Tail Risk Connectedness Between US Industries

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Abstract

We use the Least Absolute Shrinkage and Selection Operator (LASSO) quantile regression technique and the stock performance of all public firms in the US market to construct the complete tail risk connectedness network among all industries in the US economy. We also investigate the empirical relationship between input-output linkages and the tail risk spillovers among US industries. Our findings identify the tail-risk drivers, tail-risk takers, and tail-risk distributors among industries and confirm that the actual trade flow between industries is a major driver of their tail risk connectedness.

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1. Introduction

Fat tail has long been a well-recognised feature of asset returns. Many studies over the last decade have demonstrated that tail risk is an important price determining factor (see Bali et al., 2009; Bollerslev and Todorov, 2011; Huang et al., 2012; Kelly and Jiang, 2014; Chabi-Yo et al., 2017; Meine et al., 2016; Harris et al., 2016; among others). These studies show that tail risk significantly affect returns at both market level and individual security level. As a result, monitoring and predicting tail risk play a central role in risk management.

However, this cannot be done by solely examining the returns of isolated assets. Numerous evidences in the literature show strong connectedness between returns of different assets and significant risk transmission among them. This is especially true for tail risk, since the comovements of assets are significantly stronger in distress time. Ang and Chen (2002) demonstrate that the US stocks comove with the aggregate market more for downside moves than for upside moves, and the difference is significantly higher for extreme movements. Kenourgios et al. (2011) document significant contagion effects in crisis periods in international markets by showing the jumps in correlations of stock markets in the well-known financial crisis periods over the last few decades. Madaleno and Pinho (2012) find evidence of contagion between international stock markets during crisis periods using continuous wavelet analysis. Cappiello et al. (2014) use quantile regression to construct the probability of coexceedances between international equity market returns for different quantile levels and examine the dynamics of these probability conditional on economic indicators. Their results confirm the increase in the comovement of equity markets in distress periods, and the change is significantly more pronounced for left-tail comovements than right-tail comovements.

A number of studies have documented tail risk interdependence at different aggregation levels, including country, industry, and firm levels. The most popular strand in this literature is, perhaps, the tail risk connectedness between countries, for example Kenourgios et al. (2011) and Cappiello et al. (2014) mentioned above. Li and Giles (2015) use a multivariate generalized autoregressive conditional heteroskedasticity model to examine both volatility and shock spillovers between developed and emerging international stock markets. Other studies at the country level are Bae et al. (2003), Hartmann et al. (2004), Hong et al. (2009), Christiansen and Ranaldo (2009), Beine et al. (2010), among others.

At industry level, research interests on tail risk interrelationship tend to centre around the financial sectors. Adams et al. (2014) use a system of quantile regressions of Value-at-Risk (hereafter VaR) to investigate the tail risk interdependence between four types of financial services, including commercial banks, investment banks, hedge funds, and insurance companies. They show that commercial banks and hedge funds play an important role in the tail risk transmission between financial institutions. Wang et al. (2017) develop measures of sector-level tail risk connectedness for four sectors, including banks, diversified financials, insurance, and real estate. Their measures are based on the tail risk linkages between institutions across sectors, which are estimated using the Granger causality test for VaR proposed by Hong et al. (2009). Chiu et al. (2015) examine the coexceedances of US real sectors with the financial sector and report significant tail risk spillover from the financial sector to many other sectors. The spillover effect is found to be dependent on industry characteristics such as competition, debt financing, valuation, and investment levels. Pouliasis et al. (2017) is one among very few studies that examine the tail risk linkages between non-financial industries. Using Hong et al. (2009) causality test for VaR exceedance, they report the prevalent left tail spillovers between consumer service industries.

Studies on tail risk linkages at firm level also remarkably focused on financial firms (Hartmann et al., 2005; Billio et al., 2012; Hautsch et al., 2014; Hautsch et al., 2015; Betz et al., 2016; among others). This is not surprising since firms in financial sectors are strongly connected and the risk of systematic collapse is high. As shown in Härdle et al. (2016), for financial firms, the term "too connected to fail" becomes relevant. High systematic collapse risk is also the reason why many of these studies examine, in addition to the tail risk interdependence among firms, the contribution of the institutions to the tail risk of the financial system, which is known as the systemic risk. A review on systemic risk literature is available in Benoit et al. (2017).

The above discussion shows that, apart from the investigation in the financial sector, the tail risk connectedness has received little attention at the industry and firm level. Thus, our study contributes to this strand of literature by constructing a complete tail risk connectedness network between *all* industries in the US economy. We use the Least Absolute Shrinkage and Selection Operator (LASSO) quantile regression technique in our study. LASSO quantile regression is developed by Belloni and Chernozhukov (2011) and applied in the construction of the financial network tail risk spillover by Hautsch et al. (2015). The most important feature of this method is that it filters non-relevant regressors in a high-dimensional quantile regression and still consistently estimates the coefficients of the retained relevant regressors. Thus, it enables the high-dimensional investigation of the whole US industry system in our study where we simultaneously model the impacts of every industry's tail risk on the tail risk of other industries, controlling for both macroeconomic variables and industry specific characteristics. To our knowledge, this study is the first one to construct and analyse the empirical tail risk connectedness network of the whole US industry system.

Understanding the tail risk interdependence between all industries in the economy is essential for policy makers, business managers, and investors. Several studies show that the shock spillovers between industries can lead to the aggregate fluctuation of the entire economy (see Long and Plosser, 1983; Shea, 2002; Gabaix, 2011, among others). Thus, by identifying the most important shock-driving industries, the most shock-sensitive industries, as well as possible channels of shock transmissions in the economy, policy makers can properly regulate relevant industries and have prompt actions to prevent the snowball effects of industries' shocks which can potentially destabilize the whole system. Firms can make better decisions when trading with their partners in different industries, by observing and predicting shocks transmitted to and from their partners. For investors, especially fund managers, knowledge about the tail risk interdependence network of the whole economic system is essential not only for predicting the tail risk of individual securities, but also for managing the risk of their portfolio. For example, if their portfolio mainly consists of stocks in highly tail risk connected industries, their tail risk is undiversifiable. If investors ignore this linkage, they are likely to underestimate the total risk of the portfolio and cannot deliver the desired risk target. Thus, understanding the tail risk connectedness network would benefit various stakeholders in the economy.

In addition to constructing the tail risk connectedness network, we move one step further to demonstrate how this network is influenced by the actual business linkages between industries. We hypothesise that the actual trade flow between industries is a major driver of their tail risk connectedness. We utilise the Input-Output Accounts provided by the US Bureau of Economic Analysis (BEA) to quantify the strength of the supplier-customer linkages, following the method of Becker and Thomas (2011) and Ahern and Harford (2014). Specifically, we measure the role of an industry in the supplier and customer profiles of its trading partner. We then carry out a cross-sectional regression to examine the extent to which these business linkage variables explain the tail risk spillover coefficients obtained from the tail risk connectedness network. This investigation reveals the economic rationale underlying the structure of the tail risk connectedness network.

This investigation of our paper contributes to a strand in the literature regarding the impact of actual business linkages on various aspects of the stock market performance. For example, at international level, Forbes and Chinn (2004) show return spillovers in stock and bond markets across countries are significantly influenced by bilateral trade flows. At industry level, Ahern (2013) finds evidence that industry linkages affect stock returns. Industries which are more central in the network have higher risk due to higher exposure to sectoral shocks and, therefore, require a positive risk premium. Acemoglu et al. (2017) develop a theoretical model for an economy with sectoral input-output linkages and show that the level of the interconnection between industries plays a key role in economic shock spillovers among industries. Our analysis provides empirical evidence confirming the inference of their model. At firm level, Cohen and Frazzini (2008) show that customers' returns can forecast subsequent stock returns and operating incomes of their suppliers. Although some papers examine the impact of supplier-customer relationship on the interdependence of stock returns and volatility at different levels, the effect of business linkage on tail risk spillovers has gained far less attention. This paper, to our knowledge, is the first one to examine the empirical relationship between input-output linkages and the tail risk spillovers.

Our empirical results reveal a complicated tail risk connectedness network between industries. Furthermore, we find significance impact of the actual business linkages on the tail risk spillovers among industries. Specifically, the customer roles of industries significantly influence the spillover coefficients between industries. When an industry is a larger customer to the other industry, they tend to have stronger tail risk connections. We also observe that business linkages account for the majority of the explanatory power of the cross-sectional regression, suggesting that business linkage is the main driver of the tail risk connectedness network. Our results are robust to both normal and distress periods, different extreme levels of tail risk, and restricted samples of nonfinancial industries and closely business-linked industries.

The remainder of this paper is organized as follows. Section 2 discusses the tail risk connectedness between US industries using the LASSO quantile regression. Section 3 describes the construction of business linkage variables from the Input-Output Accounts, and the impact of business linkages on tail risk spillovers. Section 4 reports robustness checks and Section 5 concludes.

