The Double-Edged Sword of Global Integration: Robustness, Fragility & Contagion in the International Firm Network*

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Abstract

We use daily equity returns to estimate global inter-firm networks across all major industries from 1991–2016 and test whether the networks exhibit robust (beneficial) or fragile (harmful) behavior, relating multinational firms' health with global integration. More connected firms are less likely to be in distress, with higher profit, revenue and equity price growth; however, they are more exposed to direct contagion from distressed neighboring firms and network level crises. Our machine learning based analysis reveals the centrality of finance in the international firm network, increased globalization over time, and greater potential for crises to spread globally when they do occur.

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1 Introduction

After a series of events during the past decade with swift and severe consequences for firms across the globe — including the U.S. Sub-Prime Mortgage and Eurozone Debt Crises — researchers, investors and policymakers have challenged our understanding of systemic risk and contagion across financial firms given their perceived centrality to the transmission of these episodes. To this end, the Bank of England's then Executive Director for Financial Stability, Andrew G. Haldane, drew parallels between financial systems and complex systems in other fields and postulated that financial networks may be "robust-yet-fragile" (RyF).[1] This term describes the duality wherein greater network connectedness acts to cushion and smooth the effects of small shocks (network robustness); however, these connections may also spread crises by passing on large shocks and propagating contagion (network fragility). What research into these crisis events often misses, however, is the striking extent and breadth of these episodes, not only across the global banking system, but across all business sectors.

In this paper, we perform the first explicit tests to determine whether the global firm network is robust and/or fragile, particularly as they relate to firm crisis susceptibility and financial health. We estimate the global multinational firm network in real-time from daily equity returns using machine learning methods. Our results suggest that a one standard deviation increase in a firm's total connections in from other firms reduces the probability of firm distress by 3.6% and is associated with improved firm health — e.g., increased growth of 1.2% for monthly equity prices, 4.0% for quarterly profits, and 1.7% for both quarterly revenue and annual return on equity. At the same time, if a neighboring firm is in distress then its contagious effect is nine times greater than the diversification benefit of higher integration in the network. Further, a firms' measured network robustness and fragility can be used to create portfolios with statistically significant excess returns.

First, to infer the firm networks we perform a vector auto-regressive (VAR) estimation of their daily equity returns on one another. We utilize the adaptive elastic-net shrinkage method to avoid dimensionality problems that arise from including the numerous cross-sectional observations, as well as to limit overfitting of the data. We then use these estimates to calculate generalized impulse response functions (GIRFs) between every pair of firms. In the global network each node represents a firm, and the edges connecting them are the one day GIRFs from the source firm to the terminal one. These edges capture the strength and direction of connections — which flow in both directions — making them what is referred to as weighted, directed networks.[2] Using GIRFs, the network edges capture how much other target firms' equity prices are expected to move conditional on a change in the price of the source node, rather than the effect of an orthogonalized shock emanating from the source firm. This framework allows us to obtain measures of interconnectedness, inclusive of common exposures to broad shocks. Our work expands the analysis of market derived inter-firm networks by going beyond financial companies to include multinational firms in all major industry categories, and by the breadth of our estimated networks, across up to 49 countries from 1991-2016.

[1]See Haldane (2009) for the full speech text.

[2]For a survey of network estimation procedures applied to economics and finance refer to Allen and Babus (2008).

We identify several empirical features that characterize the global inter-firm network: both industry and locality play important roles in connectedness between firms; multinational firms have become more connected over time; and finance is typically at the center of the network.

Second, we assess whether the multinational firm network exhibits robustness, fragility, or both properties. In order to test for robustness and fragility in the firm networks, we run a series of regressions where the dependent variables are different measures of firm health, including equity returns, revenue, CDS spreads, return on equity, and profit. The explanatory variables are a firm's aggregate connectedness in the network estimated over the prior five years, these weights interacted with indicators of neighboring firms' health, and several aggregate state variables such as the TED spread, VIX and the share of firms currently in a distressed state. As previewed above, we find evidence for the existence of robustness through more connected firms having better performance and resistance to network level crises, and of fragility through direct contagion from network neighbors, vulnerability to system-wide shocks, and these latter two mechanisms reinforcing one another.

The RyF attributes of the global inter-firm network allow us to sort companies into portfolios by creating investment strategies based on firms' network exposures, specifically their network weighted proximity to other firms in distress. Our portfolios outperform the market by several benchmark measures, suggesting that firms' integration in the network is an important factor for future equity performance that investment managers should consider while building their portfolios.

Finally, we conclude the analysis by exploring different applications of our global networks and estimated RyF regressions. We run a series of contagion simulations that provide further evidence of network crises reinforcing direct contagion. These indicate that the level of global firm connectedness — and with it the potential for global contagion — increases over our sample period. The evolution of the firm network illuminated by these simulations helps explain why research developed around 2000 found robust networks and later work suggested fragility, as discussed in the next section reviewing the literature on firm networks, robustness and fragility.

Our analysis reveals a new mechanism for global contagion that has been activated by increased firm network connectedness, the crisis echo effect. When there is extensive distress in an economy that plays an important part in the global firm network, distress is prone to be transmitted to firms abroad. It is likely there will then be a large number of distressed firms abroad as contagion to them occurs, leading to an echo effect wherein spillovers then return from these firms to spread to other domestic ones. This echo effect should be an important consideration for policymakers in large economies when facing potential crises, since these disturbances can be reflected back by the global network to exacerbate domestic conditions. Further, for investors in major economies, the echo effect may indicate reduced benefits from international portfolio diversification.[3] The existence of the echo effect indicates that it is misleading to build investment portfolios or study crises with countries in isolation, with the real world implication that, going forward, large economies like the

[3]See Brooks and Del Negro (2004) and Brooks and Del Negro (2006) for further analysis of the evolving benefits of international portfolio diversification.

U.S., China and the Eurozone cannot ignore their impact on developments abroad.

Our results provide evidence that while increased network connections may make the global economy more resilient and benefit firm growth, they also may act as a conduit for contagion and elevated systemic risk. By shedding light on the nature of the global inter-firm network, we help identify the classes of models appropriate to account for these dynamics.[4] The robust network features and initially low level of connectedness at the beginning of our sample suggest why representative agent firm and closed economy models have had such success in economics; however, they are no longer adequate to study events such as the Global Financial and Eurozone Debt Crises owing to increased global integration, and the network's exhibited firm heterogeneity and fragility.[5]

A better understanding of these features of the multinational firm network would have broad implications for policymakers, as systemic importance has been used to support policies ranging from government bailouts, to import tariffs, to the sweeping Dodd-Frank reforms aimed at preventing future crises. Additionally, whether higher integration is associated with robustness, fragility or both has important consequences for investors seeking international or inter-industry diversification to insure against negative shocks to their portfolios.

2 Network Robustness and Fragility

The notion of robust-yet-fragile bridges two opposing facets of integration. For example, a bank loaning its assets to a single borrower is less likely to have an insolvent neighbor in the network since it only has one; however, its neighbor going bankrupt guarantees that it will go bankrupt itself. Alternately, a bank with more borrowers — connections in the network — is more likely to have an insolvent neighbor, but it will take many of them going bankrupt concurrently to cause insolvency due to the diversification benefit of being more broadly connected. Likewise, at the aggregate network level widespread contagion is unlikely at the extremes where there are either very few connections — as the contagion is likely to be quarantined by the lack of connectedness — or with very many connections — as it is unlikely that enough firms will become insolvent to trigger bankruptcies across the network. We wish to evaluate the relative importance of these two forces — as well as those of network level shocks — across the multinational firm network.

There are numerous real-world examples suggesting that firms are highly connected and dependent on one-another in nuanced ways, beyond the financial connections in the bank example. Baqaee (2018) and others have exemplified this interconnectedness by pointing out that in November 2008 Ford CEO Alan R. Mulally appeared before the Senate Banking Committee to lobby for bailouts for General Motors and Chrysler in the midst of the ongoing financial turmoil, though

[4]See, for example, Acemoglu et al. (2015a) on how modeling assumptions interact with the RyF behavior of modeled networks.

[5]These results align with the analysis of Acemoglu et al. (2012) that "classic" macroeconomic models that ignore firm heterogeneity — assuming differences will average out — are insufficient to capture some important real-world developments.

not Ford itself. He worried that because of the major automobile manufacturers' significant overlap in suppliers, dealers, and other business partners that "the collapse of one of our competitors would have a severe impact on Ford... because the domestic auto industry is highly interdependent. It would also have devastating ripple effects across the entire U.S. economy."[6] Ford and the automotive industry provided further reason to consider the full context of the inter-firm network structure in Australia. In May 2013, Ford Australia announced it would stop manufacturing cars in the country and did cease doing so in October 2016. Two months after the Ford announcement, Toyota followed suit by stating that it would terminate its manufacturing, too, citing a lack of volume from those in the component supply chain to keep its Australian production operations economically viable.[7] Within a few months, GM Australia announced that it would also have to shutdown, along with many of the parts suppliers, effectively ending the Australian automotive manufacturing industry.

There are many other examples demonstrating inter-firm network effects. Some, as in the case of the August 2016 bankruptcy of Hanjin Shipping, can have dramatic and sweeping ramifications through the global economy. The disruptions emanating from the Hanjin bankruptcy stranded $14 billion of goods at sea around the world.[8] In others, the reliance of firms on each other are more local but no less real, even when they are not in the same industry nor supply chain. For example, work by Benmelech et al. (2014) demonstrated how local businesses rely upon one another to attract customers when they showed that the closure of a retail chain weakens the economies of agglomeration in the area. They further showed that companies with greater geographic exposure to the closed retailer are more likely to close themselves, with the externality being higher for smaller stores. These results corroborate recent worries about what the challenges confronting large department stores in the face of increased online competition and over-development of retail might mean for shopping malls that rely upon them as anchor stores, and validates the usage of that term, "anchor," when describing them.[9]

On the labor side, Goins and Gruca (2008) used firm stock price as an aggregate measure of firm well-being to find that when a firm announces a significant permanent layoff there is a spillover beyond the announcing firm to others in the industry. They studied a longitudinal sample of layoff announcements in the U.S. oil and gas industry from 1989 to 1996 and found that if the equity price of the announcing firm responds negatively, there will be simultaneous price declines for non-announcing firms; however, close rivals see a countervailing competitive effect dampening this contagion. There are many other examples we could go into, but at this point it should not be difficult to appreciate the importance and variety of inter-firm connections.

It is an open question in economics whether inter-firm networks are a steadying or destabilizing

[6] See Mulally (2008) for details.

[7] http://www.smh.com.au/business/the-economy/australias-car-industry-one-year-from-closing-its-doors-20151012-gk7ip0.html

[8] http://www.reuters.com/article/us-hanjin-shipping-debt-usa-bankruptcy-idUSKCN11Q2TA

[9] See for example http://www.businessinsider.com/macys-store-closures-and-what-it-means-for-malls-2015-9, https://www.washingtonpost.com/news/digger/wp/2016/08/30/macys-is-closing-100-stores-does-yours-stand-a-chance/, and http://www.nytimes.com/2015/01/04/business/the-economics-and-nostalgia-of-dead-malls.html?_r=1.

force for the firms within them, or perhaps exhibit both robustness and fragility.[10] Pioneering research by Allen and Gale (2000) and Freixas et al. (2000) focused on direct firm claims on one another as the edges in the financial network connecting banks. In both cases, their results suggest that more connected firm networks are robust by mitigating risk when one of them defaults. One can think of this as diversifying counterparty risk, reducing overall systemic risk.

On the other hand, later work — especially that in the wake of the Global Financial Crisis — tends to support the idea that bank network connectedness acts as a destabilizing force producing financial fragility. Blume et al. (2011) and Blume et al. (2013) modeled the spread of cascading failures through networks that emerge in many domains, with one focus being the contagious failures that spread among financial institutions during a crisis. They found evidence of financial network fragility. Specifically, by modeling strategic financial network formation they proposed that stable network systems tend to be ones where agents "over-link," with increased contagion risks that have dire consequences for the welfare of the participants. Likewise, Vivier-Lirimont (2006) found that the higher is network connectedness, the larger is the number of banks involved in the contagion process, and the quicker is the contagion phenomenon.

These conflicting views on the role of network connectedness with regard to robustness and fragility were reconciled in subsequent work with theoretical models that predict that inter-bank networks have a RyF structure.[11] Elliott et al. (2014), Acemoglu et al. (2015b), Gai and Kapadia (2010), and Gai et al. (2011) developed models that have phase transitions between robustness and fragility at different levels of bank network connectedness.[12] The former paper breaks connectedness into two measures: integration (greater counterparty exposure) and diversification (more counterparties per organization). They found that these have different, non-monotonic effects on the extent of contagion. Diversification initially is a negative, as the small connections transmit crises; however, as it increases further organizations are better insured against one another's failures. Integration also entails a trade-off between dependence on other banks versus less sensitivity to a firm's own idiosyncratic shocks. Acemoglu et al. (2015b) found that the extent of financial contagion is sensitive to a phase transition. For small shocks there is robustness from a more densely connected financial network (corresponding to more diversified counterparties). Beyond a certain threshold, greater firm connectedness dominates in its role as a shock transmission mech-

[10] For example, Acemoglu et al. (2015b), Acemoglu et al. (2015a), Gai and Kapadia (2010), Gai et al. (2011) and the references therein.

[11] See Internet Appendix Section G for an example of these network crisis contagion models and their dynamics.

[12] These transitions arise because very low levels of connectedness with other firms are not enough to pass on contagion, and very high levels provide enough diversification over many firms to buffer against contagion. It is only for moderate levels of connectedness that the probability and potential breadth of contagion are large, creating a "contagion window" at moderate levels of network connectedness. Caccioli et al. (2012) and Caccioli et al. (2015) augment the model of Gai and Kapadia (2010), and we provide an extension of their model across all sectors of the economy in the Internet Appendix. The former paper adds firms that are heterogeneous in their degree distributions, balance sheet size and degree correlations. They find that networks with heterogeneous degree distributions are more resilient to contagion occurrences, so long as the source is not a highly connected bank. Their results recommend a targeted policy aimed at reinforcing the stability of the biggest banks to improve financial market stability. Caccioli et al. (2015) includes both direct counterparty failure risk and contagion via overlapping portfolio exposures, finding that neither channel is significant on its own, but that when both channels are active at once, bankruptcies are much more common and have large systemic effects.

anism leading to fragility. In this way, the effects of firm connectedness can be twofold, able to contribute to resilience under certain conditions or act as a source of systemic risk under others, with network integration and concentration being important for which force dominates. The latter two papers conclude that, while with more connectedness the probability of contagion may be lower, the exposure can be extremely widespread when distress events do occur.

The firm network literature has been mostly focused on the financial sector.[13] However, Acemoglu et al. (2012) and Baqaee (2018) showed that it is important to consider the network of all firms in an economy.[14] Despite a long running assumption in macroeconomic modeling that idiosyncratic firm shocks will average out and so can be ignored, Acemoglu et al. (2012) demonstrated how these shocks can generate cascade effects whereby firm problems propagate not only to immediate customers, but also to the aggregate macroeconomy.[15] This propagation occurs if there is significant asymmetry in the scopes of sectors as intermediate input suppliers to others, with the sparseness of the input-output matrix being largely immaterial to the nature of aggregate fluctuations.[16] Baqaee (2018) likewise found that the interaction of input-output networks with industrial structure affects the propagation and amplification of shocks and is an important consideration for business cycle fluctuations.

These results illustrate the duality of firm networks, with them having the potential to be either robust or fragile. With our empirical analysis, we seek to determine whether the multinational firm network is robust, fragile, or both to better understand the risks it poses, or possibly the benefits firm connectedness provides for weathering shocks and preventing outbreaks. This knowledge is a first step towards helping contend with — or even prevent — possible outbreaks in the future.

3 Data

To select our sample of multinational firms, we take the union of the largest firms by market capitalization over each year of the past two and a half decades, such that on average we cover over 50% of the total market capitalization of all exchange traded equities. If a firm is in our sample at

[13] The evolution of global financial networks was the subject of research by Billio et al. (2012) that analyzed monthly returns of hedge funds, banks, broker-dealers and insurance companies, and that of McGuire and Tarashev (2008) and Minoiu and Reyes (2013) into cross-border banking flows. Hale (2012) is the first study of bank-level networks on a global scale — using syndicated loan data to construct a global banking network from 1980 to 2009 of 7938 banking institutions across 141 countries — finding that bank linkages are less likely to form if a country is experiencing a recession or a banking crisis. See Glasserman and Young (2016) for an excellent overview of the development of research into financial networks.

[14] Other papers exploring connectedness and transmission of shocks across sectors in the macroeconomy are Bak et al. (1993), Carvalho and Gabaix (2013), Foerster et al. (2011) and Gabaix (2011).

[15] Acemoglu et al. (2015a) developed a unified framework for studying network propagation and amplification of microeconomic shocks dependent on whether the system has (log) linear agent interaction and network utility functions. This work clarifies that, with linear firm interactions, the desire for reduced output volatility lies at the heart of the results in Acemoglu et al. (2012). Likewise, for non-linear interaction functions — such as with bank defaults in Acemoglu et al. (2015b) — they characterized similar phase transitions transforming the role of network interconnections in shaping aggregate performance.

