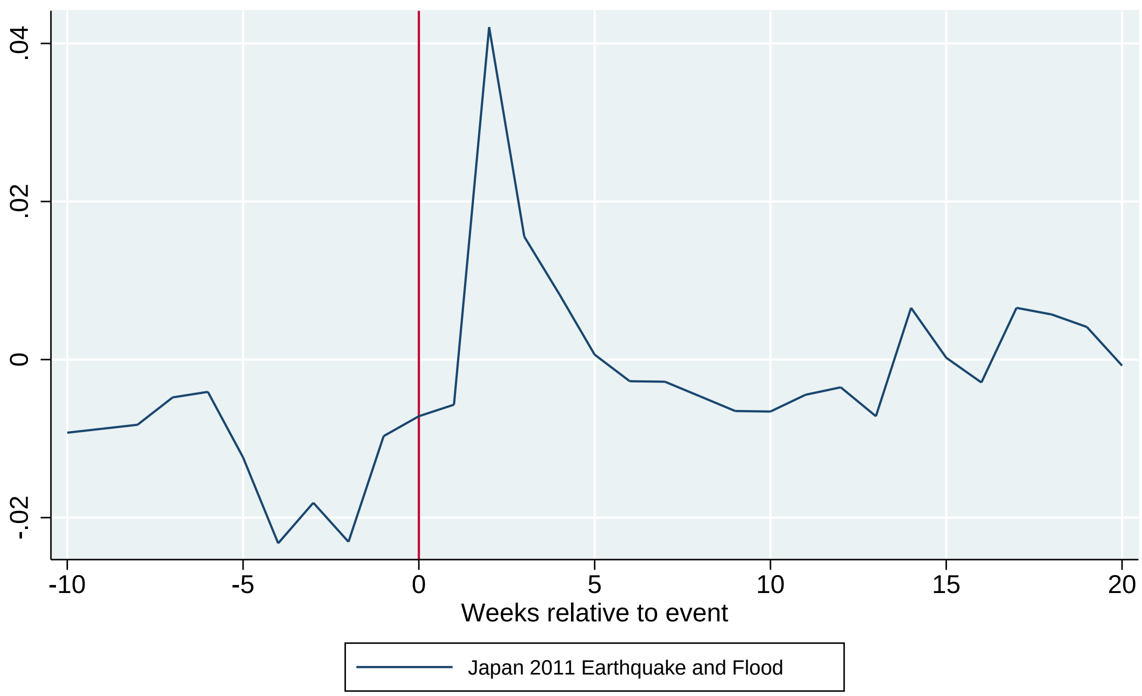
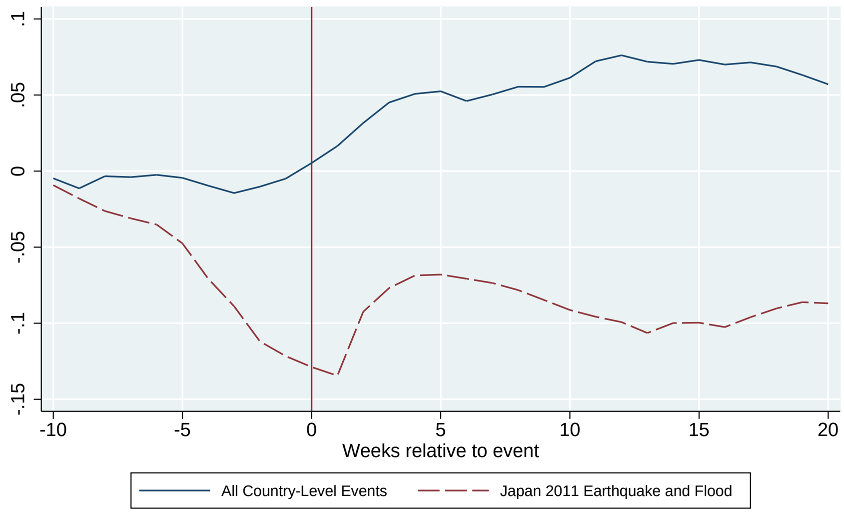


Figure 3. *Notes.* This figure presents the weekly average abnormal DCC correlation ($AADCC_t$) for the real U.S. suppliers and international customers around the most negative 0.1% (solid line), 0.5% (long-dashed line) and 2.5% (short-dashed line) BKS-style country-index shocks from 10 weeks before the country-shock to 30 weeks after. Average abnormal DCC correlation for each customer-supplier-week is estimated as the difference between the weekly DCC correlation of the firm-pair minus the firm pair's average DCC correlation over the interval from 70 to 20 weeks before the event week. If the firm-pair had fewer than 35 weekly DCC correlation estimates during the estimation window or missing weekly DCC estimates during the event window the firm-shock observation was excluded. If a shock was followed by another shock within the next 30 weeks only the first shock observation was included in the sample. After applying these filters we keep 1355, 946 and 364 firm-pair level events using the bottom 2.5%, 0.5% and 0.1% negative country-index shocks.

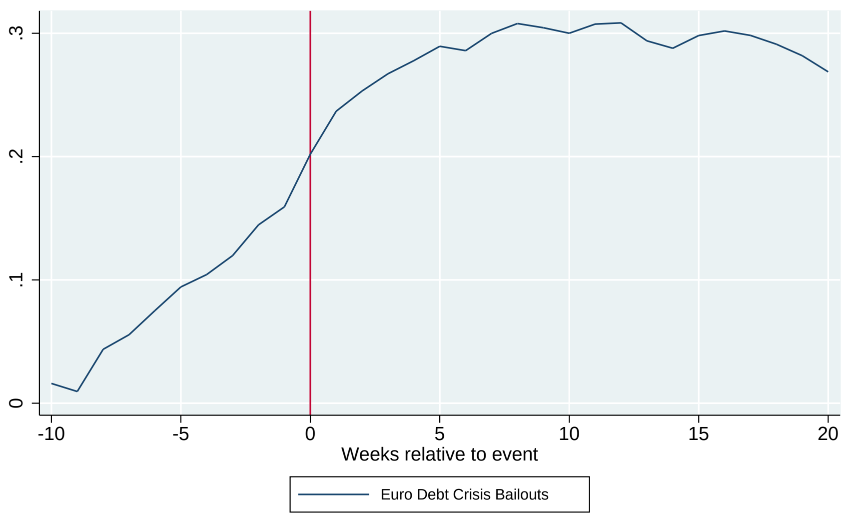


(a) Weekly Average Abnormal DCC ($AADCC_t$) correlation - Japanese Customer Firms.

Figure 4. *Notes.* This figure presents the weekly average abnormal DCC correlation ($AADCC_t$) between U.S. suppliers and Japanese customer firms for the 31 $[-10, 20]$ weeks around the 2011 earthquake and flood disaster in Japan. Average abnormal DCC correlation for each customer-supplier-week is estimated as the difference between the weekly DCC correlation of the firm-pair minus the firm pair's average DCC correlation over the interval from 70 to 20 weeks before the event week. We drop firm-event observations with insufficient DCC correlation estimates in the estimation or event window. We find 97 firm-pair-disaster observations after applying these filters.

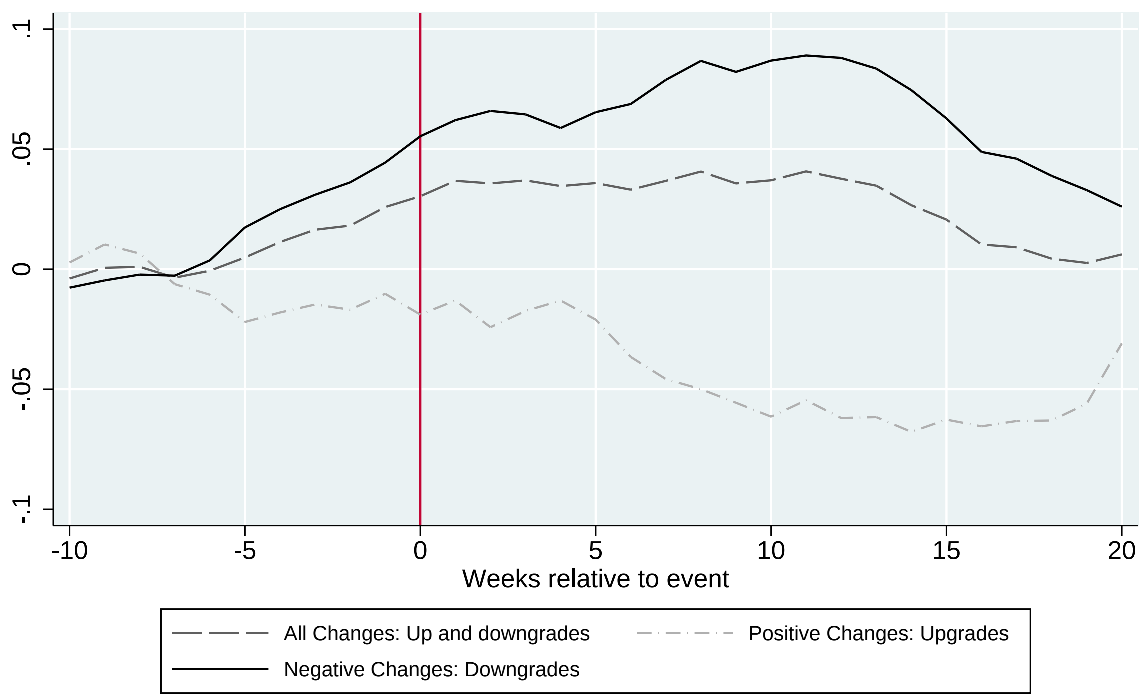


(a) Weekly Cumulative Average Abnormal DCC ($CAADCC$) correlation.



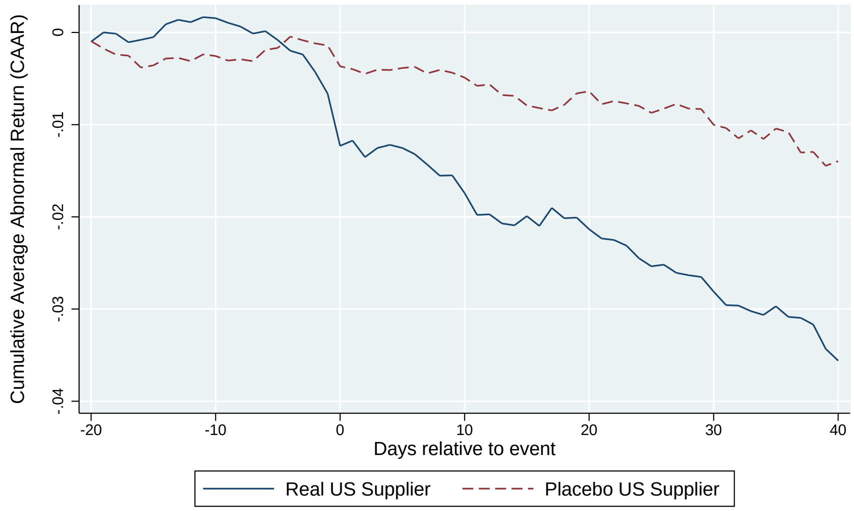
(b) Weekly Cumulative Average Abnormal DCC ($CAADCC$) correlation.

Figure 5. *Notes.* Figure (a) shows the weekly cumulative average abnormal DCC correlation ($CAADCC$) between the U.S. suppliers and their customers for the 31 $[-10, 20]$ weeks around the full sample of all country-level (disaster) events (solid line) listed in Appendix A.II and for all pairs of U.S. suppliers and customers in Japan around the 2011 earthquake and flood in Japan (dashed line). Figure (b) shows the $CAADCC$ for all U.S. suppliers and European customer firms around the announcements of the two Eurozone bailout deals in 2010. The full list of country events is shown in Appendix A.II. Average abnormal DCC correlation for each customer-supplier-week is estimated as the difference between the weekly DCC correlation of the firm-pair minus the firm pair's average DCC correlation over the interval from 70 to 20 weeks before the event week. We drop firm-event observations with insufficient DCC estimates in the estimation or event window. If a country-level event was followed by another shock within the next 20 weeks only the first shock observation was included in the sample resulting in 430 firm-event observations.

