CFCM

CENTRE FOR FINANCE, CREDIT AND MACROECONOMICS

Working Paper 16/05

Business-Linkage Volatility Spillover between US Industries

Linh Xuan Diep Nguyen, Simona Mateut and Thanaset Chevapatrakul

Produced By:

Centre for Finance, Credit and Macroeconomics
School of Economics
Sir Clive Granger Building
University of Nottingham
University Park
Nottingham
NG7 2RD

Tel: +44(0) 115 951 4763
Fax: +44(0) 115 951 4159
suzanne.robey@nottingham.ac.uk

BUSINESS-LINKAGE VOLATILITY SPILLOVER BETWEEN US INDUSTRIES

Linh Xuan Diep Nguyen, Simona Mateut and Thanaset Chevapatrakul*

November 2016

Abstract

This paper examines the volatility spillovers between US industries and their dependence on the inter-industry business linkages. Our first-stage multivariate model reveals significant volatility transmission between trading industries. Our second-stage results demonstrate that inter-industry spillovers are influenced by the strength of the trading relationship. When industries are more important to their partners, as measured by the shares of inputs or revenue, they tend to have stronger volatility spillovers toward their partners and are less affected by the volatility of their partners. Qualitatively similar results are obtained regardless of the business-linkages measures used and from samples restricted to closely-linked or to non-financial industries. Importantly, business linkages are highly relevant for shock spillovers in bad market conditions. The link between volatility spillovers and the strength of the business relationship is confirmed at portfolio level as well.

* Corresponding address: Simona Mateut, University of Nottingham, Business School, Jubilee Campus, Nottingham, NG8 1BB, UK. E-mail: simona.mateut@nottingham.ac.uk. Telephone: 44-115-8468122. Fax: 44-115-8466667. Nguyen: lixlxn@nottingham.ac.uk. Chevapatrakul: thanaset.chevapatrakul@nottingham.ac.uk
We would like to thank participants at the Royal Economic Society 2016 conference, the Scottish Economic Society 2016 conference, Kevin Amess and Piercarlo Zanchettin. We are grateful for access to the University of Nottingham High Performance Computing Facility. The usual disclaimer applies.

1. Introduction

A well-established body of literature shows evidence of volatility spillovers between international stock markets, in which the volatility of a market index can be explained by the volatility of the other markets (see Hamao et al., 1990; King and Wadhwani, 1990; Koutmos and Booth, 1995; among others). To date, however, relatively little attention has been paid to how volatility is transmitted across industries in an economy. Although some studies have examined volatility spillovers among a group of related industries, they only focus on specific sectors such as energy and financials (see Alli et al., 1994; Ewing et al., 2002; Elyasiani et al., 2007; among others).

Industries in an economy are connected through an intricate network of transactions as output produced by an industry serves as input in the production processes of other industries along the supply chain. Equally intertwined are the accompanying financial flows between industries. Consequently, the volatility of stock returns of an industry that relies on cash flow streams from another industry is likely to rise with an upsurge in the volatility of its trading partner. In this paper, we look at the relation between volatility spillovers of stock returns across all industries in an economy and the strength of their supplier-customer relationship as measured by the amount of trade flows between industries.

Our work relates to the economics literature investigating how shocks spread through the economy. For instance, Shea (2002) proves the importance of input-output linkages in the comovement of sectors in the economy. He shows that fluctuation in the production of one industry is affected by the shocks to all other industries, where the downstream propagation of supply shocks and the upstream transmission of demand shocks depends on the strength of the cost and demand linkages between industries, respectively. Acemoglu et al. (2012) develop a theoretical model to show how, via the network of input-output interconnections, idiosyncratic shocks to a sector propagate downstream to both its immediate customers and its indirect customers further down the supply chain resulting in aggregate fluctuations.

We focus on how shocks to an industry stock returns propagate to both its suppliers and customers through the input-output linkages between industries. Our methodology consists of two stages. In the first stage, we use a multivariate GARCH model to measure the extent to which shocks and return volatility are transmitted within pairs of industries in a trading relationship. Our first stage model resembles Elyasiani et al. (2007) but differs from their specification in two main respects. Firstly, while Elyasiani et al. (2007) investigate the volatility transmission between three industries in the financial sector (i.e., banks, securities firms and life insurance companies), we consider all economic sectors and calculate the volatility spillovers for all the pairs of industries in the US economy. As a result, we estimate multivariate GARCH models for 2,080 distinct industry pairs. Secondly, we include the autoregressive term in the mean equations and the shock spillovers in the variance equations.

In the second stage, we run cross-sectional regressions where the first-stage estimates of the degree of volatility spillovers (the GARCH and ARCH parameters) are explained by the amount of trade flows between industries along with other industry-specific characteristics that are thought to affect the industry return volatility (such as industry size and concentration ratio).

Our measures of economic relationship between industries are constructed from the US Input-Output (IO) accounts from the Bureau of Economic Analysis (BEA). As pointed out by Ahern and Harford (2014), the IO tables record all the dollar flows between all producers and purchasers in the entire US economy based on the classification system specifically designed to group firms into industries that best measure customer and supplier relations. Our work differs from previous studies using IO-based measures to identify the supply chain relationship (c.f. Menzly and Ozbas, 2010; Aobdia et al., 2014) in that we focus on spillovers in the second moment rather than the first moment.

As a preview of our main results, we find evidence of significant volatility spillovers between US industries. To illustrate, 83% of the industry pairs display significant volatility spillovers (either GARCH or ARCH). Importantly, our study shows that inter-industry volatility spillovers depend on the strength of the trading relationship between the two industries. Specifically, the volatility of an industry with a more important role (i.e., being a major customer or supplier) relative to its trading partner transmits strongly to its partner, while its partner's volatility has much less impact on its stock returns' volatility. Our results suggest that spillovers from external shocks are more strongly connected to business linkages than pure volatility spillovers, pointing to the vulnerability of industries to external uncertainty.

Our findings remain virtually unchanged when subjected to a series of sensitivity tests. Our results are robust to the construction of the business linkage variables using alternative yearly IO data from 2005 to 2013 and the average values for the sample period. Conducting our two-stage analysis on restricted samples produces similar results. Firstly, to acknowledge that certain pairs of industries trade relatively little with each other, we conduct our two-stage analysis on the sample of industry pairs that have substantial trade relationship and find qualitatively similar results. Secondly, we drop from our sample all industries in the financial sectors, which are expected to have stronger volatility spillover to other industries in the economy, and find that our main results remain unaltered.

We examine further whether the relation between business linkages and volatility spillovers is influenced by the overall market conditions. To this end, we repeat our two-stage analysis separately on the three sub-periods within our sample: the pre-crisis period of 2005-2006, the crisis period of 2007-2008, and the bull-market period of 2009-2013. Our estimates reveal that shock spillovers are more strongly correlated with business linkages during the bad market conditions of the 2007-2008 financial crisis.

Having identified the link between volatility spillovers and the strength of the business linkages at industry level, we then investigate whether we observe volatility spillovers at the portfolio level. Following Menzly and Ozbas (2010), we use the IO data to construct the portfolio of suppliers for each US industry. Similarly, we construct each industry's portfolio of customers. We then conduct the first-stage multivariate volatility spillover analysis for each industry and its representative supplier and representative customer, respectively. Our results suggest significant volatility spillovers at the portfolio level for 61 out of 65 industries. In line with our findings for industry pairs, we confirm the link between the strength of the business relationship and volatility spillovers at portfolio level.

Understanding how volatility transmits across industries has far reaching implications for business managers, investors and policy makers. It is not uncommon for managers and investors to maintain portfolios focusing on a group of related companies or on specific industries, such as energy funds, agriculture funds, among others. Since these portfolios may have significant weights in closely-linked industries, they are less diversified and more exposed to idiosyncratic risks.[1] To achieve the desired risk and return characteristic, it may be necessary for investment managers to rebalance their portfolios more frequently, thereby increasing their trading costs. Volatility transmission across industries has policy implications as well. For instance, responding to monetary policy changes, returns on stocks of industries with high leverage (e.g., financials, utilities, retails) are likely to be more volatile than returns on stocks of industries with low leverage (e.g., technology, services). As shocks transmit across industries via their trade relationship, uncertainty becomes more severe making policy fine-tuning especially challenging. Similarly, a fiscal policy change targeting a certain industry could potentially affect other related industries if volatility spillovers among them are high due to their close relationship.

[1] Griffin and Karolyi (1998) point out that randomly assigning investments across industries within a country results in poor diversification as the reduction in the portfolio variance is significantly smaller than diversification across countries within the same industry. Their results may be due to cross-industry volatility spillovers which cause stock prices in closely-related industries to move in tandem thereby reducing the benefit of diversification.

The rest of the paper is organized as follows. Section 2 reviews related works on volatility spillover and the impact of business linkages. Section 3 presents our two-stage methodology. Section 4 describes the data and the construction of the business-linkage measures used in this research. Section 5 reports our main empirical results and some robustness checks. Section 6 examines the relation between business linkages and volatility spillovers in different market conditions. Section 7 takes a portfolio approach and investigates whether there are volatility spillovers between an industry and its representative supplier / customer. Section 8 concludes.

2. Literature review

Research on volatility transmission has focused on countries, economic sectors or industries. Hamao et al. (1990) use a two-stage approach to study stock returns and volatility spillovers among three world major stock markets. They find evidence of asymmetric volatility transmission effects in that the Tokyo market is affected by shocks from the New York and London stock markets, but not vice versa. King and Wadhwani (1990) model contagion between stock markets as the outcome of rational attempts by domestic and foreign investors to exploit asymmetric information. Using hourly data for the US, UK and Japan stock markets, they find evidence supporting their prediction of contagion between markets: volatility in one market increases when one of the other markets reopens while it decreases when the other markets are closed. Importantly, higher volatility in one market leads to increased contagion coefficients among markets.[2]

Ewing (2002) employs monthly data for five main S&P indexes – capital goods, financials, industrials, transportation and utilities – in a generalized forecast error variance decomposition method to investigate volatility transmission across sectors. His results suggest that shocks to one sector's stock returns significantly account for the volatility of returns on the indexes of other sectors. Hassan and Malik (2007) consider every possible combination of three sectors among six US sectors: industrial, financial, consumer, energy, health and technology. Their trivariate BEKK-GARCH results using Dow Jones daily returns confirm significant volatility spillover among sectors.

[2] Other studies have investigated spillover effects within specific areas such as Scandinavia (Booth et al., 1997), Asia (Miyakoshi, 2003), and Europe (Kohonen, 2013). Koutmos and Booth (1995) examine the asymmetric impact of good and bad news on volatility spillovers at country level.

Modelling volatility spillovers for all possible sector combinations becomes unfeasible, however, when more disaggregated industry level data are employed.[3] A handful of papers have focused on the volatility transmission among a group of related industries, such as energy and financials, due to their high volatility and significant influences on other sectors of the economy. For instance, Alli et al. (1994) investigate volatility spillovers between the oil and oil-related industries in the US market while Ewing et al. (2002) use the bivariate BEKK-GARCH to model volatility transmission between the oil and the natural gas indexes.

In a paper closely related to ours, Elyasiani et al. (2007) examine returns and volatility linkages among three financial industries, namely, commercial banking, securities, and life insurance. A system-GARCH model is estimated for each industry, in which the industry return and volatility are, respectively, explained by the past return and volatility of the other two industries. Their results confirm the interdependence of returns and volatility across financial industries. Conducting the analysis separately for portfolios of large and small firms within each industry suggests that the transmission effect is size-sensitive. While small firms show a higher level of return interdependence, larger firms are found to have stronger volatility spillover linkages.

The inter-industry volatility transmission studies mentioned above have considered industries as related financial assets, ignoring the actual business linkages among them. A strand of economics literature has investigated how idiosyncratic shocks to sectors transmit in the production network, resulting in aggregate volatility. Horvath (1998) shows that if some sectors are important suppliers, i.e., they supply to a large number of other sectors in the economy, their idiosyncratic shocks contribute significantly to the aggregate shock to the economy. Acemoglu et al. (2012) develop a theoretical model showing that, due to the interconnection between sectors, idiosyncratic productivity shocks to one sector transmit downstream to its direct customers and propagate to other indirect customers further down the supply chain leading to aggregate volatility of the entire economy. They show that the interconnection network between sectors, measured by the input-output linkages, determines the rate at which aggregate volatility decays. Shea (2002) builds a theoretical model to illustrate that fluctuation in the production of an industry is affected by shocks to all other industries in the economy. Supply shocks propagate downstream and demand shocks transmit upstream, contingent on the strength of the cost and demand linkages between industries, respectively.

[3] Wang (2010) investigates the volatility transmission among 30 US industries using Granger-causality volatility structure. Despite using more disaggregated industry level data, the study is mainly interested in identifying leading-lagging industries without considering the underlying economic linkages between them.

He finds empirical evidence of shock spillovers both upstream and downstream via the input-output linkages.

In contrast to the works discussed above, we investigate the inter-industry volatility spillovers of the stock returns taking into account the supplier-customer relationship between industries. We allow each industry to act as both supplier and customer to the other industry in the trading pair. Information on trade flows between industries is obtained from the Input-Output (IO) accounts provided by the US Bureau of Economic Analysis (BEA). Our study investigates the link between volatility spillovers across industries and the strength of their trading relationship.