[16] Asymmetry in the scope of actors in a network refers to the relative weights of their edges out, with some nodes being far more influential than others. Sparseness measures how many of the potential edges in a network do not exist.

any point then we follow it for the full time that there is pricing data for it from Bloomberg. As a reference, the 919 of these firms traded on December 31st 2015 represented just over 55% of the global market capitalization of all exchange listed firms.[17] Our focus is on the largest firms in order to ensure that they all have actively traded, liquid equity securities that are highly researched and followed, providing them with accurate price discovery.

For each firm we collect a set of daily, quarterly and annual data. One of the benefits of our methodology is that it can be implemented using easily obtainable data. First, we include the daily equity closing price for each firm from January 1st, 1991 through September 30th, 2016. The closing equity values are total return indices inclusive of returns from dividends to avoid spurious price jumps when dividends are paid that do not reflect a change in the valuation of the underlying firm. We also gather daily 5-year CDS spreads from October 2013 through November 2015 from Markit. From firm quarterly statement data on Bloomberg we collect EBITDA (profit), revenue (Sales/Revenue/Turnover), and total firm equity. We also include the annual return on equity (RoE) over each calendar year. From these series we calculate log changes as well as distress/crisis state indicator variables for the worst 10% performance within our sample by each measure. All prices and market values are in local currency, so their log changes do not conflate currency movements with individual firm performance. For a summary table of the data refer to the Internet Appendix. In addition to the firm data, we collect daily data to gauge the overall health of the global economy from Global Financial Data: the 3-month TED spread; S&P 500 Total Return Index; and the CBOE S&P 500 Volatility Index (VIX).[18] The log changes of each of these variables and indicators for the worst 10% of outcomes are included in the dataset.

4 Global Network Estimation

In this section, we describe how we estimate the inter-firm networks, explore the features of the network from 1991 through 2016, and examine how interconnectedness evolves over time. In order to estimate interconnectedness across firms, we build from the work of Bonaldi et al. (2015), Demirer et al. (2018), Diebold and Yilmaz (2009, 2014, 2016), and Scida (2015) by using VAR techniques to estimate economic networks.[19] Multinational firms can be connected in myriad ways: shared product markets; sourcing from the same labor markets; obtaining credit from the same financial center; location; having similar business risks; etc. Collecting the data on the multitude of firm interactions would be near impossible, and it would be difficult to find a function to properly

[17] According to data from Bloomberg and the World Federation of Exchanges. Focusing on large multinational firms is consistent with work by Gabaix (2011), which found that the idiosyncratic movements of the 100 largest U.S. firms explained about one-third of all variation in output growth, implying that many macroeconomic questions can be resolved by only looking at the behavior of the largest firms.

[18] The TED spread is the difference between 3-month USD LIBOR and the 3-month U.S. Treasury bill yield.

[19] These papers offer noteworthy insights into a number of areas of economics by using tools from computer science and physics to characterize and visualize the relationships between the network members. For example, the Diebold-Yilmaz series demonstrates the evolution towards greater global integration over time, especially during crisis periods.

aggregate them into a single network.[20] The efficient markets hypothesis postulates that firms' equity prices reflect all available information about them, including proximity across these many dimensions. If two firms produce in the same labor market, borrow from the same banks, have similar risk profiles, hold similar assets, etc... these should be reflected in linked equity returns for the two. If this were not the case then profit opportunities would exist for investors savvy enough to trade on the omitted information. We therefore use the equity returns as both a readily available proxy for collecting data on the different channels through which firms are connected — one that can be updated in real-time — and as an aggregator function to combine them, much as Goins and Gruca (2008) exploit equity returns to measure changes in overall firm well-being.[21]

4.1 Network Estimation Methodology

We estimate inter-firm networks that represent co-movements in firms' equity returns, reflecting similarities in the firms themselves, regardless of the source of any underlying shock(s). This includes not only direct connections between firms, but also exposure to similar common shocks. An aggregate shock can only affect two firms if there is an underlying connection that is a conduit for the shock to affect both, and we intend for our estimated networks to include these latent exposure channels. For example, greater globalization would increase firms' responses to shocks abroad, which we would capture in greater estimated network connections. Our first step is to estimate a VAR model of the firms' daily equity log returns on lags of themselves and of those of the other firms:

$$\boldsymbol{X}_t = \boldsymbol{c} + \boldsymbol{A}_1\boldsymbol{X}_{t-1} + \boldsymbol{A}_2\boldsymbol{X}_{t-2} + ... + \boldsymbol{A}_p\boldsymbol{X}_{t-p} + \boldsymbol{\epsilon}_t, \tag{1}$$

where $\boldsymbol{X}_t$ is a vector of the standardized daily log returns for the included firms, $\boldsymbol{c}$ is a constant vector, and p is the order of the VAR. The primary challenge facing this approach is the curse of dimensionality from having numerous firms and potentially multiple lags of their equity returns in the VAR and is likely the obstacle which has prevented similar global network research in the past.

To contend with this issue, we follow the work of Demirer et al. (2018) in using shrinkage methods borrowed from machine learning to obtain our VAR estimates. The particular shrinkage method that we use is the adaptive elastic-net (AEN) estimator from Zou and Zhang (2009). Their method uses an elastic-net estimation combining the L_1 and L_2 penalties of the LASSO (least absolute shrinkage and selection operator) and ridge methods, with the adaptive label in the name referring to the manner in which weights are selected to further penalize coefficients that are smaller in magnitude to aid in the shrinkage. The AEN estimation procedure solves the following problem

[20] Collecting off-balance sheet items is challenging in its own right, as described by Demirer et al. (2018); however, tracking all of the inter-firm connections through the supply chain and financing of numerous companies, countries and sectors is virtually impossible. To partially overcome these data collection challenges, Hoberg and Phillips (2016) use text-based machine learning analysis of firm 10-K product descriptions to identify a new network of industries based on product classifications rather than production processes to study how industries and their competitors change.

[21] Several of the papers in the Diebold-Yilmaz series, as well as Bonaldi et al. (2015), Kitwiwattanachai (2015) and Scida (2015), also use financial market prices, volatility and credit market data to estimate firm networks.

for dependent firms $j \in \{1, 2, ..., I\}$:

$$\hat{\boldsymbol{\beta}}_{\boldsymbol{j}} = \underset{\beta_{00}^j, \{\beta_{il}^j\}}{\arg\min} \sum_{t=L+1}^{T} \left(x_{j,t} - \beta_{00}^j - \sum_{i=1}^{I} \sum_{l=1}^{L} \beta_{il}^j x_{i,t-l} \right)^2 + \rho_j \sum_{i=1}^{I} \sum_{l=1}^{L} w_{il}^j (\alpha_j |\beta_{il}^j| + (1-\alpha_j) {\beta_{il}^j}^2), \quad (2)$$

with $\tilde{\beta}_{il}^j$ being the standard OLS coefficient estimates, $w_{il}^j \equiv \frac{1}{|\tilde{\beta}_{il}^j|}$, $\{\beta_{00}^j\}$ the constant terms, $\{\beta_{il}^j\}$ the set of elements of the coefficient matrix $\boldsymbol{\beta}_{\boldsymbol{j}}$, $\{x_{it}\}$ the standardized daily log returns, and L the maximum lag considered. The $\{\rho_j\}$ and α_j penalty weights are set to fit the data. Each firm's daily log return series is standardized independently over the full sample, so that they all have mean zero and a standard deviation of one to make the GIRF values comparable across firms and over time. We do not remove the average daily market returns because these include important information about broader shocks, sensitivity to which we incorporate into our inter-firm networks. With this approach we utilize AEN for both the shrinkage and selection of the VAR lag order.[22]

When $\alpha_j = 1$ only the LASSO penalty is included, and when $\alpha_j = 0$ only the ridge penalty is applied, otherwise the two are mixed in standard elastic-net. To benefit from both techniques, we set α_j such that each penalty term is on average equal. By including both penalty arguments, strongly-correlated predictors are shrunk in or out of the model together unlike LASSO, where having only the absolute value term — and weak rather than strict convexity — makes the optimization more likely to hit a multidimensional vertex where only the "best" explanatory variable will be kept among highly correlated variables, with the others driven towards zero. We run 10-fold cross-validation to determine the ρ_j value for each firm.

We deviate from the Demirer et al. (2018) procedure in how we derive our inter-firm network from the estimated VAR model. While they use normalized generalized forecast error variance decompositions based on their estimated VARs to measure the weights of the edges connecting firms, we instead use GIRFs.[23] The precise definition of the GIRF is the expected effect when there is a shock to the return of firm i in the VAR at time t (ϵ_{it}) on the vector of firm returns at a horizon h (X_{t+h}), which is given by:

$$GIRF(h, i, \Omega_{t-1}) = \mathbb{E}(X_{t+h} | \epsilon_{it} = \sigma_i, \Omega_{t-1}) - \mathbb{E}(X_{t+h} | \Omega_{t-1}), \quad (3)$$

where Ω_{t-1} is the non-decreasing information set known at time $t-1$, and σ_i is the standard deviation of the error term ϵ_{it}.[24] Once we have the estimated VAR coefficients and residuals it is straightforward to calculate the GIRFs between all of the firms. The $I \times I$ matrix of the GIRFs between all of the sample firms' returns created by appending the $GIRF(h, i, \Omega_{t-1})$ vectors is the

[22]In the Internet Appendix, we discuss alternative estimation methods. The benefits of AEN — requiring few assumptions while dealing with the model shrinkage and selection — however, leave the AEN method as the best option for our purposes from what is currently available.

[23]There are two main reasons for using GIRFs rather than the normalized variance decompositions: GIRFs do not necessarily add to 100% at any forecast horizon as the scaled forecast error variance decompositions do, which may overestimate firms' connectedness; and GIRFs have an economic interpretation that more closely quantifies the underlying relationships between the different firm returns that we are interested in.

[24]Specifically, we use the scaled GIRFs of Pesaran and Shin (1998).

basis of our estimate of the firm network adjacency matrix. Because we care about the magnitude of the degree of connectivity — rather than the positive or negative signs of the relationships — we take the matrix of the absolute values of all of the paired GIRFs as the adjacency matrix representing the inter-firm network, A, with the value in each a_{ij} cell being the network weight from firm j to firm i. Each firm, or node in our network, is listed along the rows and columns, with the edge weights between them being the entries in the matrix, generating a network that is both weighted and directed.

We use generalized responses — rather than orthoganalized responses such as those found using Cholesky decompositions to capture shocks from individual firms — so their values are not estimating the cause and effect of a shock emanating from one firm to another.[25] The proper way to interpret the edges in our estimated networks is how many standard deviations one would expect other target firms' daily equity returns to move, conditional on a one standard deviation innovation for the source node's equity return. In this way, the network edges capture co-movements and firm connectedness regardless of the source of the shocks, whether they be idiosyncratic firm shocks or common shocks.

4.2 Features of the Global Firm Network

Our analysis of the global inter-firm network focuses on the 382 firms in our sample that were actively traded from 1991 through 2016 to provide continuity when analyzing the network over time. Our primary network is from one period ahead GIRFs derived from the AEN estimation procedure in the previous section run on the firms' daily log equity returns with one lag. To help picture the global firm network, we borrow network visualization methods used in various other disciplines (e.g., biology, physics, computer science). Specifically, we generate a series of spring plots using the ForceAtlas2 method from Bastian et al. (2014). ForceAtlas2 is a force-directed layout algorithm to display network spatialization, transforming a network into a map where nodes with greater connectedness are closer together. At a high level, all of the nodes are repulsed from one another like charged particles, while edges attract their nodes, like springs — yielding the name for this class of algorithms — with greater edge weights producing greater attraction. The final node positions provide a balanced state, helping to interpret the data without having to incorporate any other attributes of the nodes. To read these plots, think of a map without a compass rose showing the direction of true north nor a scale. In that case, as with these plots, the precise orientation of the figures is not informative and rotations do not have a clear meaning, but the relative proximity of features on the plots to one another and the center of the figure do, as do any clusters that arise and inform the underlying topology. This technique is superior to other methods to visualize the network adjacency matrix like heat maps primarily because the number of rows and columns makes

[25]Orthogonalization of the shocks is not appropriate for our purposes, since we are not trying to recover the specific structural shocks; rather, we are estimating how the system behaves for shocks similar to historical ones, taking into account the correlations among the innovations. Additionally, an often overlooked drawback of Cholesky decomposition based impulse response functions is that they do not necessarily identify the proper shocks, even if they do orthoganalize them and allocate them to particular variables.

these other methods hard to read, and the spring plots are able to capture third party or greater relationships. For example, if two tire manufacturers both have strong ties to Ford but weak ones with each other, then they would still be close in these figures because they would be near Ford.

The maps of our estimated global firm networks help visualize the connections between firms. To begin, Figure 1 shows the network with the nodes' colors based on four sets of firm characteristics. In Panel (a), the firms are colored based on their industry classification. From the quasi pie-chart appearance of the main cluster, it is evident that industry plays a key role in connecting firms in the network.[26] The firms on the edges of the network are generally near those in the same industry in the central cluster, with ICT firms at the top right, consumer non-cyclical on the right, utilities on the bottom, base materials and energy firms at the bottom left, and industrial diversified and consumer cyclical firms on the left. Further, the black center of the figure identifying a cluster of financial firms at the heart of the network indicates that finance is at the center of the network.

Panels (b) and (c) show firms colored based on locality related attributes, namely the country of a firm's headquarters and the currency in which the firm's equity was issued, respectively. There are again clear, but very different, color patterns to the figures. Both of these plots have U.S. based firms at the center, with other advanced western markets closely integrated with them. There are a number of South African, Canadian, and U.K. firms on the fringes of that central cluster, with Australian, Japanese and other Asian firms stationed in orbits farther outside, on the periphery of the panels.[27] Since all of the equity prices are in local currency, currency movements are not directly captured in the equity returns we use so they cannot be the cause of the regional organization of the plots. These results expand those of the long-standing literature in international finance studying asset prices, which finds that country factors are more important drivers of co-movement and volatility than industry factors, as established by the seminal work of Heston and Rouwenhorst (1994).

Panel (d) shows the firms grouped using a spectral clustering algorithm on their daily equity return series. The spectral clustering algorithm produced four clusters, which appear to be associated with locality, likely reflecting local equity market betas. The black region appears to cover the U.S. and other closely related advanced western firms, the orange encompasses those firms that are on the periphery of that cluster, and the red ones are the Australian, Japanese and other Asian companies. There is one cluster of two firms in green near the middle of the diagram. These two firms are the U.S. agencies Fannie Mae and Freddie Mac. While they are close to several other U.S. and financial firms, their tight connections with one another and unique return profiles during the Global Financial Crisis and subsequent government intervention placed them outside the main knot of firms.

Internet Appendix Figure B.1 presents the same global network spring plot with the nodes colored by four different categories based on the estimated network weight matrix. Unsurprisingly,

[26] These results generalize the conclusions of Demirer et al. (2018), who found that when looking at the top 150 global banks it is bank location, not bank assets, that matters for network proximity.

[27] That Asian and Australian equities are on the periphery with generally low out weights but higher in ones matches findings from Diebold and Yilmaz (2015) studying the network between country equity indices.

those nodes with the greatest weight out sums are at the center, smoothly transitioning to the lower weight out sums on the periphery. On the other hand, the firms with the lowest edge weight in sums are generally at the center, but there is not as smooth an evolution as firms get farther out, suggesting that leading firms are in the main cluster while firms on the edges are there because they do the least to lead other firms.

Exploring the estimated network further, Table 1 provides the top 25 firms in the global network by their edge weight out sums. There are a few aspects of this list that stand out. The first is that all of the firms are dollar based. The second is the preponderance of financial firms at the top of the list, with over half of the top 25 being in that industry. In fact, even though the second firm, General Electric, is not a financial firm, up until it significantly changed its businesses in June 2016, its financial dealings were great enough that the Financial Stability Oversight Council designated it a nonbank systemically important financial institution. Taking all of these results into account, it is notable how the relatively straightforward estimation procedure we use based off of easily available equity price data seems to reflect so many attributes of the firms that are consistent with expectations. In fact, there is not a single utility, consumer non-cyclical, ICT or Energy firm present. The Internet Appendix contains similar analysis for a network of only USD issued firms, and in that network other sectors are better represented in the list of most influential firms, indicating the particularly global nature of finance. This supports the results of Grant (2016) showing finance as a primary international transmission channel.

Given that a firm's importance appears to be closely connected with its currency and industry, Table 2 groups the firms at that level and has a similar ranking of the top 25 by their edge weight out sums. The prominent role of the U.S. markets is again displayed, with the top six entries — and eight of the top ten — all being based in dollars. Within the currencies, the finance sector is the most important sector for the USD, EUR, CAD, GBP, and CHF, reinforcing its central role in global connectedness.

