International tail risk connectedness: network and determinants

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Abstract

We construct a complete network of directional tail risk connectedness for 32 countries within a Least Absolute Shrinkage and Selection Operator (LASSO) Quantile Regression framework. In addition to highlighting the network's essential features, including the key drivers and receivers of tail risk, we reveal some striking new network determinants. These include the predominant role of economy size, as well as the negative net impact of economic linkages such as trade and capital flows in addition to capital stocks on cross-country tail risk connectedness.

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1. Introduction

In the wake of the various global financial crises over the last two decades, economic and financial shocks on the international stage have become a significant concern for investors and regulators. Modern portfolio management tools rely heavily upon the assumed normal distribution of market returns, yet an abundance of evidence suggests a more leptokurtic reality. As measured through the lens of Value-at-Risk (hereafter VaR) and Expected Shortfall, tail risk has become an enduring feature of investment performance and modern financial markets.

Investors who favor holding internationalized portfolios may be particularly concerned with inter-country tail risk. When they invest across several markets, there is a real need to understand the directional nature, depth, and breadth of tail risk connectedness existing between these. The importance of this further compounds when we note that a surge in correlations between markets often occurs during times of distress (Ang and Chen, 2002; Kenourgios et al., 2011). Therefore, information on the cross-country tail risk transmission is vital in determining the total risk inherent in portfolios with a globalized profile.

In this study, our investigation applies the Least Absolute Shrinkage and Selection Operator (LASSO) Quantile Regression framework in the spirit of Belloni and Chernozhukov's (2011) and Hautsch et al. (2015) to illustrate the tail risk network existing between 32 OECD (Organisation for Economic Co-operation and Development) countries. Our construction holds several critical advantages over attempts made by other scholars to characterize similar networks. First, our network features directional tail linkage, which allows us to trace the path of risk from the origin to the target countries. Second, we estimate tail risk linkage between these economic pairings while accounting for the other countries' influence in the network. Failure to adequately account for this has been an enduring criticism of most studies that attempt to trace out tail risk networks to date. Third, our network offers a practical application by capturing the predictability of tail risk; to do this, we assess the extent to which events in one market foreshadow those in another.

Our findings also allow us to identify some notable characteristics within the network relevant to international investors. For instance, the US and Canadian markets are the major tail risk drivers internationally, while Korea and Finland are the primary receivers. Our analysis also reveals some interesting patterns. We document the resilience of the US market to global shocks. We also show how Japan is a significant shock transmission hub as it exhibits large displays of both inward and outward linkage.

Another contribution which we make is to identify factors that determine the characteristics of a tail risk network. Using a second stage regression, we account for the magnitude of the tail risk link between countries by regressing the linkage coefficients for country pairs on a range of bilateral trade and capital ties, as well as on corresponding macroeconomic variables. We can explain a large proportion of the variation in the linkage coefficients and quantify each determinant's contribution using the regression's explanatory power. Our findings provide persuasive evidence for the dominating role that economy size can play in driving tail risk spillover. Moreover, we capture a novel relationship between economic linkage and tail risk spillover. When controlling for economy size, we find that economic ties such as the trade-capital imbalance, and the role imbalance between the country pair are negatively related to their spillover. Our results are robust when we employ both full sample and rolling window analysis under varying tail threshold levels, even when we group Eurozone countries together and include BRICS countries.

Our paper is structured as follows; in the first section, we deal with the literature surrounding tail risk connectedness and its determinants. We then move on to rationalize our methodological choice and explain our sourcing and use of the data. In section four, we discuss and interpret our results. The penultimate section details how we carry out our robustness checks, and in the final part, we conclude the paper.

2. Literature review

2.1. Tail risk connectedness network of international stock markets

The literature abounds with studies which report the profound impact of fat tails in stock return distribution on expected returns and risk management (see Bali et al., 2009; Bollerslev and Todorov, 2011; Huang et al., 2012; Kelly and Jiang, 2014; Chabi-Yo et al., 2018; Harris et al., 2019; among others). As a result, the monitoring and predicting of tail risk play a central strategic role in risk management. More importantly, the fact that stock returns co-move and that this becomes stronger during tail events (Ang and Chen, 2002) emphasizes the need to model tail risk for the whole stock network. In writing about this, authors use the terms spillover or contagion to refer to tail co-movement between entities. Numerous studies in the literature have documented the contagion effects among international stock markets. For example, Kenourgios et al. (2011) report a substantial global contagion effect, as evidenced by jumps in stock markets' correlations during periods of acute financial crisis over the last few decades. Another useful example is Madaleno and Pinho's (2012) demonstration of contagion between international stock markets during crisis periods using continuous wavelet analysis.

In addition to examining the changes in correlation, another approach to modelling tail linkages is through co-exceedance, i.e., an event where stock indices for a pair or a group of markets drop below a tail threshold. Notable examples of this approach appear in Bae et al. (2003), Hartmann et al. (2004), Christiansen and Ranaldo (2009), Beine et al. (2010), and Cappiello et al. (2014). In these studies, the tendency for co-exceedance and its variation is captured and explained using a range of macroeconomic variables. A potential disadvantage of this approach is that a co-exceedance event does not reflect the direction of the spillover. To account for this, directional tail risk spillover is usually investigated using Granger causality analysis; Hong et al. (2009) provide an excellent example of this method. However, their framework constructs networks using prior estimates of tail risk for individual assets; these estimations do not account for any tail risk spillover from the network.

Countries are not the exclusive focus of tail risk network analysis; other economic aggregation levels are examinable using this approach. At the industry level, the mapping of tail risk interrelationships is confined mainly to the financial sector. Adams et al. (2014) investigate the extent of interdependencies of tail risk between banks, hedge funds, and insurance companies. They show that commercial banks and hedge funds, in particular, play a pivotal role in generating tail risk transmission between financial institutions. In a similar study, Wang et al. (2017) map tail risk connectivity between different sectors, namely banking, diversified financial institutes, insurance, and real estate, using Hong et al.'s (2009) Granger causality framework. Chiu et al. (2015) examine co-exceedances between the financial and other industries in the US economy, noting that the former induces considerable spillover upon the latter. The effect is determined by industry-specific characteristics such as competition, debt financing, and valuation levels. Wang et al. (2018) investigate the cross-sectoral connectedness between banks, security firms, and insurers and find that when systemic events occur, cross-sectoral spillover may be more prominent than inter-sectoral spillover, posing a significant risk to the stability of the financial system. Evidence for the tail risk linkage between non-financial sectors can be found in Pouliasis et al. (2017) and Pouliasis et al. (2018), among others.

For firm-level studies, the focus mostly appears to remain within the financial services industry. Notable examples of these include Billio et al. (2012), Jin and De Simone (2014), Hautsch et al. (2014), Balla et al. (2014), Betz et al. (2016), and Corsi et al. (2018). Unsurprisingly, firms operating within the financial sector are inextricably linked, and the risk of systematic collapse is very high. Many financial firms are too connected to fail (see, for example, Härdle et al., 2016). Xu et al. (2019) show that financial institutional interconnectedness significantly influences each entity's conditional tail risk. Moreover, Fang et al. (2018) find evidence that the spillover from other firms is, in fact, the main driving factor of a financial firm's tail risk.

2.2. Determinants of tail risk connectedness between countries

Capital flow is perhaps the most apparent factor in influencing tail risk connectedness between international stock markets. This is not surprising as numerous studies have demonstrated that capital flows between countries can predict stock returns (Froot et al., 2001; Richards, 2005; Froot and Ramadoraj 2008). Financial contagion is the primary concern of many economists when considering the liberalization of capital flows across borders (Sachs et al., 1996; Radelet and Sachs, 1998; Krugman, 1998). Kindleberger and Aliber (2011) famously described cross-border capital flow as panics or manias. However, Stulz (1999) suggests that the evidence used to support this view is somewhat weak.

Another factor that may drive tail risk connectedness across stock markets is the degree of trade linkage between countries. The literature provides plenty of examples of how imports and exports influence the co-movement of international stock returns. For instance, Bracker et al. (1999) find evidence that the level of imports significantly affects contemporaneous co-movement across markets; Johnson and Soenen (2002) echo this point. Forbes and Chinn (2004) show that bilateral trade flows significantly affect return spillovers in both stock and bond markets between countries. Taveres (2009) also report the nontrivial positive impact of bilateral trade intensity on correlations between stock returns globally.

Evidence of the influence of business linkage on tail risk connectedness appears in Claessens and Forbes (2001), Forbes (2002), Kali and Reyes (2010). Forbes (2002) is notable among these in making an explicit connection between trade linkage and the vulnerability of countries to an international crisis. Here, the impact of trade linkage on cross-border contagion decomposes along three distinct lines, namely, the effects of competitiveness, the income level, and the presence of cheap-imports. Additionally, there is a case to say that the evidence for financial linkage is more robust than it is for trade for causing contagion, as reported in Kaminsky and Reinhart (2000). However, their study also acknowledges that it may be difficult to distinguish between the two.

Besides capital and trade linkage, a range of macroeconomic factors (stock market volatility, interest rates, exchange rates, inflation, financial liberalization, among others) appear to affect tail risk connectedness on the international equity markets, see Bae et al. (2003), Christiansen and Ranaldo (2009), Beine et al. (2010), Cappiello et al. (2014). The majority of these studies investigate how macroeconomic conditions affect the co-exceedances between markets over time. In contrast, the cross-sectional impact of macroeconomic factors on tail risk linkage receives comparatively little attention in the literature. Forbes (2002) shows how currency values and interest rate levels of crisis-generating countries affect the impact which trade linkage can have upon a contagion episode. Beine et al. (2010) also report that exchange rate fluctuation and the degree of financial liberalization of the less open economy in a country pair determines their co-exceedance level.

Our review of the literature reveals several critical gaps. First, the literature lacks studies examining the determinants of international tail risk investigate the directional spillover between country pairs, when this is conditional on the influence of the other countries within the network. Second, studies in this area tend to focus on concurrent tail events via measures like correlation jumps or co-exceedance, instead of using the tail risk of one country to predict that in others. While concurrent tail risk might be useful in portfolio construction that optimizes on an ex-ante basis the extreme downside risk-return relationship, tail risk predictability is essential for practitioners in planning the response to crisis events on the financial markets. Third, no study has yet examined the impact of the range of factors, including trade and capital linkages, stock market performance, and macroeconomic variables on international tail risk spillover simultaneously, and measured their corresponding contributions to explaining the degree of the transmission. For investors, identifying factors that may drive the tail risk network and the direction of impact is not enough; understanding their relative importance would be essential to form meaningful investment decisions. We attempt to address all of these issues in this research.

3. Methodology and data

3.1. Modelling the tail risk network through LASSO Quantile Regression

Modelling tail risk using quantile regression has a thorough grounding in prior research; notable examples of relevant work includes Giglio et al. (2016) and Adrian and Brunnermeier (2016). To map the connectedness within our network, we conduct our investigation in the spirit of Hautsch et al. (2015). They employ Belloni and Chernozhukov's (2011) LASSO Quantile Regression technique to investigate the tail risk linkages among US financial firms. Our approach demonstrates how the tail risk of stock returns for country i is determined to some extent by lags of itself, the macroeconomic variables of that country, and the loss exceedance in other connected countries. The main benefit accompanying this approach is that it considers the extent of tail risk connectedness between all countries in the system, rather than appraising this on an individual or pairwise basis.

Tail risk at time t for a country is represented by the VaR of its stock market returns during that period. This is the quantile which corresponds to the VaR significance level of the conditional distribution of stock returns for that country.

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

where $Q_{q,t}^{i}$ satisfies

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

In this instance, $VaR_{q,t}^{i}$ is the VaR for country i at the significance level q. $Q_{q,t}^{i}$ represents the q-quantile of the conditional distribution of returns X_t^i, for country i at time t. For our primary investigation, we utilize the 10% quantile; however, we expand our focus in the robustness checks to include other measurement thresholds. A point to note is that in order to facilitate interpretation of the tail risk spillover coefficients, we define VaR as an extreme negative return rather than the value of the loss (i.e., the absolute value of the negative return). Therefore, a lower VaR implies higher tail risk. As a result, the larger coefficient in the quantile regression of country i's return on country $j's$ extreme negative return implies a more serious tail risk spillover from j to i.