The IO data has been used in the finance literature before in both corporate finance and asset pricing studies. For instance, Ahern and Harford (2014) use the IO accounts provided by the BEA to examine the impact of supply-chain relationships on US merger activities.[4] Following Becker and Thomas (2011), they calculate the trade flows and the strength of the linkages between all industries to create a network of suppliers and customers. They find evidence that mergers spill over in wave-like patterns through the supplier-customer links.

Menzly and Ozbas (2010) utilize the supplier-customer relationship derived from the IO accounts in an asset pricing context. For each industry, they construct portfolios of the representative supplier (and customer) industry, taking into account the industry's trade flows with all supplier (customer) industries. They find evidence indicating that returns on an industry portfolio can be explained by the lagged returns of its representative supplier and customer industries. Aobdia et al. (2014) confirm the interdependence of returns between related industries. They disregard, however, the direction of the linkage and only consider a "source industry" and its "linked industry" (i.e., a portfolio of its trading partner industries) instead of two separate portfolios of suppliers and customers. Ahern (2013) finds significant relationships between an industry's current returns, the recent lagged returns of its close trading partners, and the old (12-month lagged) returns of the distant industries in the production network. This indicates that return spillovers depend on the closeness of the industries, as shown by the immediate impact on the closely-related industries and the delayed effect on the distant-connected industries in the economy.

The discussion above shows that the various finance studies using the economic data available in the IO tables limit themselves to return predictability and ignore volatility or higher

[4] Among others, see also Maddigan (1981), Caves and Bradburd (1988), Matsusaka (1993).

moment spillovers. In contrast, we utilize this information to examine how the inter-industry returns volatility spillover is affected by the business linkages between industries.

3. Methodology and Model

3.1. A multivariate model for volatility spillover

The multivariate GARCH model has been extensively used in studies of risk and uncertainty spillovers. We adopt a two-stage approach to investigate how the supplier-customer relationship between industries affects inter-industry volatility spillovers. In the first stage, we estimate a multivariate GARCH model for every pair of industries. Specifically, the excess stock return of an industry is modelled as a function of both its own and its trading partner's lagged excess return. Similar to Elyasiani et al. (2007), an industry's excess stock return is also influenced by the excess market return, the change in the short-term interest rate, and the percentage change in the foreign exchange rate index. The volatility of the excess return of an industry is also specified as a function of its own and its partner's lagged volatility as well as the external volatility. Following Campbell and Hamao (1992), we set the timing of the excess market return to coincide with the timing of the industry's excess return, while the other exogenous variables are lagged by one period.[5] For each industry pair, our multivariate GARCH(p, q) is specified as follows:

$$R_{i,t} = \alpha_{10} + a_{M1} R_{Mt} + a_{FX1} FX_{t-1} + a_{\Delta RF1} \Delta RF_{t-1} + \alpha_{11} R_{i,t-1} + \alpha_{12} R_{j,t-1} + \varepsilon_{i,t} \tag{1}$$

$$h_{ii,t} = \beta_{10} + \sum_{k=1}^{p} \beta_{11k} h_{ii,t-k} + \sum_{l=1}^{q} \gamma_{11l} \varepsilon_{i,t-l}^{2} + \beta_{12} h_{jj,t-1} + \gamma_{12} \varepsilon_{j,t-1}^{2} \tag{2}$$

$$R_{j,t} = \alpha_{20} + a_{M2} R_{Mt} + a_{FX2} FX_{t-1} + a_{\Delta RF2} \Delta RF_{t-1} + \alpha_{22} R_{j,t-1} + \alpha_{21} R_{i,t-1} + \varepsilon_{j,t} \tag{3}$$

$$h_{jj,t} = \beta_{20} + \sum_{k=1}^{p} \beta_{22k} h_{jj,t-k} + \sum_{l=1}^{q} \gamma_{22l} \varepsilon_{j,t-l}^{2} + \beta_{21} h_{ii,t-1} + \gamma_{21} \varepsilon_{i,t-1}^{2} \tag{4}$$

$$\varepsilon_{i,t} \left| \Omega_{t-1} \sim N\left(0, h_{ii,t}\right); \; \varepsilon_{j,t} \right| \Omega_{t-1} \sim N\left(0, h_{jj,t}\right) \tag{5}$$

$$h_{ij,t} = \rho_{ij} \sqrt{h_{ii,t} h_{jj,t}}, \; i \neq j \tag{6}$$

[5] In Campbell and Hamao (1992), the excess return of an asset is determined by the realization of price determining factors in the current period and the expected excess return of the asset in the previous period. Accordingly, the concurrent market return represents the factor realization, while the other exogenous variables are predictive variables and determine the expected excess returns.

where R stands for the industry excess returns, i and j index industries (*i, j =1, 2,…, 65; i≠ j*), and t denotes the time period. R_M, FX, and ΔRF are the excess market return, the percentage change in the foreign exchange rate index, and the change in the short-term interest rate, respectively; ε_i, ε_j are the error terms. The mean equations, Eqs. (1) and (3), describe the return spillovers between industries i and j. Eqs. (2) and (4) are the volatility spillover equations, where h_{ii} and h_{jj} represent conditional volatility, and h_{ij} is the covariance of ε_i and ε_j. Note that Eq. (6) allows for time-varying conditional volatility but restricts the correlation between the two industries to be time invariant.

Eq. (5) assumes that shocks at time t are normally distributed conditional on the information realized at time $t-1$. Specifically, at time t, the bivariate residual vector $\boldsymbol{\varepsilon}_t = \left(\varepsilon_{i,t}, \varepsilon_{j,t}\right)$ follows $N(0, \mathbf{H}_\mathrm{t})$ where

$$\mathbf{H}_\mathrm{t} = \begin{bmatrix} h_{ii,t} & h_{ij,t} \\ h_{ji,t} & h_{jj,t} \end{bmatrix}.$$

We use the maximum likelihood method to estimate the system of mean and volatility equations simultaneously. The parameter estimates are obtained by maximizing the following log likelihood function:

$$\mathrm{LL}= \sum_{t=1}^{T} \left(-\frac{1}{2}[2\ln(2\pi) + \ln|\mathbf{H}_\mathrm{t}| + \boldsymbol{\varepsilon}_t' \mathbf{H}_t^{-1} \boldsymbol{\varepsilon}_t]\right), \quad (7)$$

where T is the number of trading days in our sample and the elements of $\boldsymbol{\varepsilon}_\mathrm{t}$ and $\mathbf{H}_\mathrm{t}$ are determined by Eqs. (1) to (6).

To ensure that the estimates of variance are non-negative and that the volatility process is stationarity (i.e., the existence of constant long term volatility), we restrict β_{10}, β_{20}, β_{11k}, β_{22k}, γ_{11l}, γ_{22l}, β_{12}, β_{21}, and γ_{12}, γ_{21} to be positive for all k, and l; $\sum_{k=1}^{p} \sum_{l=1}^{q} (\beta_{11k} + \gamma_{11l}) < 1$, $\sum_{k=1}^{p} \sum_{l=1}^{q} (\beta_{2k} + \gamma_{2l}) < 1$; and $-1 < \rho_{ij} < 1$.

Our model is similar to Elyasiani et al. (2007) but differs in two respects. Firstly, we include the autoregressive terms in the mean equations, Eqs. (1) and (3), to account for the well-documented smoothing behavior of returns. Secondly, we include both the ARCH and GARCH spillover effects in Eqs. (2) and (4) to allow for a decomposition of volatility spillovers into a permanent component (the GARCH spillover), and a transitory component due to temporary shocks (the ARCH spillover).

3.2. Cross-sectional analysis of the impact of business linkages on volatility spillover

We are ultimately interested to find how the strength of the business linkages affects inter-industry volatility spillovers. Therefore, once we have estimated the volatility spillover coefficients for all the industry pairs we link them with measures of the strength of their business relationship. As an illustration, the first-stage GARCH spillover coefficient β_{21} shows the extent to which the lagged return volatility of industry *i* affects the current volatility of its trading partner industry *j*, while the ARCH spillover coefficient γ_{21} shows how the lagged shocks (residual terms) of industry *i*'s returns affect the current volatility of industry *j*. In the second stage, we regress each of these coefficients on a set of variables measuring the strength of the business linkages between the two industries. Formally, we estimate the following cross-sectional regressions:

$$GARCH\ Spillover_{ij} = \theta_0 + \theta_{C-Ind} CUST_{ji} + \theta_{S-Ind} SUPP_{ij} + \theta_{C-Part} CUST_{ij} + \theta_{S-Part} SUPP_{ji} + \theta_{Ind} x_i + \theta_{Part} x_j + u_{ij} \tag{8}$$

$$ARCH\ Spillover_{ij} = \phi_0 + \phi_{C-Ind} CUST_{ji} + \phi_{S-Ind} SUPP_{ij} + \phi_{C-Part} CUST_{ij} + \phi_{S-Part} SUPP_{ji} + \theta_{Ind} x_i + \theta_{Part} x_j + v_{ij} \tag{9}$$

where $GARCH\ spillover_{ij}$ and $ARCH\ spillover_{ij}$ are the β_{21} and γ_{21} coefficients estimated in the first stage. The parameters measure the GARCH and the ARCH spillover effects from industry *i* to industry *j*, respectively. $CUST_{ij}$, $SUPP_{ij}$, $CUST_{ji}$, and $SUPP_{ji}$ are the trading relationship variables. Specifically, $SUPP_{ij}$ shows the supplier role of industry *i* to its partner industry *j*, while $CUST_{ij}$ shows the customer role of the partner industry *j* for industry *i*. $SUPP_{ji}$ and $CUST_{ji}$ are defined similarly. The construction of these variables will be explained in the data section below. The coefficients associated with these variables show how the strength of the trading relationship (the industry's customer and supplier roles relative to its partner, and vice versa) influences the spillover effects between the industries. Finally, $x_i = (Size_i, CR_i)'$ and $x_j = (Size_j, CR_j)'$ control for industry characteristics such as the number of firms in the industry (*Size*) and the industry concentration ratio (*CR*).

4. Data and summary statistics

4.1. Industry returns and macroeconomic variables

The daily stock return data used in the first-stage estimations are obtained from the CRSP database. Stocks in the CRSP database are matched to those in the IO Benchmark Survey by their NAICS codes. We use daily return data for all the stocks in four major stock markets in the US, including NYSE, Nasdaq, Amex and Arca. Daily industry returns are computed as the sum of value-weighted returns of all the stocks in the sector where the beginning-of-the-day market capitalization of each stock is used as the weight. We use the yield on the 3-month US Treasury bills as a proxy for the risk-free rate. The excess industry return is calculated as the difference between the industry return and the risk-free rate. In the same way, excess market returns are computed as the difference between market returns, which are proxied by returns on the CRSP value weighted index, and the risk-free rate. Our sample spans a period of 9 years beginning from 1 January 2005 to 31 December 2013.[6]

Data on the 3-month T-bill interest rates and the trade weighted USD indexes against a broad group of major US trading partners are obtained from the Federal Reserve Bank of St. Louis (FRED) database. According to the Augmented Dickey-Fuller (ADF) test results, the stock return series in our model are found to be stationary but the interest rate and the foreign exchange index series follow an I(1) process. Consequently, we use the change in the interest rate and the percentage change in the foreign exchange index, which are stationary.

4.2. Input-Output accounts

We measure the extent to which industries are linked using information from the Input-Output (IO) accounts provided by the Bureau of Economic Analysis (BEA). These accounts document the value of commodities (goods and services) produced and transacted among industries. Details on the amount of flows between US industries are recorded at three levels of aggregation: the sector level (15 sectors), the summary industry level (71 industries), and the detailed industry level (389 industries). The IO tables are updated roughly every five years with each update coinciding with the Economic Census. For non-benchmark years between updates, BEA provides estimated tables. The 2007 and 2012 tables fall within the 2005-2013 sample period of our stock return data. We choose to construct our industry relationship variables based on the mid-period 2007 IO account. In Section 6.2, however, we show that using the 2012 benchmark table, the estimated tables for each year, or the average values for the sample period leaves our second-stage results unaltered.

The IO accounts consist of two main tables: the *Make* and the *Use* table (for snapshots of these tables see Appendix 1). The *Make* table gives the value of each commodity produced by industries. It is worth noting that the same commodity may be produced in more than one industry. Moreover, while an industry predominantly produces one commodity, it may also produce other commodities. The *Make* table reports the value of commodities produced by each industry. Each row in the *Make* table shows the industry while commodities are presented

[6] CRSP does not provide NAICS codes before 2005.

across different columns. Thus, the sum of all entries in a row gives the total output in that industry, which we denote by $OUTPUT_i$. Adding all the entries in a column gives the total output of a commodity produced by all the industries. The *Use* table reports the value of each commodity purchased as input by each industry (or consumed by final users). Each commodity is recorded in a row, while the columns report the value of the commodity used as input by different industries (or consumed by final users). Therefore, summing all entries in a row gives total commodity output, while adding up all commodity entries in a column gives the total input value in an industry, denoted by $INPUT_j$. Total industry output, presented in the last row of the *Use* table, is the total industry input value plus the total value added. Using the raw data provided by both tables, we calculate the industry linkage variables capturing the strength of the relationship between pairs of industries.