The centrality of the U.S. and the financial sector over this time leads to the question of whether the network estimation results are driven by the Global Financial Crisis. In order to answer this, and to understand the evolution of the global firm network more generally, Figures 2 and 3 examine the global firm network estimated in non-overlapping 5-year sub-periods during this timeframe. The former figure has the firms colored by industry, and the latter by currency. In both figures, Panel (f) has the longer term network spring plot we have been reviewing for reference. There is a distinct pattern of consolidation over the first four plots, suggesting increasing globalization throughout the sample period. The 1992-1996 period (Panel (a)) shows a loose cloud of firms that consolidates over time, hitting a maximal level of concentration over the 2007-2011 crisis period (Panel (d)) before slightly expanding outwards again in the following five years (Panel (e)). There is evidence of a particularly large increase in agglomeration between 1997-2001 and 2002-2006, notably with European firms moving into the center, likely reflecting the adoption of the Euro and the associated integration. The 2007-2011 crisis period particularly brought together North American and European firms, but many Asian firms were far out on the network periphery.

The firm positioning with regards to industry and location in these 5-year sub-periods appears generally similar to the longer term plots, and the top firms for these sub-periods also exhibit similar characteristics to those for the full sample network. An exception is that over the 5-year period from 2007-2011 covering the Global Financial Crisis, the firms with the largest weight out sums were not financial companies. Rather, over this period the top firms were in the Energy and Base Materials industries, as well as supporting firms such as Caterpillar, Inc. That firms in these industries were the most central in these years is likely due to the large run-up in commodity prices over this period. These results suggest an important role for global financial industry connectedness, and that this is not solely an artifact of the Global Financial Crisis. Importantly, the overall characteristics we observed in the longer term network are not driven by the Global Financial Crisis period.

4.3 Alternative Specifications

We explore different specifications of the network as robustness for our proposed estimation strategy, as well as for comparison to other techniques implemented in the literature. Our main estimation procedure is carefully outlined in the Internet Appendix for replicability purposes, along with an in-depth analysis of the network. We also find our below regression and simulation results to be robust to using:

1. scaled generalized forecast error variance decompositions as in Demirer et al. (2018) instead of GIRFs;
2. a set of U.S. dollar only listed firms that were publicly traded throughout 1981-2016;
3. 5-year rolling samples of firms that are publicly traded throughout each sub-period (to more dynamically capture new firms entering the network, and deal with potential survivorship bias from using a static firm sample);
4. GIRF horizons up to 10 days, instead of one;
5. up to 10 lags in the VAR, instead of one; and
6. a model-free network where the edge weights are the bilateral equity return correlations.

5 Robust-yet-Fragile Behavior of Firm Networks

In this section, we identify and measure robustness and fragility in the inter-firm networks that we estimated in Section 4, with the goal of better understanding the nature of firm networks and their susceptibility to systemic risk.

5.1 Identifying Robust-yet-Fragile Behavior in Firm Networks

To study the properties of the network, we relate a firm's health to its network connectedness, the health of its neighboring firms, and of the system as a whole. Specifically, we use a probit regression framework to measure how these other quantities predict the incidence of firm distress:

$$Pr(D_{it}) = \Phi\left(\underbrace{\beta + \hat{\phi}\sum_{j\neq i} w_{ij\tau}}_{\substack{\text{Robustness:}\\ \text{Diversification}}} \underbrace{+\hat{\gamma}\sum_{j\neq i} w_{ij\tau}D_{jt}}_{\substack{\text{Fragility:}\\ \text{Direct Contagion}}} \quad \underbrace{+\hat{\lambda}N_t}_{\substack{\text{Fragility:}\\ \text{Network}\\ \text{Vulnerability}}} \quad \underbrace{+\hat{\omega}N_t\sum_{j\neq i} w_{ij\tau}}_{\substack{\text{Robustness:}\\ \text{Network Resistance}}} \quad \underbrace{+\hat{\theta}N_t\sum_{j\neq i} w_{ij\tau}D_{jt}}_{\substack{\text{Fragility: Network Crisis}\\ \text{Reinforced Contagion}}} \quad +\epsilon_{it}\right), \quad (4)$$

where D_{it} is a distressed state indicator for firm i (e.g., monthly equity log return in the bottom 10% of the overall sample distribution), $w_{ij\tau}$ is the network weight from firm j to i estimated over the preceding 5-year window as in Section 4 (e.g., for January 2010 the network weights estimated from the daily equity log returns from January 2005-December 2009 are used), and N_t is an indicator of the aggregate network state (e.g., TED spread or VIX in the top 10% of the sample distribution).[28] We use rolling lagged 5-year network weights in order to capture how the inter-firm networks evolve over time, and to avoid simultaneity bias in the estimation. We interpret this regression as a descriptive measurement equation to empirically decompose the relationships between the various firm and network attributes, not to explicitly determine causality, which could be subject to issues of endogeneity, particularly for the D_{jt} variables. To account for potential endogeneity issues we do a separate spatial VAR analysis below in Section 5.3.

The model in Equation (4) can be used to answer several questions about the nature of the estimated inter-firm networks. Specifically, there are five aspects of RyF behavior that we investigate, broadly divided into two categories depending on whether they are expected to be beneficial or detrimental to firms. The labels for each have been included under the corresponding terms in the equation. Throughout this discussion we focus on the dependent variable in the model being a distressed state indicator where positive values reflect poor firm health; however, when we instead examine firm returns, revenue, return on equity and profits, the expected signs under the null hypotheses should accordingly be reversed, as in those cases higher levels for the dependent variables are a positive rather than a negative outcome. Additionally, we assume above that N_t is a distress indicator, but in alternate formulations we include other measures of network level economic conditions where the signs on the related coefficients should be negated.

The first form of RyF behavior that we investigate is the diversification channel of Elliott et al. (2014).[29] This channel in their model is initially expected to be a negative, as small connections transmit crises; however, as connectedness increases further it provides better insurance and diversification benefits that make this channel a net positive. We capture this in the first term of the regression, answering the question of whether greater firm connectedness is associated with

[28] The coefficients with the hats are the estimates from the latent equation. When presenting the regression results, we instead focus on the more appropriate marginal effects for the probit regressions, which will be listed without the hats. In the case of standard linear regressions, the actual coefficients will be what is referred to by the non-hat terms.

[29] Diversification here refers to greater network connectedness diversifying away individual shocks, not the distribution of the network edges themselves.

better firm outcomes. While the theory does not provide a definitive prediction for the sign of the coefficient on this term in all cases, we conjecture that the inter-firm network is integrated enough to provide the insurance and diversification benefits and $\phi < 0$.[30]

The second term in the regression captures the next facet of RyF behavior that we are interested in, the degree of pass-through to a firm from shocks affecting its neighbors, which we label direct contagion. This is what is commonly measured in both the banking and cross-country crisis contagion literatures.[31] We expect — in following with the consensuses of these literatures — that $\gamma > 0$ indicating direct contagion.

The final three channels we look at incorporate network wide disturbances, N_t, rather than only the direct neighbor relationships in the previous two terms. We use several gauges of network level disturbances, including the TED spread, VIX and within-period averages of the D_{jt} measures across all firms, giving the share of firms currently in a distressed state. The degree to which firm outcomes are related with these measures is captured by λ, and we expect this coefficient to be positive, with firms exhibiting vulnerability to the overall health of the network. On the other hand, we expect that greater connectedness may help to buffer this effect. We call this dynamic "network resistance" and predict that $\omega < 0$, since we expect the inter-firm networks to be highly connected.

The fifth and final aspect of RyF network behavior that we examine is whether network wide disturbances and direct contagion from a firm's neighbors act to amplify one another when they coincide. We refer to this situation as "network crisis reinforced contagion" and expect that each of these would make a firm more sensitive to the other. This would, for example, be similar to the network dynamics of Caccioli et al. (2015) investigating both direct counterparty failure risk and contagion via overlapping portfolio exposures in a banking network.[32] This paper found that neither channel is significant on its own, but that when both channels are active at once, bankruptcies are much more common and have large systemic effects. If reinforced contagion is an extant phenomenon in the global firm network, then it would be reflected in a positive value of θ.

5.2 Robust-yet-Fragile Regression Results

In this section, we run various permutations of Equation (4) to delve into the RyF nature of the firm networks. In particular, we measure firm health using equity returns, 5-year CDS spreads,

[30] That greater connectedness is correlated with better firm specific outcomes and a positive Diversification term coefficient for the continuous measures examined below — such as profit and equity returns — accords with the results of Grant and Yung (2018). In that model, firms' productivity shocks are passed onto other firms in direct proportion to their network weights on the source firm, with greater connectedness allowing a firm to benefit from productivity improvements across a broader set of industries (or countries). Additionally, these connections are precisely reflected in the firms' profits and equity returns.

[31] For examples of direct bank contagion see Elliott et al. (2014), Acemoglu et al. (2015b), Gai and Kapadia (2010), and Gai et al. (2011), and for cross-country contagion see Glick and Rose (1999) and Hernandez and Valdes (2001).

[32] Alternately, the interaction of direct and aggregate market dynamics could be supported by the credit freezes of Bebchuk and Goldstein (2011), wherein banks' pessimistic self-fulfilling expectations lead them to lend an inefficiently low amount, creating an aggregate shock in addition to the reduced bilateral lending to firms. In this equilibrium, banks choose to not extend loans to firms when they believe that their projects, even though worthy in an environment in which other such firms obtain financing, will fail in an environment in which credit to other firms is frozen.

revenue, return on equity, and profits. Distressed firm states are defined as being in the worst 10% tail of the overall sample distribution for the corresponding underlying health measures.[33] Also, we run standard linear regressions with the continuous versions of these measures as the dependent variables in order to see if — without specifically isolating distressed states — there is evidence that network structure is related to firm performance.

Our baseline estimates of Equation (4) with D_{it} being monthly log equity return distress indicators can be found in Table 3. The table has two panels: Panel A has the estimated marginal effects of each explanatory variable (not estimates of coefficients in the latent linear model); and Panel B has the estimated changes in the probability of a distressed state from a one standard deviation increase in each explanatory variable. To help interpret the values, the right hand columns provide the signs one would expect if the associated type of RyF behavior exists. The explanatory variables are introduced across the regressions. The first two regressions have only the average sum of weights into a firm and direct contagion variables, respectively. If one were to examine these individually then it would seem that greater network connectedness was a bad thing; however, as column (3) shows, more connectedness actually has a robust, diversifying effect, and it is the direct contagion that occurs through these same connections that has a positive impact on the probability of a firm being in distress.[34] Both of these results are in line with there being RyF behavior. The next column then adds the network crisis state variable — measured as having a monthly average TED spread in the top 10% of its sample distribution — and the final column adds interactions of the network crisis state with the former two variables. All of the estimated effects are in the hypothesized directions and, with the exception of the network crisis reinforced contagion in column (5), are statistically significant.[35] Additionally, there is substantial agreement between the magnitudes of the estimated effects in the latter three regressions.

Since it is not necessarily clear what a one unit increase in the explanatory variables represents, we focus on the standardized effects in Panel B. For the network crisis state the effect is of an increase from zero to one — indicating the difference between being in a crisis versus not — multiplied by the standard deviation of the interacted sum term. These results suggest that a one standard deviation increase in network connectedness reduces the probability of a firm being in distress by about 3.7%, while an increase in direct contagion of one standard deviation increases the probability by 5.9%. From the estimates in columns (3)-(5), it is clear that the direct contagion effect is much larger than the diversification one. These coefficients indicate that if a neighbor is in crisis, then it would take other non-crisis neighbors with in edge weights roughly nine times as great to counteract the impact. Being in a network crisis state increases the probability of being in distress

[33] We also experimented with thresholds other than 10%, attaining similar results.

[34] Hale et al. (2016) provide evidence of similar direct contagion effects. The authors construct a yearly global network of interbank exposures from 1997 to 2012 of more than 6,000 banks using long-term interbank loan data to study the transmission of financial sector shocks across borders, finding that direct exposures to crisis countries squeeze banks' profit margins, thereby reducing their returns.

[35] All standard errors are clustered at the firm level. Additionally, we did not find evidence of significant serial correlation in the estimation residuals and rerunning the regressions allowing for AR(1)-AR(10) correlation in the error terms does not alter our findings.

by 8.1%; however, when controlling for network resistance one can see that greater connectedness can significantly offset this effect. These estimates are quite large given that the unconditional probability of being in distress is 10%, with both direct contagion and network vulnerability being over half of this value.[36]

Table 4 presents the estimates of similar linear regressions where rather than a distressed indicator dependent variable, the dependent variable is the continuous monthly log equity return. The two panels are similar to the previous table, but now the bottom panel has standardized coefficients, which are more appropriate to understanding continuous linear models. The estimation produces statistically significant results in all cases in line with what one would expect given the RyF theory we outlined above, including the network crisis reinforced contagion.

Focusing on the values in Panel B, a one standard deviation increase in network connectedness corresponds with increased expected monthly returns of about 12% of a standard deviation, or roughly 1.2%. This result suggests that being connected in the network is positively related with increased firm equity returns, going beyond just reducing the probability of a firm distress event.[37] The direct contagion effect is nearly three times as large as the diversification one, with a standardized coefficient of -31%, correlating with a 3.1% equity price decline. Finally, there again is a negative expected effect of a network crisis state, with evidence that network connectedness can aid, and direct contagion can hinder, a firm's response to such a state.

It could be that firm, industry or location effects might in part be responsible for these results. To control for these possible effects, we run this estimation in first differences, effectively controlling for various fixed effects, and the results are not materially different.[38] Additionally, we estimate both the discrete and continuous versions of the model with industry interactions on all of the coefficients and do not find any substantive differences across industries. We find the coefficients on the industry interactions to be unstable over time, further challenging the idea that there are underlying structural differences across industries.

Beyond the effects on the equity returns, we wish to know whether there is "real" evidence of RyF firm network behavior, so we examine similar continuous regressions with the dependent variables and neighboring firm distress indicators based on the quarterly change in profit, as measured by EBITDA, the 5-year CDS spread, the quarterly change in revenue, and the annual return on equity (RoE). We include the monthly average 5-year CDS spread and RoE in levels and first differences, since these variables likely incorporate firm specific level effects that should be removed. The results of these regressions are presented in Table 5, where it can be seen that even across these other firm health measures and differing time frequencies, the RyF behavior still upholds. Not surprisingly, the CDS spread is strongly influenced by direct contagion, with a one standard deviation

[36]Plots of the average sums of weights and direct contagion variables used as the first two dependent variables by various firm characteristics and overall can be found in the Internet Appendix.

[37]This result is akin to those of IMF (2018), who found that increased globalization intensified the diffusion of knowledge and technology across countries, with greater international trade and competition helping to increase potential growth among countries and lift it at the global level.

[38]In untabulated results, we also control for time fixed effects, obtaining similar results with regards to diversification and direct contagion.

increase in direct contagion associated with a 46.0% standardized CDS increase. The small diversification and large direct contagion responses are intuitive, as CDS spreads are based on discrete underlying default choices which are most pertinent in very weak economic environments.

Profit and revenue growth have standardized diversification coefficients of just under 10%. In practical terms, a one standard deviation higher network in weight sum corresponds with improved firm health via increased growth of 1.2% for monthly equity prices, 4.0% for quarterly profits, 1.7% for quarterly revenue, and 1.7% for annual return on equity. Interestingly, profit and RoE growth demonstrate significantly larger effects from a network crisis than does revenue growth, -23.0% and -17.5% to -6.6%. For context, the standardized coefficients are reported in Panel B of Table 5. These results suggest that profitability is more susceptible to network crises than is income and are consistent with the fact that the two profit measures are significantly more volatile than revenue. All three dependent variables, however, are consistent in showing a positive relationship with connectedness and a negative one with the fragility terms. These continuous regressions suggest not just level improvements for the real profit and revenue quantities, but growth rate increases — especially meaningful effects.

One might expect ex-ante that growth in these real firm health indicators would correlate with greater inter-firm connectedness, with a fast growing firm being a healthy one that drives other firms, especially as it comprises a larger and larger share of its market; however, our regressions are finding a more nuanced relationship in the reverse direction. Our measures of connectedness included in the regressions focus on how firms are connected to others in the network via the sums of edge weights in from other firms only. The correlation between these sums of edge weights into firms used in the regressions and the corresponding sums of edge weights emanating from them is -0.183. Therefore, these results indicate that firms whose equity prices are more liable to move along with those of other firms are likely to have higher profit, revenue and RoE growth, as well as lower CDS spreads, a novel finding in the literature on the global firm network. This is an important distinction when thinking about the relationships between integration and firm performance, indicating significant value to being more integrated. Additionally, we find that the sum of a firm's in weights — as well as the out weight sum — is not correlated with firm size in the estimated networks by numerous measures, including total equity, sales, profits and number of employees, so the beneficial real effects are not simply because the biggest firms necessarily have the largest weights.

