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Essays on Financial Connectedness, Systemic Risk, and Performance

조선대학교 대학원

경영학과

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이 논문을 경영학박사학위 신청 논문으로 제출함

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Contents

List of Tables

List of Figures

ABSTRACT

금융시장의 연결성이 기업성과와 위험에 미치는 영향

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본 논문에는 금융시장에서 측정된 연결성이 기업성과와 위험에 미치는 영향에 대해 연구하는 세 편의 에세이가 실려 있다. 기업은 직간접적인 관계를 통해 서로 연결되고 네트워크는 이러한 관계를 기업 간의 연결로 나타낸다. 특히, 기업의 가치에 영향을 미칠 수 있는 투자자별 그룹, 금융기관, 이사회가 각각의 연결 관계를 형성할 때 네트워크의 효과와 기업이 직면한 인센티브를 실증적으로 분석한다.

첫째로, 우리는 포트폴리오 할당(portfolio allocation)과 같은 투자 결정에서 투자자 그룹 간 네트워크의 역할을 고려한다. 투자자 그룹 간 형성된 시장 전체의 연결성(system-wide connectedness)은 기존의 시스템 위험(systemic risk)의 방볍과 유사한 결과를 나타내며 역사적 글로벌 금융위기 기간에 증가하는 것이 관찰하였다. 이러한 시장 전체의 연결성에 기여하는 특정한 투자자는 개인투자자(retail investor)가 경제 상황에 무관하게 주요한 역할을 하는 것으로 관찰했다. 이는 개인투자자로부터 전달된 연결성이 시장 전체에 부정적인 충격(negative shocks)을 전달한다고 해석된다. 또한, 시스템 위험에 대한 민감도로 형성된 포트폴리오 분석을 통하여 전통적인 자산 가격 결정 모형에서 설명하기 어려운 초과 수익률을 제안하였다.

둘째로, 신디케이티드론(syndicated loan)에 의해 형성된 은행 네트워크의 구조적 특성과 경제 성과와의 연관성을 연구한다. 은행의 네트워크는 특정한 은행이 전체 네트워크의 중심성(centrality)이 큰 허브(hub) 구조가 존재하였고 그러한 은행들은 다른 은

행들과의 포트폴리오의 유사도가 높은 은행들이다. 은행 대출의 양이 증가할수록 허브 은행이 될 확률이 증가함으로 보였다. 왜냐하면, 은행의 기업 투자에 대한 포트폴리오의 다양성이 높을수록 중심성이 큰 경향이 나타났기 때문이다. 그리고 본 연구에서 제시하는 주성분 분석으로 개발된 중심성 지수가 큰 은행일수록 그 은행의 성과가 크다는 것을 관찰하였다.

셋째로, 이사진 간 겸임(interlocking directorates)을 통해 연결성을 정의하고 다양성과 Co-option이 기업의 성과에 미치는 영향력을 분석한다. 먼저 다양성은 기업의 성과에 통계적으로 유의미한 양의 회귀계수를 나타내었다. 이는 다양한 산업으로부터의 이사진 간 겸임을 통해 형성된 연결성은 그 기업들의 개인적인 정보(private information)에 대한 접근을 쉽게 만든다고 볼 수 있다. 또한, CEO의 힘을 나타내는 co-option 변수를 활용하여 4가지 그룹으로 구분한 뒤 CEO의 힘에 따른 이사회의 다양성이 미치는 결과도 흥미로웠다. 특히나, CEO의 힘이 감소하며 다양성이 증가할 경우 다양한 정보가 방대해지고 모니터링(monitoring)이 약해짐으로써 기업성과가 가장 심하게 증가함을 관찰하였다.

따라서, 경제 현상 및 기업의 성과 메커니즘을 분석하기 위해 전통적인 회귀분석과 네트워크 방법론을 함께 활용하였을 때 면밀하게 시간에 따라 변화하는 주식시장의 구조를 관찰할 수 있었고, 이를 통해 향후 네트워크 분석에 기반한 기업의 성과 및 은행과 기업의 대출 관계 결정 요소 및 자산 가격 결정 모델 등의 다양한 연구에 크게 이바지할 수 있을 것으로 기대된다.

I. Introduction

1.1 Motivation

Over the last few years, the answer to the question of the benefits of connectedness for the firm and the economy has become no longer clear. Earlier literature focused heavily on emphasizing the negative aspects of connectedness as the systemic risk of the firm embodied in the empirical model, leading to the financial crisis, causing severe instability or the collapse of an entire industry or economy (Billio et al. 2010; Diebold et al. 2014; Elliott et al. 2014; Acharya et al. 2017). However, this dark side to connectedness is just one side of the coin. This is because firms may be able to propagate risks through connectedness with related firms, but with valuable information, they cause more incredible changes to firms in terms of their performance.

From the perspective of a network approach, power-law behavior has appeared to describe finance and economic phenomena, including income and wealth, firm sizes, stock market returns, trading volume, and executive pay. (Gabix, 2009) Power law, which means that a network has a small number of nodes with a higher connection to others, has scale invariance characteristics. (Newman, 2005). Understanding this behavior makes a modern answer to how network structure impacts the function of individual firms and aggregate fluctuation (Acemoglu et al. 2012).

In addition, various studies have used big data that can accelerate connectedness (Antweiler et al. 2004; Gentzkow et al. 2019). A complex analysis due to different data development means there remains a need for comparative empirical evaluations of new methods that deviate from linear regression analysis to be studied rigorously. This doctoral thesis enriches the understanding of connectedness and how it affects the stock market.

This thesis consists of three related but separate essays on the connectedness for stock market data: trading activity of investor groups, syndicated loan relationships, and the information of a board of directors. Physical and social interactions of these sets of agents contribute to each of their stocks. This thesis analyzed a network involving multiple objectives using a stock market database in South Korea and the United States. All three studies rely on the concept of information flow across various levels of agents. In particular, the collection of essays in this thesis seeks to address the following three research questions (Q) :

1. How should financial networks be constructed using economic agents such as investors, financial institutions, and boards of directors?

2. Could the stock market account for risk-return trade-offs based on connectedness among investors?

3. Does connectedness among financial institutions provide evidence of performance quality?

4. Does the relationship between the connectedness among a board of directors and the CEO's power explain effective monitoring and performance?

The rest of this introductory chapter is organized as follows. Section 2 introduces related works and explains the key concepts or variables. Section 3 provides an overview of this thesis.

1.2 Conceptual framework

1.2.1 Investor activity and stock return

We divided literature on investor activity into three types. First of all, several studies have presented great investment strategies using a portfolio analysis and gains calculated by heterogeneous types of investors who tend to trade stocks with investments of various styles such as value stocks or growth stocks (Barberis and Thaler 2002; Barberis and Shleifer 2003; Froot and Teo 2008; Markowitz 1952; Grossman and Stiglitz 1980; Long et al. 1990). Second, since intensive transactions include information about future returns' distributions, investors act to obtain personal information through transactions by other investors (Campbell et al. 1993; Lee and Swaminathan 2000; Gervais et al. 2001). Third, stock prices reflect the investor's beliefs in the value, and the noise of their transactions occur in incomplete markets. In other words, noise signals have nothing to do with public information on stock prices (Black 1986).

Recently, bottom-up studies have emerged to analyze the patterns of investors or companies (Acharya et al. 2012; Elliott et al. 2014; Stefano Giglio 2016; Preis et al. 2013). Most of the existing research using investor activity concentrates on issues such as understanding investment strategies or information propagation (Shive 2010; Ozsoylev et al. 2013; Barberis and Thaler 2002; Shiller 2015). For example, Kaniel et al. (2008) recognized the interaction between individual trading as a liquidity provider and stock returns, and allowed us to broaden our perspective of investor activity in the sense that it is considered as a systematic factor in the stock market. An underlying assumption of these investigations is the existence of irrational investors with bounded rationality.

1.2.2 Connectedness and systemic risk

Connectedness is an essential concept when explaining financial markets. The systemic risk induced by a connection among financial objects is generally measured by the return, volatility, and the inter-bank loan. The connectedness between banks demonstrates how the contagious nature of high levels of risk among financial institutions can cause financial crises and affect future economic conditions (Battiston et al., 2012; Demirer et al. 2018; Corsi et al. 2018; Acharya et al. 2017). The network structure of the interbank market created by the syndicated loan market suggests that connections between banks should be an important channel of contagion among financial institutions (Cai et al., 2018; Ivashina et al., 2010; Fahlenbrach et al. 2012). Information contagions between banks represent a significant channel that might explain how information travels through financial systems. Recently, the application of complex networks to solve this challenging problem has become increasingly widespread in diverse areas (Rajpal et al., 2019; Tomassini et al., 2020; Wen et al., 2020).

Prior research provides evidence that interconnectedness has a considerable impact on the economy from risk exposure. Interconnection between companies or industries amplifies and propagates shock within an economy (Acemoglu et al., 2012). Negative shock and financial distress contribute to asset fire sales (Shleifer et al., 2011). Consistent with these concepts, credit concentration tends to lead to a cascade effect of shock in an economy (Cont et al. 2010). Cai et al. (2018) defined market connectedness using banks' loan specializations in a syndicated loan market that reflected systemic risk.

Furthermore, prior studies that have examined the role of diversification have focused on performance. For example, banks with a greater number of geographically-concentrated mortgage loans performed better than others with fewer of these loans (Loutskina et al., 2011). In terms of mergers and acquisitions, diversification is correlated with fluctuations in external market friction (Matvos et al., 2018).

1.2.3 Board of directors and firm performance

Board of directors has attracted increasing attention across various academic fields. It is well known that there exists a high level of interlocking directorates of the United States corporate board networks (Mariolis and Jones, 1982; Battiston and Catanzaro, 2004). This phenomenon refers to how numerous boards of directors serve on the boards of multiple corporations. There are controversial issues about how board networks affect a firm's performance. One point is a positive association between CEO network centrality and merger performance (EL-Khatib et al., 2012) and between boardroom centrality and operational performance (Larcker et al., 2013). Moreover, Dass et al. (2013) have insisted that board expertise help bridge the information gap among other industries and suggested a channel of increasing firm value. The other issue is a negative aspect between CEO connectedness and corporate fraud (Khanna et al., 2015) between director network centrality and financial reporting quality (Omer et al., 2019).

Board of directors is a traditional subject in corporate finance and corporate governance (Williamson 1988). Therefore, electing directors is vital to estimate operational performance and shareholder value. Voting rates reflected on the reputation of directors based on previous performance impact the electing mechanism. (Cai et al. 2009) Shivdasani (2006) provided evidence of an association between a busy board and effective monitoring. There is a busyness hypothesis and a reputation hypothesis to explain performance effectiveness and compensation of top executives (Jiraporn et al., 2008; Fich and Shivdasani 2007). Board independence is also considered as a key component of corporate monitoring (Rosenstein and Wyatt, 1990; Ryan and Wiggins, 2004; Knyazeva et al., 2013).

1.3 Overview of thesis

The purpose of this thesis is threefold: (i) to examine the systemic risk among investor groups and evaluate the predictability of stock returns using a portfolio analysis, (ii) to explore the interconnectedness measured by syndicated loan portfolios and impacts on performance, (iii) to investigate the effectiveness of a diversified and co-opted board.

Chapter II explains the connectedness based on investor activity as a micro element in the stock market by vector autoregression and variance decomposition (Diebold et al. (2014)). This thesis uses daily trading values of nine investor groups and the accounting information of stocks listed in the KOSPI market in South Korea from January 1, 2002, through December 30, 2018. This thesis then uncovers a cross-section sensitivity of stocks using the innovation of systemic risk in line with Ang et al. (2006).

Consistent with Diebold et al. (2014), Campbell (1990), and Ang et al. (2006), our empirical findings suggest that connectedness among investor groups is reflected in global financial crises and the impact that innovation in the systemic risk of total trading has on stock prices. These findings provide valuable insights into both systemic risks from investor networks and asset pricing models related to financial stability.

Chapter III provides the effects of syndicated loan network centrality on bank performance. Syndicated loan network centrality measures similarity with other banks and the influence on others within a given bank's network. We use a planar maximally filtered graph (PMFG) to construct an interbank network using syndicated loan portfolios at an industry level between January 1990 and December 2017, from the DealScan database in the United States.

This chapter shows the power-law distribution of an interbank network by loan portfolios. In a link with the previous studies of Cai et al. (2018), these findings imply that hub banks play a role in propagating the risk along with loan portfolios during financial crises. It also contributes to future research about bank-firm lending relationships after controlling the characteristics of banking and firms (Sufi, 2007; Schwert, 2018).

Chapter IV employs the effectiveness of relations between diversity among firms created by the board of directors and co-option. This chapter uses firms listed on the S&P 500, S&P MidCap, and S&P SmallCap between 1996 and 2015 in the United States to construct board networks. We calculate Shannon entropy using the ratio of interlocking directorates in other industries in other to measure the diversity level of each firm and estimate CEO power as a co-option variable based on the balance of directors who joined the board after the CEO assumed office (Shannon 1948; Coles et al. 2014).

We show that the effect of connections among firms is positive for firm performance. The positive effect also implies that the information channel by directorate interlocking plays an important role in future investment decisions. Consistent with Coles et al. (2014), our findings suggest that co-option has an impact on firm performance. In addition to diversity, we provide a significant effect of director selection mechanism (Cai et al. 2009) and governance mechanism (Khanna et al. 2015; Ferreira et al. 2007).

The final chapter, chapter V, briefly summarizes the conclusions and makes recommendations for future research.

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II. Investor activity and contagion

2.1 Motivation

How vary investor behavior under uncertainty over time? Do some investors lead to the movement of the stock market as supply and demand? Scholars have reviewed these questions for decades. They are essential to understanding investor activity's impact on the stock market and how stock returns reflect all relevant information (Kuma and Lee 2006, Peng *et al.* 2007). Understanding connectedness among investors has implications for the study on the risk propagation to the stock market and the inevitable impact on expected stock returns.

In this study, we use the connectedness measured by variance decomposition for a channel that propagates informational shocks. The connectedness could show relative information among investor groups and those responsible for market instability caused by the transmission of structural shocks. We start from the premise that all stock market participants are interested in private information held by others. Moreover, the relationships between them rapidly transmit structural shocks in the stock market. Specifically, densely connected financial networks are likely to propagate negative shocks and lead to more vulnerable systems (Baumhl *et al.* 2018, Acemoglu *et al.* 2015, Lux 2001).

Since the failure of Lehman Brothers on September 15, 2008, researchers and policymakers have focused on connectedness (Acharya *et al.* 2012, Billio *et al.* 2012, Diebold and Yilmaz 2014, Adrian and Brunnermeier 2011). There is no unanimous definition of systemic risk because the stock market with participants and stakeholders is a complicated and adaptive system. Billio *et al.* (2012) have shown increasing the level of systemic risk in the finance and insurance industries through principal component analysis and Granger causality networks. The result relies on the unidirectional causality and bipartite connection. Diebold and Yilmaz (2014) introduced a connectedness measure at various levels from pairwise to system-wide. They insisted that the methods had similar results with conditional value-at-risk (CoVaR) (Adrian and Brunnermeier 2011) and systemic expected shortfall (Acharya *et al.* 2012).

Our goal in this paper is to understand the connectedness among investor groups related to market stability. By doing so, we construct a time series of over 4,000 networks using daily trading value, calculated by multiplying volume with share price from 2002 to 2018 in the Korea Stock Exchange. We categorize investors into nine groups and calculate total connectedness using vector autoregression. We then conduct the variance decomposition (Diebold and Yilmaz 2014) to investigate the dynamic direction of connectedness among investor groups and the effect on market stability. We insist an information sharing through a directed network. The nodes represent investor groups, and the links between investor groups denote their contribution to the unpredictable error of the aggregated trading value of common securities. Our approach is based on the amount of information obtained from others and their information as to their location on the network.

There is empirical evidence supporting the view that information sharing among investors has an infectious role of market stability based on the systemic risk. A significant finding in this pa- per is that total connectedness among investors increases during the Subprime crises. This result is consistent with the previous studies that information linkages among traders convey positively or negatively correlated signals and that information transform in investor networks (Colla and Mele 2009, Ozsoylev *et al.* 2013). Second, retail investors play a significant role in the propagation of negative shock on the stock market. Moreover, Kuma and Lee (2006) also suggested the evidence that retail trading imbalance might give rise to comovement of stock returns and formulate an identification of the information sources. Third, the relation between the total connectedness innovation via variance decomposition and expected return has a negative association. The main contribution of this paper is measuring connectedness among heterogeneous investors using trading value, which is unique database from South Korea. While studies that measure financial institutions' connectedness using stock returns, there is not enough evidence to measure the connectedness using trading information. It is worthwhile to estimate connectivity from the perspective of investors as cornerstone in financial market. Futhurmore, we suggest that the connectedness from the retail investors who are the primary decision maker in the stock market of South Korea plays a critical role in price formation. This article is related to the literature on eco- nomic vulnerability, applying the methodology of variance decomposition to understand economic issues behind the behavior economics.