2. Tail risk connectedness

2.1. LASSO quantile regression

The use of quantile regression to capture tail risk is well-established in the literature (see, for example, Adrian and Brunnermeier, 2016; Giglio et al., 2016; among others). To model the tail risk connectedness of the whole US industry system, we follow Hautsch et al. (2015) to use the LASSO quantile regression developed by Belloni and Chernozhukov (2011). Specifically, we estimate a quantile regression equation showing how the tail risk of an industry i returns is explained by the loss exceedance (i.e., returns lower than a pre-determined tail threshold) of each of the other industries, the lagged returns of industry i, industry i's specific characteristics, and macroeconomic variables. As argued by Hautsch et al. (2015), the advantage of this approach is that it allows us to investigate the tail risk connectedness between all industries in the economy, rather than only pairs or groups of industries. The tail risk of an industry at time t is measured by the VaR of its returns at that time, which is the quantile corresponding to the VaR significance level of the conditional distribution of the industry returns at time t:

$$VaR_{q,t}^{i} = Q_{q,t}^{i} \tag{1}$$

with $Q_{q,t}^{i}$ satisfies $$P\left(X_t^i \leq Q_{q,t}^{i}\right) = q \tag{2}$$

where $VaR_{q,t}^{i}$ is the Value-at-Risk of industry i at q significance level; $Q_{q,t}^{i}$ is the q-quantile of the conditional distribution of X_t^i - the returns of industry i at time t. Similar to Hautsch et al. (2015), we use 5% quantile in our main investigation. Other tail thresholds will be examined in our robustness check. It should be noted that, for the convenience of the interpretation of the tail risk spillover coefficients in our paper, we define VaR in terms of industry returns rather than industry loss (i.e., the negative of returns). Thus, a more negative VaR implies higher tail risk. Since we quantile-regress the return of industry i on the loss exceedance of other industries, the higher coefficient associated with the impact of an industry j on industry i means that when industry j is in a more distress situation (i.e., its return gets more negative), the VaR of industry i reduces by a larger amount, implying more tail risk to industry i. In short, higher coefficient means stronger tail risk spillover.

The quantile regression equation of industry i is given as:

$$VaR_{q,t}^{i} = \alpha^i + \boldsymbol{\beta}^i \boldsymbol{C}_{t-1}^{i} + \boldsymbol{\gamma}^i \boldsymbol{M}_{t-1} + \boldsymbol{\theta}^i \boldsymbol{E}_t^{-i} + \omega^i X_{t-1}^{i} \tag{3}$$

where $\boldsymbol{C}_{t-1}^{i}$ is the lagged specific factors of industry i, $\boldsymbol{M}_{t-1}$ is the lagged macroeconomic variables, X_{t-1}^{i} is the lagged return of industry i, and $\boldsymbol{E}_{t}^{-i}$ is the loss exceedance of all other industries in the economy except industry i. The loss exceedance of an industry j is defined as:

$$E_t^j = \begin{cases} 0, \ X_t^j \geq unconditional\ 10\%\ sample\ quantile\ of\ X^j \\ X_t^j, \ otherwise \end{cases} \tag{4}$$

Thus, the coefficient θ_j^i in Equation (3) shows the level of the tail risk spillover from industry j to industry i.

Equation (3) is estimated using Belloni and Chernozhukov (2011) LASSO quantile regression method. First, the irrelevant regressors of the equation are determined as any regressor whose estimated coefficient from the l_1-penalized quantile regression has the absolute value smaller than a predetermined threshold. We follow Hautsch et al. (2015) to choose the cut-off threshold of 0.0001. Given a quantile regression of variable X^i on the set of demeaned regressor $\boldsymbol{W}^i$, the estimated parameters $\tilde{\boldsymbol{\xi}}^i$ of the corresponding l_1-penalized quantile regression are the ones that minimize:

$$\frac{1}{T}\sum_{t=1}^{T}\left(q - I\left(X_t^i \leq \boldsymbol{W}_t^i\boldsymbol{\xi}^i\right)\right)\left(X_t^i - \boldsymbol{W}_t^i\boldsymbol{\xi}^i\right) + \lambda\frac{\sqrt{q(1-q)}}{T}\sum_{k=1}^{K}\widehat{\sigma_k}\left|\xi_k^i\right| \tag{5}$$

where $I(\cdot)$ is the indicator function that equals 1 when the statement inside the bracket is true and 0 otherwise, T is the number of observations in the estimation sample, K is the number of regressors in $\boldsymbol{W}^i$, ξ_k^i is the k^{th} element of the coefficient set $\boldsymbol{\xi}^i$, and $\widehat{\sigma_k}$ is the standard deviation of the k^{th} regressors, which could be estimated as

$$\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(W_{t,k}^i\right)^2} \tag{6}$$

In Equation (5), λ is the penalty parameter and a higher level of λ means more variables would be eliminated. λ is determined specific to each industry in a data driven way that maximizes the backtesting performance of the estimated VaR of the industry. Details about this procedure is provided in Appendix 1. The coefficients of the retained relevant regressors will be then estimated consistently using a normal quantile regression of the dependent variable on the relevant regressors, which is referred to as the post-LASSO regression.

After estimating Equation (3) for every industry in the system, we construct the tail risk connectedness matrix $\boldsymbol{A} = \{A_{ij}\}$ where the entry of row i and column j, A_{ij}, equals θ_j^i if the loss exceedance of j is the relevant regressors in Equation (3) and 0 otherwise. For every pair of industries, there are two tail risk connectedness coefficients, θ_j^i showing the spillover from j to i, and θ_i^j showing the spillover from i to j. From the pairwise spillovers in the connectedness matrix, we obtain the tail risk in-degree of an industry i as the number of industries which transmit tail risk to industry i, and the tail risk out-degree of industry i as the number of industries which receive tail risk from industry i. The tail risk net-degree of industry i is the difference between its out-degree and in-degree, showing whether the industry i is a tail-risk transmitter or a tail-risk receiver in the system. We calculate the total number of connections in matrix $\boldsymbol{A}$ to capture the total level of connectedness of the whole system.

2.2. Data

We construct the industry returns as the market capital weighted average returns of all stocks traded in NYSE, AMEX, and NASDAQ with share codes 10 and 11 from the Centre for Research in Security Prices (CRSP) database. We classify stocks into industries based on the North American Industry Classification System (NAICS) codes, which are also used in the Input-Output database provided by the Bureau of Economic Analysis (BEA). This facilitates our analysis on the relationship between tail risk connectedness and business linkages among industries, which reveals the economic rationale of the tail risk network. At the summary level, the Input-Output Accounts classify the US economy into 71 industries. After eliminating industries in the government sector and industries without observations from CRSP database, we are left with 59 industries for our investigation. The list of industries and their corresponding abbreviations are provided in Appendix 2. We use weekly returns during a 12-year period from January 2005 to December 2016.

Regarding macroeconomic variables, similar to Hautsch et al. (2015) and Adrian and Brunnermeier (2016), we use the implied volatility index, the short-term liquidity spread (measured as the spread between the 3-month collateral repo rate and the 3-month Treasury Bill rate), the change in 3-month Treasury Bill rate, the change in the slope of the yield curve (measured as the spread between the 10-year Treasury Note and the 3-month Treasury Bill), the change in credit spread between BAA rated bonds and the 10-year Treasury Note, and the CRSP index returns. We obtain the implied volatility index VIX from the Chicago Board Options Exchange, the 3-month collateral repo rate from Bloomberg, and BAA bond rate, the

10-year Treasury Note rate, and the 3-month Treasury Bill rate from the Federal Reserve Bank of St. Louis.

Given the limited availability of accounting ratios for the whole US industry system, we construct a database for industry characteristics based on the accounting data of all companies in Compustat database. Specifically, we sort the companies in Compustat by their NAICS codes, then aggregate the accounting data of all firms in an industry to represent the characteristics of the whole industry.[1] In line with Hautsch et al. (2015), we control for industry characteristics, including leverage (total asset over total book value of equity), maturity mismatch (short term debt net of cash, divided by total liabilities), size (natural logarithm of total asset), and daily volatility over a week in the quantile regression. In order to obtain weekly observations of quarterly accounting ratios, similar to Hautsch et al. (2015), we use interpolation with cubic splines. Appendix 3 provides the summary statistics of all industry data in our research.

2.3. Tail risk connectedness network between US industries

We estimate the LASSO quantile regression for every industry to obtain the tail risk spillover coefficients. We then construct the connectedness matrix $\boldsymbol{A}$ between all industries in the US economy from the estimated coefficients. For a network of 59 industries, there are 3,422 possible pairwise directional spillovers. We observe 694 significant tail risk spillovers, which is about 20% of the total possible directional connections, chosen as relevant by the LASSO procedure. This is consistent with the structure of the US economy in which each industry, by its nature, only closely linked to a few related partner industries. Further evidence for this will be provided in the degree analysis and the business linkage investigation.

Figure 1 presents a directed graph which illustrates the tail risk connectedness network between US industries. An arrow with the direction from industry i to industry j implies that industry i is selected by the LASSO quantile regression as a relevant driver of the VaR of industry j. If i is eliminated by the LASSO quantile regression in explaining the VaR of j, there is no arrow from i to j. The thickness of the arrows illustrates the level of tail risk spillovers. A thin (light grey) arrow represents the tail risk spillover coefficient with absolute value smaller than 0.4, a medium-size (dark grey) arrow represents the coefficient with

[1] The accounting data are available quarterly. In a quarter, each firm in an industry may have different report date. When aggregating their data to create the representative firm of the industry, we assume that the accounting data of the representative firm is obtained at the end date of a quarter. The underlying assumption is that the values of the accounting data of the constituent firms do not change much during a quarter. This is a justifiable assumption given that we only use balance sheet data to construct industry characteristics.

absolute value from 0.4 to 0.8, and a thick (black) arrow displays the coefficient with absolute value larger than 0.8.[2] The majority (93.3%) of the tail risk connectedness are weak, as shown by thin arrows in the graph. Some of the strongest tail risk spillovers identified in the network are those from Administrative and support service (ADM) to Social Assistance (SA) with the spillover coefficient of 1.2, from Insurance carriers and related activities (INS) to Legal services (LGL) with the spillover coefficient of 1.19, and from Other transportation and support activities (OTP) to Air transportation (ARTP) with the spillover coefficient of 1.04.