Together, these results provide strong evidence of RyF behavior in the global firm network and benefits to global integration. The increased inter-firm network connectedness over time that we find signs of should then be a net positive for global firms — outside of neighboring firm distress events — via the diversification channel. Further, the direct contagion channel appears to overpower the diversification channel, and severe credit tightness substantially weakens firm health. These results suggest that globalization has had positive consequences for firm health, but that policymakers and investors should be wary of greater connectedness allowing for increased contagion. This wariness is particularly critical when there are signs of network wide distress, given the evidence we find for network crisis reinforced contagion in Table 4, with amplification between network crisis states and direct contagion.

We examine two other sets of firm networks. The first is the set of USD equities from 1981-2016 and the other is comprised of rolling 5-year windows of the top global firms that are continuously traded within each window. These results, available in the Internet Appendix, are markedly similar to our main ones, providing evidence for RyF behavior, and limiting the likelihood that sample selection is driving our results.

Our results are robust to network crisis measures other than our indicator of a credit crisis defined as a high TED spread. Internet Appendix Table D.2 provides the results when using the following crisis indicators: the continuous monthly average TED spread level; the log of this level, given the non-linear relationship that it tends to have versus the state of the macroeconomy; a crisis indicator for the VIX being in the top 10% of its monthly distribution; the monthly average VIX; a crisis indicator for the SP500 return being in the bottom 10% of its monthly distribution; the monthly SP500 return; the fraction of firms in a distressed state in a given month; and an indicator for months with the top 10% of the fraction of firms in a distressed state. These results show that our main findings are robust to the choice of network crisis state measure, with nearly every estimate matching the expected sign associated with RyF behavior and being statistically significant.

We used the GIRFs for a one day horizon throughout the above analysis. To check the robustness of our results with respect to the choice of network, Internet Appendix Table D.3 shows the results of running our main regressions for forecast horizons from 0-5 days. The table also includes the results of using the rolling 5-year bilateral equity return correlations between each firm pair a model-free estimate of the network edges. All of our main results still obtain, including the proper signs with statistical significance, the direct contagion channel being roughly an order of magnitude larger than the diversification one, and there being network vulnerability.

Furthermore, we seek to determine whether these RyF relationships vary over time. Specifically, were there significantly different relationships over the Great Moderation and is fragility a unique feature of the Global Financial Crisis period, driving our main results? In the Internet Appendix we reran the estimation for our main, fixed sample of global firms as well as the USD one, breaking the sample into ten year periods. The overall results are similar to those obtained in our longer, full samples, suggesting that the results are not solely driven by the events of the Global Financial Crisis.

5.3 Robust-yet-Fragile Spatial VAR Analysis

We implement a spatial auto-regressive model with time-varying weights to account for potential dependence among our panel observations and explicitly allow for simultaneous feedback arising from the proximity of firms to one another as determined by our estimated networks. We focus on a basic RyF formulation with network level crises:

$$\boldsymbol{Y}_t = \mathbf{1}_I\beta \underbrace{+\gamma\bar{W}_\tau\boldsymbol{Y}_t}_{\substack{\text{Spatial}\\ \text{Auto-regressive}\\ \text{Component}>0}} \underbrace{+\mathbf{1}_I\lambda N_t}_{\substack{\text{Fragility:}\\ \text{Network}\\ \text{Vulnerability}<0}} +\boldsymbol{\epsilon}_t$$

where $\boldsymbol{Y}_{it}$ is an $I \times 1$ vector of a continuous firm health measure, $\mathbf{1}_I$ is an $I \times 1$ vector of ones, N_t is the network crisis state variable (indicating an average TED spread in the top 10% of its sample distribution), and $\boldsymbol{\epsilon}_t$ is a vector of error terms. $\bar{W}_\tau$ is the time-varying adjacency matrix for the firm network estimated from the prior 5-years of daily firm equity returns, normalized so the average weights for each firm observation sum to one across each sample examined. The weights exclude self-loops (i.e., the diagonal elements are set to zero). In this case, the coefficient γ captures the spatial auto-regressive component, which accounts for the fact that the more connected firms are with one another, the more likely they are to influence each other. We expect this coefficient to be positive, and the coefficient on the network level crisis to be associated with worse outcomes (e.g., negative for equity returns and profits).

While this formulation does not explicitly have a robustness term, it can be seen that one implicitly exists when modifying the equation to get the $\boldsymbol{Y}_{it}$ variables all on the left side:

$$\boldsymbol{Y}_t = \alpha_\tau\mathbf{1}_I\beta + \alpha_\tau\mathbf{1}_I\lambda N_t + \alpha_\tau\boldsymbol{\epsilon}_t \quad \Longrightarrow \quad E[\boldsymbol{Y}_t] = \alpha_\tau\mathbf{1}_I\beta + \alpha_\tau\mathbf{1}_I\lambda N_t \tag{5}$$

where $\alpha_\tau \equiv \left(I_N - \gamma\bar{W}_\tau\right)^{-1}$.

To understand this equation it is helpful to focus on a single $\boldsymbol{Y}_{it}$ measure, so we will describe this equation assuming that it is modeling the monthly equity return series. In this case, we expect the β coefficient to be positive, reflecting the long-run positive return on equity investments. The first term then provides the pass-through of the pooled typical market return, β, as it flows through the network. Greater connectedness via the α_τ matrix increases this pass-through, producing more robustness with increased connectivity. In untabulated results, we reran this analysis with firm fixed effects in place of the single pooled β constant. In that formulation, $\alpha_\tau\mathbf{1}_I\beta$ provides how much firms benefit from the iodosyncratic return growth of others via their direct and indirect connections. This produces qualitatively similar results to the pooled version of the model here.

We estimate the model and the asymptotic variance-covariance matrix under the assumption of normality of the innovations using maximum likelihood estimation.[39] Results for different firm health measures (and frequencies) are reported in Table 6. These results support the existence of robustness and fragility, as the β and λ coefficients all have the proper signs and are statistically significant. The spatial lag is generally positive as expected, though not for the return on equity measures which are negative at statistically insignificant levels.

To help analyze these results with the time varying network weights, we plot the two robustness and fragility terms from Equation (5) in Figure 4 when the dependent variable is the monthly equity

[39] For a detailed description of the estimation algorithm refer to Ord (1975).

return. Each of the two plots in the figure provides the average, maximum and minimum values across the firms in our sample within each time period. Consistent with our earlier results, when the network experiences a crisis the firms are vulnerable to the system-wide shock.[40] Additionally, there is a level of network robustness to help counteract this effect. In fact, the network robustness measures here are very similar to those in the previous section with a correlation of 0.816.[41] It is clear that both of these series increase as the aggregate network connectedness does, especially during the Global Financial Crisis. Further, the ratio of the two ($\frac{\lambda}{\beta}$) is equal to -8.56. This is very close to the ratio of about nine between the robustness and fragility terms found in our main specification above. Overall, this analysis paints a very similar picture as our main RyF measurement approach.

6 Robust-yet-Fragile Based Equity Portfolios

Having found evidence of contemporaneous robust-yet-fragile behavior in the multinational inter-firm network, in this section we evaluate what the RyF nature of the firm network means in the context of equity investments.[42] We focus on two particular questions regarding how the diversification and direct contagion terms are related with subsequent monthly firm returns. First, we examine whether there is evidence of robustness, with greater firm connectedness diversifying and insuring against shocks. Specifically, we examine whether greater firm connectedness as measured by higher lagged sum of weights into a firm ($\sum_{j \neq i} w_{ij\tau}$) corresponds with reduced monthly equity return volatility. Second, we test whether the previous month's direct contagion term ($\sum_{j \neq i} w_{ijt-2} D_{jt-1}$) can be used to sort equities and beat a benchmark portfolio wherein all of the firms are invested in equally.

Figure 5 plots firms' monthly equity returns versus their lagged weight sum in. The plot uses the same firm sample as in Section 5, including all firms continuously traded in each prior 5-year window to calculate the firm networks and the monthly returns running from 1996 through 2016. In the figure, the distribution exhibits a cone shape, with a negative relationship between firm return volatility and the weights in.[43] This result supports the hypothesis that greater integration in the firm network provides robustness and helps to insure a firm against individual shocks and reduce volatility.

For the second question, we consider whether an investor reevaluating his portfolio on the last trading day of each month could use the previous month's direct contagion terms to classify firms into high and low risk buckets. Specifically, we focus on whether a firm's direct contagion term from the previous month was in the top (high risk) or bottom (low risk) 10% of the cumulative

[40] Kelejian et al. (2006) take a spatial modeling approach to study contagion among emerging economies, finding contagion is a statistically significant factor in currency markets, with varied effects across countries.

[41] See Internet Appendix Figure D.3 for a scatter plot of these two robustness measures.

[42] This analysis is similar to that of Herskovic (2018), who studies the asset pricing implications of sectoral input-output network information — in particular network concentration and sparsity — finding return spreads of 4.6% and -3.2% per year on sparsity and concentration beta-sorted portfolios.

[43] In untabulated results, we examine the volatility of monthly returns by quantiles of the weight sum in and also find a negative relationship.

historical distribution of the direct contagion measure up to that point. In order to avoid biasing the analysis, we only consider firms that were added to our sample from the inclusion filter over 1993-1995 and exclude the agencies Fannie Mae and Freddie Mac due to their implicit government backing. We assume a currency hedged portfolio to avoid the currency movements driving the returns and calculate portfolios from 1996 to 2016.

We create five portfolios from these indicators: long best, short worst deciles; long best decile; short worst decile; long all but the worst decile; and long all but the worst decile, short worst decile. Figure 6 plots the log values of these portfolios — each starting with an initial value of one on January 1st, 1996 — and Table 7 provides summary statistics for them. For comparison, the figure and table include the value of the benchmark portfolio investing equally in all firms in the sample, and the table also includes data for the SP500 and MSCI World Index over this period. From the figure, it is clear that on a raw basis the only portfolios that beat the benchmark in average returns are the two that exclude but do not short the worst decile portfolio. On a risk weighted basis, however, the equal weighted portfolio is not nearly as dominant, as several of the candidate portfolios have a higher Sharpe ratio over this period than the benchmark. In fact, the Sharpe ratio for the "long all but the worst decile, short worst decile" is 20% higher than that of the benchmark portfolio.

To evaluate each of the candidate portfolios versus the benchmark portfolio we utilize the Giacomini and White (2006) test of equal unconditional predictive forecasting ability. This framework compares two forecasting methods (denoted f and g), which will be the candidate and benchmark portfolios in our case. The null and alternative hypotheses of the test are:

$$H_0 : E[\Delta L_i] = 0, i = 1, 2, ...$$

$$H_A : |E[\Delta \bar{L}_T]| \geq \delta > 0 \text{ for all } n \text{ sufficiently large },$$

where $\Delta \bar{L}_T \equiv \frac{1}{T}\sum_{i=1}^{T} \Delta L_{t+i}$, and T is the number of out of sample forecasts made with each method. In words, the test is that the two forecasting methods perform equally according to the $L(*)$ loss function. The test statistic is:

$$t_T = \frac{\Delta \bar{L}_T}{\hat{\sigma}_T/\sqrt{T}} \sim \mathcal{N}(0, 1),$$

where

$$\hat{\sigma}^2_T \equiv \frac{1}{T}\sum_{i=1}^{T} \Delta L^2_{t+i}.$$

When using the Sharpe ratio as the measure of comparison these terms are:

$$\Delta \bar{L}_T = \frac{1}{T}\sum_{i=1}^{T} \frac{r_{f,t+i}}{\sqrt{\frac{1}{T}\sum_{j=1}^{T}(r_{f,t+j} - \bar{r}_f)^2}} - \frac{r_{g,t+i}}{\sqrt{\frac{1}{T}\sum_{j=1}^{T}(r_{g,t+j} - \bar{r}_g)^2}}$$

and

$$\hat{\sigma}_T^2 = \frac{1}{T}\sum_{i=1}^{T}\Big(\frac{r_{f,t+i}}{\sqrt{\frac{1}{T}\sum_{j=1}^{T}(r_{f,t+j}-\bar{r}_f)^2}} - \frac{r_{g,t+i}}{\sqrt{\frac{1}{T}\sum_{j=1}^{T}(r_{g,t+j}-\bar{r}_g)^2}}\Big)^2,$$

where $\bar{r}_X$ is the sample mean return for forecast method X.

The p-values for these tests can be found in Columns 8 and 9 of Table 7. The p-values are for the two sided tests of Sharpe ratio equality between a given portfolio and the benchmark. Values less than 0.10 indicate that the benchmark portfolio has a better Sharpe ratio at the 10% level, while values of 0.90 and above indicate that the candidate portfolio has a better Sharpe ratio at a statistically significant level. The values in Column 8 show that portfolios only focusing on the best and worst performing deciles cannot beat the benchmark portfolio; however, when using the worst decile to determine which equities to exclude or outright short there is significant improvement. This result appears to be driven by the poor performance of the "short worst decile" strategy over the beginning of the sample, likely because there is not an adequate realized distribution of crisis sum terms to train the model over this relatively tranquil period, as can be seen in the returns for this portfolio in the log index value figure. Therefore, in Column 9 we provide results comparing the Sharpe ratios of the candidate portfolios against the benchmark from 2000 onwards, utilizing the initial few years as a burn-in period for the lagged crisis weight in sum distribution to be established. Focusing on this sub-period, both the "long all but the worst decile," and "long all but the worst decile, short worst decile" portfolios beat the benchmark at the 5% level.

Also, for comparison, the final two columns of Table 7 provide the risk adjusted annualized returns for each portfolio scaled to the same volatility as the benchmark. From the latter of these two, it is clear that on this simple risk adjusted basis several of the portfolios beat the benchmark portfolio, with the "long all but the worst decile, short worst decile" having a roughly 3.00% scaled return premium over the benchmark. This portfolio is particularly interesting, because it effectively combines the "long all but the worst decile" with the money losing "short worst decile" portfolio and ends up improved on a risk adjusted basis. This is because the short portfolio acts similar to if one had purchased equity market put options — there is a small return drag over time; however, in periods of market distress the short portfolio provides positive returns allowing the total investment to avoid the worst outcomes. This can be seen in Figure 6, as the line plotting this portfolio's equity avoids the worst dips of the portfolios with a strictly long leaning, continuing steadily upwards with comparatively little volatility. In particular, the short portfolio provides a form of insurance during the Global Financial Crisis and early 2000s recession. This analysis provides examples of how a better understanding of the RyF nature of the firm network may help investors select better performing portfolios, and that the RyF tests of our inter-firm networks provide a new perspective into firms' future expected performance and overall health.

7 Fall 2008 Global Contagion

During the latter half of 2007 and the beginning of 2008 the effects of the U.S. Sub-Prime Mortgage Crisis were starting to be felt in the U.S., with heightened credit spreads, equity market declines, and, most notably, the March 2008 collapse of Bear Stearns, with its ultimately being taken over by J.P. Morgan in a government orchestrated deal. It was during the fall of 2008, however, that the crisis climaxed. Within a week in September 2008, Fannie Mae and Freddie Mac were taken under government conservatorship, Lehman Brothers announced its bankruptcy, and the government pressed a buyout of Merrill Lynch by Bank of America, escalating the U.S. Sub-Prime Mortgage Crisis into a global financial crisis. The fall of 2008 saw equity markets around the world plummet, credit spreads surge, numerous firms require government support, and both the VIX and VSTOXX reach their all-time highs.

Given the importance of this period as the height of the Global Financial Crisis, we take the data for the fall of 2008 to our model to see how well it can account for the facts. As the basis for our model, we take the estimated latent linear model from a quarterly probit regression including our five RyF terms with the average VIX as the network state, as well as the average TED spread as its own separate additional term.[44] We include the VIX as a measure of the stress or crisis level of the global economy, leaving the TED spread as a measure of global credit spreads. If the value of the latent linear model is positive for a firm, that is taken to indicate a distressed state for it and vice-versa. The sample that we focus on is the subset of our full global sample that is continuously traded throughout the previous five years, 2003-2007.[45] We use this sample instead of our long continuously traded firm sample to include several now defunct firms which were central to the events of late 2008, and to have the fullest picture possible of the firm network over this period. For the network weights, we use the sub-sample's pre-crisis network connections entering 2008, the estimation of which ran from 2003 to 2007 and does not include the actual crisis contagion period we are attempting to match.

Using this model, we start with 17 firms that are initially assumed to be in a distressed state, and the VIX and TED spread levels from this period in late 2008. By selecting these firms we are not stating that we can identify them as the source of the shocks causing the Global Financial Crisis, but rather exploring how a shock that put them all into distress would be expected to spread across the network. These firms are selected from the worst performing firms over this period — with 2008 equity returns from -49.81% to -99.96% — that also went bankrupt or needed significant government intervention and were recognizably central to the crisis, such as Lehman Brothers, Washington Mutual, and Bear Stearns.[46] We use an interacting agent modeling approach to simulate the contagion, reevaluating the latent linear model for every firm to determine whether it is in a distressed state or not, and iterating until a steady state is reached. Note that the only

[44]We also ran the model with an interaction term on the TED spread for USD issued equities, and found that the coefficient on that term was small and not statistically significant. Further, the simulation results were little changed when including it.