The remainder of this paper is organized as follows: Section 2 describes the source of our data and variance decomposition method measuring connectedness. In Section 3 and Section 4, we present and discuss main findings related to the market stability. Section 5 concludes.

2.2 Methodology

This section is divided into fifth subsections. At first, we describe the data and explain how we use the variables to estimate forecast error causality among investor groups. In the second and third, we show the definition of total connectedness using the vector autoregression (VAR). In the four subsection, we suggest investor networks to evaluate the role of source of total connectedness that they use in decision making. In the fifth, we explain the regression model to analyze the effect of the connectedness on expected return.

2.2.1 Data Description

Trading volume is an important proxy for market liquidity and is a major factor in promoting price movements. (Copeland and Galai 1983, Karpoff 1987, Lim and Coggins 2005, Zhou 2012) Our database contains buyers' and sellers' daily trading value containing a volume of 1,154 stocks that are ordinary common shares traded on the Korea composite stock price index(KOSPI) from January 1, 2002, through December 30, 2018. The trading value of each investor is stock price multiplying trading volume at a daily frequency. The closing price, stock return, and trading volume are from the FnGuide. The trading on the KOSPI market is different from the NYSE or NASDAQ exchange in that there are no specialists or market makers. We use the classification of FnGuide to group investors into nine types of investors, excluding overlapping groups: foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), other financial(OF), other corporate(OC). Table S1 defines investor

Table 2.1. Data Description of aggregate investor trading

	Aggregate Buy Trade					Aggregate Sell Trade				
Type	Mean	Std. Dev.	Skewness	Kurtosis	JB test	Mean	Std. Dev.	Skewness	Kurtosis	JB test
FO	19.03	0.48	-0.27	2.56	70.03	19.04	0.48	-0.29	2.60	78.28
RE	16.35	0.79	-0.53	2.86	194.06	16.32	0.76	-0.48	2.80	154.56
BA	13.50	0.71	-0.07	3.49	29.51	13.59	0.73	0.02	3.75	107.74
IS	15.91	0.75	0.26	2.85	132.16	15.79	0.81	0.43	2.93	228.30
IV	18.01	0.70	-0.96	3.44	500.99	18.09	0.75	-0.99	3.44	558.83
PF	15.56	1.02	-0.64	2.34	484.48	15.53	1.01	-0.64	2.34	488.08
FI	16.01	1.11	-1.00	3.35	635.55	15.88	1.23	-1.06	3.42	760.81
OF	14.75	0.61	0.01	3.32	8.66	14.85	0.63	0.49	5.05	809.84
OC	17.06	0.61	-0.04	2.56	99.80	17.09	0.63	-0.04	2.58	79.72

Note: this table presents mean, standard deviation, skewness, and kurtosis of each investor group: foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), ‘other financial(OF), and other corporate(OC). The sample consisted of 4,203 daily observations of 1,154 companies between 2002 and 2018. JB test means Jarque-Bera test for a normal distribution. Significant at the 5% level (critical value 5.97).

classification from FnGuide. We aggregate the trading value of stocks to create a time series for each investor.

We then defined total trading(TT), Net Trading Imbalance(NTI), and Normalized Net Trading Imbalance(NNTI) of investor i at time t as follows.

$$TT(i,t) = \ln(Buy(i,t) + \ln(Sell(i,t)) - \ln(Buy(i,t-1) + \ln(Sell(i,t-1)) \quad (1)$$

$$NTI(i,t) = \ln(Buy(i,t) - \ln(Sell(i,t)) - \ln(Buy(i,t-1) - \ln(Sell(i,t-1)) \quad (2)$$

$$NNTI(i,t) = \frac{\ln(Buy(i,t) - \ln(Sell(i,t))}{\ln(Buy(i,t) + \ln(Sell(i,t))} - \frac{\ln(Buy(i,t-1) - \ln(Sell(i,t-1))}{\ln(Buy(i,t-1) + \ln(Sell(i,t-1))} \quad (3)$$

where $Buy(i,t)$ is aggregate buy trading value of investor i and at a daily frequency t and $Sell(i,t)$ is aggregate sell trading value of investor i and at time t. Although each aggregate trade is non-stationary, the difference between continuous aggregated trade is stationary to estimate total connectedness.

2.2.2 Connectedness of Individual Investor Population

This section proposes a measure of total connectedness designed to change the casual relationship between investors in the stock market during the shocks of anywhere by Campbell (1991), Diebold and Yilmaz (2014). We measure the degree of connectedness and the causality among investor groups to examine the market's cascade effect through closely coupled investors. As Sims (1980) argued, a vector autoregressive(VAR) model used to capture the linear linkages among multiple time series is one of the familiar model in econometrics. All variables in this model are symmetrically considered in a structural sense (Phillips 1986). The evolution of a set of variables is over the sample period as a linear function of only past values. i.e., we forecast dynamic correlation and influence among investors. By eliminating the correlation of the error, we analyze the response of the shock for each time. To do so, we propose using variance decomposition method (VDM), which is the proportion of the variance of a variable due to each fundamental shock. Let x_t and z_t be a univariate stationary process of total trading(TT), Net Trading Imbalance(NTI), and Normalized Net Trading Imbalance(NNTI) of each investor group.

$$x_t = \sum_{i=1}^{p} \alpha_i z_{t-i} + \epsilon_{x,t} \tag{4}$$

$$z_t = \sum_{i=1}^{p} \beta_i x_{t-i} + \epsilon_{z,t} \tag{5}$$

where $\epsilon_{x,t}$ and $\epsilon_{z,t}$ are two uncorrelated white noise processes, and α_i, β_i are the coefficient of the model. To minimize the Bayesian information criterion (BIC), We used p as four, five, and five in TT, NTI, and NNTI, respectively (Schwarz *et al.* 1978). Diebold and Yilmaz (2014) noted that there are similar results when they use other lag orders. Specifically, we choose a rolling window of 250 days and an H-step of 10 days. The results do not vary depending on the various window lengths and H-steps consistent with Diebold and Yilmaz (2014). The connectedness horizon is important because it is related to issues of dynamic connectedness as opposed to purely contemporaneous connectedness. Let $Y_t = [x_t, z_t]'$ and $\epsilon_t = [\epsilon_{x,t}, \epsilon_{z,t}]'$, that these innovations reflect either changes in output of other variable as following equation:

$$A(L)Y_t = \epsilon_t \tag{6}$$

where $A(L) = 1 - A_1L^1 - \ldots - A_pL^p$, A_p is the matrix of estimators. We exploit not the most popular Cholesky decomposition but a generalized variance decomposition method(GVDM) to measure each investor's connectedness. That is why Cholesky decomposition has the limitation that exogenous variables have different results when changing variables. The proportion of variables in the prediction errors of estimator using GVDM can be written as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i^{'}B_h\Sigma e_j)^2}{\sum_{h=0}^{H-1}e_i^{'}B_h\Sigma e_i} \tag{7}$$

where $\theta_{ij}^g(H)$ is the fraction of variable is h-step forecast error variance due to shocks in j and H is the predictive horizon (H = 1, 2, 3, we set H = 10), σ_{ij}^{-1} is a diagonal element of covariance matrix estimate error, e_j is j-th element = 1 and other element = 0, B_h is coefficient matrix reflected on shock effect, and Σ is covariance matrix of estimate error. This paper generates the proportion of variables in the disturbance matrix. The directional connectedness from j to i can be written as

$$C_{ij}(t) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N}\theta_{ij}^g(H)} \tag{8}$$

Though GVDM, we show the variance decomposition table obtained by aggregating trading value within the nine investor categories (retail, financial investment, other financial, other corporate, listed foreign, insurance, pension funds, bank, and investment) and each component in the table implies the connectedness between the groups. Since the above matrix components can be interpreted as the response to other investors' impact, the diagonal term means the effect on investor groups received from themselves. This result enables us to observe the causality, which are removed the diagonal components from each investor. Each row of the matrix describes the contribution of own to others, while each column of the matrix represents the contribution of own from other.

2.2.3 System-wide Connectedness

Here, we would like to explain how to define directional connectedness and total connectedness in this paper. When shocks of micro or macro level break out of equilibrium, investors' contribution means a negative impact on other investors. The most important thing is that investors' contribution to forecast error each investor did not expect is reflected on total connectedness. Directional connectedness represents the quality of investors' information in the sense that heterogeneous investors contribute to the unpredictable factor of own and others. Directional connectedness indicates the weighted degree of off-diagonal element of each investor in the directed matrix $C_{ij}(t)$. The sum of each investor's unpredictable error to others is an outflow from each investor defined by "To". By contrast, the sum of components to each investor from others is an inflow to each investor defined by "from". "Net" value of each investor is calculated by the difference between "To" and "from" of each investor. We define the investor groups with positive(negative) net value as the contagion effect's source(sink). Finally, we derive Total Connectedness(TC) based on the database of Total Trading (TT), Net Trading Imbalance (NTI), and Normalized Net Trading Imbalance (NNTI) among nine investor groups using the matrix $C_{ij}(t)$ made by equation 8. The total connectedness is calculated by the following equation:

$$TC(t) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} C_{ij}(t)}{N} \tag{9}$$

It is the same with the average of total directional connectedness, whether to or from in the sense that diagonal terms are ignored.

2.2.4 Investor Networks

We construct simple investor networks, which are the weighted directed networks; in that case, the weight is more than the mean and two standard deviations. We build the investor networks by taking into account a database formed by the daily trading prices of 1,154 stocks traded at KOSPI market from January 2002, to December 2018. To study the financial market's contagion effect, it is necessary to examine the time evolution of the respective networks. We set a time window of length $\triangle t$ = 250 days and moving this window along time. We can obtain a sequence of networks. This window is moved by an amount of δt = 1day, and a new network is obtained after each displacement.

2.2.5 Empirical Examinations

Our goal is to test whether the average return on stocks with different sensitivity to systemic risk innovations (proxied by $\triangle TC$) is different. To estimate the sensitivity to systemic risk innovations, we use the following equation with daily data:

$$R_t^i = \alpha^i + \beta^i_{MKT} MKT_t + \beta^i_{\triangle TC} \triangle TC_t + \epsilon_t^i \tag{10}$$

where R_t^i is excess return from risk free rate, MKT_t denotes the market excess return of KOSPI, and $\triangle TC_t$ is the instrument we use for innovations in the total connectedness of total trading database. We use a call rate of South Korea from the FnGuide as a proxy for risk-free rate. We run the regression for all stocks on KOSPI with more than 16 daily observations. At the end of each month, stocks are classified into quintiles based on the realized value of $\beta^i_{\triangle TC}$ loadings on aggregate systemic risk over the past month. Firms in the 1st quintile have the lowest $\beta^i_{\triangle TC}$ coefficient, while firms in the 5th quintile have the highest $\beta^i_{\triangle TC}$ coefficient. Table 2.4 shows summary statistics for quintile portfolio sorted by $\beta^i_{\triangle TC}$ over the previous month using equation 10. We used value- weighted portfolios and do not use multiple factor models for portfolio beta because controlling over other factors can lead to misunderstanding the impact of total connectedness. After constructing a portfolio, we calculate portfolio return, beta, and alpha with the following equations:

$$R_t^i = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \epsilon_t^i \tag{11}$$

$$R_t^i = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \beta_{RMW}^i RMW + \beta_{CMA}^i CMA + \epsilon_t^i \tag{12}$$

where five factors, MKT, SMB, HML, RMW, and CMA, represent the Fama and French 5 model's market, size, value, profitability, and investment factors.

2.3 Empirical tests of connectedness

In this section, we provide evidence that the systemic risk is associated with connectedness among heterogeneous investor activities using total trading(TT), net trading imbalance(NTI), and normalized net trading imbalance(NNTI) data sets. We take this evidence as an expansion for the dynamic analysis in playing the source of systemic risk. We start our research by calculating the connectedness matrix using vector autoregressive(VAR) and variance decomposition method(VDM) defined in Section 2.2.

2.3.1 Full Sample Results

We provide a full-sample analysis by buying and selling information based on nine investor activity in the Korean stock exchange. Our goal is to test whether the interconnectedness estimated by investors' interactions is related to market stability. In detail, for each investor, we assign each investor an influence score from zero to one hundred based on the forecast error matrix estimated by the VAR and VDM. An influence score of zero indicates no connection and a one hundred score suggests a connection with maximum weight.

To check the usefulness of our approach, we introduce the major financial crises during a sample period. The dot-com bubble, which occurred roughly from 1997 to 2001, was an economic bubble due to excessive speculation. In 1999, after the Asian financial crisis, the South Korean government encouraged banks to issue credit cards to as many people as possible to bolster consumer spending. To be specific, the number of credit

Table 2.2. Full-sample Connectedness Table, Nine-Group Aggregation

Panel A : Connectedness among investor groups of Total Trading (TT)

	FO	RE	BA	IS	IV	PF	FI	OF	OC	FROM
FO	NA	8.29	5.67	5.80	9.60	5.47	10.88	2.72	3.42	51.84
RE	7.55	NA	7.90	7.49	9.78	6.44	11.49	4.49	4.84	59.97
BA	5.53	8.10	NA	6.81	8.01	5.61	7.83	3.85	5.84	51.58
IS	6.04	8.24	6.98	NA	9.00	6.55	7.80	3.73	3.96	52.31
IV	8.14	8.78	6.68	7.32	NA	8.82	12.37	2.97	5.47	60.53
PF	6.10	6.94	5.96	6.58	10.60	NA	7.69	3.05	4.02	50.93
FI	9.00	10.36	6.88	6.51	12.98	6.33	NA	3.57	3.94	59.55
OF	3.97	6.32	5.53	4.85	4.92	3.93	5.40	NA	3.26	38.18
OC	3.89	5.82	6.82	4.52	7.24	4.17	5.54	2.53	NA	40.53
TO	50.23	62.85	52.40	49.87	72.13	47.31	69.00	26.89	34.74	
NET	-1.61	2.88	0.82	-2.44	11.59	-3.62	9.45	-11.29	-5.79	465.44/9=51.72%

Note: this table lists connectedness calculated using aggregated trading value January 2002 through December 2018. Total connectedness (i, j) means the percent of forecast error variance of investor i caused by shocks from investor j that the predictive horizon (h-step) is a 10 day. Panel A, B, and C are used total trading, net trading imbalance, and normalized net trading imbalance. The labels of first column and row are the abbreviations of investor groups, e.g., foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), other financial(OF), and other corporate(OC).

Table 2.2. Full-sample Connectedness Table, Nine-Group Aggregation (continued)

Panel B : Connectedness among investor groups of Net Trading Imbalance (NTI)										
	FO	RE	BA	IS	IV	PF	FI	OF	OC	FROM
FO	NA	11.62	0.77	0.19	8.23	2.50	2.80	0.63	4.29	72.90
RE	12.97	NA	0.41	0.45	12.18	1.56	3.66	0.38	0.23	66.70
BA	1.19	0.64	NA	0.69	1.15	0.29	1.18	0.84	0.18	50.80
IS	0.66	0.97	1.22	NA	0.17	0.76	1.17	0.16	0.19	59.05
IV	3.06	18.20	0.96	0.22	NA	2.40	2.22	0.12	0.25	68.74
PF	2.78	1.66	0.30	0.89	1.57	NA	0.38	0.36	0.24	64.85
FI	2.07	4.09	0.89	0.99	2.10	0.54	NA	0.23	0.83	44.39
OF	0.69	0.29	0.88	0.17	0.12	0.27	0.29	NA	0.13	65.22
OC	4.28	1.18	0.07	0.06	0.70	0.40	0.50	0.25	NA	71.43
TO	27.70	38.64	5.50	3.66	26.22	8.72	12.21	2.98	6.32	
NET	-3.33	6.81	-0.67	-1.64	-1.22	0.53	0.48	0.16	-1.11	131.96/9=14.66%

Note: this table lists connectedness calculated using aggregated trading value January 2002 through December 2018. Total connectedness (i, j) means the percent of forecast error variance of investor i caused by shocks from investor j that the predictive horizon (h-step) is a 10 day. Panel A, B, and C are used total trading, net trading imbalance, and normalized net trading imbalance. The labels of first column and row are the abbreviations of investor groups, e.g., foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), other financial(OF), and other corporate(OC).