The equation expressing the quantile regression for country i can appear thus:

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

Here $\boldsymbol{M}_t^i$ represents the macroeconomic variables extant for country i available at time t. $\boldsymbol{E}_{t-1}^{-i}$ expresses the loss exceedance (risk event) for the remaining countries in the system at time $t-1$. X_{t-1}^i is the lagged stock return for country i. For country j, loss exceedance can be expressed as:

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

From Equation (3), the degree of tail risk spillover from country j to country i is given as the jth component of the coefficient $\boldsymbol{\gamma}^i$.

To cope with the problem of non-synchronicity, which arises from the mismatch of trading hours in the international equity markets, we use the lagged loss exceedance of countries j to estimate the quantile for i. In our sample, the opening time of the market in any country at day t is always later than the closing time on day $t-1$ of the other markets. For instance, the New York Stock Exchange, which closes at 21:00 GMT on a calendar day, is the last market to close. The first market to open in the next trading day is New Zealand's which begins trading at 22:00 GMT on the same calendar day. By using the lagged loss exceedance for other countries as explanatory variables, we are attempting to examine the predictability of tail risk, which is the key component of interest to decision-makers.

Our approach adopts that of Belloni and Chernozhukov's (2011) LASSO Quantile Regression method. Following this procedure, the l_1-penalized quantile regression identifies irrelevant regressors whose estimated coefficients have absolute values of less than a predetermined threshold. We restrict this value to 0.0001 likened to that which appears in Hautsch et al. (2015). The parameters $\tilde{\boldsymbol{\xi}}^i$ of the l_1-penalized quantile regression of variable X^i on a set of demeaned regressors $\boldsymbol{W}^i$ is estimated by minimizing the following cost function:

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

From Equation (5), $I(\cdot)$ is taken to represent the indicator function with a value equal to 1 when the statement contained within the brackets is true and 0 if it is not. K denotes the number of regressors held within $\boldsymbol{W}^i$, the k^{th} element of coefficient set $\boldsymbol{\xi}^i$ appears as ξ_k^i. Finally, $\widehat{\sigma_k}$ is the standard deviation of the k^{th} regressors, which can be estimated as:

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

The penalty parameter given in Equation (5) appears as λ, where a higher value indicates the possible removal of more variables. For each country, we use a value of λ which produces the best VaR for that country using Berkowitz et al. (2011) backtest. Full details of the process are available from the authors upon request. After removing the irrelevant regressors, in what we refer to as a post-LASSO procedure, we perform a normal quantile regression of a country's market return on all relevant regressors.

Estimating Equation (3) for all countries creates a system of equations. Since we regress the quantile of one market on the lagged exceedance of others, the estimated parameters of the system of equations can be obtained by estimating (3) for each country separately. From the estimated spillover coefficients, we create a tail risk connectedness matrix $\boldsymbol{A} = \{\mathrm{A_{ij}}\}$, with entry row i and column j. We take A_{ij} to equal the value $|\gamma_j^i|$ if the loss exceedance of country j is retained as a relevant regressor for country i's VaR by the LASSO Quantile Regression, and 0 if it is not.

We calculate several network statistics for each country. Specifically, tail risk In-strength for country i is the sum of the spillover coefficients of all other countries in the network toward country i. Similarly, tail risk Out-strength of i is the sum of the spillover coefficients from i to all other countries in the network. The Net-strength for country i shows the difference between the two and indicates whether a particular country is an emitter or receiver of tail risk.[1] We also calculate the sum of all non-zero entries in Matrix $\boldsymbol{A}$ to represent the total level of connectedness throughout the entire system.

[1] An alternative method is to use the number of non-zero spillover coefficients to and from country i to calculate the In-degree, Out-degree, and Net-degree. Using the value of the coefficients is more informative about the directed and weighted network and is recommended in the network topology literature (see, for example, Newman, 2004; Opsahl et al., 2010; among others). We thank the anonymous reviewer for this suggestion.

We examine OECD countries in our tail risk network. Table 1 provides a list of the stock market indices of countries employed in our research, for which returns are used as the dependent variable in Equation (3) and also to construct the loss exceedance in Equation (4). The macroeconomic variables which we include in our model (Equation 3) are inflation, interest rate, GDP growth and real effective exchange rate (REER).[2] GDP growth and inflation are expressed on a year-on-year basis, thus eliminating problems that seasonality could create. For interest rates, we choose those relating to ten-year government bonds. The reason for our choice of this maturity is that it captures both the government's long-term credit risk and the general condition of the interest rate environment. In some countries where ten-year government bond data is not available, we supplant this with rates that have maturities closest to this horizon. We extract the stock return and macroeconomic data from Bloomberg and DataStream. Details about the tickers of these series in the databases are available from the authors upon request.

In order to compensate for the lag in the publication of macroeconomic variables, we assume that the GDP, inflation rate, and REER is available only three months after the end date of the period to which it is associated. For example, the GDP of the 3rd quarter, the inflation and the REER of September in any given year are available from the 1st of January of the following year. We apply this reasoning to all macroeconomic variables except for interest rates which are publicly available on the day. Equation (3) is estimated using daily data. When a variable is recorded at lower frequencies, we use the most recently available value, accounting for the lags in its publication as mentioned above. Furthermore, using the augmented Dickey-Fuller (Dickey and Fuller, 1979) test, the GDP growth, interest rate, inflation, and REER series are

[2] This is the real value of a currency relative to a basket of other currencies. We justify our use of REER as opposed to bilateral exchange rates because our currencies are examined within a system rather than on a pairwise basis. REER is provided by the Bank for International Settlements and is available through Bloomberg.

integrated to the order of 1. We, therefore, use the change in these series as the macroeconomic variables in Equation (3).

Our decision to use OECD countries to investigate tail risk network determinants is driven in part by the quality and availability of capital stock and flow data. As a robustness measure, we extract data for our sample from the IMF Coordinated Portfolio Investment Survey (CPIS). Although this provides data for a broader range of countries, the survey does not carry information on capital flows. Previous studies provide no evidence to suggest that capital stock takes precedence over capital flow as a determinant of tail risk linkage between countries. We are therefore compelled to use the more restricted sample of countries where both data sets are available. Our data, in total, consists of 32 OECD countries over a period beginning in January 2000 and ending on December 2018.[3]

[Insert Table 1 about here]

3.2. Second stage Cross-sectional regressions: the determinants of tail risk connectedness

In order to further investigate the possible factors influencing the tail risk spillover between countries in our system, we perform cross-sectional regressions using the spillover coefficients across the connectedness matrix obtained in the first stage of our analysis. Specifically, we regress the spillover coefficient from market i to j on several controlling variables. We delineate these into four distinct groups, namely, the trade and capital linkages between the country pairs, their corresponding stock market risks and closing times, and their macroeconomic influencers. In the following section, we discuss each of these in detail.

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[3] We eliminate four OECD countries from our database due to the unavailability of data for macroeconomic variables. These are Israel, Luxembourg, Mexico, and Slovenia.

We retrieve the data on pairwise trade linkages between countries from the United Nations (UN) Comtrade database. The data includes annually observed values for the levels of both goods and services traded. Some inconsistencies with the data exist as imports reported by one country do not always agree with exports recorded by its trading partners. Such discrepancies can be explained by differences in the approach to valuation (for example an agent can use either the Cost, Insurance, and Freight, CIF,[4] or the Free On Board, FOB,[5] basis for the value of the goods traded), some variation may also be presented in the survey methods in different countries, exchange rates and timings to name but a few of the reasons. To counter the potential problems which could emerge as a result of this disparity, we take the average of the import and export values to represent the trade flow in either direction between country i and country j. The trade flow from i to j is the average of the export of i to j and the import of j from i, and vice versa. Flows can be then scaled according either to the size of the importer or exporter or the average between the two. As no definitive scaling method exists, we opt to account for the size of both countries in a pair by using their GDPs directly as control variables in the cross-sectional regression.

We can capture capital linkage between a pair of countries in one of two ways. First, the value of capital flows between the two countries during a period could represent the degree of linkage. Second, the total value of the capital investment which each country holds in the other at a specific time may also demonstrate the link. Part of the aim of this study is to determine which measure plays a more critical role in characterizing the connectedness between the tail risk of the two countries. To construct these measures, we extract the value of Foreign Direct Investment (FDI) data from the OECD International Direct Investment Statistics database; this

[4] Seller pays the costs, freights, and insurance to transport the goods to the buyer's port.

[5] Buyer pays the shipping costs and all other associated costs to transport the goods from the seller's port to buyer's address.

contains information on inter-country capital flows and stockholdings. We follow the approach commonly employed in other studies to use the outflow data from the investing country as it is more reliable than that held by the receiver (See, for example, Milesi-Ferretti et al., 2010). Similar to our approach in estimating trade linkage, we control for country size with GDP in the cross-sectional regression.

Our dataset contains annual information on trade and FDI flows, in addition to FDI stocks from 32 countries. Our investigation covers a period that begins in 2000 and ends in 2018. We provide detail on summary statistics for each variable employed in Table 2. In our sample, the average top net annual exporter is Germany, while the largest net importer is the US. Japan is largest country in terms of both average net FDI outflow and average holdings of FDI stock over the sample period, while Poland has the most substantial net foreign liabilities. A complete dataset is available upon request.

[Insert Table 2 about here]

To represent stock market risk, we calculate both the volatility and skewness of daily returns for each country in the pair, in an attempt to characterize the levels of uncertainty and downside risk inherent in each market. To capture possible macroeconomic influences, we incorporate economy size into the model as expressed through GDP. We also characterize the development of the financial markets by constructing a ratio based on market capitalization to GDP. To represent the relevant market's degree of financial liberalization, we use Chinn and Ito's (2008) financial openness index KAOPEN.

In our regressions, we include other macroeconomic variables, namely, government debt over GDP, GDP growth, interest rates, and REER. We omit inflation as there is a strong cross-sectional correlation (88 percent) between this and interest rates. This is not surprising as nominal interest rates contain information on inflation.

It should be noted that GDP, GDP growth and Market capitalization to GDP are related measures and capture different aspects of the marcoeconomic condition of a country. While GDP captures the size of the economy, GDP growth captures how fast the economy is growing. Market capitalization to GDP, on the other hand, is a measure extensively used in the literature to measure the development of the stock market of a nation. The divergence of these measures is pronounced in several countries in our sample. For instance, averaging over the 2000-2018 period, Switzerland has the highest market capitalization to GDP while its economy only ranks 17th in terms of size and 23rd in terms of GDP growth. Meanwhile, China is the country with highest GDP growth but it only ranks 24th in terms of market capitalization to GDP. Thus, to avoid potential omitted variable bias, we choose to include all of these measures together in the regression. In an unreported investigation, our results are robust with the exclusion of GDP growth and Market capitalization to GDP.

To account for the temporal influences that arise out of markets operating in different time zones, we include market closing time as a measure to represent this in our regression. To be more specific, it is reasonable to suppose that markets with later closing hours gather more information lending higher predictive capacity for their partner's tail risk for the next day.

Our cross-sectional regression is performed using two settings; first, we use a full sample; then, we frame it within a rolling window. For the former, we investigate the factors influencing tail risk connectedness over the long term. We do this by regressing the first stage full-sample estimated spillover coefficients on the average of the control variables over this period. The full sample of daily observations begins in January 2000 and ends in December 2018. We can express our approach as follows;

$$\begin{aligned} A_{ji} = {} & \varphi_0 + \varphi_1 Trade_{ij} + \varphi_2 Trade_{ji} + \varphi_3 Capflow_{ij} + \varphi_4 Capflow_{ji} + \\ & \varphi_5 Capstock_{ij} + \varphi_6 Capstock_{ji} + \boldsymbol{v}_{ij}\boldsymbol{\delta} + \epsilon_{ij} \end{aligned} \tag{7}$$

Where A_{ji} is the element in the connectedness matrix $\boldsymbol{A}$, which shows the tail risk spillover from country i to country j. If there is no spillover from country i to country j identified by the first stage LASSO quantile regression, A_{ji} takes the value of zero. $Trade_{ij}$ denotes the value of trade flowing from i to j. $Capflow_{ij}$ and $Capstock_{ij}$ express the FDI flows from i to j and the FDI stocks that i hold in j, respectively. $\boldsymbol{v}_{ij}$ is the row vector for the other control variables mentioned above for countries i and j, all of which are averaged over the period spanning from 2000 to 2018, φs and $\boldsymbol{\delta}$ are estimated coefficients in the regression, and the residual term is denoted as ϵ_{ij}. Also, we bootstrap the standard errors of the estimated coefficients in the second stage with 1,000 resamples to account for the fact that the dependent variable is estimated from the first stage quantile regression.