[Figure 1]

In addition to pairwise spillovers, we also observe the distributions of the connectedness degree measures of US industries. Figure 2 plots the histograms of the out-degree, in-degree and net-degree measures. The out-degree distribution reveals that the average out-degree is about 12 and the out-degree of the majority of US industries is around that level. Since the US economy is well-diversified, it is reasonable that each industry only directly influences some related industries in the network. However, there are a few industries with the out-degree levels of around 30, suggesting they are the risk drivers, with considerably high systemic contribution. Meanwhile, the in-degree distribution spreads out quite evenly between 0 and 23, implying the sensitivity to tail risk transmissions varies significantly across US industries. While some industries are quite vulnerable, receiving shocks from more than 20 other industries in the network, some industries tend not to be affected by tail risk spillovers from others.

Finally, we categorize industries into three main groups based on their net-degree measures. The first group consists of industries with very high net-degree measures. These industries receive risk from a few other industries; however, their tail risk transmit to a large number of others. Thus, they are considered as main risk drivers in the system, whose risk can significantly affect others while they are relatively unaffected by the others' shocks. The second group contains industries with very low negative net-degree measures. These industries are sensitive to shocks to other industries, thus considered as main risk takers in the

[2] Although most of the coefficients are positive, there are cases when the spillover coefficients are negative, implying a hedging relationship between the two industries. In other words, some industries may benefit from the distress of the other industries. The hedging relationship in many industry pairs is justifiable by looking at the nature of their businesses. For example, shocks to many industries have negative influence on the tail risk of legal service industry, which is reasonable since legal service should have more business opportunities when other industries are in distress.

network. The third category consists of industries which act as both risk drivers and risk takers, whose net-degree measures centre around 0. They are known as risk distributors, receiving tail risk from other industries and amplifying the risk in the system by transmitting it to others. As can be seen in the third chart of Figure 2, while there are a few main risk takers and main risk drivers in the economy, the largest category is the risk distributors.

[Figure 2]

Table 1 reports top five and bottom five industries for each tail risk connectedness degree measure. Firstly, in term of the out-degree measure, Construction (CTN), Other retail (OR), and Electrical equipment, appliances, and components (ELT) are top industries whose tail risk spills over to about half of the number of industries in the economy. In contrast, Motion picture and sound recording industries (MP) and Food services and drinking places (FDP) affect only one or two other industries. Secondly, regarding the in-degree measure, Computer system design and related services (CPTS), Printing and related support activities (PRT) and Waste management and remediation services (WAST) are the top industries which receive risk spillovers from 23 other industries, while Social assistance (SA), Chemical products (CMC), and General merchandise stores (GMST) are industries that are affected by only one industry. Oil and gas extraction (OG) is the most tail-risk resistant industry in the economy with a zero in-degree level. In other words, the tail risk of Oil and gas extraction (OG) is not significantly affected by any other industries in the economy. This is not surprising since the risk of this industry tends to be driven by the supply shocks in major oil and gas supplying countries, or the demand shocks from the whole economy rather than by shocks from any particular industry in the economy. Thirdly, it is obvious that the main risk drivers (i.e., industries with the highest net-degree level) are usually top out-degree industries (e.g., Electrical equipment, appliances, and components (ELT), Other retails (OR), and Construction (CTN)) while the main risk takers (i.e. industries with the lowest net-degree level) are bottom out-degree industries (e.g., Wholesale trade (WST) and Food services and drinking places (FDP)). The Computer systems design and related services (CPTS) is among the top risk drivers as well as the top risk receivers. It is a typical example of a risk distributor in the economy.

[Table 1]

The tail risk connectedness matrix is useful for monitoring the tail risk structure of the whole economy, and also for effectively monitoring the risk of any particular industry. This is especially important for business managers and investors who invest in a specific industry or some related industries. To demonstrate, Figure 3 shows the tail risk connectedness between the Electrical equipment, appliances, and components industry (ELT) and its related industries, where ELT takes the role of the risk driver (Panel A) and the risk receiver (Panel B). If there is a shock to ELT, investors and managers can quickly identify industries that will be directly affected. In addition, to predict the tail risk of ELT, managers and investors can observe shocks to its risk drivers (e.g., Fabricated metal products (FMTL), Computer and electronic products (CPT), and Computer systems design and related services (CPTS)).

[Figure 3]

3. The influence of industry business linkages

3.1. Input-Output Accounts and business linkages variables

We measure the strength of the business linkages between industries using the data from the Input-Output (IO) accounts provided by the Bureau of Economic Analysis. The value of commodity inputs and outputs of every industry in the US economy are reported in two main tables: the *Make* and the *Use* tables (for snapshots of these tables see Appendix 4). The *Make* table reports the value of the commodities (in columns) produced by the industries (in rows). The total output of industry i, denoted by $OUTPUT_i$, is obtained as the sum of all entries in row i. The total output of a commodity produced by all the industries is the sum of all entries in a column. The *Use* table presents the value of commodities purchased as inputs by industries (or consumed by final users). Commodities are reported in rows while industries are listed in columns. The sum of all entries in a row is the total commodity output while the sum of all entries in a column is the total industry input, denoted by $INPUT_j$ for industry j. Total industry input plus the total value added gives the total industry output, presented in the last row of the *Use* table.

To measure the strength of the supplier-customer relationship between industries, we follow Ahern and Harford (2014) and Becker and Thomas (2011) to construct the *CUST* and *SUPP* matrices. First, using information from the *Make* table, we calculate the subordinate *SHARE* matrix. Specifically, the element in row i, column c, denoted $SHARE_{ic}$, is calculated as:

$$SHARE_{ic} = \frac{Make_{ic}}{Total\,Supply_c} \qquad (7)$$

where i and c index industry and commodity, respectively. $Make_{ic}$ is the element in row i, column c of the *Make* table, showing the value of commodity c produced by industry i. $Total\ Supply_c$ is the total supply of commodity c, which includes the total output of commodity c produced by all the industries plus other components such as imports or changes in inventories. Thus, *SHARE* matrix presents the contribution of an industry in the total supply of each commodity in the economy.

Next, we construct the *REVSHARE* matrix, of which the element in row i, column j, $REVSHARE_{ij}$, is obtained as:

$$REVSHARE_{ij} = \sum_{c=1}^{C} \left(SHARE_{ic} \times Use_{cj} \right) \tag{8}$$

where $SHARE_{ic}$ (row i, column c element of the *SHARE* matrix) presents the proportion of commodity c produced by industry i, and Use_{cj} (row c, column j element in the *Use* table) shows the value of commodity c used as inputs in the production of industry j.[3] Therefore, *REVSHARE* matrix shows the value of all commodities traded between every pair of industries.

Finally, we construct the *CUST* and *SUPP* matrices, showing the customer and supplier role of an industry with respect to each other, respectively. Specifically, 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 calculated as:

$$CUST_{ij} = \frac{REVSHARE_{ij}}{OUTPUT_i} \tag{9}$$

$$SUPP_{ij} = \frac{REVSHARE_{ij}}{INPUT_j} \tag{10}$$

where $REVSHARE_{ij}$ is the total value of all commodities which industry j purchases from industry i, $OUTPUT_i$ is the total output value of industry i in the *Make* table and $INPUT_j$ is the total input value of industry j.[4] Thus, $CUST_{ij}$ shows the proportion of industry i's revenue

[3] In this calculation, we apply the assumption in Ahern and Harford (2014) and Becker and Thomas (2011) that market shares are constant for every use of commodity. To demonstrate, if 60% of the total supply of commodity c is produced by industry i (i.e., $SHARE_{ic}$ = 0.6), then industry j purchases 60% of its commodity c input from industry i.

[4] While labor (referred to as employee compensation in the *Use* table) is an important input, there is no Labor industry in the *Make* table. Thus, we follow Ahern and Harford (2014) to create an artificial Labor industry in

generated by industry j and $SUPP_{ij}$ shows the proportion of industry j's total input purchased from industry i.

Table 2 shows the summary statistics of business linkages between industries based on relationship variables (*CUST*, *SUPP*) constructed from the IO tables of 71 industries. We only report the results for 59 industries in our sample. We use the average relationship variables during the 12-year sample period.[5] For a pair of industries, we obtain four relationship variables ($CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$). Based on the value of the relationship variables, we classify industry pairs as having weak or close business linkages at different threshold ranging from 1% to 10%. The first row of Table 2 shows that at 1% threshold, 1,106 among 1,711 industry pairs, or 64.6% of the pairs, have weak linkages, with all relationship variables smaller than 1%. This is justifiable in a developed economy like the US, where industries are well classified, and each industry tends to largely trade with only a few main suppliers and customers. While 359 pairs have at least one main customer (i.e., at least one *CUST* variable is larger than 1%), 506 pairs have at least one main supplier (i.e., at least one *SUPP* variable is larger than 1%). In general, 605 pairs have strong linkages, with at least one of the four relationship variables larger than 1%. Obviously, the number of closely linked industry pairs decreases as the threshold increases. At 10% level, only 41 pairs, or about 2.4% of the pairs, have strong business relationship. This is consistent with the structure of the tail risk connectedness network. This evidence offers the first clue for the influence of business linkages on tail risk spillovers between industries, which will be examined in the next section.

[Table 2]

3.2. Cross-sectional regression for the influence of business linkages on tail risk spillovers

We now examine the extent to which the tail risk spillovers are affected by the business linkages between industry i and industry j. Specifically, we estimate a cross-sectional regression as follows:

$$A_{ji} = \varphi_0 + \varphi_1 CUST_{ji} + \varphi_2 SUPP_{ij} + \varphi_3 CUST_{ij} + \varphi_4 SUPP_{ji} + \boldsymbol{v}_{ij}\boldsymbol{\delta} + \epsilon_{ij} \quad (11)$$

the *Use* table. This step is only to ensure that the input values are accurately calculated. The industry will not be included in the final sample for investigation.

[5] The IO tables are updated every five years (year ending 2 and 7). BEA provides estimated tables for other years.