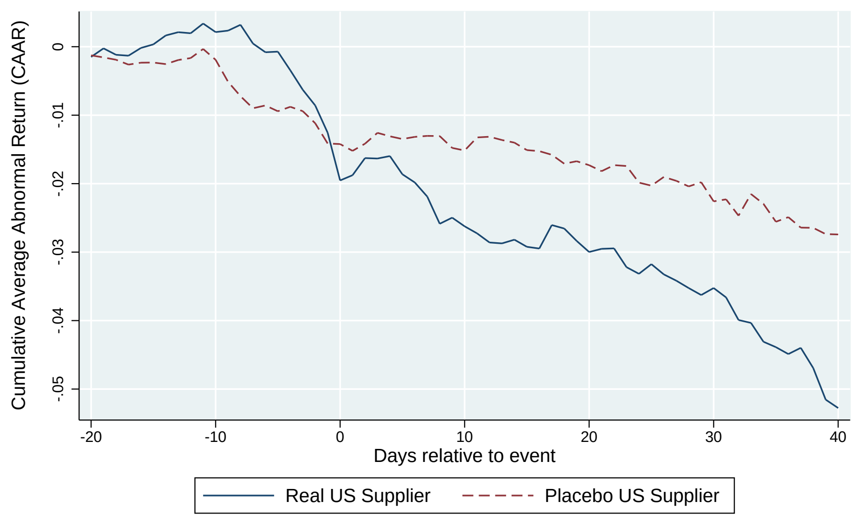


(a) Weekly Cumulative Average Abnormal DCC ($CAADCC$) correlation around Fitch Sovereign Ratings Changes.

Figure 6. *Notes.* This figure presents the weekly cumulative average abnormal DCC correlation ($CAADCC$) between U.S. suppliers and their international customer firms for the 31 $[-10, 20]$ weeks around negative (solid line), positive (short-dashed line) and the full sample of all (long-dashed line) sovereign debt ratings changes of the customer's home country. Sovereign Debt Ratings were obtained from Fitch. Average abnormal DCC correlation for each customer-supplier-week is estimated as the difference between the weekly DCC correlation of the firm-pair minus the firm pair's average DCC correlation over the interval from 70 to 20 weeks before the event week. We drop firm-event observations with insufficient DCC correlation estimates in the estimation or event window. In total we find 326 firm-pair-ratings-change observations after applying these filters.

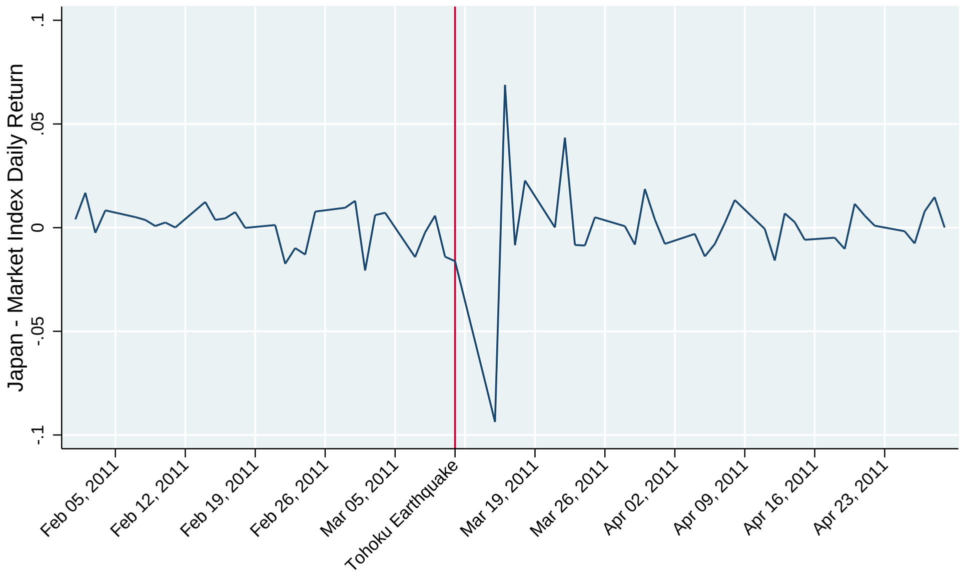


(a) $CAAR$ around 0.5% BKS country-index return shocks.

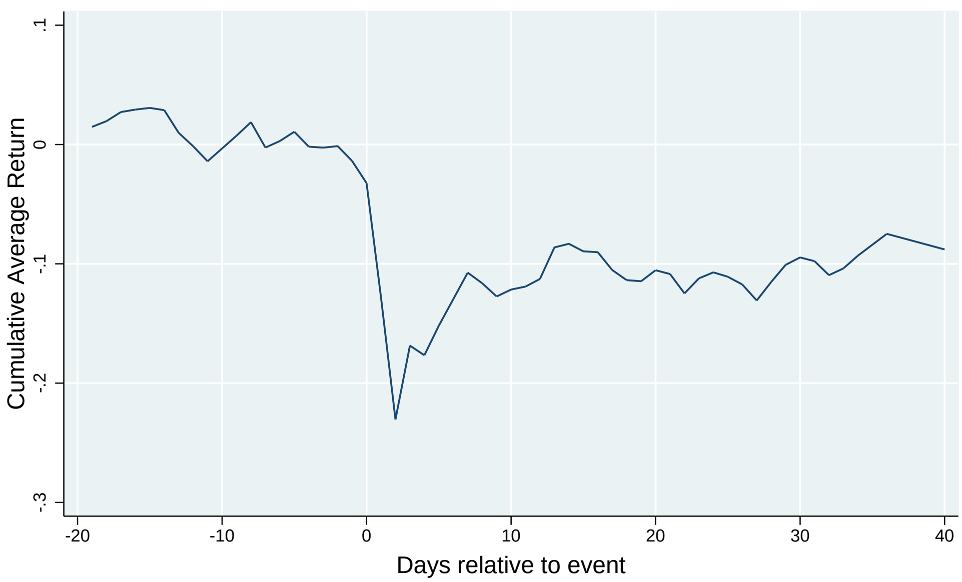


(b) $CAAR$ around 0.1% BKS country-index return shocks.

Figure 7. *Notes.* Figures (a) and (b) present the daily cumulative average abnormal returns ($CAAR$) for the real U.S. supplier firms (solid line) and the matched placebo suppliers (dashed line) in the 60 day window $[-20, 40]$ around the most negative daily 0.5% BKS country-index shocks and the most negative daily 0.1% BKS shocks in the country of the supplier's international customer. Placebo-suppliers are matched by finding the firm with the most similar average firm-size in terms of book assets (AT) within the real supplier's Fama-French 48 industry category. Abnormal returns are computed after estimating, for each firm-shock observation, a three-factor Fama-French model over the interval from 270 to 21 trading days before the event date. Firm-shock observations with missing returns in the event windows or fewer than 100 returns in the estimation window are excluded resulting in 4967 and 1496 firm-shock observations respectively.



(a) Daily Raw Index Returns for Japan, February to April 2011.



(b) Cumulative Average Raw Returns of Japanese Customers around Disaster Events.

Figure 8. *Notes.* Figure (a) shows the daily raw returns of the Japanese market index (Source: Datastream) for February to April 2011. The Tohoku earthquake and tsunami occurred on Friday, 11 March 2011 with first major foreshocks starting three to five days prior. Figure (b) shows the Cumulative Average Raw Returns of the Japanese customer firms $t = -20$ to $t = 40$ days around the Tohoku disaster event. There are 135 customer firms affected by the 2011 earthquake and tsunami in our sample.

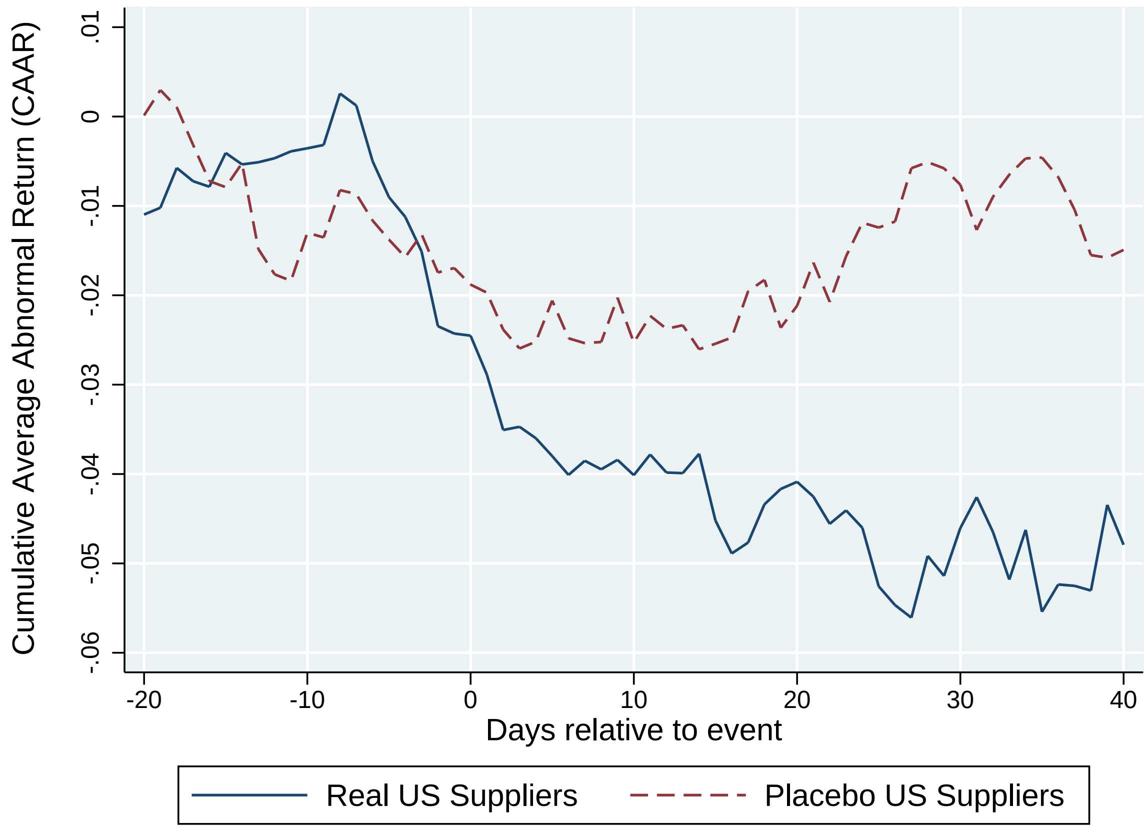


Figure 9. *Notes.* This figure presents cumulative average abnormal returns (CAAR) of U.S. supplier firms and matched placebo supplier firms around the first day of a natural disaster affecting their customer firm in Japan. Abnormal returns are computed after estimating, for each firm-disaster pair, a three-factor Fama-French model over the interval from 270 to 21 trading days before the event date. Firm-disaster observations with missing returns in the estimation or event windows, are excluded. Focusing only on Japan we find 136 supplier firm-disaster pairs satisfying these requirements.

Table 1. Summary Statistics

Notes. In **Panel A** we present summary statistics for our main variable of interest for measuring financial contagion, the weekly DCC correlation between U.S. suppliers and their international customers as well as the DCC correlation between matched placebo suppliers and international customers and the mean difference. Our sample period is from January 1985 to December 2014. For each supplier-customer pair we identify the beginning and end date of their supply-chain relationship and estimate the DCC model on the entire length of the time-series of return residuals. Time-series pairs fewer than 50 weekly observations or with *beta* parameters below 0.4 resulting from the NAGARCH estimation as well as time-series pairs for which the DCC model estimation did not converge successfully were excluded. Placebo-suppliers are matched to 'real' suppliers by finding the firm with the most similar average firm-size in terms of book assets (AT) within the real supplier's Fama-French 48 industry category. We exclude potential placebo supplier matches with insufficient return observations during the period from the beginning to the end of the 'real' supplier-customer relationship.