Table 2.2. Full-sample Connectedness Table, Nine-Group Aggregation (continued)

Panel C : Connectedness among investor groups of Normalized Net Trading Imbalance (NNTI)										
	FO	RE	BA	IS	IV	PF	FI	OF	OC	FROM
FO	NA	11.15	0.76	0.21	8.31	2.53	2.87	0.58	4.28	30.70
RE	12.43	NA	0.48	0.28	12.29	1.27	3.74	0.42	0.20	31.10
BA	1.17	0.74	NA	0.78	1.14	0.27	1.28	1.94	0.16	6.48
IS	0.80	0.69	1.41	NA	0.26	0.74	1.34	0.16	0.18	5.57
IV	3.11	18.13	0.97	0.36	NA	1.88	2.66	0.13	0.27	27.50
PF	2.88	1.39	0.30	0.75	1.26	NA	0.62	0.40	0.25	7.84
FI	1.94	4.06	0.93	1.13	2.48	0.84	NA	0.24	0.85	12.48
OF	0.64	0.30	1.00	0.16	0.12	0.25	0.33	NA	0.13	2.95
OC	4.37	1.03	0.05	0.08	0.71	0.46	0.52	0.25	NA	7.46
TO	27.34	37.49	5.90	3.75	26.58	8.24	13.35	3.12	6.32	
NET	-3.35	6.39	-0.59	-1.82	-0.92	0.40	0.87	0.17	-1.14	132.08/9=14.68%

Note: this table lists connectedness calculated using aggregated trading value January 2002 through December 2018. Total connectedness (i, j) means the percent of forecast error variance of investor i caused by shocks from investor j that the predictive horizon (h-step) is a 10 day. Panel A, B, and C are used total trading, net trading imbalance, and normalized net trading imbalance. The labels of first column and row are the abbreviations of investor groups, e.g., foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), other financial(OF), and other corporate(OC).

cards is 89.3 in 2001 and 104.8 in 2002, and 95.5 in 2003(million) from Bank of Korea and Financial Supervisory Service of Korea. Many credit card issuers were matched against going downhill, such as difficult liquidity and solvency condition, which then exposed the financial markets to systemic risk and devastated the real economy in 2003. Since imprudent trading of a commodity such as mortgage-backed securities (MBSs) and credit default swaps(CDSs) had increased, Lehman Brothers' collapse happened in 2008. The event has brought global financial markets to a turbulent period of weeks, given the company's size and status as a significant player in the U.S. and internationally. The Eurozone crisis has occurred in the European Union since 2009. This crisis had a severe economic negative impact on the European Union and the entire Eurozone. Therefore, it is worth investigating investors who play an essential role in liquidity in the financial market.

We compute the forecast error by the variance decomposition method using the full-sample data and consider it as the heterogeneous investors' connectedness. Panel A, B, and C of Table 2.2 reports the degree of connectedness as a percent of all possible connectedness of three different data sets defined in section 2, such as total trading (TT), net trading imbalance (NTI), and normalized net trading imbalance (NNTI). The heterogeneous investor group is defined by the nine investors in the KOSPI market: foreign investor(FO), retail investor(RE), bank(BA), insurance(IS), investment(IV), pension funds(PF), financial investment(FI), other financial(OF), and other corporate(OC). The *ij*-th entry in Table 2.2 can be measured as the contribution to the forecast error variance of investor i coming from innovations to investor j. The off-diagonal row sums (represented as From) and column sums (represented as To) represents contributions from others and contributions to others. "Net" stands for the "From" minus "To" value for each investor group.

We discuss the several characteristics of the connectedness matrix in Table 2.2. Demirer *et al.* (2018) presented the connectedness by the variance decomposition shows consistent results using other measures of systemic risk, such as marginal expected shortfall and CoVaR proposed by Adrian and Brunnermeier (2011), Acharya *et al.* (2012). The entries in the FROM column cannot exceed 100% because it means the sum of rows except the connectedness of themselves. According to Table 2.2, if Net of investors is greater than zero, the investor tends to give information rather than receive it. On the contrary, if Net is less than zero, the information sharing occurs to the investor from the other. Therefore, We define a source(sink) of systemic risk that transmit(receive) negative shocks in the stock market when they have positive(negative) Net value. Table 2.2 shows directional connectedness as Net values, which means specific investors could lead to cascading shocks arising elsewhere in the stock market.

The highest values of pairwise directional connectedness among investor groups are from financial institution to investment(12.37%) and from investment to financial institution(12.98%) in Panel A of Table 2. The next highest values of pairwise directional connectedness among investor groups are from financial institution to retail investor(11.49%) and from the retail investor to the financial institution(10.36%). As we saw above, financial institutions, investments, and retail investors share more connectedness than others. Retail investor, investment, and financial investment have positive directional connectedness, with 2.88%, 11.59%, and 9.45%, respectively. The lowest sinks, who receive information from others, are other financial(−11.29%), other corporate(−5.79%), and pension fund (−3.62%).

In Panel B of Table 2.2, retail investor, pension funds, financial investment, and other financial have positive directional connectedness. The highest values of pairwise directional connectedness among investor groups are from retail investor to investment(18.20%) and from investment to retail investor(12.18%) in Panel A of Table 2. The second highest values of pairwise directional connectedness among investor groups are from foreign investor to retail investor(12.97%) and the retail investor to foreign investor(11.62%). Panel C of Table 2 has consistent result with the Panel B of Table 2.2

This evidence implies which investors are the sources of total connectedness, which transmit influences to the process of others' trading behavior. We consider 51.72%, 14.66%, and 14.68% as a total connectedness among investor groups during the entire sample periods by TT, NTI, and NNTI databases, respectively. Suppose there appears to be a tendency toward market stability. In that case, this factor should be incorporated into a contagion channel of exogenous shock and considered as a factor of the capital asset pricing model(CAPM) and Fama and Fremch(1997) factor models. Additional evidences are presented in Table 2 and some of them is included in Figure 2.1.

Consider a two range of directional connectedness, shown in Figure 2.1(a), where the components are denoted by to (solid line) and by from (dotted line). The from column calculate the variability impact of the investors from the total variances of each investors forecast error. In Figure 2.1(a), the overall from column ranges from 38.18% to 60.53%. In Figure 1(b), the from column range is from 44.39% to 72.90% and in Figure 2.1(c) that is from 2.95% to 31.10%.

Similarly, contributions to the others of each investor are not limited by 100%. Therefore, the entry in the line to may exceed 100%. In contrast, the information delivered in the financial market is similar in terms of receiving information from other investors; the information provided to other investors is highly differentiated. The difference between the two types of connectedness distributions is shown in Figure 2.1. The directional connectedness to other investors is comparatively defined in a flatter and broader range than other investors' information.

Since Figure 2.1(a) begins at least 38.18% for connectedness from other financial and ends up to 60.53% for investment, the overall directional connectedness from others is somewhat dense. On the other hand, overall connectedness to others has a relatively flat distribution from 26.89% of other financial to 69.00% of financial institution. Especially, retail investors showed directional connectedness to others of 62.85% for Panel A of Table 2.2, 38.64% for Panel B of Table 2.2 and 37.49% for Panel C of Table 2.2. It means sources such as retail investors could play a role in propagating negative shocks on the stock market.

Finally, Panel A of Table 2.2 has 51.72% of total connectedness, 14.66% for Panel B of Table 2.2 and 14.68% for Panel C of Table 2.2. Total connectedness on Panel B and Panel C of Table 2.2 is small because every investor, except retail investors, actively shared their information. The information of retail investors free to trade in the stock market is easily reflected in the stock market information and delivered during the stock exchange process. It has a high value of connectedness, especially during the financial crisis, as we can see below. The reason for the increase of connectedness is that every investor involved in this transaction systematically affect the KOSPI market. Besides, the idiosyncratic shock delivered to one investor is communicated to others through connectedness based on trading value.

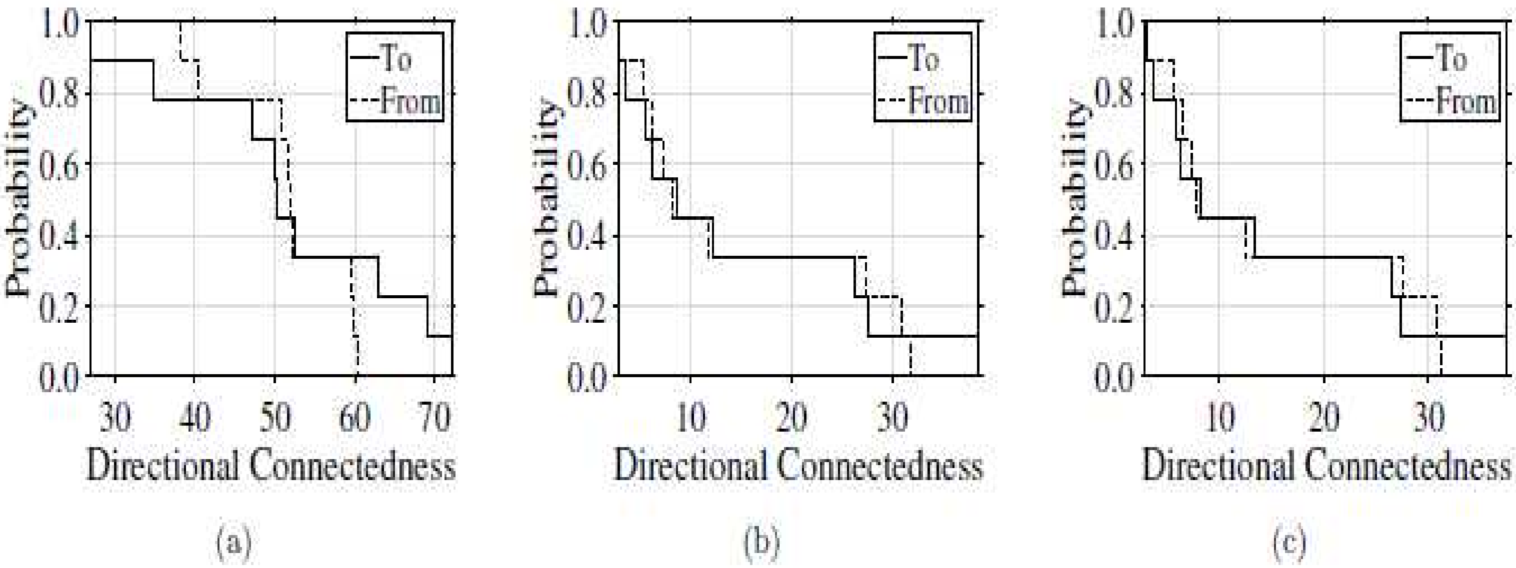
2.3.2 Rolling Sample Results

First of all, this subsection presents a dynamic analysis through a rolling window and shows how total connectedness distribution varies from 2002 to 2018. We also calculate each investor's Net value each year and provide the investors who lead the movement of information sharing in the stock market in the next section.

Figure 2.2 we plot total connectedness, defined as the average of the sum of directional connected- ness from Table 2.1, estimated using a 250-day rolling window. Figure 2.2 illustrates the corresponding VDM, performed by considering the three databases such as total trading, net imbalance, and normalized net imbalance. Observe that the pairwise-directional approach is capable of detecting time-varying characteristics based on investor strategies. The black line is total trading(TT), and the gray lines are net trading imbalance(NTI) and normalized net trading imbalance(NNTI).

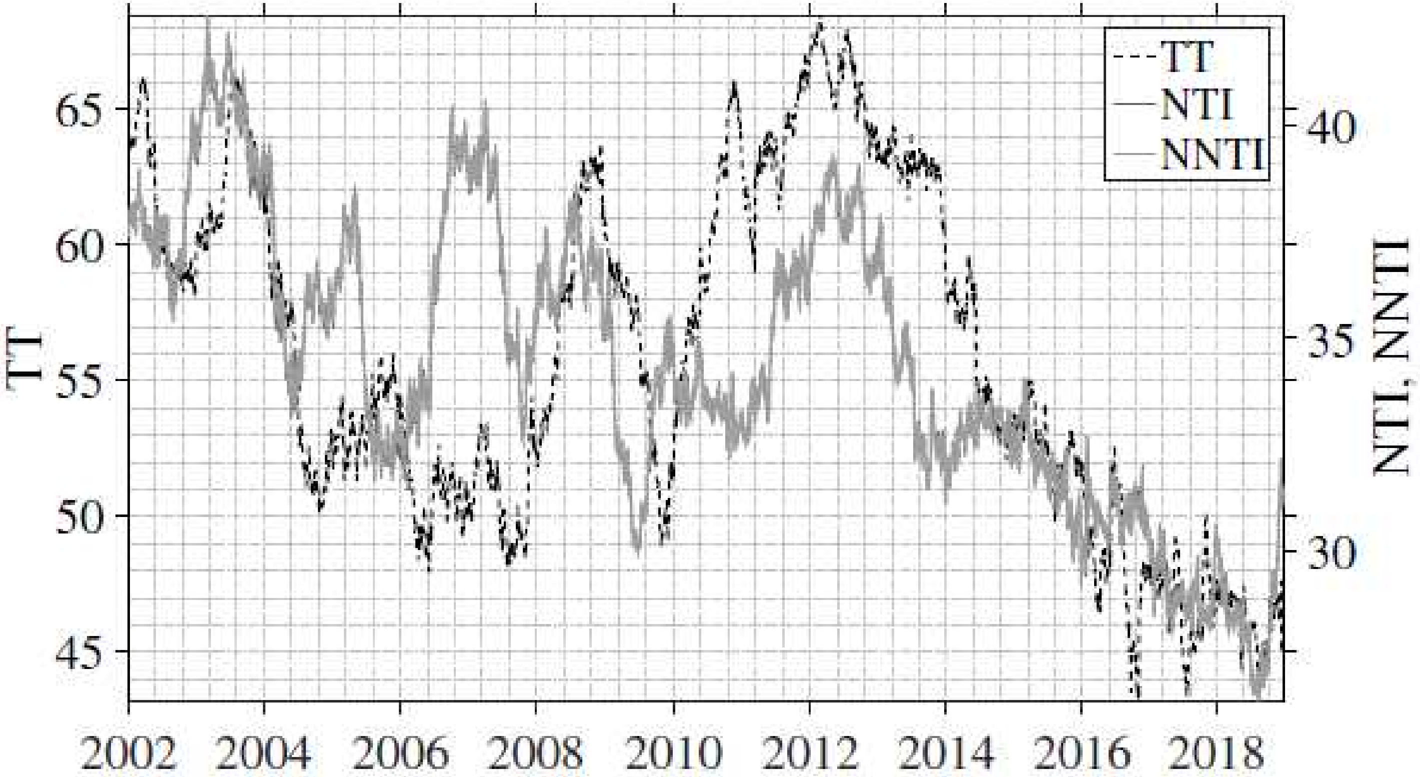
Total connectedness plotted in Figure 2.2 has similar pattern. They tend to soar during global financial crises. As negative shock among investors is shared, it is plausible explanation that finan- cial market is more destabilized. It measures investor activity though connectedness using rolling window of 250 day and prediction horizon of four, five, and five day, respectively. We marked the ending date of window in the y-axis. The right side of the x-axis means total connectedness of total trading, and the left side of the x-axis represents that of (normalized) net trading imbalance. As Figure 2.2 shows, looking at the black line features, average is 55.93 and drastically increase to 66.03 in March 2002. This result is the extensive use of credit cards in South Korea, which has caused a serious card impact on the economy. The most scale of Lehman brothers bankruptcy is propagated to the financial market globalized in 2008. Total connectedness is 48.28 before the financial crisis in June 2006 and is rising steadily by 53.3 in March 2007. It gradually gained from the European debt crisis in 2010 and dwindled from the Greek debt crisis in 2012. The result

Figure 2.1. Total Directional Connectedness



Note: the Figure 2.1(a), Figure 2.1(b), and Figure 2.1(c) indicate total directional connectedness of TT, NTI, and NNTI, respectively. We plot the cumulative distribution function for total directional connectedness "to" others and "from" others. The predictive horizon for the variance decomposition is 10 days.