[45]This sample includes 756 firms across 40 countries, with equities issued in 25 currencies.

[46]Details on these firms during this period can be found in the Internet Appendix.

firms we assume to be in a distressed state are the original 17 firms, and it is possible for other firms to go into and out of a distressed state according to the network state, their network connections and the status of their neighbors.

Figure 7 contains a series of spring plots based on the 2003-2007 global firm network that we use, which present features of the actual network and illustrate the modeled contagion. The first two panels show the industry and locality of each firm, which demonstrate distributions that are extremely similar to what we saw earlier for our main global firm sample. For example, both industry and region are important for firm connectedness, the Asian and Australian firms are on the periphery, and finance is at the center of the network. The next panel shows which firms actually experienced equity return distress over late 2008, with those affected in red. The substantial scope of the contagion across regions and industries in the fall of 2008 is evident in the plot. The final panel in the top row shows the positions of the 17 initially distressed firms in red. These are predominantly financial firms and have USD issued equities, so it is not surprising that they are all located relatively near the center of the network plot. The second row of panels then shows the modeled contagion spread over each iteration through convergence in the fourth one.

While not an exact match for the actual firm distressed states, at an aggregate level the simulation's share of 88.6% of firms in distress is quite similar to the actual level of 88.0%. This is a considerable degree of contagion given that the initially distressed firms represented only 2.2% of all firms in the sample. Delving deeper, 78.2% of firms' actual states matched their final simulated ones, with a higher rate of core firms and a lower rate of periphery firms being in distress in the model relative to the data. In this way, greater distance was even less of a buffer in actual contagion than in the model simulations. In the end, the contagion swept across virtually all but the most remote firms. Industry does not seem to be very important for contagion beyond what was captured in the network weights, though locality does seem to matter with fewer Asian and Australian firms affected. It is promising that our model, though relatively sparse, is able to match the high level aspects of the contagion process during the crisis.

As the spring plots show, the contagion quickly spread from the initially distressed firms in the first iteration, particularly to other USD and financial firms. The second iteration saw a significant increase in the spread to European firms with the U.S. market having hit a critical mass. At this point, the large number of distressed firms abroad then led to an echo effect, where the contagion spread more widely across U.S. firms that were connected to foreign ones.

The echo effect should be an important consideration for policymakers in large economies when facing potential crises, as well as investors seeking to optimize their portfolios. First, given the evidence we have found for the importance of locality in firm connectedness, such economies are likely to contain most of the firms that have important connections to others in their economy, passing on direct contagion internally as well as, by definition, leaving a smaller rest of the world to provide connections that offer robustness and buffer against firm distress. Second, a large economy is likely to have a strong influence on other economies, making a crisis more likely to spillover to other firms abroad. Combined, these two influences make it so that when a large economy is in a crisis it is liable to be severe, as there are likely to be returning echoes from contagion sent abroad that the economy is not well buffered against, leading issues to snowball at home and exacerbating the already tenuous economic situation. In this manner, crises that occur within major economies may become more globally contagious going forward, conditional on them becoming widespread internally, with increased global integration creating the circumstances for further situations like the U.S. Sub-Prime Mortgage and Eurozone Debt Crises to have a global impact instead of being smaller, regional issues. How such episodes develop depends on the RyF nature of the global firm network, highlighting the importance of understanding these properties.

8 Simulating Sectoral Shocks

Table 2 reveals that there are a handful of currency-industry pairs with outsized network impact. For example, the number one pair, USD-finance, has a weight out sum that is more than double the pair five slots down the list (USD-Energy), which in turn has a weight out sum that is more than double the pair five slots below it (EUR-consumer non-cyclical). The work of Acemoglu et al. (2012) and Acemoglu et al. (2015a) indicates that asymmetries in the scope of network members can potentially lead to network instability, so in this section we simulate how a shock to each of the currency-industry pairs propagates through the global firm network to study the consequences of having such a high concentration of influence among the top sectors.

We follow the simulation approach from Section 7, using the estimated probit latent linear model from Column (5) of Internet Appendix Table D.7 as the foundation for simulating sectoral shocks under distress for all firms in each currency-industry pair. The simulations use the network of our main global firm sample from 1991-2016, with lag and GIRF orders of one. For the network crisis state, we use the value of the average monthly TED spread in the top percentile of our sample distribution to gauge the worst case reach of contagion from each sectoral shock.

Figure 8 plots the simulation results, with the share of firms in each currency-industry pair along the x-axis, and the ultimate share of firms in distress along the y-axis.[47] The color of the marker indicates the currency region, with small share currencies that are nearby one-another given the same color, and the shape of the marker indicates the industry. For reference, the 45-degree line is also plotted in gray, with the distance above that line representing the degree of contagion from the sector experiencing the shock.

The plot shows that there is a generally positive relationship between the share of firms in a sector and the final share of firms in distress, but the relationship is far from linear. The large gap in the middle of the plot — with contagion to firms outside of a sector being less than 12% or greater than 92% — suggests a critical mass type, all-or-nothing relationship, and indicates that there are only a handful of sectors where a shock would be expected to have broad ramifications. Finance tends to have the greatest contagious effect for each major currency (e.g., for the USD,

[47]Similar results are found when grouping at the country-industry level, with many more small firm share pairs with little contagion near the origin.

CAD, GBP, EUR), but that is not the case for Japan where the industrial-diversified and consumer-cyclical industries have more influence. Unsurprisingly, the USD industries are the largest by the share of firms in them, encompassing the top six observations, with many of the most contagious sectors. Also, USD-finance is again at the top of the influence list — in a tie with USD-consumer non-cyclical, USD-ICT, USD-consumer cyclical, and EUR-finance — hinting at the significance of the echo effect for the U.S. and Eurozone.

The EUR-finance sector is an especially interesting case, as a shock to this sector results in far broader contagion than a shock to either the USD-Energy or USD-IndDiv sectors, even though those two sectors have out weight sums that are 1.7 and 2.3 times that of the EUR-finance sector. In separate results examining the pre-Eurozone period, no one currency-finance sector shock for the future member countries is simulated to have had nearly the same contagious effect as seen here for the EUR-finance sector. Although further work is needed to asses the impact of European integration on firm-level spillovers, our simulation results suggest that the propagation of shocks was intensified through higher integration during this period.[48]

9 Network Contagion Simulations

As mentioned above, the degree of integration in the global firm network varied over the past three decades, with a generally increasing trend. In this section our goal is to provide context for what that increase means and study its implications for potential crisis contagion. Has increased firm interconnectedness been a stabilizing force producing a more robust global economy, or has the distribution been such that it has engendered greater fragility?

The analysis is similar to that performed in the previous two sections in that we use an estimated probit latent linear model as the basis for running a series of interacting agent model simulations. Specifically, we use the estimates of the latent linear model associated with Column (5) in Table 3, including all five of our RyF terms with the network crisis state measured as having an average monthly TED spread in the top decile of the sample distribution.[49]

To analyze the global firm network over time, we take the same estimated network weights that the 5-year sub-period spring plots in Figures 2 and 3 are based on. We then examine how crises spread across these 5-year networks in response to different magnitude distress events that originate in one through all 382 firms in the sample. Across all of these cases the coefficients from the latent linear model are the same ones estimated over the full sample period, with only the network weights changing. We then randomly select the initially distressed firms, with the process repeated 200 times for each share of initially distressed firms to get simulated contagion distributions. This is performed with and without a network level crisis.

[48] The classification and acceptance of Greek government debt as top tier collateral by banks in other Eurozone countries has been suggested to have been an especially grievous aspect of financial integration within the single market. See Farhi and Tirole (2016) for a discussion of this issue.

[49] When the network crisis state is zero, these estimates are extremely similar to the estimated probit latent linear model when only the first two diversification and direct contagion terms are included. Therefore, the cases with $N_t = 0$ can be viewed as the results from a more concise model without the three network crisis state terms.

The results of these model simulations are presented in Figures 9 and 10. The first column of Figure 9 plots the average share of firms that end up in a distressed state across the 200 iterations for each set of network edge weights and share of firms that are initially distressed. The dashed 45-degree lines denote the share of source firms that are initially distressed, and the height of each average line above that is the share of firms experiencing contagion. The second column helps put the contagion shares into context, since as the share of firms initially in crisis increases, there are fewer firms remaining to potentially experience contagion. Rather than the simple difference between the simulation averages and the 45-degree lines, the second column shows those differences divided by the share of firms that are not assumed to initially be in crisis. In other words, these plots show the fraction of firms that could potentially experience contagion that actually do. Figure 10 shows more detailed information for each case, with the same simulation averages, the minimum and maximum shares of firms in distress, and the contagion shares. For comparison, these plots also include simulation results for the full 1991-2016 global network.

9.1 Network Contagion Simulations without a Network Crisis

The top two rows in Figure 10 show the case in which there is not a network level crisis as measured by a high TED spread indicator variable. Starting at the beginning of the sample period, the 1992-1996 based network experiences almost no contagion. The average, minimum and maximum contagion lines are right on the 45-degree line, with only a handful of non-source firms experiencing distress as the share of source firms approaches one. This result reinforces the idea that at the start of the period there was a significantly lower level of global network integration.

At the other extreme of the contagion plots is the 2007-2011 period covering the Global Financial Crisis. In this case, contagion begins to occur with an initial share of crisis source firms as low as 16%, with 80% of firms affected when the share of source firms in distress is only 34%. At this level the contagion spread fraction is already at 70%, and plateaus around 80% starting at a 54% initial share of distressed source firms. Figure 10 sheds some light on why the simulations produce so much more contagion over this period than others. Examining the maximum and minimum curves for the 2007-2011 period plots, it is clear that they are far wider than for the other periods, especially as the contagion initially begins to occur. The greater variety of simulation outcomes for this period suggests that during this time, more than any other, there was a set of firms with far more outward connectedness that were central to the particular outcomes at lower initial crisis share levels. At higher shares of distressed source firms more of these central firms are likely to be in crisis, leaving the network to be quickly overcome with contagion.[50] These results are not surprising given the perceived instability at this time, and that our estimated networks reflect all manners in which firms were integrated over this period.

The other three sub-periods were relatively tamer than the two discussed above. The late

[50]The work of Acemoglu et al. (2012), Acemoglu et al. (2017), and Gai et al. (2011) comes to similar conclusions about crisis risk, with greater asymmetry and concentration in specific firms in a network amplifying the network fragility.

1990s period covering the Dot-Com Boom and various emerging market crises was the next most contagious period, but in the simulations without a network level crisis there was not decidedly more contagion than in the periods immediately around 2007-2011. Conversely, the late 1990s period also exhibited robustness, with contagion occurring at a higher initial crisis share (28%) than either the 2002-2006 (23%) or 2012-2016 (20%) sub-periods. Additionally, the degrees of contagion in the sub-periods on either side of 2007-2011 were nearly identical, with maximum contagion fractions under 45%, well below the 80% plateau for the 2007-2011 sub-period discussed above.

9.2 Network Contagion Simulations during a Network Crisis

In our regression estimates we find evidence that being in a network crisis state can have serious consequences, so we focus on contagion simulations of the same 5-year sub-periods assuming that there is a network crisis state with high credit spreads. These results are shown in the bottom plots of Figures 9 and 10. The most noticeable change is the accelerated contagion for the 2007-2011 network, with 90% of firms on average in distress starting with an initial firm crisis share of only 30%. The contagion fraction then plateaus at 95% when the initial firm crisis share is only 32%. That is a considerable level of contagion, indicating an extremely fragile network.

The 1997-2001 contagion fraction is the second highest, and in this case it is markedly higher than those for the 2002-2006 and 2012-2016 periods. An interesting similarity between the plots with and without a crisis state is the nearly identical share of initial crisis firms at which contagion begins for all of the sub-periods in the two sets. Additionally, with a network crisis the 1992-1996 period approaches a contagion fraction near the 55-60% for the 2002-2006 and 2012-2016 periods; however, the early 1990s period approaches that level slowly in a shallow convex manner, while the latter two approach it far quicker with concave contagion fraction curves. Altogether, these behaviors suggest significant network crisis reinforced contagion when compared to the upper plots without a network crisis.

Overall, these simulation results reflect increased global firm integration, confirming what we observed looking at the 5-year sub-period spring plots. Generally, the simulations imply strong direct contagion effects, but greater integration also materializes in some cases as more robustness for moderate initial firm crisis shares. These results can guide future macroeconomic modeling choices. Specifically, firm level microeconomic dynamics may be unimportant during normal times due to the robustness of the inter-firm network; however, firm heterogeneity has meaningful aggregate consequences during crises owing to network fragility. Further, our simulations suggest that over time global firm network fragility has increased during crisis periods, underscoring the importance of capturing these effects in a model. Additionally, a network crisis state is found to be a warning sign, steepening the contagion fraction curves and increasing the maximum contagion shares as the network crisis reinforced contagion effect leads to rapid, non-linear contagion effects.

These results should guide investors and policymakers to be particularly alert for potential contagion when there are signs of system wide stress and high firm connectedness, especially when the firm connectedness distribution's upper tail fattens. However, this is not the whole story. In particular, Section 5.2 showed higher integration corresponds with a reduced probability of distress and improved stock returns, CDS spreads, profit, RoE, and revenue growth. Therefore, while contagion can spread extremely rapidly and widely with greater global firm integration — and high levels of connectedness can be a red flag — policymakers and investors should not disregard the benefits of a more integrated network, forming the double-edged sword of greater global integration.

10 Conclusion

In this paper, we estimate inter-firm networks across countries and industries by using readily available data from financial markets and the latest developments in machine learning to resolve the curse of dimensionality associated with large panel VAR models. Most importantly, our estimated global inter-firm networks provide essential information on how firms are connected with one another and how these linkages have changed over time. This framework allows us to study how network connections may transmit or mitigate idiosyncratic — as well as system-wide — shocks, consistent with the idea of integration being a double-edge sword. On the one hand, we find that integration makes the system more robust through diversification and network resistance, increasing companies' growth prospects and reducing the incidence of firm distress events. On the other hand, more connected firms become more fragile through higher exposure to direct contagion from a distressed neighbor, vulnerability to system-wide shocks, and network crisis reinforced contagion. Our equity portfolio analysis also provides evidence of RyF behavior in the global firm network that can be used to improve investment decisions.

We conclude our study with a series of counterfactual experiments and simulations that reveal non-trivial echo effects that aggravate domestic conditions during a crisis through international connections that are not well buffered. Understanding such RyF qualities of the network is one way that our empirical approach can promote better policy and investment decisions when future crises threaten.

Our findings inform future models — since we determine that any model should have both robustness and fragility in its firm network — and support the findings of Acemoglu et al. (2012) that "classic" macroeconomic models that ignore firm heterogeneity are inadequate to capture contagion episodes leading to crises. Firm level heterogeneity is especially significant during crisis periods and when there is greater globalization and firm network integration, which our work suggests has increased over the past quarter century. Finally, given that finance is at the center of the global inter-firm network, open economy models should be designed to incorporate international connections via this pivotal sector.

Although our work identifies how firms' responses to shocks are related, we do not determine the source or nature of the initial shocks. Kose et al. (2003), for example, study the common dynamic properties of business-cycle fluctuations and identify a common source of volatility that affects all countries in general, with a more muted role for regional factors. Future work should explore the presence and importance of common and region/sector-specific factors in the global network of equity returns in the context of the business cycle. We believe the identification of such shocks is an important avenue that should be explored as the literature continues to expand to understand systemic risk and contagion through global networks. Moreover, further investigating the connections between inter-firm linkages and the international co-movement of business cycles can enlighten the discussion of how macroeconomic shocks are absorbed through the system, and their repercussions in the global economy. Finally, another extension of our analysis would be a structural model that can build from our empirical findings to formally model inter-firm connections in a general equilibrium context. Building on this paper, Grant and Yung (2018) propose a model where industries' productivity and demand shocks are passed onto firms in direct proportion to their markup adjusted Leontief inverse weights on the source industry, with these responses precisely reflected in the firms' equity returns. We believe these are only some of the directions this line of work can take, as we expand our knowledge of the benefits and drawbacks of higher global integration, and its role in the propagation of shocks.

