Network Risk and Cross-Section of Expected Stock Returns

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Abstract

Current empirical asset pricing research on idiosyncratic volatility (IVOL), negatively related to cross-sectional expected returns, fails to take explicit account of risk that results from a shock to a network of economically related stocks. These stocks move together, and are therefore difficult to hedge. This paper examines the pricing of this "network risk" in the cross section of stock returns. Using the Fama-McBeth regression, I show that a newly-derived network volatility component of IVOL, 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.

JEL-Classification: G12, C58
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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

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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.

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 noticed 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 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

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

[3]See Newman (2010) for detail.

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 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. Nevertheless, previous empirical studys[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 Herskovic et al. (2013) find com-

[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.

[5]Goyal and Santa-Clara (2003), Campbell et al. (2001), Malkiel and Xu (2002), 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)

mon 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 et al. (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 Yilmaz (2011) 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. Ahern (2013) focuses on industry level pricing. He uses input-output table as a dependence structure between different sectors and finds that industries with higher central position will earn higher returns than those with non-central positions. 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 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 Model

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

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 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,

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

$$e_t = b^c f_t^c + \eta_t \tag{2}$$

where r_t is an N x 1 vector of excess returns, B is an N x K matrix of market risk exposures, f_t is an observed exogenous K x 1 vector of market risk factors. e_t is an N x 1 vector of residual returns and assumed to be orthogonal to f_t. b^c is N x1 unobserved factor loading. f_t^c is an observed 1 x 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 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 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. 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 the co-movement is not driven by market-wide shocks but idiosyncratic shocks, for example, Apple Inc.'s bad sales numbers affects stock price of its main computer chips provider Qualcomm Inc. The second part is the returns net of effect of network risk.

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 related stocks. Intuitively, A riskier stock should weights bigger 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.

2.2.1 Network and Centrality

A network, or a graph in mathematics, consists of nodes joined by edges. Nodes, or sometimes called vertices, are objects and edges that point out 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 in a banking system network, edges are money transferred, or simple binary numbers, 1 or 0 represent yes or no. The former is referred to as a *weighted* network and the later is an *unweighted* network. Networks can be represented in an *adjacency* matrix; adjacency matrix shows the values of edges in matrix form. If there is value for diagonal terms, edges are called *self-edges*. An element in row N and column M represents an edge from Vertice M to Vertice 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, degree of a node is the sum of edges and in a weighted network, degree is sum of 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 will calculate 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 weather Person A is considered as a friend of Person B by Person B, centrality will give us an answer to who is the most popular person in this class. In a citation network, every article is a vertice and its citations are edges. It is a directed but unweighted network and centrality points out 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 portal website Yahoo or Google can be identified in the network. In fact, Google's pagerank, which is their searching 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, covariance structure of residual returns can be seen as an adjacency matrix of business network besides common risk factors. Residual returns co-vary when idiosyncratic shocks spread, but not every firm is directly connected and so the degree distribution can be skewed. To study which stock is the most co-varying one as idiosyncratic shocks hit the network. Centrality gives the result.

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 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:

$$x_i = \sum_{j}^{N} a_{ij}, \ i = 1 \cdots N \tag{3}$$

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.

2.2.3 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. It is the standard of centrality in the network literature.[7]

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} x_j, \; i = 1 \cdots N \tag{4}$$

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 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 other assets x_j in the network weighted by 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 adjacency matrix and will affect her Eigenvalue centrality as well.

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

[8] It can be shown that only the highest Eigenvector will remain when we iterate equation 4. See Chapter 7.1 in Newman (2010) for detail.

2.2.4 Katz Centrality

When 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 and it will not change relative scores of nodes. The *Katz centrality* of Katz (1953) applies this idea.

$$x_i = \gamma \sum_{j=1}^{N} A_{ij} x_j + \beta_i, \; i = 1 \cdots N \tag{5}$$

Katz centrality adds up on Eigenvector centrality by β_i, which is the nodal attribute. It is very often β_i is set 1, but not restricted to it. When β_i is set to 1, it gives all nodes scores of 1, so it excludes the situation that some nodes score too closed to zero.

γ is a variable to control using Katz centrality. If $a = 0$, Katz centrality equals to β which is a vector of β_i. If $\gamma \geq 1/\lambda$, Katz centrality diverge and has no meaning.[9] There is little guidance how to choose γ. Most of researchers choose a less but closed to $1/\lambda$. So β weights less when Katz centrality is calculated. Katz centrality is also preferred to Eigenvector centrality to many researchers because of zero scores issue of Eigenvector centrality.

There are other centrality measure 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, interested readers will refer to Newman (2010) for further detail.

2.2.5 Choice of β

When β is equal to a vector of 1, it simply gives nodes some small scores of centrality for free. It will not change the relative scores in the end. However, nodes which have

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

neighbors with scores 0 will score a little more than 0.

Other information like size or leverage ratio can be used for β. Then centrality will reflect the choice of β in Equation 4. Generally speaking, β closer to zero will represent more information on *edges* themselves. Some literatures call it *global centrality* as opposed to *local centrality* when some local information β has been incorporated into the computation.

2.2.6 Construction of 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 the adjacency matrix. Katz centrality of this adjacency matrix takes pairwise covariance into calculation and yields co-varying scores of stocks. It is a generalization of pairwise correlation between two stocks.

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 x 1 normalized Katz centrality and e_t is a N x 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.

2.2.7 Relation to Principle Components

It is noticed that when adjacency matrix is equal to covariance matrix, Equation 4 will calculate the first principle components. The mimicking portfolio f_t^c is common factor and Equation 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 5 and resulting in a contradiction. So the decomposition of Equation 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.