We follow the methodology proposed by Ahern and Harford (2014) and Becker and Thomas (2011) to construct the *CUST* and *SUPP* matrices showing the roles of the industries as customers and suppliers with respect to each other. First, we construct the subordinate *SHARE* matrix, which shows each industry's share in the total supply of each commodity in the economy. The elements in the *SHARE* matrix are calculated using information from the *Make* table. Specifically, the element in row i, column c, denoted $SHARE_{ic}$, is calculated as:

$$SHARE_{ic} = \frac{Make_{ic}}{Total\ Supply_c} \tag{10}$$

where i and c index industry and commodity, respectively. $Make_{ic}$ is the value of commodity *c* produced by industry *i* (element in row i, column c of the *Make* table). $Total\ Supply_c$ is the total supply of commodity c, which includes the total output of commodity c produced by all the industries (the sum of all entries in the commodity c column in the *Make* table) plus other components such as imports or changes in inventories.

Next, we calculate the *REVSHARE* matrix, which shows the value of all commodities which customer industries purchase from their supplier industries. Thus, the element in row i, column j of this matrix, $REVSHARE_{ij}$, gives the total value of all commodities industry j purchases from industry i. Formally, it is given by:

$$REVSHARE_{ij} = \sum_{c=1}^{C} \left(SHARE_{ic} \times Use_{cj} \right) \tag{11}$$

where $SHARE_{ic}$ is the percentage of commodity c produced by industry i (element in row i, column c of the *SHARE* matrix) and Use_{cj} (row c, column j element in the *Use* table) shows the value of commodity c used in the production of industry j.[7]

Finally, we construct the *CUST* and *SUPP* matrices. *CUST* records the percentages of an industry's sales which are purchased by each of its customers while *SUPP* records the percentages of input which an industry purchases from each of its suppliers. As an example, consider the pair of industries i and j. The elements in row i, column j in the *CUST* matrix, denoted by $CUST_{ij}$, and in the *SUPP* matrix, denoted by $SUPP_{ij}$, are defined as follows:

$$CUST_{ij} = \frac{REVSHARE_{ij}}{OUTPUT_i} \tag{12}$$

$$SUPP_{ij} = \frac{REVSHARE_{ij}}{INPUT_j} \tag{13}$$

$CUST_{ij}$, the proportion of industry i's revenue generated by industry j, is the total value of all commodities which industry j purchases from industry i. It is calculated by dividing $REVSHARE_{ij}$ by the total output value of industry i ($OUTPUT_i$ in the *Make* table). $SUPP_{ij}$, the proportion of the total industry j input purchased from industry i, is defined as the total value of all commodities industry j purchases from industry i, and is calculated by dividing $REVSHARE_{ij}$ by the total input value of industry j ($INPUT_j$).[8] Therefore, for the pair of industries i and j, we obtain a total of four relationship variables, namely $CUST_{ij}$, $SUPP_{ij}$, $CUST_{ji}$, and $SUPP_{ji}$, which show the customer role of j to i, the supplier role of i to j, the customer role of i to j, and the supplier role of j to i, respectively. These variables will be used in the second-stage cross-sectional regressions to examine how the strength of the trading relationship influences the spillover effects between industries.

4.3. Industry characteristics

To account for the impact of industry-specific characteristics on the volatility spillover between industries, we include industry size and concentration ratios in our second-stage regression. A similar approach has been employed by Ahern (2013) who controls for industry size and

[7] The calculations rely on the assumption that market shares are constant for every use of commodity. In other words, if industry *i* accounts for 80% of the total supply of commodity *c* (i.e., $SHARE_{ic}$ = 0.8), then industry *j* purchases 80% of its commodity *c* input from industry *i*.

[8] Although there is no Labor industry in the *Make* table, an artificial Labor industry is created in the *Use* table as an input for production (namely employee compensation), to insure that input values are accurately calculated. This industry is not used in our final sample. Ahern and Harford (2014) use a similar approach.

concentration ratio in modelling stock returns and Kelly et al. (2013) who show that the concentration of the customer portfolio of firms can affect the firms' volatility. Industry size is measured as the number of firms in an industry. The information is obtained from the US Census Bureau's Statistics of US Businesses (SUSB) on a yearly basis. Industry concentration is measured as the percentage of the total industry revenue accounted for by the eight largest firms. The concentration ratios are reported in the Economic Census and issued by the US Census Bureau every five years (years ending in 2 and 7) which coincide with the years in which the IO benchmark data are published.

4.4. Summary statistics

We build our industry-level sample starting from the summary IO tables of 71 industries and 73 commodities. We drop five industries in the Government sector without NAICS codes and combine 2 industries with the same NAICS code. Our final sample includes 65 industries, for which we can construct 2,080 possible trading pairs. This means that in our first-stage approach we estimate 2,080 multivariate GARCH models, one for each industry pair.

Table 1 presents descriptive statistics of our data. Panel 1 reports summary statistics for the daily industry returns and the macroeconomic variables over the 2005-2013 sample period. The market excess returns, the change in the FX index, and the change in the risk free rate are negatively skewed. While the returns of most industries are negatively skewed, the returns of some industries such as social assistance and pipeline transportation display considerably large skewness during the sample period (industry return statistics available upon request).

Panel 2 of Table 1 presents descriptive statistics of the industry-level controls used in the second stage regressions. Information on industry size is available only for 63 industries in our sample. The number of firms in an industry ranges from as low as 200 firms in the smallest industry to nearly 800,000 firms in the largest industry. Concentration ratio data is available for 56 industries. There is a wide variation in industry concentration as the eight largest firms account for 85 percent of the market in the most concentrated industry and 4 percent of the market in the most competitive industry.

Table 2 gives the statistics of the *CUST* and *SUPP* variables calculated from the IO tables for each year over the period 2005-2013. We report the mean, median as well as the bottom and the top 5^{th} percentiles of the distribution of the values. Proportions (frequency percentages) of different *CUST* and *SUPP* value ranges are also reported. The numbers in this table show that the majority of the industry pairs have a weak trading relationship. Consistently across the sample period, over 80 percent of the linkage variables are below 1 percent. The fraction of weak linkages as measured by *CUST* is slightly larger than that for *SUPP* (87% relative to 81%). This implies that industries tend to have slightly more diversified customers than suppliers.

Using the data in the *CUST* matrix, each industry is assigned the role of either a main or a small customer of its trading partner. Similarly, based on data in the *SUPP* matrix, each industry is classed as either a main or a small supplier of the other industry in a trading pair. There are a total of 10 possible combinations that characterize the importance of the supplier and customer roles in an industry pair. As discussed above, over 80% of the values of the relationship measures are less than 1%. Consistent with Ahern and Harford (2014), we choose the 1% level as the smallest cut-off to classify an industry as a main or a small trading partner.

Table 3 gives a snapshot of the structure of the linkage between industries at different cut-off levels. The columns labelled 1 to 10 report the numbers of industry pairs in each combination group for each of the corresponding thresholds. According to the values in the column corresponding to the 1% threshold, we can see that the majority of the industry pairs have weak business linkages, i.e., 1,328 pairs have values for both *CUST* and *SUPP* smaller than 1%. This is in line with our expectation: when industries are finely classified, each industry is likely to have only a few main suppliers and customers while its trade flows with most industries are relatively low. The remaining 752 industry pairs are closely linked, i.e., at least one of the industries is a main customer or a main supplier.

Panel 2 provides more details for the closely-linked industry pairs. 589 pairs have a one-direction relationship in that one industry is a main supplier or a main customer. A total of 644 pairs have one main supplier while 457 pairs have one main customer. In fewer cases, an industry could serve as both major customer and supplier (162 pairs), both industries are major customers (45 pairs), or both industries are major suppliers (81 pairs). The other columns in Table 3 report the number of pairs for each combination of linkages at the different thresholds. Obviously, for a given classification of supplier and customer relationship, the number of close linkages decreases as the threshold increases.

5. Empirical results

5.1. Volatility spillovers between supplier-customer industries

A series of preliminary checks are conducted before we start the volatility spillover analysis. Firstly, we employ Engle (1982)'s Lagrange Multiplier (LM) test to confirm the existence of conditional heteroscedasticity in the return series. The minimum value of the LM test statistics including one lag for all return series is 7.6, which is larger than the 1% critical value of 6.6.

The test results indicate that the null hypothesis of constant conditional variance can be comfortably rejected at the 1% significance level and that an ARCH-type model is appropriate for our analysis.

Next, we fit the following four GARCH specifications to the daily data for the 2,080 industry pairs: GARCH(1,1), GARCH(2,1), GARCH(1,2), and GARCH(2,2). We use the Akaike information criterion (AIC) to identify the best-fitting specification for each industry pair. We can report that GARCH(2,1) is found to be the best-fitting model for 1,105 industry pairs, while the numbers of best-fitting GARCH(1,1), GARCH(1,2), and GARCH(2,2) are 415, 101, and 459, respectively. We apply the Ljung-Box (1978) test to ensure that the residuals are white noise. The results suggest that the residuals and their squared terms are independently distributed in about 73% and 90% of the cases, respectively.[9]

Note that the GARCH and ARCH coefficients for industry pair *ij* are equal in value to those obtained for industry pair *ji* but in the reverse order.[10] Purely for the purpose of presenting the first stage estimates, we choose to report the set in which *i* is the industry with the higher *REVSHARE* selling to the other industry in the industry pair *ij*. By doing this, industry *i* is more likely to be the upstream industry in the pair, but this is not always the case. For the rest of the paper, the role of the industry as a supplier or a customer of its partner industry is determined as specified in the methodology section.

Table 4 reports the summary statistics of the estimates obtained from the multivariate volatility spillover models for each of the 2,080 industry pairs. The return spillover coefficients (α_{12}, α_{21}) are statistically significant in around 25% of the cases in each direction. Volatility spillovers are statistically significant for more industry pairs: there is evidence of GARCH spillover (β_{12}) for 449 (or 21.5%) industry pairs and twice as many significant cases (891 or 42.8%) of ARCH spillover (γ_{21}). Overall, we observe significant volatility spillover, either GARCH, ARCH or both, for 83% of the industry pairs. This suggests strong volatility linkages between the US industries, which is consistent with Wang (2010).

[9] The results of the multivariate Li and McLeod (1981) test also confirm that the estimated standardized residual terms are white noise. We fail to reject the null hypothesis that the residuals (squared residuals) are white noise in approximately 63% (86%) of the cases.

[10] For example, consider industry 1 (Farms) and industry 6 (Utilities) in the Input-Output tables. Changing the order of industries in the pair leads to two sets of first stage regression parameters: set_{16} and set_{61}, where set_{16} is obtained when Farms is industry *i* and Utilities is industry *j*, and vice versa. Obviously, the coefficients showing GARCH and ARCH spillover from Farms to Utilities are identical in both sets, i.e., β_{21} and γ_{21} in set_{16} equal β_{12} and γ_{12} in set_{61}, respectively.

Close inspection of the industry pairs reveals that the volatility spillover coefficients (β_{12}, β_{21}, γ_{12}, and γ_{21}) take the highest values for the following pairs: (i) Wholesale trade and Warehousing and storage; (ii) Miscellaneous manufacturing and Social assistance; (iii) Wholesale trade and Legal service; and (iv) Wholesale trade and Social assistance, respectively. Thus it seems that the volatility of the Wholesale trade industry is strongly linked to that of a number of other industries in the economy. Considering the nature of the Wholesale trade industry this result is not unexpected.

Most of the coefficients associated with the industry and its partner's lagged GARCH and ARCH terms are statistically significant. ARCH at lag 1 is significant for 97% of industry pairs, while GARCH at lag 1 is significant for 64% of the pairs. GARCH and ARCH terms at lag 2 are also significant in 74% and 63% of the best-fitting models, respectively. This justifies the use of a GARCH type model in our study.

Turning to the impact of controls on industry returns, we find that the market return has a marked influence on all industry returns, with the coefficient value ranging from 0.558 to 1.646. The interest rate is found to affect a larger number of industries (34% of the cases) compared to the foreign exchange rate index (13% of the cases). This is not surprising since interest rates commonly affect all the industries in the economy while foreign exchange rates tend to impact mainly the industries which extensively engage in international trade.

5.2. The impact of business linkage on inter-industry volatility spillover

The results of the multivariate volatility models discussed in the previous section imply significant volatility and shock spillovers between US industries. We now investigate how the inter-industry spillovers are influenced by the business linkages between industries. To this end, our second-stage cross sectional models link the volatility spillover coefficient estimates with the business relationship variables (and other industry characteristics). For each industry pair *ij* we obtain two spillover coefficients - from *i* to *j* and from *j* to *i* - for each spillover type (GARCH and ARCH). Consequently, from the 2,080 industry pairs we obtain 4,160 cross-section observations[11]. The standard errors are bootstrapped to account for the fact that the dependent variables are estimates obtained from the first stage.

Table 5 reports the second-stage cross-sectional estimates. We observe that when an industry is relatively more important to its partner, its volatility affects its partner's more

[11] The number of observations reduces to 3,906 and 3,080, respectively, when we control for industry size (data available for 63 industries only) and concentration ratio (available for 56 industries).

strongly while it is less affected by the volatility of its partner. The signs of all the coefficients on the business linkage variables are consistent with this pattern. Specifically, the GARCH and ARCH spillovers from an industry to its partner are positively related to its customer and supplier roles with respect to its trading partner. As an industry *i* gains a more important role among all customers ($CUST_{ji}$) and all suppliers ($SUPP_{ij}$) of its trading partner *j*, there are stronger volatility spillovers from industry *i* to its partner industry *j*. At the same time, the larger the trading partner's role among all customers ($CUST_{ij}$) and all suppliers ($SUPP_{ij}$) of industry *i*, the less likely it is that industry *i*'s volatility is transmitted to its partner's. This pattern strongly suggests that volatility spillovers are related to the strength of the trading relationship between two industries.

