Three Essays on Financial Economics

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Abstract

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This thesis discusses network risk and its implications for financial economics. A stock's tendency to co-move with its related stocks is defined as network risk. In the first chapter, I propose a new econometric procedure to estimate network risk using a factor model and show that network risk is not negligible in the 2007-2008 financial crisis. The second chapter examines the pricing of network risk in the cross section of stock expected returns. Using the Fama-McBeth regression, I show that a newly-derived network volatility component of idiosyncratic volatility, termed NVOL, was priced with a 1.01 percent monthly premium between Sep. 1967 and Dec. 2012. This finding suggests a risk-based explanation of the equity premium: Stocks are compensated for risk that arises from shocks to networks that contain them. Finally, the third chapter summarizes various systemic risk measures developed after the financial crisis in 2008. These measures are classified into four categories: (1) Tail dependence; (2) Default probability; (3) Network measure; and (4) Others based on their approach and data required. *Robust-yet-Fragile* property which is one of the characteristics of a modern financial system is identified as a key to understanding the cascade effects of systemic risk. Network based systemic risk models have great potential to capture this property, both theoretically and empirically.

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DEDICATION

to my dear father, Andy Chen &
my dear wife, Han-Jung Ko

Chapter 1

NETWORK RISK AND THE FINANCIAL CRISIS

1.1 Introduction

Stocks do not exist alone. They are linked by hidden ties. These ties can be simple, such as supply chains (ARM and Apple) and industry integration, or they can be more complex ones like cross-share holdings (YAHOO! and Alibaba), holding companies and subsidiaries (Berkshire Hathaway), and so on. Firms are connected via these links and, together, they form a network. When firm-specific shocks spread out in this complicated network, some firms are robust enough to resist shocks but some are not. As a result, some stocks are likely to co-move or even plummet with others in a bad time.

Beside common risk factors, it is noted that stocks can be driven by firm specific shocks.[1] Specifically, these shocks are either caused by the firms themselves or come from their economically related stocks.[2] Currently, there is no quantitative tool to distinguish them, although, the latter was critical in the recent financial crisis in 2008. This research tries to fill this gap and provides an econometric tool. I term *network risk* as risk to co-move with other stocks due to shocks transmitted from a network.

This paper provides a measure to quantify network risk by decomposing residual returns, defined as stock returns net of common risk returns. I use a covariance matrix of stocks residual returns as an ex post network of stocks. Since each edge represents pairwise covariance,

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[1] Goyal and Santa-Clara (2003), Vassalou and Xing (2004), Ang et al. (2006), Fu (2009), Ang et al. (2009)

[2] Research related to shocks from neighbors or networks, for example: Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013), Acemoglu et al. (2012), Nier et al. (2007), Buraschi and Porchia (2012), Allen and Gale (2000), Gai and Kapadia (2010), Gai, Haldane, and Kapadia (2011) Haldane et al. (2009), Diebold and Yılmaz (2014), Soramäki et al. (2007), Huang, Zhou, and Zhu (2009), Elliott, Golub, and Jackson (2014), Korinek (2011),

calculating the Katz centrality[3] will assign co-varying scores to each stock. A *network risk* factor weighted by centrality can be constructed and considered as mimicking a portfolio of investing stocks based on these scores and interpreted as a market network risk. For each stock, the loading to the network risk factor is termed network Beta. A stock with high network Beta tends to move with related stocks and is network risky. Residual returns are then decomposed into two components: network risk and pure idiosyncratic risk. Volatility of the former is network volatility (NVOL) and of the latter is pure idiosyncratic volatility (PVOL).

I study the network risk of 76 financial institutions empirically from during the financial crisis of 2007 and 2008. Besides network volatility, the network risk component of Standard Deviation, Value-at-Risk and Expected Shortfall can be derived from the network risk factor, termed Co-Std, Co-VaR and Co-ES. I show that these new risk metrics have better explanatory and predictive power of stocks' performance than standard risk metrics in the financial crisis of 2007-08. This empirical study shows that the Co-Std has a 48 % adjusted R-squared of explanatory power. It shows that it is an important factor to explain the variation of stock performance in the financial crisis. In addition, Co-Std, Co-VaR and CoES have another advantage over the conventional risk metrics. It can be easily combined with covariates related to financial distress, such as size or leverage ratio. The Co-Std adjusted-by-leverage ratio is shown to be the best predictor of stock returns among all other risk metrics in the financial crisis.

Although network risk as defined in this paper is based on the centrality, the Katz centrality is one of many ways to define connectivity among firms. In the network literature, causality is often used. It refers to a directed network, whereas the covariance network is referred to the undirected networks. In the research which relates to a directed network, Diebold and Yılmaz (2014) calculated connectivity by decomposing forecast error variance by the vector autoregression (VAR) model for asset returns. They studied the connectivity

[3]See Newman (2010) for detail.

of 15 U.S. financial institutions among US. However, VAR is not reliable if data has too many dimensions to estimate and it is usually the case. My research does not suffer from this dimension problem. Buraschi and Porchia (2012) interpreted network connectivity as the ability to transfer a distressed state to other firm's fundamentals in a directed and timely manner. Central stocks tend to have lower prices and a lower dividend ratio and earn higher expected returns. A sizable positive price of centrality risk premium is found empirically in their research. Other researches includes Ahern (2013) studied industry level centrality. Using an input-output table as a networks between different sectors, he found that the industry with higher central position earns higher returns than non-central ones.

This research is closely related to the *systemic risk* literature. Systemic risk is defined as risk from the failure of a small numbers of firms, which can produce a huge crisis in financial markets due to interconnectedness, also known as "too interconnected to fail". The literature on systemic risk literature tends to focus on how much a single firm can damage the whole system, whereas, my research focuses on risks coming from the system to a firm. Therefore, I consider my research as a complement to rather than a substitute for the systemic risk literature. Among other research on systemic risk, Adrian and Brunnermeier (2011) proposed that the co-VaR measure be defined as the Value-at-Risk (VaR) of the system when a single financial institute is in distress. Acharya et al. (2010) proposed the marginal expected shortfall (MES), which is the expected shortfall (ES) of a financial institute when the whole market is in distress. Brownlees and Engle (2012) estimated MES by the dynamic conditional correlation (DCC) technique and ranked systemic risky financial institutions (SRISK). These papers use reduced form models to estimate the systemic risk of single firms.

Segoviano and Goodhart (2009) used nonparametric copulas to estimate the joint probability of the loss in the system and estimate the cascade effect when a single firm fails in the system. Kritzman et al. (2011) used principle components analysis to construct an absorption ratio to predict the downside risk of the market. Billio et al. (2012) suggested various ways to measure systemic risk. One of their approaches is to construct financial networks using the Granger Causality tests. If asset A Granger causes asset B, then there is a directed edge from A to B in the network. They show that out-degree and Eigenvector centrality have predictive power on maximum capital loss. Bisias et al. (2012) surveyed the systemic risk literature and Haldane et al. (2009) provided a good non-technique background about financial networks. Hansen (2012) cast some doubt on the current research of systemic risk.

The structure of this paper will be as follows: Section 2 introduces the factor model with the network risk and the factor model risk decomposition. Section 3 provides simulation result and section 4 provides an empirical study. Finally, a conclusion is given in Section 5.

1.2 Model

In this section I will introduce the model to estimate network risk.

1.2.1 Econometric Model

Asset returns can be decomposed into returns attributed to market risk factors Bf_t and residual returns e_t using a factor model. The theoretical background for the factor model is CAPM if there is only one factor in the model or APT or ICAPM if multiple factors are allowed. Generally speaking, f_t is market risk (common or systematic) and is not diversifiable. Bf_t is linear pricing kernel and e_t is diversifiable specific firm noises.

Empirically, many different procedures are developed to estimate factor models, depending on whether f_t is observable. If f_t is observable, simple OLS will suffice. If error terms are contemporaneously correlated, GLS can be used to achieve more efficient estimators. If error terms are serially correlated, HAC type estimator can be used to estimate robust standard errors.

In this paper I will assume f_t is observable, so the model is a linear asset pricing model. However, residual returns e_t will be decomposed into 2 terms: *network* term and *pure idiosyncratic* term. Specifically,

$$r_t = Bf_t + e_t,\ t = 1 \cdots T \tag{1.1}$$

$$e_t = b^c f_t^c + \eta_t \tag{1.2}$$

where r_t is an N $\times$ 1 vector of excess returns, B is an N $\times$ K matrix of market risk exposures, f_t is an observed exogenous K $\times$ 1 vector of market risk factors. e_t is an N $\times$ 1 vector of residual returns and assumed to be orthogonal to f_t. b^c is N $\times$ 1 unobserved factor loading. f_t^c is an observed 1 $\times$ 1 network risk factor and will be constructed later. η_t is i.i.d. idiosyncratic disturbance.

The assumptions of factor f^c, factor loading b^c and η_t in Equation 1.2 are :

Assumptions for factor and factor loading:

f.1 $\mathbb{E}(f_t^c f_t^{c'}) = \sigma^2_{f^c}$

f.2 $|b_i^c| \leq \bar{b^c} < \infty$

f.3 $\frac{1}{T}\sum_t f_t^c f_t^{c'} \xrightarrow{p} \sigma^2_{f^c}$

Assumption f.1 allows factors to be serially correlated but with constant unconditional second moments, so it rules out stochastic trends. Assumption f.2 assumes factor loading exists and is finite. Finally, assumption f.3 assumes that the sample second moments will converge asymptotically.

Assumptions for error η_t:

e.1 $\mathbb{E}(\eta_t \eta_t') = \Sigma_\eta$

e.2 $\frac{1}{T}\sum_t \eta_t \eta_t' \xrightarrow{p} \Sigma_\eta$

e.3 η_t is orthogonal to f_t

Assumption e.1 makes sure Σ_η exist and finite. e.1 and f.1 together imply that Σ_e exists. Assumption e.2 assumes the sample second moments converge asymptotically. These assumptions are minimal assumptions for decomposition of Equation 1.2. Assumption e.3 is orthogonality condition between f_t and η_t, this assumption makes sure consistency of factor loading b^c.

This model adds to the prior research by decomposing residual returns into two parts. f_t^c is a factor which mimics a network risk portfolio. The factor loading b^c is the risk exposure to f_t^c for each stock. If a stock has high factor loading, it is likely to co-move compared to the market network risk factor. Notice that the co-movement is not driven by market-wide shocks but the firm specific shocks; for example, Apple Inc.'s bad sales numbers affect the stock price of its main computer chip provider Qualcomm Inc, but not the entire market.

1.2.2 Network Risk Factor

A key to constructing a network risk factor is to distribute the weight appropriately. The mimicking portfolio's investing stocks are weighted by network risk, that is, the tendency to move with their related stocks. Intuitively, a riskier stock should weight higher in the portfolio and vice versa. If I can give each stock a score representing its tendency to move, a mimicking portfolio that takes score as weights can be constructed.

This score is calculated by the *Katz centrality*. Before introducing this score, it is worthwhile to give some background on network and centrality in general.

1.2.2.1 Network and Centrality

A network, or a graph in mathematics, consists of nodes joined by edges. Nodes, sometimes called vertices, are objects. Edges are indicators that show how nodes join together. For example, on the Internet, every website is a node and hyperlinks are edges, or in a friendship network in a school, every student is a node and edges are relationship between students. If edges have direction, such as hyperlinks or citation, it is called a *directed* network and if not, it is called an *undirected* network, like friendship. Edges can have values, like (a) in a banking system network, edges are money transferred, or (b) with simple binary numbers, 1 or 0 represent yes or no. The former is referred to as a *weighted* network and the latter is an *unweighted* network. Networks can be represented in an *adjacency* matrix which shows the values of edges in matrix form. If there is a value for diagonal terms, edges are called *self-edges*. An element in row N and column M represents an edge from Vertex M to Vertex N. If a network is an undirected one, such as in our case, then the adjacency matrix will be symmetric; on the other hand, a directed network has an asymmetric adjacency matrix.

Degree is a measure of connectivity. In an undirected and unweighted network, the degree of a node is the sum of the edges, and in a weighted network, degree is the sum of the value of edges. *Out-degree* and *in-degree* for a directed network report the sum of values of edges pointing out and the sum of values of edges pointing in, respectively. *Degree distribution* is normally distributed skewed to the right so most nodes have few degrees but there are nodes in the far right hand side of distribution have extremely large numbers of degrees and may account for more than 90 percent of total degrees.

Centrality calculates scores from its dependence structure. Generally speaking, this reflects how important a node is in the network. Researchers ask different questions depending on how they construct their networks. If there is a friendship network in a class, an edge represents whether Person A is considered a friend of Person B by Person B, and centrality will give us an answer to who is the most popular person in this class. In a citation network, every article is a vertex and its citations are edges. It is a directed but unweighted network and centrality shows which article is the most influential one. In world wide website networks, edges are hyperlinks to other websites. Centrality of this web network gives us ranking of influential power of different websites. A high centrality website like Yahoo or Google can be identified in the network. In fact, Google's pagerank, which is their search engine technique, is based on this idea. More examples such as the most important nodes in an electricity network or the most used ingredient in recipes can be found by centrality.

In our case, firms are connected in a network and therefore, the covariance structure of residual returns can be seen as an adjacency matrix of business networks. Residual returns co-vary when idiosyncratic shocks spread, but not every firm is directly connected and so the degree distribution can be skewed. Centrality can identify which stock is the most co-varying one as idiosyncratic shocks hit the network

There are several different definitions of centrality. In fact, the column sum of covariance matrix is called *degree centrality*. I will give a formal definition in the following section.

1.2.2.2 Degree Centrality

Degree centrality is defined as the number of connections of any particular node directly to others in a network. That is also the degree of a node. Therefore, centrality x_i of node v_i is:

$$x_i = \sum_{j}^{N} a_{ij}, \; i = 1 \cdots N \tag{1.3}$$

where a_{ij} is an element of adjacency matrix at row i and column j. Degree centrality is simple and generally assumes that higher connected node will have higher score.

1.2.2.3 Eigenvector Centrality

Eigenvector centrality is an improved version of degree centrality. Degree centrality rewards every neighbor the same centrality score. However, some neighbors might have more weights than others if distribution of edges is skewed. Eigenvector centrality scores according to its neighbors' centrality. In the other words, in a friendship network, a person will become popular if he or she has popular friends.

Bonacich (1972) proposes Eigenvector centrality, which is the standard for centrality in the network literature.[4]

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j, \; i = 1 \cdots N \tag{1.4}$$

where x_i is the Eigenvector centrality of the networks, A is the adjacency matrix and λ is the highest Eigenvalue, It is easier to see equation 1.4 in matrix form:

[4] There are several variation of this one, including "page rank" of Google.com.

$$\lambda X = AX$$

λ is the largest Eigenvalue and X is the associated N $\times$ 1 Eigenvector of the matrix A. The Eigenvector centrality is the Eigenvector associated with highest Eigenvalue.[5]

x_i can also be seen as the sum of centrality of the other assets x_j in the network weighted by the adjacency matrix A_{ij}. As we can see, centrality is calculated in a recursive way. My neighbor's high centrality will contribute to my centrality via an adjacency matrix and will affect her Eigenvalue centrality as well.

1.2.2.4 Katz Centrality

When an adjacency matrix contains a lot of zeros, it results in zero or very small numbers of Eigenvector centrality. Sometimes it is either hard to compute or hard to compare. The solution is to add the same "free" scores to all nodes so that will not change relative scores of nodes. The *Katz centrality* of Katz (1953) applies this idea.

$$x_i = \gamma \sum_{j=1}^{N} A_{ij} x_j + \beta_i, \; i = 1 \cdots N \tag{1.5}$$

Katz centrality adds to Eigenvector centrality by β_i, which is the nodal attribute. β_i is frequently set to 1, but is not restricted to it. When β_i is set to 1, it gives all nodes scores of 1, so it avoids the situation where some nodes score too close to zero.

γ is a variable to control using Katz centrality. If $a = 0$, Katz centrality equals β which is a vector of β_i. If $\gamma \geq 1/\lambda$, Katz centrality diverges and has no meaning.[6] There is little guidance for how to choose γ. Most researchers choose γ of less than but close to $1/\lambda$, so β weights less when Katz centrality is calculated. Katz centrality is also preferred over Eigenvector centrality by many researchers because of aforementioned zero scores issue.

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[5] It can be shown that only the highest Eigenvector will remain when we iterate equation 1.4. See Chapter 7.1 in Newman (2010) for detail.

[6] See Chapter 7.2 in Newman (2010) for detail.

There are other centrality measures such as *closeness centrality* which measures the mean distance from one node to another. *Betweenness centrality* focuses more on the extent to which a node lies on a path between other nodes. These are less relevant to this paper, although interested readers may refer to Newman (2010) for further detail.

1.2.2.5 Choice of β

When β is equal to a vector of 1, it simply gives nodes additional small score of centrality for free, and therefore will not change the relative scores in the end. However, nodes which have neighbors with scores 0 will score a little more than 0.

Other information like size or leverage ratio can be used for β, for which centrality will reflect the choice of β in equation 1.4. Generally speaking, β closer to zero will provide more information on *edges* themselves. Some researchers call it *global centrality* as opposed to *local centrality* when local information β has been incorporated into the computation.

1.2.2.6 Construction of a Network Risk Factor

Every stock represents a node in a network; the selection of the adjacency matrix is different depending on the context. This paper uses the residual returns covariance matrix as an adjacency matrix. Katz centrality of this adjacency matrix takes bilateral covariance into calculation and aggregates co-varying scores of stocks in a recursive manner.

As a result, taking Katz centrality as a weighting scheme can form a mimicking portfolio of network risk. That is $X'e_t$ where X is N $\times$ 1 normalized Katz centrality and e_t is a N $\times$ 1 vector of residual returns. Let $f_t^c = X'e_t$, then f_t^c is a mimicking portfolio of investing stocks that depends on their network risk.

1.2.3 Decomposition

The decomposition procedure has two steps. The first step is simply a prefiltering step to get residual returns. Since market risk factor is assumed exogenous, Equation 1.1 is estimated by time series OLS for every stock i. The second step is to estimate Equation 1.2.

Specifically, I performed a time-series regression of the Fama-French Three Factor model on daily stock returns in every month between September 1963 and December 2012 as the first step.

$$r_t - r_f = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + e_t$$

Excess daily returns are calculated as the daily returns from CRSP minus the 1 month T-bill rate which is the risk-free rate used in this research. Only stocks that have 15 or more transaction days in a month were included to avoid a liquidity issue. The risk free rate and the Fama-French Three Factors are taken from Kenneth French's website.

In a given month, I calculate covariance of the residual returns. The residual returns co-variance matrix is treated as an adjacency matrix of stock dependence. N $\times$ 1 vector of Katz centrality $\tilde{w}$ with β equal to 1 and $\gamma = 2/3 \times 1/\lambda$[7] is calculated according to Equation 1.5 and orthonormal centrality to $\tilde{w}'\tilde{w} = 1$. Finally, mimicking portfolio is constructed as follows:

$$f_t^c = \alpha^{-1} \times \tilde{w}'\hat{e}_t = w'\hat{e}_t$$

and factor loading b^c is equal to $\tilde{w}$ multiplied by a rescaling constant α and α is equal to $\sum \tilde{w}$.

To mathematically obtain factor loading, I fix f_t^c, solving Equation 1.2. This is equivalent to solving this least squares objective function:

$$\min_{\{b_i^c\}_{i=1}^N} \frac{1}{NT} \sum_i \sum_t (\hat{e}_{it} - b_i^c f_t^c)^2 \quad (1.6)$$
$$\text{s.t. } f_t^c = \alpha^{-1}\tilde{w}'\hat{e}_t$$

[7] 2/3 is chosen for computational convenience.

where b_i^c is i element of N $\times$ 1 vector b^c. To verify that b^c is equal to $\alpha\tilde{w}$, assuming b^c is known, then $f_t^c = (b^{c'}b^c)^{-1}b^{c'}\hat{e}_t$ will solve the above nonlinear minimization problem. Substitute $b^c = \alpha\tilde{w}$ and simple algebra will show that $f_t^c = \alpha^{-1}\tilde{w}'\hat{e}_t$ and one can complete the proof. For convenience, $f^c = [f_1^c, f_2^c, \cdots, f_T^c]'$ is called the *network risk* factor in later discussion.

To decompose idiosyncratic variance, let covariance of $b_c f_t^c$ equal to Σ_c and define $\Sigma_\eta = \Sigma_{\hat{e}} - \Sigma_c$, therefore, for every stock i, idiosyncratic variance can be expressed as:

$$\sigma_{\hat{e},i}^2 = \sigma_{i,c}^2 + \sigma_{\hat{\eta},i}^2,\ i = 1 \cdots N \tag{1.7}$$

The square root of the former is called *network volatility.* This is idiosyncratic volatility contributed by neighbor stocks. The square root of the latter is *pure idiosyncratic volatility* which is volatility from its own shocks.

1.2.4 Factor Model Risk Analysis

Combine Equation 1.1 and Equation 1.2:

$$r_{it} = \Sigma_{k=1}^K \beta_k f_{k,t} + b_c f_t^c + \eta_t \tag{1.8}$$

$$= \Sigma_{k=1}^K \beta_k f_{k,t} + b_c f_t^c + \sigma z_t,\ i = 1 \cdots N \tag{1.9}$$

Equation 1.8 is the model that contains network risk component. I can also rewrite the last term of Equation 1.8 η_t into σz_t in Equation 1.9 where z_t is i.i.d. with a mean of zero and a standard deviation of one, and where σ can be considered as exposure to pure idiosyncratic risk.

1.2.4.1 Factor Model Based Risk Decomposition

Risk metrics like standard deviation (Std), Value-at-Risk and Expected Shortfall are defined as:

$$Std(r_i) = \sqrt{\frac{1}{T-1}\Sigma_{t=1}^{T}(r_i - \bar{r_i})^2} \tag{1.10}$$

$$VaR(r_i)_\alpha = F^{-1}(\alpha) \tag{1.11}$$

$$ES(r_i)_\alpha = E[r_t | r_t \leq VaR_\alpha] \tag{1.12}$$

where $\bar{r_i}$ is sample mean of excess returns r_i and F is cdf of r_i. VaR is defined as how much loss at α percent in a given time will exceed this value and ES is defined as how much expected loss at α percent in a given time will exceed this value. Higher value denotes more risk. Since std,VaR and ES are functions of homogeneous degree of 1, by Euler's theorem:

$$RM(r_i) = \Sigma_{k=1}^{K}\beta_k \frac{\partial RM}{\partial \beta_k} + b_c \frac{\partial RM}{\partial b_c} + \sigma_\eta \frac{\partial RM}{\partial \sigma_\eta} \tag{1.13}$$

where RM can be Std, VaR or ES.

Comparing Equation 1.13 and the factor risk decomposition of Equation 1.1, the value of risk metrics is the same but the last two terms in Equation 1.13 are equal to $\sigma_e \frac{\partial RM}{\partial \sigma_e}$, therefore, $b_c \frac{\partial RM}{\partial b_c}$ can be interpreted as *network risk* coming from local shocks and $\sigma_\eta \frac{\partial RM}{\partial \sigma_\eta}$ is *pure* idiosyncratic risk.

1.3 Simulation

I considered three different scenarios in a simulation exercise: low covariance matrix Σ_l, high covariance matrix Σ_h and skewed distributed covariance matrix Σ_s for data generation of a residual returns covariance matrix. For every data generation process, I will generate 100 variables with 200 observations by different multi-Normal distribution. That is $r_t = a+bf_t+e_t$ where f_t is an arbitrage factor that is orthogonal to e_t. Two different centrality methods such as the degree centrality and the Katz centrality will be applied to each scenario and compared. The simulation is repeated 1000 times for each exercise. I computed variance decomposition in Equation 1.7 or $\sigma_e^2 = \sigma_c^2 + \sigma_\eta^2$. For better illustration, variance decomposition is scaled to percentage.

In the case of the low covariance matrix Σ_l, every element of the covariance matrix follows a Normal distribution with a mean of 0.2 and a standard deviation of 0.01. I also control the diagonal terms of the covariance matrix being equal to one. Figure 1.2a shows variance decomposition with the Katz centrality. It is distributed equally among variables, σ_c^2 is about 21% and σ_e^2 is about 79 %. Compared to the degree centrality shown in Figure 1.2c, σ_c^2 is about 6% and σ_e^2 is about 94%. Figure 1.2b and 1.2d report t-statistics for σ_c^2 and σ_e^2 for the Katz centrality variance decomposition and degree centrality variance decomposition respectively. The red line represents the 5 % level of significance. If the grey bar (σ_e^2) or the white bar (σ_c^2 standing next to the grey bar) exceeds the red line, the variance is significant. It shows that σ_c^2 and σ_e^2 calculated by the Katz centrality are both significant at the 5 % level but σ_c^2 calculated by degree centrality is not significant at the 5 % level. It is suggested that the Katz centrality variance decomposition is better for a low covariance matrix.

In the case of the high covariance matrix Σ_h, every element of covariance follows a Normal distribution with a mean of 0.7 and a standard deviation of 0.01. I also controlled the diagonal terms equal to 1. Figure 1.2e shows variance decomposition by Katz centrality and Figure 1.2a shows variance decomposition by degree centrality. Figure 1.2f and 1.2b report t-statistics for σ_c^2 and σ_e^2 for the Katz centrality variance decomposition and degree centrality variance decomposition, respectively. σ_c^2 is about 70 % and σ_e^2 is about 30 % with the Katz centrality variance decomposition and both are significant at the 5 % level. σ_c^2 is about 46 % and σ_e^2 is 54 % with degree centrality variance decomposition. However, only σ_e^2 is significant at the 5 % level and σ_c^2 is not significant. It shows that the Katz centrality is a better method for a high covariance matrix.

In the case of the skewed distributed covariance matrix Σ_s, I created a covariance matrix M by the Cholesky decomposition. Setting up L as a lower triangular matrix with elements followed a Normal distribution with a mean of 0.1 and a standard deviation of 0.1. The covariance matrix M = L x L'. Finally, I take diagonal terms equal to 1 to mitigate the influence of variance. The covariance matrix M will be positive definite and covariance elements go higher as toward to southwest corner.

Figure 1.2c reports the variance decomposition by the Katz centrality. It shows that variables with a higher covariance tend to have a higher network risk σ_c^2. Katz centrality decomposition values range from 0.04 % to 77%. Figure 1.2d shows t-statistics for σ_c^2 and σ_e^2, respectively. σ_e^2 is always significant but the first 18 variables of σ_c^2 are not significant at the 5% level. The first 18 variables have mean σ_c^2 from 0.04 % to 0.07 %. It is not significant because elements of the residual returns matrix of the first 18 variables are very close to 0, about 0.01 to 0.04. Therefore, I cannot distinguish σ_c^2 from σ_e^2. Degree centrality variance decomposition is shown in Figure 1.2e. σ_c^2 ranges from 1 % to 32 % but increase less rapidly than the Katz centrality variance decomposition. Figure 1.2e shows variance decomposition and a downward trend is observed. Figure 1.2e reports t-statistics. Only σ_e^2 is significant at the 5 % level but σ_c^2 is not. The reason why variance decomposition by degree centrality shows insignificant result is because it gives the same scores if column sum of covariance matrix is the same, thus they only have small difference by design.

To summarize the simulation, I find that the Katz centrality works better than the degree centrality to identify network risk. As a result, I will apply variance decomposition with the Katz centrality in the empirical section.

1.4 Empirics

1.4.1 Data

Seventy-six financial institutes were selected based on the market capitalization in 2002 to 2008. Twenty-six broker/dealers, twenty-six banks and twenty-four insurance companies are included. The range of the sample size is from July 2002 to May 2008. Size is the market capitalization, that is the stock price multiplied by the shares outstanding. Leverage ratio is calculated as book assets divided by the market value of the ordinary equity. The data is from the quarterly combined CRSP-Compustat merged database. Monthly risk free rate, Market excess returns, SMB, HML and momentum factor returns come from Kenneth French's website. Table 1.1 shows a summary of stocks' returns, cumulative returns, log market size and leverage ratio.