In **Panel B** we present summary statistics of all annual firm-level and firm-pair level explanatory and control variables for the suppliers, placebo suppliers and customer firms. Firm-year level accounting information was obtained from Compustat for the U.S. suppliers and matched placebo suppliers and from Datastream for the international customers. All continuous variables are winsorized at the 1% level. Detailed definitions of all variables are provided in table A.I in the Appendix.

Panel A: Summary Statistics - Weekly DCC Correlation

Variables	**N**	**Mean**	**SD**	**P5**	**P25**	**P50**	**P75**	**P95**
Actual Relationships:								
	297194	0.219	0.168	-0.027	0.105	0.210	0.331	0.502
Placebo Relationships:								
	297194	0.191	0.162	-0.047	0.085	0.181	0.288	0.470
Difference in Mean (t-stat in parenthesis):								
	297194	**0.028***** **(94.250)**						

Panel B: Summary Statistics - Firm-level, Relationship-, and Placebo Variables

Variable	N	Mean	SD	p5	p25	p50	p75	p95
Supplier Variables:								
AT sup	7174	2227.63	5373.31	15.53	94.81	373.31	1764.67	11221.32
AT log sup	7174	5.97	1.99	2.74	4.55	5.92	7.48	9.33
MktCap sup	7123	2053.44	5104.09	14.60	106.07	400.96	1417.26	9496.70
AR/sales sup	7087	0.19	0.15	0.04	0.12	0.17	0.23	0.40
AP/COGS sup	7049	0.20	0.29	0.03	0.09	0.14	0.20	0.51
Z score sup	6878	0.39	3.83	-5.09	0.14	1.27	2.11	3.04
KZ Index sup	6452	-4.88	21.47	-23.44	-3.92	-0.46	1.18	3.67
ROA sup	7098	-0.05	0.26	-0.51	-0.08	0.02	0.07	0.15
Customer Variables:								
AT cus	7031	74000.00	96400.00	588.63	8452.65	35500.00	101000.00	288000.00
AT log cus	7031	17.01	1.89	13.29	15.95	17.38	18.43	19.48
MktCap cus	7023	37100.00	40000.00	316.86	4908.28	19900.00	57900.00	119000.00
AT/sales cus	6894	0.23	0.19	0.08	0.14	0.20	0.26	0.41
AP/COGS cus	6659	0.20	0.15	0.07	0.11	0.15	0.24	0.42
Z score cus	6298	1.69	0.87	0.48	1.15	1.62	2.23	3.12
KZ Index cus	6012	-3.80	10.57	-21.51	-3.34	-0.88	0.48	1.62
ROA cus	7030	0.04	0.06	-0.04	0.01	0.03	0.07	0.13
Relationship Variables:								
Pct sales sup	5476	0.18	0.17	0.02	0.09	0.13	0.22	0.54
Pct COGS cus	5207	0.02	0.08	0.00	0.00	0.00	0.01	0.10
Relation Age	7212	4.16	4.23	1	1	3	5	12
Duration Relation	7212	6.80	5.72	1	3	5	9	18
Placebo Supplier Variables:								
AT sup placebo	6979	1910.60	4256.53	17.69	96.23	345.46	1536.72	10201.00
AT log sup placebo	6979	5.93	1.90	2.87	4.57	5.84	7.34	9.23
MktCap sup placebo	6899	2048.49	4589.69	12.09	88.54	421.23	1506.26	10943.53
AR/sales sup placebo	6741	0.19	0.14	0.05	0.12	0.16	0.22	0.36
AP/COGS sup placebo	6769	0.18	0.31	0.03	0.08	0.11	0.17	0.47
Z score sup placebo	6515	1.22	3.15	-3.00	0.75	1.86	2.64	3.86
KZ Index sup placebo	6244	-5.52	21.30	-23.52	-4.47	-0.92	0.79	3.09
ROA sup placebo	6806	-0.01	0.21	-0.37	-0.02	0.04	0.08	0.18
Placebo Relationship Variables:								
Relation Age placebo	6979	4.17	4.47	1	1	3	5	12
Duration Relation placebo	6979	7.24	6.34	1	3	5	10	19

Table 2. Descriptive Statistics for Weekly Customer-, Supplier- and Country-Index Returns.

Notes. In **Panel A** we report the first four sample moments of the annualized weekly returns on the firm level for every customer-year observation by country of the customer firm. N is the number of annualized firm-year customer return observations by country, returns are obtained from Datastream.

Panel B reports the first four sample moments of the annualized weekly returns (Source: Datastream) on the country-index level for each country with at least one customer firm in our sample. N represents the number of annualized country-year index return observations.

In **Panel C** we report the first four sample moments of the annualized weekly returns on the firm level for every supplier- and placebo-supplier-year observation by year as well as the value-weighted market return for the US. N is the number of annualized firm-year return observations per year, returns for suppliers and placebo suppliers as well as the U.S. value-weighted market are obtained from CRSP.The sample period is from January 1985 to December 2014.

Panel A: Annualized Customer Return Observations by Country

	N	Annual mean (%)	Annual SD	Skewness	Excess Kurtosis
Developed Markets:					
Belgium	123	0.15	0.37	0.823	2.85
Canada	1619	0.21	0.66	6.461	74.47
Denmark	59	0.25	0.70	2.232	6.38
Finland	164	0.18	0.56	1.569	3.59
France	1223	0.15	0.50	2.158	11.23
Germany	1200	0.12	0.55	3.448	30.94
Ireland	55	0.25	0.62	1.020	3.13
Italy	222	0.08	0.44	2.117	11.06
Japan	5696	0.10	0.59	6.665	102.02
Netherlands	333	0.17	0.51	2.398	14.38
New Zealand	71	0.16	0.42	1.352	3.26
Norway	149	0.30	0.92	1.644	3.38
South Korea	750	0.25	1.50	20.340	498.63
Spain	227	0.14	0.41	1.152	2.94
Sweden	332	0.22	0.56	4.215	39.63
Switzerland	445	0.14	0.47	2.097	13.77
United Kingdom	817	0.17	0.59	7.114	107.46
Emerging Markets:					
Argentina	160	1.07	6.50	10.315	114.82
Brazil	54	0.18	0.63	0.836	0.82
Chile	104	0.40	1.01	4.926	31.32
China	844	0.22	0.73	1.990	5.64
Colombia	18	0.18	0.49	0.660	0.63
Greece	40	0.21	0.99	3.425	13.28
India	561	0.40	1.08	3.342	16.96
Indonesia	57	0.55	2.23	5.661	36.28
Israel	188	0.09	0.60	2.959	14.06
Malaysia	129	0.12	0.45	1.135	4.22
Mexico	163	0.33	0.60	1.113	1.78
Pakistan	57	0.25	0.79	1.608	3.14
Philippines	87	0.18	0.55	1.682	4.45
Poland	15	0.09	0.57	2.497	8.16
Portugal	26	-0.03	0.45	1.131	1.05
Russia	86	0.36	1.05	4.776	33.15
Singapore	243	0.17	0.74	2.107	7.02
South Africa	243	0.27	0.65	5.901	56.73
Sri Lanka	8	0.49	1.02	1.127	0.01
Taiwan	996	0.16	0.65	2.124	8.11
Thailand	27	0.63	2.53	3.589	13.19
Turkey	61	0.67	1.41	2.070	5.07
Venezuela	12	0.37	0.76	0.739	1.04

Panel B: Annualized Country-Index Return Observations by Customer County

	N	Annual mean (%)	Annual SD	Skewness	Excess Kurtosis
Developed Markets:					
Belgium	30	0.14	0.26	-0.346	0.43
Canada	30	0.11	0.16	-0.609	0.57
Denmark	30	0.16	0.27	-0.254	-0.26
Finland	27	0.17	0.46	1.447	3.32
France	30	0.14	0.25	-0.320	-0.46
Germany	30	0.12	0.25	-0.219	-0.13
Ireland	30	0.17	0.29	-0.639	0.72
Italy	30	0.13	0.32	0.969	2.07
Japan	30	0.06	0.27	0.440	0.01
Netherlands	30	0.12	0.23	-0.818	1.15
New Zealand	27	0.11	0.19	-0.623	1.35
Norway	30	0.17	0.29	-0.007	-0.47
South Korea	27	0.13	0.36	0.616	0.66
Spain	28	0.12	0.23	-0.068	-0.44
Sweden	30	0.18	0.30	-0.084	-0.53
Switzerland	30	0.13	0.22	-0.193	-0.13
United Kingdom	30	0.12	0.17	-0.861	0.31
Emerging Markets:					
Argentina	21	0.20	0.41	0.762	0.15
Brazil	21	0.21	0.42	1.506	4.20
Chile	26	0.23	0.38	1.889	5.24
China	21	0.16	0.44	0.910	0.97
Colombia	23	0.21	0.35	1.277	2.94
Greece	25	0.14	0.45	0.629	0.47
India	25	0.23	0.39	0.165	-0.36
Indonesia	25	0.17	0.40	0.063	-0.46
Israel	22	0.13	0.29	0.114	0.08
Malaysia	29	0.16	0.30	0.697	2.71
Mexico	26	0.28	0.36	1.333	3.93
Pakistan	22	0.23	0.41	-0.312	-0.46
Philippines	27	0.23	0.47	1.282	2.99
Poland	21	0.10	0.35	0.343	2.28
Portugal	25	0.07	0.27	0.092	0.28
Russia	17	0.39	0.76	2.231	7.02
Singapore	30	0.12	0.32	0.582	0.03
South Africa	30	0.22	0.23	0.366	-0.20
Sri Lanka	28	0.24	0.46	0.876	0.12
Taiwan	27	0.11	0.35	0.314	0.02
Thailand	28	0.21	0.44	0.773	0.71
Turkey	27	0.82	1.49	2.267	4.85
Venezuela	25	0.76	1.33	2.079	4.32

Panel C: Annualized Supplier and Placebo Supplier Return Observations by Year

	Suppliers					Placebo Suppliers					US Market
Year	N	Annual mean (%)	Annual SD	Skewness	Excess Kurtosis	N	Annual mean (%)	Annual SD	Skewness	Excess Kurtosis	Annual Return (%)
1985	555	0.16	0.67	2.78	13.98	544	0.23	0.55	2.71	17.86	0.30
1986	594	0.02	0.61	5.22	65.70	591	0.07	0.48	2.32	16.10	0.16
1987	640	-0.03	0.57	3.02	19.99	648	-0.03	0.51	2.31	9.27	0.02
1988	669	0.15	0.56	2.42	11.45	680	0.20	0.51	2.10	8.84	0.14
1989	700	0.20	0.67	2.13	8.61	694	0.21	0.70	4.36	40.93	0.26
1990	721	-0.14	0.63	5.85	61.55	728	-0.15	0.43	2.24	15.67	-0.05
1991	742	0.62	1.75	8.37	108.49	751	0.58	1.28	5.18	45.96	0.23
1992	796	0.35	1.97	17.64	401.93	798	0.35	1.91	19.18	451.31	0.14
1993	845	0.27	0.80	2.80	12.47	854	0.29	0.79	3.50	18.41	0.11
1994	928	-0.01	0.72	6.42	81.82	918	0.04	0.60	3.84	26.50	-0.01
1995	976	0.50	1.20	4.20	27.05	954	0.47	1.16	5.71	48.47	0.33
1996	1093	0.23	0.94	7.28	104.73	1030	0.22	0.70	5.42	66.58	0.22
1997	1162	0.18	0.75	3.48	24.28	1087	0.27	0.72	4.13	40.08	0.25
1998	1203	-0.11	0.67	3.29	18.70	1128	-0.05	0.70	5.18	52.37	0.21
1999	1159	0.96	2.28	4.96	39.23	1120	0.72	2.19	6.66	70.50	0.21
2000	1230	-0.03	0.85	3.25	23.34	1137	0.05	0.90	4.52	41.39	-0.13
2001	1234	0.26	1.20	7.31	105.81	1134	0.43	1.30	7.33	95.17	-0.09
2002	1166	-0.23	0.71	7.77	120.92	1109	-0.15	0.53	2.79	19.01	-0.29
2003	1089	1.13	1.87	5.52	50.66	1073	0.91	1.49	5.98	66.30	0.25
2004	1072	0.15	0.62	2.92	16.98	1063	0.22	0.68	5.57	64.50	0.11
2005	1071	0.06	0.56	2.91	19.39	1063	0.11	0.54	2.66	14.68	0.06
2006	1073	0.16	0.53	2.54	14.52	1049	0.17	0.50	2.72	16.84	0.13
2007	1066	0.07	0.63	4.04	39.91	1045	0.09	0.56	2.22	10.16	0.06
2008	1045	-0.51	0.31	1.51	4.34	1012	-0.43	0.38	3.31	29.93	-0.42
2009	964	0.90	1.58	4.65	30.99	972	0.86	3.43	22.66	615.52	0.28
2010	939	0.30	0.61	2.36	11.02	944	0.33	0.58	2.99	17.89	0.14
2011	917	-0.14	0.46	2.85	22.57	914	-0.07	0.40	1.56	7.66	-0.05
2012	897	0.12	0.51	2.40	12.20	890	0.14	0.50	3.88	34.14	0.14
2013	848	0.45	0.73	2.49	9.14	855	0.50	0.81	5.83	60.14	0.24
2014	808	0.02	0.47	1.88	10.59	811	0.04	0.46	3.20	24.38	0.08

Table 3. Summary of ARMA-NAGARCH Estimation using Weekly Firm-level Returns.