Based on the significance level of these coefficients, we can further infer that the inter-industry linkages tend to influence more the ARCH than the GARCH spillovers. The business linkages seem to significantly affect GARCH spillovers only in the defensive direction, i.e. when the importance of an industry to its partner increases (as the values of its $CUST_{ij}$ and $SUPP_{ji}$ with respect to its partner increase), the industry is less affected by its partner. Since the GARCH terms measure persistent components in volatility, while the ARCH terms represent components of volatility that are due to short-term shocks, our results suggest that, compared to pure volatility spillovers, shocks are more easily transmitted between industries and are also more affected by the strength of the industry linkages. These findings are not unexpected since external shocks, by their very nature, are harder to predict and prevent. Industries are therefore likely to be more vulnerable to them.

Other industry characteristics, such as size and concentration, are also found to have an impact on the inter-industry volatility spillover. The negative and statistically significant coefficients associated with the number of firms operating in the trading partner industry indicate that a larger partner industry is less affected by the volatility spillover from the examined industry. This is not surprising since an industry with a large number of firms tends to have more trading partners (at both firm and industry level). Diversifying trading partners help the industry better protect itself from volatility transmitted from its partner. Similarly, a more concentrated industry, in which a few companies dominate the product market, tends to be less sensitive to the volatility spillover from its trading partner. This is evidenced by the negative coefficient associated with the concentration ratio in the trading partner industry. Importantly, controlling for industry size and concentration further strengthen our results regarding the importance of business linkages on inter-industry volatility spillovers.

5.3. Robustness checks

This section reports several robustness checks of our results. Sub-section 5.3.1 tests sensitivity of our second-stage cross-sectional results. Here, we calculate the trading relationship variables using information from (i) an alternative benchmark IO table (year 2012), (ii) the estimated IO tables of each year, and (iii) the average trading relationship values within our sample period (2005-2013).

We then repeat the two-stage analysis on restricted samples. Sub-section 5.3.2 focuses on industry pairs with substantial trade relationships. Sub-section 5.3.3 considers only pairs of non-financial industries. As will be discussed below, all of the sensitivity analyses confirm the link between the strength of the business relationship and cross-industry volatility spillovers.

5.3.1 Industry linkage variables calculated from different IO matrices

In the second stage cross-sectional regressions presented above, our business linkage variables are calculated using the 2007 IO benchmark matrices. Although the structure of the inter-industry trading in a developed market like the US is expected to stay relatively stable over time, we test this conjecture by constructing the industry linkage variables for every year within our sample. The results of the second-stage cross-sectional regressions using the information from the IO matrices for every year from 2005 to 2013 as well as the average values of these variables for the period 2005-2013 are reported in Appendix 2.[12] These results are similar to those using the 2007 benchmark, confirming both the stable structure of the US economy and our earlier findings regarding the impact of business linkages on volatility spillovers.

5.3.2 Industry pairs with substantial trade flows

Close inspection of our dataset shows that there are a number of industries which trade relatively little with each other. To account for very low trade flows between some industries, we sample only pairs of closely related industries. We classify an industry pair as having a strong trading relationship if the value of any of the four trading relationship variables ($CUST_{ij}$, $SUPP_{ij}$, $CUST_{ji}$, $SUPPj_i$) is larger than or equal to 1 percent. As shown in Table 3, our new sample contains 752 industry pairs. We repeat our two-stage volatility spillover analysis on the new sample and report the second stage results in Table 6. These estimates are similar to our main results reported in the previous section and confirm the robustness of our findings.

[12] Industry size data is available every year. However, the eight-firm industry concentration ratios from the Economic Census are published by the US Census Bureau in the same years as the IO benchmark data are published, namely 2007 and 2012.

5.3.3 Exclusion of financial industries

Industries in the financial sector are likely to have stronger volatility spillover effects on the other industries in the economy. Here, we check whether our results are due to the six industries in the financial sector, namely Federal Reserve Bank, credit intermediation and related activities; Securities, commodity contracts and investments; Insurance carriers and related activities; Funds, trusts, and other financial vehicles; Real estate; and Rental and leasing services and lessors of intangible assets. We drop these six industries from the industry pool and conduct our two-stage analysis on the sample of non-financial industries. The results reported in Table 7 confirm the importance of the business linkages on volatility spillovers between non-financial industries.

6. Inter-industry volatility spillover in different market conditions

The sample period employed in all the analyses performed thus far includes the 2007-2008 Financial Crisis and the strong bull market observed during 2009-2013.[13] In this section, we conduct the two-stage analysis on separate sub-samples corresponding to the three different market conditions. In other words, we estimate the first-stage multivariate GARCH using daily data for the pre-crisis period of 2005 - 2006, the crisis period of 2007-2008, and the bull market period of 2009-2013, respectively.

The second-stage cross-sectional results of these investigations are reported in Tables 8 to 10. Relative to the results for the whole sample period presented in Table 5, all coefficients preserve their signs and most parameters maintain statistical significance across samples confirming the impact of business linkages on volatility spillovers. Importantly, however, Tables 8 to 10 reveal that the strength of the business linkages played a more important role for spillovers across industries during the financial crisis period. In terms of GARCH spillovers, important suppliers ($SUPP_{ij}$) are likely to transmit their volatility to their customers during the 2007-2008 period (Table 10). At the same time, the ability of an industry to protect itself from volatility spillovers from its partners depends on its supplier and customer role to its partners. An industry's volatility is less likely to be transmitted to its important customers ($CUST_{ij}$) and even more so to its main suppliers ($SUPP_{ji}$). Overall, these results suggest a

[13] In a separate exercise, we add a dummy variable for the period 2007-2008 in the first-stage Eqs. (1) and (3) to control for the impact of the financial crisis in our analysis using the whole sample period. We then proceed with the second-stage cross-sectional estimations as before. The results (available upon request) are qualitatively similar to our earlier findings.

stronger impact of business linkages on the downward transmission of GARCH spillovers during the financial crisis.

Business linkages tend to become highly relevant for shock (ARCH) spillovers in bad market conditions. Comparing the coefficient values in columns 5-8 across Table 8 – 10, the impact of business linkages on shock spillover increases during the crisis period and subsequently declines after the crisis. This suggests that business linkages influence shock spillovers stronger when shocks are more prevalent. This would be expected since industries with higher trade flows are likely to have more influence over their partners, and at the same time, they can better protect themselves from their partners' volatility during bad times.

The weaker impact of business linkages on volatility spillover in the post-crisis sample might be due to the more stringent risk management framework employed by the US firms in the aftermath of the financial crisis. Businesses and industries which were affected by the sharp downturn during the crisis period may have implemented strategic measures to isolate themselves from the effect of external shocks spilled over from their trading partners.

7. Volatility spillovers between industries and their representative trading partners

Our analysis so far has revealed the link between inter-industry volatility spillovers and the strength of their trading relationship between industries. We investigate now whether spillovers exist at the portfolio level as well. Following Menzly and Ozbas (2010), we construct two separate portfolios for each industry to mark its representative supplier and representative customer industry. Specifically, the industry *i*'s representative supplier is a portfolio which consists of all the industries selling goods to industry *i*. Each supplier industry receives a weight in the portfolio based on its share in total industry *i*'s inputs. The weights are calculated from the elements in the column corresponding to industry *i* in the *SUPP* matrix, using the 2007 IO benchmark.[14] The representative customer is constructed in a similar way using elements in the *CUST* table.

For each industry, two separate multivariate volatility spillover models are estimated — one with its representative supplier and one with its representative customer.[15] Similar to our analysis at the industry level, for each multivariate volatility model, we use the Akaike

[14] Although firms supply some amount of goods to other firms within the same industry, we exclude an industry from the list of its suppliers when we calculate its representative supplier industry.

[15] As we focus on the spillovers caused by direct business linkages, we do not consider indirect spillovers between an industry's representative supplier and its representative customer. Even if such indirect spillovers might exist, there is no economic rationale for further investigation; these linkages are spurious since the representative supplier and customer industries are constructed from the same pool of industries with different weighting schemes.

information criterion (AIC) to choose the best-fitting GARCH model among the following specifications: GARCH(1,1), GARCH(1,2), GARCH(2,1), and GARCH(2,2).

Table 11 presents the results for the portfolio analysis for the 65 industries in our sample. Panel 1 reports descriptive statistics for the estimates of volatility spillover between an industry and its representative supplier, while Panel 2 shows the statistics regarding the representative customer. Panel 3 groups this data to focus on the direction of the spillovers. We observe significant volatility spillovers between industries and their representative trading partners. Most industries (54 out of 65) are affected by their representative suppliers and/or customers and nearly two thirds of the industries (40 out of 65) influence their representative suppliers or customers. The lower part of Panel 3 distinguishes downstream and upstream spillovers. While volatility appears to transmit downstream (supplier - industry and industry – customer) equally as likely as upstream (industry - supplier and customer - industry), shock spillovers are more likely to occur downward rather than upward along the supply chain according to the respective numbers of significant ARCH coefficients.

Panel 4 provides details for all possible combinations of volatility spillovers between an industry (I), its representative supplier (S) and customer (C). The number of significant estimates of volatility spillovers, regardless of whether they are from lagged volatility or lagged shocks, is reported for each of the 15 possible combinations. Arrows (→ or ←) indicate the direction of the spillover, where "↔" means volatility spillover both ways, and "…" indicates no spillovers. For example, the first row (S … I → C) indicates volatility spillovers only from industry I to its representative customer C. There is evidence of significant spillovers from / to their representative trading partners for 61 out of 65 industries. Only 4 industries - namely Construction, Food services and drinking places, Miscellaneous professional, scientific, and technical services, and Legal services - display no volatility spillovers from / to their representative suppliers and customers. These industries trade mostly with personal consumers rather than with other industries. While the first three industries are among the industries with the largest share of output accounted by personal consumption, Legal services is one of the top labor-intensive industries.

We want now to further scrutinize the determinants of the volatility spillovers from the industry's representative trading partners shown in Panel 3. We define the binary variable *SuppInd* equal to 1 when we observe significant volatility spillovers from the representative supplier to the industry, 0 otherwise. *CustInd* is defined similarly regarding spillovers from the representative customer to the industry. As in the industry pairwise analysis, we look at the relation between spillovers to the industry and the strength of the trading relationship at portfolio level. To this end, we calculate the Herfindahl-Hirschman index (HHI) of the two portfolios as the sum of the squared weights used in constructing the portfolios. Specifically, the HHI of the supplier portfolio is the sum of each industry's squared share in total industry *i*'s inputs. The concentration index of the customer portfolio is calculated similarly using elements in the *CUST* table.

We estimate simple probit models and report the marginal effects in Table 12. These estimates show that volatility spillovers from the representative supplier are negatively related with the suppliers' degree of concentration. This means that an industry is likely to be affected by the volatility of its suppliers the more diversified its supplier portfolio is. At first glance, this finding might seem to come at odds with our previous results that smaller suppliers are less likely to transmit their volatility over to their partner industries. At the supplier portfolio level we need to account for each supplier's contribution to an industry's total inputs as well as for the possible correlation between shocks affecting individual suppliers. It may be possible, for instance, that we find no evidence of volatility spillovers from individual suppliers to an industry in the pairwise analysis, but we find spillovers from the supplier portfolio if the shocks to individual suppliers are positively correlated. Calculating, therefore, the volatility of the supplier portfolio considers both shocks to individual suppliers and the correlation among these shocks. Our results are thus consistent with positively correlated shocks to individual suppliers in the portfolio.

The estimates in column 3 reveal a weak positive relationship between spillovers from the representative customer and the concentration of the customer portfolio. Volatility seems to be transmitted upward the production chain the more concentrated the customer portfolio. Finally, similar to our previous results for pairs of industries, the estimates in columns 2 and 4 stress that industry size and concentration ratio matter. Smaller industries (in terms of number of firms) are more likely to suffer from shocks transmitted from their suppliers and customers. A higher industry concentration ratio, however, helps reduce volatility transmission from the supplier portfolio (column 2).

Overall, the results at the portfolio level are in line with those considering industry pairs and highlight the importance of the strength of the business relationship in the transmission of volatility across industries.

8. Conclusions

This paper investigates whether the strength of the customer - supplier relationship can explain the characteristics of volatility spillovers among the US industries. Our approach consists of two stages. In the first stage, we employ a multivariate GARCH model to quantify the degree of spillover between industry pairs in the US. The results from the first stage suggest that cross-industry volatility spillovers are indeed prevalent: 83% of the industry pairs under investigation are found to exhibit either GARCH or ARCH volatility spillovers.

In the second stage, we examine if the estimated degree of spillover can be explained by the strength of the customer-supplier relationship. We measure the strength of the business linkages using information from the IO accounts. Our expectation is that industries with high shares of revenues or inputs relative to their trading partners exhibit greater degrees of volatility spillover toward their partners. Our findings confirm this. The extent to which volatility tends to spread from an industry to its trading partner depends on its relative importance in the customer-supplier relationship between the trading industry pair. Interestingly, an industry which plays a more essential role in the partnership is better protected from volatility spillovers originating from its trading partner.