1.4.2 Empirical network Risk

Fama and French (1993) Three factors model is used to estimate e_t. The Fama-French model has had great success in empirical asset pricing modeling. Seventy-six monthly time series data are estimated one by one with the Fama-French Three factor model from July 2002 to May 2008 (before Bear Sterns, Lehman brothers are delisted). Thus there are no missing values in residuals from Equation 1.14.

$$r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t \tag{1.14}$$

With residual returns e_t, I calculate its degree centrality and Katz centrality based on Equation 1.3 and 1.4 with β equal to 1, then calculate its network risk, pure idiosyncratic risk, and factor risk decomposition for Std, VaR and ES. Table 1.1 shows network Beta. The highest is Bear Sterns (BSC) with a network Beta of 2.71 and the lowest is Stifel Financial Corp. (SF) with a network Beta equal to -0.38.

Table 1.2 shows the results of the decomposition of Equation 1.7, notably the degree of variation. Stocks such as Wachovia (WB), Bear Sterns (BSC), Lehman Brothers (LEH), UBS AG (UBS) and Merrill Lynch (MER) have high network risk $\sigma^2(c_t)$. Notice that these firms were heavily distressed in 2007-2008 financial crisis. They also have been shown with high *systemic risk* in several studies[8]. One interesting point is that high volatility does not guarantee high network risk(see Investment Technology Group Inc.(ITG), Cigna Corp.(CI) or Radian group (RDN)). Instead, network risk captures how they co-vary with others.

I also calculate the variance decomposition before crisis for comparison. I use samples from July 2002 to Deccember 2006, with the results reported in Table 1.3. The five financial

[8] Adrian and Brunnermeier (2011), Acharya et al. (2010), Brownlees and Engle (2012), Kritzman et al. (2011), Segoviano and Goodhart (2009) and survey by Bisias et al. (2012)

institutions with the highest network risk are Labranche Co Inc. (LAB) at 30.94%, Investment Technology Group Inc. (ITG) at 20.64%, Charles Schwab Corps (SCH) at 15.44%, Southest Secrurities group (SWS) at 13.61% and Janus Cap Group (JNS) at 12.93%.

1.4.3 Risk Metrics Decomposition

Regarding to the factor model risk decomposition to standard deviation, Value-at-Risk and Expected Shortfall, Table 1.5a shows 5 % VaR for every asset. Bear Sterns (BSC) again has the highest network risk component to VaR by 7.01 %. Surprisingly, its pure idiosyncratic component to VaR is only 0.98 %, that is to say, the conventional idiosyncratic component will attribute 7.99 % to idiosyncratic risk component to VaR, whereas with new risk decomposition, it is less than 1%. A large proportion of VaR is actually created by its networks.

VaR is insensitive to extreme values. It shows the loss of the asset in a certain probability. If there is a small probability of a huge loss, VaR does not reflect that. On the other hand, Expected Shortfall (Expected Tail Loss, Conditional VaR) calculates the potential loss under certain probability, it is more robust to the fat tail distribution. Table 1.5b shows 5% ES components.

Wachovia (WB) at 3.74 % ranks first among 76 financial institutions, followed by AMBAC Financial Group (ABK) at 2.94%, CITI (C) at 2.46% and SLM Corp (SLM) at 2.45%. Whereas ABK contributes 20.76 % of the pure idiosyncratic component to ES, other stocks have pure idiosyncratic component contributions to ES very similar to their network risk component contributions to ES. It suggests that there is a lot of variation in network risk among financial institutions.

Finally, the component contribution to Standard Deviation is shown in Table 1.5c. The five highest component contributions to Standard Deviation to network risk are Bear Sterns (BSC), Wachovia (WB), W.P. Stewart (WPL) (delisted in 2009), SLM and Merrill Lynch (MER).

1.4.4 Network Risk and Financial Crisis in 2007-2008

Starting in 2000, the financial market became more integrated than ever due to financial innovations, such as CDO, ABS, and SIV, the goal of which is to better share risk. However, investors tend to underestimate the network effect of too much risk sharing and spreading of shocks when market is highly interconnected, thereby creating systemic risk[9].

The risk decomposition provided in this study can help investors identify risk due to interconnectedness. I plot the network component contribution to three risk metrics: Std, VaR and ES against asset cumulative returns, and I also plot total Std, VaR, ES against cumulative returns for comparison. The cumulative returns of each asset are calculated from January 2007 to May 2008. The idea is to mimic an investing strategy, and to see how much would be earned by May 2008 from a dollar invested in January 2007.

Figure 1.3a and Figure 1.3b show the network risk component contribution to Std (Co-Std) against cumulative returns and total Std against cumulative returns respectively. Co-Std shows a downward-sloping relationship to cumulative returns. BSC, WB, WPL, SLM, and LEH have been identified as high co-Std risky assets. On the other hand, Total Std does not show a clear negative slope. A best fit linear line shows R^2 is as high as 0.48 with Co-Std compared to 0.10 with Std.

The same comparisons for VaR and ES are shown in Figure 1.3d, 1.3c, 1.3e and 1.3f. The network risk component contribution to VaR (Co-VaR) and network risk component contribution to ES (Co-ES) show downward sloping tendency as well. (R^2 is 0.38 with Co-VaR versus 0.22 with total VaR and 0.35 with Co-ES versus 0.20 with total ES).

Overall, component Co-Std has the best explanatory power followed by Co-VaR and Co-ES. They all have considerably more explanatory power than total Std, VaR and ES (Table 1.7 reports coefficients and R^2). It suggests that network risk was one of the important factors in the financial crisis in 2007-08.

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[9] Haldane et al. (2009), Cont, Moussa, and Santos (2011), Nier et al. (2007), and Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013)

1.4.4.1 Leverage Ratio

Studies such as Acharya et al. (2010),and Brownlees and Engle (2012) show that the leverage ratio was another key factor in the financial crisis. High leverage ratio firms are vulnerable to shocks and therefore, easily distressed. In highly interconnected networks, distressed firms will generate further shocks and hit other firms. Leverage ratio can be incorporated into the centrality calculation by allowing the leverage ratio equal to β in Equation 1.4. Leverage ratio in this paper is defined as total assets divided by market capitalization.[10]

Figure 1.4a shows cumulative returns against component contribution to Std to network risk adjusted by leverage. I found a very similar result to before but with a slightly stronger relationship than non-adjusted Co-Std (adjusted R^2 is 0.53).

Figure 1.4c shows cumulative returns against component contribution to VaR to network risk (adjusted R^2 is 0.42). Finally, Figure 1.4e shows cumulative returns against component contribution to ES to network risk (adjusted R^2 is 0.39). The first three columns of Table 1.8 report coefficients and R^2.

1.4.4.2 Market Capitalization

Size can be a factor in financial robustness too. Bigger firms may have lower network risk since they have a higher market share and are less vulnerable to shocks. I use the inverse of the log of size as β in Equation 1.4 and repeat the whole exercise.

Figure 1.4b shows cumulative returns against component contribution to Std to network risk adjusted by size. The best-fit linear line shows that R^2 is 0.46. Figure 1.4d shows cumulative returns against component contribution to VaR to network risk adjusted by size (with R^2 of 0.37). Figure 1.4f shows cumulative returns against component contribution to ES to network risk adjusted by size and R^2 is 0.34.

Overall, network risk adjusted by leverage has the highest explanatory power in fitting Co-Std and Co-VaR, Co-ES against cumulative returns, followed by the risk measures adjusted

[10] I delete three stocks because of missing data.

by size.

1.4.5 Predictive Power

I am also interested in the power of network risk measures in predicting expected returns. I use data from January 2002 to February 2008 to calculate risk decomposition to Std, VaR and ES. I then regressed mean returns of the last three months data from March 2008 to May 2008. Table 1.9 reports result of basic Co-Std, Co-ES, Co-VaR, network risk σ^2_{fc} and percentage network risk. For comparison purposes, I also regressed the mean return on Std, ES, VaR.

Only total ES, Co-Std and percentage network risk are significant at 5 the % level. They have negative coefficients of -0.56, -3.07 and -0.19, respectively, with R^2 is 5 %, 6 %, and 6 %, respectively. Co-Std and percentage network risk have the highest R^2.

Table 1.11a reports the predictive regression of mean returns on risk metrics with leverage adjusted. R^2 increases among all models. All coefficients are negative and significant at 5 %. Co-Std and Co-VaR have the highest adjusted R^2 of 0.09 .

Table 1.11b reports the predictive regression of mean returns on risk metrics with size adjusted. All except percentage network risk are significant at the 5 % level. Other covariates do not show significance. I conclude that size adjusted risk metric are the worst predictors.

1.5 Conclusion

Network risk is defined as a stock's tendency to move with its related stocks. When a firm specific shock spreads via a network, it will push related stocks to move together. Network risky stocks are likely to be affected and co-move, especially in a financial distressed time. However, this risk has not yet been discussed in the current literature. This paper provides a tool to measure network risk with a factor model.

I use residual return covariance to calculate centrality and it is used to distribute the weights to construct a network risk factor mimicking portfolio. The degree centrality and the Katz centrality methods have been closely reviewed in the simulation. The latter is preferred due to the level of significance of variance decomposition.

For the empirical study, I estimate the network risks of 76 financial institutes from January 2002 to May 2008. I find Wachovia (WB), Bear Sterns (BSC), Lehman Brothers (LEH), UBS AG (UBS), and Merrill Lynch (MER) to have the highest network risk. Moreover, I find that the stocks with high network risk perform badly during financial crisis. The network risk component contribution to standard deviation, VaR, ES (Co-Std, Co-Var, Co-ES) has better explanatory power than more basic counterparts. Co-Std has 48 % adjusted R^2, compared to Std which only has 11 %. It shows that the network risk is an important factor to explain the financial crisis and it is not neglible. In addition, Co-Std adjusted by leverage ratio is used, and has higher explanatory power with adjusted R^2 equal to 53 %. For predictive power, Co-Std is significant and the best model among all risk metrics. Co-Std adjusted by leverage ratio is even better and has as high as 11 % predictive power in the 2008 financial crisis.

Table 1.1: Summary Statistics

	CMA	MTB	WB	WFC	FNM	NTRS	AXP	BAC	PNC	KEY
Mean.Ret	-0.19	0.29	-0.15	0.50	-0.81	1.10	0.75	0.39	0.74	0.05
Cum.Ret	-0.45	-0.08	-0.48	0.15	-0.69	0.72	0.25	-0.11	0.36	-0.48
Lsize	8.83	9.23	11.25	11.59	10.67	9.65	11.04	12.18	10.05	9.28
Lev	9.73	6.48	9.14	7.97	23.57	4.70	2.30	9.16	8.30	9.84
Net.Beta	0.56	0.94	1.63	0.91	0.65	0.57	0.74	0.91	0.70	1.15

	USB	SLM	C	BBT	STT	FRE	COF	BMO	RY	TD
Mean.Ret	0.98	0.17	-0.14	0.18	1.01	-0.75	0.31	1.46	1.92	2.05
Cum.Ret	0.56	-0.35	-0.42	-0.26	0.55	-0.69	-0.36	1.14	2.11	2.16
Lsize	10.94	9.60	12.07	9.88	10.25	10.20	10.04	10.27	11.10	10.84
Lev	4.38	12.70	13.04	7.23	5.48	35.21	7.09	13.61	9.79	9.29
Net.Beta	0.53	2.04	1.51	1.03	0.50	0.63	1.11	0.73	0.09	0.32

	BCM	HBC	UBS	DB	BNS	BRK.A	CINF	MMC	CNA	HUM
Mean.Ret	1.61	1.04	0.65	1.22	1.93	1.06	0.06	-0.27	0.42	2.23
Cum.Ret	1.14	0.76	0.10	0.50	2.32	0.81	-0.28	-0.36	-0.03	1.54
Lsize	10.27	9.24	11.36	11.04	10.80	11.85	8.79	9.56	9.16	9.30
Lev	12.23	NA	24.55	48.60	9.11	1.95	2.36	1.18	5.94	1.22
Net.Beta	0.41	-0.29	1.53	0.27	0.14	-0.16	0.25	0.45	0.69	1.52

	LNC	AFL	CB	AOC	CI	PGR	AIG	MBI	CVTY	ABK
Mean.Ret	0.83	1.22	0.91	1.21	1.02	0.82	-0.58	-2.12	2.18	-3.10
Cum.Ret	0.30	1.10	0.58	0.78	0.15	0.44	-0.59	-0.91	1.41	-0.98
Lsize	9.67	10.28	9.91	9.48	9.53	9.51	11.88	8.43	9.03	8.20
Lev	11.60	2.42	2.49	1.86	2.99	1.40	7.06	11.35	0.90	9.60
Net.Beta	0.56	0.04	0.34	0.46	0.49	0.54	1.16	1.71	1.15	1.57

	ALL	HIG	XL	MFC	SLC	MET	AET	PFG	UNH	TROW
Mean.Ret	0.79	0.69	-0.80	1.73	1.42	1.23	2.31	1.00	0.79	2.18
Cum.Ret	0.43	0.23	-0.71	1.74	1.16	0.94	2.39	0.46	0.15	2.79
Lsize	10.31	10.20	9.22	11.01	10.25	10.73	10.14	9.65	11.01	9.59
Lev	4.97	12.59	5.86	6.00	6.61	11.78	1.80	9.37	0.92	0.21
Net.Beta	0.29	0.35	1.17	-0.15	-0.06	-0.06	0.85	0.18	0.94	0.14

	EV	IDC	BEN	ITG	MER	SEIC	MS	RJF	SF	SCH
Mean.Ret	1.83	1.27	1.50	0.93	0.55	1.08	0.73	1.58	3.07	1.49
Cum.Ret	1.76	0.94	1.30	0.02	-0.14	0.72	0.12	1.24	4.50	1.01
Lsize	8.49	7.91	10.24	7.58	10.89	8.58	11.01	8.19	6.66	10.14
Lev	0.20	0.45	0.35	1.01	16.98	0.24	15.25	5.06	1.96	1.82
Net.Beta	0.06	-0.12	0.57	0.94	1.74	0.30	0.55	0.61	-0.38	0.74

	SWS	RDN	OPY	AMG	WDR	SMHG	JEF	GS	LAB	JNS
Mean.Ret	1.81	-1.94	1.00	1.66	1.13	0.62	1.21	1.58	-0.55	1.23
Cum.Ret	0.90	-0.97	0.39	1.20	0.79	0.13	0.73	1.51	-0.69	0.48
Lsize	6.08	7.19	6.36	8.18	7.87	5.46	7.98	11.28	5.86	8.50
Lev	12.10	9.83	3.38	0.95	0.33	1.27	9.13	13.16	13.97	0.72
Net.Beta	1.31	1.11	-0.12	0.66	0.17	0.72	1.19	0.73	1.83	0.68

	WPL	LYG	NMR	JPM	BSC	LEH
Mean.Ret	-2.05	0.49	0.65	0.98	-0.71	0.67
Cum.Ret	-0.92	-0.04	0.10	0.27	-1.00	-0.33
Lsize	5.67	7.47	7.12	11.94	9.20	10.32
Lev	0.37	NA	NA	11.65	31.44	20.62
Net.Beta	2.37	0.39	0.14	0.99	2.71	1.74

Note: 76 financial institutes are selected based on the market capitalization in 2002 to 2008. 26 broker/dealers, 26 banks and 24 insurance companies are included in the sample. The range of the sample is from July 2002 to May 2008. Size is the market capitalization which is the stock price multiplied by shares outstanding. Leverage ratio is calculated as book assets divided by market value of equity. The data is from the quarterly combined CRSP-Compustat merged dataset. Monthly risk free rate, Market excess returns, SMB, HML, momentum factor returns come from Kenneth French's website.

Table 1.2: Residual Variance Decomposition into Pure Idiosyncratic Risk and Network Risk

	BSC	WPL	SLM	LAB	MER	LEH	MBI	WB	ABK
σ_η^2	90.67	116.53	67.84	199.81	18.77	28.88	64.49	11.55	110.33
σ_c^2	40.38	30.89	22.75	18.3	16.58	16.57	15.95	14.58	13.54
	UBS	HUM	C	SWS	JEF	XL	AIG	KEY	CVTY
σ_η^2	18.94	79.9	17.17	93.11	35.46	23.26	24.08	18.34	58.27
σ_c^2	12.81	12.68	12.5	9.42	7.78	7.45	7.4	7.22	7.19
	RDN	COF	BBT	JPM	UNH	MTB	ITG	BAC	WFC
σ_η^2	127.82	56.45	20.4	27.41	36.21	14.89	101.04	10.2	11.01
σ_c^2	6.74	6.73	5.78	5.4	4.88	4.88	4.81	4.59	4.51
	AET	SCH	AXP	BMO	GS	SMHG	PNC	CNA	JNS
σ_η^2	58.24	41.91	8.19	17.92	26.18	63.88	17.99	26.11	58.9
σ_c^2	3.95	3.01	2.99	2.89	2.89	2.84	2.66	2.58	2.51
	AMG	FNM	FRE	RJF	NTRS	BEN	LNC	CMA	MS
σ_η^2	23.05	50.63	38.35	28.12	22.39	17.07	13.97	20.57	25.09
σ_c^2	2.37	2.33	2.18	2.05	1.81	1.8	1.72	1.7	1.64
	PGR	USB	STT	CI	AOC	MMC	BCM	LYG	SF
σ_η^2	32.95	13.94	32.19	92.86	58.42	41.33	29.03	31.93	86.55
σ_c^2	1.58	1.53	1.35	1.31	1.16	1.12	0.94	0.81	0.79
	HIG	CB	TD	SEIC	ALL	HBC	DB	CINF	PFG
σ_η^2	27.71	15.65	21.09	35.93	18.18	10.35	24	11.95	14.6
σ_c^2	0.66	0.65	0.56	0.5	0.48	0.46	0.41	0.33	0.18
	WDR	BRK.A	MFC	BNS	TROW	NMR	OPY	IDC	RY
σ_η^2	35.03	13.16	16.02	16.3	19.9	56.45	62.37	23.53	15.01
σ_c^2	0.15	0.15	0.12	0.11	0.1	0.1	0.09	0.08	0.04
	EV	SLC	MET	AFL					
σ_η^2	30.74	11.4	12.35	15.08					
σ_c^2	0.02	0.02	0.02	0.01					

Note: 76 monthly time series data from July 2002 to May 2008 is used. Return is filtered by $r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t$ and is decomposed by $e_t = b_c f_t^c + \eta_t$ (Equation 1.2) for each asset. Variance is decomposed by $\sigma_e^2 = b_c^2 \sigma_{fc}^2 + \sigma_\eta^2$ (Equation 1.7). σ_c^2 is defined as $b_c^2 \sigma_{fc}^2$ which represents volatility from network, and σ_η^2 represents pure idiosyncratic risk volatility.

Table 1.3: Residual Variance Decomposition into Pure Idiosyncratic Risk and Network Risk Before the Crisis

	LAB	ITG	SCH	SWS	JNS	WDR	NTRS	STT	AMG
σ_η^2	184.35	102.66	30.62	52.22	43.35	22.59	14.15	22.52	21.28
σ_c^2	30.94	20.64	15.44	13.61	12.93	9.38	9.15	7.83	7.04
	COF	WPL	JEF	HUM	JPM	SEIC	PNC	MER	DB
σ_η^2	45.4	49.55	36.25	79.36	19.33	32.49	12.44	13.91	20.9
σ_c^2	6.35	5.98	5.26	5.24	4.99	4.47	4.28	4.22	4
	LEH	LYG	SLM	BEN	LNC	HIG	AIG	WB	NMR
σ_η^2	19.34	26.28	22.87	13.92	12.45	24.11	23.12	11.38	57.19
σ_c^2	3.92	3.73	3.71	3.49	3.49	3.41	3.13	2.97	2.69
	C	AOC	UNH	TROW	CB	CVTY	USB	RJF	MS
σ_η^2	13.2	62.98	27.68	17.06	17.47	67.19	10.61	19.43	19.03
σ_c^2	2.39	2.34	2.33	2.23	2.17	1.88	1.85	1.82	1.64
	AET	UBS	GS	KEY	BAC	BSC	CI	AXP	PFG
σ_η^2	69.85	10.46	17.72	10.82	7.92	19.41	108.03	5.92	10.02
σ_c^2	1.54	1.36	1.32	1.31	1.31	1.29	0.98	0.97	0.97
	MMC	MTB	AFL	EV	WFC	CMA	PGR	BBT	IDC
σ_η^2	44.95	11.64	15.75	14.77	7.92	16.99	30.34	12.72	20.83
σ_c^2	0.94	0.91	0.79	0.72	0.65	0.62	0.52	0.5	0.46
	TD	OPY	CNA	MET	XL	ALL	CINF	ABK	SF
σ_η^2	21.37	44.11	20.8	11.84	16.34	17.48	8.23	15.73	80.39
σ_c^2	0.33	0.31	0.27	0.25	0.23	0.21	0.2	0.18	0.15
	RY	RDN	BCM	FRE	FNM	BMO	MBI	BNS	BRK.A
σ_η^2	15.28	40.77	21.76	25.06	40.67	17.54	14.52	18.33	11.71
σ_c^2	0.12	0.11	0.11	0.1	0.07	0.05	0.04	0.03	0.01
	MFC	SLC	HBC	SMHG					
σ_η^2	16.24	9.18	6.58	64.51					
σ_c^2	0.01	0	0	0					

Note: 76 monthly time series data from July 2002 to May 2008 is used. Return is filtered by $r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t$ and is decomposed by $e_t = b_c f_t^c + \eta_t$ (Equation 1.2) for each asset. Variance is decomposed by $\sigma_e^2 = b_c^2 \sigma_{f^c}^2 + \sigma_\eta^2$ (Equation 1.7). σ_c^2 is defined as $b_c^2 \sigma_{f^c}^2$ which represents volatility from network, and σ_η^2 represents pure idiosyncratic risk volatility.

Table 1.4: The Ten Financial Institutions with the Highest Component Contributions to VaR, ES, Std

	VaR	Mkt	SMB	HML	network	resid
BSC	12.01	5.35	-0.92	-0.41	7.01	0.98
SLM	11.70	0.17	-0.00	-0.13	4.99	6.67
WB	11.42	2.77	-0.06	0.19	4.85	3.67
C	11.85	4.32	0.02	0.00	3.60	3.91
ABK	28.84	-0.24	-0.03	0.67	3.53	24.91
MER	11.33	4.44	-0.13	-0.04	3.47	3.60
JPM	9.66	3.55	-0.16	-1.17	2.79	4.65
LEH	15.19	6.34	-0.57	-0.10	2.60	6.92
SWS	16.97	2.90	1.42	-0.83	2.41	11.07
LAB	20.32	0.41	0.06	-0.11	2.41	17.56

(a) VaR

	ES	mkt	SMB	HML	co.f	resid
WB	9.56	2.13	-0.05	0.15	3.74	2.83
ABK	28.32	-0.20	-0.03	0.56	2.94	20.76
C	9.13	2.96	0.01	0.00	2.46	2.68
SLM	6.26	0.08	-0.00	-0.07	2.45	3.28
MER	7.74	2.85	-0.08	-0.03	2.23	2.31
LEH	12.41	5.02	-0.45	-0.08	2.06	5.48
BSC	4.83	1.38	-0.24	-0.11	1.81	0.25
XL	11.02	3.10	-0.23	-0.04	1.67	4.86
SWS	10.92	1.94	0.95	-0.56	1.61	7.40
BAC	4.59	0.52	0.32	0.01	1.41	2.37

(b) ES

	Std	mkt	SMB	HML	co.f	resid
BSC	12.31	1.59	-0.05	0.12	3.28	7.36
WB	5.90	1.53	-0.07	0.01	2.47	1.96
WPL	13.13	1.38	0.51	0.00	2.35	8.88
SLM	10.01	0.92	-0.00	0.04	2.27	6.78
MER	7.98	3.66	-0.10	-0.02	2.08	2.35
LEH	8.47	3.27	-0.15	-0.02	1.96	3.41
C	7.24	3.21	-0.04	-0.03	1.73	2.37
UBS	7.95	4.18	-0.19	-0.03	1.61	2.38
MBI	10.28	2.38	0.03	0.04	1.55	6.28
KEY	5.58	0.80	-0.04	0.24	1.29	3.29

(c) Std

Note: 76 monthly time series data from July 2002 to May 2008 is used. Return is filtered by $r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t$ and is decomposed by $e_t = b_c f_t^c + \eta_t$ (Equation 1.2) for each asset. Variance is decomposed by $\sigma_e^2 = b_c^2 \sigma_{f^c}^2 + \sigma_\eta^2$ (Equation 1.7). To calculate component contribution to VaR, ES, and Std, respectively, risk metrics (RM) is decomposed according to $RM(r_i) = \Sigma_{k=1}^{K} \beta_k \frac{\partial RM}{\partial \beta_k} + b_c \frac{\partial RM}{\partial b_c} + \sigma_\eta \frac{\partial RM}{\partial \sigma_\eta}$ (K=MKT, SMB, HML). VaR, ES and Std are defined in Equation 1.10, 1.11,and 1.12. Result is sorted by network column which is network component contribution to network ($b_c \frac{\partial RM}{\partial b_c}$) from highest to lowest. Unit is percentage. Panel A is VaR, Panel B is ES and Panel C is Std.

Table 1.5: The Ten Financial Institutions with the Highest Component Contributions to VaR, ES, Std with Leverage Adjusted Centrality

	VaR	mkt	SMB	HML	co.f	resid
BSC	12.01	5.35	-0.92	-0.41	8.61	-0.62
ABK	28.84	-0.24	-0.03	0.67	5.99	22.45
WB	11.42	2.77	-0.06	0.19	5.33	3.20
SLM	11.70	0.17	-0.00	-0.13	5.18	6.49
C	11.85	4.32	0.02	0.00	3.88	3.63
MER	11.33	4.44	-0.13	-0.04	3.62	3.45
LEH	15.19	6.34	-0.57	-0.10	2.72	6.81
XL	12.95	4.29	-0.31	-0.06	2.62	6.42
MBI	16.56	10.56	0.15	-0.23	2.51	3.57
JPM	9.66	3.55	-0.16	-1.17	2.49	4.95

(a) VaR

	ES	mkt	SMB	HML	co.f	resid
ABK	28.32	-0.20	-0.03	0.56	4.99	18.72
WB	9.56	2.13	-0.05	0.15	4.11	2.46
C	9.13	2.96	0.01	0.00	2.66	2.48
SLM	6.26	0.08	-0.00	-0.07	2.54	3.18
MER	7.74	2.85	-0.08	-0.03	2.32	2.21
BSC	4.83	1.38	-0.24	-0.11	2.22	-0.16
LEH	12.41	5.02	-0.45	-0.08	2.15	5.39
XL	11.02	3.10	-0.23	-0.04	1.89	4.64
MTB	5.78	0.47	0.12	-0.17	1.62	3.59
SWS	10.92	1.94	0.95	-0.56	1.56	7.45

(b) ES

	Std	mkt	SMB	HML	co.f	resid
BSC	12.31	1.59	-0.05	0.12	4.18	6.47
WB	5.90	1.53	-0.07	0.01	2.58	1.85
SLM	10.01	0.92	-0.00	0.04	2.46	6.59
MER	7.98	3.66	-0.10	-0.02	2.21	2.23
LEH	8.47	3.27	-0.15	-0.02	2.15	3.21
WPL	13.13	1.38	0.51	0.00	2.08	9.16
MBI	10.28	2.38	0.03	0.04	1.98	5.85
C	7.24	3.21	-0.04	-0.03	1.84	2.26
UBS	7.95	4.18	-0.19	-0.03	1.72	2.27
ABK	12.58	2.76	-0.01	-0.01	1.57	8.27

(c) Std

Note: 76 monthly time series data from July 2002 to May 2008 is used. Return is filtered by $r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t$ and is decomposed by $e_t = b_c f_t^c + \eta_t$ (Equation 1.2) for each asset. Variance is decomposed by $\sigma_e^2 = b_c^2 \sigma_{f^c}^2 + \sigma_\eta^2$ (Equation 1.7). To calculate component contribution to VaR, ES, and Std, respectively, risk metrics (RM) is decomposed according to $RM(r_i) = \Sigma_{k=1}^K \beta_k \frac{\partial RM}{\partial \beta_k} + b_c \frac{\partial RM}{\partial b_c} + \sigma_\eta \frac{\partial RM}{\partial \sigma_\eta}$ (K=MKT, SMB, HML). VaR, ES and Std are defined in Equation 1.10, 1.11,and 1.12. Result is sorted by network column which is network component contribution to network ($b_c \frac{\partial RM}{\partial b_c}$) from highest to lowest. Unit is percentage. Panel A is VaR, Panel B is ES and Panel C is Std.