Notes. For each customer and supplier firm in our sample we estimate an ARMA(p,q)-NAGARCH(1,1) model (Nonlinear Asymmetric GARCH model, following Engle and Ng (1993)) using the longest available time-series of weekly firm-level returns between January 1985 and December 2014. The p and q values are chosen according to the AIC criterion. We exclude customer or supplier firms with fewer than 100 weekly returns during our sample period. The residuals in our NAGARCH(1,1) model are distributed following a skewed student t-distribution as in Hansen (1994) with parameters ν and λ. The sample period is from January 1985 to December 2014. In **Panel A** we report the proportion of respective (p,q) combinations chosen across all firms following the AIC criterion. In **Panels B and C** we report parameter estimates and model diagnostics for the NAGARCH(1,1) on the ARMA(p,q) residuals. Firm-observations with estimates of $beta < 0.4$ were excluded from our further analysis.

Panel A: Conditional Mean Dynamics

	Suppliers		**Customers**	
Model Chosen by AIC Criterion	**Freq.**	**Percent**	**Freq.**	**Percent**
ARMA(0,0)	289	19.73	116	18.74
ARMA(1,0)	93	6.35	36	5.82
ARMA(0,1)	102	6.96	26	4.20
ARMA(1,1)	170	11.60	83	13.41
ARMA(2,1)	83	5.67	31	5.01
ARMA(1,2)	70	4.78	43	6.95
ARMA(2,0)	41	2.80	18	2.91
ARMA(0,2)	35	2.39	26	4.20
ARMA(2,2)	582	39.73	240	38.77
Total	**1465**	**100.00**	**619**	**100.00**

Panel B: Parameter Estimation and Residual Distribution - Suppliers

	Suppliers (N=1465)						
	Mean	SD	p5	p25	p50	p75	p95
Parameter Estimates:							
α	0.106	0.14	0.00	0.04	0.07	0.11	0.34
β	0.771	0.26	0.00	0.77	0.87	0.92	0.98
γ	0.539	0.57	-0.14	0.16	0.47	0.87	1.58
ω	0.006	0.09	0.00	0.00	0.00	0.00	0.01
ν	16.828	284.66	2.52	3.29	4.10	5.42	9.59
λ	0.112	0.10	-0.05	0.05	0.11	0.18	0.27
Diagnostics:							
Number of weekly returns	716.033	421.18	168.00	374.00	641.00	973.00	1561.00
Log-likelihood	891.427	675.17	145.30	368.62	706.14	1231.43	2325.50
Residual Mean	-0.008	0.03	-0.03	-0.02	-0.01	0.00	0.02
Residual SD	0.999	0.46	0.85	0.96	0.99	1.00	1.07
Residual Skewness	0.900	1.66	-0.40	0.12	0.54	1.26	3.19
Residual Excess Kurtosis	13.171	28.66	3.81	5.26	7.14	11.36	32.71

Panel C: Parameter Estimation and Residual Distribution - Customers

	Customers (N=619)						
	Mean	SD	p5	p25	p50	p75	p95
Parameter Estimates:							
α	0.100	0.07	0.03	0.06	0.08	0.11	0.23
β	0.835	0.13	0.61	0.82	0.87	0.90	0.94
γ	0.427	0.43	-0.17	0.15	0.39	0.64	1.38
ω	0.000	0.00	0.00	0.00	0.00	0.00	0.00
ν	5.776	6.19	2.88	3.99	5.13	6.39	9.58
λ	0.081	0.07	-0.04	0.03	0.09	0.13	0.19
Diagnostics:							
Number of weekly returns	1074.932	421.30	360.00	726.00	1112.00	1529.00	1538.00
Log-likelihood	1777.214	823.75	480.51	1102.61	1747.48	2502.63	3030.88
Residual Mean	-0.004	0.01	-0.02	-0.01	0.00	0.00	0.01
Residual SD	0.990	0.04	0.91	0.98	1.00	1.00	1.03
Residual Skewness	0.477	1.02	-0.34	0.09	0.32	0.64	1.76
Residual Excess Kurtosis	9.021	17.77	3.84	4.76	5.84	8.07	20.91

Table 4. Summary of DCC Estimation using Weekly ARMA-NAGARCH Residuals.

Notes. This table reports summary statistics of the parameter estimates for our DCC model using the ARMA(p,q)-NAGARCH(1,1) residuals of the customer and suppliers firms across emerging and developed countries in **Panel A** and the residuals of the U.S. value-weighted market return residuals with the country-index return residuals of the international customers in **Panel B**. The sample period is from January 1985 to December 2014. Supplier-customer pairs for which the DCC model estimation did not converge or produced very low estimates of *beta* were excluded in the following analysis. The composite likelihood reported in Panel A and B is the average of the quasi-likelihoods (correlation log likelihood + all marginal log likelihoods) of all pairs of assets.

Panel A: Firm-Level Parameter Estimates for DCC model

Variable	**Mean**	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**
Emerging Countries (N=306):							
α	0.0611	0.0943	0.0000	0.0000	0.0212	0.0808	0.2668
β	0.4046	0.3407	0.0000	0.0613	0.3283	0.7140	0.9424
Developed Countries (N=2011):							
α	0.0653	0.1005	0.0000	0.0000	0.0247	0.0883	0.2688
β	0.3773	0.3313	0.0000	0.0385	0.2981	0.6698	0.9250
Total (N=2317):							
α	0.0647	0.0997	0.0000	0.0000	0.0244	0.0870	0.2688
β	0.3809	0.3326	0.0000	0.0390	0.3003	0.6698	0.9291

Panel B: Country-Level Parameter Estimates for DCC model

Variable	**Mean**	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**
Emerging Countries (N=30):							
α	0.0253	0.0277	0.0090	0.0133	0.0196	0.0266	0.0574
β	0.9083	0.2019	0.4342	0.9380	0.9740	0.9816	0.9884
Developed Countries (N=18):							
α	0.0265	0.0188	0.0049	0.0148	0.0201	0.0281	0.0714
β	0.9565	0.0443	0.8468	0.9606	0.9713	0.9826	0.9932
Total (N=48):							
α	0.0258	0.0245	0.0090	0.0145	0.0197	0.0273	0.0616
β	0.9264	0.1625	0.7405	0.9498	0.9740	0.9820	0.9884

Table 5. Event Study Results - The Effect of Country-Index Shocks on Financial Contagion.

Notes. This table presents event study estimates of the weekly cumulative average abnormal DCC ($CAADCC$) correlation between U.S. suppliers and their international customers around BKS-type country-index return shocks. In **Panels A and C** we use the most negative 2.5% of weekly standardized BKS returns, in **Panel B** and **Panel C** we use the 0.5% and 0.1% negative country-index BKS shocks.

In **Panels A to C** the abnormal DCC correlation for each customer-supplier-week $ADCC_t$ is estimated as the difference between the weekly DCC correlation DCC_t of the firm-pair minus the firm pair's average DCC correlation $\frac{1}{T}\sum_{t=1}^{T} DCC_t$ over the interval from 70 to 20 weeks before the event week. We drop firm-event observations with fewer than 35 DCC correlation estimates DCC_t in the estimation window and any firm-event observation with missing DCC_t in the event window. N reports the total number of firm-event observations used to calculate the cumulative average abnormal DCC ($CAADCC$) in each panel. In **Panel D** the abnormal DCC correlation for each customer-supplier-week $ADCC_t$ is calculated as the difference between the DCC_t minus the DCC correlation between the U.S. and the customer country market index compared to the average of $DCC_t - DCC_t^{indices}$ during the estimation window.

For each $CAADCC$ estimate we report t statistics in parentheses following a battery of parametric- and non-parametric significance tests: In columns (1) and (2) we report the standard cross-sectional t-statistic using robust standard errors and the Crude Dependence Adjustment (CDA) test following Brown and Warner (1980) respectively. In columns (3) to (5) we report the t statistics using the non-parametric Rank Test following Corrado and Zivney (1992) as well as the Sign Test and Generalized Sign Test introduced in Cowan (1992). The sample period is from 1985 to 2014. *, ** and *** denotes significance at the 10%, 5%, and 1%, respectively. We conservatively use the maximum of the p-Values corresponding to the "weakest" t-statistic across all significance tests reported in this table to determine the reported level of statistical significance.

Panel A: 2.5% **percentile weekly country-index shocks**

	Cumulative Average Abnormal DCC correlation (CAADCC)						
	CAADCC	N	Cross. Sect. t-Test	CDA Test	Corrado-Zivney Rank Test	Cowan Sign Test	Cowan Gen. Sign Test
			(1)	(2)	(3)	(4)	(5)
[-10,-6]	-0.0158	1349	(-1.918)	(-0.576)	(-1.291)	(-0.354)	(-1.775)
[-5,-1]	0.0021	1355	(0.265)	(0.076)	(1.167)	(2.418)	(1.012)
[0,5]	0.0925***	1355	(8.083)	(3.705)	(5.422)	(10.568)	(9.168)
[6,10]	0.0670**	1350	(6.985)	(2.452)	(5.313)	(6.913)	(5.526)
[11,15]	0.0676**	1341	(7.208)	(2.471)	(5.443)	(7.619)	(6.249)
[16,20]	0.0268	1335	(2.776)	(0.979)	(2.665)	(1.560)	(0.190)
[21,25]	0.0662**	1330	(6.168)	(2.421)	(5.024)	(7.020)	(5.655)
[26,30]	0.0385	1320	(4.003)	(1.409)	(3.976)	(4.569)	(3.236)
[-10,-1]	**-0.0136**	**1355**	**(-0.93)**	**(-0.704)**	**(-0.079)**	**(-0.136)**	**(-1.544)**
[0,10]	**0.1593*** **	**1355**	**(8.274)**	**(8.640)**	**(5.757)**	**(10.894)**	**(9.494)**
[0,20]	0.2525***	1355	(7.624)	(18.926)	(5.552)	(10.187)	(8.787)
[0,30]	0.3550***	1355	(7.516)	(32.328)	(5.649)	(10.839)	(9.440)
[-10,30]	0.3414***	1355	(6.150)	(35.754)	(4.369)	(8.829)	(7.428)