Figure 2.2. Total Connectedness among Investor Groups



Note: this figure plots total Connectedness using black lines of TT (left scale) and grey line of NTI and NNTI (right scale), respectively. The arrows indicate the major crises related to systemic uncer- tainty in this period. We use rolling window of 250 days, and prediction horizon (H-step) of 10 days to calculate variance decomposition.

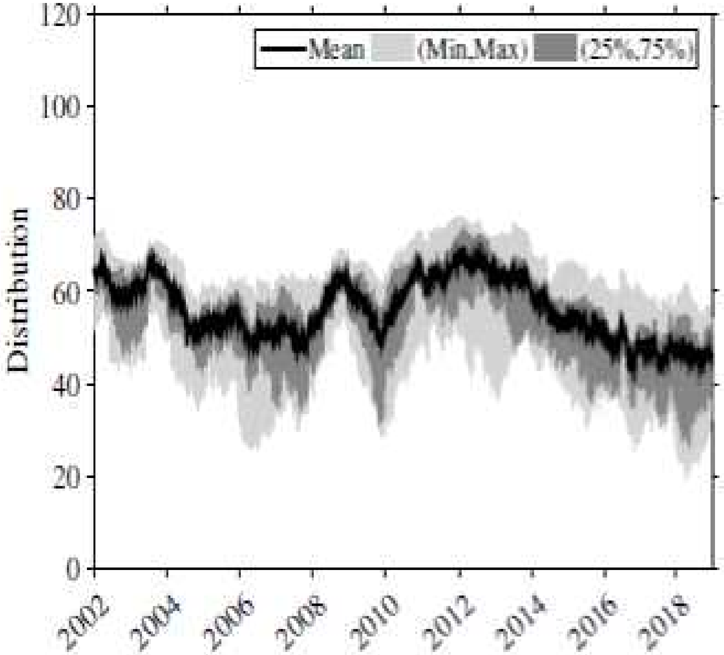
indicates that the total connectedness of the KOSPI market is reflected in the domestic crisis and the global financial crisis.

Additionally, total trading's total connectedness is reflected in the South Korea political scandal at the end of 2016. In those periods, foreign investors sold a large number of stocks under uncertainly of the stock market. It could be evidence that political issues are closely related to investors' decision-making in the stock market. The total connectedness of net trading imbalance and normalized net trading imbalance have consistent patterns with total trading, which is drastically increased in 2002, 2008, and 2011. The unemployment rate increase(3.8%), and government debt increase(27%) in 2005 from the International Monetary Fund report.

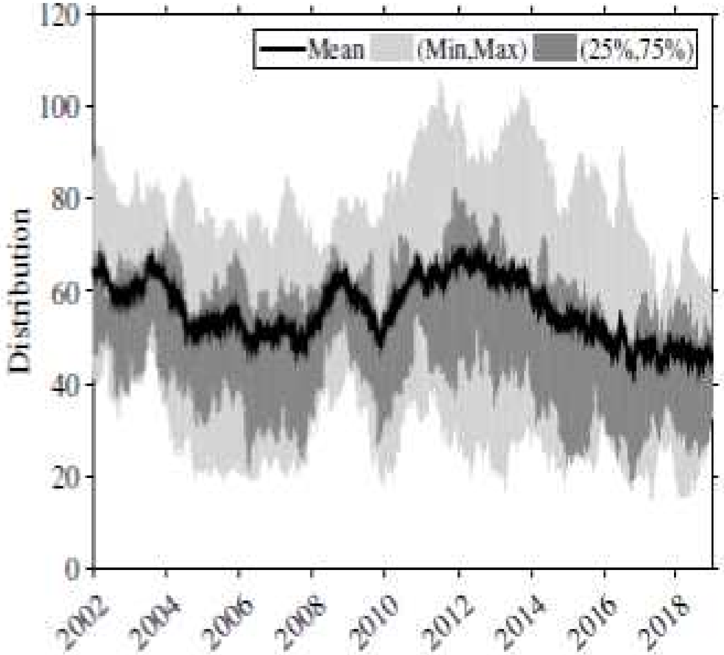
Figure 2.3 shows the dynamic directional distribution of connectedness measured for total trading, net trading imbalance, normalized net trading imbalance, respectively. The solid line represents the rolling distribution of total directional connectedness each year. Figure 2.3 on the left side such as (a), (c), (e) represent "from", and Figure 2.3 on the right side such as (b), (d), (f) represent "to", using total trading, net trading imbalance, normalized net trading imbalance, respectively. The different colors represent the range of 25% and 75% or the value of maximum and minimum of connectedness.

The reason for showing the distribution of total directional connectedness is to describe how much information an investor sends and receives when an economic event occurs. During the financial crisis, we observed that the distribution of outflow of connectedness among investors is broader than inflow. This result shows that the propensity of investors to spread negative shock when the stock market becomes unstable. In order words, specific investors play the role of propagating information in the market. Also, Figure 2.3 shows the result that our results have similar patterns. Consistent with Diebold and Yilmaz (2014), the overall amount of directional connectedness also increases during global financial crises in this study.

Figure 2.3. Rolling Distribution of Total Directional Connectedness



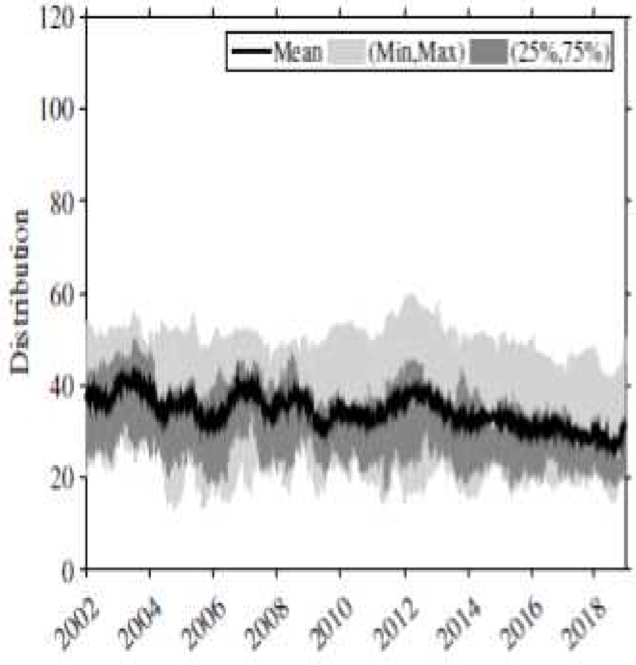
(a)



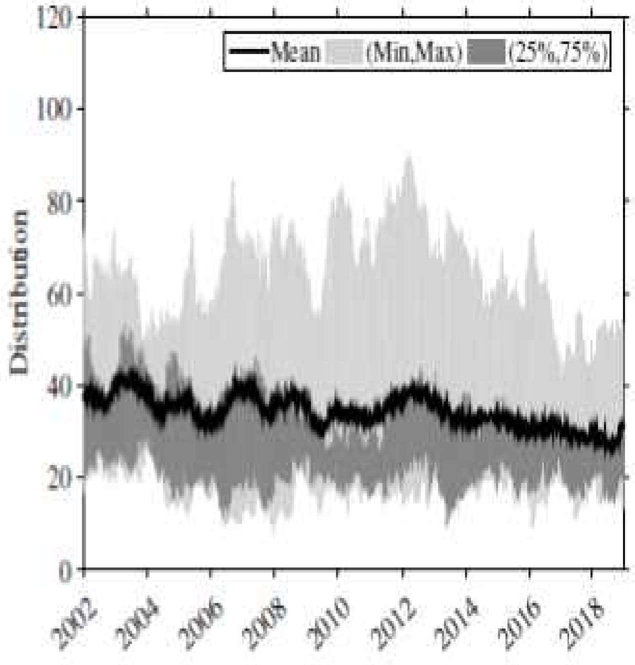
(b)

Note: ((a), (b): from, to of TT (c), (d): from, to of NTI (e), (f): from, to of NNTI) to and from, which means total directional connectedness of each investor. The rolling estimation window width is 250 days, and the predictive horizon for the underlying variance decomposition is 10 days.

Figure 2.3. Rolling Distribution of Total Directional Connectedness (continued)



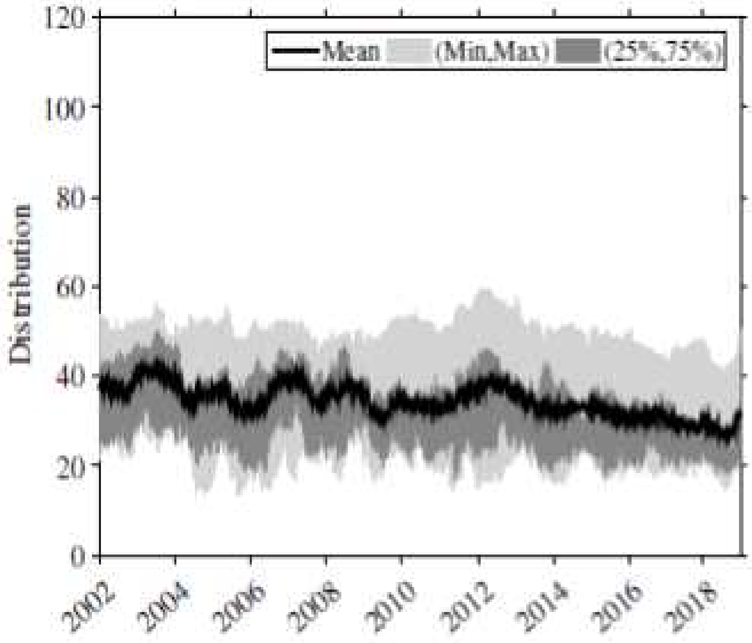
(c)



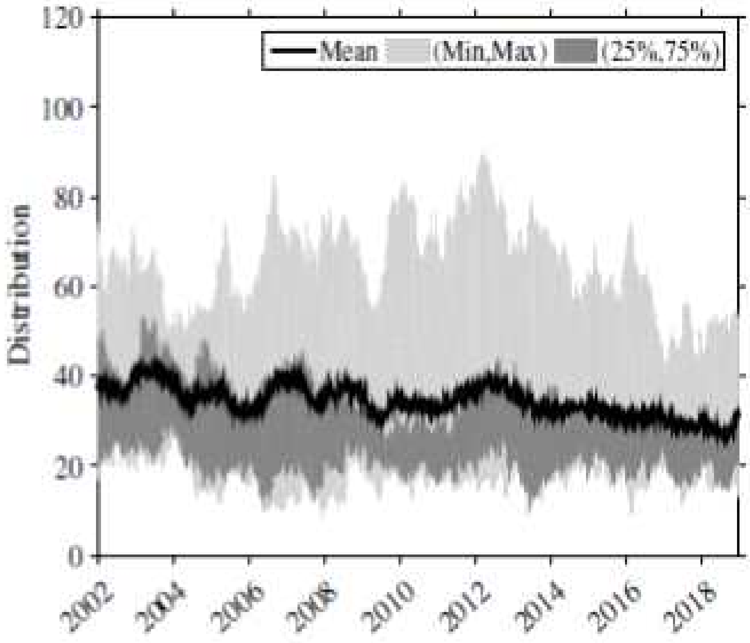
(d)

Note: ((a), (b): from, to of TT (c), (d): from, to of NTI (e), (f): from, to of NNTI) to and from, which means total directional connectedness of each investor. The rolling estimation window width is 250 days, and the predictive horizon for the underlying variance decomposition is 10 days.

2.3. Rolling Distribution of Total Directional Connectedness (continued)



(e)

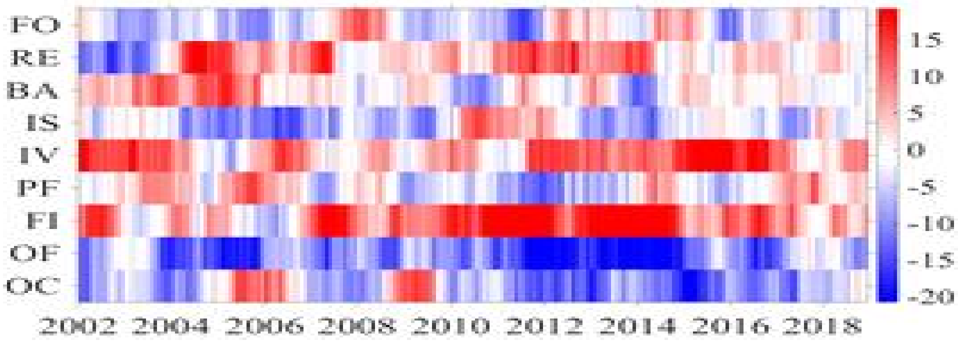


(f)

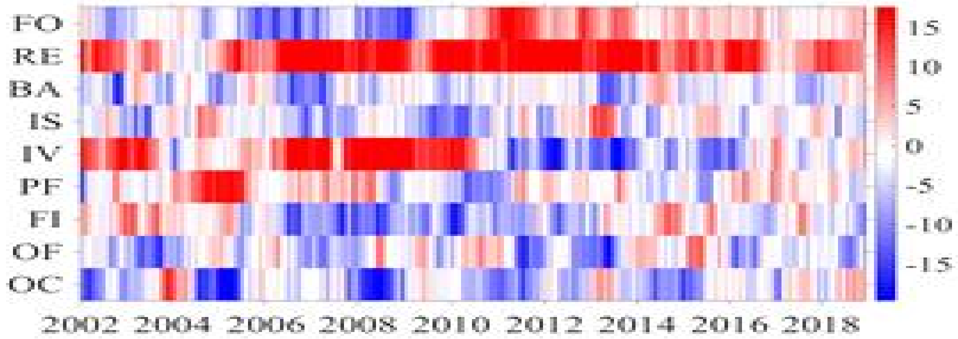
Note: ((a), (b): from, to of TT (c), (d): from, to of NTI (e), (f): from, to of NNTI) to and from, which means total directional connectedness of each investor. The rolling estimation window width is 250 days, and the predictive horizon for the underlying variance decomposition is 10 days.

Figure 2.4. The dynamics of source and sink as regards connectedness

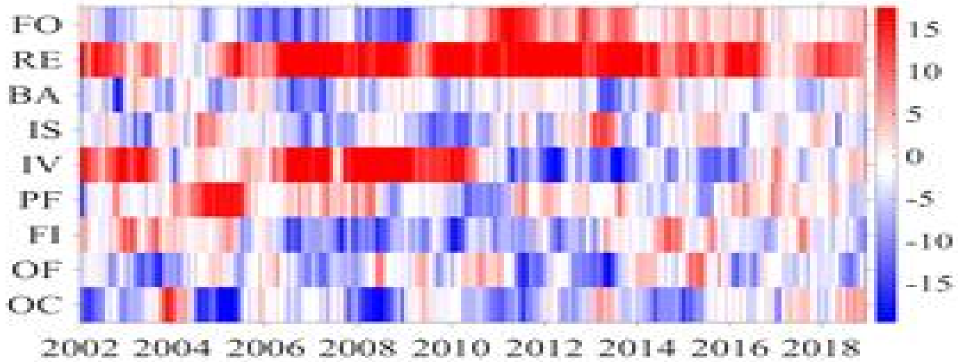
(a)



(b)



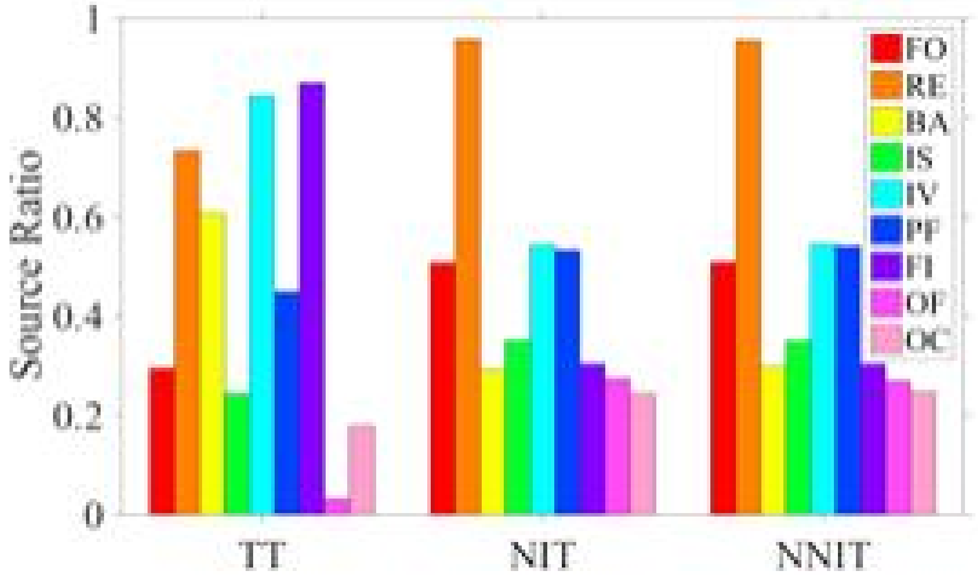
(c)



Note: (a) “Net” value of TT (b) “Net” value of NTI (c) “Net” value of NNTI (d) the ratio of date engaged on system source among investor groups from each database.