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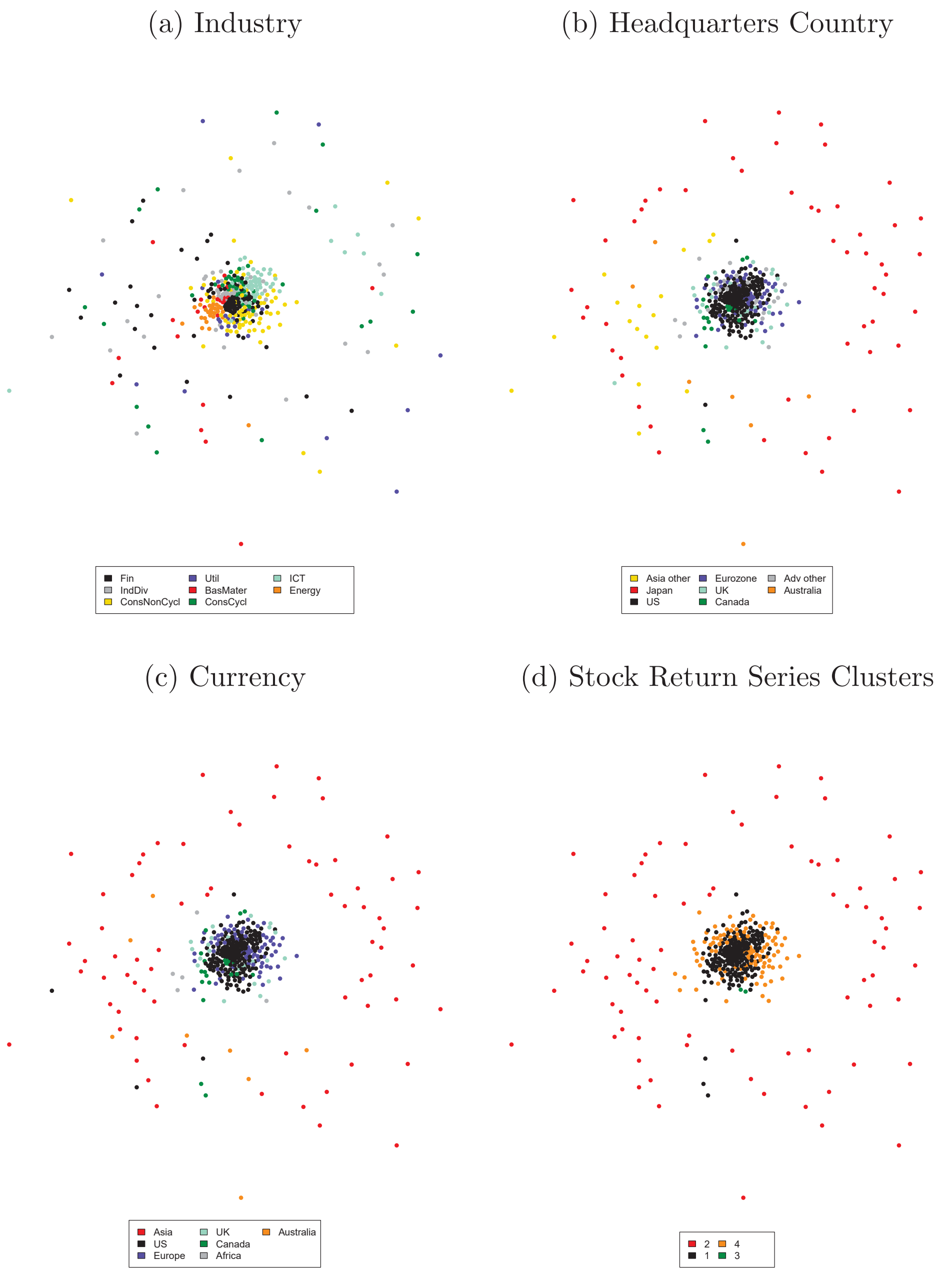
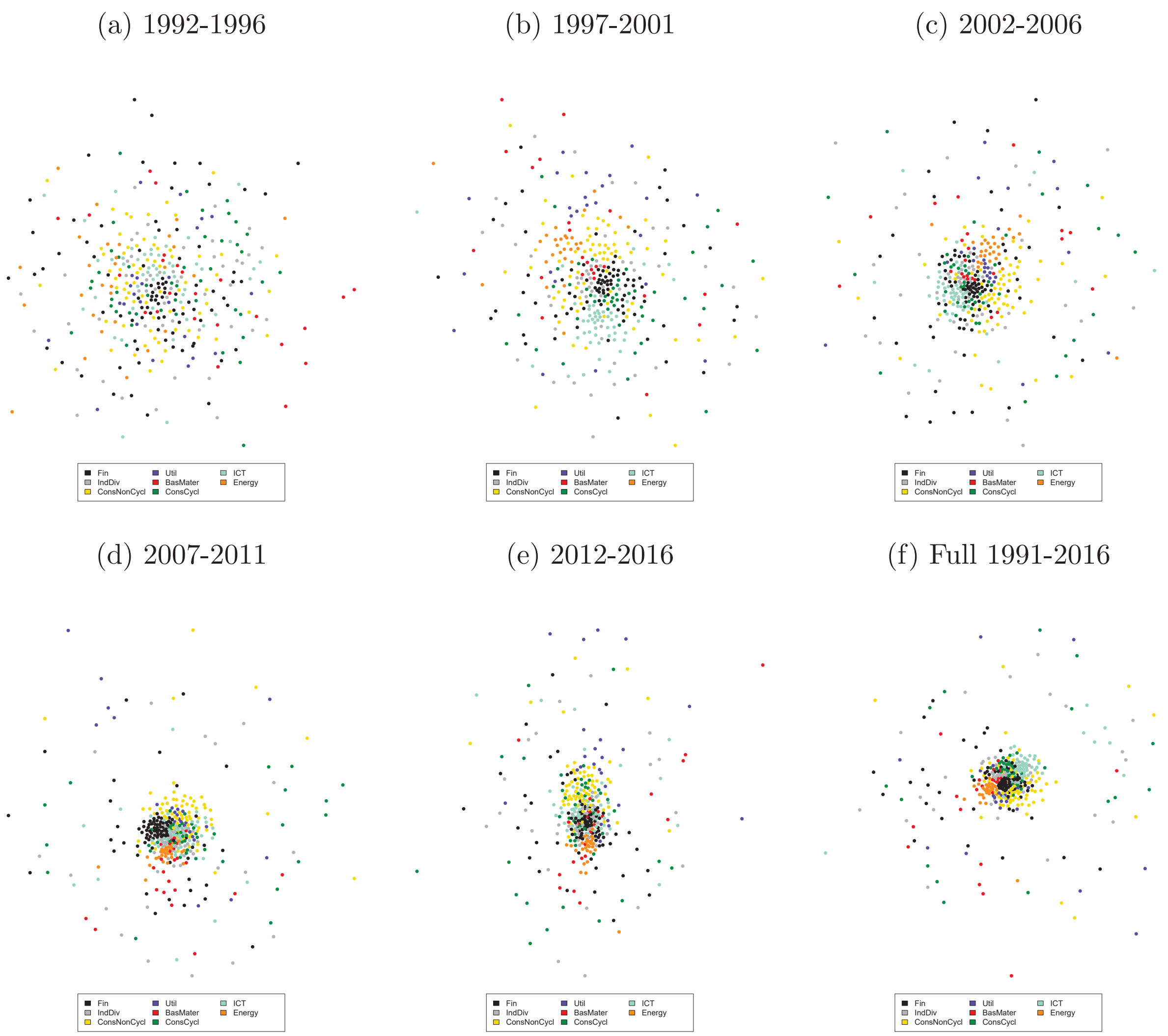
Figure 1: Global Network (1991-2016) by Firm Categories



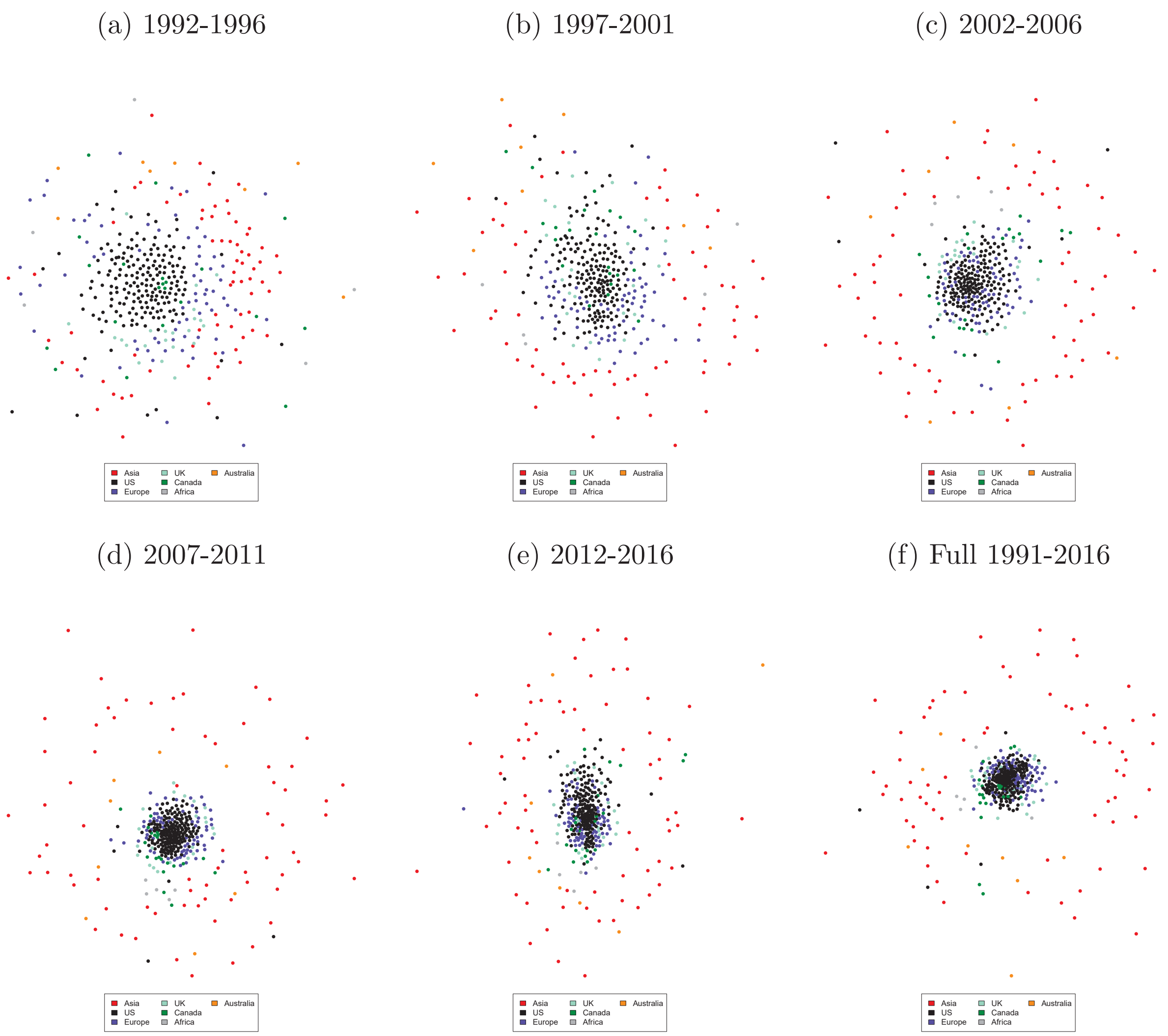
Note: Daily equity return based network for all firms available continuously from January 1991 through September 2016. Estimated using 1 lag in the VAR and GIRF horizon=1. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Figure 2: Global Dynamic Networks by Industry



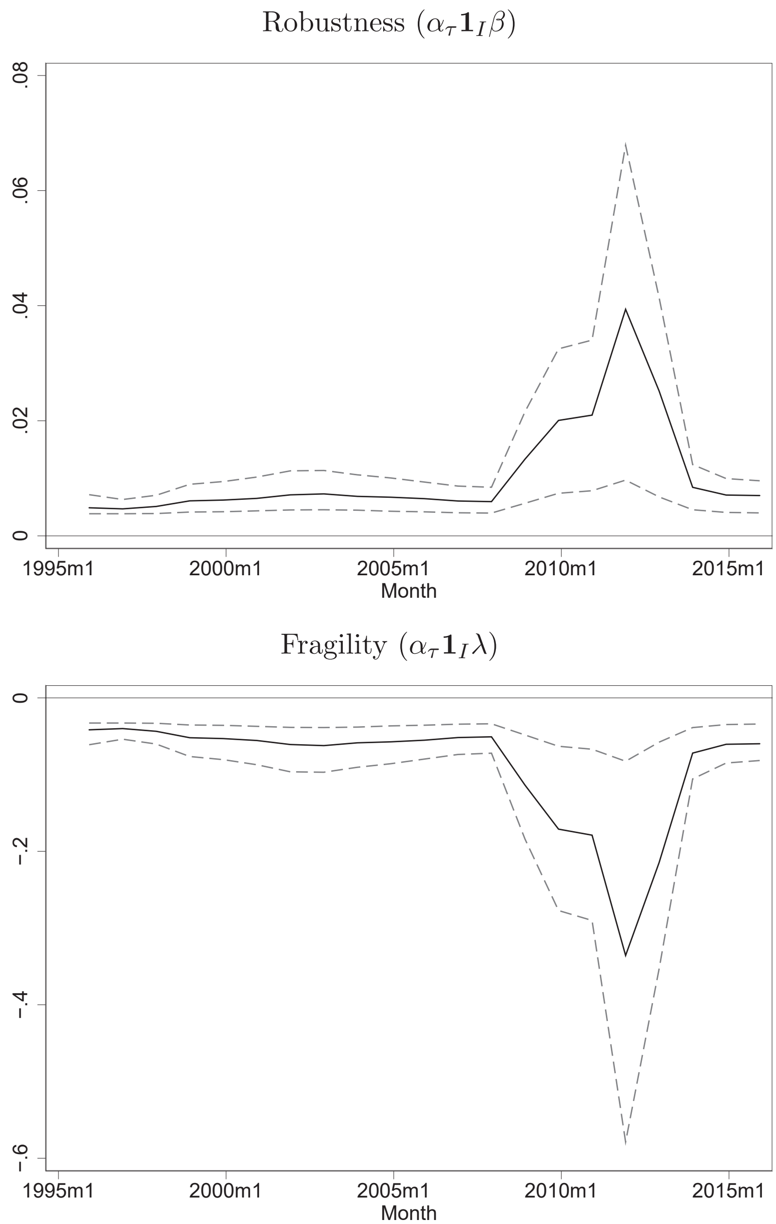
Note: Daily equity return based network for all firms available continuously during each period. Estimated using 1 lag in the VAR and GIRF horizon=1. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Figure 3: Global Dynamic Networks by Currency



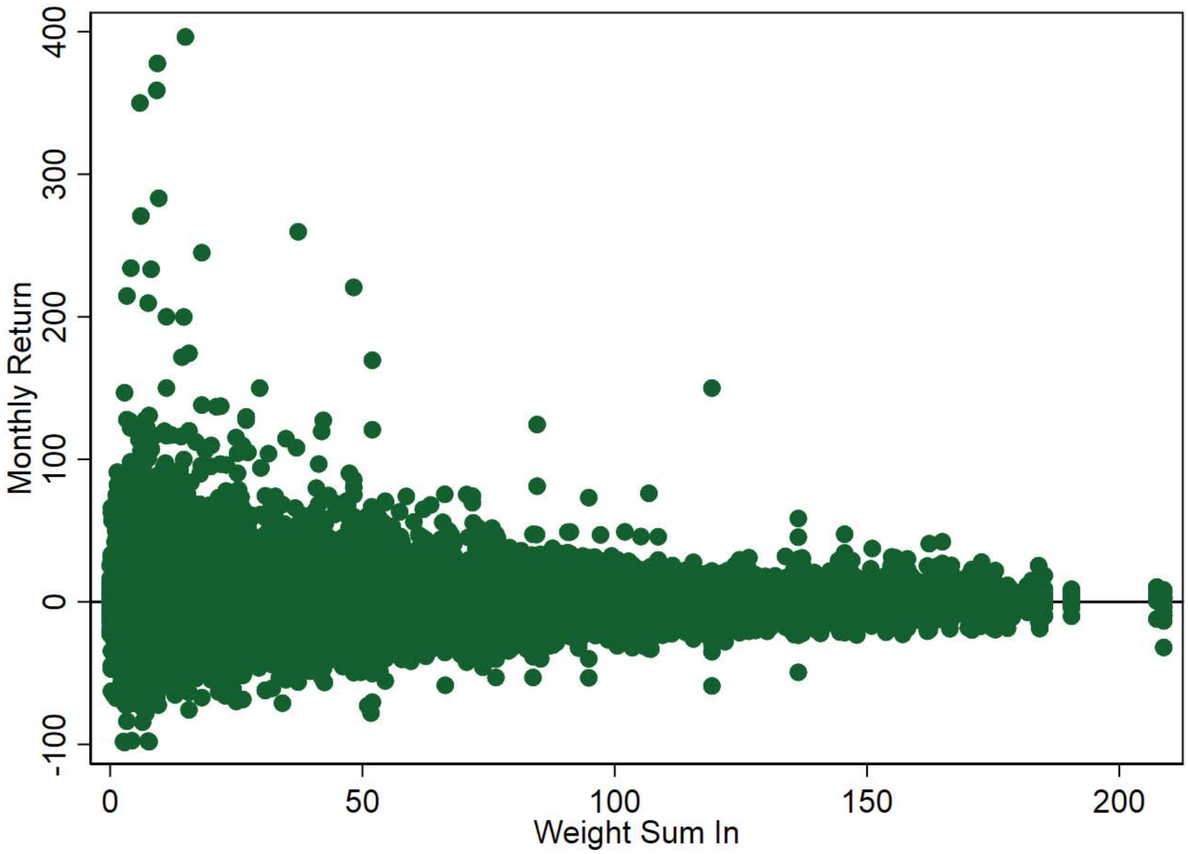
Note: Daily equity return based network for all firms available continuously during each period. Estimated using 1 lag in the VAR and GIRF horizon=1. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Figure 4: Global Network Spatial Model RyF Term Series