Panel B: Robustness - 0.5% percentile weekly country-index shocks

	Cumulative Average Abnormal DCC correlation (CAADCC)						
	CAADCC	N	Cross. Sect. t-Test	CDA Test	Corrado-Zivney (1992) Rank Test	Cowan Sign Test	Cowan Gen. Sign Test
			(1)	(2)	(3)	(4)	(5)
[-10,-6]	0.0030	937	(0.343)	(0.112)	(-1.654)	(-1.666)	(-2.561)
[-5,-1]	0.0142	946	(1.564)	(0.537)	(0.802)	(1.886)	(0.934)
[0,5]	0.1938***	946	(11.947)	(8.023)	(5.931)	(15.606)	(14.661)
[6,10]	0.0895***	944	(7.77)	(3.38)	(5.332)	(7.356)	(6.416)
[11,15]	0.0665**	942	(6.353)	(2.512)	(4.789)	(5.995)	(5.06)
[16,20]	0.0886***	935	(8.213)	(3.349)	(5.317)	(8.143)	(7.202)
[21,25]	0.0925***	929	(7.928)	(3.495)	(5.292)	(7.185)	(6.245)
[26,30]	0.0231	926	(2.266)	(0.875)	(0.157)	(-1.577)	(-2.514)
[-10,-1]	**0.0172**	**946**	**(1.066)**	**(0.917)**	**(-0.535)**	**(-0.52)**	**(-1.473)**
[0,10]	**0.2831*** **	**946**	**(10.976)**	**(15.866)**	**(5.768)**	**(13.72)**	**(12.774)**
[0,20]	0.4369***	946	(10.265)	(33.833)	(5.717)	(13.005)	(12.058)
[0,30]	0.5504***	946	(9.809)	(51.784)	(5.074)	(12.745)	(11.798)
[-10,30]	0.5676***	946	(8.674)	(61.411)	(3.9)	(11.965)	(11.018)

Panel C: Robustness - 0.1% percentile weekly country-index shocks

	Cumulative Average Abnormal DCC correlation (CAADCC)						
	CAADCC	N	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	0.0156	360	(1.233)	(0.587)	(-0.692)	(-0.843)	(-1.111)
[-5,-1]	0.0086	364	(0.602)	(0.323)	(-0.944)	(-0.419)	(-0.715)
[0,5]	0.2448***	364	(9.74)	(10.1)	(5.126)	(10.064)	(9.769)
[6,10]	0.1016***	364	(5.551)	(3.828)	(3.433)	(3.564)	(3.269)
[11,15]	0.0737**	364	(4.442)	(2.774)	(2.653)	(3.774)	(3.479)
[16,20]	0.1206***	363	(6.874)	(4.544)	(4.036)	(5.091)	(4.785)
[21,25]	0.0846***	360	(5.044)	(3.187)	(3.862)	(4.533)	(4.228)
[26,30]	0.0056	360	(0.348)	(0.211)	(-1.149)	(-2.424)	(-2.73)
[-10,-1]	**0.024**	**364**	**(0.972)**	**(1.278)**	**(-1.071)**	**(-1.782)**	**(-2.078)**
[0,10]	**0.3464*****	**364**	**(8.508)**	**(19.353)**	**(4.816)**	**(8.806)**	**(8.511)**
[0,20]	0.5404***	364	(7.829)	(41.714)	(4.718)	(8.281)	(7.987)
[0,30]	0.6296***	364	(7.158)	(59.05)	(3.997)	(8.491)	(8.197)
[-10,30]	0.6536***	364	(6.405)	(70.497)	(2.915)	(8.596)	(8.301)

Panel D: Robustness - 2.5% percentile weekly country-index shocks - vs. index

	Cumulative Average Abnormal DCC correlation (CAADCC)					
	CAADCC	N	Cross. Sect. t-Test (1)	Corrado-Zivney Rank Test (2)	Cowan Sign Test (3)	Cowan Gen. Sign Test (4)
[-10,-6]	0.0392	1349	(3.723)	(3.046)	(1.606)	(1.506)
[-5,-1]	0.0379**	1355	(3.755)	(2.725)	(2.363)	(2.274)
[0,5]	0.0028	1355	(0.201)	(-0.013)	(0.625)	(0.535)
[6,10]	-0.0081	1350	(-0.696)	(-0.665)	(0.98)	(0.895)
[11,15]	-0.0151	1341	(-1.306)	(-2.177)	(-1.502)	(-1.608)
[16,20]	-0.0369**	1335	(-2.945)	(-3.464)	(-2.272)	(-2.39)
[21,25]	-0.0154	1330	(-1.127)	(-4.084)	(-3.236)	(-3.369)
[26,30]	-0.0123	1320	(-0.969)	(-4.081)	(-3.578)	(-3.712)
[-1,1]	**0.0274****	**1355**	**(3.94)**	**(2.333)**	**(3.07)**	**(2.98)**
[0,1]	**0.022****	**1355**	**(4.423)**	**(2.1)**	**(3.45)**	**(3.361)**
[-10,-1]	0.0769***	1355	(4.024)	(3.63)	(2.689)	(2.6)
[0,10]	-0.0053	1355	(-0.217)	(-0.417)	(0.407)	(0.318)
[0,20]	-0.0566	1355	(-1.3)	(-2.377)	(-0.299)	(-0.388)
[0,30]	-0.0837	1355	(-1.315)	(-3.758)	(-1.548)	(-1.638)
[-10,30]	-0.0068	1355	(-0.088)	(-1.464)	(-0.516)	(-0.606)

Table 6. Event Study Results - The Effect of Country-Level (Disaster) Events on Financial Contagion.

Notes. This table presents event study estimates of the weekly cumulative average abnormal DCC ($CAADCC$) correlation between U.S. suppliers and their international customers around three sets of country-level (disaster) events. In **Panels A** we use the full sample of all country-level (disaster) events listed in Appendix A.II. In **Panel B** we report event study results for the $CAADCC$ between U.S. suppliers and with customers in Japan around the 2011 earthquake and flood in Japan. **Panel C** reports the results for U.S. suppliers with European customer firms around the Eurozone Bailout Deals in 2010.

The abnormal DCC correlation in **Panels A to C** for each customer-supplier-week $ADCC_t$ is estimated as the difference between the weekly DCC correlation DCC_t of the firm-pair minus the firm pair's average DCC correlation $\frac{1}{T}\sum_{t=1}^{T} DCC_t$ over the interval from 70 to 20 weeks before the event week. We drop firm-event observations with fewer than 35 DCC correlation estimates DCC_t in the estimation window and any firm-event observation with missing DCC_t in the event window. N reports the total number of firm-event observations used to calculate the cumulative average abnormal DCC ($CAADCC$) in each panel.

For each $CAADCC$ estimate we report t statistics in parentheses following a battery of parametric- and non-parametric significance tests: In columns (1) and (2) we report the standard cross-sectional t-statistic using robust standard errors and the Crude Dependence Adjustment (CDA) test following Brown and Warner (1980) respectively. In columns (3) to (5) we report the t statistics using the non-parametric Rank Test following Corrado and Zivney (1992) as well as the Sign Test and Generalized Sign Test introduced in Cowan (1992). The sample period is from 1985 to 2014. *, ** and *** denotes significance at the 10%, 5%, and 1%, respectively. We report the number of test statistics indicating statistical significance at the 10% level and conservatively use the maximum of the p-Values corresponding to the "weakest" t-statistic across all significance tests to determine the reported level of statistical significance.

Panel A: All Country-Level Events

	Cumulative Average Abnormal DCC correlation (CAADCC)							
	CAADCC	N	# Tests significant at 10%	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	0.0003	430	2/5	(0.023)	(0.011)	(-1.095)	(-2.315)	(-2.232)
[-5,-1]	-0.0025	430	0/5	(-0.190)	(-0.092)	(-1.005)	(-1.640)	(-1.556)
[0,5]	0.0574	430	2/5	(3.252)	(2.315)	(0.989)	(0.386)	(0.469)
[6,10]	0.0077	430	0/5	(0.570)	(0.284)	(-0.786)	(-1.543)	(-1.460)
[11,15]	0.0117	429	0/5	(0.761)	(0.432)	(0.193)	(-0.145)	(-0.050)
[16,20]	-0.0159	429	2/5	(-1.041)	(-0.584)	(-1.076)	(-2.752)	(-2.657)
[0,3]	**0.0500**	**430**	**4/5**	**(4.065)**	**(1.667)**	**(1.44)**	**(1.736)**	**(1.819)**
[-10,-1]	**-0.0022**	**430**	**2/5**	**(-0.091)**	**(-0.114)**	**(-1.425)**	**(-2.604)**	**(-2.521)**
[0,10]	**0.0651**	**430**	**2/5**	**(2.264)**	**(3.556)**	**(0.197)**	**(-0.193)**	**(-0.110)**
[0,20]	0.0610	430	1/5	(1.305)	(4.601)	(-0.230)	(-0.193)	(-0.110)
[-10,20]	0.0588	430	1/5	(0.922)	(5.389)	(-0.857)	(-2.604)	(-2.521)

Panel B: Japan Earthquake and Flood 2011

	Cumulative Average Abnormal DCC correlation (CAADCC)							
	CAADCC	N	# Tests significant at 10%	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	-0.0264	95	4/5	(-2.59)	(-1.053)	(-1.721)	(-3.591)	(-3.54)
[-5,-1]	**-0.0865***	**95**	**5/5**	**(-3.735)**	**(-3.452)**	**(-1.947)**	**(-3.796)**	**(-3.746)**
[0,5]	**0.0536**	**95**	**4/5**	**(1.960)**	**(2.344)**	**(0.848)**	**(2.360)**	**(2.410)**
[6,10]	-0.0186	95	2/5	(-1.161)	(-0.744)	(-0.983)	(-2.36)	(-2.309)
[11,15]	-0.0084	95	0/5	(-0.418)	(-0.333)	(-0.199)	(0.308)	(0.358)
[16,20]	0.0127	95	0/5	(0.604)	(0.508)	(0.074)	(-0.103)	(-0.052)
[1,2]	0.0364	95	3/5	(3.176)	(0.918)	(0.843)	(3.591)	(3.642)
[-10,-1]	**-0.1129****	**95**	**5/5**	**(-3.938)**	**(-6.371)**	**(-2.448)**	**(-4.822)**	**(-4.772)**
[0,10]	**0.035**	**95**	**1/5**	**(0.880)**	**(2.071)**	**(0.142)**	**(1.539)**	**(1.590)**
[0,20]	0.0393	95	3/5	(0.655)	(3.219)	(0.036)	(2.360)	(2.410)
[-10,20]	-0.0735	95	1/5	(-0.979)	(-7.307)	(-1.021)	(-0.923)	(-0.873)

Panel C: Eurozone Bailouts 2010

	Cumulative Average Abnormal DCC correlation (CAADCC)							
	CAADCC	N	# Tests significant at 10%	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	0.075*	118	5/5	(1.986)	(2.777)	(1.824)	(2.946)	(2.603)
[-5,-1]	**0.0841***	**118**	**5/5**	**(2.413)**	**(3.114)**	**(1.741)**	**(2.946)**	**(2.603)**
[0,5]	**0.1302**	**118**	**2/5**	**(2.891)**	**(5.281)**	**(1.441)**	**(0.736)**	**(0.393)**
[6,10]	0.0106	118	0/5	(0.312)	(0.392)	(-0.928)	(-2.025)	(-2.37)
[11,15]	-0.0019	118	0/5	(-0.054)	(-0.069)	(-0.354)	(-0.921)	(-1.265)
[16,20]	-0.0286	118	1/5	(-0.881)	(-1.058)	(-1.329)	(-1.657)	(-2.002)
[-1,1]	**0.0921****	**118**	**5/5**	**(4.054)**	**(2.643)**	**(2.367)**	**(4.051)**	**(3.708)**
[-10,-1]	**0.1591****	**118**	**5/5**	**(2.264)**	**(8.332)**	**(2.282)**	**(2.762)**	**(2.419)**
[0,10]	0.1408	118	2/5	(1.846)	(7.732)	(0.459)	(-0.368)	(-0.713)
[0,20]	0.1103	118	1/5	(0.891)	(8.373)	(-0.333)	(-1.473)	(-1.818)
[-10,20]	0.2695	118	1/5	(1.455)	(24.842)	(0.75)	(-1.105)	(-1.449)

Table 7. Event Study Results - The Effect of Sovereign Debt Ratings Changes on Financial Contagion.