Figure 2.4. The dynamics of source and sink as regards connectedness (continued)

(d)



Note: (a) "Net" value of TT (b) "Net" value of NTI (c) "Net" value of NNTI (d) the ratio of date engaged on system source among investor groups from each database.

2.3.3 Identifying the Source of Destabilization

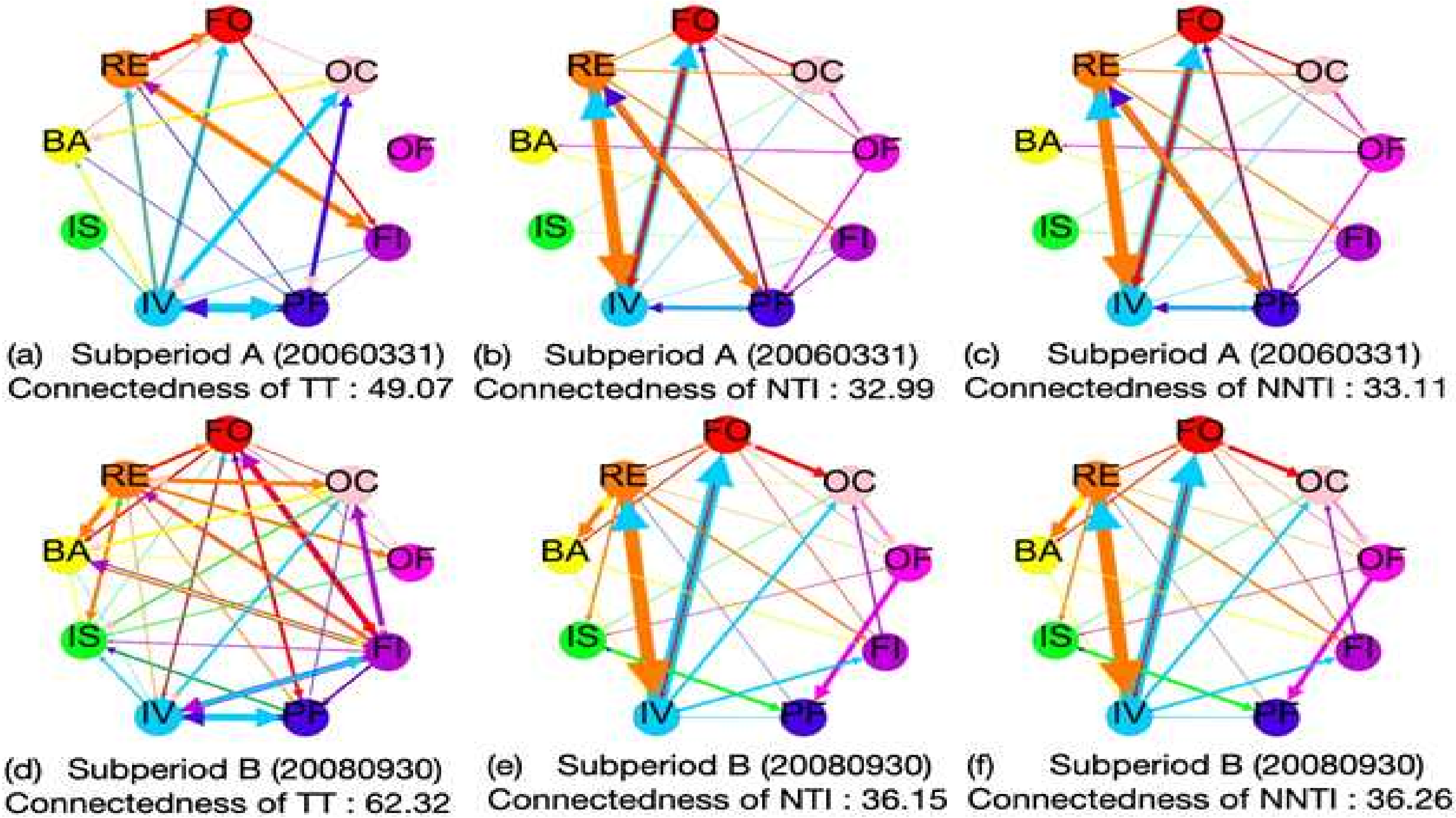
This chapter shows that dynamic connectedness among investors through visualization, such as the network diagram, presents the relation between connectedness and stability in the financial market. In our study, unlikely the fact that Ozsoylev *et al.* (2013) revealed whether the channel of information diffusion among investors is the public or private arena, we sought the source of connectedness within investors. An essential finding of this study is that all investor shares their information through trading volume and individual investors and listed foreign investors have a significant role in market uncertainty. We then use the variance of the domestic stock index across the same period as a robustness check.

We define the investor who has a positive Net value as a source and has a negative Net value as a sink. Figure 2.4 indicates that the amount of connectedness accounts for destabilizing the financial market. Figure 2.4(a), (b), and (c) represent retail investors seem to detrimental role of market viability. The evidence is that retail investors tend to receive information from the other investors in the market as a source each year. Considering Figure 2.4(a), investment and financial institution also have a significant role in the US subprime crisis and the European debt crisis. Figure 2.4(a) shows that the amount of information by sources increases before the 2008 financial crisis. We likely focus on part for the retail investor as source of systemic risk. There are no consistent patterns in the other investor groups. Figure 2.4(d) explains that the source ratio denotes the number of months with positive net value divided by the number of sample months. As a result, the retail investor has a significant role in transmitting information to the stock market in all cases.

It has been controversial that retail investors have psychological bias and are considered a sort of noise trader in previous studies (Black 1986, Long *et al.* 1990). Our paper also supports the evidence with a consistent view that retail investors have a lot of information in Table 2.3 and could play a deteriorating role in the stock market. To complex networks display heterogeneous structures, we present weighted directed networks to show which investor is a deteriorating role of the system during a global financial crisis. Note that investors connected if they gave and took the information of forecast error. A node represents investor groups, and node color indicates the same with Figure 2.4. Node size means the out-degree of pair-wise connectedness. Links between two investor groups represent pair-wise directional connectedness, and link color represents the origin of connectedness. The link arrow sizes indicate the strength of the pair-wise directional connectedness. Each network is created by links above a threshold of the connectedness matrix in each database by each time t. We define different thresholds as $\mu - \alpha\sigma$ for each matrix, which is μ is the mean of the matrix, and σ is the standard deviation of the matrix. The α for the networks illustrated in Figure 2.5 is 0.3 for each database. Because this threshold is a good representation of the strength of the connection and the node's degree to visualize the spillover effect during tranquil and crisis periods, Figure 2.5 plots the pairwise directional connectedness between investor groups during the sub-period. Figure 2.5 shows individual investors is always a robust transmitter of information to others. It is characteristic of the KOSPI market. In line with literature about systemic risk, the important time is Lehman's bankruptcy, which was announced on September 15, 2008. Figure 2.5 shows the network graphs on March 31, 2006, and on September 30, 2008. This is because a clear difference between the connectedness on the two dates from Figure 2.2. Figure 2.5 highlights the role of retail investors in the financial market. The remarkable thing is Figure 2.5(a)-(c) have lower connectedness than Figure 2.5(d)-(f). It means that indiscriminate contribution from retail investors was spread across the market before the Lehman Brothers collapse.

A study by Ozsoylev *et al.* (2013) found that the trading activity was active before transmitting information on the event from mainstream media due to information diffusion and information diffusion was caused from other channels than mainstream media. We have a similar pattern in that the amount of connectedness caused by systemic risk sources increases before the global financial crises. It seems that spillover among investors better reflects risks in the real market than volatility, known as measuring the existing market risk.

Figure 2.5. Investor Network Graph, periods of tranquil (20060331)-crisis (20080930)



(a) Subperiod A (20060331) Connectedness of TT : 49.07

(b) Subperiod A (20060331) Connectedness of NTI : 32.99

(c) Subperiod A (20060331) Connectedness of NNTI : 33.11

(d) Subperiod B (20080930) Connectedness of TT : 62.32

(e) Subperiod B (20080930) Connectedness of NTI : 36.15

(f) Subperiod B (20080930) Connectedness of NNTI : 36.26

Note: this figure plots network of pair-wise connectedness. There are networks during a tranquil period of (a) total trading (b) net trading imbalance (c) normalized net trading imbalance and during a crisis period of (d) total trading (e) net trading imbalance (f) normalized net trading imbalance. Node represents each investor group and edge represents directional connectedness between investor groups.

Table 2.3. The Role of Destabilization of the Investor Networks

Panel A : NET value of each investor of Total Trading (TT)									
	FO	RE	BA	IS	IV	PF	FI	OF	OC
2002	-2.58	-12.36	4.96	-1.43	14.76	-0.22	12.13	-7.14	-8.11
2003	-7.55	-8.18	10.11	-0.15	13.95	6.60	-1.40	-6.46	-6.91
2004	-3.80	14.62	9.89	-8.57	2.72	1.22	5.41	-14.35	-7.16
2005	-8.73	9.51	11.55	-11.10	-0.93	9.65	-0.03	-18.02	8.11
2006	-5.79	6.55	0.95	-12.79	11.08	3.83	-1.83	-6.52	4.53
2007	4.19	7.40	1.40	-6.16	0.74	-4.82	17.44	-11.37	-8.81
2008	6.06	1.20	-1.87	-6.52	4.77	0.83	8.09	-10.56	-1.99
2009	-6.42	4.05	1.85	-8.18	3.70	-5.84	10.54	-7.15	7.45
2010	-4.60	4.22	-9.01	8.81	4.69	-3.85	16.94	-11.22	-5.97
2011	-11.49	12.21	1.92	6.70	4.57	-10.76	25.38	-17.54	-10.99
2012	4.40	11.62	-0.23	-1.38	13.34	-9.21	14.96	-19.82	-13.66
2013	-0.48	10.28	-1.96	-8.37	10.42	-5.31	25.33	-20.22	-9.70
2014	3.34	4.35	-5.34	-7.48	11.74	5.40	21.93	-21.68	-12.26
2015	-1.55	0.14	1.80	-1.04	21.70	-4.98	7.27	-8.15	-15.19
2016	-6.05	4.56	0.93	-2.85	16.95	-2.01	12.19	-13.72	-9.99
2017	0.84	0.35	0.78	-5.41	4.15	7.65	4.92	-4.64	-8.64
2018	-3.19	1.74	-1.80	-1.61	6.24	2.34	5.18	-5.48	-3.42

Note: the table provides yearly average of Net value from the connectedness matrix. Investors with positive net value are defined the source of connectedness and those with negative net value are defined as the sink of connectedness.

Table 2.3. The Role of Destabilization of the Investor Networks (continued)

Panel B : NET value of each investor of Net Trading Imbalance (NTI)									
	FO	RE	BA	IS	IV	PF	FI	OF	OC
2002	-4.69	12.43	-7.06	-1.90	12.30	-1.28	2.53	-3.64	-8.69
2003	-1.40	5.13	-1.61	-5.44	9.35	-1.26	5.96	-10.67	-0.07
2004	-2.71	-0.36	-2.80	2.88	-1.02	10.50	0.53	-1.74	-5.29
2005	-6.48	10.28	-1.74	-1.29	2.23	10.36	-0.11	-2.24	-11.01
2006	-11.15	20.02	-7.87	-5.14	15.90	1.70	-8.11	-2.80	-2.55
2007	-5.77	21.35	-5.57	-7.36	15.07	4.76	-10.72	-7.60	-4.17
2008	-11.38	19.18	-3.29	-0.94	23.26	-0.85	-10.73	0.02	-15.28
2009	-5.73	14.94	-3.31	-9.29	15.34	-1.81	-7.99	-1.44	-0.71
2010	4.26	21.49	-2.64	-8.21	7.46	-9.56	-9.04	2.82	-6.58
2011	14.22	21.51	-0.55	-2.27	-8.81	-0.63	-5.89	-7.98	-9.60
2012	7.05	22.62	-1.76	-0.19	-11.26	1.72	-7.15	-5.67	-5.37
2013	7.52	19.89	-8.89	4.44	-14.27	1.20	-1.39	-8.77	0.27
2014	1.80	12.39	1.44	-2.96	-4.85	-4.01	4.38	0.92	-9.11
2015	3.58	11.53	-2.62	1.63	-9.37	-3.61	0.38	3.86	-5.39
2016	2.42	13.37	-2.27	-1.67	-3.11	4.14	-4.68	-6.61	-1.58
2017	0.61	6.03	-4.81	0.09	-0.98	1.99	0.92	-3.31	-0.55
2018	2.55	10.23	-0.31	-3.07	0.57	-1.32	-4.71	-5.93	1.98

Note: the table provides yearly average of Net value from the connectedness matrix. Investors with positive net value are defined the source of connectedness and those with negative net value are defined as the sink of connectedness.

Table 2.3. The Role of Destabilization of the Investor Networks (continued)

Panel C : NET value of each investor of Normalized Net Trading Imbalance (NNTI)									
	FO	RE	BA	IS	IV	PF	FI	OF	OC
2002	-4.29	12.79	-6.89	-2.19	12.36	-1.34	2.33	-3.60	-9.18
2003	-1.29	5.33	-1.86	-5.40	9.27	-0.97	6.02	-11.05	-0.05
2004	-3.30	-0.23	-2.72	3.08	-0.89	10.54	0.86	-2.02	-5.33
2005	-6.58	10.07	-1.42	-0.85	1.97	10.07	-0.37	-2.17	-10.72
2006	-10.98	19.88	-7.48	-5.18	15.99	1.77	-8.19	-3.07	-2.76
2007	-5.87	21.80	-5.37	-7.45	15.04	4.55	-10.42	-7.86	-4.43
2008	-11.80	19.38	-3.48	-0.92	23.33	-0.85	-10.42	-0.06	15.17
2009	-5.77	14.78	-3.40	-9.32	15.13	-2.12	-7.42	-1.53	-0.35
2010	3.84	21.63	-2.79	-8.01	7.48	-9.22	-9.09	2.56	-6.40
2011	13.99	21.19	-0.48	-2.21	-8.77	-0.15	-5.93	-7.96	-9.68
2012	6.71	22.19	-1.65	-0.09	-11.02	2.19	-7.49	-5.77	-5.08
2013	7.88	20.20	-8.77	4.06	-14.09	1.26	-1.05	-9.66	0.16
2014	1.55	12.38	1.76	-2.99	-4.56	-4.09	4.69	0.60	-9.32
2015	3.31	11.54	-1.69	1.51	-9.31	-3.61	0.04	3.96	-5.75
2016	2.72	13.25	-2.52	-1.96	-3.38	4.09	-4.74	-6.06	-1.40
2017	0.46	5.58	-4.18	-0.06	-0.80	1.98	0.95	-3.89	-0.03
2018	2.51	10.11	-0.06	-3.14	0.32	-1.60	-4.58	-6.03	2.47

Note: the table provides yearly average of Net value from the connectedness matrix. Investors with positive net value are defined the source of connectedness and those with negative net value are defined as the sink of connectedness.

2.3.4 Pricing Connectedness Shocks of Total Trading in the Cross-Section

Finally, we compare the expected returns to the total connectedness innovation of the total trading database represented by investors' transactions. We use 1-month excess returns and the regression intercept from CAPM, and FF three- and five-factor models. Our objective is to examine whether the average return on stocks with different sensitivities to total connectedness innovations (proxied by $\beta^{i}_{\triangle TC}$) is other.