Where A_{ji} is the element of the connectedness matrix $\boldsymbol{A}$, showing the tail risk spillover from industry i to industry j. $CUST_{ji}$, $SUPP_{ij,}$ $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. $\boldsymbol{v}_{ij}$ is a vector of industry characteristics of industry i and industry j; φ_0, φ_1, φ_2, φ_3, φ_4 are estimated coefficients, $\boldsymbol{\delta}$ includes all estimated coefficients of the industry specific characteristics; and ϵ_{ij} is the residual term. We include in $\boldsymbol{v}_{ij}$ the industry characteristics used in the quantile regression of industries. The explanatory variables in the cross-sectional regression in Equation (11) are the average of the characteristic and linkage variables of an industry over the whole sample period. For each pair of industry i and industry j, we obtain two spillover coefficients - A_{ij} and A_{ji}. Consequently, from the 1,711 industry pairs, we obtain 3,422 cross-section observations. We bootstrapped the standard errors of the estimated coefficient with 1,000 resampling to account for the fact that the dependent variables are estimated from the first stage quantile regression. The sign and the significance of the coefficients φ_1, φ_2, φ_3, φ_4 reveal the influence of the actual business linkages between industries on the tail risk spillovers between them.

Table 3 reports the results of the cross-sectional regression. We observe significant impact of business linkages on the tail risk spillovers between industries. We find the tail risk spillover from industry i to industry j is significantly and positively related to the customer roles of the two industries. This means when an industry becomes a larger customer of the other industry, its tail risk tends to spill more strongly to its partner and is also more affected by its partner. The fact that the customer relationship significantly influences the tail risk connectedness between industries reflects the customer-oriented culture of the US business. Moreover, we observe that the business linkage variables account for the majority of the explanatory power of the regression. The inclusion of industry characteristic variables only marginally increases the R-squared of the regression and most of the coefficients are insignificant. This result strongly confirms our hypothesis that the main rationale underlying the spillover dynamics between industries in the economy is the actual business linkages between them.

[Table 3]

4. Robustness checks

4.1. Tail risk connectedness in different market conditions

In this section, we examine the tail risk connectedness network between US industries, and how the spillovers are affected by their business linkages in different market conditions. We include a crisis dummy variable as well as its interaction terms with all explanatory variables in the first stage LASSO quantile regression. The crisis dummy (D) takes the value of 1 for weeks starting from 1 January 2007 to 31 December 2009, and 0 otherwise. The LASSO quantile regression provides us with relevant tail risk spillover coefficients between industries in normal period. The coefficients of the interaction terms between the crisis dummy and industries' loss exceedance show the change in tail risk spillovers between industries in crisis period.

We obtain two tail risk connectedness matrices from estimating the LASSO quantile regression: $\boldsymbol{A}$ is the tail risk connectedness matrix in normal period, and $\boldsymbol{DA}$ is the change in $\boldsymbol{A}$ due to crisis. We also construct matrix $\boldsymbol{ADA}$ as the sum of $\boldsymbol{A}$ and $\boldsymbol{DA}$ matrices, which shows the value of the spillover coefficients in the crisis period. There are several possibilities for the change in tail risk spillovers between normal time and distress time. For a non-zero entry in $\boldsymbol{A}$, we say that the tail risk connectedness changes in crisis time if its corresponding entry in $\boldsymbol{DA}$ is different from zero, and there is no change in the crisis period if its corresponding entry in $\boldsymbol{DA}$ is zero. If the corresponding non-zero entry in $\boldsymbol{DA}$ has the opposite sign and almost similar magnitude with the entry in $\boldsymbol{A}$, the tail risk spillover between the two industries almost disappears in crisis period. For a zero entry in $\boldsymbol{A}$, a corresponding non-zero entry in $\boldsymbol{DA}$ implies that an industry starts to affect its partner in crisis time. Due to the large scale of the $\boldsymbol{A}$, $\boldsymbol{DA}$, and $\boldsymbol{ADA}$ matrices, we do not report these tables in our paper. The tables are available from the authors upon request.

The results of this investigation show that there are changes in the tail risk transmissions between industries in crisis period. We observe a 5.4% increase in the number of relevant spillovers, from 608 spillovers in normal time to 641 spillovers in crisis time. No tail risk connectedness disappears in crisis period. In contrast, 57 spillover coefficients change values due to crisis. Taking a closer look at the financial industries (NAICS codes from 52X to 53X) in the crisis period, we observe an average increase of 0.05 in the values of their spillover coefficients. However, there are only three new spillovers from financial industries to the other industries. Thus, although the tail risk spillovers between the financial industries and other industries increase during crisis, they tend to retain within the established spillover channels rather than spreading out to more industries in the system.

We also examine the influence of business linkages on tail risk spillovers in different market conditions using the cross-sectional regression. Table 4 shows the results of this investigation for normal period (Panel A) and distress period (Panel B). The dependent variables in normal and distress periods are obtained from the matrix $\boldsymbol{A}$ and $\boldsymbol{ADA}$, respectively. Our results in Panel A is similar to the standard framework results in Table 3. Specifically, the customer roles of both industries significantly and positively affect the magnitude of tail risk spillovers between them. Panel B confirms the robustness of our results in the distress period, where the customer roles are highly significant and positive. Moreover, in the distress period, the supplier role of an industry to its partner also has a significant and positive impact on the industry's tail risk spillover to its partner. The R-squared is also slightly higher in the distress period regressions compared to that of the normal period. This implies that, business linkages can explain the tail risk spillovers among industries more in distress time.

[Table 4]

4.2. The connectedness at different tail risk levels

Our standard framework investigates the tail risk connectedness and business linkages between US industries at 5% VaR level. In this section, we vary tail risk level, using 1% VaR and 10% VaR. The results of LASSO quantile regressions show stronger risk connectedness between industries at a less extreme level of the tail. The number of relevant tail risk spillover coefficients increases from 574 at 1% VaR, to 694 at 5% VaR, and 745 at 10% VaR. The average out-degree and in-degree of an industry also increase from 9.73 at 1% VaR to 11.76 and 12.63 at 5% and 10% VaR, respectively. When the very extreme shock of an industry tends to be generated from its own problem, the tail risk at a higher significance level (i.e., less extreme tail) can be accounted for by other factors, such as spillovers from other industries in the network.

Table 5 reports the results of the cross-sectional regression showing the influence of business linkages on tail risk spillover corresponding to different VaR significant levels. Comparing the results in this table and in Table 3, the R-squared coefficients increase as tail risk significance level increases. Thus, for a less extreme definition of tail risk, not only industries are getting more connected, but their connectedness is also more related to their actual business linkages. We still find the significant impacts of the customer roles of both industries i and j on the tail risk spillover from i to j, which is qualitatively similar to our main results.

[Table 5]

4.3. Business linkages and tail risk spillovers between closely-linked industries

The data we obtain from the *SUPP* and *CUST* tables reveal that, while some industry pairs have strong linkages, with at least one industry is the main supplier and/or main customer of the other one, many industry pairs show weak relationship, represented by very small *SUPP* and *CUST* variables. Therefore, in this robustness check, we examine the impact of business linkages on tail risk spillovers between only closely related industries. Our sample are reduced to include only pairs of industries in which the value of at least one of the four relationship variables ($CUST_{ji}$, $SUPP_{ij,}$ $CUST_{ij}$, and $SUPP_{ji}$) is larger than or equal to a certain threshold. Thus, we are left with 605, 350, and 222 industry pairs at 1%, 2%, and 3% threshold, respectively. The results shown in Table 6 are similar to our main results and confirm the relevance of business linkages in explaining the tail risk connectedness. More importantly, the R-squared coefficients in the regressions of restricted samples of closely-linked pairs are significantly higher than that of the full sample. This is consistent with our hypothesis that business linkage is the main driver of tail risk spillover.

[Table 6]

4.4. Business linkages and tail risk spillovers between nonfinancial industries

Financial industries are commonly known as influential industries, since their risk are expected to easily and strongly propagate to other industries in the economy. Thus, to focus on the impact of business linkages on tail risk transmission apart from any possible financial effect, we eliminate five industries in the financial services (i.e., Federal Reserve Bank, credit intermediation and related activities (FED); Securities, commodity contracts and investments (INV); Insurance carriers and related activities (INS); Funds, trusts, and other financial vehicles (FUND); Real estate (RE); and Rental and leasing services and lessors of intangible assets (RL)), and carry out our cross-sectional analysis. The results reported in Table 7 are similar to our main findings, showing significant impacts of economic relationships on the tail risk transmission between industries. We also observe a slightly increase in the R-squared coefficient, as well as a significantly more relevance of the supplier role of tail risk driver as compared to the standard framework. Thus, this is a solid evidence that tail risk spillover stems from the actual trade flows rather than from the comovement with the financial sector.

[Table 7]

5. Conclusion

Tail risk measures and tail risk connectedness have recently gained attention due to their importance implication, especially in practice. In this paper, we construct the complete tail risk connectedness network among all industries in the US economy using the LASSO quantile regression technique developed in Belloni and Chernozhukov (2011) and Hautsch et al. (2015). Our results suggest a sophisticated tail risk connectedness network between US industries. We also show that the level of the connectedness increases with a less extreme tail measure. The estimated network reveals important tail risk drivers as well as highly systemic industries in the US economy. This is valuable information for business managers, investors, and policy makers in decision making.

More importantly, we reveal the economic rationale underlying the tail risk interdependence network. Using the Input-Output Accounts provided by the Bureau of Economic Analysis to measure the strength of business relationships between US industries, we reveal that economic linkages is the main driver of the tail risk spillover network. Our findings are in line with Acemoglu et al. (2017) theoretical model regarding the influence of the interconnection between industries on their tail risk spillovers.

Our findings could be relevant for future research, specifically in the two directions. The first direction is to examine the impacts of business linkages on tail risk spillovers at firm level. The supplier-customer relationship can be obtained from the information of main customers reported by US public companies and available in Compustat. This investigation will reveal if business linkages also influence the tail risk spillovers between firms. Another direction is to examine the impact of business linkages on international tail risk transmission. This may answer the important question regarding the true mechanism of tail risk spillovers between markets, whether it is trade flow or capital flow.