We perform a rolling window investigation for our second stage cross-sectional regressions in the spirit of Fama and MacBeth (1973). Adopting this approach allows us to account for possible endogeneity problems while attempting to examine the relationship between capital linkage and tail risk spillover. For each year, we estimate the tail risk spillover coefficient at the first stage using data from that year and regress this against control variables from the previous year. We can express this approach as follows;

$$\begin{aligned} A_{ji,t} = \varphi_0 + \varphi_1 Trade_{ij,t-1} + \varphi_2 Trade_{ji,t-1} + \varphi_3 Capflow_{ij,t-1} + \\ \varphi_4 Capflow_{ji,t-1} + \varphi_5 Capstock_{ij,t-1} + Capstock_{ji,t-1} + \boldsymbol{v}_{ij,t-1}\boldsymbol{\delta} + \epsilon_{ij} \end{aligned} \quad (8)$$

Where the notations expressed above are similar to those used in the full sample case (Equation 7) with an additional time indicator to express whether the observation for the variable is referring to year t or $t-1$. We then execute the cross-sectional regressions and interpret the average value of the resulting coefficients alongside their corresponding Newey and West (1987) standard errors to make inferences about the factors influencing tail risk spillover.

4. Empirical Analysis

4.1. Inter-country tail risk network

4.1.1. Full sample analysis

In Table 3, we summarise the result of the first stage regression that we employ in order to construct the tail risk spillover network. Table 3 indicates that the majority of countries in the network have a tail risk that is affected by other countries. There are only three countries that are unaffected by tail events elsewhere; these are Italy, the Slovak Republic, and the US. As the leading country in the global economy, the resilience of the US market to tail events elsewhere is not a surprise. Similarly, Italy is the country with the most stable market in the sample, with daily volatility during the sample period being the smallest among all investigated countries. The insensitivity of the Slovak Republic market might be due to a combination of several factors. For example, they have one of the cheapest currencies in the system; their market is also quite stable with low daily volatility relative to other countries. It is also the second least developed market in the system. As we will show in the second-stage regression analysis, all of these factors point in the same direction of having less sensitivity to international tail events. Japan is the country most affected by the tail events of others, upon which 13 countries in our sample exert an influence.

For nine of our countries, lagged returns offer some predictive power in forecasting tail risk. On average, a decline in lagged returns leads to higher tail risk as exhibited through lower VaRs. Except for interest rates, the macroeconomic controls do not appear to hold forecasting power for future tail risk. In 23 of our sample countries, interest rate can be seen to affect tail risk. A possible reason for the inability of the other macroeconomic variables to provide explanatory power is that the incorporation of these in our model at a lag of 3 months, the effects of the reported change may have dissipated somewhat during the intervening period.

[Insert Figure 1 about here]

[Insert Table 3 about here]

Figure 1 illustrates the tail risk spillover throughout the entire system of countries in our sample. Arrows denote the direction of the impact, and the line's width is proportional to the spillover coefficient's value. The diameter of each node corresponds to the number of countries to which the node transmits its tail risk. The most influential countries in the network are the US, Canada, and Japan, where the former affects the largest number of countries and has the greatest influence in terms of magnitude.

[Insert Table 4 about here]

In conducting the connection strength analysis for the network (Table 4), we make the following observations. Korea, Japan and Finland display the highest levels of In-strength. The Korean market has the highest level of In-strength although it has less inward spillover connections than Japan. This means that Korea is more sensitive to the shock spillover from the shock driving partners. As alluded to above, the least significantly affected are the US, Italy and the Slovak Republic. Our Out-strength analysis indicates that the most popular tail risk drivers are the US and Canada.

To consider the Out- and In-strength together, we employ Net-strength classifications. Following this approach, markets can be classified either as tail risk drivers or receivers when Net-strength is highly positive or highly negative respectively. From our analysis, we find that the most important tail risk drivers are the US and Canada with significantly higher Net-strength than the other countries. Our finding is consistent with evidence in Buncic and Gisler (2016) where the US market plays an important role in driving uncertainty worldwide. The main risk receivers are Korea, Finland, and Spain. These countries are, in fact, among the top five countries with the highest In-strength levels. Their Out-strength is also in the low end of the Out-strength spectrum across countries. Thus, they are typical risk receivers which are highly sensitive to external shocks and do not really emit risks to others. There are multiple factors which may contribute to this behaviour of these countries. For example, they are among the top markets in terms of volatility and real currency value, both of which suggest a higher level of spillover coefficient for shock receiving country according to our second stage cross-sectional regression in the next section.

We also note that although Japan has the largest number of In-degree, which is the number of inward connections from other countries, it also emits risk to many other countries. This makes Japan's Net-strength is less negative than other risk receivers. Thus, Japan can be considered as a hub receiving and transmitting risks globally.

4.1.2. Rolling window analysis

We begin our annualized estimation of the tail risk connectedness matrix in 2000 and end it in 2018. Figure 2 illustrates the rolling window estimations of the In-strength, Out-strength, and Net-strength for the most developed countries in our sample (figures representing the remaining countries in our sample are available upon request). We also include Greece in this figure as the 2009 Greek debt crisis was a notable event that affected international tail risk during this period.

From our estimations, it is apparent that the US remains the largest driver of tail risk consistently in the examined period. It experiences Out-strength surges at particularly high levels in the periods covering 2005 to 2006 and in 2016. From time to time, other countries feature as significant risk drivers. Germany, for instance, drives risk in 2001 and 2015, while Canada is a major risk driver in 2002, 2005, 2007 and 2011. Greece is, in fact, the most significant risk driver in 2009 when its Net-strength is even higher than the US.

The total connectedness in the system, which we calculate as the total value of all spillover coefficients in the whole network, was at its highest level in 2006 immediately before the global financial crisis. Although the level of global connectedness has generally reduced since then, it remains at levels of similar magnitude to that of 2000-2001 dot-com crash in 2014, 2016 and 2018. This suggests that the global systematic and systemic risks are frequently at high levels in recent years.

[Insert Figure 2 about here]

4.2. Determinants of tail risk connectedness

4.2.1. Full-sample analysis

In this section, we first use the full sample period to regress the spillover coefficient obtained at the first stage on a group of possible determinants. Table 5 indicates the strength of the possible relationship between tail risk spillover and trade and capital flows, capital stocks, and economy sizes. These are the variables expected to be the main drivers within the tail risk network. We can observe that the spillover coefficients correlate positively with these. Of particular note is the correlation with GDP (76%), this confirms our intuition that larger countries hold greater sway over their counterparts. The trade and capital flows, in addition to capital stocks existing between country pairs, are also positively associated with GDP. This highlights the importance of examining the net effect of these linkages to the spillover coefficient given the presence of GDP.

There are very high correlations (78% on average and some are as high as 95%) between variables capturing trade flows and capital flows and stocks from country i to country j and vice versa. The multicollinearity displayed here may cause some difficulty for interpretation of the regression results, to address this, we use principal component analysis to obtain the orthogonal factors for these six variables. We then employ these factors in the regression where the weights of the factors facilitate the economic interpretation.

[Insert Table 5 about here]

First, we investigate the cross-sectional regression without recourse to principal component analysis. The results detailed in Table 6 display a tendency for the impact on tail risk spillover to be negative and insignificant from the trade and capital linkage variables in the presence of other controls. This result appears counterintuitive; one possible explanation is that we do not control for potential problems with multicollinearity between each of the economic linkage variables. From Table 6, the only significant and positive coefficient in our regression is that of the capital stock held by the shock receiving country in the risk driver host. To understand this observation, we hypothesize that if country j holds a large amount of stock in country i, then a crisis in the latter will reduce the value of the asset and therefore increase the risk aversive tendency of residents in j.

[Insert Table 6 about here]

We employ principal component analysis (PCA) to account for the multicollinearity between economic linkage variables to obtain a meaningful interpretation of the impact of economic linkages on tail risk spillover. Table 7 presents the weights in constructing each component of the PCA and the proportion of the system variation explained by the components cumulatively. Due to the high correlations between all six economic linkage variables, the first three principal components explain more than 99% of the variation within these variables. Thus, we employ these in the cross-sectional regression.

The first component is constructed from positive weights in all linkage variables, we interpret this as the total level of economic linkage between a country pair. The second component exhibits positive weights with trade and capital flow in addition to the capital stock in the direction of i to j, but when viewed from j to i, the weights are negative. We can regard this as a role imbalance between i and j. The third component is positively weighted for trade flows but holds negative weights for capital linkages. Therefore, it represents the trade-capital imbalance of the relationship between countries.

Amongst principal components, we observe that the weights of the capital flows are relatively small. Noting this helps us to understand why capital flows make a modest contribution to the explanation of tail risk spillover as compared to capital stocks in the results in Table 6. This observation paves the way to expand our sample to include BRICS countries in the later section.

[Insert Table 7 about here]

[Insert Table 8 about here]

Table 8 details the result of the cross-sectional regression using these principal components alongside other determinants of tail risk spillover. At first glance, the resulting coefficients of the economic linkages appear insignificant (total linkage) or negative and significant (role imbalance and trade-capital imbalance). From our correlation analysis, it is clear that the spillover effect between country pairs is positively related to the value of trade and capital linkages. However, the size of the economies can account for most of this relationship. Large countries tend to have sizeable trade and capital linkages with their counterparts, and therefore have a greater capacity to spill risk to these trading partners. Our analysis demonstrates that the additional economic linkage not related to the size of the economy tends to be negatively related to the spillover effect instead.

There are different possible explanations for the significantly negative relationship between role imbalance, trade-capital imbalance and tail risk spillover. The role imbalance is captured by the second principal component, which is constructed with much higher weights of the capital flow and stock than those of trade flow. Therefore, we can explain its negative relationship with tail risk spillover using a diversification argument, where, in the wake of a crisis, investors may turn their attention to other markets in an effort to diversify. One possible explanation for the negative relationship between trade-capital imbalance and tail risk spillover could be the 'cheap import effect' recognized by Forbes (2002), where a country benefits by importing more cheaply from existing trading partners who are experiencing a crisis. When the trade link between the two countries dominates their economic linkages, the perceived benefit of this effect becomes more prominent.

We also investigate whether the volatility of returns is a determining factor of tail risk spillover. From Table 8, we see a negative coefficient for the tail risk generating country while the counterparty displays a significantly positive value. These results suggest that the risk of a more turbulent market tends to be idiosyncratic and confined within the market. However, a more turbulent market is also significantly more sensitive to external shocks.

When we consider the effect of the skewness of daily returns, we observe regression coefficients with negative and positive values for the risk generating and receiving countries, respectively. Thus, when the stock return of a country has a higher tendency to display positive jumps, the stock market is less likely to influence tail risk in other markets and is more sensitive to international shocks. Tail events in this market will be short-lived and followed by some upward reversal. As a result, it tends not to drive the tail risk in international financial markets. Under normal conditions, a buy-and-hold strategy would be beneficial for investors in these countries. However, in periods of global financial turbulence, investors should be skeptical of the upside potential as well as the perceived diversification benefits of investing in such markets.

When we examine the role of economy size, as measured by GDP, in explaining tail risk we can see that the coefficient showing the influence of this factor is highly significant and positive for the risk generating country. We, therefore, confirm our earlier supposition that the larger the economy is, the higher the transferable risk to its economic partners. Size is, in fact, the variable that provides the majority of explanatory power in the regression. We can also note that the GDP of the risk receiving country does not help in explaining the spillover effect.