Table 1.6: The Ten Financial Institutions with the Highest Component Contributions to VaR, ES, Std with Size Adjusted Centrality

	VaR	mkt	SMB	HML	co.f	resid
BSC	12.01	5.35	-0.92	-0.41	6.93	1.06
SLM	11.70	0.17	-0.00	-0.13	5.10	6.56
WB	11.42	2.77	-0.06	0.19	4.53	4.00
MER	11.33	4.44	-0.13	-0.04	3.47	3.60
C	11.85	4.32	0.02	0.00	3.44	4.06
ABK	28.84	-0.24	-0.03	0.67	3.18	25.26
LAB	20.32	0.41	0.06	-0.11	3.05	16.91
JPM	9.66	3.55	-0.16	-1.17	2.63	4.80
SWS	16.97	2.90	1.42	-0.83	2.60	10.88
LEH	15.19	6.34	-0.57	-0.10	2.56	6.97

(a) VaR

	ES	mkt	SMB	HML	co.f	resid
WB	9.56	2.13	-0.05	0.15	3.49	3.08
ABK	28.32	-0.20	-0.03	0.56	2.65	21.06
SLM	6.26	0.08	-0.00	-0.07	2.51	3.22
C	9.13	2.96	0.01	0.00	2.36	2.78
MER	7.74	2.85	-0.08	-0.03	2.22	2.31
LEH	12.41	5.02	-0.45	-0.08	2.03	5.51
BSC	4.83	1.38	-0.24	-0.11	1.79	0.27
SWS	10.92	1.94	0.95	-0.56	1.74	7.27
XL	11.02	3.10	-0.23	-0.04	1.67	4.86
LAB	12.62	0.23	0.03	-0.06	1.67	9.23

(b) ES

	Std	mkt	SMB	HML	co.f	resid
BSC	12.31	1.59	-0.05	0.12	3.20	7.44
WPL	13.13	1.38	0.51	0.00	2.67	8.56
WB	5.90	1.53	-0.07	0.01	2.33	2.10
SLM	10.01	0.92	-0.00	0.04	2.29	6.76
MER	7.98	3.66	-0.10	-0.02	2.04	2.39
LEH	8.47	3.27	-0.15	-0.02	1.92	3.45
C	7.24	3.21	-0.04	-0.03	1.67	2.42
UBS	7.95	4.18	-0.19	-0.03	1.55	2.44
LAB	15.59	1.69	-0.07	-0.02	1.54	12.45
MBI	10.28	2.38	0.03	0.04	1.40	6.43

(c) Std

Note: 76 monthly time series data from July 2002 to May 2008 is used. Return is filtered by $r_t = \alpha + b_M Mkt_t + b_S SMB_t + b_H HML_t + e_t$ and is decomposed by $e_t = b_c f_t^c + \eta_t$ (Equation 1.2) for each asset. Variance is decomposed by $\sigma_e^2 = b_c^2 \sigma_{f^c}^2 + \sigma_\eta^2$ (Equation 1.7). To calculate component contribution to VaR, ES, and Std, respectively, risk metrics (RM) is decomposed according to $RM(r_i) = \Sigma_{k=1}^K \beta_k \frac{\partial RM}{\partial \beta_k} + b_c \frac{\partial RM}{\partial b_c} + \sigma_\eta \frac{\partial RM}{\partial \sigma_\eta}$ (K=MKT, SMB, HML). VaR, ES and Std are defined in Equation 1.10, 1.11,and 1.12. Result is sorted by network column which is network component contribution to network ($b_c \frac{\partial RM}{\partial b_c}$) from highest to lowest. Unit is percentage. Panel A is VaR, Panel B is ES and Panel C is Std.

Table 1.7: Model Comparison of Cumulative Returns on Different Risk Metrics

	Co-VaR	VaR	Co-ES	ES	Co-Std	Std	σ_c^2	$\%\sigma_c^2$	2Fs
(Intercept)	-0.13^{**}	0.12	-0.12^{**}	0.00	-0.09^{*}	0.04	-0.14^{***}	-0.11^{**}	-0.02
	(0.04)	(0.09)	(0.04)	(0.07)	(0.04)	(0.12)	(0.04)	(0.04)	(0.09)
co.var	-15.44^{***}								
	(2.25)								
t.var		-3.63^{***}							
		(0.77)							
co.es			-25.74^{***}						
			(4.01)						
t.es				-3.80^{***}					
				(0.86)					
co.std					-32.85^{***}				-31.47^{***}
					(3.91)				(4.23)
t.std						-4.41^{**}			-1.05
						(1.47)			(1.21)
σ_c^2							-2.95^{***}		
							(0.40)		
$\%\sigma_c^2$								-1.62^{***}	
								(0.24)	
R^2	0.39	0.23	0.36	0.21	0.49	0.11	0.42	0.38	0.49
Adj. R^2	0.38	0.22	0.35	0.20	0.48	0.10	0.42	0.37	0.48
Num. obs.	76	76	76	76	76	76	76	76	76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: I calculate cumulative returns of each asset from January 2007 to May 2008 for each asset to mimic returns gained in May 2008 if a dollar invested in January 2007. I then regress cumulative returns on Co.Std, Co.VaR, Co.ES, total Std, VaR and ES σ_c^2, and $\%\sigma_c^2$, respectively. All risk metrics are calculated by Equation 1.13 with residual returns filtered by the Fama-French Three Factors model.

Table 1.8: Model Comparison of Cumulative Returns on Different Risk Metrics adjusted by Leverage or Size

	Co-VaR,lev	Co-ES,lev	Co-Std,lev	Co-VaR,size	Co-ES,size	Co-Std,size
(Intercept)	-0.14^{***}	-0.14^{***}	-0.10^{**}	-0.13^{**}	-0.12^{**}	-0.10^{**}
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
co.var	-13.74^{***}			-15.37^{***}		
	(1.87)			(2.30)		
co.es		-22.18^{***}			-26.13^{***}	
		(3.26)			(4.13)	
co.std			-30.64^{***}			-32.25^{***}
			(3.39)			(4.00)
R^2	0.43	0.39	0.54	0.38	0.35	0.47
Adj. R^2	0.42	0.39	0.53	0.37	0.34	0.46
Num. obs.	73	73	73	76	76	76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: I calculate cumulative returns of each asset from January 2007 to May 2008 for each asset to mimic returns gained in May 2008 if a dollar invested in January 2007. I then regress cumulative returns on Co.Std, Co.VaR, Co.ES, total Std, VaR and ES σ_c^2, and $\%\sigma_c^2$, respectively. All risk metrics are calculated by Equation 1.13 with residual returns filtered by the Fama-French Three Factors model. $e_t = b_c f_t^c + \eta_t$ is decoposed (Equation 1.2) for time each series and f_t^c is leverage or size adjusted centrality factor with β_i equal to leverage ratio in Equation 1.4.

Table 1.9: Predictive Regression : Mean Returns on Different Risk Metrics

	Co-VaR	VaR	Co-ES	ES	Co-Std	Std	Net.Risk	Per.Net.Risk
(Intercept)	-0.03^{*}	0.00	-0.03^{*}	0.00	-0.03^{*}	-0.02	-0.03^{*}	-0.02
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)	(0.01)
co.var	-1.44							
	(0.81)							
t.var		-0.40						
		(0.25)						
co.es			-1.88					
			(1.41)					
t.es				-0.56^{*}				
				(0.28)				
co.std					-3.07^{*}			
					(1.40)			
t.std						-0.40		
						(0.45)		
net.risk							-0.24	
							(0.13)	
per.net.risk								-0.19^{*}
								(0.08)
R^2	0.04	0.03	0.02	0.05	0.06	0.01	0.05	0.06
Adj. R^2	0.03	0.02	0.01	0.04	0.05	0.00	0.03	0.05
Num. obs.	76	76	76	76	76	76	76	76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: I calculate cumulative returns of each asset from January 2007 to May 2008 for each asset to mimic returns gained in May 2008 if a dollar invested in January 2007. I then regress cumulative returns on Co.Std, Co.VaR, Co.ES, total Std, VaR and ES σ_c^2, and $\%\sigma_c^2$, respectively. All risk metrics are calculated by Equation 1.13 with residual returns filtered by the Fama-French Three Factors model.

Table 1.10: Predictive Regression : Mean Returns on Different Risk Metrics adjusted by Leverage or Size

	Co-VaR	Co-ES	Co-Std	Net.Risk	Per.Net.Risk
(Intercept)	−0.02	−0.03	−0.02	-0.03^{*}	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
co.var	-2.01^{**}				
	(0.69)				
co.es		-3.01^{*}			
		(1.18)			
co.std			-3.69^{**}		
			(1.27)		
net.risk				-0.32^{**}	
				(0.12)	
per.net.risk					-0.22^{**}
					(0.08)
R^2	0.11	0.08	0.11	0.09	0.10
Adj. R^2	0.09	0.07	0.09	0.08	0.08
Num. obs.	73	73	73	73	73

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

(a) Leverage Adjusted

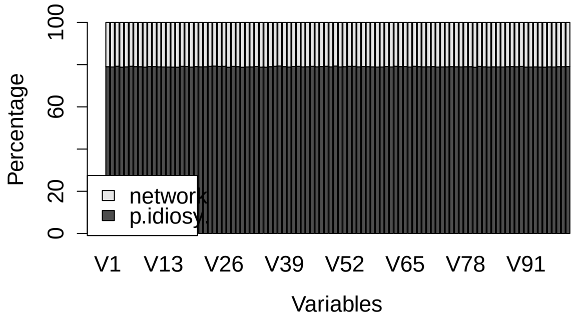
	Co-VaR	Co-ES	Co-Std	Net.Risk	Per.Net.Risk
(Intercept)	-0.03^{*}	-0.04^{*}	-0.03^{*}	-0.04^{**}	−0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
co.var	−1.20				
	(0.81)				
co.es		−1.48			
		(1.41)			
co.std			−2.63		
			(1.40)		
net.risk				−0.19	
				(0.13)	
per.net.risk					-0.18^{*}
					(0.09)
R^2	0.03	0.01	0.05	0.03	0.05
Adj. R^2	0.02	0.00	0.03	0.02	0.04
Num. obs.	76	76	76	76	76

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

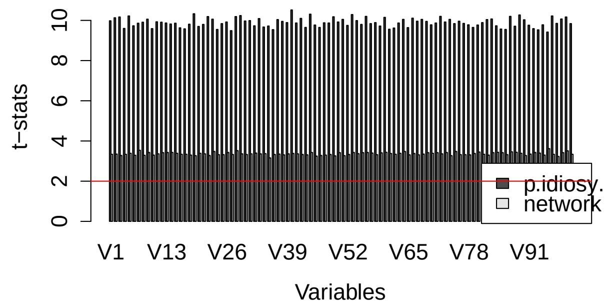
(b) Size Adjusted

Note: I calculate cumulative returns of each asset from January 2007 to May 2008 for each asset to mimic returns gained in May 2008 if a dollar invested in January 2007. I then regress cumulative returns on Co.Std, Co.VaR, Co.ES, total Std, VaR and ES σ_c^2, and $\%\sigma_c^2$, respectively. All risk metrics are calculated by Equation 1.13 with residual returns filtered by the Fama-French Three Factors model. $e_t = b_c f_t^c + \eta_t$ is decoposed (Equation 1.2) for time each series and f_t^c is leverage or size adjusted centrality factor with β_i equal to leverage ratio in Equation 1.4.

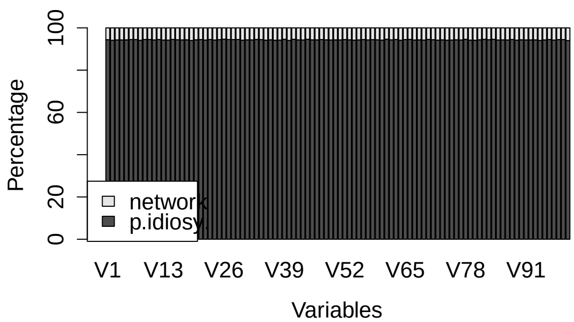
Figure 1.1: Comparison of Percentage of Variance Decomposition with Different Covariance Structure and Centrality Method



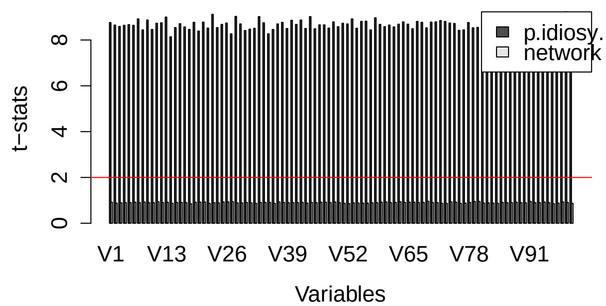
(a) Percentage Variance Decomposition with Katz Centrality, Low Covariance



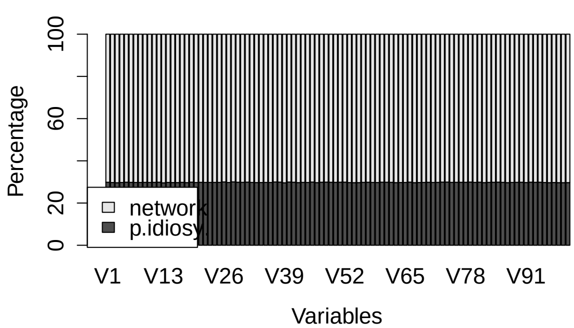
(b) T-stats of Percentage Variance Decomposition with Katz Centrality, Low Covariance



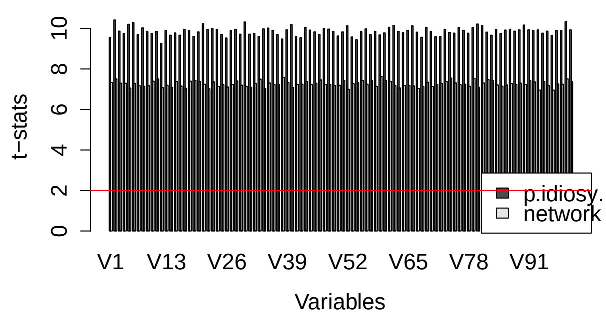
(c) Percentage Variance Decomposition with Degree Centrality, Low Covariance



(d) T-stats of Percentage Variance Decomposition with Degree Centrality, Low Covariance

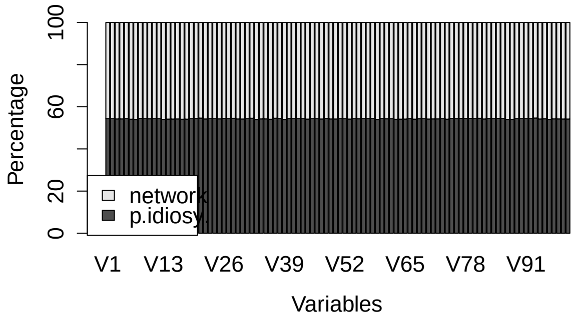


(e) Percentage Variance Decomposition with Katz Centrality, High Covariance

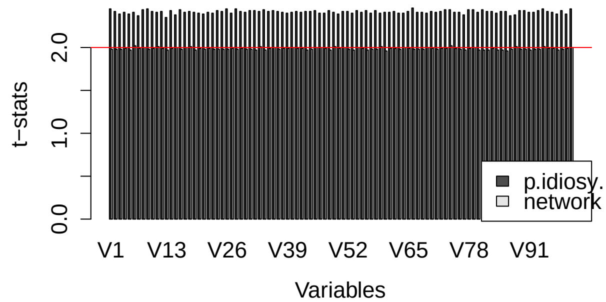


(f) T-stats of Percentage Variance Decomposition with Katz Centrality, High Covariance

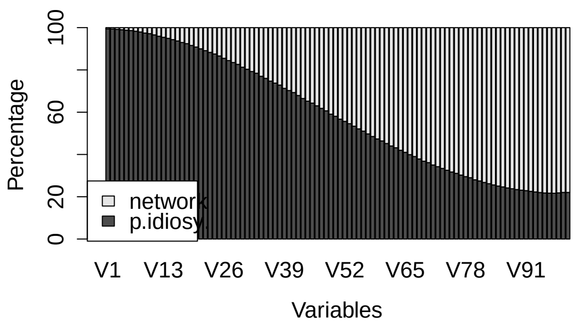
Figure 1.1: (continued)



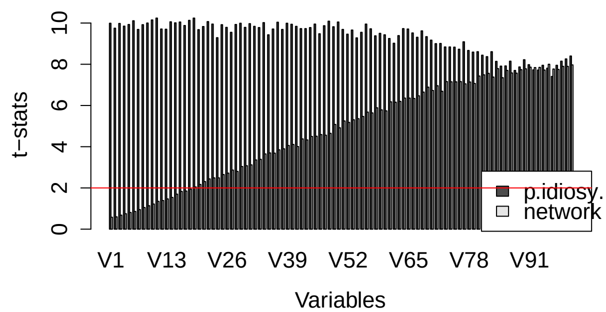
(a) Percentage Variance Decomposition with Degree Centrality, High Covariance



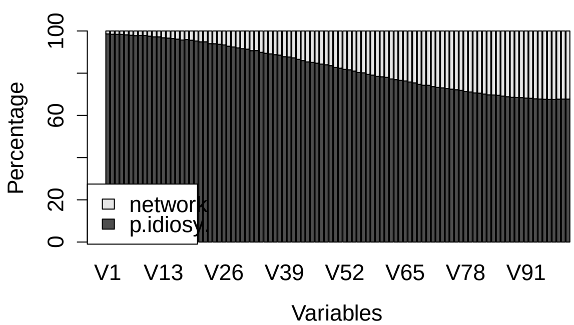
(b) T-stats of Percentage Variance Decomposition with Degree Centrality, High Covariance



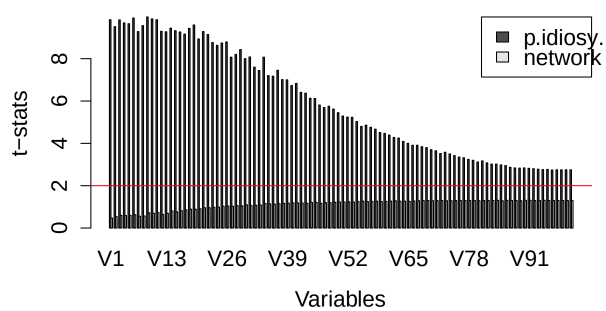
(c) Percentage Variance Decomposition with Katz Centrality, Skewed-distributed Covariance



(d) T-stats of Percentage Variance Decomposition with Katz Centrality, Skewed-distributed Covariance



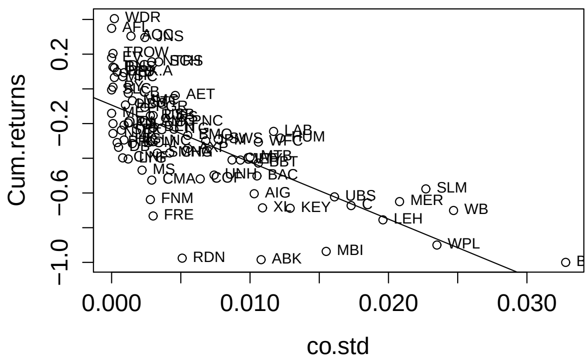
(e) Percentage Variance Decomposition with Degree Centrality, Skewed-distributed Covariance



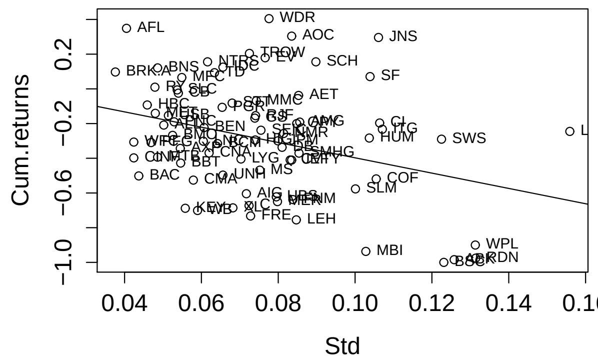
(f) T-stats of Percentage Variance Decomposition with Degree Centrality, Skewed-distributed Covariance

Note: The low covariance matrix : $a_{ij} \cong N(0.2, 0.01^2), i \neq j, a_{ii} = 1$. The high covariance matrix : $a_{ij} \cong N(0.7, 0.01^2), i \neq j, a_{ii} = 1$. The skewed-distributed covariance matrix : $l_{ij} \cong N(0.1, 0.01^2), i < j$, L is lower triangular matrix. M = L X L', $m_{ii} = 1$. Regression $r_t = \beta mkt_t + e_t$ is calculated and e_t follows multi-Normal distribution with a mean of 0 and covariance of the above. N = 100, T = 200, simulation = 1000. Variance decomposition is calculated according to $\sigma_e^2 = b_c^2 \sigma_{fc}^2 + \sigma_\eta^2$. $b_c^2 \sigma_{fc}^2$ is termed network risk and σ_η^2 is termed pure idiosyncratic risk.

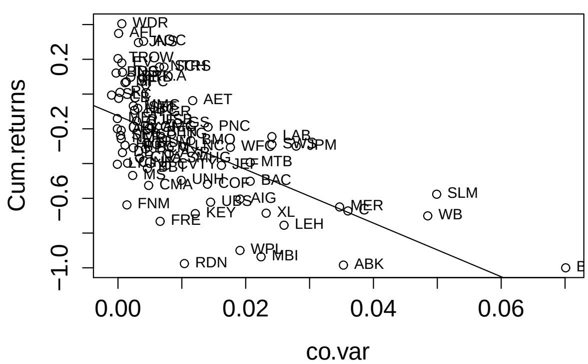
Figure 1.2: Comparison of Contribution to Std to network risk, VaR, ES and total Std, VaR, ES.



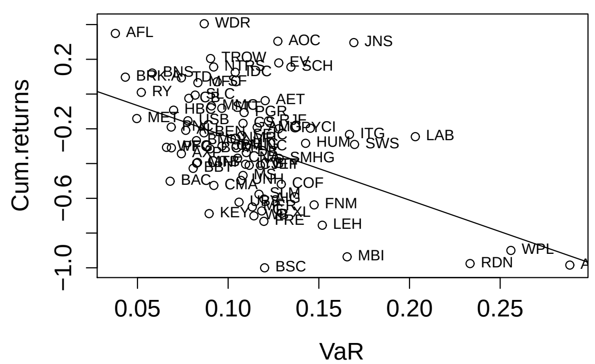
(a) Component Contribution to Std to Network Risk vs Cumulative Returns



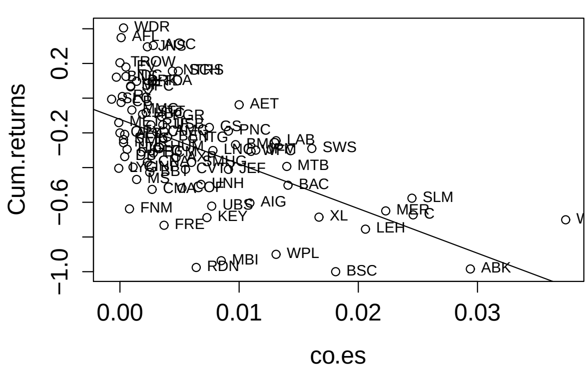
(b) Std vs Cumulative Returns



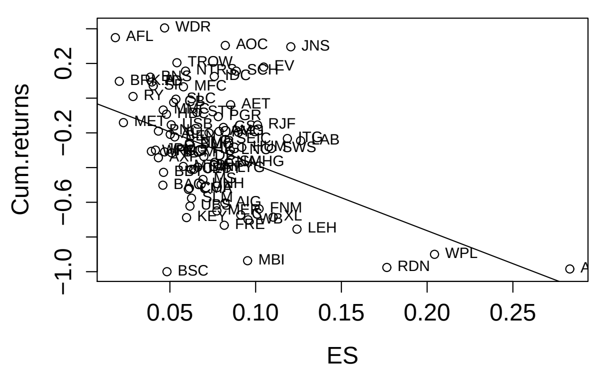
(c) Component Contribution to VaR to Network Risk vs Cumulative Returns



(d) VaR vs Cumulative Returns

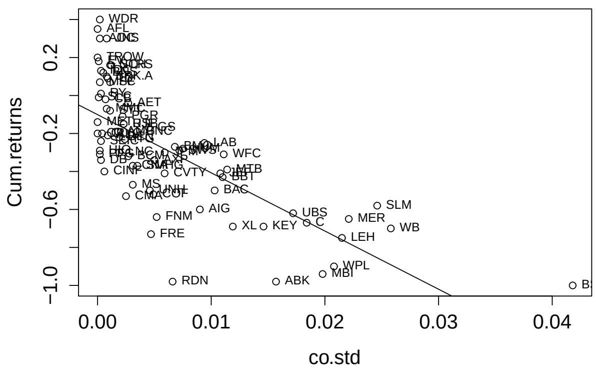


(e) Component Contribution to ES to Network Risk vs Cumulative Returns

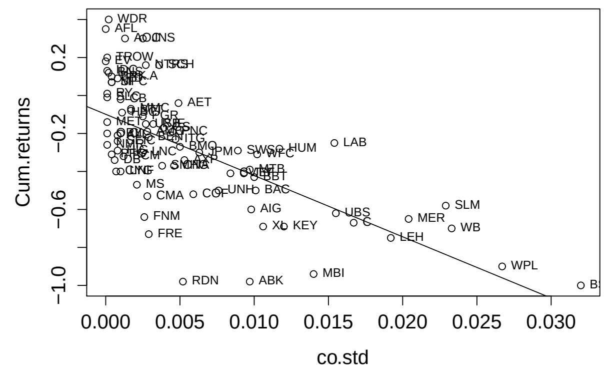


(f) ES vs Cumulative Returns

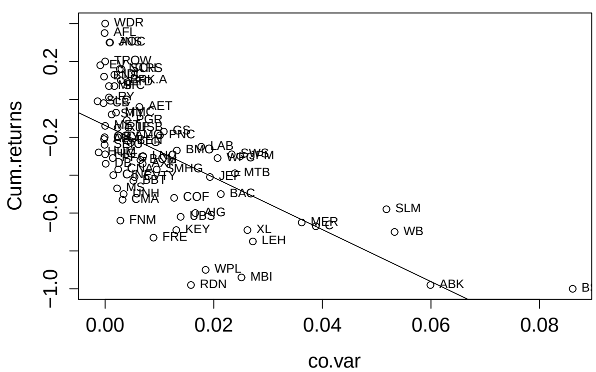
Figure 1.3: Comparison of Risk Component Contribution to Std, VaR, ES to Network Risk and with Leverage or Size Adjusted Centrality.