Appendix 1 – Selecting the penalty parameter λ for the LASSO quantile regression

We determine λ for each industry in a data driven way that maximizes the backtesting performance of the estimated VaR of the industry. Specifically, for an industry i, we carry out the following steps:

Step 1: For each c in the ν-equidistant grid $C = \{c_1 < \cdots < c_k = c_1 + (k-1)\nu < \cdots < c_L\}$, we determine the penalty parameter $\lambda^i(c)$ using four following steps.

- **Step 1a**. Take T i.i.d. draw from the Uniform distribution $U[0,1]$ independent of the timing of the dataset of the regression, denoted as $u_1, u_2, \cdots, u_T$. Calculate the following variable:

$$\Lambda^i = T \times \max_{1 \le k \le K} \frac{1}{T} \left| \sum_{t=1}^{T} \frac{W_{t,k}^i \big(q - I(u_t \le q)\big)}{\widehat{\sigma_k} \sqrt{q(1-q)}} \right| \tag{A1.1}$$

- **Step 1b.** Repeat Step 1a for 500 times to obtain an empirical distribution of Λ^i, conditional on the value of $\boldsymbol{W}^i$. Given a confidence level $1-\alpha$, the penalty parameter is calculated as

$$\lambda^i(c) = c \times Q\big(\Lambda^i, 1-\alpha\big) \tag{A1.2}$$

  where $Q\big(\Lambda^i, 1-\alpha\big)$ is the $1-\alpha$ quantile of the empirical distribution of Λ^i.

- **Step 1c.** Estimate the l_1-penalized quantile regression according to Equation (5) and retain only variables in $\boldsymbol{W}^i$ whose absolute value is greater than 0.0001. Using the remaining variables, estimate the post-LASSO quantile regression to obtain the corresponding post-LASSO estimated coefficients and the fitted value of the quantile (VaR) of the dependent variable over time.
- **Step 1d**. Backtest the estimated VaR using Hautsch et al. (2015) log likelihood ratio test: obtain the VaR exceedance series $VE_t = I\big(X_t^i < \widehat{VaR}_{q,t}\big)$ and estimate the logistic regression model:

$$VE_t = \theta_0 + \big(VE_{t-1}, VE_{t-2}, VE_{t-3}, \widehat{VaR}_{q,t-1}\big)\boldsymbol{\theta} + \varepsilon_t = \theta_0 + \boldsymbol{V}_t'\boldsymbol{\theta} + \varepsilon_t \tag{A1.3}$$

The log likelihood ratio test statistic for the null hypothesis that the VaR exceedance is i.i.d. Bernoulli distributed with success probability q is

$$LR = -2(ln\mathcal{L}_r - ln\mathcal{L}_u) \overset{a}{\sim} \chi^2_5 \qquad \text{(A1.4)}$$

where

$$ln\mathcal{L}_u = \sum \left[VE_t lnF_{log}(\theta_0 + \boldsymbol{V}'_t\boldsymbol{\theta}) + (1 - VE_t)ln\left(1 - F_{log}(\theta_0 + \boldsymbol{V}'_t\boldsymbol{\theta})\right)\right]$$

$$ln\mathcal{L}_r = \sum VE_t ln(q) + \left(T - \sum VE_t\right) ln(1 - q)$$

and $F_{log}(\theta_0 + \boldsymbol{V}'_t\boldsymbol{\theta})$ is the fitted value of the logistic regression. Obtain the p-value of the test $p(c)$.

Step 2. Repeat step 1 for every c in the C grid and select the c that produces the highest $p(c)$ to be the optimal value of c. The corresponding value of the penalty parameter is the optimal λ for the LASSO quantile regression.

Appendix 2 – List of US industries

No	Full name	Abbreviation
1	Farms	FARM
2	Oil and gas extraction	OG
3	Mining, except oil and gas	MNG
4	Support activities for mining	MNGS
5	Utilities	UTL
6	Construction	CTN
7	Wood products	WP
8	Nonmetallic mineral products	MNR
9	Primary metals	MTL
10	Fabricated metal products	FMTL
11	Machinery	MCN
12	Computer and electronic products	CPT
13	Electrical equipment, appliances, and components	ELT
14	Motor vehicles, bodies and trailers, and parts	MOTP
15	Other transportation equipment	OTPE
16	Furniture and related products	FURN
17	Miscellaneous manufacturing	MMFG
18	Food and beverage and tobacco products	FB
19	Textile mills and textile product mills	TXT
20	Apparel and leather and allied products	LEA
21	Paper products	PAP
22	Printing and related support activities	PRT
23	Petroleum and coal products	PECO
24	Chemical products	CMC
25	Plastics and rubber products	PLA
26	Wholesale trade	WST
27	Motor vehicle and parts dealers	MOTD
28	Food and beverage stores	FBST
29	General merchandise stores	GMST
30	Other retail	OR
31	Air transportation	ARTP
32	Rail transportation	RLTP
33	Water transportation	WATP
34	Truck transportation	TRTP
35	Pipeline transportation	PTP
36	Other transportation and support activities	OTP
37	Publishing industries, except internet (includes software)	PUB
38	Motion picture and sound recording industries	MP
39	Federal Reserve banks, credit intermediation, and related activities	FED

(continued)

Appendix 2 – continued

No	Full name	Abbreviation
40	Securities, commodity contracts, and investments	INV
41	Insurance carriers and related activities	INS
42	Funds, trusts, and other financial vehicles	FUND
43	Real Estate	RE
44	Rental and leasing services and lessors of intangible assets	RL
45	Legal services	LGL
46	Computer systems design and related services	CPTS
47	Miscellaneous professional, scientific, and technical services	MTEC
48	Administrative and support services	ADM
49	Waste management and remediation services	WAST
50	Educational services	EDU
51	Ambulatory health care services	AH
52	Hospitals	HOSP
53	Nursing and residential care facilities	NURS
54	Social assistance	SA
55	Performing arts, spectator sports, museums, and related activities	ART
56	Amusements, gambling, and recreation industries	RCT
57	Accommodation	ACM
58	Food services and drinking places	FDP
59	Other services, except government	OS

Appendix 3 – Summary statistic of US industries

This appendix shows the mean, standard deviation, skewness, and kurtosis of the returns of each industry in our sample from January 2005 to December 2016. The Jarque-Bera test statistic for the normality test of the returns of each industry is also reported. The appendix also contains the average value of the specific characteristics of each industry during the examined period. See Appendix 2 for the full names of the industries.

Industry	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Test statistic	Average Leverage	Average Maturity Mismatch	Average Size	Average Weekly Volatility
FARM	0.003	0.042	0.017	4.944	98.718	2.090	-0.104	9.306	0.017
OG	0.002	0.045	-0.622	8.194	745.065	2.210	-0.065	13.634	0.019
MNG	0.002	0.050	-0.059	6.515	323.208	2.068	-0.129	12.515	0.020
MNGS	0.002	0.050	-0.685	7.840	661.094	1.893	-0.118	12.344	0.020
UTL	0.002	0.022	-1.393	14.076	3407.663	3.777	0.018	15.127	0.009
CTN	0.001	0.047	0.820	10.376	1491.364	3.242	-0.087	12.358	0.018
WP	0.001	0.046	0.140	10.577	1501.788	2.646	-0.133	9.386	0.017
MNR	0.002	0.046	-0.139	7.194	461.479	3.015	-0.017	11.889	0.017
MTL	0.002	0.047	-0.004	8.423	768.285	2.419	-0.039	12.693	0.018
FMTL	0.003	0.032	-0.270	7.401	513.722	3.166	-0.068	11.554	0.012
MCN	0.002	0.035	0.134	8.312	739.181	2.907	0.012	12.969	0.013
CPT	0.002	0.028	-0.333	5.696	201.478	1.944	-0.408	14.125	0.011
ELT	0.002	0.031	-0.182	6.082	251.606	2.806	-0.146	11.755	0.013
MOTP	0.002	0.041	-0.077	7.202	461.815	3.643	0.079	13.971	0.015
OTPE	0.003	0.029	-0.456	6.768	392.682	4.181	-0.092	12.932	0.011
FURN	0.001	0.043	0.186	6.377	301.572	2.389	-0.091	9.760	0.016
MMFG	0.002	0.023	-1.061	10.388	1543.471	1.872	-0.351	11.884	0.009
FB	0.002	0.018	-1.470	16.577	5041.553	3.085	-0.007	13.639	0.007
TXT	0.002	0.048	0.512	9.762	1221.857	2.301	0.032	9.353	0.016
LEA	0.002	0.034	0.033	7.080	435.013	2.040	-0.128	11.802	0.013
PAP	0.002	0.026	-0.315	6.502	330.702	3.020	-0.012	12.284	0.011
PRT	0.001	0.036	-0.219	7.543	544.213	3.795	-0.020	10.000	0.013
PECO	0.002	0.030	-0.790	8.556	871.832	2.036	-0.066	14.678	0.013
CMC	0.002	0.021	-0.899	10.747	1652.280	2.287	-0.169	14.437	0.009
PLA	0.002	0.037	0.003	8.667	838.946	5.228	-0.044	11.010	0.013
WST	0.002	0.024	-0.627	8.772	911.360	3.178	-0.046	13.036	0.009
MOTD	0.003	0.034	0.597	12.567	2428.518	3.729	0.228	10.772	0.013
FBST	0.002	0.029	-0.085	4.822	87.513	2.829	-0.071	11.636	0.012
GMST	0.001	0.024	-0.432	6.955	428.286	2.636	-0.035	12.809	0.010
OR	0.002	0.028	-0.088	6.933	404.845	2.429	-0.062	13.376	0.011
ARTP	0.003	0.053	0.237	6.418	311.035	14.286	-0.113	12.868	0.021
RLTP	0.004	0.037	-0.237	5.113	122.515	2.252	-0.022	12.322	0.015
WATP	0.001	0.039	-0.477	8.143	714.683	2.364	0.007	12.059	0.015
TRTP	0.002	0.037	0.129	4.812	87.517	2.974	-0.014	10.007	0.015
PTP	0.003	0.038	-0.575	8.871	935.201	2.934	0.011	13.045	0.014
OTP	0.001	0.029	0.010	5.556	170.659	2.581	-0.111	11.612	0.012
PUB	0.002	0.027	-0.490	6.481	341.708	2.019	-0.576	12.974	0.011
MP	0.003	0.036	0.315	11.875	2068.042	2.611	-0.071	11.674	0.014
FED	0.001	0.044	0.949	18.025	5992.016	18.198	-0.009	17.621	0.016