In considering the ratio of market capitalization to GDP, we observe a marginally significant negative value for the risk generating country. As a consequence, it appears that countries with more developed financial markets have smaller spillover than their less-developed counterparts. At first glance, this may appear counter-intuitive, as one would think that the more developed markets would have a more significant effect on its trading partners. However, as our analysis has already controlled for economy size, the residual negative effect can be explained by the developed markets' capacity to be more resilient in the face of financial distress. Investors in these markets view such episodes as short-lived and usually expect the market to recover quickly.

When we consider the effect of the level of government debt as a proportion of GDP in explaining spillover, we observe that the risk generating country exhibits significantly negative values while the trading counterpart produces a positive coefficient. One possible explanation for this observation is that if the risk generating countries tend to carry more debt, leveraged positions can exacerbate fundamental business problems. The result is that while the problem is magnified within the originator country, the effect of the spillover to partner economies is modest by comparison. However, if there is a high debt level within the shock receiving country, the spillover effect could be amplified as a result. Countries on the receiving end of tail risk should exercise caution in extending their levels of government debt.

We also observe that GDP growth of the risk receiving country has a positive and marginally significant effect on tail risk spillover, implying that when an economy is in its growth phase, it may be more sensitive to international financial market shocks, consistent with the suggestion of the skewness discussed above. Real effective exchange rates of risk generators and receivers appear to generate negative and positive effects on the spillover, respectively. Our observation agrees with Forbes (2002), who points out that the contagion effect from one crisis country to another will be more significant if its currency devalues. We also observe that the more open an economy is, the higher risk it can spill over to other markets. Finally, when we control for the effect of the financial market closing hours, we see that this is positively related to the spillover in the case of the generator but negatively for the receiver. When the market closes later, it includes more information in its prices which helps in improving the accuracy of tail risk prediction for other markets.

We further analyze the goodness-of-fit of the regression through the R-squared investigation. As shown in the last row of Table 8, the R-squared value for the regression is at 62.54%, implying that our independent variables explain a large proportion of the cross-sectional variation in the tail risk spillover measure. An incremental R-squared analysis decomposes the explanatory power of these variables by grouping all independent variables into five categories which we name; economic linkages, stock market risk, shock generator GDP, other macroeconomic variables, and closing time. For each group, we express incremental R-square as the difference between the value produced through a complete regression and that achieved when we remove the relevant category.

We can see that the primary determinant of the spillover effect is the GDP of the shock generator. With an incremental R-squared value of 39.76%, it accounts by far for most of the explanatory power of the independent variable set. Notably, although the closing time group produces significant coefficients, it has an incremental R-squared value of 0.68%, and therefore adds little in terms of explanatory power to our regression. We can assume that the differentials in the closing hours of financial markets do not drive our observations about the tail risk network discussed in section 4.1.

4.2.2. Rolling window analysis

To confirm our findings, we employ an alternative investigative approach, where we obtain the spillover coefficients between country pairs using the LASSO Quantile Regression on a year by year basis. We then run the cross-sectional regressions for tail risk spillover on the set of independent variables. We lag these explanatory variables by one year to account for possible endogeneity between the independent and dependent variables. In the spirit of Fama and MacBeth (1973), we then report the historical average of the estimated coefficients alongside the corresponding Newey-West (1987) t-statistics.

Similar to our full sample analysis, we observe high multicollinearity amongst the trade and capital linkage variables. To deal with this, we conduct Principal Component Analysis and select the first three factors to use in the cross-sectional regressions for each year. On average, these explain 99.1% of variation across all six economic linkage variables. We observe that the weights of the variables in constructing the principal components are similar to those used in our earlier analysis.[6] Therefore, the economic interpretation of each principal component is consistent with the full sample investigation.

[6] This is unreported but is available from the authors upon request.

The results we obtain from this approach are reported in Table 9 and are consistent with those delivered through the full sample analysis. Our results demonstrate that after controlling for the dominant influence of GDP in the risk generating country, a negative relationship between economic linkage and tail risk spillover remains. For most other variables, the relationship with spillover is similar in direction to that revealed through the full sample analysis. However, there are some exceptions such as the skewness and government debt on the GDP of the risk receiver. These inconsistencies suggest that the relationship between these variables and the tail risk spillover effect is not constant over time. However, this is of little consequence as the results produced through incremental R-squared analysis detailed below show that all of these factors play only a minor role in explaining tail risk spillover.

[Insert Table 9 about here]

Upon examining R-squared values produced by the rolling window cross-sectional regressions, we can observe that they are smaller in comparison with those produced through the full sample analysis. This could be explained in part by the use of a smaller number of observations to estimate the first stage regression and as a result a greater level of noise in the estimated coefficients. Moreover, we use independent variables lagged by one year to explain the spillover coefficients in the network. Notwithstanding, the model performs reasonably well and produces an R-squared value of 19.99%.

When we decompose this figure through the incremental R-squared approach (Figure 3), the first point to note is that the GDP of risk generating country occupies a more substantial proportion of the value and this is consistent with the full sample results. On average, throughout the entire sample window, the incremental R-squared of the risk generating country GDP is 8.64%. The GDP of the risk generating country accounts for the majority of explanatory power in the regression except for the years 2003, 2009, 2011, and 2015. There are two possible reasons to explain the fall in the explanatory power of the GDP of the risk generating country for these years. First, in 2003 and 2015, only a few non-zero spillover coefficients remain once we eliminated observation points where data is unavailable in the second stage regression. Second, in 2009 and 2011, we can observe a strong spillover effect from a few relatively smaller countries such as Greece, Chile, and the Czech Republic. Also, these years showed relatively good stock market performances in the US and Japan, leading to their tail risk spillover becoming moderate during this period.

For the other groupings, the economic linkage and macroeconomic categories are next in terms of power, exhibiting incremental R-squared values of 2.31% and 2.25% respectively. Of the five groups, the closing hour has the least explanatory power and accounts for 0.68% of incremental R-squared value. Thus, our rolling window analysis allows us to confirm the robustness of our findings for the full sample. Furthermore, it serves to allay fears that the initial analysis was biased as a consequence of possible endogeneity between tail risk spillover and capital linkage.

[Insert Figure 3 about here]

5. Robustness check

5.1. Different tail thresholds

In the primary analysis, we examine our sample using a 10% tail risk threshold. To check the robustness of our findings, we analyze the data again using variations of tail risk at 5% and 1% respectively.[7] The results we produce agree with those attained for the initial tail risk threshold which we investigated. From an analysis of the full sample, we can observe in Table 8 that the GDP of the risk generating country is still significantly positive and accounts for the majority

[7] We obtain similar conclusions using 20% tail threshold. The result is available upon request.

of the R-squared value of the regression. We also produce negative and mostly significant coefficients for the role imbalance and trade-capital imbalance linkage variables. The other explanatory variables remain mostly consistent with earlier findings.

We can also note that there is lower explanatory power as thresholds move toward the extremes. Lower power does not, however, imply less spillover at these levels, a point well documented in earlier research (see for instance Cappiello et al., 2014; Polanski and Stoja, 2015; amongst others). The implication from this observation is that with more extreme tails, it becomes more challenging to explain spillover using commonly referred to explanatory variables. The reason for this could be that extreme movements will be more specifically related to rather more unusual causative factors.

When we shift perspective using rolling window regressions (Table 9), we note that economic linkage coefficients continue to be negative. The impact of the GDP of the risk generator is also significant and positive. It should be noted that although the incremental R-squared of the GDP of the risk generator is smaller than that of the group of other macroeconomic variables collectively, it remains the most critical factor among the explanatory variables when the variables are assessed individually. Furthermore, we can observe that as the tail threshold becomes extreme, the regression loses explanatory power in a manner similar to that produced in the full sample analysis.

5.2. Grouping Eurozone countries

As many countries in our sample are members of the Eurozone, they share common economic conditions. Sarafrazi et al. (2014) show that there is no strong downside risk diversification between countries within this economic area. To account for this, we realign our sample and conduct spillover analysis. There are 15 Eurozone members in our sample,[8] we group these and consider them as a single economic unit in our analysis. We change the corresponding explanatory factors to include Eurozone macroeconomic variables, and use Eurostoxx 600, with the UK excluded, to represent the market. For the economic linkage variables, we calculate the trade flows, FDI flows, and stocks by summing the values of these from the Eurozone countries to non-members and also in the reverse direction. We then cancel out all flows and stocks held between members.

We begin with the first stage regressions to explore the tail risk network in a spirit similar to the primary analysis. We present the summary statistics for these in Table 10. We note that almost every country, except the US, is affected by the tail risk of one or a few other international markets. On average, a country is affected by four other markets. We also observe that in five of the sample countries, lagged returns appear to predict future tail risk. Except for interest rates, the other macroeconomic variables included in the regressions do not predict future tail risk.

[Insert Table 10 about here]

Figure 4 and Table 11 convey the network structure and corresponding connection strength analysis. From this, it is clear that the US, Canada, and Japan are the most critical nodes in the system as they affect the highest number of countries. However, in terms of Out-strength, Japan is smaller than other countries such as Australia and the Eurozone, suggesting that its spillover to other markets tends to be low and moderate. Given the size of the economic block, the Eurozone appears linked to a relatively small number of markets via the spillover effect. It only affects about half of the markets as compared to Japan. This observation suggests that economic

[8] Austria, Belgium, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Netherland, Portugal, Slovak Republic, and Spain.

problems tend to stay within the group rather than permeate broadly. However, it should be noted that Eurozone surpasses Japan in terms of Out-strength. This clearly illustrates the significance influence of this economic area to other markets if they are connected.

In terms of In-strength level, similar to the case where countries in the Eurozone are not grouped, Japan and Korea are among countries with the highest In-strength while the US and Canada have the lowest. As a result, the US and Canada remain the two most important tail risk generators for international markets and display the largest Net-strength.

When we examine the tail risk network through rolling window regressions (results are available from the author upon request), we arrive at broadly the same conclusions as we do through the primary analysis. The US still appears to be the most significant driver of risk, exhibiting the highest Net-strength over many of the years examined.

[Insert Figure 4 about here]

[Insert Table 11 about here]

The second stage regressions for the full sample also generate results that are consistent with the main framework. As shown in Table 12, the coefficients of the role imbalance and trade-capital imbalance economic linkage variables are significant and negatively related to tail risk spillover. They can explain an additional 2.48% of the total variation. The GDP of the risk generating economy is significant, positively relates to spillover, and produces an incremental R-squared value of 27.08%. Other macroeconomic variables offer the incremental explanatory power for tail risk spillover more than triple that of the standard framework with a value of 6.23%.

[Insert Table 12 about here]

Similar results are observable when we employ the cross-sectional regression for the rolling window (Table 13). We find that the economic linkage variables explain an additional 3.06% of the spillover effect with negative coefficients. The risk generator's GDP is positively related to the spillover effect; however, its explanatory power is reduced and smaller than the combined macroeconomic variables. Nevertheless, it remains the single most crucial factor in determining spillover. One possible explanation for the reduction of the impact of the risk driver's GDP could be the aforementioned limited number of spillover connections from the significantly large Eurozone block.

[Insert Table 13 about here]

5.3. Using IMF CPIS data to include BRICS

Our standard framework includes countries in the OECD; this selection is due to the availability of FDI flow data. However, international investors with an eye on the emerging markets will be particularly interested in how the BRICS[9]countries feature in the tail risk spillover network. Data on FDI stocks are available for BRICS countries from the International Monetary Fund's (IMF) Coordinated Portfolio Investment Survey (CPIS) database. Therefore, to draw these economies into our analysis framework, we need to remove the FDI flow variables. From the results of the primary analysis, which are available in Table 6, it is clear that sacrificing the FDI flow linkage variables will not detract to any great extent from the power of the model to explain spillover. The CPIS database contains details of the asset holdings of one country in another. Data on the liabilities that one country holds to another is also available in the database. We use the asset rather than liability data because, with the latter, it is difficult for an issuer to know the current owner's identity.

[9] Brazil, Russia, India, China, and South Africa

When we analyze the full sample to trace the tail risk network, we attain results similar to those produced by our primary analysis and the Eurozone countries' grouping. It is apparent from Figure 5 and the connection strength analyses reported in Table 14 that Brazil, alongside the US and Canada, is one of the three major tail risk drivers. The prominent role of Brazil as a risk driver is not a surprise, as it is a large economy, with the second-highest interest rate and cheapest currency among all countries in the sample. In the cross-sectional regression result discussed below, these factors strongly impact the tail risk spillover effect. Other countries in the BRICS group tend to be tail risk receivers, with Russia and India being the two countries with the lowest Net-strength in the network.