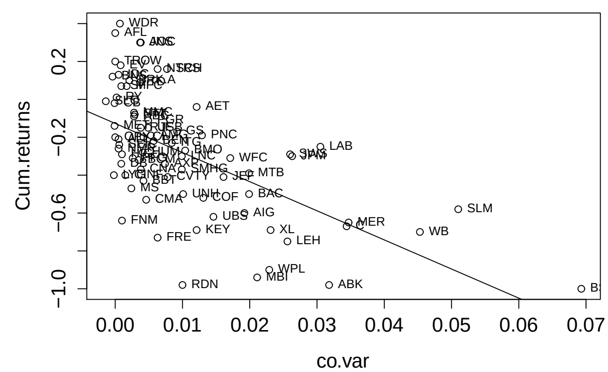
(a) Component Contribution to Std to Network Risk Adjusted by Leverage vs Cumulative Returns



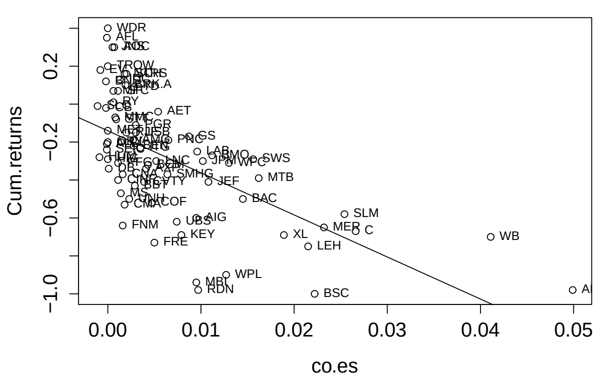
(b) Component Contribution to Std to Network Risk Adjusted by Size vs Cumulative Returns



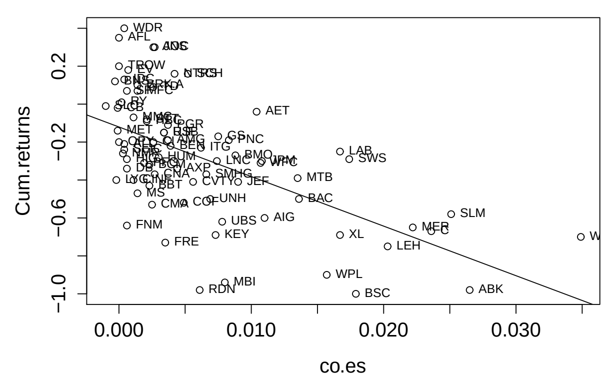
(c) Component Contribution to VaR to Network Risk Adjusted by Leverage vs Cumulative Returns



(d) Component Contribution to VaR to Network Risk Adjusted by Size vs Cumulative Returns



(e) Component Contribution to ES to Network Risk Adjusted by Leverage vs Cumulative Returns



(f) Component Contribution to ES to Network Risk Adjusted by Size vs Cumulative Returns

Chapter 2

NETWORK RISK AND CROSS-SECTION OF EXPECTED STOCK RETURNS

2.1 Introduction

Economically related stocks tend to move together and form a correlation network.[1] The tendency to move with related stocks is called *network risk*: stocks receive shocks from their suppliers or customers through a network, as a result, move together, this risk becomes undiversified and the risk should be priced.[2] A question is asked whether network risk is empirically priced in cross-section of stock returns. In addition, it is noted that network risk arises not from market-wide shocks but non-market-wide shocks transmitted via a network, hence, network risk accounts for a portion of idiosyncratic risk. If network risk is priced, it provides an alternative risk-based explanation to returns and idiosyncratic risk that a stock needs more compensation if its network risk relative to idiosyncratic risk is high. Previous literature tends to treat network risk as part of idiosyncratic risk, however, this is misleading because it is possible that low idiosyncratic risk stocks are high in network risk.

I provide a measure to quantify network risk by decomposing idiosyncratic volatility (IVOL). When a firm shocks itself, shocks will transmit to its related firms and create idiosyncratic volatility of others. Therefore, idiosyncratic volatility is either caused by the firm itself or by its neighbors. IVOL can be decomposed into two parts: the first part is volatility contributed by the network and the second part is contributed by itself. By looking

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[1] Previous research such as Lang and Stulz (1992) and Hendricks and Singhal (2005) find stocks in the same industry tend to move together since their businesses are closely related to each other. Other research like Hou (2007), Cohen and Frazzini (2008) and Menzly and Ozbas (2010) find returns predictability across firms because they are economically related.

[2] I do not distinguish characteristics or co-movement in this paper. See Daniel and Titman (1997) for more detail.

at the idiosyncratic volatility contributed by the network, one can infer how much volatility is affected by a network. In other words, network risk.

Decomposing IVOL is equivalent to decompose residual returns. I use a covariance matrix of stocks residual returns, defined as stock returns net of common risk returns, as an ex post network. Since each edge represents pairwise covariance, calculating the Katz centrality[3] will assign co-varying scores to each stock. A *network risk* factor weighted by centrality can be constructed and considered as a mimicking portfolio of investing stocks based on these scores and interpreted as a benchmark of network risk. For each stock, the loading to the network risk factor is network Beta (NBeta). A stock with high NBeta tends to move with related stocks and is risky. Residual returns is then decomposed into two components: network risk and pure idiosyncratic risk. Volatility of the former is network volatility (NVOL) and the later is pure idiosyncratic volatility (PVOL).

I argue that higher network volatility stocks tend to move with its related stocks, so the risk becomes undiversified and investors demand higher returns. As a result, a positive risk premium of NBeta and NVOL is expected. I use the Fama and MacBeth (1973) regression to test if the above hypothesis is true. Controlling for size, book-to-market ratio (BM), market Beta which are suggested by Fama and French (1993) and IVOL, I find the NBeta is priced positively, which is consistent to the previous research. In addition, when IVOL is decomposed into two, I find significant positive risk premium of NVOL and negative monthly risk premium of PVOL, 1.01 % and -0.07 %, respectively. That is to say, higher volatility contributed to network will have higher expected returns in cross-section. Compare to a model that does not decompose the two, the gain of positive risk premium comes from better model fit. Although PVOL is negatively priced, the risk premium of IVOL dominates that of PVOL by 8 times. It suggests that a better risk-based explanation of market behavior is that investors react to co-movement of related stocks, but not to the IVOL of a single stock.

To further address the dominance of NVOL, it is possible investors care about relative

[3]See Newman (2010) for detail.

risk rather than absolute risk. Network variance to idiosyncratic variance ratio (NVR) is constructed and found to be positively related to expected returns with a 0.13 % monthly risk premium. This evidence shows that a stock is riskier and rewarded more if its NVOL relative to IVOL is high, rather than high IVOL itself.

The model is extended to the Fama-French Four Factor model, including a momentum factor. The result is robust to adding a momentum factor. It shows significant and positive risk premium of NVOL and negative monthly risk premium of PVOL, 1.20 % and -0.07 % respectively. NVR is also significant with a 0.12 % monthly premium.

To test for pricing anomaly, I form quintile portfolios based on NVOL and NVR. The idea is to average out the noises of individual stocks while the effect of characteristics interested on returns will remain. If there were no pricing anomaly, quintile portfolios returns can be explained by the Fama-French Three or the Four Factor model. It turns out that high NVR portfolio earns positive Alpha and vice versa, whereas NVOL does not due to noises.

This research also contributes to understand idiosyncratic volatility (IVOL) better. Previous IVOL research finds that IVOL is negatively priced cross-sectionally, contradicts to any risk-based explanation. It is often referred to as "idiosyncratic volatility puzzle" in the literature.[4] This research provides another perspective and evidence to explain the IVOL puzzle: even PVOL is still negatively priced but NVOL is *positively* priced and risk premium of NVOL is way higher than PVOL. Most importantly, NVR is positively related to expected returns. It suggests that IVOL puzzle may not be a real puzzle because investors react to co-movement of related stocks, but not to the volatility of a single stock.

Another contribution of this research to the idiosyncratic risk literature of empirical study is to show network risk which accounts for part of idiosyncratic risk is priced cross-sectionally. Theoretically, idiosyncratic terms should not be priced because of diversification.

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[4]It was first documented by Ang et al. (2006) with U.S. data and later investigated by Ang et al. (2009) using international data.

Nevertheless, previous empirical studies[5] present evidence that idiosyncratic risk is priced.[6] However, they tend to study idiosyncratic volatility rather than idiosyncratic co-movement.

Other research such as Duarte et al. (2012) and Van Nieuwerburgh et al. (2014) find common factors in idiosyncratic volatility and show that these factors explain most of idiosyncratic volatility. However, they do not explain what these common factors are or whether they are priced. The network risk factor could be a potential explanation for one of these common factors.

Previous research regarding the estimation of stock network includes Tse, Liu, and Lau (2010) which connections are determined by cross correlations of the variations of the stock prices, price returns and trading volumes within a chosen period of time. Billio et al. (2012) which is based on Granger causality. If a stock Granger causes another one, there is a tie constructed. Therefore, a network topology can be constructed applying N $\times$ (N-1) tests. However, even if stock A Granger causes stock B, it cannot rule out another stock C may Granger cause stock A and stock B together. Diebold and Yılmaz (2014) uses VAR and variance decomposition. Variance of a stock can be decomposed into different parts contributed by other stocks. This idea is similar to research presented here. However, VAR is dimensionally restricted and impossible to apply to cross-section stock market research. Finally, Barigozzi and Brownlees (2013) propose a new 2 steps LASSO procedure to estimate high dimensional sparse long run partial correlation networks.

Others have studied pricing of network risk with slightly different approaches. Buraschi and Porchia (2012) define network connectivity as the ability of a firm to transfer a distressed state to others in a directed and timely manner. Central stocks have lower price-to-dividend ratio and earn higher expected returns. A positive centrality price of risk and a sizable centrality risk premium is found empirically. Buraschi and Porchia (2012) has a different connectivity definition from us. Connectivity in this study is the dependence structure of idiosyncratic shocks, in contrast to Buraschi and Porchia (2012) where it is defined as the

[5] Goyal and Santa-Clara (2003), Campbell et al. (2001), Ang et al. (2006) and Ang et al. (2009)

[6] A few papers disagree that idiosyncratic risk is priced, such as Bali et al. (2005), Bali and Cakici (2008)

ability to transfer distress. In a sense they embedded the ability to resist shocks in their measure. Therefore, it is not surprising that they find centrality premium can explain part of value premium because value stocks preform badly during bad times. Compared to them, I focus on network risk related to idiosyncratic volatility. Two researches are complementary rather than competitive.

The paper is organized as follows, Section 2 will introduce the econometrics model. Section 3 will show empirical evidence on pricing of network risk. Section 4 will extend the model for robust check and the conclusion will be given in Section 5.

2.2 Model

In this section I will introduce the model to estimate network risk and idiosyncratic risk.

2.2.1 Econometric Model

Asset returns can be decomposed into returns attributed to market risk factors Bf_t and residual returns e_t using a factor model. The theoretical background for the factor model is CAPM if there is only one factor in the model or APT or ICAPM if multiple factors are allowed. Generally speaking, f_t is market risk (common or systematic) and is not diversifiable. Bf_t is linear pricing kernel and e_t is diversifiable idiosyncratic noises.

Empirically, many different procedures are developed to estimate factor models, depending on whether f_t is observable. If f_t is observable, simple OLS will suffice. If error terms are contemporaneously correlated, GLS can be used to achieve more efficient estimators. If error terms are serially correlated, HAC type estimator can be used to estimate robust standard errors.

In this paper I will assume f_t is observable, so the model is a linear asset pricing model. However, residual returns e_t will be decomposed into 2 terms: *network* term and *pure idiosyncratic* term. Specifically,

$$r_t = Bf_t + e_t,\ t = 1 \cdots T \tag{2.1}$$

$$e_t = b^c f_t^c + \eta_t \tag{2.2}$$

where r_t is an N $\times$ 1 vector of excess returns, B is an N $\times$ K matrix of market risk exposures, f_t is an observed exogenous K $\times$ 1 vector of market risk factors. e_t is an N $\times$ 1 vector of residual returns and assumed to be orthogonal to f_t. b^c is N $\times$ 1 unobserved factor loading. f_t^c is an observed 1 $\times$ 1 network risk factor and will be constructed later. η_t is i.i.d. idiosyncratic disturbance.

The assumptions of factor f^c, factor loading b^c and η_t in Equation 2.2 are :

Assumptions for factor and factor loading:

f.1 $\mathbb{E}(f_t^c f_t^{c'}) = \sigma_{f^c}^2$

f.2 $|b_i^c| \leq \bar{b^c} < \infty$

f.3 $\frac{1}{T}\sum_t f_t^c f_t^{c'} \xrightarrow{p} \sigma_{f^c}^2$

Assumption f.1 allows factors to be serially correlated but with constant unconditional second moments, so it rules out stochastic trends. Assumption f.2 assumes factor loading exists and is finite. Finally, assumption f.3 assumes that the sample second moments will converge asymptotically.

Assumptions for error η_t:

e.1 $\mathbb{E}(\eta_t \eta_t') = \Sigma_\eta$

e.2 $\frac{1}{T}\sum_t \eta_t \eta_t' \xrightarrow{p} \Sigma_\eta$

e.3 η_t is orthogonal to f_t

Assumption e.1 makes sure Σ_η exist and finite. e.1 and f.1 together imply that Σ_e exists. Assumption e.2 assumes the sample second moments converge asymptotically. These assumptions are minimal assumptions for decomposition of Equation 2.2. Assumption e.3 is orthogonality condition between f_t and η_t, this assumption makes sure consistency of factor loading b^c.

This model adds to prior research by decomposing residual returns into two parts. f_t^c is an unobserved factor which mimics a benchmark network risk portfolio and the factor loading b^c is the risk exposure to it. If a stock has high factor loading, it tends to move with its suppliers or customers compared to the benchmark. Notice that the co-movement is not driven by market-wide shocks but idiosyncratic shocks, for example, Apple Inc.'s bad sales numbers affect stock price of its main computer chip provider Qualcomm Inc. The second part is the returns net of effect of network risk.

2.2.2 Network Risk Factor

A key to decomposing residual returns is to construct network risk factor. It can be achieved by constructing a mimicking portfolio investing stocks weighted by network risk, that is, tendency to move with their related stocks. Intuitively, A riskier stock should weight higher in the portfolio and vice versa. If I can give each stock a score representing its tendency to move, a mimicking portfolio that takes score as weights can be constructed.

This score is calculated by *Katz centrality.* Before introducing this score, it is worthwhile to give some background on network and centrality in general.

2.2.2.1 Network and Centrality

A network, or a graph in mathematics, consists of nodes joined by edges. Nodes, sometimes called vertices, are objects. Edges are indicators that show how nodes join together. For example, on the Internet, every website is a node and hyperlinks are edges, or in a friendship network in a school, every student is a node and edges are relationship between students. If edges have direction, such as hyperlinks or citation, it is called a *directed* network and if not, it is called an *undirected* network, like friendship. Edges can have values, like (a) in a banking system network, edges are money transferred, or (b) with simple binary numbers, 1 or 0 represent yes or no. The former is referred to as a *weighted* network and the latter is an *unweighted* network. Networks can be represented in an *adjacency* matrix which shows the values of edges in matrix form. If there is a value for diagonal terms, edges are called *self-edges*. An element in row N and column M represents an edge from Vertex M to Vertex N. If a network is an undirected one, such as in our case, then the adjacency matrix will be symmetric; on the other hand, an directed network has an asymmetric adjacency matrix.

Degree is a measure of connectivity. In an undirected and unweighted network, the degree of a node is the sum of the edges, and in a weighted network, degree is the sum of the value of edges. *Out-degree* and *in-degree* for a directed network report the sum of values of edges pointing out and the sum of values of edges pointing in, respectively. *Degree distribution* is normally distributed skewed to the right so most nodes have few degrees but there are nodes in the far right hand side of distribution have extremely large numbers of degrees and may account for more than 90 percent of total degrees.

Centrality calculates scores from its dependence structure. Generally speaking, this reflects how important a node is in the network. Researchers ask different questions depending on how they construct their networks. If there is a friendship network in a class, an edge represents whether Person A is considered a friend of Person B by Person B, and centrality will give us an answer to who is the most popular person in this class. In a citation network, every article is a vertex and its citations are edges. It is a directed but unweighted network and centrality shows which article is the most influential one. In the world wide website networks, edges are hyperlinks to other websites. Centrality of this web network gives us ranking of influential power of different websites. A high centrality website like Yahoo or Google can be identified in the network. In fact, Google's pagerank, which is their search engine technique, is based on this idea. More examples such as the most important nodes in an electricity network or the most used ingredient in recipes can be found by centrality.

In our case, firms are connected in a network and therefore, the covariance structure of residual returns can be seen as an adjacency matrix of business networks. Residual returns co-vary when idiosyncratic shocks spread, but not every firm is directly connected and so the degree distribution can be skewed. Centrality can identify which stock is the most co-varying one as idiosyncratic shocks hit the network

There are several different definition of centrality. In fact, column sum of covariance matrix is called *degree centrality.* I will give formal definition in the following section.

2.2.2.2 Degree Centrality

Degree centrality is defined as the number of connections of any particular node directly to others in a network. That is also the degree of a node. Therefore, centrality x_i of node v_i is:

$$x_i = \sum_{j}^{N} a_{ij},\ i = 1 \cdots N \tag{2.3}$$

where a_{ij} is an element of adjacency matrix at row i and column j. Degree centrality is simple and generally assumes that higher connected node will have higher score.

2.2.2.3 Eigenvector Centrality

Eigenvector centrality is an improved version of degree centrality. Degree centrality rewards every neighbor the same centrality score. However, some neighbors might have more weights than others if distribution of edges is skewed. Eigenvector centrality scores according to its neighbors' centrality. In the other words, in a friendship network, a person will become popular if he or she has popular friends.

Bonacich (1972) proposes Eigenvector centrality, which is the standard for centrality in the network literature.[7]

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j,\ i = 1 \cdots N \tag{2.4}$$

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[7]There are several variation of this one, including "page rank" of Google.com.

where x_i is the Eigenvector centrality of the networks, A is the adjacency matrix and λ is the highest Eigenvalue, It is easier to see equation 1.4 in matrix form:

$$\lambda X = AX$$

λ is the largest Eigenvalue and X is the associated N $\times$ 1 Eigenvector of the matrix A. The Eigenvector centrality is the Eigenvector associated with highest Eigenvalue.[8]

x_i can also be seen as the sum of centrality of the other assets x_j in the network weighted by the adjacency matrix A_{ij}. As we can see, centrality is calculated in a recursive way. My neighbor's high centrality will contribute to my centrality via an adjacency matrix and will affect her Eigenvalue centrality as well.

2.2.2.4 Katz Centrality

When an adjacency matrix contains a lot of zeros, it results in zero or very small numbers of Eigenvector centrality. Sometimes it is either hard to compute or hard to compare. The solution is to add the same "free" scores to all nodes so that will not change relative scores of nodes. The *Katz centrality* of Katz (1953) applies this idea.

$$x_i = \gamma \sum_{j=1}^{N} A_{ij} x_j + \beta_i, \; i = 1 \cdots N \tag{2.5}$$

Katz centrality adds to Eigenvector centrality by β_i, which is the nodal attribute. β_i is frequently set to 1, but is not restricted to it. When β_i is set to 1, it gives all nodes scores of 1, so it avoids the situation where some nodes score too close to zero.

γ is a variable to control using Katz centrality. If $a = 0$, Katz centrality equals β which is a vector of β_i. If $\gamma \geq 1/\lambda$, Katz centrality diverges and has no meaning.[9] There is little guidance for how to choose γ. Most researchers choose γ of less than but close to $1/\lambda$,

[8] It can be shown that only the highest Eigenvector will remain when we iterate equation 2.4. See Chapter 7.1 in Newman (2010) for detail.

[9] See Chapter 7.2 in Newman (2010) for detail.

so β weights less when Katz centrality is calculated. Katz centrality is also preferred over Eigenvector centrality by many researchers because of the aforementioned zero score issue.

There are other centrality measures such as *closeness centrality* which measures the mean distance from one node to another. *Betweenness centrality* focuses more on the extent to which a node lies on a path between other nodes. These are less relevant to this paper, although interested readers may refer to Newman (2010) for further detail.

2.2.2.5 Choice of β

When β is equal to a vector of 1, it simply gives nodes an additional small score of centrality for free, and therefore will not change the relative scores in the end. However, nodes which have neighbors with scores 0 will score a little more than 0.

Other information like size or leverage ratio can be used for β, for which centrality will reflect the choice of β in equation 1.4. Generally speaking, β closer to zero will provide more information on *edges* themselves. Some researchers call it *global centrality* as opposed to *local centrality* when local information β has been incorporated into the computation.

2.2.2.6 Construction of a Network Risk Factor

Every stock represents a node in a network; the selection of the adjacency matrix is different depending on the context. This paper uses the residual returns covariance matrix as an adjacency matrix. Katz centrality of this adjacency matrix takes bilateral covariance into calculation and aggregates co-varying scores of stocks in a recursive manner.

As a result, taking Katz centrality as a weighting scheme can form a mimicking portfolio of network risk. That is $X'e_t$ where X is N $\times$ 1 normalized Katz centrality and e_t is a N $\times$ 1 vector of residual returns. Let $f_t^c = X'e_t$, then f_t^c is a mimicking portfolio of investing stocks that depends on their network risk.

2.2.2.7 Relation to Principle Components

It is noticed that when adjacency matrix is equal to covariance matrix, Equation 2.4 will calculate the first principle components. The mimicking portfolio f_t^c is common factor and Equation 2.2 is a single factor orthogonal factor model.

However, this research uses Katz centrality where is numerically different from Eigenvector centrality. It can be easily shown by plugging Eigenvector centrality to Equation 2.5 and resulting in a contradiction. So the decomposition of Equation 2.2 does not apply principle components methods to construct network risk factor. Also this research assumes that f_t^c is observable while principle components method does not. As a result, choosing number of factors is not a problem in this research since the mimicking portfolio is observable.

2.2.3 Decomposition

The decomposition procedure has two steps. The first step is simply a prefiltering step to get residual returns. Since market risk factor is assumed exogenous, Equation 1.1 is estimated by time series OLS for every stock i. The second step is to estimate Equation 1.2.

Specifically, I performed a time-series regression of the Fama-French Three Factor model on daily stock returns in every month between September 1963 and December 2012 as the first step.

$$r_t - r_f = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + e_t$$

Excess daily returns are calculated as the daily returns from CRSP minus the 1 month T-bill rate which is the risk-free rate used in this research. Only stocks that have 15 or more transaction days in a month were included to avoid a liquidity issue. The risk free rate and the Fama-French Three Factors are taken from Kenneth French's website.

In a given month, I calculate covariance of the residual returns. The residual returns co-variance matrix is treated as an adjacency matrix of stock dependence. N $\times$ 1 vector of

Katz centrality $\tilde{w}$ with β equal to 1 and $\gamma = 2/3 \times 1/\lambda$[10] is calculated according to Equation 1.5 and orthonormal centrality to $\tilde{w}'\tilde{w} = 1$. Finally, mimicking portfolio is constructed as follows:

$$f_t^c = \alpha^{-1} \times \tilde{w}'\hat{e}_t = w'\hat{e}_t$$

and factor loading b^c is equal to $\tilde{w}$ multiplied by a rescaling constant α and α is equal to $\sum \tilde{w}$.

To mathematically obtain factor loading, I fix f_t^c, solving Equation 2.2. This is equivalent to solving this least squares objective function:

$$\min_{\{b_i^c\}_{i=1}^N} \frac{1}{NT} \sum_i \sum_t (\hat{e}_{it} - b_i^c f_t^c)^2 \quad (2.6)$$
$$\text{s.t. } f_t^c = \alpha^{-1}\tilde{w}'\hat{e}_t$$

where b_i^c is i element of N $\times$ 1 vector b^c. To verify that b^c is equal to $\alpha\tilde{w}$, assuming b^c is known, then $f_t^c = (b^{c'}b^c)^{-1}b^{c'}\hat{e}_t$ will solve the above nonlinear minimization problem. Substitute $b^c = \alpha\tilde{w}$ and simple algebra will show that $f_t^c = \alpha^{-1}\tilde{w}'\hat{e}_t$ and one can complete the proof. For convenience, $f^c = [f_1^c, f_2^c, \cdots, f_T^c]'$ is called the *network risk* factor in later discussion.

To decompose idiosyncratic variance, let covariance of $b_c f_t^c$ equal to Σ_c and define $\Sigma_\eta = \Sigma_{\hat{e}} - \Sigma_c$, therefore, for every stock i, idiosyncratic variance can be expressed as:

$$\sigma_{\hat{e},i}^2 = \sigma_{i,c}^2 + \sigma_{\hat{\eta},i}^2,\ i = 1 \cdots N \quad (2.7)$$

The square root of the former is called *network volatility*. This is idiosyncratic volatility contributed by neighbor stocks. The square root of the latter is *pure idiosyncratic volatility* which is volatility from its own shocks.

[10] 2/3 is chosen for computational convenience.

2.3 Empirics

2.3.1 Data

I use all NYSE, AMEX and NASDAQ listed stocks on the CRSP annual stock return files and Compustat annual industrial files between September 1963 and December 2012. I consider ordinary stocks with shares codes in CRSP equal to 10 and 11, so ADRs, REITs, and units of beneficial interest are excluded. To avoid survivor bias, following Fama and French (1993), I do not include the firm in the test until it has appeared on COMPUSTAT for consecutive 2 years. Also to avoid illiquidity effect, I only take stocks with price higher than 1 dollar. There are 15893 stocks in total.

2.3.2 Summary Statistics

Table 2.1 shows the descriptive statistics of the variables from the pooled sample. RET is monthly raw returns. It has mean of 1.39 % and standard deviation of 16.93 %. Median is around 0, the 25 percent quantile is -6.29 % and the 75 percent quantile is 7.41 %. Skewness shows the distribution is skewed to the right. Most values are concentrated on the left of the mean, with extreme values to the right. Kurtosis shows monthly returns has a huge fat tail.

EXRET, stands for monthly excess returns which is monthly raw returns minus one-month T-Bill rate. Mean is around 0.97 %, standard deviation is also around 16.94 %. Median is negative and is equal to -0.32 %. It is very similar to RET. It is also right skewed and has a fat tail.

Log(Size) is natural log of market capitalization calculated by monthly closing price and the number of outstanding shares in every month. Mean is around 4.23 and standard deviation is 2.07. It is slightly skewed to the right.

BM stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to the book value divided by market value in the same year. Therefore, book value will be the same and market capitalization will be different every month. Monthly average of BM is 0.78 with standard deviation 1.02. Median is 0.6, and shows right skewed and a fat tail.

Beta is the market Beta of Fama-French Three Factor model with daily returns in a given month. Mean Beta is around 1 with standard deviation 1.87. It is fairly symmetric because skewness is close to 0 but shows some degrees of a fat tail.

Idiosyncratic volatility relative to the Fama-French Three Factor model is volatility of residuals returns.[11] NVOL is σ_c, monthly network volatility which is calculated as :$\sqrt{\text{business days}} \times$ volatility of (NBeta $\times$ network risk factor) in a given month. The mean is 1.04 % and standard deviation is 0.73 %. Whereas PVOL stands for pure idiosyncratic volatility σ_η. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month. Comparing NVOL and PVOL, NVOL has lower value and is less volatile. It is not surprising because pure idiosyncratic volatility is considered as noises. The former is as skewed (5.24 compared to 4.32) as network volatility but fatter (115.66 versus 41.42) than NVOL.

NBeta is network Beta b^c. It is the factor loading to the network risk factor f^c. Mean of NBeta is 0.98 and median is also 0.98. It is mildly skewed to the right and has a fat tail. NVR is network variance ratio, which is defined as $\sigma_c^2/(\sigma_c^2 + \sigma_\eta^2)$. it has mean of 2.28 % and standard deviation of 4.49 %. It is skewed to the right and also has a fat tail.

2.3.3 Cross-Section Correlation

In order to explore more cross-sectional behavior of variables, I estimate correlation between variables cross-sectionally and average them over time. Time series standard deviation is also calculated and the correlation coefficients are marked asterisk ($*$) if it is significant at 5 percent level. I find that almost every correlation coefficient is significant. log(Size) is negatively related to BM, NVOL, PVOL and NBeta, but positively correlated to NVR. Negative relationship between size and BM is expected because the size is the denominator of BM. Regarding NVOL, small stocks tend to have high NVOL and PVOL. PVOL is positively

[11] Daily volatility is transformed to monthly volatility by multiplying square root of business days.

related to NVOL and negatively related to size. This suggests that controlling for PVOL is important when I run Fama-MacBeth regression. NBeta is perfect correlated to network volatility by definition. NVR is positively correlated to size but negative related to other variables, although very closed to zero.