Notes. This table presents event study estimates of the weekly cumulative average abnormal DCC ($CAADCC$) correlation between U.S. suppliers and their international customers around Sovereign Debt Credit Ratings downgrades (**Panel A**) and upgrades (**Panel B**) in the customer's home country. Sovereign Debt Ratings were obtained from Fitch. The abnormal DCC correlation as well as the reported t-statistics were computed similarly as in table 6. We report t-stats (in parentheses) and the proportion of test statistics indicating statistical significance at the 10% level.

Panel A: Sovereign Rating Downgrades

	CAADCC	N	# Tests significant at 10%	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	0.0049	218	0/5	(0.316)	(0.178)	(0.672)	(-0.948)	(-0.171)
[-5,-1]	**0.0382**	**219**	**3/5**	**(2.523)**	**(1.396)**	**(1.513)**	**(2.635)**	**(3.427)**
[0,5]	0.0199	219	0/5	(0.855)	(0.797)	(-0.024)	(-0.878)	(-0.092)
[6,10]	0.0214	216	0/5	(1.217)	(0.781)	(0.803)	(0.680)	(1.442)
[11,15]	-0.0228	218	2/5	(-1.264)	(-0.834)	(-1.161)	(-2.574)	(-1.777)
[16,20]	**-0.0365**	**214**	**3/5**	**(-2.079)**	**(-1.335)**	**(-1.446)**	**(-2.461)**	**(-1.662)**
[-10,-1]	**0.0430**	**219**	**3/5**	**(1.575)**	**(2.226)**	**(1.424)**	**(2.500)**	**(3.292)**
[0,10]	0.0410	219	1/5	(1.099)	(2.223)	(0.489)	(0.608)	(1.397)
[0,20]	-0.0174	219	2/5	(-0.285)	(-1.305)	(-0.721)	(-2.500)	(-1.716)
[-10,20]	0.0256	219	1/5	(0.324)	(2.333)	(0.125)	(-0.068)	(0.720)

Panel B: Sovereign Rating Upgrades

	CAADCC	N	# Tests significant at 10%	Cross. Sect. t-Test (1)	CDA Test (2)	Corrado-Zivney Rank Test (3)	Cowan Sign Test (4)	Cowan Gen. Sign Test (5)
[-10,-6]	-0.0109	107	0/5	(-0.351)	(-0.407)	(-0.570)	(-0.870)	(-0.857)
[-5,-1]	0.0002	106	0/5	(0.005)	(0.007)	(1.345)	(0.777)	(0.794)
[0,5]	-0.0107	107	0/5	(-0.253)	(-0.439)	(-0.041)	(-0.097)	(-0.083)
[6,10]	**-0.0396**	**107**	**2/5**	**(-1.207)**	**(-1.479)**	**(-1.227)**	**(-2.223)**	**(-2.210)**
[11,15]	-0.0005	103	0/5	(-0.016)	(-0.019)	(0.652)	(0.099)	(0.116)
[16,20]	0.0318	102	0/5	(0.902)	(1.186)	(1.686)	(0.000)	(0.014)
[-10,-1]	-0.0107	107	0/5	(-0.17)	(-0.565)	(0.548)	(0.870)	(0.883)
[0,10]	-0.0503	107	1/5	(-0.704)	(-2.789)	(-0.781)	(-0.870)	(-0.857)
[0,20]	-0.0206	107	1/5	(-0.168)	(-1.574)	(0.392)	(-1.643)	(-1.630)
[-10,20]	-0.0313	107	1/5	(-0.179)	(-2.908)	(0.479)	(-1.063)	(-1.050)

Table 8. Difference-in-Difference Results: The Effect of Country-Level Index Shocks on Financial Contagion.

This table presents the results of panel regressions analyzing the impact of BKS country-index shock events on the dynamic conditional correlation (DCC) at the weekly frequency. The dependent variable in all models is the weekly DCC_t estimate between the U.S. supplier and international customer. Our main variables of interest in **Panels A, B and D** are the dummy variable *BKS Event (t)*, taking a value of one if a BKS country-index return event occurred in the home country of the customer firm in the given week and zero otherwise, and the weekly lags *BKS Event (t-1)* to *BKS Event (t-4)*. All regressions include firm-pair relationship fixed effects and weekly time fixed effects as well as an intercept not tabulated for brevity. When indicated we control for a host of firm-level and firm-pair relationship level control variables explained and listed in Appendix A.I. The sample period is from January 1985 to December 2015. t statistics presented in parentheses were calculated based on standard errors clustered at the firm-pair level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

In **Panel A** we report our main results. We show regression estimates using the most negative and most positive 2.5% of BKS country-index return shocks. In **Panel B** we present robustness checks for Panel A using a number of alternative specifications as well as sub-sample tests. In columns (7) and (8) we split the sample into firm-pairs with relatively strong and weak relationships according to the percentage of total sales the supplier represents to the customer (above and below median of relationship-strength measure). In columns (9) and (10) we consider all observations after and before the year 2000 respectively.

For the tests reported in **Panel C** we estimate the same DCC models as for our "real" customer-supplier sample on the sample of matched placebo suppliers and international customers and pool the results of our original and placebo DCC sample. *Supl is real* is a dummy variable, taking the value of one if the supplier is in our supply-chain sample and not a matched placebo supplier. We report results of **Difference-in-Difference-in-Difference panel regressions** on the differential effect of BKS country-index shocks on the "real" U.S. suppliers compared to the matched placebo suppliers. Our main variables of interest are the interaction effects of the dummy variables *BKS Event (t)* (=1 if customer country experiences index return shock) and *supl is real.* All regressions include firm-pair relationship fixed effects and weekly time fixed effects as well as an intercept not tabulated for brevity. When indicated we control for a host of firm-level and firm-pair relationship level control variables explained and listed in Appendix A.I. , taking the value of one if the supplier is in our supply-chain sample and not a matched placebo supplier.

In **Panel D** we show results for similar regressions as reported in Panel A using the most negative 0.5% and 0.1% of BKS country-index return shocks to define our main variables of interest, the dummies *BKS Event (t)* to *BKS Event (t-4)*. Again, all regressions include firm-pair relationship fixed effects and weekly time fixed effects as well as an intercept not tabulated for brevity. When indicated we control for a host of firm-level and firm-pair relationship level control variables explained and listed in Appendix A.I. , taking the value of one if the supplier is in our supply-chain sample and not a matched placebo supplier.

Panel A: Negative and Positive 2.5% Country-Index Shocks

	Dependent Variable: Weekly DCC Correlation (t)											
	Negative 2.5% BKS Shocks						**Positive 2.5% BKS Shocks**					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
BKS Event (t-0)	0.0004					0.002	-0.001					-0.001
	(0.242)					(1.098)	(-0.508)					(-0.582)
BKS Event (t-1)		0.011***				0.012***		0.002				0.001
		(5.125)				(5.397)		(0.778)				(0.714)
BKS Event (t-2)			0.011***			0.012***			-0.001			-0.001
			(6.031)			(5.930)			(-0.438)			(-0.362)
BKS Event (t-3)				0.005***		0.006***				-0.001		-0.001
				(2.954)		(3.284)				(-0.893)		(-0.807)
BKS Event (t-4)					0.005***	0.006***					0	-0.00004
					(3.376)	(3.676)					(-0.002)	(-0.021)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	254475	252977	251479	249981	248483	248483	254475	252977	251479	249981	248483	248483
R2	0.792	0.791	0.791	0.791	0.791	0.791	0.792	0.791	0.791	0.791	0.791	0.791
Adjusted R2	0.789	0.788	0.788	0.788	0.788	0.788	0.789	0.788	0.788	0.788	0.788	0.788

Panel B: Negative 2.5% Country-Index Shocks - Robustness

	Dependent Variable: Weekly DCC Correlation (t)									
	Alternative Specifications					**Robustness**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
BKS Event (t-0)	0.007***	0.016***	0.0005	-0.005***	0.002	0.002	0.004*	-0.001	0.002	0.001
	(3.443)	(6.266)	(0.408)	(-3.745)	(1.371)	(1.098)	(1.743)	(-0.395)	(0.773)	(0.498)
BKS Event (t-1)	0.034***	0.025***	0.028***	0.022***	0.010***	0.012***	0.017***	0.005	0.014***	0.006
	(13.386)	(8.868)	(15.054)	(12.372)	(5.574)	(5.397)	(5.860)	(1.545)	(5.297)	(1.354)
BKS Event (t-2)	0.031***	0.025***	0.025***	0.018***	0.011***	0.012***	0.013***	0.010***	0.012***	0.009**
	(12.169)	(9.124)	(14.778)	(11.497)	(6.668)	(5.930)	(4.798)	(3.471)	(5.255)	(2.500)
BKS Event (t-3)	0.019***	0.019***	0.013***	0.006***	0.006***	0.006***	0.008***	0.004	0.008***	0.0003
	(7.729)	(7.090)	(8.933)	(4.011)	(3.481)	(3.284)	(3.039)	(1.259)	(3.695)	(0.065)
BKS Event (t-4)	0.017***	0.019***	0.010***	0.005***	0.006***	0.006***	0.005*	0.007***	0.006***	0.006
	(7.659)	(7.380)	(7.921)	(3.778)	(3.687)	(3.676)	(1.882)	(2.904)	(3.133)	(1.644)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls						Yes	Yes	Yes	Yes	Yes
Relationship controls						Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes			Yes						
Year-Week FE		Yes			Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Close Relationship							**Yes**	**No**		
Year >2000									**Yes**	**No**
N	358486	358486	358486	358486	358486	248483	125974	122509	178657	69826
R2	0.142	0.145	0.775	0.781	0.783	0.791	0.808	0.769	0.778	0.752
Adjusted R2	0.141	0.141	0.774	0.779	0.781	0.788	0.804	0.765	0.776	0.747

Panel C: Real vs. Placebo Suppliers - Negative 2.5% Country-Index Shocks

	Dependent Variable: Weekly DCC Correlation (t)					
	(1)	(2)	(3)	(4)	(5)	(6)
Supl is real	**0.028*****	**0.028*****	**0.028*****	**0.028*****	**0.028*****	**0.028*****
	(12.566)	**(12.591)**	**(12.578)**	**(12.559)**	**(12.517)**	**(12.447)**
BKS Event (t-0)	-0.006***					-0.005***
	(-4.633)					(-3.561)
BKS Event (t-1)		0.007***				0.008***
		(3.788)				(3.922)
BKS Event (t-2)			0.007***			0.008***
			(4.225)			(4.310)
BKS Event (t-3)				0.004***		0.005***
				(2.937)		(3.156)
BKS Event (t-4)					0.002	0.003*
					(1.547)	(1.813)
BKS Event (t-0)*Supl is real	**0.008*****					**0.008*****
	(4.380)					**(4.149)**
BKS Event (t-1)*Supl is real		**0.003**				**0.003**
		(1.096)				**(1.119)**
BKS Event (t-2)*Supl is real			**0.003**			**0.004**
			(1.404)			**(1.440)**
BKS Event (t-3)*Supl is real				**0.001**		**0.001**
				(0.601)		**(0.662)**
BKS Event (t-4)*Supl is real					**0.004****	**0.004****
					(2.055)	**(2.079)**
Intercept	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level & Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes
N	685641	681645	677649	673653	669657	669657
R2	0.669	0.668	0.668	0.669	0.669	0.669
Adjusted R2	0.667	0.666	0.666	0.667	0.667	0.667

Panel D: Negative 0.5% and 0.1% Country-Index Shocks

	Dependent Variable: Weekly DCC Correlation (t)											
	Negative 0.5% BKS Shocks						**Negative 0.1% BKS Shocks**					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
BKS Event (t-0)	-0.006					-0.006	-0.003					-0.001
	(-1.569)					(-1.620)	(-0.512)					(-0.253)
BKS Event (t-1)		0.014**				0.014**		0.029***				0.030***
		(2.300)				(2.264)		(2.667)				(2.711)
BKS Event (t-2)			0.004			0.004			0.017**			0.017**
			(0.717)			(0.737)			(2.074)			(2.102)
BKS Event (t-3)				0.006		0.006				0.012*		0.013*
				(1.346)		(1.357)				(1.648)		(1.675)
BKS Event (t-4)					0.008*	0.008*					0.019***	0.020***
					(1.854)	(1.850)					(2.712)	(2.719)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	254475	252977	251479	249981	248483	248483	254475	252977	251479	249981	248483	248483
R2	0.792	0.791	0.791	0.791	0.791	0.791	0.792	0.791	0.791	0.791	0.791	0.791
Adjusted R2	0.789	0.788	0.788	0.788	0.788	0.788	0.789	0.788	0.788	0.788	0.788	0.788

Table 9. Difference-in-Difference Results: The Effect of Country-Level (Disaster) Events on Financial Contagion.