When we employ rolling window estimation, Brazil tends to be a consistent tail risk driver amongst the BRICS countries. China tends to be a tail risk driver across most years; however, its Net-strength values often approach zero. Over the same period, South Africa, India, and Russia are risk receivers. For brevity, these results are not reported here but are available upon request.

[Insert Figure 5 about here]

[Insert Table 14 about here]

Using the second stage regression (Table 12), we find that the results returned are, in general, consistent with the primary analysis. The trade-capital imbalance effect on spillover is statistically significant and negative. The role imbalance effect remains negative, although it is not statistically significant. In comparison with the primary analysis, the incremental R-squared value for this group is smaller. The GDP of the risk generating country is significant and positively related to the spillover. It accounts for the majority of the explanatory power of the regression. When we consider other macroeconomic variables, we can see that the relationship with spillover is broadly similar to that illustrated through the primary analysis. However, we can note that the incremental R-squared values are more than double that revealed through earlier investigations. The variable representing stock market risk and closing hours also exhibit a significant increase in explanatory power. Table 13 also suggests that the cross-sectional rolling window analysis for the extended sample with BRICS yields similar results to those produced through the full sample analysis.

5.4. Panel regression framework for the rolling window cross-sectional regression

The Fama and Macbeth (1973) framework used in our rolling window analysis does not explicitly account for possible time fixed effects of the cross-sectional regression in each year. Although the use of a sample average of the estimated coefficients should have theoretically removed such effects, we test the robustness of our result through a panel regression framework. Since our focus is on the cross-sectional relationship, we run the panel regression with a time fixed effect. In our unreported result, testing following Hausman (1978) confirms the suitability of the fixed effects model over the random-effects version. We still use bootstrapping with 1000 resamples to account for the use of the estimated dependent variable. We report the panel regression results for different samples used in our study in Table 15, including the cases of 32 OECD countries, grouping Eurozone countries, and including BRICS.

Table 15 agrees with our analysis of the results produced in other investigations. We observe the dominant role of the GDP of the tail risk generating country and the significantly negative effect of role and trade-capital imbalance. The sign and significance of other factors are also broadly consistent with our results in the previous sections.

[Insert Table 15 about here]

6. Conclusion

In this paper, we construct a tail risk spillover network amongst international stock markets using the LASSO Quantile Regression method developed by Belloni and Chernozhukov (2011) and Hautsch et al. (2015). Using the network, we can identify key players in the global tail risk transmission, for example, the US, Canada, or Japan. The network also reveals markets that are highly sensitive to external shocks, such as Korea and Finland. This information is useful for both investors and regulators in decision making within their respective roles. For investors, identifying markets where shocks tend to affect their local stock index significantly is essential for their decisions on risk management and asset allocation in general. It also helps them to respond appropriately to tail events in international markets when such episodes occur. For regulators, the network brings a clear understanding of the vulnerability of their own country's stock market to externally generated contagion. A full picture of the tail risk network becomes an input for proposing and monitoring policies to strengthen and protect their local market.

Our study adds another layer of information available to practitioners by investigating the tail risk network determinants and successfully identifying the role of these factors in influencing tail risk spillover. Ours is the first study to reveal and confirm the central role of economy size in driving tail risk networks. Moreover, we reveal a hitherto undocumented observation that after controlling for size, economic linkages (that is, trade and capital flows, and capital stocks) tend to negatively affect the spillover. This observed tendency builds empirical support for the effects of cheap imports and diversification. Through a fuller understanding of tail risk network determinants, investors and policymakers can make ex-ante evaluations on their markets sensitivity to international shocks given certain economic conditions. This predictability is useful to investors when shaping their investment decisions, and it raises the awareness of policymakers regarding the impact of their actions, which can directly affect these determinants.

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Figure 1: Tail risk spillover network: Full sample analysis

This figure illustrates the tail risk spillover network estimated by the LASSO Quantile Regression for all countries using the full sample from January 2000 to December 2018.

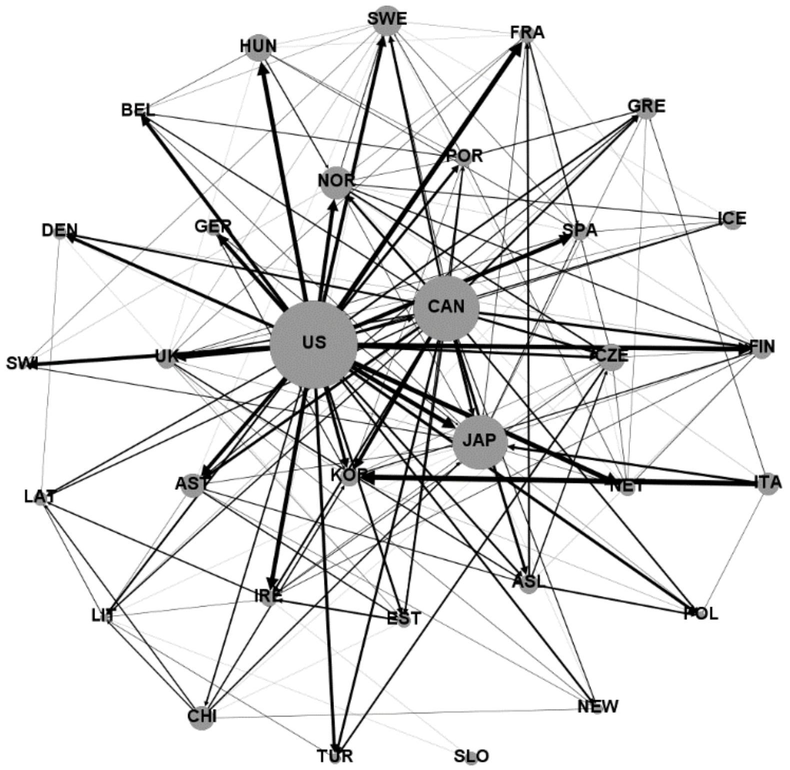

Figure 2: Connection strength analysis of the tail risk network – Rolling window

This figure illustrates the In-strength, Out-strength, and Net-strength over time of the major economies in the world. The bottom panel shows the total connectedness level of the network over time. The result for each year is estimated through LASSO Quantile Regression using daily returns of stock market indices within the corresponding years.

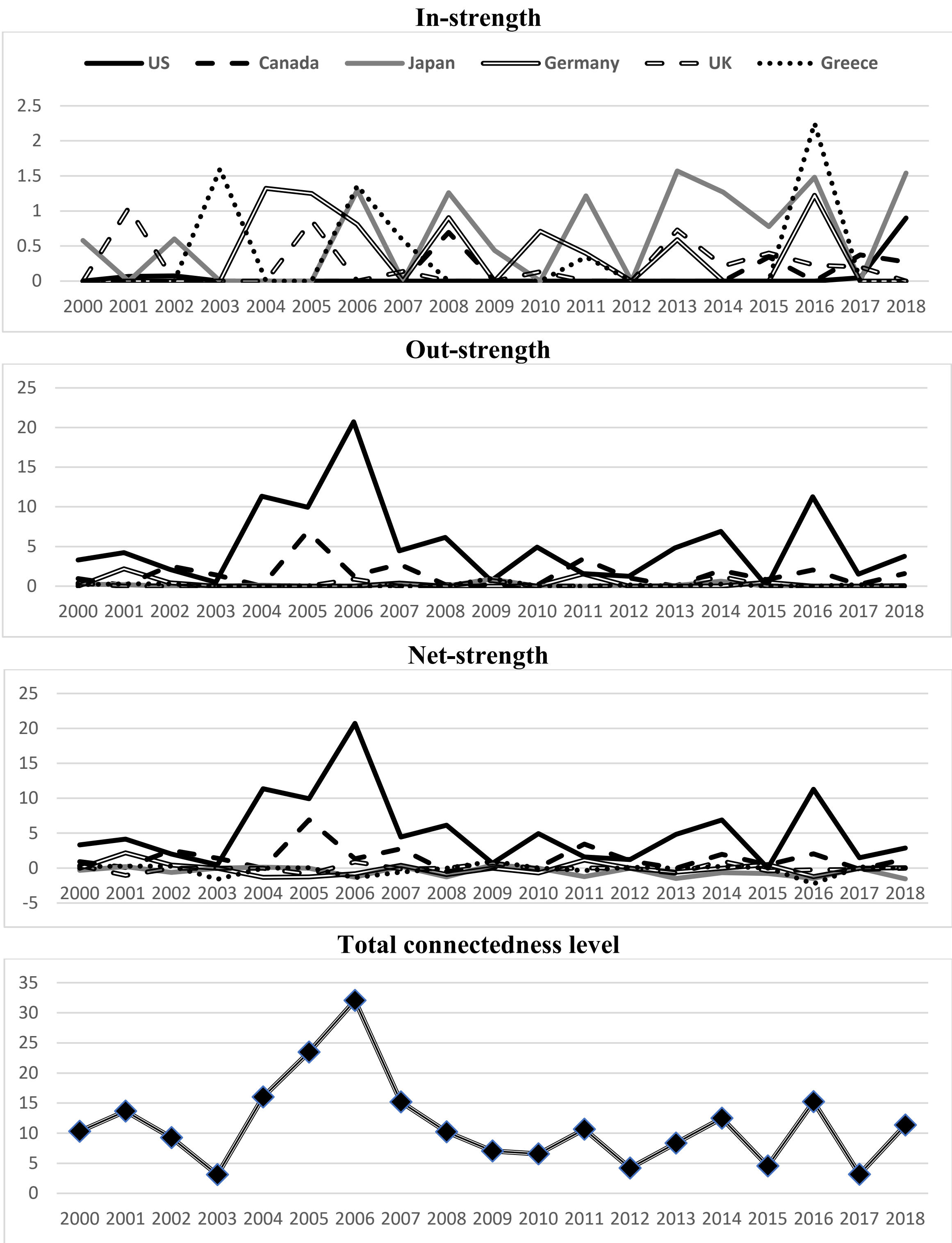

Figure 3: Over-time Incremental R-squared of the cross-sectional regression

This figure illustrates the over-time Incremental R-squared of the cross-sectional regression of the tail risk spillover coefficient; the spillover coefficient is estimated by the LASSO Quantile Regression in a year on the set of independent variables lagged by one year.

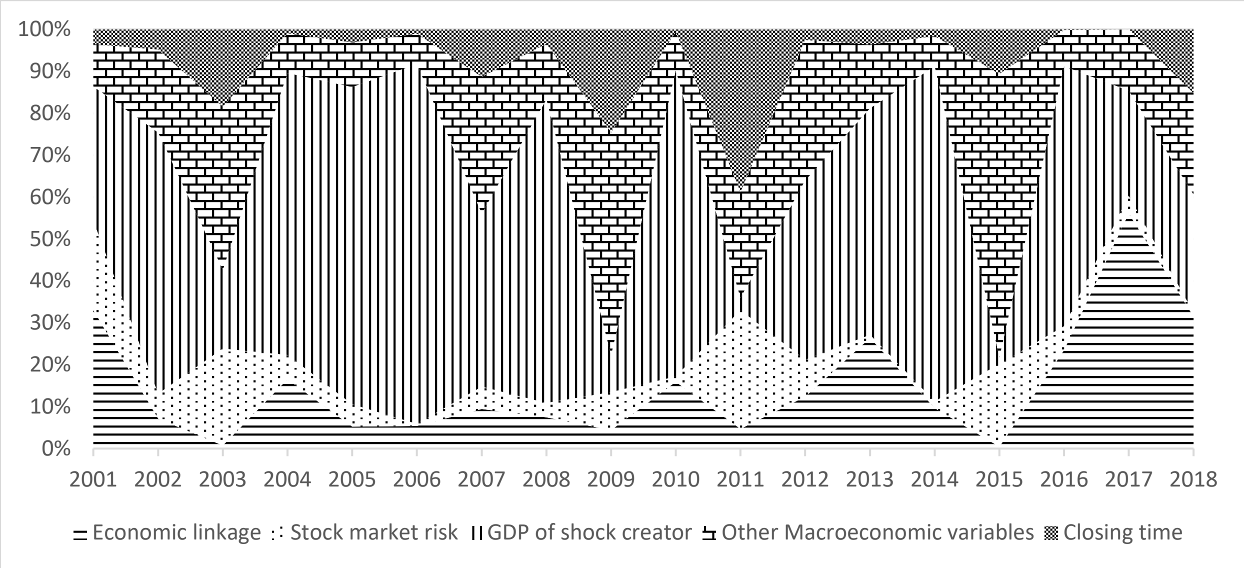

Figure 4: Tail risk spillover network: Grouping Eurozone countries

This figure illustrates the tail risk spillover network estimated by the LASSO Quantile Regression using the sample where all Eurozone countries are grouped into a single economic entity. The estimation sample period begins in January 2000 and ends in December 2018.