2.3.4 Risk Premium

To determine whether network risk is priced cross sectionally in stock market, I run the Fama and MacBeth (1973) regression and correct the standard errors with HAC estimator. I use monthly stock returns from September 1963 to December 2012, 592 periods in total. For a given time period, I run the following risk premium regression cross-sectionally:

$$r_{i,t} = X_{i,t}\beta_t + \epsilon_{i,t},\ i = 1 \cdots N_t \tag{2.8}$$

where $r_{i,t}$ is 1×1 vector of excess returns and X_i is $1 \times$ K vector of independent variables. K is the number of independent variables. β_t is K $\times$ 1 vector of risk premia. ϵ_i is residuals. Then, the risk premium variable of interest can be found by taking the time series average of estimated coefficients $\hat{\beta}_t$ and the standard error is simply the standard deviation of the time series $\hat{\beta}_t$. That is:

$$\bar{\beta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t \tag{2.9}$$

$$var(\bar{\beta}) = \frac{1}{T-1}\sum_{t=1}^{T}(\hat{\beta}_t - \bar{\beta})^2 \tag{2.10}$$

The standard deviation will be corrected using Fama-MacBeth technique shown by Petersen (2009) if residuals are related cross-sectionally. In some cases, $\hat{\beta}$ is serial correlated, standard error can be corrected by Newey and West (1987) type estimator. I use HAC estimator to correct standard error for risk premium in this research.

Returns used in Equation 2.8 are expected returns (future returns) and all covariates are lagged ones. That is to say, size, BM and Beta, IVOL and so on are from time $t-1$ and returns is from time t. For convenience, I use subscript $t-1$ as t on these variables.

Results of Fama-MacBeth regression is shown in Table 2.3. Model 1 has been shown in many IVOL research such as Fu (2009) and Huang et al. (2010). It has negative -0.07 % monthly risk premium. This result is slightly lower than previous research because of financial crisis but consistent to previous research showing that IVOL earns negative premium. Model 2 reports risk premium of NBeta controlling size BM, market Beta and IVOL. It shows monthly risk premium of NBeta is 0.57 % and is significant at 1 percent level. This result is consistent to previous research, such as Buraschi and Porchia (2012) which find positive monthly risk premium of centrality.

The main result of this paper is shown in Model 3 in Table 2.3. It breaks down IVOL into two components: NVOL and PVOL. It turns out NVOL is priced with monthly risk premium of 1.01 % and is significant at 1 % level. Compared to Model 1, PVOL also shows -0.07 % monthly riks premium. This Model improves goodness-of-fit compared to Model 1 because the pricing error Alpha is lower and the amount is explained by NVOL.

In addition, model 3 gives another perspective of the IVOL puzzle. IVOL puzzle is first documented in Ang et al. (2006) and is replicated in model 1 in this table. When IVOL is decomposed into 2 parts, the NVOL earns *positive* risk premium. In addition, compared to the magnitude of risk premium of the two components, the risk premium of NVOL dominates that of PVOL. Although adding NVOL does not solve the whole puzzle because PVOL is still significant and negatively related, the result suggests another prospective to IVOL puzzle: network risk should be priced. Stocks which tend to move with related stocks in the network should receive higher compensation to hold it.

Table 2.1 shows that NVOL is smaller and less volatile than PVOL. It implies that variation of IVOL comes mostly from PVOL rather than NVOL. As a result, an alternative way to look at network risk is to find the ratio of variance contributed by network to total idiosyncratic variance since network volatility is less variable and anticipated. Model 4 tests this hypothesis. *Network Variance Ratio* (NVR), σ_c^2/σ_e^2, is defined as a ratio of network variance to idiosyncratic variance and normalized to percentage. NVR represents network variance per total idiosyncratic variance. High ratio shows most of the volatility of residual returns comes from the network. Model 4 shows that NVR is priced and earns *positive* monthly risk premium of 0.13 %. Controlling for the level of IVOL, investors view stocks with high network variance riskier and require higher compensation. This result suggests the IVOL puzzle maybe due to a misunderstanding of idiosyncratic risk. If investors care about NVR but not magnitude of IVOL, IVOL puzzle may mean nothing other than a statistical relationship.

Finally, Huang et al. (2010) argues returns reversals could explain part of the negative risk premium of IVOL. They find that lag returns are positively related to lag volatility and negatively related to current returns. Therefore, lag volatility is negatively related to current returns. Model 5 includes 1 period lag returns to take returns reversal into consideration. Lag returns has negative sign as expected. It is significant at 1 %. Nevertheless, NVOL is still significant at 1 percent level and earns slightly lower risk premium (0.96 % monthly). PVOL shows the same pattern, slightly higher risk premium but still negative (-0.06% monthly). Lagged returns explains part of PVOL but do not affect the main result.

2.3.5 Portfolio Approach

Another way to look at whether network risk is priced in the stock market is to form portfolios. The portfolio method assumes that when we group stocks with the same characteristics together, idiosyncratic noises will be averaged out. Thus we will observe less noisy returns and be able to identify a pattern.

2.3.5.1 Network Volatility Quintiles Portfolios

Row 1 in Table 2.4 shows mean returns of value weight quintile portfolios formed every month by sorting stocks based on network volatility relative to the Fama-French (1993) model. This is computed using daily data over the previous month. The lowest is the portfolio of stocks with the lowest NVOL. Mean returns increases while NVOL increases for the lowest NVOL quintile portfolio to the second highest NVOL quintile portfolios. Mean returns of portfolio with highest NVOL declines. Column “1-5” is the difference between Portfolio 1 (the lowest quintile) and Portfolio 5 (the highest quintile). The difference is -0.04 % but not significant at 5 % significance level.

Row 2 in Table 2.4 shows monthly mean returns of equal weight portfolios. The overall mean of each portfolio is higher than the value weight portfolios by 0.2-0.3 %, suggesting that small stocks tend to have higher returns for each portfolio. The pattern is very similar to value weight portfolio. Portfolio with the highest NVOL has the lowest returns. The mean difference between the lowest NVOL portfolio and the highest one is -0.13 %, but it is still insignificant at 5 % significance level.

There are several reasons why mean returns difference is insignificant. It could be NVOL overlaps some characteristics of stocks, such as size, BM, etc. so that the portfolio approach cannot average out the idiosyncratic noises.

Table 2.5 shows summary of quintile portfolios. Row 1 shows the numbers of firms. It has monthly average of 432 firms in our data. Size is in Row 2, stocks with lower NVOL tend to have bigger market capitalization, Portfolio 1 (the lowest 20 %) has monthly average of $ 1171.6 million, as opposed to Portfolio 5 (the highest 20 %), which has only $ 622.01 million monthly on average. However, it is not monotone. Monthly average book-to-market ratio is shown in Row 3. Portfolio 2,3,4 has similar book-to-market value. Portfolio 1 and 5 have higher BM than the rest. Row 4 shows monthly average of NVOL. It ranges from 0.73 % to 1.08 % on a monthly basis. Row 5 shows monthly average of PVOL. It has an inverse hump shape. Row 6 shows monthly average of NBeta. When NBeta is 1, it means the stock has the same movement magnitude as the network risk factor. It ranges from 0.83 to 1.15. Row 7 shows monthly average of market Beta. Surprisingly, Beta shows a U shape too.

2.3.5.2 Pricing Anomalies of Network Volatility Quintiles Portfolios

Table 2.6 shows pricing anomalies of NVOL quintile portfolios. Beta in row 1 shows fitting CAPM with monthly excess returns of quintile portfolios. Beta shows U shape. Portfolio 1 and 5 have highest value but Portfolio 2,3,4 have lower value. *LS* in column 7 represents long-short portfolio that buy long in the lowest NVOL portfolio and sell short the highest

NVOL portfolio. The Beta shows -.20, suggesting it is a safe strategy. Row 3 is Alphas from the Fama-French Three Factor model. If Alpha is positive and significant, it means it has positive returns more than model predicts and vice versa. Alphas are positive for Portfolio 2,3,4 but not significant. Alpha is -.21 for Portfolio 5 and significant at 5 %. The difference between Portfolio 1 and 5 is 0.20 but not significant at 1 % level both sides, showing there is no pricing anomaly if I sort stocks with NVOL. Row 5 shows Alphas using the Fama-French Four Factor model, that is a Three Factor model plus a momentum factor. The Alphas are less anomalous and significance drops, suggesting that momentum picks up some variation of returns.

In general, pricing anomaly of portfolios formed by NVOL is not found in the data. However, hump shape of Alphas is not normal and suggests sorting on NVOL may not be appropriate. Ideally, a monotone behavior of Alphas is expected if sorting is correct.

2.3.5.3 Network Variance Ratio Quintiles Portfolios

Model 3 from Table 2.3 suggests that investors might care about ratio of NVOL to IVOL so I sort NVR to form quintile portfolios in this section. The Second panel in Table 2.4 shows value weight quintile portfolios sorted by NVR. Portfolio 1 has the smallest NVR and Portfolio 5 has the highest value of NVR. It turns out portfolio 1 has least mean returns about 0.46 % and the rest is fairly flat around 0.9 %. The difference is 0.44 % monthly and significant at 5 %. Row 2 shows equal weight quintile portfolios. Mean returns are higher and peak at Portfolio 3.

Table 2.7 shows summary of NVR quintile portfolios. Row 1 shows the numbers of firms. It has monthly average of 432 firms in our data. Size is in Row 2, stocks with lower NVR tend to have smaller market capitalization, Portfolio 1 (the lowest 20 %) has monthly average of $ 239.15 millions, as opposed to, Portfolio 5 (the highest 20 %) which has $ 4642.68 million monthly on average. Monthly average book-to-market ratio is shown in Row 3. Portfolio 1 has highest BM ratio while Portfolio 2,3,4 and 5 have similar BM value. Row 4 shows monthly average of NVOL. It shows that NVOL is flat among all 5 quintile portflios. Row

5 shows monthly average of PVOL. The value declines while NVR increases and confirms that NVR is driven by PVOL. Row 6 shows monthly average of NBeta. It is fairly flat among NVR quintile portfolios. Row 7 shows monthly average of market Beta. It declines monotonically.

Either size or BM of NVR quintile portfolios show asymmetry. Low NVR stocks tend to be small in size and high in BM. It is possible the pattern of quintile portfolios reflect size or BM factors rather than NVR. In order to distinguish these factors, double sorting is needed. For example, to distinguish size from NVR, I first sort stocks on size into three groups, then sort on NVR in each size group. The small group consists of stocks less than 30 % quantile of size, the medium group consists of stocks from 30 % to 70 % quantiles of size, and the large group has stocks more than 70 % quantile of size. Then, in each size group, stocks are sorted into quintile portfolios as before. The logic of double sorting is as followed: if NVR overlaps size effect, there is no pattern of returns of NVR quintile portfolios in each size group. As a result, Portfolio 1 minus Portfolio 5("1-5") in each size group will show no returns difference.

Panel A in Table 2.8 shows 15 portfolios sorted on size and then on NVR. Small and medium size stocks show stronger increasing pattern than single sorting. In small and medium size groups, the pattern is monotone and returns difference is significant at 1 % level. It suggests that double sorting makes portfolios less noise than single sorting. Portfolio returns difference declines while size of stocks increases. For the large group, the portfolios returns difference is not clear and shows insignificant.

Panel B in Table 2.8 shows 15 portfolios sorted on BM and then on NVR. High and medium stocks show monotone and increasing pattern. The portfolio returns difference is significant at 1 % and suggests positive relation between NVR and expected returns. Surprisingly, the highest and the second highest NVR quintile portfolios in low BM group show lower returns.

I find NVR is positively related to expected returns controlled for size or BM, although the evidence for low BM or large size stocks is not clear. This phenomenon is addressed in the later section which most of these stocks are from utilities and telecoms industry and earn no positive risk premium of NVR.

2.3.5.4 Pricing Anomalies of Network Variance Ratio Quintiles Portfolios

Table 2.9 shows pricing anomalies of NVR quintile portfolios. Beta in row 1 shows fitting CAPM with monthly excess returns of quintile portfolios. Beta has U shape. Portfolio 1 has highest Beta and it decreases while NVR increases. LS in column 7 represents long-short portfolio that buy long in the lowest NVR portfolio and sell short the highest NVR portfolio. The Beta shows 0.64. Row 3 shows Alphas from the Fama-French Three Factor model. If Alpha is positive and significant, it means that it has positive returns more than model predicts and vice versa. Alphas are negative for Portfolio 1 and 2 but closed to zero for Portfolio 3 and 4, and they turn positive for Portfolio 5. The difference between Portfolio 1 and 5 is -0.72 % and is significant at 1 % both sides, showing there is evidence of pricing anomaly of NVR portfolios. Row 5 shows Alphas using the Fama-French Four Factor model, that is the Three Factor model plus a momentum factor. The Alphas are less anomalous and significance drops but LS portfolio has -0.55 % and still significant at 1 % level.

This sorting shows the importance of NVR. This ratio can be considered as normalized network volatility where IVOL is the denominator. A stock is considered risky if it has low IVOL but high NVOL. These stocks are less volatile but when related stocks move, they will move as well. Therefore, they are harder to hedge. On the other hand, if a stock is already volatile, it is less risky in the sense that its volatility is expected, and it does not matter whether volatility comes from the network or itself.

2.4 Extension

2.4.1 Fama-French Four Factor Model

The first extension is to use the Fama-French Four Factor model rather than the Three Factor model to filter market-wide risk. Table 2.9 shows that Alpha becomes less significant if the Four Factor model is used. If the momentum factor overlaps with the network risk factor, we should not see NVR priced or any other pricing anomaly when the Four Factor model is used to filter market-wide risk.

In this exercise, Fama-French Four Factor model is used to get residual returns and the same procedure as the one above is repeated. Table 2.10 shows that Fama-MacBeth regression of the Four Factor model. Model 1 shows that IVOL puzzle still remains at about -0.07 % monthly. Model 2 reports risk premium of NBeta. It shows monthly risk premium of NBeta is 0.66 % and is significant at 1 percent level. Model 3 uses NVOL and PVOL. Both are significant with 1.20 % and -0.07 %, respectively. Risk premium of NVOL is slightly higher than the Three Factor model due to smaller Alpha. Model 4 shows NVR is significant and it is 0.12 % per month, compared to 0.13 % for the Three Factor model. Model 5 shows NVOL and PVOL are still significant controlled for lag returns.

Table 2.11 shows value weight and equal weight quintile portfolios returns. The first panel shows value weight quintile portfolios formed by NVOL. It is flat and the difference between the highest and the lowest portfolios is not significant. The difference of equal weight quintile portfolios returns is significant, showing that small or tiny firms have stronger NVOL effects. The second panel shows quintile portfolios formed by NVR. The difference between the highest and the lowest value weight quintile portfolios is significant and about 0.51 % monthly. Equal weight portfolios show less pattern in this case.

Summary of NVR quintile portfolios is shown in Table 2.12. The overall pattern is similar to the Three Factor model. Size increases and BM decreases as NVR increases. NVR ranges from 0.44 % to 2.08 %. NVOL is flat but PIVOL declines as NVR goes up. It also shows that the decline of IVOL drives the ratio.

Result of double sorting on size/BM and NVR is shown in Table 2.13. The overall pattern is similar to three factors model. Panel A shows that stocks in small and medium groups have clear monotone increasing returns as NVR increases, but less clear on large stocks. Panel B shows stocks in medium and high BM groups have monotone increasing returns as NVR increases, but less obvious on low BM stocks.

Finally, Table 2.14 shows time series CAPM Beta, Alphas of the Three Factor model and Four Factor model of NVR quintile portfolios. It shows stocks with high NVR having lower Beta. On average, they are bigger and earn higher returns. Alphas increases from negative to positive in both Three Factor model and Four Factor model. Long-short portfolio which buy long the lowest and sell short the highest stocks shows significant negative Alpha, suggesting pricing anomaly among NVR quintile portfolios.

Overall, using the Fama-French Four Factor model does not change the results dramatically. NVOL and NVR are still priced. In addition, pricing anomaly is still found with NVR quintile portfolios. Therefore, there is no evidence to suggest that the momentum factor overlaps network volatility effect.

2.4.2 Industry Subsamples

This exercise divides samples to 12 industry subsamples according to the definition of the Fama-French 12 Industries. (available on Kenneth French's website.) Stocks are grouped by their SIC codes into 12 different industries. There are non-durables, durables, manufacturing, energy, chemicals, business equipment, telecoms, utilities, shops, health, money and others. NVR is focused in this subsample extension since it combines the information about NVOL and IVOL together. Previous analysis shows more significant results and the implication is more compelling.

Table 2.15 shows Fama-MacBeth regression with 11 different industry stocks (Others has been ignored.). Telecoms and utilities industry stocks earns no positive risk premium of NVR. This explains why double sorting on size(BM) and NVR fails to find monotone increasing pattern in the large(low) size(BM) group because these stocks tend to have low BM or large size.

On the other hand, other industry stocks show significant results. Compared to 0.13 % risk premium per month of full sample analysis, health, shops, durables, nondurables stocks have much higher monthly risk premium of 0.30 %, 0.28 %, 0.27 % and 0.25 %, respectively. Manufacturing, energy, chemicals, business equipment and finance stocks earn similar amount of risk premium as full samples do, they are 0.13 %, 0.14 %, 0.16 %, 0.21 % and 0.16 %, respectively. The difference between risk premium of different industry stocks may be due to industry characteristics such as regulation on balance sheet and market segmentation, market power, or behavior of investors such as risk aversion toward different industry stocks. All in all, if telecoms and utilities industry stocks are deleted from our samples, the results are more significant and the risk premium is higher.

2.4.3 Time Subsamples

To consider the impact of the Great Moderation which refers to the phenomenon of low volatility of several macroeconomic variables since mid 1980,[12] I split the whole samples into 2 subsamples in 1983. The first period ranges from August 1963 to December 1982 and the second one is from January 1983 to December 2012. The result is shown in Table 2.16. Before the Great Moderation, the risk premium of NVR is 0.21 % monthly and significant at 1 percent level, however, higher than the risk premium of the whole samples. After the Great Moderation, the risk premium of NVR drops to 0.08 % monthly. The later also has lower standard deviation of NVR risk premium, 0.03 %, compared to 0.07 % of the first subsamples. The lower risk premium of NVR could be one of the phenomenon of the Great Moderation due to the more stable economic structure and the better ability of hedging loss from related stocks co-movement.

2.5 Conclusion

This research studies whether network risk of stocks is priced in the stock market. Idiosyncratic shocks spread through a local network and make economically related stocks move together, network risk arises as stocks co-move and become undiversified. How network risk affects the pricing of cross-section expected returns? and what is the implication of network risk to understand idiosyncratic risk? This research tries to answer these questions.

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[12]See Kim and Nelson (1999), McConnell and Perez-Quiros (2000) and Stock and Watson (2003) for details.

In order to differentiate market-wide risk from idiosyncratic risk, the Fama-French Three Factor model is applied to filter out market-wide risk explained returns. Then centrality is created from the residual returns covariance matrix and a network risk factor weighted by centrality is constructed. Residual returns is decomposed to network term and pure idiosyncratic term. The second moment version of the decomposition is that the idiosyncratic variance can be shown to consist of network variance and pure idiosyncratic variance.

The Fama and MacBeth (1973) regression technique is applied and test whether network risk is priced in cross-section of stock returns. The data ranges from September 1963 to December 2012. The result shows network volatility (NVOL) is priced with a monthly 1.01 % premium. In addition, the factor loading of network Beta (NBeta) or equivalently, scaled Katz centrality, is also priced. Finally, controlled for IVOL, network variance ratio (NVR), which is the ratio of network variance to idiosyncratic variance, is also found priced with a monthly 0.13 % premium. These findings confirm that network risk is positively *priced* in cross-section of stock returns. It also suggest that another perspective to IVOL puzzle which high IVOL is negative related to low expected returns: stocks are riskier if they exhibit low idiosyncratic volatility while also tending to move with their related stocks, as a result, high NVOL.

Robustness check on using the Fama-French Four Factor model in the first stage estimation is also performed. NBeta, NVOL and NVR are priced with a positive monthly premium, 0.66 %, 1.2 % and 0.12 %, respectively.

A portfolio approach is applied to both NVOL and NVR. It is assumed that if stocks with the same features are grouped together, idiosyncratic noises will be averaged out and a pattern of returns will show. NVOL quintile portfolios do not show any pattern of returns. It is because NVOL overlaps other characteristics and noises failed to be averaged out. On the contrary, quintile portfolios formed by NVR show a strong pattern and are positively related to expected returns. Alphas estimated with the Fama-French Three Factor model and the Four Factor model including the momentum factor of NVR quintile portfolios are positive and show significant pricing anomaly. Further checks on double sorting of size (BM) show stronger results except large size (low BM) stocks.

Industry subsamples are tested. I find utilities and telecoms industry stocks do not have NVR risk premium. They are most large size (low BM) stocks so it explains that portfolio approach tests fails on these stocks. Other industry subsamples all show positive and significant NVR risk premium and the value is higher than full samples test.

Time subsamples are also tested. To consider the impact of the Great Moderation which macroeconomics time series data exhibit low volatility after 1982, I split the whole samples into two subsamples in December 1982. Both subsamples show positive and significant NVR risk premium. The difference is that stocks before the Great Moderation has higher risk premium than after.

Future extensions include using different adjacency matrices to estimate centrality. It will be great if real world data could be used to test the hypothesis. Furthermore, from a practitioner's point of view, if there exists a pricing anomaly of network variance ratio portfolios, is it possible to construct a profitable strategy accordingly?

Table 2.1: Variables descriptive statistics for the pooled sample: Sep.1963-Dec.2012

	Mean	Std.Dev	Median	Q1	Q3	Skew	Kurt
RET	1.39	16.93	0.00	-6.29	7.41	5.98	310.96
EXRET	0.97	16.94	-0.32	-6.73	6.98	5.98	310.56
log(Size)	4.69	2.07	4.51	3.17	6.06	0.40	2.95
BM	0.78	1.02	0.60	0.33	1.01	23.23	1962.09
log(BM)	-0.57	0.92	-0.49	-1.07	0.02	-0.76	5.64
Beta	1.01	1.87	0.94	0.21	1.74	0.11	34.83
NVOL	1.04	0.73	0.84	0.64	1.16	4.32	41.42
PVOL	11.35	9.09	8.88	5.82	13.96	5.24	115.66
NBeta	0.98	0.14	0.98	0.92	1.03	1.63	53.81
NVR	2.28	4.49	0.97	0.39	2.36	7.46	93.43

Note: This table reports the pooled descriptive statistics of stocks that are traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec 2012. *RET* is the monthly raw returns reported in percentage. EXRET is monthly excess returns, which is the raw returns net of the one month T-bill rate. *log(Size)* is the log of market value of equity, calculated by the product of monthly closing price and the number of outstanding shares in each month. *BM* stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market Beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. *NVOL* is network volatility which is square root of business days multiply volatility of NBeta times network risk factor in a given month. *PVOL* stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month. *NVR* is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage. Q1 is the 25% quantiles and Q3 is the 75 % quantiles.

Table 2.2: Times series means of the cross-sectional correlation

	lSize	Beta	lBM	NVOL	PVOL	NBeta	NVR
RET	-0.02*	-0.00	0.02*	0.00	-0.01	0.00	-0.00
lSize		0.04*	-0.31*	-0.08*	-0.49*	-0.08*	0.17*
Beta			-0.07	0.02	0.12	0.02	-0.02*
lBM				0.00	-0.00	0.00	-0.04*
NVOL					0.16*	1.00*	-0.02*
PVOL						0.15*	-0.12*
NBeta							-0.02*

Note: This table presents the time series means of the cross-sectional Pearson correlations. The variables relate to a sample of stocks traded in the NYSE, Amex,or Nasdaq between Sep. 1963 and Dec. 2012. Variables are defined in Table 2.1 .The correlation coefficients followed by * are significant at the 5 % level based on their time-series standard error.

Table 2.3: Fama-MacBeth Regression

	Alpha	Size	Beta	BM	NBeta	IVOL	NVR	NVOL	PVOL	EXRET.lag1
Model 1	2.24***	-0.20***	0.01	0.25***		-0.07***				
SE	0.38	0.03	0.03	0.09		0.01				
Model 2	1.68***	-0.20***	0.01	0.25***	0.57**	-0.07***				
SE	0.45	0.03	0.03	0.09	0.26	0.01				
Model 3	1.66***	-0.20***	0.01	0.25***				1.01**	-0.07***	
SE	0.45	0.03	0.03	0.09				0.39	0.01	
Model 4	1.00***	-0.10**	-0.02	0.29***			0.13***			
SE	0.45	0.04	0.04	0.09			0.03			
Model 5	1.54***	-0.18***	0.00	0.21**				0.96**	-0.06***	-0.03***
SE	0.44	0.03	0.03	0.09				0.40	0.01	0.00

"." 10 %, " * " 5 %," ** "1 %, " *** "0.1% significance level.

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. Dependent variable at each time t is monthly stock returns minus monthly risk free rate which is one month US T-bill rate. *Size* is market value of equity, calculated by the product of monthly closing price and the number of outstanding shares in each month. *BM* stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. *IVOL* is idiosyncratic volatility relative to the Fama-French Three Factor model. It is calculated by square root of business days multiply by daily volatility. *NVOL* is network volatility which is square root of business days multiply network volatility in a given month. *PVOL* stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month. *NVR* is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage. *EXRET.lag1* is 1 period lag excess returns. Standard errors are adjusted by Newey-West HAC estimators.

Table 2.4: Network Volatility & Variance Ratio Quintile Portfolio

Panel A: Network Volatility

Net.Vol	Lowest	2	3	4	Highest	1-5	t-stats
VWRET	0.83	0.89	0.87	0.98	0.87	-0.04	-0.27
EWRET	1.05	1.17	1.17	1.30	1.19	-0.13	-1.61

Panel B: Network Variance Ratio

NVR	Lowest	2	3	4	Highest	1-5	t-stats
VWRET	0.46	0.89	0.94	0.90	0.91	-0.44	-1.89
EWRET	0.88	1.22	1.36	1.28	1.12	-0.23	-1.07

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq from Sep. 1963 to Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month, compute its value weight returns, equal weight returns and then rebalance. $VWRET$ stands for value weight returns, $EWRET$ is equally weighted returns.

Table 2.5: Summary Statistics of Network Volatility Quintile Portfolios

Net.Vol	Lowest	2	3	4	Highest
Number	432.13	431.54	431.56	431.54	431.93
Size	1171.60	2527.36	2516.63	1738.00	622.01
BM	0.75	0.70	0.70	0.73	0.77
NVOL	0.73	0.84	0.88	0.93	1.08
PVOL	12.54	8.05	7.59	8.94	14.93
NBeta	0.83	0.93	0.97	1.02	1.15
Beta	1.15	1.00	0.97	1.05	1.23

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month. Quintile portfolios is shown in Row 1. Every variables in Column 1 are time series mean of monthly average. *Number* numbers of firms. *Size* is market capitalization, calculated by monthly closing price multiply by outstanding shares,unit in million dollars. *BM* is book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. $NVOL$ is network volatility which is square root of business days multiply volatility of NBeta times network risk factor in a given month. $PVOL$ stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month.

Table 2.6: Pricing Anomalies

NVOL	Lowest	2	3	4	Highest	LS
Beta	1.09	0.93	0.92	1.03	1.28	-0.20
t-stats	43.21	66.19	72.59	49.24	33.78	-3.54
3f Alpha	-0.01	0.08	0.05	0.07	-0.21	0.20
t-stats	-0.12	1.66	1.23	1.21	-1.86	1.22
4f Alpha	-0.09	0.02	0.05	0.14	-0.03	-0.07
t-stats	-1.33	0.54	1.20	2.28	-0.26	-0.45

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month, compute its value weight returns and then rebalance. Every row shows Network volatility portfolios from lowest to highest. Network volatility is computed using daily data in a given month by Chen (2013). Beta is from CAPM using monthly portfolio excess returns. 3f Alpha is alphas of the Fama-French Three Factor (MKT, SMB, HML) using monthly data and 4f Alpha is 4 factors including momentum (MOM). *LS* is a long-short portfolio formed by long stocks with the lowest 20 % network volatility and short stocks with highest 20% network volatility.. Standard deviation is corrected by Newey-West HAC with 4 lags.