We subject our results to a variety of sensitivity checks. Firstly, we examine if our results are robust to calculating the measure of strength of the customer-supplier relationship using information from the IO accounts from different years. We then conduct our two-stage analysis on several restricted samples: (i) we exclude industry pairs with low trade flows; (ii) eliminate industries in the financial sectors; (iii) conduct our analysis on samples separated by the financial crisis. Our results remain virtually unaltered: we observe substantial spillovers between industries and the strength of the customer-supplier relationship appears to be a good predictor of the degree of spillover. Moreover, the strength of the business linkages seems to matter more during bad market conditions.

We investigate also whether we observe volatility spillovers at the portfolio level following an approach adopted by Menzly and Ozbas (2010). Using the IO data for each US industry, we construct the portfolio of suppliers / customers and their degree of concentration. Our results suggest significant volatility spillovers for 61 out of 65 industries and confirm the link between the strength of the business relationship and volatility spillovers at portfolio level.

Our findings of volatility interdependence between industries in a trading relationship are useful for investors whose portfolios concentrate on some specific industries or sectors. By observing the volatility of the closely related industries, investors are able to better predict the volatility of their positions, which is essential to achieve an enhanced risk-return profile. Understanding the volatility transmission between industries is also important for policy makers, since the awareness about how a policy change in a specific sector could cause business uncertainty in related sectors would be essential.

A natural extension of our study would be the investigation of tail-dependent spillovers between related industries by exploiting the information on higher moments such as skewness or kurtosis spillover. Another research direction would be the examination of volatility spillovers between related firms and the possible impact of their actual business relationship.

REFERENCES

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A. 2012. The network origins of aggregate fluctuations. *Econometrica*, 80(5), pp.1977–2016.

Ahern, K.R., 2013. Network centrality and the cross section of stock returns. *Available at SSRN 2197370*.

Ahern, K.R., Harford, J., 2014. The importance of industry links in merger waves. *Journal of Finance*, 69(2), pp.527–576.

Alli, K., Thapa, S., Yung, K., 1994. Stock price dynamics in overlapped market segments: Intra and Inter - industry contagion effects. *Journal of Business Finance , Accounting*, 21(7), pp.1059–1071.

Aobdia, D., Caskey, J., Ozel, N.B., 2014. Inter-industry network structure and the cross-predictability of earnings and stock returns, *Review of Accounting Studies* 19, pp. 1191–1224

Becker, M.J., Thomas, S.E., 2011. Changes in concentration across vertically related industries, Available at: http://papers.ssrn.com/abstract=1816638

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31, pp.307–327.

Booth, G.G., Martikainen, T., Tse, Y., 1997. Price and volatility spillovers in Scandinavian stock markets. *Journal of Banking and Finance*, 21(6), pp.811-823.

Campbell, J.Y., Hamao, Y., 1992. Predictable stock returns in the United States and Japan : A study of long-term capital market integration. *The Journal of Finance*, XLVII(1), pp.43–69.

Caves, R.E. , Bradburd, R.M., 1988. The empirical determinants of vertical integration. *Journal of Economic Behavior and Organization*, 9(3), pp.265–279.

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. *Journal of Finance*, 63(4), pp.1977–2011.

Elyasiani, E., Mansur, I., Pagano, M.S., 2007. Convergence and risk-return linkages across financial service firms. *Journal of Banking and Finance*, 31(4), pp.1167–1190.

Engle, R.F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), pp.987–1007.

Ewing, B.T., 2002. The transmission of shocks among S&P indexes. *Applied Financial Economics*, 12(4), pp.285–290.

Ewing, B.T., Malik, F., Ozfidan, O., 2002. Volatility transmission in the oil and natural gas markets. *Energy Economics*, 24(6), pp.525–538.

Griffin, J.M., Karolyi, G.A., 1998. Another look at the role of the industrial structure of markets for international diversification strategies. *Journal of Financial Economics*, 50(3), pp.351-373.

Hamao, Y., Masulis, R.W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. *Review of Financial Studies* , 3 (2), pp.281–307.

Hassan, S.A. , Malik, F., 2007. Multivariate GARCH modeling of sector volatility transmission. *The Quarterly Review of Economics and Finance*, 47(3), pp.470–480.

Horvath, M. T. K., 1998. Cyclicality and sectoral linkages: Aggregate fluctuations from independent sectoral shocks. *Review of Economic Dynamics*, 1(4), pp.781–808.

Hosking, J.R., 1980. The multivariate Portmanteau statistic. *Journal of the American Statistical Association*, 75(371), pp.602-608.

Kelly, B., Lustig, H., Van Nieuwerburgh, S., 2013. Firm volatility in granular networks (No. w19466). *National Bureau of Economic Research*.

King, M., Wadhwani, S., 1990. Transmission of volatility between stock markets. *The Review of Financial Studies*, 3(1), pp.5–33.

Kohonen, A., 2013. On detection of volatility spillovers in overlapping stock markets. *Journal of Empirical Finance*, 22, pp.140-158.

Koutmos, G., Booth, G.G., 1995. Asymmetric volatility transmission in international stock markets. *Journal of International Money and Finance*, 14(6), pp.747-762.

Li, W.K. , McLeod, A.I., 1981. Distribution of the residual autocorrelations in multivariate ARMA time series models. *Journal of the Royal Statistical Society*. Series B (Methodological), pp.231-239.

Ljung, G.M., Box, G.E., 1978. On a measure of lack of fit in time series models. *Biometrika*, 65(2), pp.297-303.

Maddigan, R.J., 1981. The measurement of vertical integration. *The Review of Economics and Statistics*, 63(3), pp.328–335.

Matsusaka, J.G., 1993. Takeover motives during the conglomerate merger wave. *The RAND Journal of Economics*, 24(3), pp.357–379.

Menzly, L., Ozbas, O., 2010. Market segmentation and cross-predictability of returns. *Journal of Finance*, 65(4), pp.1555–1580.

Miyakoshi, T., 2003. Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of International Financial Markets, Institutions and Money*, 13(4), pp.383–399.

Shea, J., 2002. Complementarities and comovements. *Journal of Money, Credit and Banking*, 34(2), pp.412-433.

Wang, Z., 2010. Dynamics and causality in industry-specific volatility. *Journal of Banking and Finance*, 34(7), pp.1688–1699.

Table 1: Summary statistics of the industry returns, macroeconomic variables and industry characteristics

This table provides summary statistics. Panel 1 reports the descriptive statistics of the time series used in the first-stage regression: the market returns, the percentage change in the foreign exchange index, and the change in the risk-free rate over the period 1 January 2005 - 31 December 2013. Panel 2 presents statistics for the cross-sectional industry data used in the second-stage analysis. Industry size (the number of firms in an industry) and concentration ratio (the eight-firm concentration ratio) statistics refer to 2007.

	Number of Observations	Mean	Median	Standard deviation	Skewness	Min	Max
Panel 1: Time series statistics of macroeconomic variables							
Market return (%)	2,265	0.038	0.098	1.342	-0.173	-8.976	11.490
Percentage change in FX index (%)	2,265	-0.004	-0.012	0.332	-0.004	-2.275	1.748
Change in risk-free rate (%)	2,265	-0.002	0.000	0.058	-1.166	-0.810	0.740
Panel 2: Cross-sectional statistics of industry variables							
Industry size	63	97190	22954	171865	2.443	241	799811
Industry concentration ratio (%)	56	27.868	23.250	19.083	0.946	4.000	85.000

Table 2: Summary statistics of *CUST* and *SUPP* variables

This table presents the statistics of the *CUST* and *SUPP* variables calculated from the IO tables from 2005 to 2013. The mean, median, 5% and 95% quantiles of the distribution of values in the constructed *CUST* and *SUPP* matrices, as well as the proportion (frequency percentage) of different value ranges are reported in separate panels for *CUST* and *SUPP*, respectively.

Panel 1: *CUST*

	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean	0.671	0.664	0.668	0.664	0.635	0.642	0.646	0.647	0.653
Median	0.109	0.107	0.110	0.109	0.103	0.103	0.102	0.108	0.107
5 % percentile	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
95 % percentile	2.452	2.438	2.583	2.557	2.363	2.352	2.425	2.451	2.472
Frequency percentage									
0 to 1%	87.030	87.219	87.077	86.698	87.669	87.172	87.172	87.219	87.337
1% to 2%	6.414	6.509	6.651	6.746	6.249	6.391	6.320	6.438	6.201
2% to 3%	2.675	2.391	2.107	2.296	2.083	2.367	2.391	2.154	2.296
3% to 4%	0.828	0.970	1.183	1.325	1.112	1.136	1.160	1.231	1.089
4% to 5%	0.568	0.450	0.544	0.497	0.521	0.639	0.592	0.473	0.592
over 5%	2.485	2.462	2.438	2.414	2.367	2.296	2.367	2.485	2.485

Panel 2: *SUPP*

	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean	0.836	0.836	0.841	0.834	0.800	0.821	0.832	0.835	0.841
Median	0.152	0.148	0.147	0.146	0.140	0.150	0.148	0.150	0.155
5 % percentile	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001
95 % percentile	3.618	3.622	3.602	3.625	3.506	3.522	3.656	3.635	3.570
Frequency percentage									
0 to 1%	81.870	82.012	81.751	81.941	82.414	82.201	82.249	82.272	82.343
1% to 2%	8.118	8.000	8.118	8.047	8.024	8.284	8.189	7.953	7.882
2% to 3%	3.834	3.763	3.763	3.716	3.432	3.550	3.456	3.598	3.527
3% to 4%	1.751	1.822	1.917	1.870	1.964	1.657	1.633	1.633	1.728
4% to 5%	1.018	0.970	1.041	0.994	1.065	0.923	1.065	1.136	1.112
over 5%	3.408	3.432	3.408	3.408	3.101	3.385	3.408	3.408	3.408

Table 3: Descriptive statistics of business linkages between industries

This table presents summary statistics for 2,080 industry pairs according to the strength of their trading relationship. Panel 1 displays the 10 possible combinations which define the supplier and customer roles between two industries. An industry is classified as a main customer / supplier with respect to its partner if its corresponding *CUST* / *SUPP* value is equal or greater than the classifying threshold (in percentage), which ranges from 1% to 10% (by columns). Capital letters S and C denote main supplier and main customer, while small letters (s and c) denote small supplier and small customer. For example, Sc - sC stands for pairs in which industry *i* is a main supplier and small customer of industry *j*, and industry *j* is a small supplier and main customer of industry *i*. Panel 2 shows a summary of the pairs with close linkages described in Panel 1.

Panel 1:

		Threshold (%)									
		1	2	3	4	5	6	7	8	9	10
(1)	Pairs with weak linkage sc - sc	1328	1637	1790	1877	1930	1966	1984	2003	2017	2024
	Pairs with close linkage	752	443	290	203	150	114	96	77	63	56
(2)	sC - sc	108	69	60	49	38	32	31	29	27	28
(3)	Sc - sc	294	222	149	109	74	53	47	33	26	20
(4)	SC - sc	67	28	13	4	2	1	1	1	1	1
(5)	sC - sC	0	0	0	0	0	0	0	0	0	0
(6)	Sc - sC	187	104	62	38	34	26	16	13	8	7
(7)	SC - sC	15	4	2	1	0	0	0	0	0	0
(8)	Sc - Sc	1	0	0	0	0	0	0	0	0	0
(9)	SC - Sc	50	12	3	1	2	2	1	1	1	0
(10)	SC - SC	30	4	1	1	0	0	0	0	0	0

Panel 2: Pairs with close linkages

	Threshold (%)									
	1	2	3	4	5	6	7	8	9	10
Pairs with 1 direction close linkage [groups (2), (3), (6)]	589	395	271	196	146	111	94	75	61	55
Pairs with at least one main supplier [groups (3), (4), (6), (7), (8), (9), (10)]	644	374	230	154	112	82	65	48	36	28
Pairs with at least one main customer [groups (2), (4), (5), (6), (7), (9), (10)]	457	221	141	94	76	61	49	44	37	36
One industry as both main supplier and main customer [groups (4), (7), (9), (10)]	162	48	19	7	4	3	2	2	2	1
Both industries are main suppliers [groups (8), (9), (10)]	81	16	4	2	2	2	1	1	1	0
Both industries are main customers [groups (5), (7), (10)]	45	8	3	2	0	0	0	0	0	0

Table 4: Summary statistics of the multivariate volatility spillover model estimates

This table shows summary statistics for the coefficient estimates obtained from Equs (1)-(6).

$$R_{i,t} = \alpha_{10} + a_{M1}R_{Mt} + a_{FX1}FX_{t-1} + a_{\Delta RF1}\Delta RF_{t-1} + \alpha_{11}R_{i,t-1} + \alpha_{12}R_{j,t-1} + \varepsilon_{i,t} \quad (1)$$

$$h_{ii,t} = \beta_{10} + \sum_{k=1}^{p}\beta_{11k}h_{ii,t-k} + \sum_{l=1}^{q}\gamma_{11l}\varepsilon^2_{i,t-l} + \beta_{12}h_{jj,t-1} + \gamma_{12}\varepsilon^2_{j,t-1} \quad (2)$$

$$R_{j,t} = \alpha_{20} + a_{M2}R_{Mt} + a_{FX2}FX_{t-1} + a_{\Delta RF2}\Delta RF_{t-1} + \alpha_{22}R_{j,t-1} + \alpha_{21}R_{i,t-1} + \varepsilon_{j,t} \quad (3)$$

$$h_{jj,t} = \beta_{20} + \sum_{k=1}^{p}\beta_{22k}h_{jj,t-k} + \sum_{l=1}^{q}\gamma_{22l}\varepsilon^2_{j,t-l} + \beta_{21}h_{ii,t-1} + \gamma_{21}\varepsilon^2_{i,t-1} \quad (4)$$

$$\varepsilon_{i,t}\left|\Omega_{t-1} \sim N\left(0, h_{ii,t}\right);\ \varepsilon_{j,t}\right|\Omega_{t-1} \sim N\left(0, h_{jj,t}\right) \quad (5)$$

$$h_{ij,t} = \rho_{ij}\sqrt{h_{ii,t}h_{jj,t}},\ i \neq j \quad (6)$$

The multivariate volatility spillover model is estimated for each industry pair using 2,285 daily observations. The table reports the mean, the minimum, and the maximum value of the estimated coefficients for the 2,080 industry pairs. The number and percentage of estimated coefficients with t-statistics above 1.645 (10% significance level).