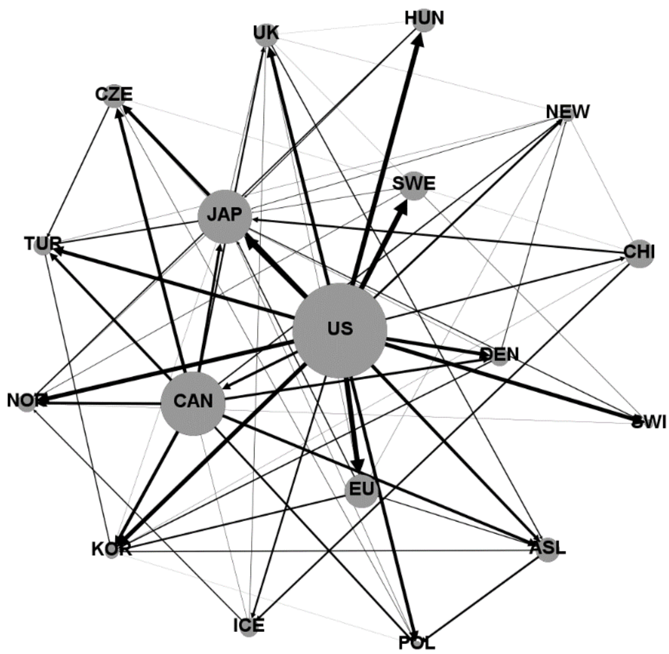

Figure 5: Tail risk spillover network: Adding BRICS

This figure illustrates the tail risk spillover network estimated by the LASSO Quantile Regression for all countries using the extended sample, where BRICS are included. The estimation sample runs from January 2000 to December 2018.

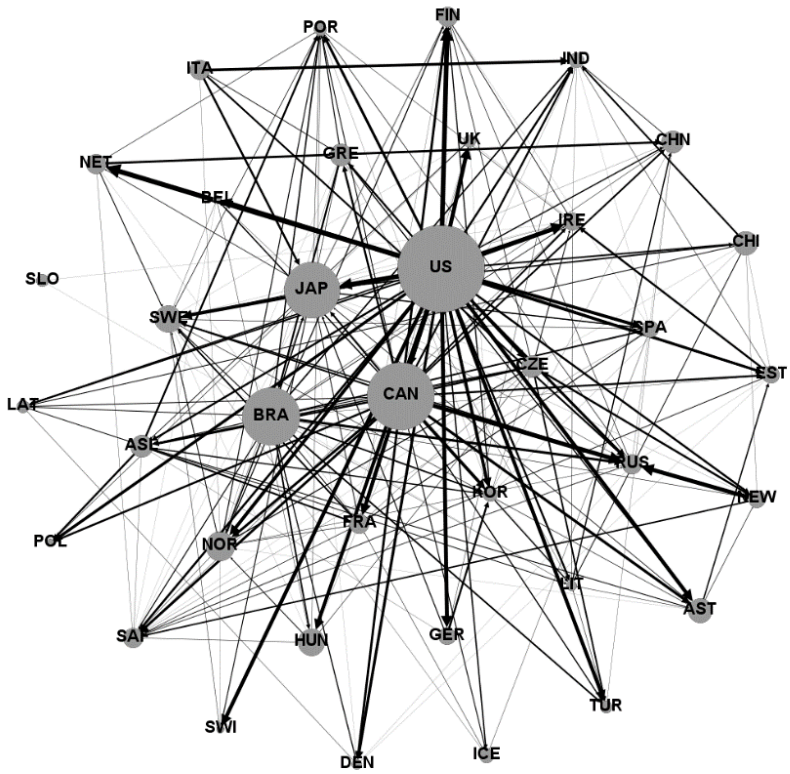

Table 1: List of countries and stock market indexes

The table below details the stock market indices of the sample of countries investigated. The second and fourth columns indicate the country code used in the network graphs and the closing time for each market respectively.

Country	Country code	Stock index	Closing time (GMT)
Australia	ASL	S&P/ASX 200 Index	06:00:00
Austria	AST	Austrian Traded (ATX) Index	16:35:00
Belgium	BEL	BEL 20 Index	16:30:00
Canada	CAN	S&P/TSX Composite Index	21:00:00
Chile	CHI	S&P/CLX IPSA (CLP) Index	20:00:00
Czech Republic	CZE	Prague Stock Exchange Index	15:30:00
Denmark	DEN	OMX Copenhagen 20 Index	16:00:00
Estonia	EST	OMX Tallinn Index	14:30:00
Finland	FIN	OMX Helsinki Index	16:30:00
France	FRA	CAC All-Tradable Index	16:30:00
Germany	GER	Prime All Share Index	19:00:00
Greece	GRE	Athex Composite Index	15:20:00
Hungary	HUN	Budapest Stock Exchange Index	16:00:00
Iceland	ICE	OMX Iceland All-Share Index	16:30:00
Ireland	IRE	Ireland Stock Exchange Overall Index	16:30:00
Italy	ITA	FTSE Italia All-Share Index	16:30:00
Japan	JAP	NIKKEI 225 Index	07:00:00
Korea	KOR	KOSPI Index	07:30:00
Latvia	LAT	OMX Riga Index	14:00:00
Lithuania	LIT	OMX Vilnius Index	14:00:00
Netherlands	NET	AEX All-Share Index	16:40:00
New Zealand	NEW	S&P/NZX 50 Index	05:00:00
Norway	NOR	OSE All Share Index	15:30:00
Poland	POL	WSE WIG Index	16:00:00
Portugal	POR	PSI All-Share Index	16:30:00
Slovak Republic	SLO	Slovak Share Index	14:30:00
Spain	SPA	Madrid Stock Exchange General Index	16:30:00
Sweden	SWE	OMX Stockholm All-Share Index	16:30:00
Switzerland	SWI	Swiss All Share Index	16:30:00
Turkey	TUR	BIST 100 Index	16:00:00
United Kingdom	UK	FTSE All-Share Index	16:30:00
United States	US	S&P 500 Index	21:00:00

Table 2: Economic linkage summary

This table shows the average value (in billion USD) from 2000 to 2018 of trade flow, FDI flow, and FDI stock of a country to and from the other countries in the network.

Country	Export	Import	Net	FDI Outflow	FDI Inflow	Net	FDI Stock Outward	FDI Stock Inward	Net
Australia	91.26	110.73	-19.47	7.94	22.25	-14.31	196.05	255.33	-59.28
Austria	138.58	134.21	4.38	5.80	6.53	-0.73	88.30	104.60	-16.30
Belgium	374.54	350.93	23.61	25.00	38.86	-13.87	527.71	499.03	28.67
Canada	394.49	330.81	63.67	38.22	33.42	4.80	434.50	472.87	-38.38
Chile	28.31	22.30	6.01	1.10	9.72	-8.62	13.32	96.77	-83.45
Czech Republic	115.72	92.34	23.38	0.98	5.17	-4.19	8.45	85.35	-76.89
Denmark	92.25	88.10	4.15	5.59	3.90	1.69	138.26	99.68	38.58
Estonia	11.53	11.17	0.36	0.39	1.10	-0.71	3.51	14.71	-11.19
Finland	59.78	59.95	-0.17	4.70	3.69	1.01	97.95	64.78	33.17
France	474.48	498.27	-23.79	66.00	32.98	33.02	973.78	605.46	368.32
Germany	1041.49	857.53	183.96	46.17	26.75	19.42	852.16	634.88	217.28
Greece	28.51	40.96	-12.45	0.66	1.72	-1.06	8.54	20.17	-11.63
Hungary	76.57	70.17	6.40	1.00	1.88	-0.88	38.43	83.79	-45.36
Iceland	5.44	5.30	0.14	0.91	0.53	0.38	7.70	2.75	4.96
Ireland	145.08	107.39	37.68	9.57	11.99	-2.42	187.22	258.93	-71.72
Italy	373.75	340.89	32.86	22.03	17.58	4.45	301.92	235.56	66.37
Japan	325.40	265.91	59.48	55.13	8.52	46.61	498.67	117.84	380.83
Korea	144.41	159.69	-15.28	7.77	4.60	3.17	59.71	91.42	-31.71
Latvia	9.07	10.92	-1.85	0.15	0.20	-0.05	1.05	10.69	-9.64
Lithuania	16.32	16.87	-0.55	0.28	0.43	-0.15	2.57	14.93	-12.36
Netherlands	415.42	319.13	96.29	73.64	41.00	32.64	1569.79	1210.47	359.32
New Zealand	25.62	26.56	-0.94	-0.02	1.64	-1.66	10.16	48.22	-38.06
Norway	119.09	69.62	49.47	13.16	5.28	7.88	101.20	94.08	7.13
Poland	141.48	126.92	14.57	1.82	9.72	-7.90	12.04	132.61	-120.58
Portugal	58.09	65.83	-7.74	2.22	3.37	-1.15	34.89	77.26	-42.37
Slovak Republic	54.10	41.91	12.19	0.25	2.24	-1.99	1.87	35.91	-34.04
Spain	254.95	245.04	9.92	29.41	24.29	5.12	336.15	449.98	-113.83
Sweden	148.76	141.69	7.06	13.71	12.07	1.64	255.44	221.71	33.73
Switzerland	143.61	151.96	-8.36	30.17	26.68	3.49	507.83	428.02	79.82
Turkey	55.08	82.62	-27.54	1.42	6.57	-5.15	12.25	88.23	-75.99
United Kingdom	516.53	562.71	-46.18	56.88	65.68	-8.80	964.84	928.45	36.39
United States	769.92	983.74	-213.82	148.17	181.94	-33.77	2217.71	2032.78	184.93

Table 3: LASSO Quantile Regression estimate for tail risk spillover

This table summarizes the estimated parameters of the LASSO Quantile Regression for all countries in the sample during the period from January 2000 to December 2018. The second column shows the number of countries whose tail risk is explained in the LASSO Quantile Regression by the variables in the first column. The next 3 columns show the minimum, maximum, and average values of the coefficients corresponding to the variables on the first column across the regressions of 32 countries in the system. Since each regression exhibits 31 tail exceedances, the minimum, maximum, and average values on the first row are related to the number of relevant tail exceedances in a regression rather than to the value of the estimated coefficients.

	Number of relevant cases	Min	Max	Average
Tail exceedances from other countries	29	0	13	5.2188
Lagged return	9	-0.1187	0.2091	0.0353
Change in GDP growth	0	NA	NA	NA
Change in Inflation	3	0.0080	0.0140	0.0107
Change in REER	0	NA	NA	NA
Change in Interest rate	23	-0.0334	0.1394	0.0548

Table 4: Connection strength analysis of the tail risk network

This table shows countries with the highest and lowest levels of Out-strength, In-strength, and Net-strength in the tail risk network estimated using LASSO Quantile Regression for the full sample period beginning in January 2000 and ending in December 2018.