(Continued)

Appendix 3 – continued

Industry	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera Test statistic	Average Leverage	Average Maturity Mismatch	Average Size	Average Weekly Volatility
INV	0.002	0.038	0.042	9.411	1073.952	16.191	0.007	15.706	0.015
INS	0.002	0.029	-0.393	16.981	5123.029	9.868	-0.069	16.017	0.011
FUND	0.002	0.032	-0.562	9.530	1147.168	5.509	0.611	12.482	0.012
RE	0.001	0.045	-0.280	8.560	815.830	3.320	0.041	13.426	0.017
RL	0.002	0.043	0.064	9.785	1203.079	4.489	0.005	12.002	0.016
LGL	0.005	0.044	0.198	6.043	246.065	3.843	0.014	9.076	0.017
CPTS	0.002	0.029	-0.155	6.112	255.473	2.441	-0.248	12.042	0.012
MTEC	0.002	0.028	-0.229	6.901	402.965	3.578	-0.118	12.355	0.012
ADM	0.002	0.028	0.046	6.448	310.859	3.345	-0.147	11.499	0.011
WAST	0.002	0.024	-0.688	9.546	1168.916	3.217	-0.004	11.001	0.010
EDU	0.000	0.043	-0.037	6.290	282.884	2.103	-0.391	9.858	0.016
AH	0.002	0.027	-1.024	10.741	1675.196	2.624	-0.186	11.342	0.010
HOSP	0.002	0.039	-0.553	7.137	479.051	38.601	-0.018	11.291	0.015
NURS	0.001	0.040	-0.632	9.112	1017.667	3.746	-0.049	9.769	0.015
SA	0.004	0.051	1.533	18.060	6170.899	7.525	-0.029	7.321	0.018
ART	0.001	0.041	0.919	15.928	4454.740	2.620	-0.181	9.237	0.014
RCT	0.002	0.040	-0.015	7.748	588.978	5.871	-0.028	10.557	0.015
ACM	0.002	0.048	0.528	10.230	1394.843	4.480	-0.079	11.903	0.017
FDP	0.002	0.028	0.053	5.461	158.581	4.072	-0.136	10.015	0.012
OS	0.002	0.031	-0.091	7.059	431.334	6.428	-0.023	9.923	0.012

Appendix 4:

Input-Output Accounts and Constructed Tables

Table A4.1: MAKE Table (2012)

This table is extracted from the Make table (2012) of 73 commodities by 71 US industries, provided by the Bureau of Economic Analysis (BEA). Industries are shown in rows and commodities are presented in columns. Each element shows the value of the commodity in the corresponding column produced by the industry in the corresponding row. The Total Industry Output is the sum of all entries in a row and the Total Commodity Output is the sum of all entries in a column.

(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	395278	3741	0	…	0	0	0	400924
113FF	Forestry, fishing, and related activities	14	45445	0	…	0	0	0	46377
211	Oil and gas extraction	0	0	273868	…	0	0	0	341268
…	…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0	0	0	…	0	0	0	97995
GSLG	State and local general government	558	3257	0	…	0	4553	0	1982000
GSLE	State and local government enterprises	0	0	0	…	82544	0	0	264528
	Total Commodity Output	395976	53391	274708	…	84135	11389	2906	28663246
	Total Commodity Supply [1]	446422	69554	609789	…	84135	117896	294848	31424569

[1] To account for the actual total supply of a commodity, we add the Total Commodity Supply as the last row of this table. This shows the total output of commodity c produced by all industries and is calculated as the sum of all entries in commodity c column in the Make table, plus other components which increase its actual supply in the economy such as imports or changes in inventories.

Table A4.2: USE Table (2012)

This table is extracted from the Use table (2012) of 73 commodities by 71 US industries and Final users, provided by the Bureau of Economic Analysis (BEA). Commodities are shown in rows and industries are presented in columns. Each element shows the value of the commodity in the corresponding row that the industry in the corresponding column uses as the input for its production. The Total Commodity Output is the sum of all entries in a row and the Total Industry Output is the sum of all entries in a column.

(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	68231	560	0	…	3	2317	0	328943	66304	…	0	67033	395976
113FF	Forestry, fishing, and related activities	23929	4742	0	…	41	1533	0	57259	5231	…	0	-3867	53391
211	Oil and gas extraction	0	0	21797	…	1189	0	8409	598886	0	…	0	-324178	274708
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
GSLE	State and local government enterprises	0	4	0	…	265	4074	1006	22369	61765	…	0	61765	84135
Used	Scrap, used and second-hand goods	-44	0	0	…	0	0	0	24444	47979	…	0	-13055	11389
Other	Noncomparable imports and rest-of-the-world adjustment	729	55	778	…	1047	0	0	118565	-74655	…	0	-115659	2906
	Total Intermediate	249436	12066	73836	…	48250	622222	145208	12507991	0	…	0	0	0
V001	Compensation of employees	27584	20292	34983	…	56694	1180884	94071	8618544	0	…	0	0	0
V002	Taxes on production and imports, less subsidies	-1381	1609	31468	…	-5124	0	-17402	1074019	0	…	0	0	0
V003	Gross operating surplus	125286	12410	200982	…	-1825	178895	42651	6462692	0	…	0	0	0
	Total Value Added	151489	34311	267432	…	49745	1359779	119320	0	0	…	0	16155255	0
	Total Industry Output	400924	46377	341268	…	97995	1982000	264528	0	11050627	…	30977	0	28663246

Table A4.3: SHARE Table (2012)

This table is extracted from the constructed SHARE table (2012), showing the contribution of industries in the supply of commodities. Industries are shown in rows and commodities are displayed in columns. Each element shows the percentage of the total supply of the commodity in the corresponding column accounted for 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	88.54%	5.38%	0.00%	…	0.00%	0.00%	0.00%
113FF	Forestry, fishing, and related activities	0.00%	65.34%	0.00%	…	0.00%	0.00%	0.00%
211	Oil and gas extraction	0.00%	0.00%	44.91%	…	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	0.12%	4.68%	0.00%	…	0.00%	3.86%	0.00%
GSLE	State and local government enterprises	0.00%	0.00%	0.00%	…	98.11%	0.00%	0.00%

Table A4.4: REVSHARE Table (2012)

This table is extracted from the constructed REVSHARE table (2012), showing the trade flows between US industries. The element of row i, column j ($REVSHARE_{ij}$) displays the total value of goods that industry i sells to industry j.

(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	61702	751	0	…	5	2145	2
113FF	Forestry, fishing, and related activities	15639	3098	2	…	29	1020	29
211	Oil and gas extraction	441	11	11651	…	622	1956	4092
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	177	5	39	…	117	2838	158
GSLG	State and local general government	1520	255	273	…	366	9474	1593
GSLE	State and local government enterprises	955	33	268	…	928	11430	1584

Table A4.5: CUST Table (2012)

This table is extracted from the constructed CUST table (2012), showing the customer role of an industry to each of the other industries in the economy. The element of row i and column j ($CUST_{ij}$) shows the importance of industry j as a customer of industry i, measured by 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	0.154	0.002	0.000	…	0.000	0.005	0.000
113FF	Forestry, fishing, and related activities	0.337	0.067	0.000	…	0.001	0.022	0.001
211	Oil and gas extraction	0.001	0.000	0.034	…	0.002	0.006	0.012
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0.002	0.000	0.000	…	0.001	0.029	0.002
GSLG	State and local general government	0.001	0.000	0.000	…	0.000	0.005	0.001
GSLE	State and local government enterprises	0.004	0.000	0.001	…	0.004	0.043	0.006

Table A4.6: SUPP Table (2012)

This table is extracted from the constructed SUPP table (2012), showing the supplier role of an industry to each of the other industries in the economy. The element of row i and column j ($SUPP_{ij}$) shows the importance of industry i as a customer of industry j, measured by 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	0.223	0.023	0.000	…	0.000	0.001	0.000
113FF	Forestry, fishing, and related activities	0.056	0.096	0.000	…	0.000	0.001	0.000
211	Oil and gas extraction	0.002	0.000	0.107	…	0.006	0.001	0.017
…	…	…	…	…	…	…	…	…
GFE	Federal government enterprises	0.001	0.000	0.000	…	0.001	0.002	0.001
GSLG	State and local general government	0.005	0.008	0.003	…	0.003	0.005	0.007
GSLE	State and local government enterprises	0.003	0.001	0.002	…	0.009	0.006	0.007

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Figure 1: Tail risk connectedness network between US industries

This graph shows the tail risk connectedness between 59 US industries estimated from the LASSO quantile regression. Thick black arrows show the spillovers with the absolute values of the estimated coefficient greater than 0.8. Medium dark grey arrows show the spillovers with the absolute values of the estimated coefficient from 0.4 to 0.8. Small light grey arrows show the spillovers with the absolute values of the estimated coefficient less than 0.4. The direction of an arrow shows the direction of the pairwise spillover.