Table 2.7: Summary Statistics of Network Variance Ratio Quintile Portfolios

Net.Vol	Lowest	2	3	4	Highest
Number	432.13	431.54	431.56	431.54	431.93
Size	239.15	527.63	1031.18	2130.57	4642.68
BM	0.85	0.74	0.71	0.69	0.67
NVR	0.45	0.74	1.00	1.33	2.15
NVOL	0.86	0.92	0.91	0.90	0.88
PVOL	20.45	12.06	8.82	6.49	4.20
NBeta	0.96	1.00	0.99	0.98	0.97
Beta	1.28	1.23	1.13	0.98	0.79

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month. Quintile portfolios is shown in Row 1. Every variables in Column 1 are time series mean of monthly average. *Number* numbers of firms. *Size* is market capitalization, calculated by monthly closing price multiply by outstanding shares,unit in million dollars. *BM* is book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. $NVOL$ is network volatility which is square root of business days multiply volatility of NBeta times network risk factor in a given month. $PVOL$ stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month. NVR is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage.

Table 2.8: 15 Portfolios Sorted by Size/BM and Network Variance Ratio

Panel A: Size & Network Variance Ratio

Size \ NVR	Lowest	2	3	4	Highest	1-5	t-stats
Small	-3.45	-2.71	-2.40	-2.02	-1.04	-2.42	-10.79
Medium	-0.82	-0.45	-0.23	0.13	0.34	-1.16	-5.57
Large	1.07	1.01	0.93	1.02	0.91	0.16	0.76

Panel B: BM & Network Variance Ratio

BM \ NVR	Lowest	2	3	4	Highest	1-5	t-stats
Low	1.81	1.88	1.86	1.64	1.25	0.55	2.07
Medium	-0.31	0.27	0.56	0.62	0.75	-1.06	-4.67
High	-2.78	-1.90	-1.26	-0.69	-0.28	-2.5	-9.26

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq from Sep. 1963 to Dec. 2012, total 592 periods. At each month end, I sort stocks by size(BM) into small(low), medium(medium) and large(high) groups, then sort stocks in each size group by network variance ratio into quintiles, holding these portfolios for a month, compute its value weight returns and then rebalance. Small(Low) group consists of stocks less than 30 % quantiles of size(BM), large(high) group contains stocks more than 70 % quantile of size(BM), and medium(medium) group contains stocks between 30 % and 70 % quantile of size(BM).

Table 2.9: Pricing Anomalies of Network Variance Ratio Quintile Portfolios

NVR	Lowest	2	3	4	Highest	LS
Beta	1.46	1.41	1.24	1.05	0.82	0.64
t-stats	26.93	40.36	68.62	68.75	39.77	9.14
3f Alpha	-0.62	-0.14	-0.03	0.02	0.10	-0.72
t-stats	-5.06	-1.40	-0.38	0.35	2.27	-4.86
4f Alpha	-0.49	-0.06	0.01	0.03	0.06	-0.55
t-stats	-3.82	-0.56	0.21	0.56	1.25	-3.56

Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month, compute its value weight returns and then rebalance. Every row shows Network volatility portfolios from lowest to highest. Network volatility is computed using daily data in a given month by Chen (2013). Beta is from CAPM using monthly portfolio excess returns. 3f Alpha is Alphas of the Fama-French Three Factor (MKT, SMB, HML) using monthly data and 4f Alpha is 4 factors including momentum (MOM). *LS* is a long-short portfolio formed by long stocks with the lowest 20 % network volatility and short stocks with highest 20% network volatility.. Standard deviation is corrected by Newey-West HAC with 4 lags.

Table 2.10: FF4F: Fama-MacBeth Regression

	Alpha	Size	Beta	BM	MOM	NBeta	IVOL	NVR	NVOL	PVOL	EXRET.lag1
Model 1	2.22***	-0.20***	0.00	0.26***	0.02		-0.07***				
SE	0.38	0.03	0.03	0.09	0.03		0.01				
Model 2	1.58***	-0.20***	0.00	0.26***	0.02	0.66**	-0.07***				
SE	0.43	0.03	0.03	0.09	0.03	0.24	0.01				
Model 3	1.56***	-0.20***	0.00	0.26***	0.02				1.20***	-0.07***	
SE	0.43	0.03	0.03	0.09	0.03				0.40	0.01	
Model 4	1.01***	-0.10***	-0.02	0.30***	0.02			0.12***			
SE	0.45	0.04	0.04	0.09	0.03			0.03			
Model 5	1.45***	-0.18***	-0.00	0.21***	0.01				1.11***	-0.06***	-0.03***
SE	0.43	0.04	0.03	0.09	0.03				0.40	0.01	0.00

"." 10 %, " * " 5 %," ** "1 %, " *** "0.1% significance level.

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. Dependent variable at each time t is monthly stock returns minus monthly risk free rate which is one month US T-bill rate. *Size* is market value of equity, calculated by the product of monthly closing price and the number of outstanding shares in each month. *BM* stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *MOM* is momentum beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. *IVOL* is idiosyncratic volatility relative to the Fama-French Three Factor model. It is calculated by square root of business days multiply by daily volatility. *NVOL* is network volatility which is square root of business days multiply network volatility in a given month. *PVOL* stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month. *NVR* is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage. *EXRET.lag1* is 1 period lag excess returns. Standard errors are adjusted by Newey-West HAC estimators.

Table 2.11: FF4F : Network Volatility Quintile Portfolio

Panel A: Network Volatility

NVOL	Lowest	2	3	4	Highest	1-5	t-stats
VWRET	0.70	0.87	0.92	1.04	0.87	-0.17	-1.39
EWRET	1.04	1.16	1.19	1.27	1.22	-0.18	-2.34

Panel B: Network Variance Ratio

NVR	Lowest	2	3	4	Highest	1-5	t-stats
VWRET	0.41	0.84	0.99	0.87	0.91	-0.51	-2.11
EWRET	0.86	1.25	1.36	1.28	1.12	-0.25	-1.14

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month, compute its value weight returns, equal weight returns and then rebalance. $VWRET$ stands for value weight returns, $EWRET$ is equally weighted returns.

Table 2.12: FF4F: Summary Statistics of Network Variance Ratio Quintile Portfolios

NVOL	Lowest	2	3	4	Highest
Number	432.13	431.54	431.56	431.54	431.93
Size	231.44	512.33	1023.32	2101.68	4702.55
BM	0.85	0.74	0.71	0.69	0.67
NVR	0.44	0.71	0.96	1.29	2.08
NVOL	0.80	0.84	0.84	0.83	0.82
PVOL	19.86	11.63	8.48	6.24	4.03

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month. Quintile portfolios is shown in Row 1. Every variables in Column 1 are time series mean of monthly average. *Number* numbers of firms. *Size* is market capitalization, calculated by monthly closing price multiply by outstanding shares,unit in million dollars. *BM* is book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *NBeta* is the coefficient that regress daily residual returns on network risk factor model which is a factor constructed by residual returns at the same time weighted by centrality. $NVOL$ is network volatility which is square root of business days multiply volatility of NBeta times network risk factor in a given month. $PVOL$ stands for pure idiosyncratic volatility. It is defined as square root of daily idiosyncratic variance minus network risk variance and scaled by square root of business days in a given month.

Table 2.13: FF4F: 15 Portfolios Sorted by Size/BM and Network Variance Ratio

Panel A: Size & Network Variance Ratio

Size \ NVR	Lowest	2	3	4	Highest	1-5	t-stats
Small	-3.33	-2.69	-2.49	-2.05	-1.01	-2.32	-10.3
Medium	-0.85	-0.41	-0.21	0.11	0.33	-1.17	-5.62
Large	0.98	1.08	0.89	1.05	0.89	0.09	0.43

Panel B: BM & Network Variance Ratio

BM \ NVR	Lowest	2	3	4	Highest	1-5	t-stats
Low	1.70	1.85	1.82	1.65	1.26	0.45	1.66
Medium	-0.26	0.25	0.50	0.68	0.74	-1.01	-4.36
High	-2.77	-1.94	-1.18	-0.72	-0.26	-2.51	-8.96

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I sort stocks by size(BM) into small(low), medium(medium) and large(high) groups, then sort stocks in each size group by network variance ratio into quintiles, holding these portfolios for a month, compute its value weight returns and then rebalance. Small(Low) group consists of stocks less than 30 % quantiles of size(BM), large(high) group contains stocks more than 70 % quantile of size(BM), and medium(medium) group contains stocks between 30 % and 70 % quantile of size(BM).

Table 2.14: FF4F: Pricing Anomalies of Network Variance Ratio Quintile Portfolios

NVR	Lowest	2	3	4	Highest	LS
beta	1.49	1.40	1.23	1.05	0.82	0.67
t-stats	25.93	39.75	64.27	68.46	41.12	9.20
3f Alpha	-0.71	-0.19	0.03	-0.03	0.12	-0.83
t-stats	-5.47	-1.86	0.45	-0.61	2.58	-5.29
4f Alpha	-0.51	-0.09	0.09	-0.04	0.08	-0.59
t-stats	-3.77	-0.96	1.36	-0.75	1.38	-3.58

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. At each month end, I calculate network volatility of each stock to sort portfolios into quintiles, holding these portfolios for a month, compute its value weight returns and then rebalance. Every row shows Network volatility portfolios from lowest to highest. Network volatility is computed using daily data in a given month by Chen (2013). Beta is from CAPM using monthly portfolio excess returns. 3f Alpha is Alphas of the Fama-French Three Factors (MKT, SMB, HML) using monthly data and 4f Alpha is 4 factors including momentum (MOM). *LS* is a long-short portfolio formed by long stocks with the lowest 20 % network volatility and short stocks with highest 20% network volatility.. Standard deviation is corrected by Newey-West HAC with 4 lags.

Table 2.15: Industry Subsamples Fama-MacBeth Regression

nodur	Alpha	Size	Beta	BM	NVR
RM	0.54	-0.05	-0.01	0.26**	0.25***
SE	0.39	0.04	0.05	0.10	0.04
durbl	Alpha	Size	Beta	BM	NVR
RM	0.81.	-0.15*	0.04	0.55***	0.27***
SE	0.44	0.06	0.07	0.16	0.08
manuf	Alpha	Size	Beta	BM	NVR
RM	0.89*	-0.09*	-0.03	0.38***	0.13***
SE	0.36	0.04	0.05	0.09	0.04
engy	Alpha	Size	Beta	BM	NVR
RM	1.33**	-0.11*	-0.09	0.45*	0.14*
SE	0.51	0.05	0.07	0.18	0.06
chems	Alpha	Size	Beta	BM	NVR
RM	0.57	-0.09.	-0.03	0.97***	0.16**
SE	0.47	0.05	0.07	0.24	0.05
buseq	Alpha	Size	Beta	BM	NVR
RM	1.61**	-0.17**	-0.08	0.39*	0.21*
SE	0.53	0.06	0.05	0.19	0.09

tele	Alpha	Size	Beta	BM	NVR
RM	1.82**	-0.16*	-0.02	-0.04	0.00
SE	0.62	0.07	0.09	0.26	0.08
util	Alpha	Size	Beta	BM	NVR
RM	0.84**	-0.09*	0.04	0.43.	-0.01
SE	0.31	0.04	0.09	0.23	0.03
shops	Alpha	Size	Beta	BM	NVR
RM	0.53	-0.06	-0.03	0.47***	0.28***
SE	0.41	0.04	0.05	0.11	0.05
hlth	Alpha	Size	Beta	BM	NVR
RM	1.41*	-0.18**	0.05	0.73*	0.30***
SE	0.57	0.06	0.05	0.29	0.07
fin	Alpha	Size	Beta	BM	NVR
RM	0.30	-0.02	-0.01	0.37**	0.16*
SE	0.35	0.05	0.05	0.13	0.07

“.” 10 %, “ * ” 5 %,“ ** ”1 %, “ *** ”0.1% significance level.

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. Dependent variable at each time t is monthly stock returns minus monthly risk free rate which is one month US T-bill rate. *Size* is market value of equity, calculated by the product of monthly closing price and the number of outstanding shares in each month. *BM* stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *NVR* is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage. *tele* and *util* start from July 1964 due to few observations.

Table 2.16: Time Subsamples Fama-MacBeth Regression

1963M8-1982M12	Alpha	Size	Beta	BM	NVR
RM	0.98	-0.15*	0.05	0.23	0.21***
SE	0.65	0.06	0.04	0.13	0.07
1983M1-2012M12	Alpha	Size	Beta	BM	NVR
RM	1.00.	-0.07.	-0.06	0.33***	0.08**
SE	0.52	0.04	0.05	0.12	0.03

"." 10 %, " * " 5 %," ** "1 %, " *** "0.1% significance level.

Note: Samples are stocks traded in the NYSE, Amex, Nasdaq between Sep. 1963 and Dec. 2012, total 592 periods. The First time period is from Aug. 1963 to Dec. 1982 and the second period is from Jan. 1983 to Dec. 2012. Dependent variable at each time t is monthly stock returns minus monthly risk free rate which is one month US T-bill rate. *Size* is market value of equity, calculated by the product of monthly closing price and the number of outstanding shares in each month. *BM* stands for book-to-market ratio. Book value is the annual fiscal year-end book value of common equity and market value is the monthly market of equity. BM is equal to book value divided by market value in the same year. *Beta* is the market beta of the Fama-French Three Factor model with daily returns in a given month. *Net.VR* is Network variance ratio or σ_c^2/σ_e^2. It is defined as ratio of network variance to idiosyncratic variance and normalized to percentage.. *tele* and *util* start from July 1964 due to few observations.

Chapter 3

AN OVERVIEW TO SYSTEMIC RISK MEASURES

3.1 Introduction

The concept of *Systemic Risk* was first introduced after the financial crisis of 2007-2008. Numerous measures have been developed so far. However, there is little consensus of a formal mathematical definition of systemic risk. One reason is because the concept of systemic risk is very broadly defined. Federal Reserve Chairman Ben Bernanke once said:[1] "Systemic risks are developments that threaten the stability in the financial system as a whole and consequently the broader economy, not just that of one or two institutions," Because financial stability is related to different aspects and issues, it is impossible to use one simple measure to capture the whole concept of systemic risk. As a result, systemic risk measures and models are developed from different approaches and different perspectives. This survey tries to summarize various types of systemic risk measures, with a focus on empirical market based systemic measures.

Although the definition of systemic risk has not yet reached consensus, it linked to the development of the modern financial system. Haldane et al. (2009) provides a great summary of the characteristics of the modern financial system: (1) Robust-yet-fragile system: the system is not only risk sharing but also risk amplifying. If a system is highly interconnected, shocks are easier to distribute to each other, and it is also easier to trigger a domino event of defaults. (2) Long tail degree distribution: the degree measures the number of links of a node (financial institution) to other nodes. So the degree distribution is a distribution of the number of links for each node. In the modern financial system, the degree distribution is fat, meaning that most of the nodes have small a number of links but some nodes have a

[1] In a letter sent to Sen. Bob Corker (R., Tenn.) on Oct. 30, 2009.

significantly high number of links. They are the *hubs* in the financial system. This type of the network is robust to random shocks but vulnerable to targeted shocks to hubs. (3) Small world phenomenon: Although degrees of nodes are distributed unequally, transmission of disturbances and shocks is rapid in this system.[2] There are *shortcuts* connecting nodes that are not directed linked to each other.

The most interesting characteristics of the modern financial system is its *robust-yet-fragile* property, which results from the interconnectedness in the financial system. It is not trivial to estimate the robust-yet-fragile property because the connections between each financial institution are unobservable and sometimes confidential. Alternatively, researchers can focus on the fragile phase (tail dependence) and estimate how much damage a financial institution can bring to the entire financial system if the system is in distress, or vice versa. A reduced form model is often used for this branch. Adrian and Brunnermeier (2011) propose the CoVaR measure which is the Value-at-Risk (VaR) of the system when a single financial institution is in distress. Acharya et al. (2010) propose marginal expected shortfall (MES) which is the expected shortfall (ES) of a financial institution when the whole market is in distress. Brownlees and Engle (2015) estimate long run MES (LRMES) by using a dynamic conditional correlation (DCC-GARCH) technique. They further construct the SRISK index based on LRMES to measure the systemic risk contribution of a financial firm to the system.

Another branch of systemic research directly challenges the unobservable connections problem, aiming to build the financial network based on the observable data. Billio et al. (2012) propose to identify links between financial institutions using Granger-causality tests. Chen (2015) uses equity residuals returns covariance as a proxy to financial networks and apply Katz centrality to calculate network risk factor. Diebold and Yılmaz (2014) utilize VAR variance decomposition to define a weighted and directed financial network.

One other approach tries to estimate the joint default probability of a financial system.

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[2]More evidence suggests financial system is scale-free rather than small world. For example, Soramäki et al. (2007) find that the interbank payments in U.S. is a scale free network. There are a few hubs and small peripheries in the network.

This approach is related to tail dependence but is more ambitious. It aims to recover the joint dependence structure and calculates the risk contribution to the system. Huang, Zhou, and Zhu (2009) use CDS spread to calculate the probability of defaults in the financial system and estimate the expected loss of the system. Segoviano and Goodhart (2009) use nonparametric copula to estimate the joint probability of the loss in the system and estimate the cascade effect when a single firm fails in the system.

In addition, there are statistical models like Kritzman et al. (2011) that use principle components technology to construct an absorption ratio in order to predict the downside of the market. Giglio, Kelly, and Pruitt (2014) propose partial quantile regression (PQR) to construct an index of systemic risk. They show that this index has better forecast power over economic activity. Finally, Bisias et al. (2012) survey 31 different systemic risk measures.

To better understand the robust-yet-fragile property, some theoretical models of financial networks are also summarized. Nier et al. (2007) construct an interbanking system model. They investigate the resilience of the interbank network responding to shocks and how it relates to bank capital, the size of the interbank exposures or the degree of connectivity. Similar simulation research is proposed by Gai and Kapadia (2010) and Gai, Haldane, and Kapadia (2011) who study fragility in the financial system under different levels of liquidity and haircut. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013) propose a tractable theoretical model which explains the robust-yet-fragile property. They find that as shocks exceed certain degrees of threshold, a network will show risk amplifying rather than risk absorbing if the topology of the network is more complete. A *phase transition* happens and turns financial networks instable.

It is not straightforward to perform a comparison of different systemic risk measures. Different measures may have different purposes and goals to achieve. However, Benoit et al. (2013) derive MES, CoVaR, SRISK under the same DCC-GARCH framework and successfully compare them together. They also compare the systemic risks with the systematic risk (β) and find the similarity among them. In contrast to this theoretical comparison, a pure empirical comparison is made by Giglio, Kelly, and Pruitt (2014) where the only goal is to compare the forecasting power over different macroeconomic variables.

In considering the relationship between systemic risk measures and macroeconomics, empirical evidence shows how tail risk in the financial market can predict future macroeconomic downturn. Allen, Bali, and Tang (2012) develop a new measure, termed CATFIN based on the Value-at-Risk to estimate tail risk in the financial market. They find that tail risk has strong predictive power in the financial sector to predict future macroeconomic downturn. This paper conducts similar research and finds that VaR in the financial sector has predictive power to the different macroeconomic variables using data from 2000 to 2014.

The structure of this paper is as follows: Section 2 introduces the market based systemic risk measures; Section 3 provides an overview of theoretical financial network models; Section 4 provides systemic risk comparisons; Section 5 provides empirical results on the predictive power of tail risk in the financial sector; and finally, a short conclusion is given in Section 6.

3.2 Market Based Systemic Risk Measures

This section introduces different market-based systemic risk measures. Financial data sometimes is confidential and not easy to access. Even researchers who can access the data find it costly to publish stress testing or other risk evaluations. As a result, market-based risk measures are useful because any researcher can use publicly available data to calculate systemic risk in a timely and economic base. Depending on the approach and data used, this survey classifies systemic risk measures into: (1) Tail dependence; (2) Default probability; (3) Network Measure; and (4) Other categories.

3.2.1 Tail Dependence

3.2.1.1 Δ CoVaR

Adrian and Brunnermeier (2011) propose to measure systemic risk via conditional value-at-risk (CoVaR) in the financial system, conditional on institutions being in a state of distress. An institution's contribution to systemic risk is defined as the difference between CoVaR with the institution being in distress and CoVaR in the median state of the institution. Specifically,

$$Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q \tag{3.1}$$

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=Median^i} \tag{3.2}$$

where i is the financial institution. If j is the system, $\Delta CoVaR_q^{j=sys|i}$ captures the marginal contribution of a particular institution i to the overall systemic risk. X^i is marked to market value asset growth rate of financial institution i.

Adrian and Brunnermeier (2011) use weekly data and calculate $CoVaR$ using the following quantile regression:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \epsilon_t^i \tag{3.3a}$$

$$X_t^{sys} = \alpha_q^{sys|i} + \beta_q^{sys|i} X_t^i + \gamma_q^{sys|i} M_{t-1} + \epsilon_t^{sys|i} \tag{3.3b}$$

where X_t^i is defined as the rate of change of market capitalization multiplied by the book leverage ratio (total assets/book equity):

$$X_t^i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i} \tag{3.4}$$

M_{t-1} are the lagged state variables, including VIX, liquidity spread (3M REPO rate minus 3M T-Bill rate), the change of 3MTB rate, yield spread (the change of 10YTB-3MTB), credit spread (the change of BAA-3MTB), market return, and real estate return-market return.

Finally, $VaR_t^i(q)$ and $CoVaR_t^{j|i}(q)$ can be calculated using coefficients estimated in Equation (3.3a) and (3.3b):

$$VaR_t^i(q) = \hat{\alpha_q^i} + \hat{\gamma_q^i} M_{t-1} \tag{3.5a}$$

$$CoVaR_t^{Sys|i}(q) = \hat{\alpha_q^{sys|i}} + \hat{\beta_q^{sys|i}} VaR_t^i(q) + \hat{\gamma_q^{sys|i}} M_{t-1} \tag{3.5b}$$

The $\Delta CoVaR_q^{Sys|i}(q)$ for each institute i can be calculated as:

$$\begin{aligned} \Delta CoVaR_q^{Sys|i}(q) &= CoVaR_q^{Sys|i} - CoVaR_{50\%}^{Sys|i} \\ &= \hat{\beta_q^{sys|i}} (VaR_t^i(q) - VaR_t^i(50\%)) \end{aligned} \tag{3.6}$$

3.2.1.2 Systemic Expected Shortfall and Marginal Expected Shortfall

Acharya et al. (2010) argue that each financial institution's contribution to systemic risk can be measured as its systemic expected shortfall (SES), i.e., its propensity to be undercapitalized when the system as a whole is undercapitalized. For example, a bank's systemic expected shortfall is defined as :

$$SES^i \equiv E[za^i - \omega_1^i | W < zA] \tag{3.7}$$

where ω_1^i is financial institution's equity, W is the system's total equity, z is some degree of fraction, a^i is financial institution's assets and A is the system's total assets.

SES is a theoretical construction and the authors use the following three measures to proxy it:

1. The outcome of stress tests performed by regulators. The SES metric of a firm here is defined as the recommended capital that it was required to raise.

2. The decline in equity valuations of large financial firms during the crisis, as measured by their cumulative equity return.

3. The widening of the credit default swap spreads of large financial firms as measured by their cumulative CDS spread.

Marginal expected shortfall of financial institution i is defined as net equity returns during bad market outcomes.

$$MES_{5\%}^i \equiv -E[\frac{\omega_1^i}{\omega_0^i} - 1 | I_{5\%}] \tag{3.8}$$

where ω_0^i is the initial equity and $I_{5\%}$ is the worst 5% market outcomes. Acharya et al. (2010) show that sytemic expected shortfall is related to marginal expected shortfall and leverage as:

$$\frac{SES^i}{\omega_0^i} = \frac{za^i}{\omega_0^i} - 1 + kMES_{5\%}^i + \delta^i \tag{3.9}$$

The first component is excess ex ante leverage. The second component is pre-crisis MES scaled by extreme tail distribution, and the third component is the adjustment term.

Empirically, MES and leverage ratio is calculated using the following equations:

$$MES_{5\%} = \frac{\sum_{system\, is\, in\, its\, 5\%} R_t}{\#days} \tag{3.10a}$$

$$LVG = \frac{book\, assets - book\, equity + market\, equity}{market\, equity} \tag{3.10b}$$

Besides original MES, Acharya et al. (2010) also provide several different variations of MES:

- W-MES, an exponentially weighted MES, which uses exponentially declining weights ($\lambda = 0.94$ following the Risk Metrics parameter) on past observations to estimate the average equity returns on the top 5% of badly performing days in the market;

- D-MES, a dynamic approach to estimating MES, which uses a dynamic conditional correlation (DCC) model with fat idiosyncratic tails;

- F-MES, which uses the financial industry return series obtained from the data on 30 industry portfolios provided by Kenneth French's website as market returns;

- CDS-MES, which uses credit default swaps (CDS) returns to form MES.

3.2.1.3 SRISK: A Conditional Capital Shortfall Index for Systemic Risk Measurement

Brownlees and Engle (2015) propose a systemic risk measure (SRISK) that captures the capital shortage of a firm conditional on a systemic event. They define the capital shortfall of firm i on day t as:

$$CS_{i,t} = kA_{i,t} - W_{i,t} = k(D_{i,t} + W_{i,t}) - W_{i,t}$$

where W_{it} is the market value of equity, D_{it} is the book value of debt, A_{it} is the value of quasi assets and k is the prudential capital fraction. The capital shortfall can be thought of as negative working capital of the firm.

A systemic event is defined as a market declining below a threshold C over a time horizon h. SRISK is then defined as :

$$\begin{aligned} SRISK_{i,t} &= E_t(CS_{i,t+h}|R_{m,t+1:t+h} < C), \\ &= kE_t(D_{i,t+h}|R_{m,t+1:t+h} < C) - (1-k)E_t(W_{i,t+h}|R_{m,t+1:t+h} < C) \end{aligned}$$

Assuming that in the case of a systemic event, debt cannot be renegotiated, it implies that $E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) = D_{i,t}$, therefore:

$$SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}(1 + LRMES_{i,t}), \tag{3.11}$$

$$= W_{i,t}[kLVG_{i,t} - (1-k)LRMES_{i,t}] \tag{3.12}$$

where $LVG_{i,t} = (D_{i,t} + W_{i,t})/W_{i,t}$ and $LRMES = E_t(R_{i,t+1:t+h}|R_{m,t+1:t+h} < C)$ is the long run MES. Equation (3.11) also shows SRISK is higher when the firm size, the leverage or the tail dependence on the market is higher. In addition, the total amount of systemic risk in the financial system is :

$$SRISK_t = \sum_{i=1}^{N} \max\left(SRISK_{i,t}, 0\right) \tag{3.13}$$

Brownlees and Engle (2015) further assume that the firm returns $r_{i,t}$ and the market compound returns $r_{m,t}$ follow an unspecified distribution conditional on the information set F_{t-1} with zero mean and time varying covariance. The time varying volatility and correlation is specified as a TGARCH-DCC model. In this case, LRMES is generally not available in closed form. The authors provide a simulation based procedure to obtain LRMES predictions. Using the Monte Carlo average of the simulated returns, the LRMES of simulation with sample S at horizon h is:

$$LRMES_{i,t} = \frac{\sum_{s=1}^{S} R^s_{i,t+1:t+h} I\{R^s_{m,t+1:t+h}\}}{\sum_{s=1}^{S} I\{R^s_{m,t+1:t+h}\}} \tag{3.14}$$

where R^s is simulated returns and I is the indicator function.

3.2.1.4 CATFIN

Unlike the previous "micro-level" systemic risk measures, Allen, Bali, and Tang (2012) intend to measure an overall systemic risk on macroeconomics, especially macroeconomic forecasting power. They propose a systemic risk measure that calculates the aggregate level of risk taking in the financial sector rather than an individual bank's systemic risk exposures. This measure is denoted as *CATFIN*, and is used to forecast the likelihood that systemic risk taking in the banking system as a whole will have detrimental real macroeconomic effects. CATFIN complements micro-level systemic risk measures because systemic risk can emerge through general economic factors that cause the financial market to freeze credit, trigger catastrophic declines in asset price and reduce liquidity.

CATFIN is estimated using both value-at-risk (VaR) and expected shortfall (ES) methodologies, although the former is more focused. For every month, VaR is estimated using three approaches: generalized Pareto distribution (GPD), skewed generalized error distribution (SGED) and a nonparametric method, CATFIN is the average of the three.