		Country	Value of sorting measure
Out-strength	Highest	United States	12.776
		Canada	5.931
		Italy	1.249
	Lowest	Lithuania	0.000
		Poland	0.000
		Belgium	0.000
In-strength	Highest	Korea	2.115
		Japan	2.019
		Finland	1.573
	Lowest	United States	0.000
		Slovak Republic	0.000
		Italy	0.000
Net-strength	Highest	United States	12.776
		Canada	5.592
		Italy	1.249
	Lowest	Korea	-1.829
		Finland	-1.403
		Spain	-1.257

Table 5: Correlation matrix of tail risk spillover, economic linkages, and GDP

This table shows the correlation matrix between the tail risk spillover coefficient of a country to its partner, the trade and capital flows between the two countries, the capital stock one country holds in the other, and the size of their economies captured by GDP. The spillover coefficients are estimated using the daily returns of stock indices from 2000 to 2018. The other variables are the 2000-2018 average values of trade and capital flows, capital stocks between the two countries, and their GDPs.

	Spillover *i* to *j*	Trade *i* to *j*	Trade *j* to *i*	Capital flow *i* to *j*	Capital flow *j* to *i*	Capital stock *i* to *j*	Capital stock *j* to *i*	GDP of *i*	GDP of *j*
Spillover *i* to *j*	**1.00**	0.15	0.21	0.28	0.27	0.28	0.27	**0.76**	-0.02
Trade *i* to *j*	0.15	**1.00**	**0.95**	**0.69**	**0.64**	**0.67**	**0.64**	0.28	0.33
Trade *j* to *i*	0.21	**0.95**	**1.00**	**0.64**	**0.69**	**0.64**	**0.67**	0.33	0.28
Capital flow *i* to *j*	0.28	**0.69**	**0.64**	**1.00**	**0.64**	**0.91**	**0.74**	0.34	0.31
Capital flow *j* to *i*	0.27	**0.64**	**0.69**	**0.64**	**1.00**	**0.74**	**0.91**	0.31	0.34
Capital stock *i* to *j*	0.28	**0.67**	**0.64**	**0.91**	**0.74**	**1.00**	**0.86**	0.34	0.31
Capital stock *j* to *i*	0.27	**0.64**	**0.67**	**0.74**	**0.91**	**0.86**	**1.00**	0.31	0.34
GDP of *i*	**0.76**	0.28	0.33	0.34	0.31	0.34	0.31	**1.00**	-0.01
GDP of *j*	-0.02	0.33	0.28	0.31	0.34	0.31	0.34	-0.01	**1.00**

Table 6: Full sample Cross-sectional regression - Raw economic linkages variables

This table shows the results of the cross-sectional regressions of the tail risk spillover coefficient obtained from the first stage LASSO Quantile Regression on its possible determinants. This includes trade and capital flows, and capital stocks between the two countries; volatility and skewness of the daily stock market indices of the two countries; macroeconomics variables of these and the closing time of the two stock markets. The result of each regression is presented in 2 columns, where the first shows the estimated coefficient values, and the second shows the corresponding t-statistics.

		Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Const		0.035	0.558	0.059	0.955	0.061	0.989	0.044	0.724
Trade flow	*i* to *j*	-0.049	-0.944					-0.070	-1.358
	j to *i*	0.010	0.182					-0.043	-0.823
Capital flow	*i* to *j*			-0.154	-1.105			0.047	0.204
	j to *i*			0.338	2.482			0.028	0.121
Capital stock	*i* to *j*					-0.031	-2.539	-0.014	-0.779
	j to *i*					0.044	3.568	0.061	3.250
Other controls	Volatility *i*	-1.327	-1.720	-1.271	-1.649	-1.224	-1.603	-1.089	-1.452
	Volatility *j*	2.806	3.555	2.684	3.401	2.619	3.320	2.742	3.519
	Skewness *i*	-0.003	-3.644	-0.003	-4.056	-0.003	-4.078	-0.003	-3.558
	Skewness *j*	0.001	1.705	0.001	1.455	0.001	1.453	0.001	2.039
	GDP *i*	0.028	29.742	0.027	28.930	0.027	29.138	0.027	29.249
	GDP *j*	0.000	-0.227	-0.001	-1.222	-0.001	-1.171	-0.001	-0.856
	Mkt/GDP *i*	-0.005	-0.844	-0.005	-0.958	-0.005	-0.926	-0.008	-1.457
	Mkt/GDP *j*	0.005	0.978	0.005	0.843	0.005	0.829	0.002	0.345
	GovDEBT *i*	-0.021	-2.450	-0.022	-2.536	-0.021	-2.544	-0.019	-2.277
	GovDEBT *j*	0.015	1.674	0.012	1.401	0.013	1.470	0.015	1.779
	GDPgrowth *i*	0.214	0.816	0.222	0.852	0.191	0.733	0.088	0.339
	GDPgrowth *j*	0.414	1.586	0.466	1.786	0.512	1.977	0.409	1.584
	Interest *i*	0.094	0.956	0.095	0.977	0.089	0.922	0.049	0.510
	Interest *j*	-0.163	-1.695	-0.137	-1.437	-0.132	-1.387	-0.169	-1.798
	REER *i*	-0.145	-3.452	-0.160	-3.841	-0.162	-3.919	-0.147	-3.568
	REER *j*	0.054	1.367	0.047	1.196	0.048	1.219	0.064	1.651
	KAOPEN *i*	0.010	2.282	0.010	2.318	0.010	2.261	0.008	1.765
	KAOPEN *j*	0.001	0.293	0.002	0.401	0.002	0.445	0.000	-0.072
	Closetime *i*	0.040	2.850	0.033	2.388	0.033	2.356	0.035	2.587
	Closetime *j*	-0.043	-3.018	-0.045	-3.135	-0.045	-3.168	-0.043	-3.025
R2(%)		61.15		61.16		61.44		62.55	

Table 7: Principal Component Analysis of the economic linkage variable

This table shows the loading of the principal components of the six economic linkage variables: trade and capital flows between two countries, and the capital stocks which one country holds in another.

	1st component	2nd component	3rd component	4th component	5th component	6th component
			Weight			
Trade flow *i* to *j*	0.262	0.020	0.657	0.707	-0.009	-0.005
Trade flow *j* to *i*	0.262	-0.020	0.657	-0.707	0.009	-0.005
Capital flow *i* to *j*	0.039	0.049	-0.010	-0.010	-0.705	0.706
Capital flow *j* to *i*	0.039	-0.049	-0.010	0.010	0.705	0.706
Capital stock *i* to *j*	0.656	0.705	-0.262	-0.020	0.049	-0.040
Capital stock *j* to *i*	0.656	-0.705	-0.262	0.020	-0.049	-0.040
			Cumulative variation explanability (%)			
	87.259	93.466	99.619	99.937	99.969	100.000

Table 8: Full sample CSR – principal components of economic linkages variables

This table shows the results of the cross-sectional regressions of tail risk spillover coefficient obtained from the first stage LASSO Quantile Regression on groups of determinants of the spillover. This includes the principal components of trade and capital flows, and capital stocks between the two countries (i.e., Total linkage, Role Imbalance, and Trade-Capital Imbalance); volatility and skewness of the daily stock market indices of the two countries; GDP of the shock driver country; other macroeconomics variables and the closing time of the each stock market in the pair. The third column of each regression shows the incremental R-squared (%) of each variable group on the left.

		Main result 10% tail threshold			Robustness 5% tail threshold			Robustness 1% tail threshold		
		Coeff	t-stat	IncR2	Coeff	t-stat	IncR2	Coeff	t-stat	IncR2
Const		0.044	0.723		0.094	1.010		0.450	1.708	
Economic linkage	Total linkage	0.004	0.725	1.67	-0.001	-0.189	1.27	-0.009	-0.433	0.52
	Role Imbalance	-0.053	-3.262		-0.044	-1.804		-0.051	-0.746	
	TradeCap Imbl	-0.087	-5.471		-0.108	-4.658		-0.152	-2.300	
Stock market risk	Volatility *i*	-1.098	-1.470	1.43	-2.949	-2.510	1.96	-7.003	-2.131	2.54
	Volatility *j*	2.743	3.526		4.778	4.001		10.166	3.145	
	Skewness *i*	-0.003	-3.571		-0.003	-2.838		-0.009	-2.785	
	Skewness *j*	0.001	2.033		0.001	0.984		-0.007	-2.211	
GDP *i*	GDP *i*	0.027	29.416	39.76	0.032	23.968	32.69	0.037	9.946	9.69
Other macro-economic variables	GDP *j*	-0.001	-0.857	1.89	0.000	0.360	2.13	0.002	0.566	2.07
	Mkt/GDP *i*	-0.008	-1.428		-0.015	-1.855		-0.029	-1.264	
	Mkt/GDP *j*	0.002	0.345		-0.003	-0.334		-0.034	-1.524	
	GovDEBT *i*	-0.019	-2.274		-0.028	-2.268		-0.028	-0.815	
	GovDEBT *j*	0.015	1.796		0.014	1.044		-0.020	-0.523	
	GDPgrowth *i*	0.091	0.352		-0.258	-0.687		-0.463	-0.443	
	GDPgrowth *j*	0.413	1.602		0.520	1.320		-0.023	-0.020	
	Interest *i*	0.050	0.529		0.154	1.084		0.186	0.461	
	Interest *j*	-0.170	-1.818		-0.370	-2.570		-0.258	-0.615	
	REER *i*	-0.147	-3.584		-0.158	-2.566		-0.442	-2.534	
	REER *j*	0.063	1.639		0.071	1.176		-0.021	-0.123	
	KAOPEN *i*	0.008	1.764		0.011	1.746		0.027	1.552	
	KAOPEN *j*	0.000	-0.069		-0.002	-0.249		0.025	1.327	
Closing time	Closetime *i*	0.035	2.572	0.68	0.012	0.580	0.38	-0.011	-0.191	0.03
	Closetime *j*	-0.043	-3.028		-0.052	-2.443		-0.032	-0.567	
R2(%)				62.54			49.46			15.44

Table 9: Rolling window CSR – principal components of economic linkages variables

This table shows the results of the Fama and Macbeth (1973) cross-sectional regressions of tail risk spillover coefficient obtained from the yearly first stage LASSO Quantile Regression on groups of lagged determinants of the spillover. This includes the principal components of trade and capital flows, and capital stocks between the two countries (i.e., Total linkage, Role Imbalance, and Trade-Capital Imbalance); volatility and skewness of the daily stock market indices of the two countries; GDP of the shock driver country; other macroeconomics variables and the closing time of the each stock market in the pair. The third column of each regression shows the over-time average incremental R-squared (%) value for each variable group on the left.

		Main result 10% tail threshold			Robustness 5% tail threshold			Robustness 1% tail threshold		
		Coeff	t-stat	IncR2	Coeff	t-stat	IncR2	Coeff	t-stat	IncR2
Const		-0.008	-1.018		0.033	1.715		0.040	1.358	
Economic linkage	Total linkage	-0.004	-0.679	2.31	-0.001	-0.240	1.52	-0.001	-0.177	1.31
	Role Imbalance	-0.013	-3.566		-0.021	-3.794		-0.023	-2.267	
	TradeCap Imbl	-0.045	-3.023		-0.049	-2.508		-0.038	-3.920	
Stock market risk	Volatility *i*	-0.713	-2.844	0.84	-1.068	-1.833	0.97	-3.613	-5.060	1.71
	Volatility *j*	1.309	6.268		0.613	3.062		1.199	1.544	
	Skewness *i*	-0.001	-0.557		0.000	-0.197		-0.008	-2.268	
	Skewness *j*	-0.004	-1.917		0.004	3.051		-0.005	-1.201	
GDP *i*	GDP *i*	0.013	4.056	8.64	0.013	5.169	6.55	0.007	15.986	1.71
Other macro-economic variables	GDP *j*	0.000	1.619	2.25	0.000	-0.046	3.25	0.000	1.198	4.22
	Mkt/GDP *i*	-0.004	-1.544		-0.009	-2.983		-0.007	-2.021	
	Mkt/GDP *j*	-0.003	-1.081		0.003	1.453		-0.007	-0.997	
	GovDEBT *i*	-0.012	-3.513		-0.012	-6.022		-0.001	-0.159	
	GovDEBT *j*	-0.003	-1.066		0.011	1.982		0.018	3.708	
	GDPgrowth *i*	0.116	2.662		0.211	2.486		0.214	2.323	
	GDPgrowth *j*	-0.077	-1.144		0.152	1.351		0.093	1.402	
	Interest *i*	0.068	3.495		-0.029	-0.366		-0.037	-0.363	
	Interest *j*	-0.106	-2.737		-0.147	-1.599		-0.326	-6.155	
	REER *i*	-0.009	-0.592		0.009	0.456		-0.029	-2.081	
	REER *j*	0.014	1.011		-0.029	-1.151		0.033	1.552	
	KAOPEN *i*	0.001	1.057		0.000	-0.223		-0.005	-2.685	
	KAOPEN *j*	-0.001	-0.373		-0.003	-0.942		-0.003	-2.411	
Closing time	Closetime *i*	0.027	3.050	0.68	0.029	4.146	0.90	0.024	3.118	0.57
	Closetime *j*	-0.026	-6.423		-0.033	-2.273		0.005	0.315	
R2(%)				19.99			16.71			9.79

Table 10: LASSO Quantile Regression estimate for tail risk spillover – Grouping Eurozone countries

This table summarizes the estimated parameters of the LASSO Quantile Regression for all countries in the sample using the period extending from January 2000 to December 2018. Countries in the Eurozone are grouped to form a single economic entity. The second column shows the number of countries whose tail risk can be explained in the LASSO Quantile Regression by the variables in the first column. The next 3 columns show the minimum, maximum, and average values of the coefficients corresponding to the variables on the first column across the regressions of 18 countries in the system. Since each regression exhibits 17 tail exceedances, the minimum, maximum, and average values on the first row are related to the number of relevant tail exceedances in a regression rather than to the value of the estimated coefficients.