Table 2.4 shows summary statistics for quintile portfolios classified by past $\beta^{i}_{\triangle TC}$ over the previous month through equation 10 consistent with Ang *et al.* (2006). The empirical model we examine in Table 4 is equation 11 and equation 12 to check how systemic risk is priced using regression analysis. The first two columns show the mean and standard deviation of monthly excess returns. The columns marked "CAPM Alpha", "FF-3 Alpha", and "FF-5 Alpha" means time-series alpha in their portfolios of the CAPM, FF-3 model, and FF-5 model, respectively. A previous study of Fama and French (2015) provides evidence that cross-section factors have explanatory power to explain the cross-section of returns. After controlling Fama and French three- and five-factor, the result is consistent with the CAPM model. We reject the hypothesis that the ex post $\beta^{i}_{\triangle TC}$ loadings are equivalent to zero. Sorting stocks on past $\beta^{i}_{\triangle TC}$ suggests strong, significant transmissions in aggregate systemic risk sensitivities.

This result implies that the total connectedness of total trading among investor groups has a negative relationship with the stock returns in the Republic of Korea. It could help us understand the pricing of systemic risk and trading activities. We suggest negative returns of portfolios based on systemic risk by variance decomposition using trading value. This initiative contributes to the advancements of this field and enhances the development of asset pricing models.

Table 2.4. Portfolio sorted by Exposure to Aggregate Information Shocks of Total Trading

Rank	Mean	Std. Dev.	Size	B/M	CAPM Alpha	FF-3 Alpha	FF-5 Alpha	β
1	1.4472	6.7435	11.896	6.9512	1.0006***	1.5017***	1.2279***	-3.3631
					[3.2303]	[3.0792]	[2.2316]	
2	1.6999	6.3612	11.9013	7.0937	1.2528***	1.5493***	1.3845***	-1.0228
					[4.6242]	[3.1310]	[2.6786]	
3	1.5438	6.0362	11.8601	7.1318	1.1247***	1.2997***	1.2191***	-0.0404
					[4.3034]	[2.7955]	[2.4265]	
4	1.4992	6.3185	11.9246	7.1068	1.0555***	1.2798***	1.2018***	0.9060
					[3.7818]	[2.6455]	[2.4167]	
5	1.3477	6.6658	11.8602	6.9570	0.8915***	1.2368***	1.1295**	3.0962
					[2.9726]	[2.4202]	[1.9136]	
5-1	-0.0995				-0.1091	-0.2649	-0.0984	
					[-0.5223]	[-1.2134]	[-0.4437]	

Note: value-weighted quantile portfolio is generated every month with regression of excess individual stock returns on $\triangle TC$, to control the MKT factor as in equation 14, using previous month's daily data. Stocks are sorted into quantiles 1 through quantiles 5 based on a coefficient of $\beta^i_{\triangle TC}$. Mean and Std. Dev. indicate as a distribution of monthly excess returns. Size presents defined by the natural lognithm of market capitalization for firms within the portfolio and B/M shows the boo-to-market ratio. The row labeled 5-1 reports the difference between the monthly return of portfolio five and that of portfolio one. The T-statistics, which tested the null hypothesis that the average portfolio return is equal to zero, are shown in parentheses adjusted using six lags following Newey and West (1987). The Alpha column refer to the Jensen's alpha for the CAPM, Fama-French (1993) 3-factor, 5-factor model. The β indicates a value-weighted beta into each quantile portfolios at the beginning of the month.

2.4 Summary and concluding remarks

This paper investigates a connectedness of investor activities to enhance understanding of the stability of the stock market. The connectedness among nine investors is used to measure market stability and test asset pricing models. In line with previous studies related to systemic risk, we find sufficient evidence to detect financial crises. Like systemic risk measures calculated by a connectedness among the individual stock returns, the network of investor activities produces a sufficiently large explanation of the systemic risk to distinguish between normal and abnormal market status. In other words, the connectedness among heterogeneous investors enables us to exploit the specific nature of systemic risk induced by connections among financial subjects. To demonstrate the benefits of the systemic risk measure based on an investor activity level, we revisited the performance of five factor model proposed by Ang *et al.* (2006).

We summarize our findings as follows. First, the source of connectedness, such as retail investors, causes the effect of contagion in the stock market. We suggested a consistent view with the study of previous researches by Choe *et al.* (1999), Kim and Jo (2019). Kuma and Lee (2006) has said that retail investors' systematic trading brings about systematic effect on the stock markets and return comovements for stocks. Second, the results reveal the systematic impact of the dynamic relationship on the KOSPI market rather than each investor's trading pattern. Our connectedness measure reflects global financial crises and contributes to the literature of systemic risk. Third, our empirical results highlight the role of connectedness beta, which measures the sensitivities of individual firm's returns to market-wide interconnection among investors in several asset pric- ing models. Based on the asset pricing model, we observe that low(high) connected beta stocks outperform(underperform). These results could be useful to regulators and policymakers.

These findings shed light on future research about the anomaly of asset pricing and the complex network of market participants such as investor activities in the behavior finance. First of all, we do not reveal the source of destabilizing the stock market across the level of stocks. Future researchers could prolong the results to investigate using the network method about concerning the dynamic pattern of style investing of heterogeneous investors and the additional factor of price formation. Secondly, the amount of information among retail investors could lead to stock returns beyond general risk factors. Finally, the connectedness among investors has a possibility that it can extend in explaining asset pricing theory due to negative relationships with return and risk. This extension would allow for an analysis of network characteristics of investor activities.

III. Lending diversification and interconnectedness of the syndicated loan market

3.1 Motivation

In this chapter, we study interbank networks in the form of common exposures among financial institutions to analyze bank performance based on banks' exposure to large syndicated loans. Syndicated loans represent one of the crucial sources of external financing for many firms and provide an ideal experimental setting for studying the interconnectedness of banks. In this study, the network between banks is constructed from data sets that contain information regarding both the borrowers and lenders of syndicated loans. The common exposures of banks are able to measure banks' investment strategies in this market in terms of loan portfolio diversification.

Based on social exchange theory as proposed by blau et al. (2017), we present different perspectives to understand the banking industry in the United States; these perspectives recognize the complex and rich social relationships that define interbank network. When the economy is growing, banks actually benefit from promoting the sharing of information with network members for business expansion; as a result of this sharing, they are able increase their profits. Nonetheless, during periods of economic contraction, banks cannot force network members to restructure because they may be subject to strict constraints due to their obligations. Banks are expected to expend effort monitoring and screening their borrowers to mitigate risk exposure. Additionally, bank performance is negatively affected within a contracting economy.

To assess the level of connectedness between the banks of syndicated loan portfolios, we establish a measure of interconnectedness that utilizes the similarity between banks' syndicated loan portfolios at the industry level as proposed by Cai et al. (2018). An advantage provided by the use of loan portfolios is the ability to investigate the response of banking systems via direct connections. To extract meaningful information from all-to-all connected networks, we employ the planar maximally filtered graph (PMFG)

(Tumminello et al. 2005). We utilize the centrality measure to drive an important component that may affect whether a bank's centrality in the interbank network created in the financial sector is related to its performance. In this paper, the centrality is measured by the principal component analysis (PCA) method based on four common measures of centrality in the context of networks: degree, eigenvector, closeness, and betweenness.

To date, only the lending relationship between banks and firms has been studied through analyzing the characteristics of individual banks or firms using corporate loan data. The aim of this paper is to study an interbank network, namely, the syndicated loan market. We investigate the evolution of several types of syndicated loans over time using a Dealscan database, with a special emphasis on the amount of syndicated loans that have been extended. More interestingly, the syndicated loan data used in this study allow us to investigate the effect of the centrality of interbank networks on bank performance.

We show that banks with a higher level of network centrality are more likely to pursue diversification and that this diversification is more likely to increase during market instability. To extend our examination of the relationship between interbank networks and bank performance, we move beyond bank-to-firm lending by studying interbank networks in the context of the syndicated loan market. We further find that banks with a high level of centrality have higher returns than do banks with a low level of centrality. Since a bank's centrality within the network plays an important role in its loan portfolio strategy, it also plays a significant role for lending market participants. We also found that in the core group, there was a negative correlation between diversification and centrality; however, a positive relation was observed in the peripheral group.

The paper is organized as follows. Section 2 explains the methodology that we employed. Section 3 presents a description of the database used, and Section 4 contains an empirical analysis. Section 5 concludes this paper.

3.2 Methodology

In this section, we explain the network construction and regression variables. For each month, we define an interconnectedness based on the similarities between syndicated loan portfolios. The results are not qualitatively sensitive to bank performance measures, e.g., we obtain essentially the same results even if we use different financial variables to measure bank performance.

3.2.1 Network Construction

In this subsection, we explain the way in which we estimate the distance between two banks based on their loan portfolios. We then describe the way in which we construct an interbank network. To map our interbank network, we obtain information on the relationships between banks and firms between 1990 and 2017 from the DealScan database.

First, we investigate bank syndicated loans in the U.S. lending industry classified using two-digit SIC industry codes. This measure was developed by Cai et al.(2018) and uses the Euclidean distance between two banks. For each month, we calculate the distance between bank i and bank k by quantifying the similarity of these two banks in a J-dimensional space as follows.

$$Distance_{i,k,t} = \sqrt{2}\sum_{j=1}(w_{i,j,t} - w_{i,k,t}) \tag{13}$$

where $w_{i,j}$ is the portfolio weight of bank i invested in industry j within the 12 months prior to month t. The loan portfolio weight for all pairs of i and t as well as the number of industries in which J is invested, is denoted as: $\sum_{j=1} w_{i,j,t} = 1$. The distance is normalized between 0 and 1; 0 refers to perfectly matched portfolios and 1 refers to portfolios that do not overlap at all.

We then construct a filtered network that connects all the banks so that a planar maximally filtered graph(PMFG) can be used Tumminello et al. (2005).

The most common method of forming a stock network is based on the correlation of stock returns using threshold (Onnela et al. 2004; Chi et al. 2010). This method has a problem in which correlation coefficient only assumes a linear relationship and lead to neglect of some information. In addition, the minimum spanning tree (MST), a tree formed by a subset of the edges of a given undirected graph, is also a common method in complex network analysis (Onnela et al. 2003). However, this method reflect hierarchical clustering with information loss to generate a efficient network. To address these issues, we use PMFG measure to construct a network related on relationship among banks.

3.2.2 Main Dependent and Independent Variables

We investigate how network structure affects bank performance using the banks in the U.S. between January 1, 1990 and December 31, 2017. To do, we use the Return on asset (ROA) variable as the dependent variable to measure the bank's performance and employ the several financial variables, such as the bank size, an amount of syndicated loan, etc. as a control variables to examine network effect on bank's performance.

(A) Diversification

In information theory, following Shannon (1948)}, the entropy of a discrete random variable X is denoted as

$$H(X) = \frac{-p(x_i)\sum_{i}^{n}\log(p(x_i))}{-p^m(x_i)\sum_{i}^{n}\log(p^m(x_i))} \tag{14}$$

where $p(x_i)$ is the probability distribution of outcome X and $p^m(x_i)$ is defined by the 1/n. x_i is the proportion of the total loan amount of industry i held by a bank and n is the number of industries invested from the bank. It is well known that entropy is viewed as a measure of the uncertainty of a random variable. Concept of entropy have manifested useful across a wide range of fields, so it is remarkable they have begun to make noticeable effect into economics and finance. It has also been a popular diversity index in previous literature. In this paper, we use the concept of diversification that corresponds to the above measure within the range of zero to one. When H is zero, the bank has concentration of loan portfolio. Otherwise, when H is one, the bank has perfect diversification of loan portfolio.

(B) Network Centrality

The effect of bank network centrality on bank performance is due to the importance of bank-firm lending structure in the context of information asymmetry. A bank's network created by bank-to-firm loan information should affect the profit of lending banks. Generally, centrality refers to a bank's location in a network compared to that of others. The four indices of centrality are frequently discussed in the social network literature (Newman, 2003). These four indices are degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality. These indices represent different dimensions of connectedness that affect information sharing via a network. Degree centrality is the sum of the first-degree connections of an entity in a network. The raw score is divided by the total number of nodes in the network minus 1, because the size of the interbank network changes each month (Wasserman et al., 1994). Eigenvector centrality measures an individual bank's ability to obtain or influence information within the network. This measure increases as connections with other highly connected neighbors are added. The raw score is divided by the total number of nodes in the network minus 1 because the size of the interbank network changes each month. Closeness centrality is the inverse of the mean of the shortest path length between an individual bank and all the other reachable banks in the network. The raw score is multiplied by the total number of nodes in the network minus 1 because the size of the interbank network changes each month. Betweenness centrality describes the extent to which an individual bank is connected to the other banks in the network. When the shortest path of all the bank pairs passes a bank, the betweenness centrality of that bank is high; this is the reason why it is important to control the flow of the entire network. The raw score is divided by the total number of the connected nodes because the size of the interbank network changes each month.

To generate our composite centrality index (CCI) in Table 3.4, we standardize four of the centrality indices to a mean of 0 and a standard deviation of 1. Consistent with Omer et al. (2014, 2019), Larcker et al. (2013), we use the factor score to aggregate CCI using the first principal component for each bank with four centrality indices in the PMFG network.

(C) Bank Performance Measure

Return on assets (ROA) is an indicator of how well a company generates a profit from its total assets. We calculated ROA by dividing firms' profit or loss before taxes by their total assets in month t and converted this figure to a percentage. The previous studies related to the current research area show that ROA is the best used as a measure of performance when comparing similar companies in the same industry

3.3 Data Description

To test the hypotheses outlined in Section 1, we construct a sample of syndicated loans matched according to firm and bank characteristics. Below, we describe the sample construction and summarize the sample characteristics.

3.3.1 Data Source

We build our datasets from a comprehensive sample of syndicated loans and the associated lender and borrower information by merging data derived from Standard & Poor's Compustat and from Thomson Reuters' LPC Dealscan from 1990 to 2017. The Compustat database is free of survival bias, as it contains the monthly historical accounting data of borrowing companies, and data regarding syndicated loans are included in the Dealscan database. Our starting points are the DealScan-Compustat Link (Chava and Roberts, 2008) and the Lender link (Schwert, 2018).

Syndicated loans play a crucial role in the American corporate loan market. These loans are typically offered by a group of lenders. The lenders in a syndicate are large banks that fall into two categories of lenders: lead arrangers and participants. In this study, following the work of Cai et al. (2018), we classify lenders as lender-to-lead arrangers and participants. We refer to lead arrangers as banks from now on, but we do not refer to participants in this way. Following the literature, we exclude loans made to financial companies (i.e., SIC codes between 6000 and 6999) as well as classified companies belonging to the Fama-French 12th industrial classification (i.e. others).

The use of syndicated loan data allows us to explore the activities of the financial intermediaries in the loan market. Our loan data, with 52,685 facilities and 35,632 packages, comprises a complex structure. After excluding banks with negative total assets, the study sample is composed of 62-151 banks listed in the United States during the period 1990-2017.

3.3.2 Sample Characteristics

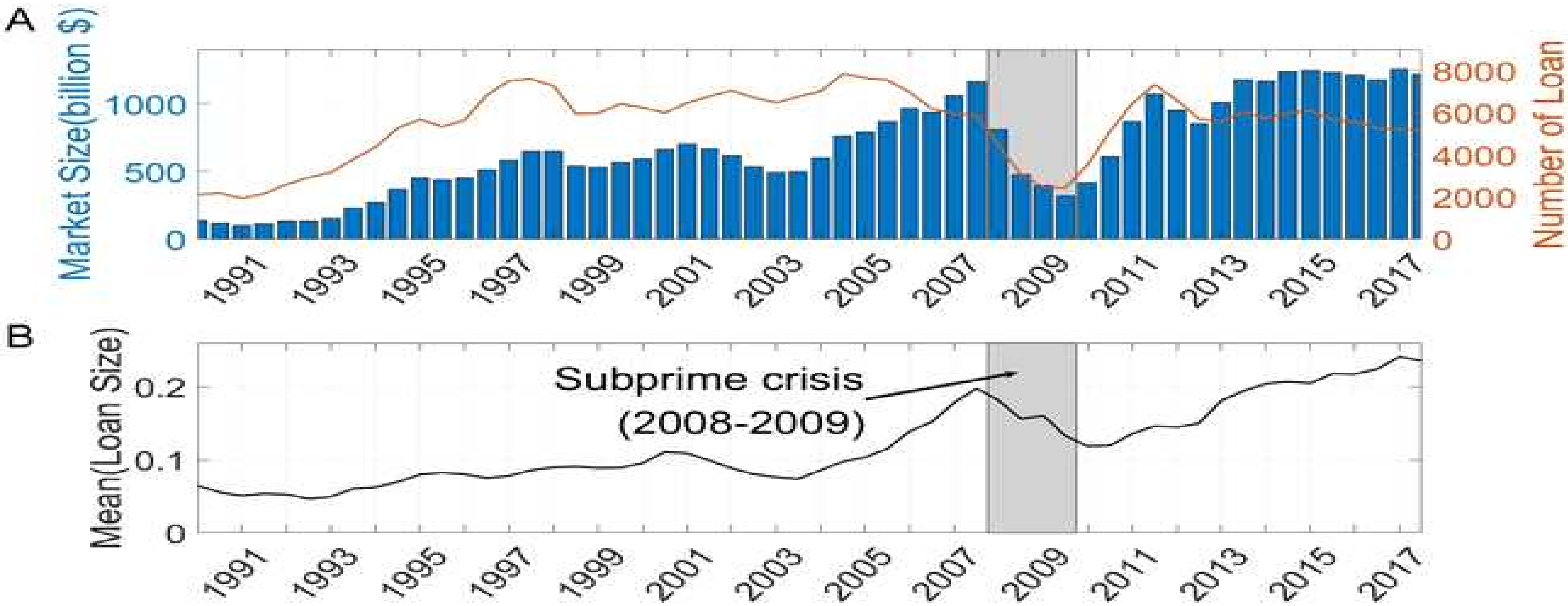
Table 3.2 summarizes the comparison of the sample in terms of diversification, centrality indices, and the control variables described in Section 2. The coefficients of the variables are reported at the lead-arranger level. Our sample is consisted of 33,386 matched lead arranger-month sets drawn from U.S. institutions heavily invested in the U.S. syndicated loan market. Diversification (DIV) is highly correlated with the composite centrality index (CCI) (0.62) in Table 3.2 and Figure 2.4. In terms of multicollinearity, we control the effect of dummy variables related to 2008-2009 financial crisis in the centrality variables.