For GPD, 10 % quantiles of monthly returns for financial firms (SIC code $\geq$ 6000 and SIC $\leq$ 6999) in excess of the one-month Treasury bill rate are used. The parameters $\mu, \xi, and \sigma$ of the GPD are estimated cross-sectionally for each month:

$$G_{min,\xi}(M; \mu, \sigma) = [1 + \xi \left(\frac{\mu - M}{\sigma} \right)]^{-\frac{1}{\xi}} \tag{3.15}$$

For each month from January 1973 to December 2009, the 1 % VaR of GPD (ϑ_{GPD}) is calculated using the estimated parameters. The VaR of GPD (ϑ_{GPD}) has a closed form as follows:

$$\vartheta_{GPD} = \mu + \left(\frac{\sigma}{\xi} \right) \left[\left(\frac{\alpha N}{n}^{-\xi} - 1 \right) \right] \tag{3.16}$$

where n and N are the numbers of extremes and the numbers of total data points, respectively. μ, σ and ξ are the location, scale and shape parameters of the GPD.

VaR of SGED is calculated in a similar manner. The probability density function for the

SGED is:

$$f(r_i;\mu,\sigma,\kappa,\lambda)=\frac{C}{\sigma}exp\left(-\frac{1}{[1+sign(r_i-\mu+\theta\sigma)\lambda]^{\kappa}\theta^{\kappa}\sigma^{\kappa}}|r_i-\mu+\theta\sigma|^{\kappa}\right) \tag{3.17}$$

where $C=\kappa/(2\theta\Gamma(1/\kappa))$, $\theta=\Gamma(1/\kappa)^{0.5}\Gamma(3/\kappa)^{-0.5}S(\lambda)^{-1}$, $S(\lambda)=\sqrt{1+3\lambda^2-4A^2\lambda^2}$, $A=\Gamma(1/\kappa)\Gamma(1/\kappa)^{-0.5}\Gamma(3/\kappa)^{-0.5}$, μ and σ are the mean and standard deviation of excess stock returns r, λ is a skewness parameter, $sign$ is the sign function and $\Gamma(\cdot)$ is the gamma function.

To derive the 1 % VaR, they use the cross-section of excess returns on financial firms and estimate the parameters of the SGED density. Given the estimates of the parameters $(\mu,\sigma,\kappa,\lambda)$, SGED VaR ($\vartheta_{SGED}$) is calculated numerically at the level α by :

$$\int_{-\infty}^{\vartheta_{SGED}(\alpha)} f_{\mu,\sigma,\kappa,\lambda}(z)dz=\alpha$$

For the 1 % nonparametric method VaR (ϑ_{NP}) in a given month, it is measured as the cutoff point for the lower one percentile of the monthly excess returns on financial firms cross-sectionally.

The CATFIN for each month is the arithmetic average of ϑ_{GPD}, ϑ_{SGED} and ϑ_{NP}. Their sample period is between January 1973 and December 2009. They show that CATFIN has predicted the CFNAI index (The Chicago Fed National Activity Index) up to six months in advance by running the predictive regression as follows:

$$CFNAI_{t+n}=\alpha+\gamma CATFIN_t+\beta X_t+\sum_{i=1}^{12}\lambda_i CFNAI_{t-i+1}+\epsilon_{t+n} \tag{3.18}$$

where X_t denotes a vector of controlled variables.[3] The γ is negative and significant up to six months. They conclude that CATFIN has strong predictive power over macroeconomic variables.

They also show that the result holds if they (1) use ES rather than VaR ; (2) use the GDP growth rate, the NBER recession dummy variable, the Aruoba-Diebold-Scotti (ADS) Business Conditions Index maintained by the Federal Reserve Bank of Philadelphia or the

[3]See Allen, Bali, and Tang (2012) for details.

Kansas City Financial Stress Index instead of CFNAI; and (3) control for conditional tail risk (Kelly and Jiang (2014)), MES (Acharya, Engle, and Richardson (2012)) or Merton's option based distance-to-default.

Interestingly, they find that the VaR constructed by non-financial firms does not have predictive power over macroeconomic variables. However, no reason is given and it is left for future research.

3.2.2 Default Probability: CDS Spread

Credit Default Swap (CDS) is also broadly used to measure systemic risks. The reason is because CDS contains default information of a reference entity. CDS is designed to transfer the credit exposure of bonds issued by a reference entity between two parties. The buyer of the CDS will make payments to the seller until maturity under a contract. When the bond defaults, the seller will pay off a third party debt to the buyer instead. As a result, the buyer hedges their position by purchasing CDS. See Hull and White (2000), Hull and White (2001) or Lando (2004) for details.

CDS spread contains information on the probability of default of a reference entity. A systemic risk event will happen when a group of firms default together. If the default probability is known, it is possible to estimate risks of a systemic event. However, the dependence structure remains unknown and inestimable in practice without further assumption. Researchers often choose different kinds of copula to estimate the dependence structure of a financial system. A copula is a statistical tool that combines marginal probability into join probability. Segoviano and Goodhart (2009) estimate joint default probability using non-parametric copula, whereas Oh and Patton (2013) estimate time-varying systemic risk using dynamic copula.

3.2.2.1 Distressed Insurance Premium

Huang, Zhou, and Zhu (2009) propose a hypothetical insurance premium against a systemic financial distress where total losses exceed a given threshold of 15 % of major banks' liability.

They use CDS spread to calculate the probability of default as well as high-frequency equity data to calculate *forecasted* asset return correlation. They estimate the distressed insurance premium with these two variables using Monte Carlo simulation.

Risk neutral probability of default is derived from the single-name CDS spreads s:

$$PD_{i,t} = \frac{a_t s_{i,t}}{a_t LGD_{i,t} + b_t s_{i,t}}, \tag{3.19}$$

where $a_t \equiv \int_t^{t+T} e^{-r\pi} d\pi$ and $b_t \equiv \int_t^{t+T} \pi e^{-r\pi} d\pi$, and LGD is the loss give default and r is the risk-free rate.

The assets returns correlation is proxied by equity returns correlation since the leverage is nearly constant in a short time. Using 30-minute intervals of high-frequency tick-by-tick equity data from the TAQ database, they estimate the pairwise realized returns correlation of 12 major banks in U.S. The forecasted correlation is estimated by the following predictive regression:

$$\rho_{t,t+12} = c + k_1 \rho_{t-12,t} + \sum_{i=1}^{l} k_{2i} \rho_{t-i,t-i+1} + \eta X_t + v_t \tag{3.20}$$

where ρ refers to the average asset returns correlation and time frequency is weekly. X includes a list of financial market variables such as the FED fund rate, term spread, one-month S&P500 returns and VIX.

To compute the distressed insurance premium, they construct a hypothetical portfolio that consists of debt instruments issued by member banks, weighted by the liability size of each bank. Technically, it is calculated as the risk-neutral expectation of portfolio credit losses that equal or exceed 15 % of the sectors total liabilities. The expectation is calculated using Monte Carlo method of Tarashev and Zhu (2008).

They assume that the loss-given-default (LGD) follows a symmetric triangular distribution with a mean of 0.55 and in the range of [0.1, 1]. The mean LGD of 0.55 is taken down from the Basel II IRB formula.

3.2.2.2 Default Risk of Seller and Reference Entity

The above measures actually ignore the possibility of default by the seller, although it is near zero in a normal time. However, it did matter in the 2008 financial crisis when AIG failed to provide insurance payments. CDS spread should reflect joint default risk of the reference entity and counterparty, not only the default risk of the reference entity. As a result, the counterparty risk can be calculated as the difference between joint default probability and default probability implied by bond yield. Giglio (2011) tries to address this counterparty risk by using linear programming to construct the tightest possible bounds on systemic default risk of degree r. It is defined as the probability of at least r financial institutions defaulting together with the available information set containing marginal and pairwise default probabilities. In a three institution example, A_i is the default event of bank i and the probability is defined as following:

$$\begin{aligned}&P(A_i) = 0.2,\ i = 1, 2, 3;\\&P(A_1 \cap A_2) = P(A_3 \cap A_2) = 0.07,\ P(A_1 \cap A_3) = 0.01\end{aligned}$$

As a result,

$$\begin{aligned}0.45 &\leq P(A_1 \cup A_2 \cup A_3) \leq 0.46;\\0.13 &\leq P((A_1 \cap A_2) \cup (A_2 \cap A_3) \cup (A_1 \cap A_3)) \leq 0.15;\\0 &\leq P(A_1 \cap A_2 \cap A_3) \leq 0.01\end{aligned}$$

In general, for each institution i and its bond k:

$$\begin{aligned}B(t,T) = c&\left(\sum_{s=t+1}^{T} \delta(t,s)(1-h_t)^{s-t}(1-\gamma_t)^{s-t}\right) +\\&\delta(t,T)(1-h_t)^{T-t}(1-\gamma_t)^{T-t} +\\&R\left(\sum_{s=t+1}^{T} \delta(t,s)(1-h_t)^{s-t-1}(1-\gamma_t)^{s-t-1}h_t\right)\end{aligned}$$

where $\delta(t,s)$ is the risk free discount factor, c is the coupon payment, B is the bond price, h_t is the hazardous rate, γ_t is the liquidity premium, and R is recovery rate. γ_t is unobservable and imposed a lower bond so that probability of default is $h_t(\gamma_t)$. The dynamics for CDS spread are:

$$\begin{aligned}&\sum_{s=t}^{T-1}\delta(t,s)(1-h_t^i-h_t^j+h_t^{ij})^{s-t}z_t^{ji}\\&=\sum_{s=t+1}^{T}\delta(t,s)(1-h_t^i-h_t^j+h_t^{ij})^{s-t-1}\{[h_t^i-h_t^{ij}](1-R)+h_t^{ij}S(1-R)\}\end{aligned}$$

where z_t^{ji} is the CDS spread, h_t^{ij} is the hazardous rate of double default of seller and reference entity, S is the recovery rate at double default. RHS is the PV of protection seller and LHS is the expected payment if default.

Empirically, Giglio (2011) finds that systemic risk increases in the early 2009 before the stress test release. However, idiosyncratic risk (at least one financial institution defaults) is high while systemic risk (at least more than one financial institutions default) is low in early 2008, as opposed to other systemic risk measure.

Other papers that consider counterparty risks include Duffie (2011b), Singh and Basurto (2008), Duffie (2011a), Arora, Gandhi, and Longstaff (2012) and Gorton and Metrick (2012).

Hovakimian, Kane, and Laeven (2012) adopt Merton (1974)'s corporate debt model. They take the value of banking sector losses from systemic default risk as the value of a put option written on a portfolio of aggregate bank assets. As a result, an individual bank's systemic risk is its contribution to the value of this potential sector-wide put option.

3.2.3 Network Measure

Instead of estimating the expected loss of a financial system when a financial institution is distressed, the network approach tries to establish the interconnectedness of a financial network using public available data. The question in this approach is to find or estimate links which are often unobserved between financial institutions. Once the links are established, the network related measures such as degree, betweenness and centrality can be calculated.

3.2.3.1 Network Risk

Chen (2015) notices that some stocks are prone to co-move with their related stocks and become *network riskier*. They are also more vulnerable to shocks transmitted in a bad time. He proposes a new econometric procedure to estimate network risk using a factor model, specifically,

$$r_t = \Sigma_{k=1}^{K} \beta_k f_{k,t} + e_t,\ t = 1 \cdots T \tag{3.21}$$

$$e_t = b^c f_t^c + \eta_t \tag{3.22}$$

where r_t is an N × 1 vector of excess returns, β_k is a N × 1 vector of market risk exposures, and $f_{k,t}$ is an observed exogenous market risk factor. e_t is an N × 1 vector of residual returns and assumed to be orthogonal to f_t. b^c is N × 1 unobserved factor loading. f_t^c is an observed 1 × 1 network risk factor and will be constructed later. η_t is i.i.d. idiosyncratic disturbance.

To construct the network risk factor f_t^c, compute the *Katz Centrality* x_i with :

$$x_i = \gamma \sum_{j=1}^{N} A_{ij} x_j + \beta_i,\ i = 1 \cdots N \tag{3.23}$$

β_i is the nodal attribute and very often β_i is set to 1, but is not restricted to it. γ is less than the inverse of the highest eigenvalue of matrix A. Finally, let $X = [x_1, x_2, \cdots, x_N]'$ and network risk factor $f_t^c = X' e_t$.

The advantage of incorporating network risk into a factor model is the use of the factor risk decomposition analysis. Let $\eta_t = \sigma z_t$ where z_t is i.i.d. with a mean of 0 and a standard deviation of 1. σ is considered as exposure to pure idiosyncratic risk. By Euler's theorem, any linear risk metrics of r_t: Value-at-Risk, Standard deviation and Expected shortfall can be decomposed linearly:

$$RM(r_i) = \Sigma_{k=1}^{K} \beta_k \frac{\partial RM}{\partial \beta_k} + b_c \frac{\partial RM}{\partial b_c} + \sigma_\eta \frac{\partial RM}{\partial \sigma_\eta} \tag{3.24}$$

where RM can be Std, VaR or ES. $b_c \frac{\partial RM}{\partial b_c}$ is interpreted as network risk coming from local shocks and $\sigma_\eta \frac{\partial RM}{\partial \sigma_\eta}$ is *pure* idiosyncratic risk.

An empirical study shows that the component of the standard deviation, value-at-risk or expected shortfall attributing to the network risk better explains and predicts stocks performance than their conventional counterparts did in the 2007-2008 financial crisis.

3.2.3.2 Granger-causality Network

Billio et al. (2012) propose several econometric measures of systemic risk to capture the interconnectedness among the monthly returns of hedge funds, banks, brokers, and insurance companies. One of the measures uses the Granger-causality test to identify links between different financial institutions.

Under efficient market assumption, lagged return should not have predictive power. Thus Granger-causality effect can be viewed as return-spillover effect among the market participants due to the propagation of return. For any two financial institutions i and j, if j Granger causes i, a directional edge is established from j to i ($j \to i$). If a system contains N financial institutions, there are most $(N-1)(N-2)/2$ edges in a network. Several network level measures can be calculated, for example, the degree of Granger-causality (DGC) :

$$DGC = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \to i) \tag{3.25}$$

They find that DGC increases during crisis and the number of banks Granger-caused hedge funds is much higher than its inverse relationship during the crisis of the 2007-2008, suggesting banks are important for the financial network.

Since linear Granger-causality cannot catch the higher order causal correlation, Billio et al. (2012) also provide the higher moment version of Granger-causality network; for example, j's volatility leads to i's volatility. The method is based on a regime-switching model, suppose equity returns follow:

$$R_{j,t} = \mu(Z_{j,t}) + \sigma(Z_{j,t}) u_{j,t}$$

where Z is two state Markov chain with transition probability:

$$P(Z_{j,t}, Z_{i,t}|Z_{j,t-1}, Z_{i,t-1}) = P(Z_{j,t}|Z_{i,t}, Z_{j,t-1}, Z_{i,t-1}) \\ \times P(Z_{i,t}|Z_{j,t-1}, Z_{i,t-1})$$

if j not $\rightarrow i$:

$$P(Z_{i,t}|Z_{j,t-1}, Z_{i,t-1}) = P(Z_{i,t}|Z_{i,t-1})$$

and vice versa

This shows that a nonlinear Granger-causality likelihood test shows more connection than the linear case.

3.2.3.3 VAR Forecasting Error Networks

Diebold and Yılmaz (2014) use VAR forecasting error variance decompositions to define a weighted and directed network. They also define different connectedness measures that are intimately related to key measures of connectedness used in the network literature. Let d^H_{ij} denote the ij-th H-step variance decomposition component; that is, the fraction of variable i' H-step forecast error variable due to shocks in variable j. Several connectedness measures can be defined. *Pairwise directional connectedness* from j to i is defined as:

$$C^H_{i\leftarrow j} = d^H_{ij},\ \forall i \neq j,\ i, j = 1 \cdots N \tag{3.26}$$

In general $C^H_{i\leftarrow j} \neq C^H_{j\leftarrow i}$, so *Net pairwise directional connectedness* is:

$$C^H_{ij} = C^H_{j\leftarrow i} - C^H_{i\leftarrow j} \tag{3.27}$$

In aggregate level, *total directional connectedness form others to i* is:

$$C^H_{i\leftarrow \bullet} = \sum_{j=1, j\neq i}^{N} d^H_{ij} \tag{3.28}$$

and *total directional connectedness to others from j* is:

$$C^H_{\bullet\leftarrow j} = \sum_{i=1, j\neq i}^{N} d^H_{ij} \tag{3.29}$$

Finally, *total connectedness* is:

$$C^H = \frac{1}{N} \sum_{i,j=1,j\neq i}^{N} d_{ij}^H \tag{3.30}$$

The caveat of Diebold and Yılmaz (2014) is that they link the current econometric techniques to network topology theory to measure systemic risk. Unlike other systemic measures built on the pairwise relationship between a market and a financial institution, they provide a system-wide measure which is rigorous in theory and can be implemented easily in practice.

The most closely related work to Diebold and Yılmaz (2014) is the Granger-causality network of Billio et al. (2012). There is a trade-off between two measures. On the one hand, variance decomposition is more appealing due to the construction of a directional and weighted network. (Granger-causality will produce an unweighted network). On the other hand, VAR requires identifying assumptions and is limited to dimensions, whereas Granger-causality is less demanding on that.

The authors also point out the limit of the connectedness measures. It generally will not and should not be robust to the choices of reference universe. The choice of the objects of interest will have important implications for the appropriate approximating model, such as serial correlation or conditional heteroskedastic, etc.

3.2.4 Others

3.2.4.1 Principle Components Analysis

Billio et al. (2012) provide another systemic risk measure based on Principle Components Analysis. The contribution $PCAS_{i,n}$ of institution i to the risk of the system conditional on a strong common component across the returns of all financial institutions:

$$\begin{aligned} PCAS_{i,n} &= \frac{1}{2}\frac{\sigma_i^2}{\sigma_S^2}\frac{\partial \sigma_S^2}{\partial \sigma_i^2}|_{h_n \geq H} \\ &= \sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_S^2} L_{ik}^2 \lambda_k |_{h_n \geq H} \end{aligned} \tag{3.31}$$

If returns follows multivariate Gaussian, this measure is related to the co-kurtosis of multivariate distribution.

This measure is similar to the *Absorption Ratio* (AR) of Kritzman et al. (2011) where they utilize the variance ratio derived from principle components analysis. The AR is defined as the proportion of the variance in the system explained by a fixed number of common factors. A higher AR shows that markets are more closely moved, suggesting that shocks will propagate through the system more quickly.

3.3 Overview of Theoretical Financial Network Models

Besides systemic risk measures based on the market data, a new type of financial economics model has been developed, the *financial network model*. Although this paper tends to survey empirical systemic risk models, it is useful to provide readers a brief overview of the new financial network model, since *interconnectedness* is one of the consequences of the modern financial system. As Schweitzer (2009) points out, network modeling in a financial system is important to understanding systemic risk.[4]

It is noted that there are different sources resulting in a systemic risk event, such as liquidity hoarding, procyclical leverage, counterparty risks and uncertainty, and even model misspecification of debt linked financial derivatives. This paper will not survey these types of models. Interested readers are referred to Benoit et al. (2015) for further details.

3.3.1 Characteristics of the Modern Financial System

Haldane et al. (2009) provide a great overview of the modern financial system. It is not a theoretical paper,[5] but it provides remarkable insights on the systemic risk of the modern financial system. There are three characteristics of the modern financial system:

1. Robust-yet-fragile system: the system is robust because it shares the shocks if someone

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[4]Interested readers are also referred to Allen and Babus (2008) for a great review of network models in finance.

[5]Please refer to Haldane and May (2011) for a theoretical model.

fails in the system. If one bank fails, its counterparts will help to absorb the shocks. As a result, the systemic breakdown is very rare to see. However, the channel amplifies the shock if some certain important players fail and their counterparts fail to absorb the shock and default, resulting in *cascade* effects in the system and eventually wiping out the system.

2. Long tail degree distribution: the degree of network is the number of the connections (edges) from one financial institution (node) to its counterparts. The degree distribution is right-skewed. Most of the nodes are connected to a small number of nodes but there are some hub nodes connected almost most of the nodes. The feature of this network is that the system is robust to random shocks since most of them do not have many neighbors. The shock will be controlled regionally. However, if the shock hits the hub nodes, it will create a huge impact on the system.

3. Small world: Although most of the nodes connect to small numbers of other nodes, the shock travels rapidly from one side of the nodes to the other side of the nodes (diameter) due to the hub-spoke structure in the network. A low degree node will connect to a small hub and a small hub connects to a huge hub. These hubs feature as a shortcut and help shocks spread out.

3.3.2 A Network Interbanking Model

Nier et al. (2007) use a network model to study the resilience of the interbank system. Their model shows how capital, the sizes of the interbank exposures and degrees of connectivity affect the stability of the financial system. It is a small model but has a lot of insights.

The model contains N banks (nodes). p_{ij} is the probability that Bank i has lent to another Bank j. Their model is a random network model. Other variables are defined as followed:

- a: an individual banks assets; $a_i = e_i + i_i$, where $i = 1 \cdots \mathrm{N}$;

- e: external assets (investors borrowing);
- i: interbank assets (other banks borrowing).
- l: a banks liabilities; $l_i = c_i + d_i + b_i$, where $i = 1 \cdots \text{N}$;
- c: net worth of a bank;
- d: customer deposits;
- b: interbank borrowing;
- $\beta = E/A$: the percentage of external assets in total assets where the capital letters are aggregate variables.
- $\theta = I/A$: θ is the percentage of interbank assets in total assets.
- $\omega = I/Z$: Z is the total number of links. ω is how much one bank lends to another.
- Net worth is set as a fixed proportion γ of total assets at bank level, that is, $c_i = \gamma a_i$

When a shock s_i occurs to a bank i, s_i is absorbed by c_i first. If the bank does not have enough net worth, then the bank defaults and the residual loss $s_i - c_i$ transmits to its creditor banks (interbank borrowing b_i). If $s_i - c_i > b_i$, then all the loss cannot be absorbed by creditor banks, so the depositor has to absorb the loss of $s_i - c_i - b_i$. It is assumed that all creditor banks receive an equal share of the residual shock, which in turn, is first absorbed by their net worth.

The price of assets will drop if any banks sell their assets on the market. The price dynamics are: $P = e^{-\alpha x}$. P is price, α is measure of illiquidity, and x is the quantity of externality assets. Therefore, price decreases when x increases. It is also assumed that $P(0) = 1$ and P(∞)=0. The remaining externality assets after the shock are sold on the market with price P. Thus the first bank will suffer an additional cost $1 - P$ per unit of external assets sold. The fire sale of assets will be triggered if a great amount of assets is sold to the market.

They find that (1) if the percentage of net worth γ is higher, the numbers of default is lower, although, the relationship is not linear and that (2) interbank connectivity p has two contradicting effects: shock transmitting and shock absorbing. When p is high, shocks transmit more rapidly and the numbers of defaults are high. However, the numbers of defaults will not increase without limits. When p is high enough, there are more banks to absorb shocks and thus the system is stabilized.

It is noted that they assume random probability in the paper but the degree distribution is highly skewed in the real world. Few banks have high numbers of interbank linkages whereas most of the banks only have few links. See Boss et al. (2004) for an Austrian bank network example or Cont, Moussa, and Santos (2011) for a Brazilian bank example.

Other similar studies such as Gai and Kapadia (2010) examine the capital adequacy, liquidity hoarding and network structure. They show that the financial system is indeed robust-yet-fragile. Gai, Haldane, and Kapadia (2011) study the fragility of financial networks under different haircut shocks with heavy-tailed degree network structure. They suggest higher liquid assets holding, systemic surcharges, network transparency and a central-clearing market. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2013) develop a tractable theoretical model to explain the *robust-yet-fragile* phenomenon. They find that when shocks exceed a certain threshold, a system becomes risk amplifying rather than risk absorbing if a network is complete. A so called *phase transition* happens and turns financial networks instable.

Acemoglu et al. (2012) propose a network macroeconomic model. They argue that microeconomic idiosyncratic shocks may lead to aggregate fluctuations in the presence of intersectoral inputoutput linkages. As a result, the network topology of different sectors will have an effect on the volatility of the aggregate economy. He and Krishnamurthy (2014) propose a macroeconomic model with a financial intermediation sector and study the reciprocal feedback effects.

Finally, Chinazzi and Fagiolo (2013) survey theoretical network-based models of systemic risk and point out several challenges in the future, including the causal links between network structure, the likelihood of systemic risk and the empirical knowledge about real-world financial-network structures to calibrate theoretical models.

3.4 Comparison of Systemic Risk Measures

The causes of a systemic event are profound and cannot be simply explained by a single factor. As a result, different measures are developed to try to capture different causes from different perspectives. It is not straightforward to make a comparison between different systemic risk measures.

As discussed in the previous section, some measures such as ΔCoVaR, MES and SRISK are based on the tail dependence. Some measures like distressed insurance premium are based on CDS spread and others like Granger-causality and network risk are based on network connectivity. It is meaningless to do a line-by-line comparison because they refer to different causes of systemic risk. Although one may want to know the rankings of systemic important financial institutions, a simple index or measure cannot represent the whole picture.

Even though a simple comparison is almost impossible, some measures are similar in nature and is possible to compare. This idea gives the birth of the possibility of theoretical comparison.

3.4.1 Theoretical Comparison

ΔCoVaR, MES and SRISK are similar in construction among the many systemic risk measures. They are based on the tail dependence of the market returns and the returns of a financial institution. It is possible to compare them in a common framework. Benoit et al. (2013) derive the risk measures in a common framework and try to uncover the driving forces of each systemic risk measure. They assume the market returns and financial institution returns follow bivariate distribution D :

$$r_{mt} = \sigma_{mt}\epsilon_{mt}$$
$$r_{it} = \sigma_{it}\rho_{it}\epsilon_{mt} + \sigma_{it}\sqrt{1-\rho_{it}^2}\xi_{it},\ (\epsilon_{mt}, \xi_{it}) \sim D$$

where $\nu = (\epsilon_{mt}, \xi_{it})'$ satisfied $\mathbf{E}(\nu) = 0$ and $\mathbf{E}(\nu\nu') = I_2$, and D denotes the bivariate distribution of the standardized innovations.

Under this framework, ΔCoVaR, MES and SRISK can be rewritten as:[6]

$$MES_{it}(\alpha) = \frac{\rho_{it}\sigma_{it}}{\sigma_{mt}}\mathbf{E}\left(r_{mt}|r_{mt} < VaR_{mt}(\alpha)\right) = \beta_{it}ES_{mt}(\alpha)$$
$$SRISK_{it} \cong kD_{it} - (1-k)W_{it} \times exp(18 \times \beta_{it} \times ES_{mt}(\alpha))$$
$$\Delta CoVaR_{it}(\alpha) = \frac{\rho_{it}\sigma_{mt}}{\sigma_{it}} \times (VaR_{it}(\alpha) - VaR_{it}(0.5))$$

They find theoretically that (1) MES is positively proportional to systematic risk measure β, (2) ΔCoVaR is strongly related to β, and (3) rankings of a systemic risk firm can be different based on different measures.

Empirically, they use an unbalanced panel of 94 firms with daily returns from January 2000 to December 2010. They show that (1) β is positively related to MES and explains 95 % of the variability of MES cross-sectionally; (2) liability can explain 83 % of the variability of SRISK cross-sectionally; and (3) although ΔCoVaR is not related to VaR cross-sectionally, it is equivalent to VaR in Time Series.

3.4.2 Statistical Dimension Reduction

Another way to compare different systemic risk measures is pure empirically driven. It does not aim to estimate a specific aspect of systemic risk, but rather evaluates systemic risk measures with respect to a specific empirical criterion: *Forecasting Power*. Ultimately, the goal is to determine how good these measures are at macroeconomic forecasting. Giglio,

[6] SRISK is defined according to Acharya, Engle, and Richardson (2012) which is slightly different from Brownlees and Engle (2015).