Coefficients		Mean	Min	Max	Number (t>1.645)	% (t>1.645)
a_{M1}	Market return - Ind	1.070	0.591	1.645	2080	100.00
a_{FX1}	% change in FX index - Ind	0.010	-0.356	0.500	281	13.51
$a_{\Delta RF1}$	Change in risk-free rate - Ind	-0.024	-3.585	2.385	704	33.85
a_{M2}	Market return - Partner	1.058	0.558	1.646	2080	100.00
a_{FX2}	% change in FX index - Partner	0.011	-0.326	0.428	257	12.36
$a_{\Delta RF2}$	Change in risk-free rate - Partner	0.010	-3.276	2.620	673	32.36
α_{11}	Ind's return autocorrelation	0.008	-0.128	0.138	756	36.35
α_{22}	Partner's return autocorrelation	0.012	-0.137	0.136	763	36.68
α_{12}	Return spillover Partner-Ind	0.006	-0.114	0.237	488	23.46
α_{21}	Return spillover Ind-Partner	0.008	-0.207	0.212	565	27.16

	Coefficients	Mean	Min	Max	Number (t>1.645)	% (t>1.645)
$\beta_{11,1}$	Ind's GARCH lag 1	0.433	0.000	0.991	1321	63.51
$\beta_{22,1}$	Partner's GARCH lag 1	0.405	0.000	0.989	1330	63.94
$\gamma_{11,1}$	Ind's ARCH lag 1	0.080	0.000	0.582	2005	96.39
$\gamma_{22,1}$	Partner's ARCH lag 1	0.083	0.000	0.455	2018	97.02
$\beta_{11,2}$	Ind's GARCH lag 2	0.519	0.000	0.968	1148	73.40*
$\beta_{22,2}$	Partner's GARCH lag 2	0.499	0.000	0.974	1157	73.98*
$\gamma_{11,2}$	Ind's ARCH lag 2	0.041	0.000	0.265	293	52.32*
$\gamma_{22,2}$	Partner's ARCH lag 2	0.076	0.000	0.722	353	63.04*
ρ_{ij}	Correlation	0.030	-0.381	0.735	1516	72.88
β_{12}	GARCH spillover Partner-Ind	0.078	0.000	8.623	449	21.59
β_{21}	GARCH spillover Ind-Partner	0.220	0.000	13.966	607	29.18
γ_{12}	ARCH spillover Partner-Ind	0.033	0.000	2.643	796	38.27
γ_{21}	ARCH spillover Ind-Partner	0.068	0.000	10.738	891	42.84

[*] These statistics are based on the number of best-fitting models which include these lags as shown below. For example, the coefficient of industry's GARCH lag 2 is statistically significant for 1,148 industry pairs among the 1,564 best-fitting GARCH(2,1) and GARCH(2,2) models (73.40%).

Model	Number of best-fitting models
GARCH (1,1)	415
GARCH (2,1)	1,105
GARCH (1,2)	101
GARCH (2,2)	459

Table 5: Business linkages and volatility spillover in 2005-2013

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.300	1.177	3.493	2.913	0.269*	0.153	0.519*	0.342
($CUST_{ji}$)	(1.096)	(1.253)	(2.694)	(2.720)	(0.152)	(0.182)	(0.304)	(0.315)
Supplier role of Industry	0.579	0.514	0.799	0.394	0.635*	0.589*	1.184***	1.045***
($SUPP_{ij}$)	(0.515)	(0.513)	(0.843)	(0.821)	(0.337)	(0.330)	(0.378)	(0.328)
Customer role of Partner	-0.924***	-0.967***	-1.710**	-1.101*	-0.497***	-0.503***	-1.026***	-0.843***
($CUST_{ij}$)	(0.310)	(0.307)	(0.688)	(0.588)	(0.179)	(0.181)	(0.355)	(0.295)
Supplier role of Partner	-2.050**	-2.083*	-4.893***	-4.186***	-0.521**	-0.491**	-1.134***	-0.935***
($SUPP_{ji}$)	(0.983)	(1.107)	(1.333)	(1.315)	(0.212)	(0.227)	(0.223)	(0.191)
Industry Size		0.024		0.113		0.034		0.047
		(0.078)		(0.142)		(0.033)		(0.046)
Partner Size		-0.047		-0.354***		-0.013		-0.095***
		(0.030)		(0.052)		(0.011)		(0.016)
Industry Concentration			-0.001	0.032			-0.032	-0.018
			(0.069)	(0.087)			(0.034)	(0.028)
Partner Concentration			-0.628***	-0.735***			-0.149***	-0.178***
			(0.083)	(0.091)			(0.032)	(0.034)
Observations	4,160	3,906	3,080	3,080	4,160	3,906	3,080	3,080
Adjusted R^2	0.003	0.002	0.025	0.027	0.002	0.002	0.011	0.012

Table 6: The impact of business linkages on volatility spillover for closely related industries

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The sample includes only industry pairs for which at least one of the four trading variables meets the minimum 1% threshold in Table 3. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.233	0.838	3.421	2.611	0.182	-0.043	0.387	0.033
($CUST_{ji}$)	(1.066)	(1.243)	(2.742)	(2.770)	(0.181)	(0.248)	(0.318)	(0.391)
Supplier role of Industry	0.383	0.122	0.433	-0.263	0.406	0.297	0.758***	0.439*
($SUPP_{ij}$)	(0.431)	(0.382)	(0.716)	(0.659)	(0.252)	(0.211)	(0.270)	(0.252)
Customer role of Partner	-0.842***	-0.666**	-1.365**	-0.595	-0.538***	-0.490***	-1.073***	-0.729**
($CUST_{ij}$)	(0.310)	(0.321)	(0.674)	(0.559)	(0.191)	(0.188)	(0.407)	(0.286)
Supplier role of Partner	-1.761*	-1.612	-4.220***	-3.392***	-0.667**	-0.580*	-1.471***	-1.117***
($SUPP_{ji}$)	(1.003)	(1.005)	(1.309)	(1.277)	(0.339)	(0.322)	(0.384)	(0.287)
Industry Size		0.161		0.238*		0.074		0.127*
		(0.099)		(0.137)		(0.058)		(0.075)
Partner Size		-0.128***		-0.483***		-0.045**		-0.191***
		(0.039)		(0.103)		(0.020)		(0.054)
Industry Concentration			-0.188*	-0.096			-0.030	0.020
			(0.102)	(0.092)			(0.094)	(0.083)
Partner Concentration			-0.553***	-0.749***			-0.220***	-0.297***
			(0.127)	(0.156)			(0.079)	(0.096)
Observations	1,504	1,430	1,158	1,158	1,504	1,430	1,158	1,158
Adjusted R^2	0.006	0.008	0.031	0.040	0.002	0.002	0.009	0.012

Table 7: The impact of business linkages on volatility spillover for non-financial industries

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The sample includes only non-financial industry pairs. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.838	1.862	4.210	3.557	0.359**	0.256	0.646*	0.444
($CUST_{ji}$)	(1.307)	(1.512)	(3.501)	(3.549)	(0.166)	(0.203)	(0.386)	(0.402)
Supplier role of Industry	1.455*	1.398*	1.760	1.183	1.037***	0.968***	1.279**	1.086**
($SUPP_{ij}$)	(0.784)	(0.823)	(1.276)	(1.228)	(0.347)	(0.350)	(0.533)	(0.455)
Customer role of Partner	-1.172***	-1.275***	-2.152**	-1.444*	-0.614***	-0.612***	-1.068**	-0.859**
($CUST_{ij}$)	(0.399)	(0.453)	(1.033)	(0.868)	(0.197)	(0.214)	(0.483)	(0.399)
Supplier role of Partner	-3.621***	-3.952***	-5.607***	-4.801***	-0.811***	-0.800***	-1.191***	-0.967***
($SUPP_{ji}$)	(1.032)	(1.106)	(1.853)	(1.844)	(0.160)	(0.164)	(0.288)	(0.256)
Industry Size		0.009		0.134		0.035		0.063
		(0.082)		(0.156)		(0.035)		(0.049)
Partner Size		-0.024		-0.377***		-0.012		-0.091***
		(0.032)		(0.061)		(0.010)		(0.017)
Industry Concentration			0.024	0.062			-0.034	-0.015
			(0.082)	(0.099)			(0.040)	(0.035)
Partner Concentration			-0.771***	-0.900***			-0.150***	-0.180***
			(0.108)	(0.119)			(0.041)	(0.044)
Observations	3,422	3,192	2,500	2,500	3,422	3,192	2,500	2,500
Adjusted R^2	0.004	0.004	0.026	0.029	0.003	0.003	0.009	0.010

Table 8: Business linkages and volatility spillovers over the pre-crisis period 2005-2006

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2006. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2005. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	3.332**	3.261*	1.488	1.511
($CUST_{ji}$)	(1.663)	(1.836)	(0.948)	(1.036)
Supplier role of Industry	3.761*	3.397	0.906*	0.732
($SUPP_{ij}$)	(2.274)	(2.325)	(0.518)	(0.512)
Customer role of Partner	-2.881**	-2.777**	-0.701***	-0.545**
($CUST_{ij}$)	(1.176)	(1.240)	(0.264)	(0.271)
Supplier role of Partner	-3.688**	-3.577**	-1.389**	-1.277*
($SUPP_{ji}$)	(1.536)	(1.559)	(0.667)	(0.687)
Industry Size		0.180		0.051
		(0.149)		(0.033)
Partner Size		-0.130		-0.077***
		(0.090)		(0.019)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.005	0.005	0.009	0.010

Table 9: Business linkages and volatility spillovers over the crisis period 2007-2008

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2007 – 31 December 2008. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.188*	1.078	2.870*	2.324	1.488	1.489	3.584	3.396
($CUST_{ji}$)	(0.646)	(0.780)	(1.539)	(1.534)	(1.114)	(1.283)	(2.845)	(2.872)
Supplier role of Industry	2.546*	2.311	4.266***	3.775***	1.012*	0.928	1.468**	1.307*
($SUPP_{ij}$)	(1.382)	(1.406)	(1.455)	(1.366)	(0.599)	(0.583)	(0.718)	(0.693)
Customer role of Partner	-1.609**	-1.531**	-3.221***	-2.671***	-0.882***	-0.954***	-1.256**	-1.064*
($CUST_{ij}$)	(0.641)	(0.705)	(1.063)	(0.974)	(0.317)	(0.334)	(0.622)	(0.570)
Supplier role of Partner	-2.143***	-2.052**	-4.031***	-3.497***	-1.587**	-1.642*	-3.096**	-2.901**
($SUPP_{ji}$)	(0.832)	(0.894)	(0.857)	(0.833)	(0.809)	(0.893)	(1.267)	(1.294)
Industry Size		0.145		0.198		0.027		0.061
		(0.097)		(0.165)		(0.051)		(0.068)
Partner Size		-0.050		-0.233***		0.013		-0.088***
		(0.052)		(0.059)		(0.026)		(0.033)
Industry Concentration			0.009	0.068			-0.048	-0.030
			(0.060)	(0.078)			(0.042)	(0.040)
Partner Concentration			-0.208**	-0.278**			-0.224***	-0.251***
			(0.103)	(0.111)			(0.047)	(0.049)
Customer role of Industry								
Observations	4,160	3,906	3,080	3,080	4,160	3,906	3,080	3,080
Adjusted R^2	0.004	0.005	0.009	0.010	0.003	0.002	0.021	0.021

Table 10: Business linkages and volatility spillovers over the post-crisis period 2009-2013

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2009 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) refer to year 2007. The concentration ratios refer to year 2012. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.669	1.796	3.969	3.508	0.022	-0.055	-0.033	-0.125
($CUST_{ji}$)	(1.389)	(1.862)	(3.230)	(3.298)	(0.229)	(0.249)	(0.261)	(0.320)
Supplier role of Industry	0.861	0.916	1.814	1.552	0.276	0.338	0.833**	0.780**
($SUPP_{ij}$)	(0.672)	(0.753)	(1.110)	(1.129)	(0.275)	(0.271)	(0.408)	(0.357)
Customer role of Partner	-1.328***	-1.542**	-2.568***	-1.965**	-0.505**	-0.659**	-0.797**	-0.678**
($CUST_{ij}$)	(0.501)	(0.625)	(0.900)	(0.833)	(0.197)	(0.267)	(0.355)	(0.303)
Supplier role of Partner	-3.051**	-3.125**	-5.673***	-5.052***	-0.612	-0.657	-1.156***	-1.034***
($SUPP_{ji}$)	(1.278)	(1.445)	(1.520)	(1.524)	(0.383)	(0.442)	(0.242)	(0.219)
Industry Size		-0.062		0.014		-0.060		0.004
		(0.098)		(0.147)		(0.048)		(0.051)
Partner Size		-0.090*		-0.377***		0.012		-0.073***
		(0.046)		(0.063)		(0.024)		(0.024)
Industry Concentration			0.096	0.099			0.052	0.053
			(0.100)	(0.113)			(0.066)	(0.065)
Partner Concentration			-0.614***	-0.723***			-0.201***	-0.222***
			(0.103)	(0.112)			(0.052)	(0.056)
Observations	4,032	3,782	2,970	2,970	4,032	3,782	2,970	2,970
Adjusted R^2	0.003	0.003	0.020	0.021	-0.000	-0.000	0.007	0.007

Table 11: Volatility spillover between industries and their representative trading partners

This table shows the results of the multivariate volatility spillover regressions of 65 US industries with their portfolios of suppliers and customers. Panel 1 presents the statistics of the estimated volatility spillover coefficients between an industry and its representative supplier, while Panel 2 gives the statistics for an industry and its representative customer. Panels 1 and 2 report the number of daily observations for each model, the minimum, maximum, and the mean value of the estimated coefficients. The number and the percentage of estimated coefficients with t-statistics above 1.645 (10% significance level) are also reported. Panel 3 details the direction of spillovers identified in Panels 1 and 2.