Table 3.1. The Pearson correlation of regression variables

	ROA	Market size	Market share	Bank size	DIV	CCI	DEGREE	EIGEN	BTWN	CLOSE
ROA	1.00	-0.05	-0.12	-0.27	-0.04	0.02	-0.09	-0.09	0.02	-0.13
Market size		1.00	0.37	0.57	0.15	0.00	-0.07	-0.06	-0.02	0.03
Market share			1.00	0.38	0.08	0.57	0.45	0.57	0.36	0.63
Bank size				1.00	0.16	0.03	0.08	0.11	0.02	0.18
DIV					1.00	0.62	0.44	0.62	0.36	0.69
CCI						1.00	0.84	0.88	0.88	0.76
DEGREE							1.00	0.82	0.78	0.67
EIGEN								1.00	0.70	0.86
BTWN									1.0	0.56
CLOSE										1.0

Note: this table presents correlation coefficient of two variables. All value is statistically significant ($p < 0.01$). ROA is defined as net income divided by total assets. Market size is defined as the log of the sum of all outstanding loans. Market share is defined as the log of the amount of loans extended by each bank. Bank size is decided by log of total assets of each bank. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of the loans extended to ten industries by each bank. Composite centrality index (CCI) is calculated by using principal component analysis of four centrality measures pertaining to the PMFG network, namely, degree centrality (DEGREE), eigenvector centrality (EIGEN), betweenness centrality (BTWN), and closeness centrality (CLOSE).

Figure 3.1. Syndicated loan market



Note: this figure is related to the syndicated loan market in the United States from 1990 to 2017. (A) describes market size and the number of loans extended by lead arrangers to borrowers every quarter. Market size is defined as the sum of the loan amounts extended by each bank. The number of loans is defined as the total number of loans extended during each quarter. (B) represents the average loan size, which is the market size divided by the number of loans each quarter

3.4 Empirical Results

In this section, we first empirically explore the degree of distribution of the PMFG network in the U.S. syndicated loan market. We then examine the ways in which network topology and investment characteristics impact bank performance. We investigate the effect of bank network centrality on bank performance because of the importance of the bank-firm lending structure in terms of information asymmetry. The structure of an interbank network should affect bank performance. Interbank networks, which are created by the degree of information asymmetry during the bank-firm lending process, should affect the performance of lending banks. A bank with a higher level of information asymmetry might mimic the loan portfolio structure of a bank with a lower level of information asymmetry to reduce this asymmetry and generate profits. The systemic risk research has identified network connectivity and centrality as channels that transmit contagions related to negative events (Battiston et al., 2012; Elliott et al., 2014; Demirer et al., 2018; Cai et al., 2018). This implies that a highly interconnected structure can increase systemic risk. Ultimately, increased connectivity and rapid propagation in bank-to-bank networks can allow high-centrality banks to address market instability. In summary, we expect that well-connected banks should experience lower levels of information asymmetry than do poorly connected banks and that they should also experience higher levels of market performance.

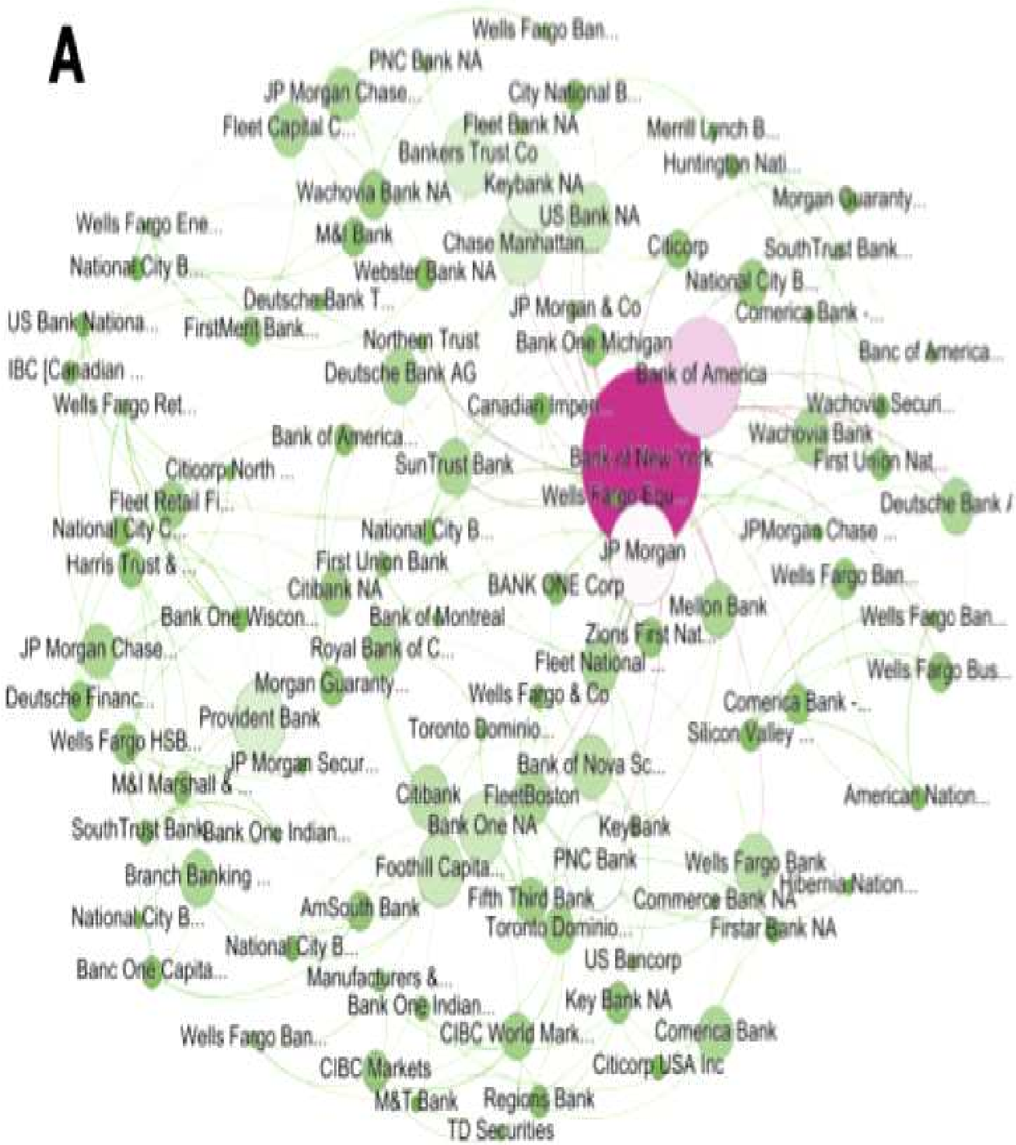
3.4.1 The Analysis of Interbank Network

Since the amount of syndicated loans is related to exposure to assets, a decline in asset prices should affect the stability of the banking system. We analyze the amount of and the number of the syndicated loans issued during each quarter from 1990 to 2017. A visual inspection of the amount of syndicated loans over time suggests that this figure reflects the state of the financial market. Figure 3.1(A) shows the amount of syndicated loans as a measure of overall banking loans and the number of syndicated loans. We measure the total amount of syndicated loans in each quarter. First, we find that both the overall amount and the number of syndicated loans follow a similar pattern. The total amount of syndicated loans started to increase in 2003 and continued to rise until Q4 of 2007, finally decreasing in 2009. After the subprime crisis, these loans rapidly increased until 2012. Second, the mean amount of syndicated loans is calculated as follows: Mean(Loan) = Market size/number of loans. Figure 1(B) shows a pattern similar to that of the results in Figure 3.1(A).

The main goal of this paper is to conduct more rigorous tests on the relationship between the interconnectivity of banks and bank performance. To test the validity of our hypothesis, we construct an interbank network using the PMFG method developed by Tumminello et al. (2005) based on loan portfolio data in Figure 3.2. In January 2002 (2006), this interbank network for the normal market status consisted of 513 (428) connections and 105 (88) nodes. The interbank network during and after the financial market crisis consisted of 423 (328) connections and 87 (68) nodes in January 2008 (2010). If the loan portfolio of each bank tended to have a distinct and unique investment strategy, then the interbank network would be disconnected, and each bank would correspond to a random network. We construct interbank networks for normal and abnormal periods based on the banks' loan portfolio structures to test whether the characteristics of the network are related to the market status. The obtained interbank network, shown in Figure 3.2 (A), (B), (C), and (D), displays the banks with higher connections between banks, regardless of market status, suggesting that the syndicated loan portfolios of banks are shared with other banks.

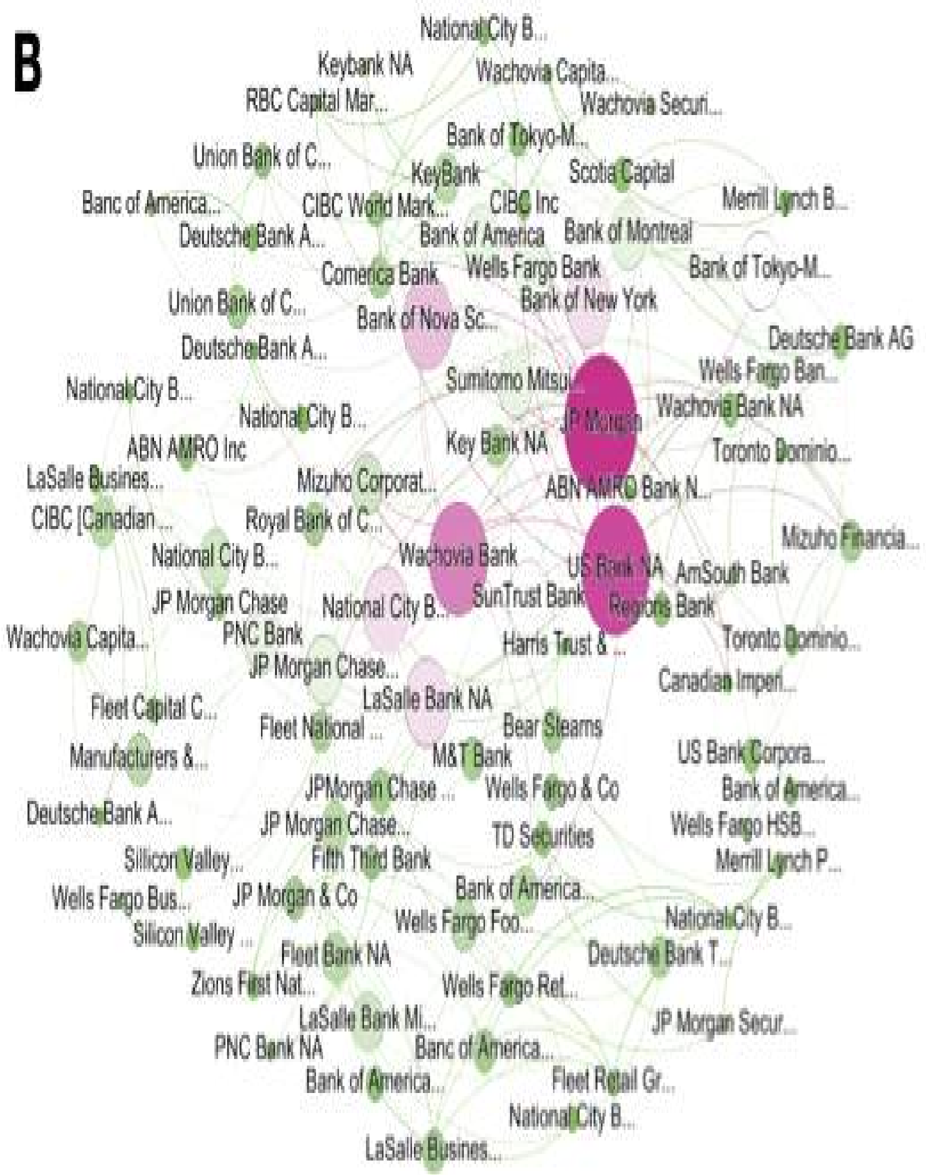
The degree (k) distribution of the interbank network indicates that most of the banks are linked to a few other banks, whereas a few banks with a large amount network of capital represent core that are connected to many individual banks. As shown in Figure 3.3, the degree distribution in 2006 (2010) follows the power-law distribution with an exponent of 4.09 (4.1). Consistent with Clauset et al. (2009); Virkar and Clauset (2014), Table 3.1 compiles the results of the likelihood ratio test and includes judgments supported by the statistical methods for the power-law hypothesis with each distribution over the four years. We find that the degree distributions follow power-law relative to exponential, stretched exponential, power law with cutoff, and log normal distribution. The power-law exponents

Figure 3.2. PMFG Network Configuration



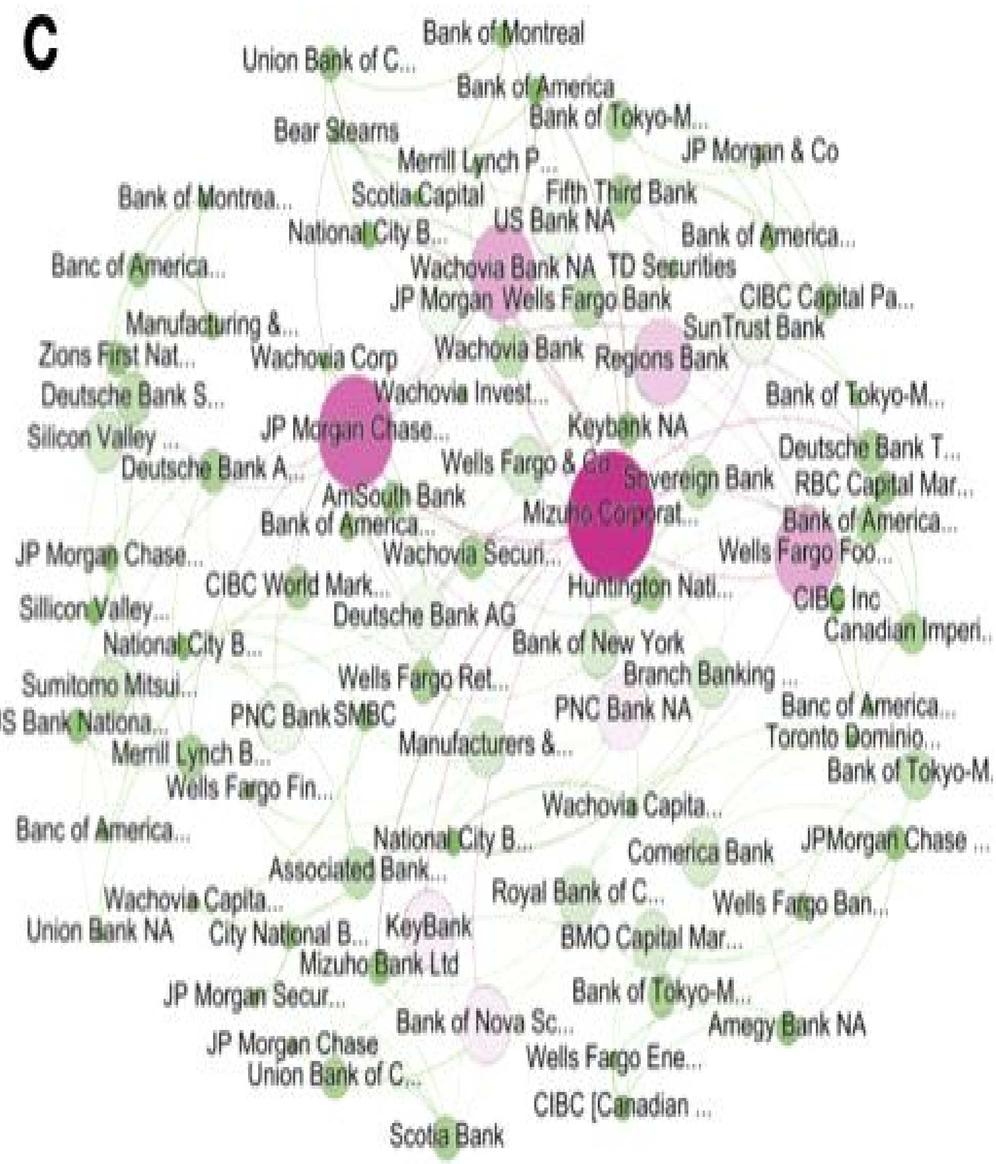
Note: (A) 2002 (B) 2006 (C) 2008 (D) 2010. The nodes represent each bank, and the node size is determined by the corresponding bank's degree centrality. A node with a higher degree centrality is colored pink and one with a lower degree centrality is colored light green. A pink edge denotes that from the node with higher degree.