Kelly, and Pruitt (2014) try to compare systemic risk measures based on the empirical forecasting power evaluation. They construct time series of different systemic risk measures using long range of data in the US, the UK and the EU.[7] Some of the measures are cross-sectionally based, estimating the largest 20 financial institutions and summing them together as the time series systemic risk. For out-of-sample 20th percentile industrial production growth forecasts, Allen, Bali, and Tang (2012)'s CATFIN Value-at-Risk measure performs the best in the US, UK, and EU samples. Kritzman and Li (2010)'s measure of turbulence is significant in the US data but not in the UK or EU data. Market leverage is also good for the US data from 1976-2012.

In addition to comparisons, Giglio, Kelly, and Pruitt (2014) proceed a step further. They synthesize a systemic risk index from different systemic risk measures using either principle components quantile regression (PCQR) or partial quantile regression (PQR).[8] Principle components analysis aims to reduce the dimension statistically and build a common factor among all time series variables. A similar approach has been used widely in finance and macroeconomics forecasting literature. See Stock and Watson (2002a), Stock and Watson (2002b), Bai and Ng (2008) and Ludvigson and Ng (2009) for examples.

They find that the systemic risk indexes via PQR provide significant predictive information out-of-sample over other 22 systemic risk measures for the lower tail of future macroeconomic shocks. It suggests that an overall index absorbing different aspects of systemic risks works better. They also find that the indexes have better predictability for the lower tail (20th percentile) than the median of macroeconomic variables.

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[7]Sample for the US is the entire postwar era 1946-2011.14 For the UK, data begin in 1978. EU sample begins in 1994.

[8]See Kelly and Pruitt (2014) for detail.

3.5 Empirics: Tail Risk in the Financial Sector and Macroeconomics

The financial market has played an increasingly important role in macroeconomics in the past 20 years.[9] Shocks from the financial sector are more likely to spread out to other sectors and impact the economy. Bad shocks are especially more influential than good shocks. As a result, the lower tail risk in the financial sector is able to predict future macroeconomics activities. This section provides some empirical evidence.

3.5.1 Data

To estimate the tail risk of the financial sector, I calculate empirical 5 % Value-at-Risk (VaR) of the stock returns of big financial institutions cross-sectionally in a given month from March 2000 to August 2014.[10] The VaR shows the 5 % loss in the financial sector. The formula is

$$VaR_{\alpha}(R) = F_R^{-1}(\alpha) \tag{3.32}$$

where R is the random variable and F^{-1} is the quantile function of random variable R. α is the probability level and is equal to 5% in this empirical study. The VaR in the financial sector time series is termed FinVaR.

The top-left of Figure 3.1 shows the empirical time series Value-at-Risk of the financial sector from March 2000 to August 2014. The shaded area shows the NBER recession indicator. The biggest loss in the financial sector happened in the recent 2007-2008 financial crisis. The worst affected 5 % of the financial sector lost more than 60 % of its market capitalization. By comparison the earlier dot-com bubble crisis had a smaller loss of around 20 %. The first row of Table 3.1 shows that the mean is about -10 % and standard deviation is also 10 % around over this period.

Compared with the tail risk in the financial sector, 5 % VaR of non-financial sector is also

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[9]Pozsar et al. (2012), Brunnermeier, Dong, and Palia (2012), Allen, Bali, and Tang (2012), Acharya and Thakor (2014)

[10]SIC codes are between 6000 and 6999 and market capitalizations are bigger than 5 billions in July 2007. 92 firms in total.

estimated using Equation 3.32 with S&P 500 stock returns, rather than individual financial institutions, are used to estimate the non-financial sector VaR (NonFinVaR). The top-right of Figure 3.1 shows time series of NonFinVaR. Compared to FinVaR, it has less tail loss than the recent financial crisis (-40 %) but more than the previous dot-com bubble crisis (-40 %). The monthly mean VaR is -12 % and the standard deviation is 8 % which is less volatile than FinVaR. The monthly returns data comes from CRSP.

Three macroeconomic variables are targeted for prediction. The graph in the middle left of Figure 3.1 shows the time series of the Chicago Fed National Activity Index (CFNAI). CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. A zero value for the index indicates that the national economy is expanding at its historical trend rate of growth and negative values indicate below-average growth. This index is constructed with the mean 0 and the standard deviation 1. Table 3.1 row 3 shows that the time series mean is slightly negative at -0.3 and the standard deviation is at 0.9. It is also shown that CFNAI was in a trough in the 2007-2008 financial crisis. The graph in the lower left of Figure 3.1 shows the time series of Total Nonfarm Payroll monthly rate of change (EMrate). It plummeted in the recent financial crisis by -60 %. In the sample period, the mean is 0.04 % monthly and standard deviation is 0.18 %. Finally, the Industrial Production Index monthly rate of change (IPrate) is shown in the middle-right graph of Figure 3.1. The mean is 0.08 % monthly and standard deviation is 0.7 %. These three variables are from the Federal Researve of St. Louis Database.

Other macroeconomic and finance variables are used for controlled variables. The NBER based recession indicator (NBER), the US 3-Month Treasury Bill (TB3M), the spread between Moody's seasoned Baa corporate bond yield and yield on 10-Year Treasury constant maturity (BAA10Y), the spread between 10-Year Treasury constant maturity and 3-Month Treasury constant maturity (T10Y3M), the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED), the spread between 3-Month REPO and 3-Month Treasury Bill (RepoTb3M), value weight returns of the U.S. stock market (VWRET) and the CBOE Volatility Index (VIX). The summary statistics are shown in Table 3.1 from Row

6 to Row 13. The interest rate data comes from the Federal Reserve of St. Louis Database and stock related data comes from CRSP. All data shown are monthly.

3.5.2 Predictive Model

The goal is to explore the predictive power of the tail risk of the financial sector up to 12 months ahead. The model is specified as:

$$y_{t+\tau} = x_t + y_t + \sum_{k=1}^{K} Z_t,\ t = 1, \cdots, T,\ \tau = 1, \cdots, 12 \tag{3.33}$$

where y_t is a 1×1 macroeconomics variable, x_t is 1×1 tail risk measure, and Z_t is 1×7 vector that contains the change in TB3M (dTB3M), the change in BAA10Y (dBAA10Y), the change in (dT10Y3M), the change in TED (dTED), the change in RepoTb3M (dRepoTb3M), and the change in VIX (dVIX) and VWRET.[11] Z_t covers various controlled variables of term spreads, credit spreads, liquidity, market volatility and market returns.

The contemporaneous correlation matrix of macroeconomic variables, tail risk measures and controlled variables are shown in the Table 3.2. It is not surprised that FinVaR is positive related to CFNAI, IPrate, EMrate and VWRET at 57 %, 39 %, 50 % and 69 %, respectively. At the same time, FinVaR is also positively related to NonFinVaR as much as 70 %. Comparing FinVaR with NonFinVaR, it is noted that FinVaR has higher correlation with CFNAI, IPrate, EMrate and NBER indicator (negative relationship) than does NonFinVaR. Both series have similar correlation with dVIX, -52 % and -56 %, respectively.

Table 3.3 shows the predictive regression of CFNAI on FinVaR from one month to twelve months in advance. Controlling for other variables, it shows that FinVaR has predictive power from one month to five months ahead. The magnitudes range from 0.02 to 0.04 and are significant at 5 % level. It also shows higher FinVaR predict higher CFNAI. The adjusted R-square peaks in the two months ahead at 68 %. It has about 50 % predictive power up to four months ahead. The tail risk in the financial sector can predict future macreonomic activity.

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[11] Taking the difference to remove the unit root in the time series.

Does the predictive power exist because the effect of the huge negative shock in the 2007-2008 recession and does not relate to the financial sector at all? One might argue that stocks returns and CFNAI dropped at the same time in the financial crisis and tail risk in any sector can show the predictive power. In order to respond this argument, I repeat the exercise but use the tail risk of the non-financial sector to predict CFNAI. If NonFinVaR can predict CFNAI, the predictive power is not only due to the tail risk in the financial sector.

The predictive regression of CFNAI on NonFinVaR is shown in the Table 3.4. It shows that tail risk of the non-financial sector does not have any predictive power, except in the two-month forecast horizon. As a result, the predictive power of tail risk does not exist in the non-financial sector. Only in the financial sector does tail risk have predictive power.

Can tail risk in the financial sector predict other macroeconomic variables ? Table 3.5 of Panel A shows a prediction of the rate of change of monthly industrial production on tail risk. FinVaR shows a significantly positive coefficient up to four months ahead. In contrast, NonFinVaR does not show significant predictive power in general, except two months and five months ahead. Table 3.5 of Panel B shows a prediction of the rate of change of total nonfarm monthly payroll. FinVaR shows significant predictive power up to ten months ahead. NonFinVaR also shows significant predictive power up to nine months ahead. It may be that total nonfarm payroll includes every sector, and is not restricted to the financial sector. Therefore, the tail risk shows predictive power as well.

3.5.3 Remarks

I demonstrate that tail risk in the financial sector can predict future economic activity in the last 15 years. In other words, bad shocks in the financial sector matter for future macroeconomics. The channels between the financial sector and economic activity are important to identify, although they are not provided in this paper. Recent outlooks and development in the financial market might shed some light on the reasons behind this. Brunnermeier, Dong, and Palia (2012) point out that non-interest income banking activities increased in 2000 and peaked before the 2007 financial crisis in the United States. Banks depend on trading income, investment banking income or venture capital income but not conventional deposit and lending business. As a result, banking sector are more intervened with the real sector than ever. Once banks are distressed and stop providing credit to the real sector, other firms will lose liquidity and may be negatively impacted as well.

Another explanation bases on the rapid growth of the shadow banking system.[12] The shadow banking system refers to non-banking financial intermediaries who fund themselves through short term bonds with lower rates and longer term loans and gain spread. These financial intermediaries could be broker-dealers who fund themselves with repurchase agreement (REPO) or big insurance companies, money market funds and hedge funds. They behave like banks, but are not subject to bank regulations. They leverage high and provide liquidity to the real economy. Once the shadow banking system is distressed, liquidity is frozen and the shocks carry over to the real economy.

3.6 Conclusion

This paper summarizes systemic risk research developed recently. After the financial crisis of the 2007-2008, systemic risk has been an active research area, particularly research that seeks to understand failures of a handful financial institutions could bring such catastrophic damage to the global economy? Such an event had never happened before and no one had ever predicted before it happened.

Unlike other risks have been well understood and carefully defined in the literature, systemic risk has not been rigorously defined mathematically. Generally speaking, it refers to (a) the risks imposed by failures of a single or a small number of financial institutions and financial intermediaries to a whole economy or (b) a single event that can cause cascading failures and bring down the entire system or market, causing financial instability, crisis or even economic recession. It is believed that the causes of a systemic event are complicated and profound. As a result, different measures of systemic risk are developed and aim to

[12] Adrian and Shin (2009), Pozsar et al. (2012) and Gennaioli, Shleifer, and Vishny (2013).

evaluate different aspects of systemic risks.

Interconnectedness is one of the causes of a systemic event, and is the most important factor causing cascade effects in a system. Network theory is by far the best tool to analyze cascading effects. Although network theory has been studied and applied broadly in the research of sociology, physics and epidemiology, I introduce it to the subject of risk analysis of economics for the first time. This paper introduces both theoretical network models and empirical network models of systemic risk. Although the development of network theory in systemic risk is still in its infancy, it has shown potential to capture the most interesting *robust-yet-fragile* properties in the financial network.

Finally, it is noted that the Financial Stability Oversight Council (FSOC) recently announced *Systemically Important Financial Institutions* (SIFIs). These institutions are expected to face tougher regulation and higher capital requirements, or even risk premiums to a crisis fund. How to estimate systemic risk accurately and understand the channels causing cascade effects will be an ongoing task. This survey tries to summarize the existing research and to suggest areas for future study.

Table 3.1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
FinVaR	174	−10.407	10.638	−65.118	6.209
NonFinVaR	174	−12.166	8.006	−41.181	1.459
CFNAI	174	−0.326	0.907	−4.570	0.920
IPrate	174	0.077	0.707	−4.300	1.500
EMrate	174	0.039	0.179	−0.600	0.400
NBER	174	0.149	0.358	0	1
TB3M	174	0.071	0.061	0.001	0.179
BAA10Y	174	0.113	0.019	0.082	0.177
T10Y3M	174	0.082	0.056	−0.115	0.139
TED	174	0.029	0.021	0.009	0.126
RepoTb3M	174	0.013	0.013	−0.005	0.061
VWRET	174	0.484	4.436	−16.716	10.884
VIX	174	20.999	8.446	10.420	59.890

Note: Value-at-Risk at the financial sector (FinVaR), Value-at-Risk at the non-financial sector (NonFinVaR), the Chicago Fed National Activity Index (CFNAI), Industrial Production Index monthly rate of change (IPrate) ,All Employees: Total nonfarm monthly rate of change (EMrate), NBER based recession indicator (NBER), US 3-Month Treasury Bill (TB3M), spread between Moody's seasoned Baa corporate bond yield and yield on 10-Year Treasury constant maturity (BAA10Y), spread between 10-Year Treasury constant maturity and 3-Month Treasury constant maturity (T10Y3M), spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED), spread between 3-Month REPO and 3-Month Treasury Bill (RepoTb3M), value weight returns of U.S. stock market (VWRET) and CBOE Volatility Index (VIX). Monthly Frequency.

Table 3.2: Contemporaneous Correlation Matrix

	NonFinVaR	CFNAI	IPrate	EMrate	NBER	dTB3M	dBAA10Y	dT10Y3M	dTED	dRepoTb3M	VWRET	dVIX
FinVaR	0.7	0.57	0.39	0.5	-0.51	0.41	-0.36	-0.1	-0.12	-0.04	0.69	-0.52
NonFinVaR		0.36	0.23	0.31	-0.31	0.37	-0.49	0.03	-0.05	-0.07	0.82	-0.56
CFNAI			0.81	0.81	-0.75	0.33	-0.06	-0.12	0.1	0.05	0.18	0.04
IPrate				0.51	-0.56	0.23	-0.03	-0.11	-0.04	-0.06	0.07	0.05
EMrate					-0.7	0.28	0.05	-0.1	0.16	0.1	0.15	0.07
NBER						-0.37	0.08	0.15	-0.11	-0.13	-0.18	0
dTB3M							-0.45	-0.43	-0.42	-0.34	0.27	-0.24
dBAA10Y								-0.14	0.32	0.19	-0.52	0.53
dT10Y3M									0.31	0.24	0.07	-0.09
dTED										0.73	-0.11	0.23
dRepoTb3M											-0.1	0.06
VWRET												-0.75
dVIX												

Note: Value-at-Risk at the financial sector (FinVaR), Value-at-Risk at the non-financial sector (NonFinVaR), the Chicago Fed National Activity Index (CFNAI), Industrial Production Index monthly rate of change (IPrate) ,All Employees: Total nonfarm monthly rate of change (EMrate), NBER based recession indicator (NBER), US 3-Month Treasury Bill (TB3M), spread between Moody's seasoned Baa corporate bond yield and yield on 10-Year Treasury constant maturity (BAA10Y), spread between 10-Year Treasury constant maturity and 3-Month Treasury constant maturity (T10Y3M), spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED), spread between 3-Month REPO and 3-Month Treasury Bill (RepoTb3M), value weight returns of U.S. stock market (VWRET) and CBOE Volatility Index (VIX). Monthly Frequency.

Table 3.3: Predictive Regression: FinVaR

	CFNAI											
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6	Lag7	Lag8	Lag9	Lag10	Lag11	Lag12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FinVaR	0.02^{***}	0.03^{***}	0.03^{***}	0.04^{***}	0.03^{**}	0.03	0.03^{**}	0.03^{*}	0.03	0.04^{**}	0.02^{*}	0.03^{**}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
lCFNAI	0.48^{***}	0.49^{***}	0.45^{***}	0.36^{**}	0.30^{**}	0.24^{*}	0.15	0.12^{*}	0.12	-0.10	-0.03	-0.22^{*}
	(0.09)	(0.07)	(0.09)	(0.19)	(0.15)	(0.13)	(0.12)	(0.06)	(0.09)	(0.09)	(0.08)	(0.13)
dTB3M	23.51^{**}	20.47^{*}	1.77	7.74	15.83	19.28	0.43	4.50	-3.88	11.18	9.30	24.07
	(10.03)	(12.36)	(11.48)	(18.37)	(17.85)	(20.03)	(23.35)	(17.30)	(15.49)	(18.88)	(17.28)	(21.81)
dVIX	0.03	0.004	0.01	0.04^{**}	0.02^{*}	0.04^{**}	0.03	0.03	0.03	0.07^{**}	0.03	0.04
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
VWRET	0.02	-0.02	0.005	-0.01	-0.004	0.01	-0.01	-0.004	-0.02	-0.01	-0.01	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
dBAA10Y	-15.41	-24.53^{*}	-36.47^{***}	-33.94^{***}	-25.85^{*}	-28.69^{**}	-46.23^{***}	-34.93^{**}	-33.21	-60.84^{***}	-53.10^{**}	-48.84^{*}
	(12.56)	(12.84)	(12.96)	(11.81)	(13.38)	(13.05)	(12.48)	(16.58)	(20.73)	(22.56)	(20.75)	(25.07)
dT10Y3M	-2.29	-1.54	-2.43	-0.86	-2.31	-1.22	-4.83	-5.15	-2.98	-5.11	-4.68	-3.08
	(3.88)	(2.51)	(2.02)	(3.57)	(2.00)	(3.22)	(3.83)	(4.68)	(3.37)	(5.15)	(6.40)	(7.09)
dTED	18.51^{**}	14.32^{**}	-2.50	-0.24	-2.07	-12.02	-10.89	-1.10	-7.86	3.98	5.84	8.04
	(7.21)	(6.08)	(6.52)	(9.97)	(7.26)	(10.07)	(9.90)	(13.31)	(11.55)	(6.31)	(7.43)	(10.16)
dRepoTb3M	-0.50	-4.37	17.84^{**}	5.74	19.13^{**}	21.30^{**}	25.38^{*}	12.75	11.80	12.09	10.67	9.54
	(6.30)	(5.30)	(7.56)	(7.71)	(8.79)	(10.35)	(13.32)	(9.98)	(13.91)	(12.03)	(10.88)	(7.01)
Constant	0.06	0.18^{***}	0.13	0.18^{**}	0.07	0.05	0.06	0.02	0.02	0.07	-0.07	-0.001
	(0.07)	(0.07)	(0.08)	(0.08)	(0.11)	(0.16)	(0.13)	(0.13)	(0.18)	(0.15)	(0.16)	(0.13)
Observations	173	172	171	170	169	168	167	166	165	164	163	162
R^2	0.62	0.69	0.64	0.52	0.40	0.38	0.30	0.23	0.16	0.23	0.15	0.18
Adjusted R^2	0.60	0.68	0.62	0.49	0.37	0.35	0.26	0.19	0.12	0.18	0.10	0.13

Note: *p<0.1; **p<0.05; ***p<0.01. Standard Error is adjusted by HAC type estimator.

Table 3.4: Predictive Regression: NonFinVaR

	CFNAI											
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6	Lag7	Lag8	Lag9	Lag10	Lag11	Lag12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NonFinVaR	0.01	0.03^{***}	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.01	−0.003	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
lCFNAI	0.59^{***}	0.62^{***}	0.60^{***}	0.55^{***}	0.42^{**}	0.37^{*}	0.30	0.26	0.26	0.10	0.10	−0.02
	(0.08)	(0.08)	(0.10)	(0.17)	(0.18)	(0.19)	(0.20)	(0.17)	(0.16)	(0.12)	(0.10)	(0.08)
dTB3M	25.13^{**}	19.57	4.30	10.39	15.39	19.69	1.19	5.54	−1.84	14.77	12.77	29.76
	(11.02)	(14.03)	(11.40)	(17.10)	(16.43)	(20.42)	(23.08)	(25.11)	(19.01)	(23.17)	(22.33)	(27.46)
dVIX	0.03	−0.01	0.001	0.02	0.01	0.03^{*}	0.02	0.01	0.02	0.06^{*}	0.02	0.03
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
VWRET	0.04	−0.02	0.03	0.02	−0.003	0.02	−0.0001	0.01	0.003	0.02	0.02	0.04
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)
dBAA10Y	−11.99	−16.57	-31.54^{**}	-27.69^{*}	−19.37	-22.71^{*}	-39.44^{***}	-28.93^{*}	−27.43	-53.80^{**}	-49.72^{**}	−44.48
	(12.88)	(12.01)	(13.40)	(14.72)	(13.23)	(12.32)	(14.45)	(17.40)	(20.31)	(25.47)	(23.13)	(27.97)
dT10Y3M	−2.71	−2.47	−3.04	−1.62	-3.09^{*}	−1.94	-5.64^{*}	−5.80	−3.55	−5.79	−4.97	−3.46
	(3.55)	(2.35)	(2.35)	(3.44)	(1.79)	(3.01)	(3.29)	(4.08)	(2.98)	(4.36)	(5.54)	(5.95)
dTED	14.64^{**}	7.03	−8.06	−7.05	−8.13	-17.82^{*}	−17.49	−6.89	−13.40	−2.97	2.13	2.91
	(6.82)	(5.79)	(7.39)	(11.44)	(7.62)	(9.90)	(11.65)	(13.92)	(12.68)	(7.44)	(7.81)	(10.72)
dRepoTb3M	2.76	0.91	22.55^{***}	11.40	23.60^{***}	25.75^{**}	30.46^{*}	17.23	16.27	17.91	14.08	14.44
	(6.76)	(5.78)	(8.41)	(9.01)	(8.02)	(11.00)	(15.59)	(10.48)	(17.07)	(15.77)	(14.44)	(10.31)
Constant	−0.06	0.25^{**}	−0.06	−0.02	0.10	0.02	0.004	−0.06	−0.12	−0.19	−0.31	−0.41
	(0.12)	(0.10)	(0.15)	(0.15)	(0.19)	(0.24)	(0.31)	(0.38)	(0.39)	(0.48)	(0.47)	(0.47)
Observations	173	172	171	170	169	168	167	166	165	164	163	162
R^2	0.60	0.67	0.60	0.47	0.39	0.36	0.27	0.20	0.14	0.18	0.13	0.14
Adjusted R^2	0.58	0.66	0.58	0.44	0.35	0.32	0.23	0.16	0.09	0.13	0.08	0.09

Note: *p<0.1; **p<0.05; ***p<0.01. Standard Error is adjusted by HAC type estimator.

Table 3.5: Other Dependent Variables

	Panel A: Industrial Production Rate of Change											
	IPrate											
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6	Lag7	Lag8	Lag9	Lag10	Lag11	Lag12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FinVaR	0.01^{**}	0.02^{**}	0.02^{*}	0.02^{**}	0.01	0.01	0.004	−0.0001	0.02	0.01	0.001	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Adjusted R^2	0.22	0.23	0.34	0.18	0.08	0.13	0.08	0.03	0.01	0.03	−0.01	0.01
NonFinVaR	0.01	0.03^{***}	0.01	−0.003	0.03^{***}	0.01	0.01	0.01	0.01	0.01	0.003	−0.004
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Adjusted R^2	0.20	0.24	0.30	0.16	0.09	0.11	0.08	0.04	−0.01	0.03	−0.01	0.01
Observations	173	172	171	170	169	168	167	166	165	164	163	162

Note: *p<0.1; **p<0.05; ***p<0.01. Standard Error is adjusted by HAC type estimator.

	Panel B: Non-Farming Total Employment Monthly Rate of Change											
	EMrate											
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag6	Lag7	Lag8	Lag9	Lag10	Lag11	Lag12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FinVaR	0.005^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.005^{*}	0.01^{***}	0.01^{***}	0.01^{**}	0.01^{**}	0.005	0.01^{**}
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Adjusted R^2	0.67	0.69	0.58	0.56	0.52	0.44	0.39	0.40	0.30	0.32	0.22	0.22
NonFinVaR	0.003^{**}	0.01^{***}	0.004	0.01^{***}	0.01^{***}	0.004^{*}	0.01^{***}	0.01^{**}	0.01^{**}	0.01	0.005	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.005)	(0.01)
Adjusted R^2	0.65	0.64	0.54	0.51	0.50	0.42	0.38	0.36	0.27	0.28	0.20	0.18
Observations	173	172	171	170	169	168	167	166	165	164	163	162

Note: *p<0.1; **p<0.05; ***p<0.01. Standard Error is adjusted by HAC type estimator.

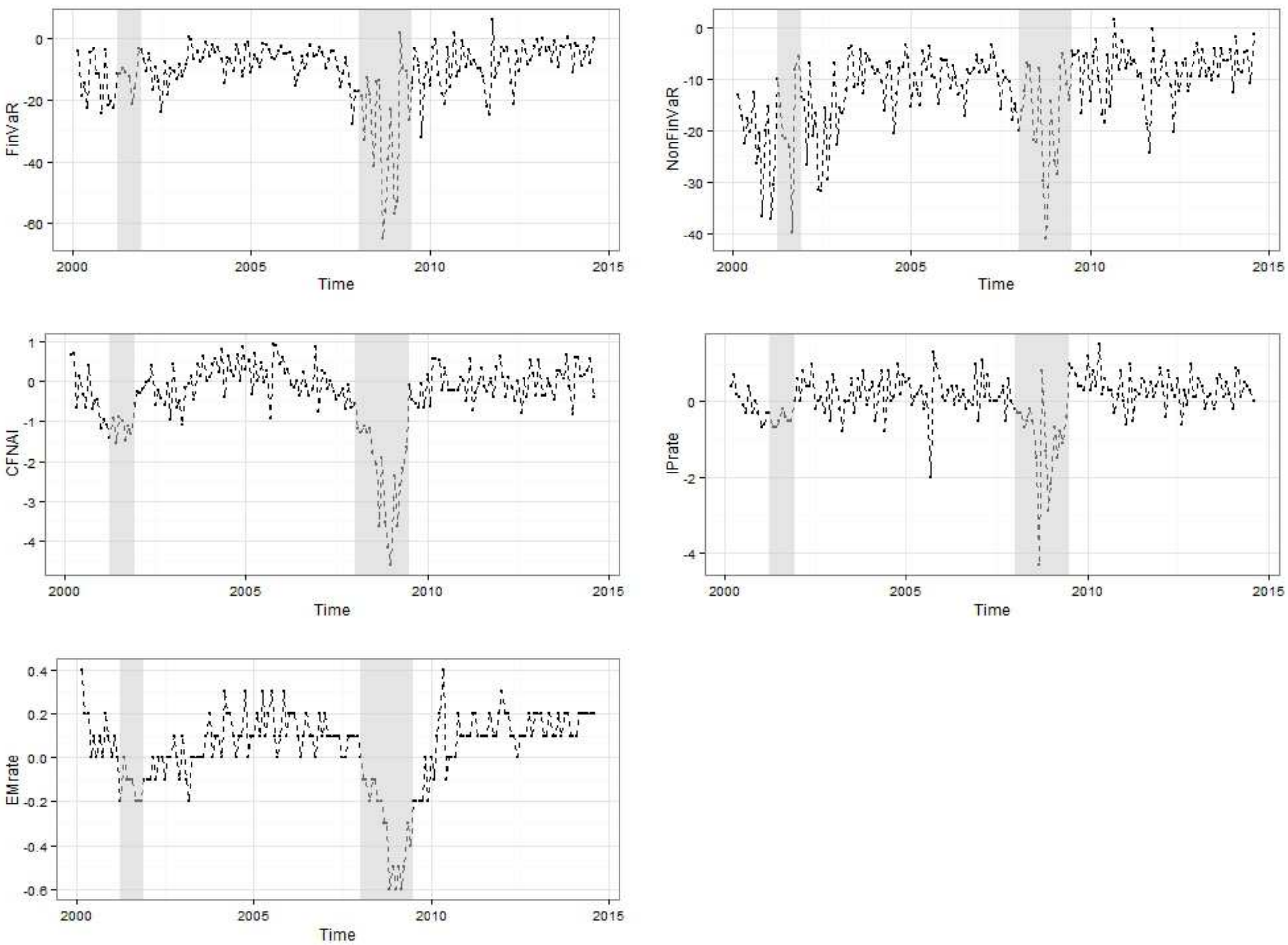

Figure 3.1: Tail Risk and Macroeconomics

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