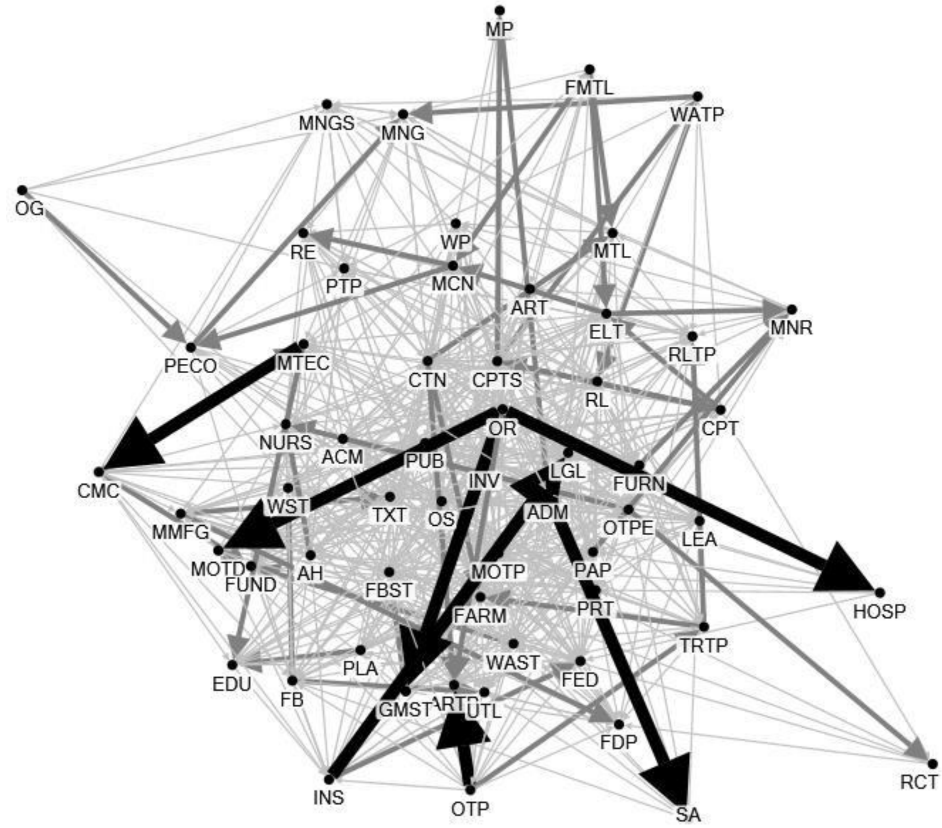
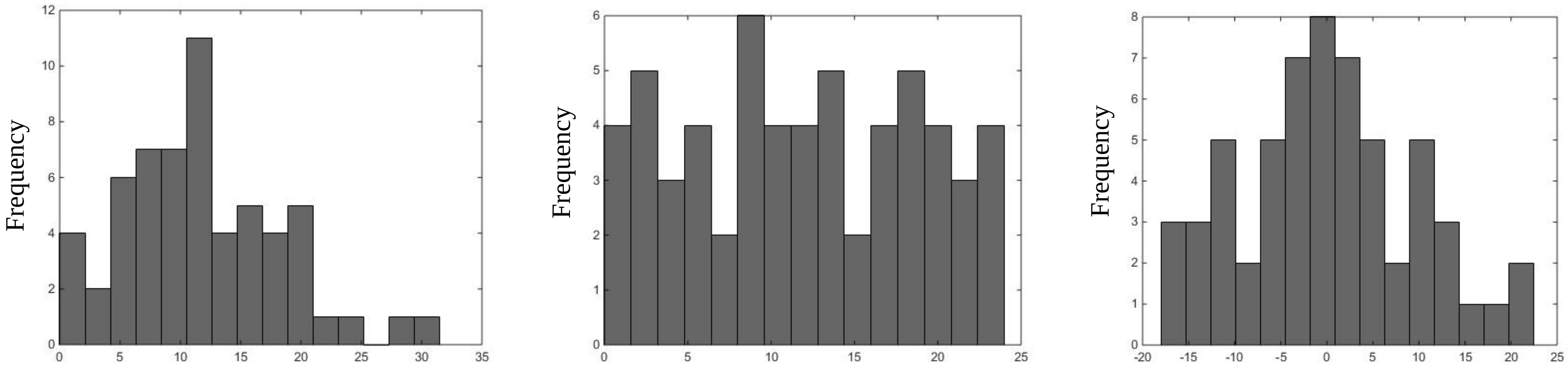


Figure 2: Distributions of the degree measures of 59 US industries

This figure shows the histograms of the tail risk connectedness degree measures of 59 US industries, calculated from the pairwise tail risk spillovers estimated from the LASSO quantile regression. Panel 1, 2 and 3 plots the out-degree, in-degree, and net-degree, respectively.

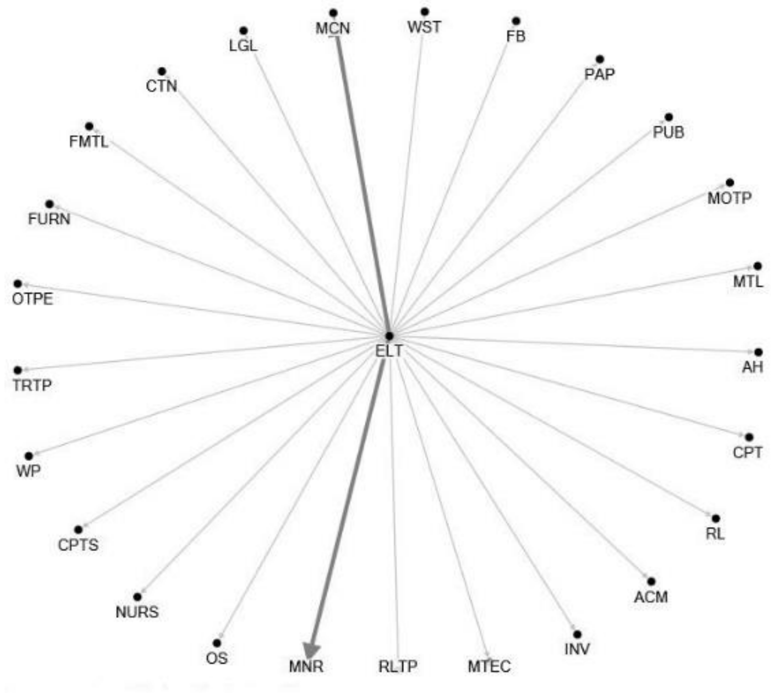


Out-degree In-degree Net-degree

Figure 3: Tail risk spillover network of ELT industry

This graph shows the tail risk spillover network of the Electrical equipment, appliances, and components (ELT) industry. ELT takes the role of tail risk transmitter in Panel A and tail risk receiver in Panel B. Dark grey arrows show the spillovers with the absolute values of the estimated coefficient from 0.4 to 0.8. Light grey arrows show the spillovers with the absolute values of the estimated coefficient smaller than 0.4. The direction of an arrow shows the direction of the pairwise spillover.

Panel A



Panel B

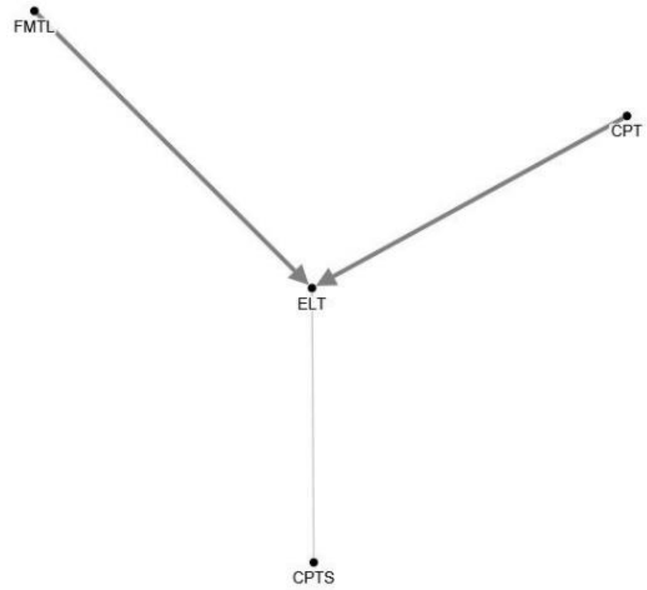


Table 1: Tail risk connectedness degree measures - Top and bottom industries

This table shows the top and bottom industries for the tail risk degree measures, including the out-degree, in-degree and net-degree.

		Industry Name	Abbre-viation	Value of sorting measure
Out-degree	Highest	Construction	CTN	31
		Other retail	OR	28
		Electrical equipment, appliances, and components	ELT	25
		Computer systems design and related services	CPTS	23
		Furniture and related products	FURN	20
	Lowest	Amusements, gambling, and recreation industries	RCT	3
		Support activities for mining	MNGS	2
		Wholesale trade	WST	2
		Food services and drinking places	FDP	2
		Motion picture and sound recording industries	MP	1
In-degree	Highest	Computer systems design and related services	CPTS	23
		Printing and related support activities	PRT	23
		Waste management and remediation services	WAST	23
		Other transportation equipment	OTPE	23
		Other services, except government	OS	21
	Lowest	Hospitals	HOSP	2
		General merchandise stores	GMST	1
		Chemical products	CMC	1
		Social assistance	SA	1
		Oil and gas extraction	OG	0

(continued)

Table 1: continued

		Industry Name	Abbre-viation	Value of sorting measure
Net-degree	Highest	Electrical equipment, appliances, and components	ELT	22
		Other retail	OR	20
		General merchandise stores	GMST	18
		Construction	CTN	16
		Other transportation and support activities	OTP	13
	Lowest	Federal Reserve banks, credit intermediation, and related activities	FED	-14
		Funds, trusts, and other financial vehicles	FUND	-14
		Other transportation equipment	OTPE	-16
		Food services and drinking places	FDP	-16
		Wholesale trade	WST	-18

Table 2: Summary statistic of the business linkages between US industries

This table shows the summary statistics of the business linkages of 1,711 industry pairs based on the relationship variables ($CUST_{ji}$, $SUPP_{ij,}$ $CUST_{ij}$, and $SUPP_{ji}$) at different thresholds ranging from 1% to 10% (by columns). Pairs with weak linkage are pairs with all four relationship variables smaller than the threshold. Pairs with at least one main customer (supplier) are pairs with at least one *CUST* (*SUPP*) variable larger than the threshold. Pairs with at least one main customer or supplier are pairs with at least one of the four relationship variables larger than the threshold.