In this table we summarize the results of panel regressions analyzing the impact of country-level (disaster) events on the dynamic conditional correlation (DCC) of returns between US suppliers and international customers at the weekly frequency. The dependent variable in all models is the weekly DCC_t estimate. Our main variables of interest in both **Panels A** and **Panel B** are the dummy variable *Event Dummy (t-0)* and the weekly lags *Event Dummy (t-1)* to *Event Dummy (t-4)*. *Event Dummy (t-0)* takes the value of one if a country-level event occurred in the home country of the customer firm in the given week and zero otherwise. The sample period is from January 1985 to December 2015. t statistics presented in parentheses were calculated based on standard errors clustered at the firm-pair level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

In **Panel A** we present cross-sectional estimates including relationship-pair fixed-effects in columns (1) to (6) and difference-in-difference estimates including firm-pair- and weekly time fixed effects in columns (7) to (12) for the full sample of country-level events as tabulated in Appendix A.II. Since all events occurred after the year 2003 we focus on that sub-sample period in **Panel A**. All regressions include an intercept not tabulated for brevity. We control for a host of firm-level and firm-pair relationship level control variables explained and listed in Appendix A.I.

In **Panel B** we report the results of several extensions of our main result as well as robustness checks. In columns (1) and (2) we split the sample according to the relationship strength of customer and supplier. Column (1) includes pair observations with below median and column (2) includes firm-pair observations with above median relationship strength according to the percentage of sales the supplier represents to the customer. Columns (3) to (5) report the regression results for the sub-periods from 1985 to 2003, 2004 to 2010 and 2011 to 2015 respectively. In column (6) we present the results including the sub-period from 2010 to 2014 and focusing on the Earthquake and Floor in Japan in 2011 as the only country-level disaster events. Column (7) reports similar regression results focusing on only the weeks of the Eurozone Bailouts as country-level "disaster" events. All regressions include an intercept not tabulated for brevity. We control for a host of firm-level and firm-pair relationship level control variables explained and listed in Appendix A.I.

Panel A: All Country-Level Event Shocks

	Dependent Variable: Weekly DCC Correlation (t)											
	Cross-sectional Models						**Difference-in-Difference Models**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Event Dummy (t-0)	0.016***					0.016***	0.014***					0.014**
	(3.492)					(3.465)	(2.604)					(2.541)
Event Dummy (t-1)		0.013***				0.013***		0.012**				0.012**
		(2.961)				(2.997)		(2.371)				(2.382)
Event Dummy (t-2)			0.019***			0.020***			0.008			0.008
			(3.142)			(3.163)			(1.081)			(1.100)
Event Dummy (t-3)				0.010**		0.011**				0.0004		0.001
				(2.102)		(2.140)				(0.059)		(0.095)
Event Dummy (t-4)					0.006	0.006					0.005	0.005
					(1.333)	(1.387)					(0.956)	(0.973)
AT log sup	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007**	0.007*	0.007*	0.007*
	(1.803)	(1.798)	(1.804)	(1.795)	(1.791)	(1.800)	(1.953)	(1.952)	(1.962)	(1.952)	(1.952)	(1.959)
AT log cus	0.018***	0.018***	0.018***	0.018***	0.018***	0.018***	0.008	0.008	0.008	0.008	0.008	0.008
	(2.901)	(2.906)	(2.890)	(2.891)	(2.894)	(2.879)	(1.168)	(1.170)	(1.159)	(1.158)	(1.157)	(1.154)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE							Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year >2003	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	143747	143080	142413	141746	141079	141079	143747	143080	142413	141746	141079	141079
Adjusted R2	0.761	0.76	0.76	0.76	0.76	0.76	0.77	0.769	0.769	0.769	0.769	0.769

Panel B: Subsamples and Individual Shock Events

	Dependent Variable: Weekly DCC Correlation (t)						
	Relationship Strength		**Sub-Periods**			**Individual Events**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Event Dummy (t-0)	0.005	0.023***	0.008	0.015**	0.024***	0.024***	0.017*
	(0.590)	(3.129)	(1.086)	(2.035)	(3.664)	(3.420)	(1.811)
Event Dummy (t-1)	0.007	0.018***	-0.003	0.016**	0.019***	0.016**	0.018**
	(0.981)	(2.616)	(-0.337)	(2.207)	(2.917)	(2.404)	(2.176)
Event Dummy (t-2)	-0.01	0.023**	-0.004	0.001	0.030**	0.029*	-0.0002
	(-1.089)	(2.336)	(-0.589)	(0.190)	(2.131)	(1.934)	(-0.020)
Event Dummy (t-3)	-0.006	0.007	0.003	-0.003	0.020**	0.016	-0.004
	(-0.679)	(0.928)	(0.465)	(-0.463)	(1.964)	(1.522)	(-0.412)
Event Dummy (t-4)	-0.002	0.011	-0.001	0.001	0.025***	0.022**	-0.001
	(-0.223)	(1.543)	(-0.200)	(0.184)	(2.661)	(2.224)	(-0.102)
AT log sup	-0.001	0.010*	0.005*	0.011**	0.006	0.006	0.007*
	(-0.281)	(1.903)	(1.656)	(2.364)	(1.019)	(1.014)	(1.953)
AT log sup	0.001	0.01	0.013**	0.0003	0.024	0.024	0.008
	(0.173)	(1.038)	(2.205)	(0.049)	(1.024)	(1.029)	(1.158)
Pct sales sup	-0.018	-0.013	0.009	-0.022	0.029	0.029	-0.016
	(-1.014)	(-0.525)	(0.754)	(-1.480)	(1.594)	(1.589)	(-1.144)
Pct COGS cus	8.923**	0.042	0.014	0.041	-0.048	-0.048	0.051
	(2.486)	(0.956)	(0.331)	(1.040)	(-0.847)	(-0.836)	(1.256)
AR/sales sup	-0.002	-0.001	-0.003	-0.001	-0.003	-0.003	-0.004
	(-0.161)	(-0.065)	(-0.385)	(-0.123)	(-0.130)	(-0.129)	(-0.378)
AP/COGS cus	-0.081***	-0.011	-0.014	-0.019	0.016	0.016	-0.018
	(-2.812)	(-0.856)	(-0.902)	(-0.976)	(0.833)	(0.831)	(-1.501)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-pair controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country			Full Sample			Japan	EUR
Year	Year >2003		1985-03	2004-10	2010-15	Year >2010	Year >2003
N	65215	75864	107404	100173	40906	40906	141079
R2	0.762	0.78	0.788	0.774	0.784	0.784	0.772
Adjusted R2	0.758	0.777	0.785	0.772	0.781	0.781	0.769

Table 10. Value Implications of Country-Level Shocks for Supplier and Customer Firms

Notes. This table presents cumulative average abnormal returns (CAAR) of U.S. supplier firms and matched placebo suppliers around the day when an extreme negative index return shock occurred in the country of the customer linked to the supplier. In **Panel A** we use the bottom 0.5% most negative index returns per country (after correcting for time-varying return volatility) over our sample period as 'shock events'; in **Panel B** the bottom 0.1% most negative standardized index return shocks are used. In **Panel C** and **Panel D** we use the natural disasters affecting the subsample of Japanese customers. The placebo suppliers were matched within the same Fama-French 48 industry classification according to average asset size over the length of the supplier-customer relationship period. Abnormal returns are computed after estimating, for each (placebo) supplier, a three-factor Fama-French model over the interval from 271 to 21 trading days before the event date. We exclude firm-shock observations with missing returns in the estimation or event windows, or when the customer firm's country are hit by another index return shock within 40 trading days around the event. In Panels A to C, columns (1) and (4) present the CAAR for the respective window around the shock event. Panel D lists the Cumulative Average Raw Return (CARR) instead. In each panel we list ADJ-BMP t-statistics in parentheses in columns (2) and (5), computed with the parametric, standardized cross-sectional method of Boehmer et al. (1991) and adjusted for cross-sectional correlation as in Kolari and Pynnönen (2010). In columns (3) and (6) we list Corrado-Zivney t-statistics in parentheses, computed with the non-parametric rank test of Corrado and Zivney (1992) and Kolari and Pynnonen (2011). The sample period is from 1980 to 2014. *, **, and *** denotes significance at the 10%, 5%, and 1%, respectively, conservatively using the maximum of the p-Values corresponding to the parametric Adj-BMP test and the non-parametric Corrado-Zivney rank test.

Panel A: Bottom 0.5% of Negative Country-Index Return Shocks

	CAAR: Full Sample					
	Real Suppliers			Placebo Suppliers		
	(N=4967) (1)	Adj-BMP test (2)	Corrado test (3)	(N=4268) (4)	Adj-BMP test (5)	Corrado test (6)
[-20,-10]	0.0015	(0.360)	(-0.370)	0.1065	(-0.722)	(-0.937)
[-10,-1]	-0.0083**	(-2.239)	(-2.488)	0.001	(0.178)	(1.132)
[-1,1]	-0.0074***	(-3.351)	(-3.620)	-0.0028	(-1.252)	(-0.606)
[-1,10]	-0.0131**	(-2.476)	(-2.920)	-0.0037	(-0.751)	(-0.352)
[11,20]	-0.0039	(-1.177)	(-1.716)	-0.0015	(-0.547)	(-0.060)
[21,30]	-0.0068	(-0.849)	(-1.142)	-0.0036	(-0.452)	(-0.517)
[31,40]	-0.0075	(-1.459)	(-2.178)	-0.0039	(-0.940)	(-1.183)
[-10,40]	**-0.0373*** **	**(-3.341)**	**(-3.631)**	**-0.0116**	**(-0.991)**	**(-0.446)**
[-20,40]	-0.0356***	(-2.924)	(-3.309)	-0.014	(-1.194)	(-0.740)

Panel B: Bottom 0.1% of Negative Country-Index Return Shocks

	CAAR: Full Sample					
	Real Suppliers			Placebo Suppliers		
	(N=1496)	Adj-BMP test	Corrado test	(N=1287)	Adj-BMP test	Corrado test
	(1)	(2)	(3)	(4)	(5)	(6)
[-20,-10]	0.0021	(0.240)	(-0.155)	-0.0019	(-0.263)	(-0.401)
[-10,-1]	-0.0159***	(-3.132)	(-2.631)	-0.0138	(-2.244)	(-1.195)
[-1,1]	-0.0102***	(-3.089)	(-3.055)	-0.004	(-1.570)	(-1.598)
[-1,10]	-0.0176***	(-2.738)	(-2.968)	-0.004	(-1.145)	(-1.470)
[11,20]	-0.0038	(-0.837)	(-1.353)	-0.0021	(-0.805)	(-0.357)
[21,30]	-0.0053	(-1.085)	(-1.598)	-0.0053	(-0.429)	(-0.368)
[31,40]	-0.0175**	(-2.462)	(-3.433)	-0.0048	(-1.085)	(-0.140)
[-10,40]	**-0.0562*****	**(-4.453)**	**(-4.241)**	**-0.0271**	**(-2.288)**	**(-1.298)**
[-20,40]	-0.0528***	(-4.003)	(-3.744)	-0.0274	(-2.024)	(-1.185)