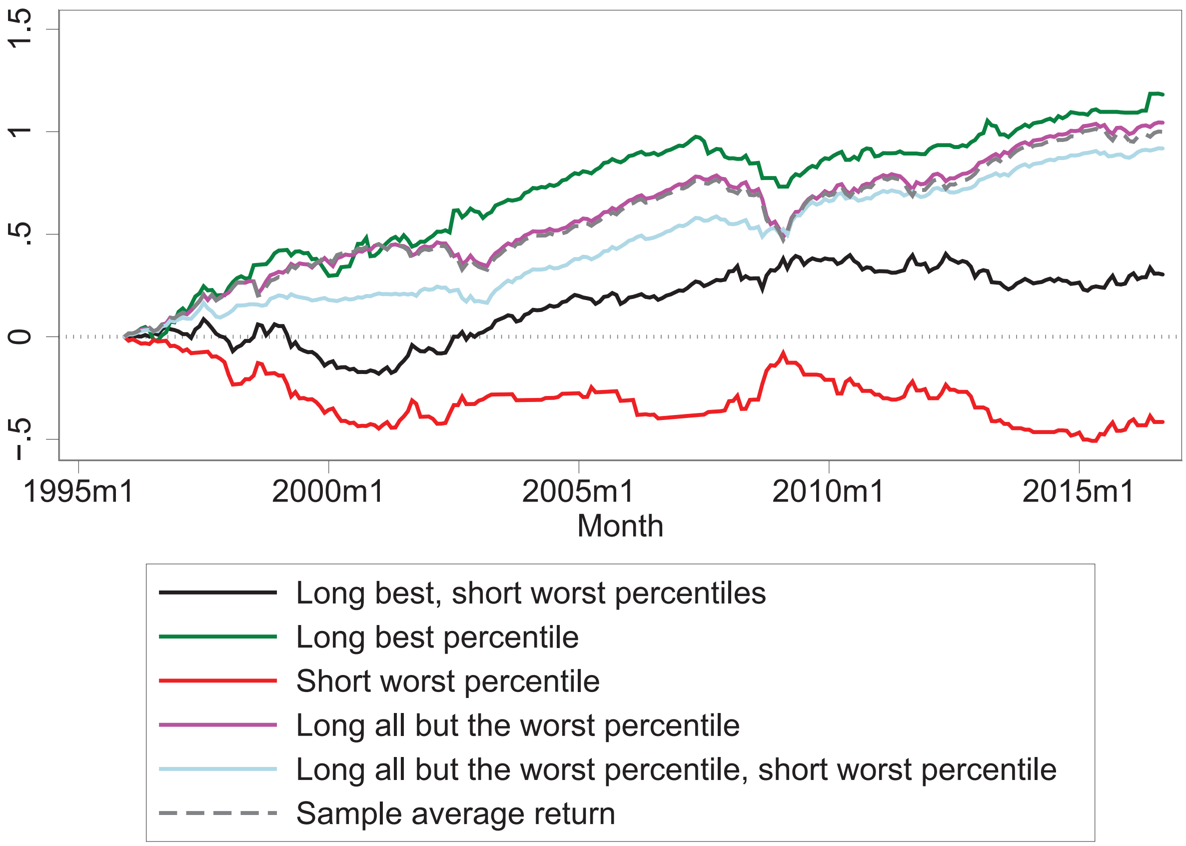
Note: The dependent variables in the estimated model are the monthly firm equity returns, the weight adjacency matrices are normalized so the average weights for each firm observation sum to one across each sample examined, and the network state variable is an indicator for the average monthly TED spread being in the top 10% of its sample distribution. The network parameter estimates are γ=0.630, β=0.0034 and λ=-0.0291. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies. The solid black lines are the within period averages, and the dashed lines are the minimum and maximum values.

Figure 5: Sum of Weights In Vs. Monthly Equity Returns



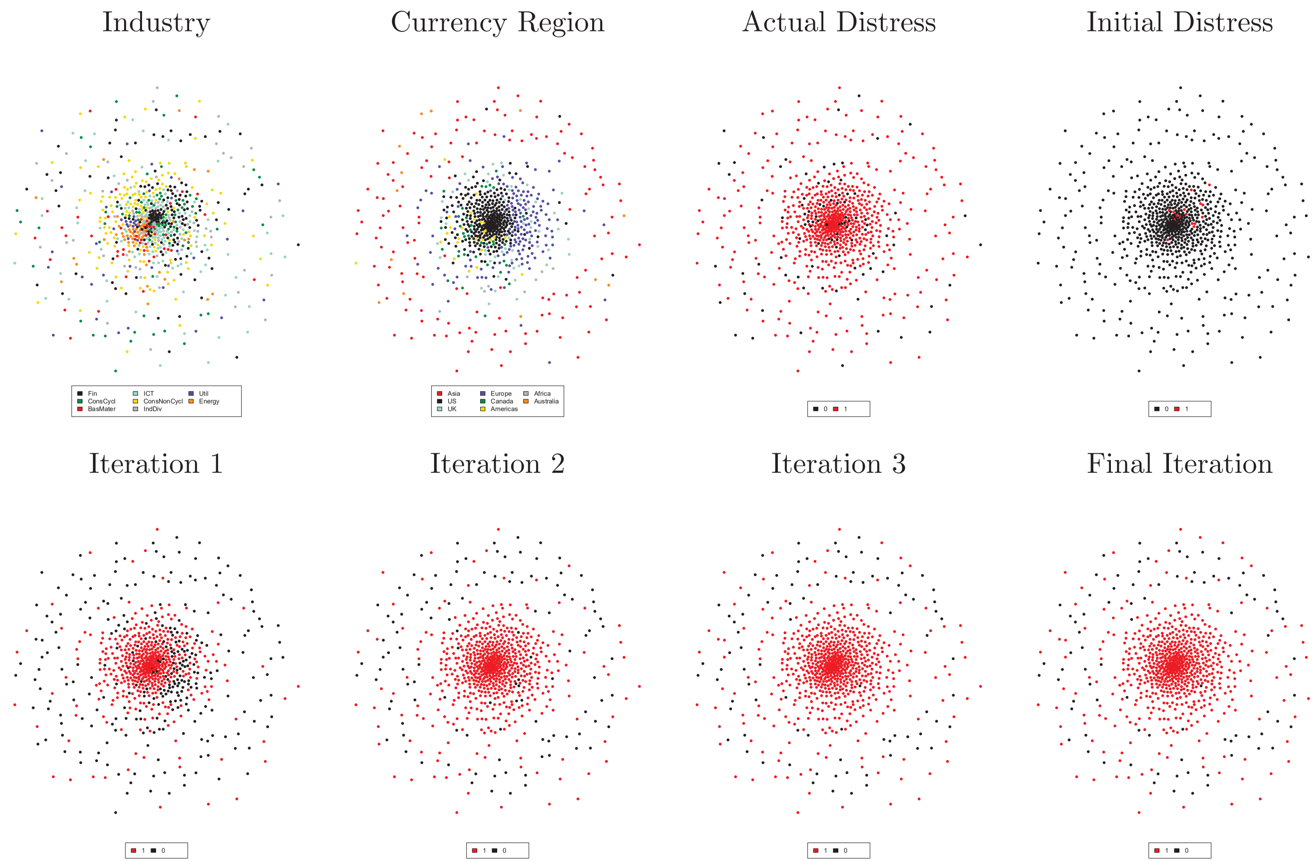
Note: Firms' weight in sum from the prior 5-years' network versus their current monthly equity returns. Rolling firm sets of those continuously traded throughout each 5-year window ending in 1995 through 2015.

Figure 6: Robust-yet-Fragile Portfolio Log Indices



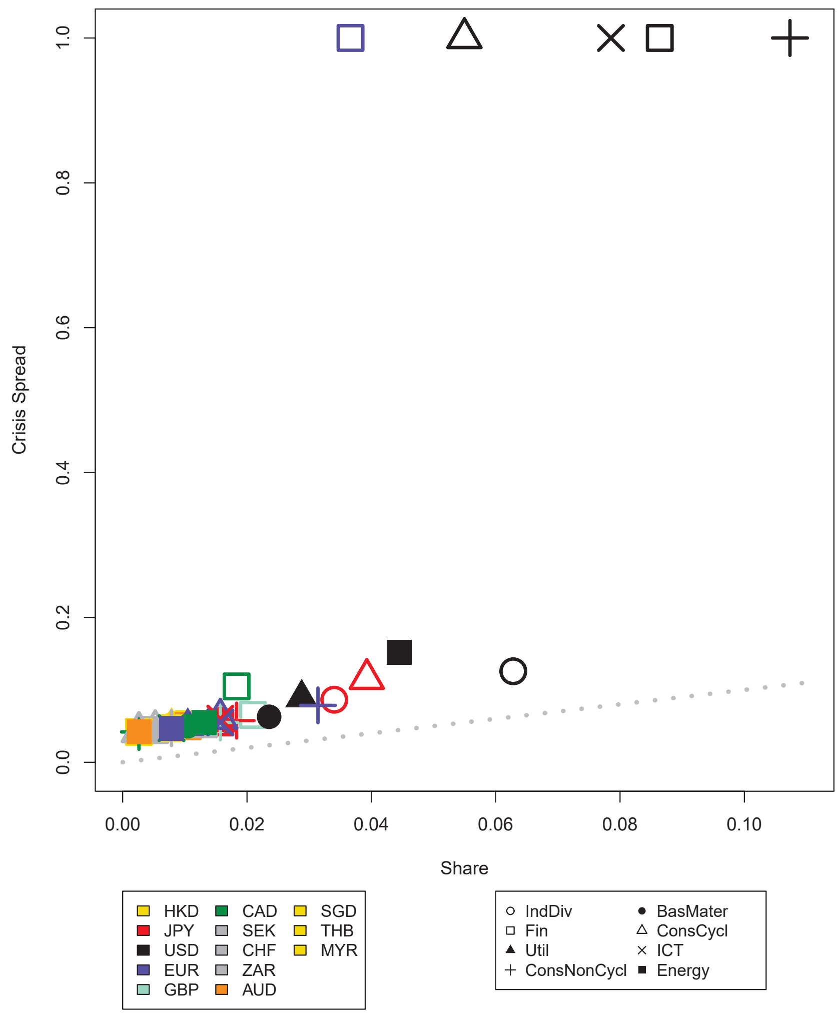
Note: Portfolios are created from the firms first entering our sample from 1993-1995 excluding the government agencies Fannie Mae and Freddie Mac, using the previous month's lagged crisis weight in sum being in the top or bottom deciles of the cumulative historical distribution of those sums as an indicator. Portfolio values are initially set at one on January 1st, 1996, and returns are calculated monthly from 1996 through 2016.

Figure 7: Fall 2008 Contagion — Actual Data vs Model Simulations



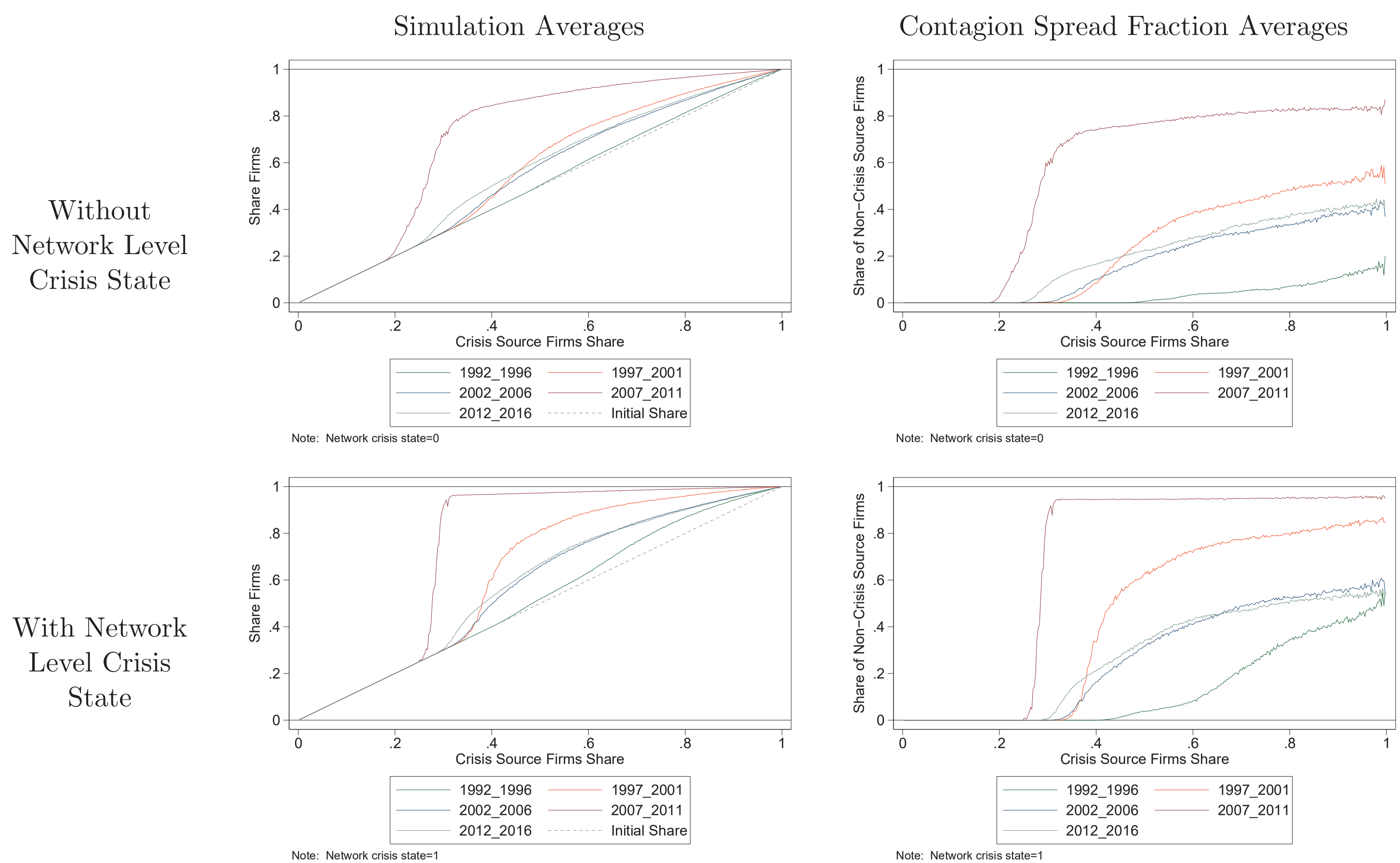
Note: Spring plots are based on the rolling global firm sample network from 2003-2007. Simulations are based off of quarterly predictions from the main sample using the latent linear model estimates from a probit model estimated from 1996-2016, with firm distress as the dependent variable and the five robust and fragile terms from our main regressions with the level of the VIX as the network crisis variable, in addition to the TED spread as its own term. VIX and TED spread levels from the end of 2008 and the above initially distressed firms are entered into the model, which is simulated until reaching a steady state. See Internet Appendix Table F.1 for details on the initially distressed firms, and Table F.2 for the estimated latent probit model used. This sample includes 756 firms across 40 countries, with equities issued in 25 currencies. 0=not in distress and 1=distress.