Panel 1: Industry and Representative Supplier

	Obs	Min	Max	Mean	No (t>1.645).	% (t>1.645).
GARCH spill from Industry to Representative Supplier	2265	0.000	0.187	0.006	8	12.31
GARCH spill from Representative Supplier to Industry	2265	0.000	5.896	0.526	16	24.62
ARCH spill from Industry to Representative Supplier	2265	0.000	0.053	0.003	15	23.08
ARCH spill from Representative Supplier to Industry	2265	0.000	2.127	0.308	34	52.31

Panel 2: Industry and Representative Customer

GARCH spill from Representative Customer to Industry	2265	0.000	4.283	0.414	17	26.15
GARCH spill from Industry to Representative Customer	2265	0.000	0.073	0.004	4	6.15
ARCH spill from Representative Customer to Industry	2265	0.000	9.632	0.391	38	58.46
ARCH spill from Industry to Representative Customer	2265	0.000	0.054	0.005	27	41.54

Panel 3: Direction of volatility spillover

	GARCH spillover	ARCH spillover	Either GARCH or ARCH spillover
Spillovers to Industry	33	72	89
No industries affected by partners	23	47	54
Spillovers from Industry	12	42	50
No industries affecting their partners	11	34	40
Downstream spillover cases	20	61	69
Representative Supplier to Industry	16	34	40
Industry to Representative Customer	4	27	29
No industries involved in downstream spillover	20	45	50
Upstream spillover cases	25	53	70
Industry to Representative Supplier	8	15	21
Representative Customer to Industry	17	38	49
No industries involved in downstream spillover	24	40	54

Panel 4: Volatility spillover combinations

Panel 4 considers the 15 possible combinations of volatility spillover between an industry (I), its representative supplier (S) and its representative customer (C). Arows (→ or ←) show the direction of the volatility spillover, "↔" means bidirectional volatility spillover, and "…" denotes no volatility spillover. For example, (S ← I → C) means the volatility of industry I affects the volatility of its representative supplier S and representative customer C, but not vice versa. The column reports the number of industries with significant (either GARCH or ARCH) spillovers for each combination.

Cases of volatility spillover						Either GARCH or ARCH spillover
(1)	S	⋯	I	→	C	3
(2)	S	⋯	I	←	C	5
(3)	S	⋯	I	↔	C	3
(4)	S	→	I	⋯	C	2
(5)	S	→	I	→	C	2
(6)	S	→	I	←	C	14
(7)	S	→	I	↔	C	11
(8)	S	←	I	⋯	C	3
(9)	S	←	I	→	C	1
(10)	S	←	I	←	C	3
(11)	S	←	I	↔	C	3
(12)	S	↔	I	⋯	C	0
(13)	S	↔	I	→	C	1
(14)	S	↔	I	←	C	5
(15)	S	↔	I	↔	C	5
Number of industries with spillover						61

Table 12: Volatility spillovers and portfolio concentration

This table reports probit marginal effects and robust standard errors (in parentheses). The dependent variables are the dummy variables *SuppInd* in columns 1-2 and *CustInd* in columns 3-4. *SuppInd* takes value 1 for significant volatility spillovers from the representative supplier to the industry as identified in Table 11 Panel 3, 0 otherwise. Similarly, *CustInd* is equal to 1 for significant volatility spillovers from the representative customer to the industry, 0 otherwise. The Herfindahl-Hirschman index (HHI) of the degree of concentration of the representative supplier / customer is calculated as the sum of the squared weights used to construct the respective portfolios. The IO data, industry size (millions of firms), and industry concentration ratios (CR8) refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	(1) *SuppInd*	(2) *SuppInd*	(3) *CustInd*	(4) *CustInd*
Representative Supplier HHI concentration	-6.925**	-9.071**		
	(3.331)	(3.977)		
Industry size		-0.001**		-0.001**
		(0.000)		(0.000)
Industry concentration		-1.560***		-0.317
		(0.484)		(0.287)
Representative Customer HHI concentration			1.659*	0.151
			(0.983)	(1.206)
Observations	65	56	65	56
Pseudo Rsq	0.0718	0.260	0.0281	0.106
Log likelihood	-40.20	-27.01	-35.26	-26.02

APPENDIX 1:

Input-Output Accounts and Constructed Tables

Table A1.1: MAKE Table (2007)

This table is extracted from the Make table (2007), provided by the Bureau of Economic Analysis (BEA), showing the make of 73 commodities by 71 industries in the US Each industry is presented in a row and each commodity is shown in a column. Each entry documents the value of the commodity in the corresponding column produced by the industry in the corresponding row. The sum of all entries in a row is the Total Industry Output and the sum of all entries in a column is the Total Commodity Output.

(Millions of dollars)

	Industries/Commodities	**111CA**	**113FF**	**211**	**…**	**GSLE**	**Used**	**Other**	
IO Code	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**State and local government enterprises**	**Scrap, used and second-hand goods**	**Noncomparable imports and rest-of-the-world adjustment**	**Total Industry Output**
111CA	Farms	297412	3502	0	…	0	0	0	302485
113FF	Forestry, fishing, and related activities	15	44384	0	…	0	0	0	44457
211	Oil and gas extraction	0	0	234820	…	0	0	0	293640
…	…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0	0	0	…	0	0	0	96005
GSLG	State and local general government	463	2715	0	…	0	3796	0	1787992
GSLE	State and local government enterprises	0	0	0	…	67345	0	0	224087
	Total Commodity Output	298058	51457	235813	…	68727	10223	1703	26151297
	Total Commodity Supply [1]	322648	66696	516716	…	68727	124674	242784	28583161

[1] The Total Commodity Supply is added to this table, showing the actual total supply of the commodity in the corresponding column. This is equal to the total output of commodity c produced by all industries, which is the sum of all entries in the corresponding column of commodity c in the Make table, plus other components such as imports or changes in inventories which increase the actual supply of commodity to be used in the production of industries (or consumption of final users).

Table A1.2: USE Table (2007)

This table is extracted from the Use table (2007), provided by the Bureau of Economic Analysis (BEA), showing the use of 73 commodities by 71 industries and Final users in the US Each commodity is displayed in a row and each industry is presented in a column. Each entry documents the value of the commodity in the corresponding row that the industry in the corresponding column uses as the input for its production. The sum of all entries in a row is the Total Commodity Output and the sum of all entries in a column is the Total Industry Output.

(Millions of dollars)

	Commodities/Industries	**111CA**	**113FF**	**211**	**…**	**GFE**	**GSLG**	**GSLE**		**F010**	**…**	**F10N**		
IO Code	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**Federal govern-ment enterprises**	**State and local general govern-ment**	**State and local govern-ment enterprises**	**Total Intermediate**	**Personal consump-tion expendi-tures**	**…**	**State and local: Gross investment in intellectual property products**	**Total Final Uses (GDP)**	**Total Commodity Output**
111CA	Farms	45189	637	0	…	2	2088	0	231705	52756	…	0	66354	298058
113FF	Forestry, fishing, and related activities	19526	5785	0	…	4	1228	0	56330	5424	…	0	-4872	51457
211	Oil and gas extraction	0	0	38347	…	846	0	11949	509219	0	…	0	-273406	235813
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
GSLE	State and local government enterprises	0	4	0	…	253	3236	643	18111	50615	…	0	50615	68727
Used	Scrap, used and second-hand goods	0	1	0	…	0	0	0	22312	67057	…	0	-12089	10223
Other	Noncomparable imports and rest-of-the-world adjustment	592	46	712	…	946	0	0	111725	-48866	…	0	-110022	1703
	Total Intermediate	188952	15991	88353	…	29944	577797	131386	11673662	0	…	0	0	0
V001	Compensation of employees	25013	16486	22573	…	60988	1065499	84938	7908768	0	…	0	0	0
V002	Taxes on production and imports, less subsidies	-3878	1353	27024	…	-3044	0	-15629	979978	0	…	0	0	0
V003	Gross operating surplus	92398	10628	155691	…	8118	144696	23392	5588888	0	…	0	0	0
	Total Value Added	113534	28466	205288	…	66061	1210195	92701	0	0	…	0	14477634	0
	Total Industry Output	302485	44457	293640	…	96005	1787992	224087	0	9750504	…	25758	0	26151297

Table A1.3: SHARE Table (2007)

This table is extracted from the constructed SHARE table (2007), demonstrating the proportion of the commodity supplies that each industry accounts for. Each industry is presented in a row and each commodity is shown in a column. Each entry displays the percentage of the total supply of the commodity in the corresponding column produced by the industry in the corresponding row.

	Industries/Commodities	**111CA**	**113FF**	**211**	**…**	**GSLE**	**Used**	**Other**
IO Code	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**State and local government enterprises**	**Scrap, used and second-hand goods**	**Noncomparable imports and rest-of-the-world adjustment**
111CA	Farms	92.18%	5.25%	0.00%	…	0.00%	0.00%	0.00%
113FF	Forestry, fishing, and related activities	0.00%	66.55%	0.00%	…	0.00%	0.00%	0.00%
211	Oil and gas extraction	0.00%	0.00%	45.44%	…	0.00%	0.00%	0.00%
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0.00%	0.00%	0.00%	…	0.00%	0.00%	0.00%
GSLG	State and local general government	0.14%	4.07%	0.00%	…	0.00%	3.04%	0.00%
GSLE	State and local government enterprises	0.00%	0.00%	0.00%	…	97.99%	0.00%	0.00%

Table A1.4: REVSHARE Table (2007)

This table is extracted from the constructed REVSHARE table (2007), showing the value of goods traded between any pairs of industries in the US The element of row i, column j ($REVSHARE_{ij}$) demonstrates the total value of the goods flowing from industry i to industry j (i.e. the total value of all commodities that industry j buys from industry i, or the revenue industry j generates for industry i).

(Millions of dollars)

	Industries/Commodities	**111CA**	**113FF**	**211**	**…**	**GFE**	**GSLG**	**GSLE**
IOCode	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**Federal government enterprises**	**State and local general government**	**State and local government enterprises**
111CA	Farms	42681	891	0	…	2	1999	2
113FF	Forestry, fishing, and related activities	12996	3850	0	…	3	818	1
211	Oil and gas extraction	477	38	19149	…	471	2534	5793
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	168	9	53	…	47	3356	191
GSLG	State and local general government	1069	278	176	…	241	7719	1314
GSLE	State and local government enterprises	851	35	361	…	582	9432	1068

Table A1.5: CUST Table (2007)

This table is extracted from the constructed CUST table (2007), showing the importance of the role of an industry as the customer of the other industry. The element of row i and column j ($CUST_{ij}$) demonstrates the role of industry j in the customer profile of industry i (i.e., the proportion of the revenue of industry i that is generated by industry j).

	Industries/Commodities	**111CA**	**113FF**	**211**	**…**	**GFE**	**GSLG**	**GSLE**
IO Code	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**Federal government enterprises**	**State and local general government**	**State and local government enterprises**
111CA	Farms	0.141	0.003	0.000	…	0.000	0.007	0.000
113FF	Forestry, fishing, and related activities	0.292	0.087	0.000	…	0.000	0.018	0.000
211	Oil and gas extraction	0.002	0.000	0.065	…	0.002	0.009	0.020
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0.002	0.000	0.001	…	0.000	0.035	0.002
GSLG	State and local general government	0.001	0.000	0.000	…	0.000	0.004	0.001
GSLE	State and local government enterprises	0.004	0.000	0.002	…	0.003	0.042	0.005

Table A1.6: SUPP Table (2007)

This table is extracted from the constructed SUPP table (2007), demonstrating the importance of an industry as the supplier of the other industry. The element of row i and column j ($SUPP_{ij}$) shows the role of industry i in the supplier profile of industry j (i.e., the proportion of the total input of industry j that is purchased from industry i).