Panel C: Tohoku Earthquake & Tsunami in Japan - Suppliers

	CAAR: Japan Disasters					
	Real Suppliers			Placebo Suppliers		
	(N=136)	Adj-BMP test	Corrado test	(N=127)	Adj-BMP test	Corrado test
	(1)	(2)	(3)	(4)	(5)	(6)
[-20,-10]	-0.0035	(-1.466)	(-0.189)	-0.013	(-0.940)	(-0.546)
[-10,-1]	-0.0204	(-1.200)	(-1.895)	0.0014	(2.416)	(0.856)
[-1,10]	-0.0167	(-2.068)	(-1.287)	-0.0078	(-0.196)	(-0.836)
[11,20]	-0.0007	(-1.059)	(-1.309)	0.0041	(0.209)	(-0.912)
[21,30]	-0.0052	(-0.177)	(-0.416)	0.0135	(2.347)	(1.125)
[31,40]	-0.0019	(0.912)	(0.295)	-0.0073	(-0.514)	(-0.254)
[-10,40]	**-0.044***	**(-1.947)**	**(-1.805)**	**0.0035**	**(1.785)**	**(-0.106)**
[-20,40]	-0.0479	(-2.479)	(-1.633)	-0.0149	(-0.284)	(-0.483)

Panel D: Tohoku Earthquake & Tsunami in Japan - Customers

	Cumulative Average Raw Return (CARR)		
	(N=135)	Adj-BMP test	Corrado test
	(1)	(2)	(3)
[-20,-10]	-0.0033	(0.702)	(-0.533)
[-10,-1]	0.0003	(0.588)	(0.142)
[-1,5]	**-0.1505****	**(-2.373)**	**(-2.018)**
[-1,10]	-0.1202	(-2.355)	(-1.429)
[11,20]	0.0162	(0.746)	(0.113)
[21,30]	0.0107	(-0.109)	(-0.198)
[31,40]	0.0067	(-0.018)	(-0.008)
[-10,40]	-0.0739	(-0.663)	(-0.426)
[-20,40]	-0.0879	(-0.503)	(-0.666)

Table 11. Average Annual DCC correlation and the use of Trade Credit.

This table presents cross-sectional regression results analyzing the effect of the use of trade credit on the average annual DCC correlation between connected U.S. supplier and international customer firms. The dependent variable in all models is the average annual DCC correlation per firm-pair, our main variables of interest are the contemporaneous and lagged ratio of accounts receivable (AR) to sales for the supplier firm (*AR/sales sup*) and the ratio of accounts payable (AP) to cost of goods sold (*AP/COGS cus*) for the customer firm. In all models we include country-year fixed effects and control for a host of firm-level and firm-pair control variables listed in Appendix A.I. t statistics presented in parentheses are computed using standard errors clustered on the firm-pair-level in each model. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Annual Average DCC Correlation (t)		
	(1)	(2)	(3)
AR/sales sup	0.0327**	0.0585***	
	(2.19)	(3.29)	
AP/COGS cus	0.0227***	0.0265***	
	(2.75)	(2.73)	
AR/sales (t-1)			0.0853***
			(3.73)
AP/COGS cus (t-1)			0.0375**
			(2.53)
AT log sup	0.0301***	0.0296***	0.0309***
	(17.34)	(14.29)	(11.92)
AT log cus	0.00840***	0.0104***	0.00818***
	(4.88)	(4.94)	(3.15)
Pct sales sup		-0.0233	-0.0165
		(-1.38)	(-0.86)
Pct COGS cus		-2.609	-74.08
		(-0.04)	(-1.23)
Intercept	-0.121***	-0.152***	-0.126***
	(-4.15)	(-4.42)	(-3.01)
Country-Year-FE	Yes	Yes	Yes
N	6897	5104	3310
R-sq	0.503	0.541	0.597
adj. R-sq	0.462	0.492	0.538

Appendix A. Variable Definitions and Country-Level Events

Table A.I. Variable Definitions and Data Sources.

Variable	Short Description	Detailed Comments
DCC_t	Weekly DCC correlation	DCC correlation between return residuals of U.S. supplier (placebo supplier) and international customer firms on weekly frequency. (Data sources: CRSP and Datastream)
BKS Event (t-k)	Country-Index Return event	Dummy variable taking the value of one if a BKS-type country-index return shock occurred in the country of the customer firm in the given week (with lag k) and zero otherwise. We identify BKS index shocks as the top or bottom 2.5%, 0.5% or 0.1% of weekly (or daily) index returns standardized by the moving average of the index return's standard deviation per country.
Event Dummy (t-k)	Country (disaster) event	Dummy variable taking the value of one if a country-level (disaster) event occurred in the country of the customer firm in the given week (with lag k) and zero otherwise. (Data source: `http://www.emdat.be/` from the Centre for Research on the Epidemiology of Disasters (CRED)) The full list of country events is presented in Table A.II in the appendix.
Supl is real	Supplier firm is not a placebo	Dummy variable taking the value of one if the supplier firm in our pooled sample of real U.S. suppliers and matched placebo suppliers is a "real" supplier and zero otherwise. Placebo suppliers were matched to real suppliers in our sample using the average of the total book value of assets (AT sup) across the duration of the supplier-customer relationship within the same Fama-French 48 industry classification. (Data source: Compustat)
AT log cus(sup)	Firm size customer (supplier)	Logarithm of the book value of assets of the customer (supplier) firm. (Data sources: Compustat and Datastream)
MktCap cus(sup)	Market Value customer (supplier)	Total market capitalization of the customer (supplier) firm. (Data sources: Compustat and Datastream)
AR/sales cus(sup)	Accounts Receivale to Sales of customer (supplier)	Ratio of Accounts Receivable to Sales of the customer (supplier) firm. (Data sources: Compustat and Datastream)
AP/COGS cus(sup)	Accounts Payable / COGS of customer (supplier)	Ratio of Accounts Payable to Costs of Goods Sold (COGS) of the customer (supplier) firm. (Data sources: Compustat and Datastream)

(continued)

(continued)

KZ Index cus(sup)	KZ Index of customer (supplier)	Kaplan-Zingales Index following Kaplan, Zingales, et al. (1997) for customer (supplier) firm. Calculated as follows: -1.001909*((dp + ib)/ ppent) + 0.2826389*((at + mcap - seq + txditc)/at) + 3.139193*(((dltt + dlc))/((dltt +dlc) + seq)) - 39.3678*((dvp + dvc)/ppent) - 1.314759*(ch/ppent). (Variable defintions as in Compustat. Data sources: Compustat and Datastream)
ROA cus(sup)	Return on Assets customer (supplier)	Ratio of Net Income to Total Book Value of Assets for customer (supplier) firm. (Data sources: Compustat and Datastream)
Pct sales sup	Relationship intensity	Sales of supplier to customer firm/ Total sales of supplier firm. (Data source: Compustat Segment Files and Compustat)
Pct COGS cus	Relationship intensity	Sales of supplier to customer firm/ Total Cost of Goods Sold of customer. (Data source: Compustat Segment Files and Compustat)
Relation Age	Current relationship length	Number of years the supplier and customer have been connected in the current year. (Data source: Compustat Segment Files and Compustat)
Duration Relation	Total relationship length	Total number of years the relationship of the supplier and customer lasted in our sample. (Data source: Compustat Segment Files and Compustat)

Table A.II. List of Country-Level Events and Disasters.

This table summarizes all disaster and country-level events used in this paper including information on the date of the occurrence of the event, the type of hazard and the number of total deaths, affected population and damages in USD as far as data is available. Disasters are obtained from `http://www.emdat.be/` provided by the Centre for Research on the Epidemiology of Disasters (CRED). All other country-level events are hand-collected.

Popular name	**Countries affected**	**Date of event**	**Type of hazard**	**Total deaths**	**Total affected**	**Total damages (US$)**
ERM Currency attack	Europe	01-09-1992	Currency Crisis	n.a.	n.a.	n.a.
Third Taiwan Strait Crisis	China	21-07-1995	Political Conflict	n.a.	n.a.	n.a.
Third Taiwan Strait Crisis	Taiwan	21-07-1995	Political Conflict	n.a.	n.a.	n.a.
Thai currency attack	Thailand	14-05-1997	Currency Crisis	n.a.	n.a.	n.a.
Asian Financial Crisis	South Korea	01-08-1997	Currency and Debt Crisis	n.a.	n.a.	n.a.
End of Fixed Exchange Rate	Indonesia	14-08-1997	Currency Crisis	n.a.	n.a.	n.a.
Malaysia currency attack	Malaysia	14-08-1997	Currency Crisis	n.a.	n.a.	n.a.
Asian Crisis - Currency attack	Hong Kong	27-08-1997	Currency Crisis	n.a.	n.a.	n.a.
Asian Crisis - Overnight Rate Hike	Hong Kong	15-08-1998	Currency Crisis	n.a.	n.a.	n.a.
End of Fixed Exchange Rate	Brazil	01-02-1999	Currency Crisis	n.a.	n.a.	n.a.
IMF refused tranche, riots, turmoil	Argentina	05-12-2001	Currency Crisis	n.a.	n.a.	n.a.
Debt Default, End of Fixed Exch Rate	Argentina	27-12-2001	Debt Default	n.a.	n.a.	n.a.
Dresden floods	Germany	11-08-2002	Flood	27	330,108	11.6 billion
European heatwave	France	01-07-2003	Extreme heat	14802	n.a.	n.a.
European heatwave	Portugal	01-07-2003	Extreme heat	2039	n.a.	n.a.
European heatwave	Netherlands	01-07-2003	Extreme heat	1500	n.a.	n.a.
European heatwave	Spain	01-07-2003	Extreme heat	12963	n.a.	n.a.
European heatwave	Italy	01-07-2003	Extreme heat	n.a.	n.a.	n.a.
European heatwave	Germany	01-07-2003	Extreme heat	9000	n.a.	n.a.
European heatwave	United Kingdom	01-07-2003	Extreme heat	2000	n.a.	n.a.
European heatwave	Ireland	01-07-2003	Extreme heat	n.a.	n.a.	n.a.
European heatwave	Switzerland	01-07-2003	Extreme heat	n.a.	n.a.	n.a.
Bam earthquake	Iran	26-12-2003	Earthquake	26,796	267,628	500 million
South Asian tsunami	South East Asia	26-12-2004	Earthquake and tsunami	226,408	2,321,700	9.2 billion
Mumbai floods	India	26-07-2005	Flood	1,200	20,000,055	3.3 billion
Hurricane Katrina	United States	29-08-2005	Tropical cyclone	1,833	500,000	125 billion
Kashmir earthquake	Pakistan	08-10-2005	Earthquake	73,338	5,128,000	5.2 billion
Java earthquake	Indonesia	27-05-2006	Earthquake	5,778	3,177,923	3.1 billion
Cyclone Nargis	Myanmar	01-05-2008	Tropical cyclone	138,366	2,420,000	4 billion
Sichuan earthquake	China	12-05-2008	Earthquake	87,476	45,976,596	85 billion
Haiti earthquake	Haiti	12-01-2010	Earthquake	222,570	3,400,000	n.a.
First Euro Bailout Package	Europe	11-04-2010	Euro Collapse	n.a.	n.a.	n.a.
Second Euro Bailout Package	Europe	07-09-2010	Euro Collapse	n.a.	n.a.	n.a.
Gujurat earthquake	India	26-01-2011	Earthquake	20,005	6,321,812	2.6 billion
Japan earthquake	Japan	11-03-2011	Earthquake and tsunami	5178	n.a.	n.a.