	Number of relevant cases	Min	Max	Average
Tail exceedances from other countries	17	0	9	4.0000
Lagged return	5	-0.0731	0.2091	0.0328
Change in GDP growth	0	NA	NA	NA
Change in Inflation	1	0.0012	0.0012	0.0012
Change in REER	0	NA	NA	NA
Change in Interest rate	15	-0.0271	0.1417	0.0580

Table 11: Connection strength analysis – Grouping Eurozone countries

This table shows countries with the highest and lowest levels of Out-strength, In-strength, and Net-strength in the tail risk network estimated using LASSO Quantile Regression for the full sample covering the period from January 2000 to December 2018. Countries in Eurozone are grouped into a single economic unit.

		Country	Value of sorting measure
Out-strength	Highest	United States	7.697
		Canada	3.239
		Australia	0.699
	Lowest	Poland	0.000
		Switzerland	0.000
		Korea	0.007
In-strength	Highest	Korea	1.680
		Japan	1.615
		Norway	1.300
	Lowest	United States	0.000
		Chile	0.248
		Canada	0.340
Net-strength	Highest	United States	7.697
		Canada	2.899
		Chile	0.293
	Lowest	Korea	-1.673
		Norway	-1.257
		Poland	-1.052

Table 12: Full sample CSR – Accounting for Eurozone countries and BRICS

This table shows the results of the cross-sectional regressions of tail risk spillover coefficient obtained from the first stage LASSO Quantile Regression on groups of determinants of the spillover. This includes the principal components of trade and capital flows, and capital stocks between the two countries (i.e., Total linkage, Role Imbalance, and Trade-Capital Imbalance); volatility and skewness of the daily stock market indices of the two countries; GDP of the shock driver country; other macroeconomics variables and the closing time of the each stock market in the pair. Regression results for different samples are provided. The left one is where all European countries are grouped into a single economic entity. The right one is where the BRICS countries are included. The third column of each regression shows the incremental R-squared (%) of each variable group.

		Grouping Eurozone Countries			Adding BRICS		
		Coeff	t-stat	IncR2	Coeff	t-stat	IncR2
Const		-0.259	-1.918		0.212	4.119	
Economic linkage	Total linkage	-0.003	-0.811	2.48	0.004	1.095	1.12
	Role Imbalance	-0.055	-2.472		-0.009	-0.647	
	TradeCap Imbl	-0.059	-3.022		-0.073	-5.076	
Stock market risk	Volatility *i*	-0.810	-0.312	3.01	-4.124	-6.181	4.37
	Volatility *j*	4.225	1.589		3.511	5.050	
	Skewness *i*	-0.006	-3.518		-0.004	-6.604	
	Skewness *j*	0.002	0.996		0.001	1.514	
GDP *i*	GDP *i*	0.022	12.612	27.08	0.023	27.735	28.70
Other macro-economic variables	GDP *j*	-0.001	-0.435	6.23	-0.001	-1.430	4.90
	Mkt/GDP *i*	0.018	1.342		0.010	1.999	
	Mkt/GDP *j*	-0.002	-0.187		0.004	0.931	
	GovDEBT *i*	0.034	1.556		-0.018	-2.957	
	GovDEBT *j*	0.014	0.604		0.000	0.000	
	GDPgrowth *i*	6.499	5.379		0.169	0.930	
	GDPgrowth *j*	-0.126	-0.110		-0.041	-0.228	
	Interest *i*	0.091	0.386		0.328	3.942	
	Interest *j*	-0.337	-1.475		-0.166	-2.103	
	REER *i*	-0.154	-1.839		-0.278	-8.735	
	REER *j*	0.050	0.594		0.004	0.112	
	KAOPEN *i*	0.067	4.782		0.018	6.013	
	KAOPEN *j*	-0.011	-0.822		-0.003	-1.069	
Closing time	Closetime *i*	0.083	2.872	1.81	0.071	5.741	1.51
	Closetime *j*	-0.048	-1.667		-0.030	-2.459	
R2(%)				60.05			49.65

Table 13: Rolling window CSR – Accounting for Eurozone countries and BRICS

This table shows the results of the Fama and Macbeth (1973) cross-sectional regressions of tail risk spillover coefficient obtained from the yearly first stage LASSO Quantile Regression on groups of lagged determinants of the spillover. This includes the principal components of trade and capital flows, and capital stocks between the two countries (i.e., Total linkage, Role Imbalance, and Trade-Capital Imbalance); volatility and skewness of the daily stock market indices of the two countries; GDP of the shock driver country; other macroeconomics variables and the closing time of the each stock market in the pair. Regression results for different samples are provided. The left one is where all European countries are grouped into a single economic entity. The right one is where the BRICS countries are used. The third column of each regression shows the incremental R-squared (%) of each variable group on the left.

		Grouping Eurozone Countries			Adding BRICS		
		Coeff	t-stat	IncR2	Coeff	t-stat	IncR2
Const		0.100	1.887		0.026	2.185	
Economic linkage	Total linkage	-0.003	-1.649	3.06	0.001	0.229	1.56
	Role Imbalance	-0.049	-3.214		-0.011	-2.623	
	TradeCap Imbl	-0.030	-6.349		-0.044	-3.239	
Stock market risk	Volatility *i*	-3.039	-2.590	2.04	-1.576	-9.206	0.86
	Volatility *j*	4.383	3.546		0.609	4.451	
	Skewness *i*	0.016	0.914		-0.003	-2.918	
	Skewness *j*	-0.040	-5.248		-0.004	-2.419	
GDP *i*	GDP *i*	8.500	4.397	3.51	0.011	2.867	5.87
Other macro-economic variables	GDP *j*	1.987	2.081	5.65	0.000	-0.469	2.26
	Mkt/GDP *i*	0.002	0.300		-0.004	-2.454	
	Mkt/GDP *j*	0.008	1.199		-0.001	-1.410	
	GovDEBT *i*	-0.007	-0.597		-0.009	-1.488	
	GovDEBT *j*	-0.007	-0.437		-0.001	-0.391	
	GDPgrowth *i*	0.706	4.614		0.117	5.090	
	GDPgrowth *j*	-0.458	-4.617		-0.042	-2.412	
	Interest *i*	-0.227	-4.240		0.130	7.278	
	Interest *j*	-0.258	-1.059		-0.063	-2.242	
	REER *i*	-0.096	-3.321		-0.024	-1.412	
	REER *j*	0.011	0.636		-0.015	-1.510	
	KAOPEN *i*	-0.001	-0.278		0.002	5.276	
	KAOPEN *j*	-0.006	-0.726		0.000	-0.868	
Closing time	Closetime *i*	0.046	4.438	1.51	0.045	7.770	1.10
	Closetime *j*	-0.062	-6.988		-0.021	-9.313	
R2(%)				22.38			13.93

Table 14: Connection strength analysis – Adding BRICS

This table shows countries with the highest and lowest levels of Out-strength, In- strength, and Net-strength in the tail risk network estimated using LASSO Quantile Regression for the extended sample with BRICS countries added. The estimation period begins in January 2000 and ends in December 2018.

		Country	Value of sorting measure
Out-strength	Highest	United States	13.507
		Canada	6.541
		Brazil	3.187
	Lowest	Switzerland	0.000
		Poland	0.000
		Belgium	0.000
In-strength	Highest	Russia	2.585
		Japan	2.017
		Korea	1.619
	Lowest	Italy	0.000
		Slovak Republic	0.000
		United States	0.000
Net-strength	Highest	United States	13.507
		Canada	6.201
		Brazil	2.934
	Lowest	Russia	-2.466
		India	-1.428
		Portugal	-1.420

Table 15: Rolling window CSR – Panel regression framework

This table shows the results of the panel regressions of tail risk spillover coefficient obtained from the yearly first stage LASSO Quantile Regression on groups of lagged determinants of the spillover. This includes the principal components of trade and capital flows, and capital stocks between the two countries (i.e., Total linkage, Role Imbalance, and Trade-Capital Imbalance); volatility and skewness of the daily stock market indices of the two countries; GDP of the shock driver country; other macroeconomics variables and the closing time of the each stock market in the pair. The third column of each regression shows the incremental R-squared (%) value for each variable group on the left.

		32 OECD Countries			Grouping Eurozone Countries			Adding BRICS		
		Coeff	t-stat	IncR2	Coeff	t-stat	IncR2	Coeff	t-stat	IncR2
Time effect			Yes			Yes			Yes	
Economic linkage	Total linkage	0.000	0.135	0.40	-0.003	-2.149	1.07	0.001	1.097	0.37
	Role Imbalance	-0.013	-2.848		-0.024	-4.483		-0.005	-1.275	
	TradeCap Imbl	-0.040	-6.187		-0.029	-4.568		-0.046	-8.730	
Stock market risk	Volatility *i*	-0.555	-1.975	0.09	-2.032	-2.987	0.33	-1.087	-5.911	0.24
	Volatility *j*	0.649	2.261		1.317	1.852		0.659	3.557	
	Skewness *i*	0.000	0.001		-0.003	-1.031		0.000	0.211	
	Skewness *j*	-0.001	-0.794		-0.001	-0.294		0.000	-0.253	
GDP i	GDP *i*	0.011	29.796	7.36	7.910	13.800	4.45	0.008	30.596	4.39
Other macro-economic variables	GDP *j*	0.000	0.179	0.32	1.328	2.315	0.73	0.000	-0.736	0.25
	Mkt/GDP *i*	-0.005	-1.941		0.002	0.483		0.000	-0.070	
	Mkt/GDP *j*	-0.001	-0.546		0.004	0.737		0.000	0.063	
	GovDEBT *i*	-0.009	-2.765		-0.001	-0.098		-0.007	-3.275	
	GovDEBT *j*	0.004	1.198		0.008	1.175		0.002	0.947	
	GDPgrowth *i*	0.075	1.608		0.316	2.529		0.045	1.559	
	GDPgrowth *j*	0.026	0.558		-0.113	-0.880		-0.003	-0.119	
	Interest *i*	0.080	2.682		0.120	2.159		0.100	4.849	
	Interest *j*	-0.061	-2.141		-0.011	-0.199		-0.057	-2.651	
	REER *i*	0.012	1.293		0.010	0.577		-0.001	-0.183	
	REER *j*	0.013	1.463		-0.011	-0.624		0.002	0.369	
	KAOPEN *i*	0.002	1.242		0.003	1.066		0.002	2.827	
	KAOPEN *j*	0.000	0.016		0.000	0.046		0.000	-0.304	
Closing time	Closetime *i*	0.031	4.596	0.22	0.049	4.106	0.64	0.047	10.771	0.68
	Closetime *j*	-0.014	-2.018		-0.039	-3.213		-0.016	-3.984	
R2(%)				11.97			10.17			7.96