Figure 8: Spread of Local Sector Shocks vs Sector Firm Share



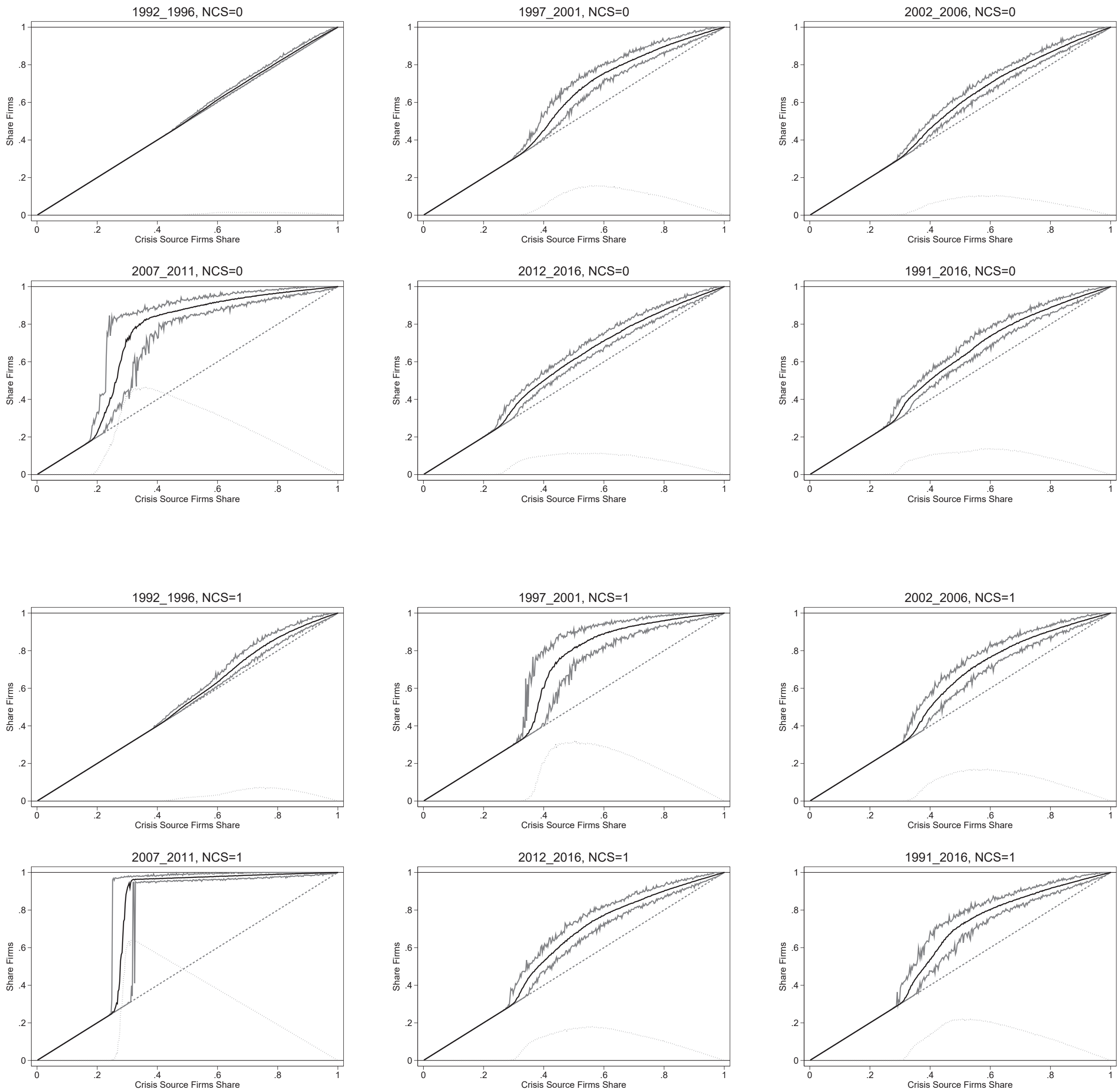
Note: This figure plots the final extent of contagion from a shock to each currency-industry locality pair. The simulations use a firm network of our main global firm sample from 1991-2016, using lag and GIRF orders of one. Simulations are based off of the latent linear model estimates of the probit model from column (5) of Table D.7. The TED spread is assumed to be 2.9, the value of the top percentile of its sample distribution, in order to consider the worst case extent of contagion from a shock to each local sector. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Figure 9: Network Contagion Simulations Using Various Time Period Networks



Note: Network contagion simulations using daily equity return based networks for all firms available continuously during each period. Estimated using 1 lag in the VAR and GIRF horizon=1. Contagion determined using simulations based upon estimates from the latent equation of Column (5) in Table 3. NCS=1 is equivalent to a TED spread crisis state. The contagion fractions are the average contagion minus the initial crisis share divided by one minus the initial crisis share.

Figure 10: Details of Network Contagion Simulations Using Various Time Period Networks



Note: Network contagion simulations using various global continuous sample estimated monthly networks based on regression estimates from Column (5) in Table 3. Crisis state/NCS=1 is equivalent to a TED spread crisis state. Black lines are simulation averages, gray lines are minimum and maximum levels, and the dotted lines are the spread of contagion (the distance between the averages and the 45-degree line that marks the initial share of firms in crisis). Sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Table 1: Global Top Firms by Network Out Weights

Rank	Ticker	Name	Industry	Currency	Measure
1	jpm-us	JPMORGAN CHASE	Fin	USD	29.42
2	ge-us	GENERAL ELECTRIC	IndDiv	USD	29.4
3	ben-us	FRANKLIN RES INC	Fin	USD	29.36
4	c-us	CITIGROUP INC	Fin	USD	29.04
5	axp-us	AMERICAN EXPRESS	Fin	USD	28.75
6	bac-us	BANK OF AMERICA	Fin	USD	28.27
7	bk-us	BANK NY MELLON	Fin	USD	28.22
8	ntrs-us	NORTHERN TRUST	Fin	USD	28.2
9	ppg-us	PPG INDS INC	BasMater	USD	27.93
10	emr-us	EMERSON ELEC CO	IndDiv	USD	27.82
11	pcar-us	PACCAR INC	ConsCycl	USD	27.16
12	wfc-us	WELLS FARGO AND CO	Fin	USD	27.11
13	sti-us	SUNTRUST BANKS	Fin	USD	27.06
14	dd-us	DU PONT (EI)	BasMater	USD	26.98
15	itw-us	ILLINOIS TOOL WO	IndDiv	USD	26.96
16	key-us	KEYCORP	Fin	USD	26.93
17	l-us	LOEWS CORP	Fin	USD	26.8
18	pnc-us	PNC FINANCIAL SE	Fin	USD	26.78
19	stt-us	STATE ST CORP	Fin	USD	26.71
20	etn-us	EATON CORP PLC	IndDiv	USD	26.62
21	cat-us	CATERPILLAR INC	IndDiv	USD	26.46
22	aa-us	ALCOA CORP	BasMater	USD	26.46
23	utx-us	UNITED TECH CORP	IndDiv	USD	26.28
24	hd-us	HOME DEPOT INC	ConsCycl	USD	26.23
25	schw-us	SCHWAB (CHARLES)	Fin	USD	26.07

Note: Daily equity return based network for all firms available continuously from January 1991 through September 2016. Estimated using 1 lag in the VAR and GIRF horizon=1. Self-loops not included. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Table 2: Global Top Currency & Industry Aggregates by Network Out Weights

Rank	Name	Measure
1	USD-Fin	760.26
2	USD-ConsNonCycl	728.06
3	USD-ICT	622.75
4	USD-IndDiv	515
5	USD-ConsCycl	445.44
6	USD-Energy	366.96
7	EUR-Fin	221.46
8	USD-BasMater	212.46
9	USD-Util	190.03
10	CAD-Fin	147.84
11	EUR-ConsNonCycl	143.07
12	GBP-Fin	118.74
13	EUR-ConsCycl	91.96
14	EUR-IndDiv	82.55
15	EUR-ICT	81.63
16	CAD-Energy	80.71
17	CHF-Fin	78.79
18	GBP-ConsNonCycl	59.89
19	EUR-Util	57.42
20	JPY-ConsCycl	54.57
21	JPY-IndDiv	51.15
22	CAD-BasMater	48.13
23	EUR-Energy	43.53
24	EUR-BasMater	43.15
25	CAD-ICT	42.58

Note: Daily equity return based network for all firms available continuously from January 1991 through September 2016. Estimated using 1 lag in the VAR and GIRF horizon=1. Self-loops not included. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies.

Table 3: Global Network Monthly Equity Return Crises (1996-2016)

Panel A: Regression Estimates

	(1)	(2)	(3)	(4)	(5)	
Robustness: Diversification	0.000208*		-0.00248***	-0.00232***	-0.00226***	-
$\phi \sum_{j \neq i} w_{ij\tau}$	(0.000108)		(0.000205)	(0.000200)	(0.000197)	
Fragility: Direct Contagion		0.0170***	0.0217***	0.0210***	0.0211***	+
$\gamma \sum_{j \neq i} w_{ij\tau} D_{jt}$		(0.000904)	(0.000936)	(0.000927)	(0.000952)	
Fragility: Network Vulnerability				0.0811***	0.137***	+
λN_t				(0.00684)	(0.0117)	
Robustness: Network Resistance					-0.00269***	-
$\omega N_t \sum_{j \neq i} w_{ij\tau}$					(0.000602)	
Fragility: Network Crisis Reinforced Contagion					0.000388	+
$\theta N_t \sum_{j \neq i} w_{ij\tau} D_{jt}$					(0.00139)	
Observations	95,118	95,118	95,118	95,118	95,118	

Panel B: Standardized Coefficients

	ΔPr(Crisis) for one StdDev increase in explanatory variable for regression:		
	(4)	(5)	
Robustness: Diversification	-3.7%	-3.6%	-
Fragility: Direct Contagion	5.9%	5.9%	+
Fragility: Network Vulnerability	8.1%	13.7%	+
Robustness: Network Resistance		-4.3%	-
Fragility: Network Crisis Reinforced Contagion		0.1%	+

Note: The dependent variable is the monthly equity return distress indicator for firm i, the neighboring firm health variable (D_{jt}) is the equity return distress indicator for firm j, and the network state variable (N_t) is an indicator for the average monthly TED spread being in the top 10%. Effects of a network crisis state indicate the effect of the indicator variable going from zero to one, and the interactions with the weight ($w_{ij\tau}$) and crisis sums are this times the standard deviation of the interacted sum term. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies. Robust standard errors clustered at the firm level in parentheses. The marginal effects for the probit regressions are provided in place of the latent regression coefficient estimates. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Global Network Continuous Monthly Equity Returns (1996-2016)

Panel A: Regression Estimates

	(1)	(2)	(3)	(4)	(5)	
Robustness: Diversification	-1.48e-05		0.000821***	0.000771***	0.000749***	+
$\phi \sum_{j \neq i} w_{ij\tau}$	(1.49e-05)		(4.12e-05)	(3.89e-05)	(3.81e-05)	
Fragility: Direct Contagion		-0.00962***	-0.0116***	-0.0111***	-0.0112***	-
$\gamma \sum_{j \neq i} w_{ij\tau} D_{jt}$		(0.000432)	(0.000503)	(0.000492)	(0.000516)	
Fragility: Network Vulnerability				-0.0388***	-0.0602***	-
λN_t				(0.00266)	(0.00466)	
Robustness: Network Resistance					0.00218***	+
$\omega N_t \sum_{j \neq i} w_{ij\tau}$					(0.000268)	
Fragility: Network Crisis Reinforced Contagion					-0.00196***	-
$\theta N_t \sum_{j \neq i} w_{ij\tau} D_{jt}$					(0.000610)	
Observations	95,118	95,118	95,118	95,118	95,118	
R-squared	0.000	0.079	0.094	0.099	0.101	

Panel B: Standardized Coefficients

	Standardized coefficients for regression:		
	(4)	(5)	
Robustness: Diversification	12.3%	12.0%	+
Fragility: Direct Contagion	-31.0%	-31.2%	-
Fragility: Network Vulnerability	-38.8%	-60.2%	-
Robustness: Network Resistance		34.9%	+
Fragility: Network Crisis Reinforced Contagion		-5.5%	-

Note: The dependent variable is the monthly equity return for firm i, the neighboring firm health variable (D_{jt}) is the equity return distress indicator for firm j, and the network state variable (N_t) is an indicator for the average monthly TED spread being in the top 10%. Effects of a network crisis state indicate the effect of the indicator variable going from zero to one, and the interactions with the weight ($w_{ij\tau}$) and crisis sums are this times the standard deviation of the interacted sum term. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies. Robust standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Global Network RyF Regressions with Various Firm Health Measures (1996-2016)

Panel A: Regression Estimates

	(1) EQ Return	(2) Change 5yr CDS Spread†	(3) 5yr CDS Spread†	(4) Change EBITDA	(5) Change Revenue	(6) Change RoE	(7) RoE	
Robustness: Diversification	0.000771***	-0.479***	-1.114***	0.00229***	0.000990***	0.0984***	-0.0859*	+
$\phi \sum_{j \neq i} w_{ij\tau}$	(3.89e-05)	(0.0872)	(0.218)	(0.000453)	(0.000183)	(0.0350)	(0.0496)	
Fragility: Direct Contagion	-0.0111***	7.823***	14.38***	-0.0310***	-0.0120***	-1.120**	-1.572***	-
$\gamma \sum_{j \neq i} w_{ij\tau} D_{jt}$	(0.000492)	(0.739)	(2.078)	(0.00556)	(0.00198)	(0.462)	(0.464)	
Fragility: Network Vulnerability	-0.0388***			-0.0989***	-0.0151	-5.289***	-2.910**	-
λN_t	(0.00266)			(0.0201)	(0.0133)	(1.553)	(1.447)	
Observations	95,118	7,620	7,976	21,479	27,913	6,375	6,571	
R-squared	0.099	0.028	0.010	0.007	0.004	0.005	0.009	
Period	M	M	M	Q	Q	Y	Y	

Panel B: Standardized Coefficients

	Standardized coefficients for regression:							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Robustness: Diversification	12.3%	-10.4%	-31.1%	9.2%	7.2%	5.6%	-3.6%	+
Fragility: Direct Contagion	-31.0%	46.0%	30.2%	-11.9%	-10.4%	-6.8%	-6.3%	-
Fragility: Network Vulnerability	-38.8%	-	-	-23.0%	-6.6%	-17.5%	-7.3%	-

Note: The dependent variables are the monthly averages of each variable for firm i, the neighboring firm health variable (D_{jt}) indicates the most extreme 10% of distress as measured by the corresponding dependent variable for firm j, and the network state variable (N_t) is an indicator for the average monthly TED spread being in the top 10%. CDS data covers October, 2013 - November, 2015 during which there were no network distress events so that term is excluded from those regression results. Effects of a network crisis state indicate the effect of the indicator variable going from zero to one, and the interactions with the weight ($w_{ij\tau}$) and crisis sums are this times the standard deviation of the interacted sum term. †Expected to have coefficients with signs opposite the other regressions. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies. Robust standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Global Network Spatial Model with Various Firm Health Measures (1996-2016)

	(1) EQ Return	(2) Change EBITDA	(3) Change Revenue	(4) Change RoE	(5) RoE	
Spatial Lag (γ)	0.630***	0.282***	0.441***	-0.323	-0.030	+
	(0.009)	(0.067)	(0.019)	(0.308)	(0.085)	
Spatial Robustness (β)	0.0034***	0.0264***	0.0108***	2.02*	20.28***	+
	(0.0003)	(0.0080)	(0.0026)	(1.15)	(2.54)	
Spatial Fragility (λ)	-0.0291***	-0.0302**	-0.0035	-3.38*	-4.45*	−
	(0.0017)	(0.0122)	(0.0040)	(1.90)	(2.70)	
Period	M	Q	Q	Y	Y	

Note: The weight adjacency matrices are normalized so the average weights for each firm observation sum to one across each sample examined, and the network state variable (N_t) is an indicator for the average monthly TED spread being in the top 10%. This sample includes 382 firms across 18 countries, with equities issued in 13 currencies, whenever data are available. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Robust-yet-Fragile Portfolio Summary Statistics, 1996-2016

Portfolio	Obs	Average	Std Dev	Min	Max	Sharpe Ratio	p-Value	2000 on p-Value	Annualized Scaled Return	Scaled Return Premium
Equal Weighted Portfolio	249	1.02	4.23	-16.36	15.80	0.71	-	-	12.94	-
Long best, short worst deciles	249	0.40	4.78	-13.71	15.96	0.15	0.07*	0.33	4.29	-8.64
Long best decile	249	1.22	4.93	-18.56	27.63	0.77	0.53	0.70	13.39	0.45
Short worst decile	249	-0.25	5.13	-15.46	19.36	-0.29	0.01***	0.10*	-2.46	-15.40
Long all but the worst decile	249	1.06	4.10	-17.26	15.75	0.77	0.94*	0.97**	13.84	0.91
Long all but the worst decile, short worst decile	249	0.90	3.00	-10.46	15.75	0.85	0.85	0.95**	15.94	3.00
SP500	249	0.76	4.38	-16.80	10.93	0.47	-	-	9.20	-3.74
MSCI World	249	0.63	4.42	-18.93	11.32	0.36	-	-	7.50	-5.43

Note: Portfolios are created from the firms first entering our sample from 1993-1995 excluding the government agencies Fannie Mae and Freddie Mac, using the previous month's lagged crisis weight in sum being in the top or bottom deciles of the cumulative historical distribution of those sums as an indicator. Portfolio values are initially set at one on January 1st, 1996, and returns are calculated monthly from 1996 through 2016. The p-values in Columns 8 and 9 are for the two sided test that the given portfolio has the same Sharpe Ratio as the Equal Weighted Portfolio. Values less than 0.10 indicate that the Equal Weighted Portfolio has a better Sharpe Ratio at the 10% level, while values of 0.90 and above indicate that the candidate portfolio has a better Sharpe Ratio at a statistically significant level. Column 9 focuses on the Sharpe Ratio from 2000 onwards, providing a burn-in period for the lagged crisis weight in sum distribution to be established. The scaled returns are the annualized returns for the candidate portfolios scaled to the standard deviation of the Equal Weighted Portfolio, and the Scaled Return Premium column contains those returns minus the average of those for the Equal Weighted Portfolio. *** p<0.01, ** p<0.05, * p<0.1