	Business linkage threshold (percent)									
	1	2	3	4	5	6	7	8	9	10
Pairs with weak linkage	1106	1361	1489	1549	1588	1622	1640	1654	1663	1670
Pairs with at least one main customer	359	178	101	72	56	46	39	30	25	22
Pairs with at least one main supplier	506	283	179	124	93	64	50	39	31	24
Pairs with at least one main customer or main supplier	605	350	222	162	123	89	71	57	48	41

Table 3: The impact of business linkages on tail risk spillovers

This table shows the impact of business linkages and other industry specific variables on the tail risk spillover from industry i to industry j obtained from the LASSO quantile regression. $CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. Lev, MM, $Size$, and Vol represents the leverage, maturity mismatch, size, and volatility of the industries, respectively. The first line of each regression shows the estimated coefficients, and the second line shows the corresponding t-statistics (in brackets).

$Const$	$CUST_{ji}$	$SUPP_{ij}$	$CUST_{ij}$	$SUPP_{ji}$	Lev_i	Lev_j	MM_i	MM_j	$Size_i$	$Size_j$	Vol_i	Vol_j	$R\ squared$
0.019***	0.425***	0.150	0.408***	-0.041									2.05%
(10.478)	(4.588)	(1.680)	(4.311)	(-0.418)									
0.027	0.402***	0.120	0.429***	-0.012	-0.047	0.022	-0.016	0.003	0.070	-0.039	-1.402**	0.586	2.52%
(1.255)	(4.330)	(1.337)	(4.505)	(-0.118)	(-1.503)	(0.664)	(-1.408)	(0.295)	(0.752)	(-0.401)	(-2.422)	(1.015)	

Table 4: The impact of business linkages on tail risk spillovers: normal and distress time

This table shows the impact of business linkages and other industry specific variables on the tail risk spillover from industry i to industry j obtained from the LASSO quantile regression in normal and distress time. $CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. Lev, MM, $Size$, and Vol represents the leverage, maturity mismatch, size, and volatility of the industries, respectively. The first line of each regression shows the estimated coefficients, and the second line shows the corresponding t-statistics (in brackets).

$Const$	$CUST_{ji}$	$SUPP_{ij}$	$CUST_{ij}$	$SUPP_{ji}$	Lev_i	Lev_j	MM_i	MM_j	$Size_i$	$Size_j$	Vol_i	Vol_j	$R\ squared$
Panel A: Normal time													
0.020***	0.331***	0.142	0.330***	-0.035									1.27%
(10.778)	(3.512)	(1.587)	(3.456)	(-0.371)									
0.038	0.302***	0.098	0.360***	0.005	-0.050*	0.007	-0.016	-0.001	0.075	-0.079	-1.998***	0.556	1.84%
(1.545)	(3.195)	(1.076)	(3.774)	(0.055)	(-1.651)	(0.233)	(-1.444)	(-0.112)	(0.737)	(-0.778)	(-2.686)	(0.758)	
Panel B: Distress time													
0.019***	0.305***	0.191**	0.320***	-0.018									1.30%
(10.127)	(3.353)	(2.090)	(3.310)	(-0.193)									
0.019	0.278***	0.170*	0.336***	0.009	-0.121***	0.017	-0.005	-0.002	0.177*	-0.080	-0.839**	0.484	1.93%
(0.885)	(3.042)	(1.825)	(3.485)	(0.094)	(-2.921)	(0.410)	(-0.391)	(-0.126)	(1.685)	(-0.756)	(-2.175)	(1.275)	

Table 5: The influence of business linkages on tail risk spillovers: different tail risk levels

This table shows the impact of business linkages and other industry specific variables on the tail risk spillover from industry i to industry j obtained from the LASSO quantile regression. The tail risk of an industry is captured by 1% and 10% VaR, respectively. $CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. Lev, MM, $Size$, and Vol represents the leverage, maturity mismatch, size, and volatility of the industries, respectively. The first line of each regression shows the estimated coefficients, and the second line shows the corresponding t-statistics (in brackets).

$Const$	$CUST_{ji}$	$SUPP_{ij}$	$CUST_{ij}$	$SUPP_{ji}$	Lev_i	Lev_j	MM_i	MM_j	$Size_i$	$Size_j$	Vol_i	Vol_j	$R\ squared$
							1% VaR						
0.018***	0.540***	0.002	0.443***	-0.031									0.95%
(6.260)	(3.716)	(0.017)	(2.962)	(-0.224)									
-0.032	0.525***	-0.014	0.445***	-0.019	-0.065	0.051	-0.020	-0.003	0.122	0.111	-0.165	1.645*	1.24%
(-0.922)	(3.599)	(-0.094)	(2.946)	(-0.135)	(-1.352)	(1.045)	(-1.142)	(-0.198)	(0.809)	(0.761)	(-0.185)	(1.785)	
							10% VaR						
0.020***	0.708***	-0.017	0.373***	-0.105									3.43%
(12.375)	(8.554)	(-0.216)	(4.709)	(-1.397)									
0.015	0.687***	-0.047	0.390***	-0.083	-0.039	0.015	-0.020**	0.008	0.075	0.019	-1.230**	0.751	4.05%
(0.819)	(8.277)	(-0.576)	(4.927)	(-1.077)	(-1.425)	(0.567)	(-2.146)	(0.838)	(0.930)	(0.229)	(-2.502)	(1.484)	

Table 6: The influence of business linkages on tail risk spillovers: closely-linked industries

This table shows the impact of business linkages and other industry specific variables on the tail risk spillover between closely-linked industries obtained from the LASSO quantile regression. The main business linkage cut-off thresholds are 1%, 2%, and 3%, respectively. $CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. Lev, MM, $Size$, and Vol represents the leverage, maturity mismatch, size, and volatility of the industries, respectively. The first line of each regression shows the estimated coefficients, and the second line shows the corresponding t-statistics (in brackets).

$Const$	$CUST_{ji}$	$SUPP_{ij}$	$CUST_{ij}$	$SUPP_{ji}$	Lev_i	Lev_j	MM_i	MM_j	$Size_i$	$Size_j$	Vol_i	Vol_j	$R\ squared$
1% threshold													
0.027***	0.385***	0.100	0.370***	-0.071									2.78%
(6.884)	(3.724)	(0.884)	(3.398)	(-0.675)									
0.005	0.345***	0.102	0.381***	-0.019	-0.049	-0.034	-0.041	-0.040	-0.024	0.010	-0.923	2.541**	3.66%
(0.110)	(3.248)	(0.873)	(3.434)	(-0.176)	-0.782	-0.544	-1.389	-1.278	-0.121	0.053	-0.819	2.189	
2% threshold													
0.036***	0.338***	0.060	0.354***	-0.125									2.82%
(5.873)	(2.701)	(0.508)	(2.875)	(-1.005)									
0.019	0.260**	0.048	0.389	-0.010	-0.011	0.035	-0.079	-0.056	-0.016	-0.317	-0.870	4.350***	4.81%
(0.282)	(2.037)	(0.384)	(3.089)	(-0.077)	-0.119	0.373	-1.621	-1.163	-0.055	-1.052	-0.524	2.735	
3% threshold													
0.038***	0.322**	0.038	0.353***	-0.110									3.69%
(4.708)	(2.537)	(0.290)	(2.956)	(-0.886)									
-0.044	0.259*	0.009	0.380***	-0.043	0.020	0.034	-0.054	-0.039	0.257	-0.107	0.073	3.970*	4.90%
(-0.468)	(1.942)	(0.067)	(3.036)	(-0.326)	0.161	0.280	-0.916	-0.678	0.605	-0.245	0.036	1.883	

Table 7: The influence of business linkages on tail risk spillovers: nonfinancial industries

This table shows the impact of business linkages and other industry specific variables on the tail risk spillover between nonfinancial industries. $CUST_{ji}$, $SUPP_{ij}$, $CUST_{ij}$, and $SUPP_{ji}$ represent the customer role of i to j, the supplier role of i to j, the customer role of j to i, and the supplier role of j to i, respectively. Lev, MM, $Size$, and Vol represents the leverage, maturity mismatch, size, and volatility of the industries, respectively. The first line of each regression shows the estimated coefficients, and the second line shows the corresponding t-statistics (in brackets).

$Const$	$CUST_{ji}$	$SUPP_{ij}$	$CUST_{ij}$	$SUPP_{ji}$	Lev_i	Lev_j	MM_i	MM_j	$Size_i$	$Size_j$	Vol_i	Vol_j	$R\ squared$
0.018***	0.385***	0.546***	0.259**	-0.063									2.71%
(8.560)	(3.621)	(3.736)	(2.402)	(-0.465)									
0.018	0.360***	0.481***	0.295***	-0.015	-0.041	0.024	-0.015	-0.010	0.078	-0.052	-0.921	0.589	3.02%
(0.633)	(3.314)	(3.261)	(2.719)	(-0.108)	(-1.112)	(0.666)	(-0.925)	(-0.661)	(0.583)	(-0.412)	(-1.365)	(0.868)	