2.3 Decomposition

Decomposition procedure has two steps. The first step is simply a pre-filtering step to get residual returns. Since market risk factor is assumed exogenous, Equation 1 is estimated by time series OLS for every stock i. The second step is to estimate Equation 2.

Specifically, I perform time-series regression of the Fama-French Three Factor model on daily stock returns every month between September 1963 and December 2012 for 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 as risk-free rate. Only stocks that have 15 or more transaction days in a month will be included to exclude liquidity issue. Risk free rate and the Fama-French Three Factors are 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 5 and orthonormal centrality to $\tilde{w}'\tilde{w} = 1$. Finally, mimicking portfolio is constructed as follows:

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

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

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, we fix f_t^c, solving Equation 2. This is equivalent to solving this least squares objective function:

$$\min_{\{b_i^c\}_{i=1}^N} \frac{1}{NT} \sum_i \sum_t (\hat{e}_{it} - b_i^c f_t^c)^2 \tag{6}$$
$$\text{s.t. } f_t^c = \alpha^{-1} \tilde{w}' \hat{e}_t$$

where b_i^c is i element of N $\times$ 1 vector b^c. To verify that b^c is equal to $\alpha\tilde{w}$, pretending 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 complete the proof. For convenience, $f^c = [f_1^c, f_2^c, \cdots, f_T^c]'$ is called *network risk* factor in the later discussion.

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

$$\sigma_{\hat{e},i}^2 = \sigma_{i,c}^2 + \sigma_{\hat{\eta},i}^2, \; i = 1 \cdots N \tag{7}$$

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

3 Empirics

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.

3.2 Summary Statistics

Table 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 simliar 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.

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

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 related to NVOL and negatively related to size. This suggests that controlling for PVOL is important when we 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.

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:

$$r_{i,t} = X_{i,t}\beta_t + \epsilon_{i,t},\ i = 1 \cdots N_t \tag{8}$$

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:

$$\bar{\beta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t \tag{9}$$

$$var(\bar{\beta}) = \frac{1}{T-1}\sum_{t=1}^{T}(\hat{\beta}_t - \bar{\beta})^2 \tag{10}$$

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 type estimator. I use HAC estimator to correct standard error for risk premium in this research.

Returns used in Equation 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 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) and Ahern (2013) which find positive monthly risk premium of centrality.

The main result of this paper is shown in Model 3 in Table 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 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 % mothly). 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.

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.

3.5.1 Network Volatility Quintiles Portfolios

Row 1 in Table 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 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 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. Portolio 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 aveage of NBeta. When NBeta is 1, it means the stock has the same movement magnitute 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.

3.5.2 Pricing Anomalies of Network Volatility Quintiles Portfolios

Table 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. We can see 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 we 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.

3.5.3 Network Variance Ratio Quintiles Portfolios

Model 3 from Table 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 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 quintle portfolios. Mean returns are higher and peak at Portfolio 3.

Table 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. Portolio 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 quintle portoflios. 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 aveage of NBeta. It is faily flat among NVR quintle portfolios. Row 7 shows monthly average of market Beta. It declines monotonicaly.

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 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 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.

3.5.4 Pricing Anomalies of Network Variance Ratio Quintiles Portfolios

Table 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 portoflios. 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.

4 Extension

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 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 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 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 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 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 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.

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 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 becuase 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, engergy, 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 utilites industry stocks are deleted from our samples, the results are more significant and the risk premium is higher.

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

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

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 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 phonomenum of the Great Moderation due to the more stable economic structure and the better ability of hedging loss from related stocks co-movement.

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.

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?

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Table 1: Variables descriptive statistics for the pooled sample: Sep.1963-Dec.2012

This table reports the pooled descriptive statistics of stocks that are traded in the NYSE, Amex or 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.

	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

Table 2: Times series means of the cross-sectional correlation

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 1 .The correlation coefficients followed by * are significant at the 5 % level based on their time-series standard error.

	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*

Table 3: Fama-MacBeth Regression

Samples are stocks traded in the NYSE, Amex,or 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.

	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.

Table 4: Network Volatility & Variance Ratio Quintile Portfolio

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 5: Summary Statistics of Network Volatility Quintile Portfolios

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 6: Pricing Anomalies:

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 7: Summary Statistics of Network Variance Ratio Quintile Portfolios

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 8: 15 Portfolios Sorted by Size/BM and Network Variance Ratio

Samples are stocks traded in the NYSE, Amex,or 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).

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

Table 9: Pricing Anomalies of Network Variance Ratio Quintile Portfolios:
Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 10: FF4F: Fama-MacBeth Regression

Samples are stocks traded in the NYSE, Amex,or 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.

	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.

Table 11: FF4F : Network Volatility Quintile Portfolio

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 12: FF4F: Summary Statistics of Network Variance Ratio Quintile Portfolios

Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 13: FF4F: 15 Portfolios Sorted by Size/BM and Network Variance Ratio

Samples are stocks traded in the NYSE, Amex,or 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).

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

Table 14: FF4F: Pricing Anomalies of Network Variance Ratio Quintile Portfolios:
Samples are stocks traded in the NYSE, Amex,or 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.

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

Table 15: Industry Subsamples Fama-MacBeth Regression

Samples are stocks traded in the NYSE, Amex,or 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.

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.

Table 16: Time Subsamples Fama-MacBeth Regression

Samples are stocks traded in the NYSE, Amex,or 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.

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.