	Industries/Commodities	**111CA**	**113FF**	**211**	**…**	**GFE**	**GSLG**	**GSLE**
IO Code	**Name**	**Farms**	**Forestry, fishing, and related activities**	**Oil and gas extraction**	**…**	**Federal government enterprises**	**State and local general government**	**State and local government enterprises**
111CA	Farms	0.199	0.027	0.000	…	0.000	0.001	0.000
113FF	Forestry, fishing, and related activities	0.061	0.119	0.000	…	0.000	0.000	0.000
211	Oil and gas extraction	0.002	0.001	0.173	…	0.005	0.002	0.027
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0.001	0.000	0.000	…	0.001	0.002	0.001
GSLG	State and local general government	0.005	0.009	0.002	…	0.003	0.005	0.006
GSLE	State and local government enterprises	0.004	0.001	0.003	…	0.006	0.006	0.005

APPENDIX 2

Industry linkage variables calculated using the Input-Output matrices of different years

Table A2.1:

The impact of business linkages on volatility spillover - using the 2005 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2005. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.428	1.282	0.260*	0.127
($CUST_{ji}$)	(1.179)	(1.336)	(0.155)	(0.186)
Supplier role of Industry	0.481	0.417	0.686*	0.634*
($SUPP_{ij}$)	(0.511)	(0.507)	(0.373)	(0.356)
Customer role of Partner	-0.911***	-0.954***	-0.517***	-0.517***
($CUST_{ij}$)	(0.314)	(0.306)	(0.197)	(0.197)
Supplier role of Partner	-2.268**	-2.275**	-0.554***	-0.514**
($SUPP_{ji}$)	(1.050)	(1.151)	(0.213)	(0.221)
Industry Size		0.026		0.036
		(0.082)		(0.034)
Partner Size		-0.045		-0.012
		(0.031)		(0.011)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.003	0.003	0.002

Table A2.2:

The impact of business linkages on volatility spillover - using the 2006 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2006. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.366	1.217	0.261*	0.135
($CUST_{ji}$)	(1.152)	(1.291)	(0.154)	(0.182)
Supplier role of Industry	0.495	0.428	0.675*	0.624*
($SUPP_{ij}$)	(0.494)	(0.482)	(0.377)	(0.364)
Customer role of Partner	-0.912***	-0.938***	-0.509***	-0.505***
($CUST_{ij}$)	(0.303)	(0.293)	(0.195)	(0.194)
Supplier role of Partner	-2.174**	-2.179*	-0.541**	-0.503**
($SUPP_{ji}$)	(1.051)	(1.154)	(0.220)	(0.229)
Industry Size		0.025		0.035
		(0.080)		(0.033)
Partner Size		-0.047		-0.013
		(0.031)		(0.011)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.002	0.002	0.002

Table A2.3:

The impact of business linkages on volatility spillover - using the 2008 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2008. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.446	1.377	0.296*	0.192
($CUST_{ji}$)	(1.193)	(1.379)	(0.155)	(0.190)
Supplier role of Industry	0.657	0.600	0.686**	0.645*
($SUPP_{ij}$)	(0.523)	(0.521)	(0.345)	(0.340)
Customer role of Partner	-0.944***	-1.013***	-0.528***	-0.546***
($CUST_{ij}$)	(0.320)	(0.325)	(0.190)	(0.198)
Supplier role of Partner	-2.157**	-2.221**	-0.540***	-0.516**
($SUPP_{ji}$)	(0.970)	(1.104)	(0.199)	(0.216)
Industry Size		0.024		0.035
		(0.081)		(0.033)
Partner Size		-0.036		-0.010
		(0.031)		(0.011)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.002	0.003	0.002

Table A2.4:

The impact of business linkages on volatility spillover - using the 2009 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2009. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.234	1.114	0.253*	0.141
($CUST_{ji}$)	(0.989)	(1.135)	(0.146)	(0.180)
Supplier role of Industry	0.688	0.606	0.741*	0.688*
($SUPP_{ij}$)	(0.593)	(0.579)	(0.408)	(0.396)
Customer role of Partner	-0.911***	-0.993***	-0.527**	-0.548**
($CUST_{ij}$)	(0.327)	(0.331)	(0.207)	(0.213)
Supplier role of Partner	-2.139**	-2.184*	-0.549**	-0.522**
($SUPP_{ji}$)	(1.005)	(1.135)	(0.224)	(0.243)
Industry Size		0.032		0.037
		(0.083)		(0.035)
Partner Size		-0.024		-0.007
		(0.034)		(0.012)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.002	0.002	0.002	0.002

Table A2.5:

The impact of business linkages on volatility spillover - using the 2010 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2010. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.564	1.509	0.320*	0.219
($CUST_{ji}$)	(1.250)	(1.438)	(0.164)	(0.198)
Supplier role of Industry	0.594	0.554	0.765*	0.732*
($SUPP_{ij}$)	(0.539)	(0.534)	(0.425)	(0.420)
Customer role of Partner	-0.885***	-0.977***	-0.572**	-0.603**
($CUST_{ij}$)	(0.328)	(0.335)	(0.231)	(0.237)
Supplier role of Partner	-2.216**	-2.269*	-0.558***	-0.532**
($SUPP_{ji}$)	(1.029)	(1.161)	(0.213)	(0.232)
Industry Size		0.028		0.035
		(0.083)		(0.034)
Partner Size		-0.021		-0.006
		(0.034)		(0.012)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.002	0.003	0.003

Table A2.6:

The impact of business linkages on volatility spillover - using the 2011 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2011. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.652	1.621	0.342**	0.252
($CUST_{ji}$)	(1.340)	(1.531)	(0.168)	(0.199)
Supplier role of Industry	0.596	0.565	0.736*	0.709*
($SUPP_{ij}$)	(0.522)	(0.520)	(0.398)	(0.398)
Customer role of Partner	-0.876***	-0.979***	-0.559**	-0.589***
($CUST_{ij}$)	(0.333)	(0.346)	(0.221)	(0.226)
Supplier role of Partner	-2.201**	-2.280**	-0.549***	-0.532**
($SUPP_{ji}$)	(0.989)	(1.119)	(0.196)	(0.217)
Industry Size		0.027		0.035
		(0.084)		(0.034)
Partner Size		-0.018		-0.006
		(0.035)		(0.012)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.002	0.003	0.003

Table A2.7: The impact of business linkages on volatility spillover - using the 2012 Input-Output Benchmark

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2012. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.579	3.345	3.504	2.965	0.326*	0.414	0.511	0.333
($CUST_{ji}$)	(1.319)	(2.986)	(2.928)	(3.001)	(0.169)	(0.347)	(0.325)	(0.345)
Supplier role of Industry	0.603	0.783	0.831	0.446	0.689*	1.178***	1.230***	1.098***
($SUPP_{ij}$)	(0.536)	(0.804)	(0.818)	(0.782)	(0.370)	(0.414)	(0.439)	(0.396)
Customer role of Partner	-0.910***	-1.553***	-1.622**	-0.999*	-0.533***	-0.970***	-1.033***	-0.834***
($CUST_{ij}$)	(0.342)	(0.587)	(0.681)	(0.592)	(0.207)	(0.329)	(0.370)	(0.319)
Supplier role of Partner	-2.168**	-4.281***	-4.562***	-3.989***	-0.544***	-0.956***	-1.069***	-0.890***
($SUPP_{ji}$)	(0.998)	(1.304)	(1.316)	(1.322)	(0.202)	(0.194)	(0.225)	(0.197)
Industry Size		0.069		0.115		0.047		0.044
		(0.117)		(0.140)		(0.048)		(0.044)
Partner Size		0.055		-0.304***		0.005		-0.092***
		(0.050)		(0.052)		(0.017)		(0.016)
Industry Concentration			0.030	0.063			-0.025	-0.012
			(0.069)	(0.088)			(0.034)	(0.030)
Partner Concentration			-0.602***	-0.690***			-0.161***	-0.188***
			(0.080)	(0.087)			(0.031)	(0.033)
Observations	4,160	3,080	3,080	3,080	4,160	3,080	3,080	3,080
Adjusted R^2	0.003	0.006	0.024	0.026	0.003	0.005	0.013	0.014

Table A2.8:

The impact of business linkages on volatility spillover - using the 2013 IO Tables

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) refer to year 2013. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover		ARCH spillover	
	(1)	(2)	(3)	(4)
Customer role of Industry	1.627	1.602	0.329*	0.243
($CUST_{ji}$)	(1.327)	(1.525)	(0.170)	(0.200)
Supplier role of Industry	0.513	0.493	0.666*	0.636*
($SUPP_{ij}$)	(0.496)	(0.487)	(0.359)	(0.355)
Customer role of Partner	-0.886***	-1.025***	-0.537***	-0.571***
($CUST_{ij}$)	(0.335)	(0.352)	(0.205)	(0.208)
Supplier role of Partner	-2.197**	-2.296**	-0.545***	-0.534**
($SUPP_{ji}$)	(1.015)	(1.151)	(0.201)	(0.223)
Industry Size		0.025		0.034
		(0.082)		(0.034)
Partner Size		-0.000		-0.002
		(0.036)		(0.013)
Observations	4,160	3,906	4,160	3,906
Adjusted R^2	0.003	0.002	0.003	0.002

Table A2.9: The impact of business linkages on volatility spillover - using the average values of the IO Tables from 2005-2013

This table reports cross-sectional estimated coefficients and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equations (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013. The relation between the two volatility spillover coefficients and the business linkage variables are specified in equations (8) and (9). The business linkage variables and the industry size (millions of firms) are the average during 2005-2013 sample period. The industry concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.503	1.420	3.631	3.077	0.301*	0.192	0.511*	0.345
($CUST_{ji}$)	(1.227)	(1.408)	(2.800)	(2.844)	(0.162)	(0.195)	(0.307)	(0.324)
Supplier role of Industry	0.589	0.541	0.783	0.389	0.711*	0.671*	1.314***	1.184***
($SUPP_{ij}$)	(0.536)	(0.529)	(0.859)	(0.833)	(0.387)	(0.379)	(0.457)	(0.411)
Customer role of Partner	-0.925***	-1.015***	-1.626**	-1.024*	-0.544***	-0.566***	-1.063***	-0.886***
($CUST_{ij}$)	(0.331)	(0.331)	(0.682)	(0.590)	(0.208)	(0.211)	(0.385)	(0.332)
Supplier role of Partner	-2.217**	-2.269*	-5.067***	-4.394***	-0.553**	-0.527**	-1.162***	-0.974***
($SUPP_{ji}$)	(1.047)	(1.178)	(1.369)	(1.363)	(0.216)	(0.234)	(0.227)	(0.199)
Industry Size		0.025		0.105		0.035		0.042
		(0.082)		(0.143)		(0.034)		(0.045)
Partner Size		-0.028		-0.334***		-0.008		-0.089***
		(0.033)		(0.052)		(0.012)		(0.015)
Industry Concentration			-0.003	0.028			-0.031	-0.019
			(0.069)	(0.087)			(0.034)	(0.029)
Partner Concentration			-0.628***	-0.729***			-0.149***	-0.176***
			(0.083)	(0.090)			(0.032)	(0.034)
Observations	4,160	3,906	3,080	3,080	4,160	3,906	3,080	3,080
Adjusted R^2	0.003	0.002	0.025	0.027	0.003	0.002	0.012	0.012

APPENDIX 3

Table A3: Business linkages and volatility spillover – controlling for the crisis period

This table reports cross-sectional estimates and bootstrapped standard errors (in parentheses). The dependent variables are the GARCH spillover and the ARCH spillover coefficients obtained from the multivariate GARCH model (equs (1)-(6)) using daily returns over the period 1 January 2005 – 31 December 2013 adding the crisis dummy variable in equs (1) and (3). The relation between the two volatility spillover coefficients and the business linkage variables are specified in equs (8) and (9). The business linkage variables, industry size (millions of firms) and the concentration ratios refer to year 2007. *, ** and *** denote the 10%, 5% and 1% significance levels, respectively.

	GARCH spillover				ARCH spillover			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Customer role of Industry	1.826	1.653	4.929	4.167	0.254*	0.128	0.466	0.280
($CUST_{ji}$)	(1.300)	(1.422)	(3.271)	(3.158)	(0.152)	(0.182)	(0.299)	(0.314)
Supplier role of Industry	1.022	0.876	1.656	1.004	0.652*	0.600*	1.228***	1.085***
($SUPP_{ij}$)	(0.839)	(0.792)	(1.217)	(1.014)	(0.349)	(0.337)	(0.398)	(0.343)
Customer role of Partner	-1.190***	-1.164***	-2.246**	-1.471**	-0.509***	-0.503***	-1.058***	-0.865***
($CUST_{ij}$)	(0.454)	(0.433)	(0.923)	(0.709)	(0.186)	(0.187)	(0.371)	(0.307)
Supplier role of Partner	-2.403**	-2.371*	-5.638***	-4.851***	-0.532**	-0.495**	-1.145***	-0.934***
($SUPP_{ji}$)	(1.186)	(1.268)	(1.633)	(1.561)	(0.218)	(0.230)	(0.223)	(0.189)
Industry Size		0.112		0.248		0.035		0.047
		(0.115)		(0.198)		(0.034)		(0.047)
Partner Size		-0.063**		-0.356***		-0.019*		-0.102***
		(0.031)		(0.053)		(0.011)		(0.016)
Industry Concentration			-0.041	0.033			-0.034	-0.020
			(0.065)	(0.085)			(0.035)	(0.029)
Partner Concentration			-0.597***	-0.705***			-0.140***	-0.171***
			(0.083)	(0.091)			(0.032)	(0.035)
Observations	4,160	3,906	3,080	3,080	4,160	3,906	3,080	3,080
Adjusted R^2	0.003	0.003	0.020	0.023	0.002	0.002	0.010	0.011