Figure 3.2. PMFG Network Configuration (continued)



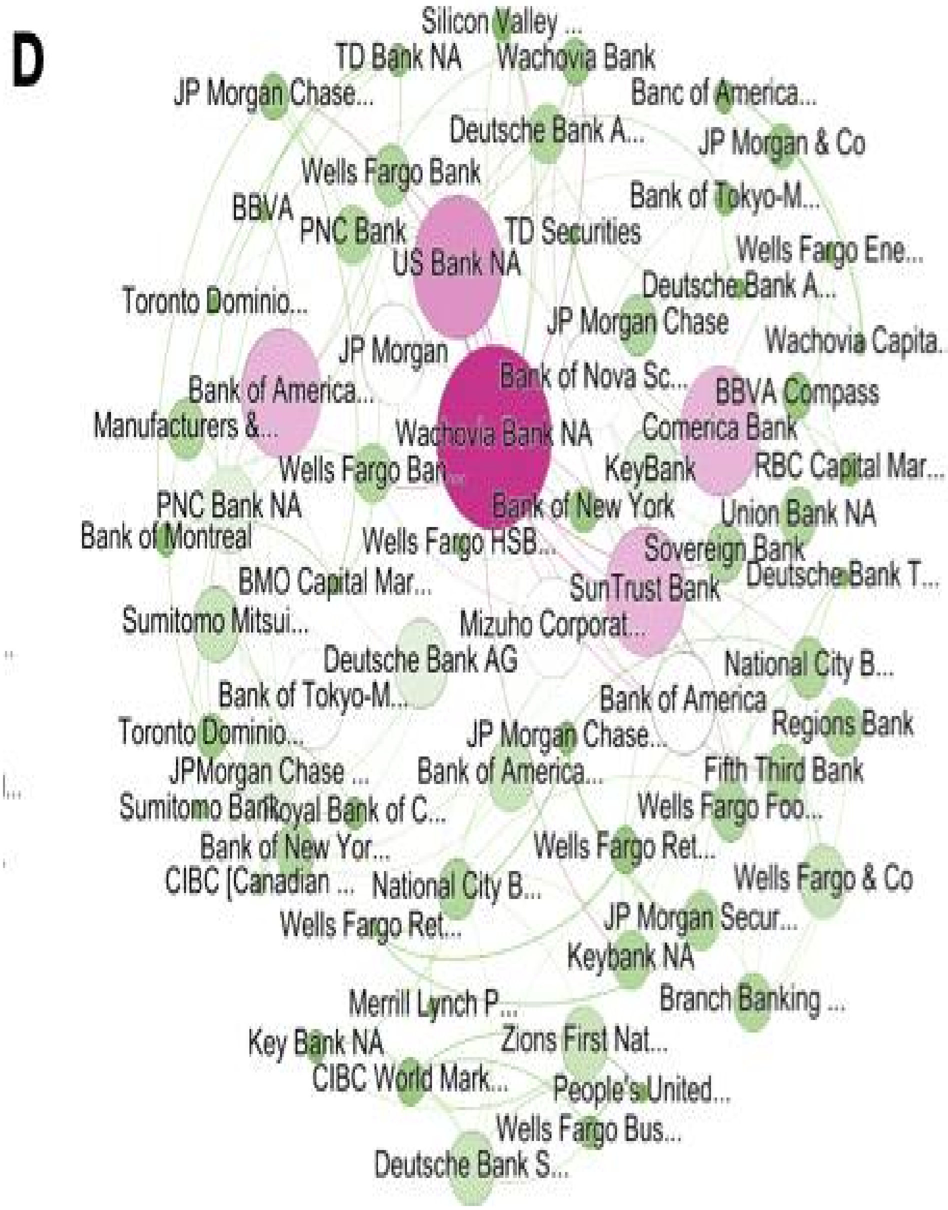
Note: (A) 2002 (B) 2006 (C) 2008 (D) 2010. The nodes represent each bank, and the node size is determined by the corresponding bank's degree centrality. A node with a higher degree centrality is colored pink and one with a lower degree centrality is colored light green. A pink edge denotes that from the node with higher degree.

Figure 3.2. PMFG Network Configuration (continued)



Note: (A) 2002 (B) 2006 (C) 2008 (D) 2010. The nodes represent each bank, and the node size is determined by the corresponding bank's degree centrality. A node with a higher degree centrality is colored pink and one with a lower degree centrality is colored light green. A pink edge denotes that from the node with higher degree.

Figure 3.2. PMFG Network Configuration (continued)



Note: (A) 2002 (B) 2006 (C) 2008 (D) 2010. The nodes represent each bank, and the node size is determined by the corresponding bank's degree centrality. A node with a higher degree centrality is colored pink and one with a lower degree centrality is colored light green. A pink edge denotes that from the node with higher degree.

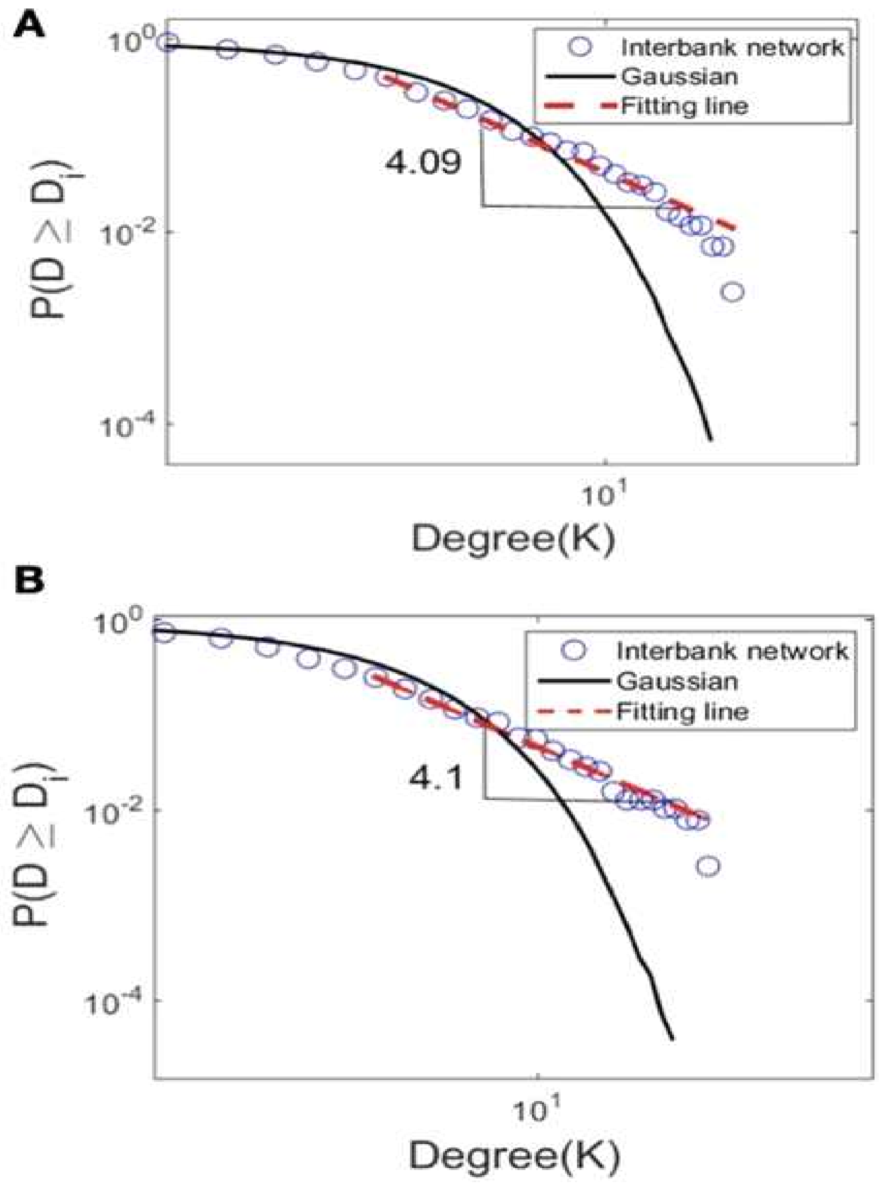
of degree distributions of PMFG network is in the range 3.49 and 4.43. As a result, we think that there are the influential banks with a lot of connections in interbank network.

The diversification of loan portfolios has important implications for the role that banks' investment strategies play in the syndicated loan market. Is this loan portfolio strategy, i.e., the diversification of syndicated loans at the industry level, related to the interbank network? We estimate the correlation between the diversification of portfolios and network structure to test whether the investment strategy of a bank is related to the other banks in the network.

Figure 3.4 shows the correlation between diversification and the degree of network centrality for each year. Overall, there is a positive correlation between diversification and degree of centrality, regardless of the subperiod observed. In particular, the correlation value starts to increase in 2002 and continues to rise until 2007 before the subprime crisis; after this, it decreased rapidly in 2011, suggesting that the correlation between the loan portfolio strategies of banks and the centrality of the network connectivity among banks should be understood as indicators of the financial crisis.

To observe the relationship between the degree of network centrality and portfolio strategies, we divided the whole sample into three groups according to centrality: G(high), G(middle), and G(low). Figure 3.5 displays the distribution function of these three groups using box plots and calculates the similarity of each distribution function using the Kolmogorov-Smirnov test (K-S test) (Chakravarti et al. 1967). The results are reported in Table 3.4. In addition, we calculate the average diversification of the three groups over time. Figure 3.6 shows the time evolution of the average diversification of these three groups defined according to their degrees of network centrality from January 1990 to December 2017. The diversification of the three groups is calculated based on the loan portfolios using the entropy method. The red circles, blue diamonds, and black triangles indicate the high-, middle-, and low-centrality groups, respectively. As shown in Figure 3.6, we find that since 2004, the diversification levels of low-centrality groups have moved more volatile than high-centrality groups.

Figure 3.3. The Cumulative distribution function of the degree of interbank



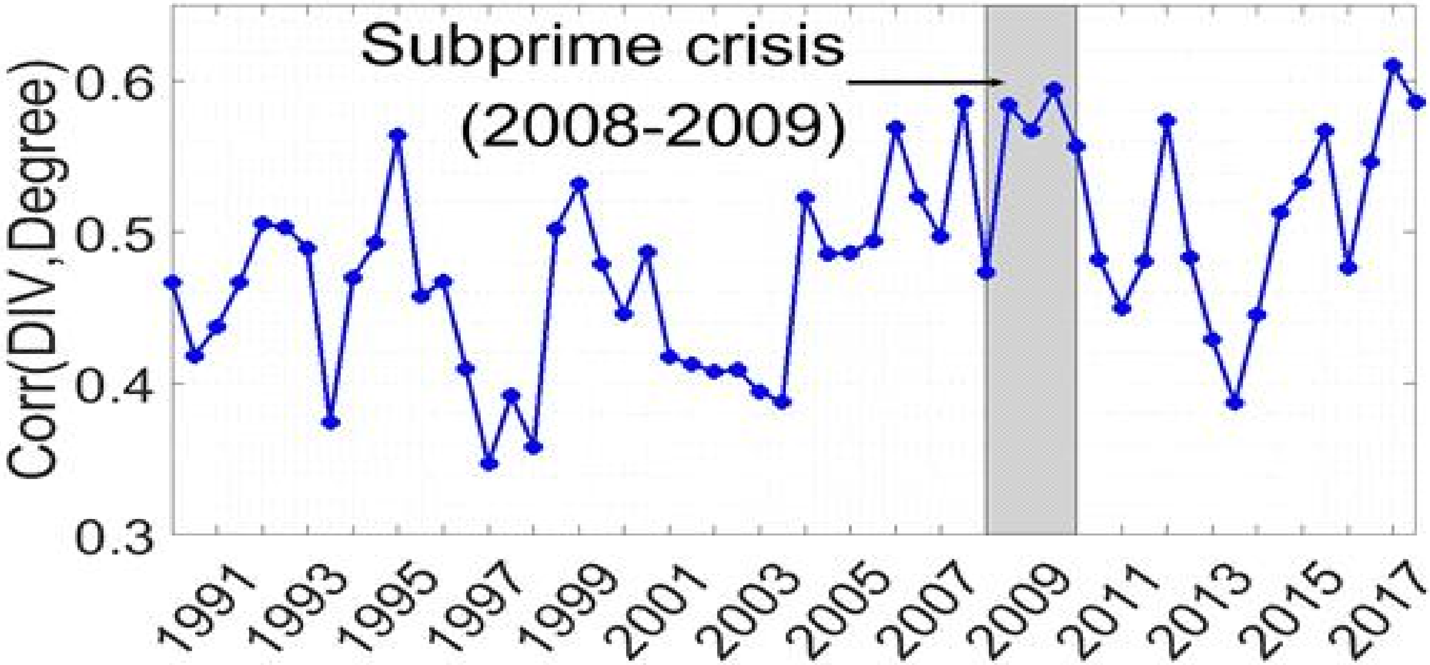
Note: the CDF for the degree of the interbank network is plotted with a double logarithmic scale. The cumulative distribution function for the degree of network during four years (A) from 2006 to 2009 and (B) from 2010 to 2013, the Gaussian distribution, and the fitted line are denoted using dotted blue lines, a black line, and dashed red lines, respectively.

Table 3.2. Comparisons of the fitted power-law behavior to alternatives

			Exponential		Stretched exp.		Power law+cutoff		Log-normal	
Year	Power law p	est. α	LR	p	LR	p	LR	p	LR	p
1990	0.43	4.23	2.32	0.02	1.03	0.30	4.44	0.00	-0.14	0.89
1994	0.34	4.43	2.74	0.01	1.22	0.22	5.85	0.00	-0.47	0.64
1998	0.10	3.76	4.29	0.00	0.87	0.06	8.60	0.00	-0.02	0.99
2002	0.02	3.57	2.41	0.02	1.74	0.08	5.77	0.00	0.29	0.77
2006	0.41	4.10	3.27	0.00	2.13	0.03	5.94	0.00	0.75	0.45
2010	0.30	4.11	1.86	0.06	1.36	0.17	4.85	0.00	-0.31	0.76
2014	0.22	3.49	1.50	0.13	1.17	0.24	4.49	0.00	0.05	0.96

Note: we checked the power law significant test of the degree distribution of PMFG networks during four years by Clauset et al. (2009); Virkar and Clauset (2014). Bold values indicate statistical significance of each likelihood ratio test. Estimated α is the power-law exponent of the degree distribution.

Figure 3.4. Correlation between diversification and degree of interbank network



Note: this figure shows the correlation between diversification (DIV) and the degree of the PMFG network during the sample period of six months. Gray shadows represent recessions as measured as the subprime mortgage crisis periods during 2008-2009.

3.4.2 The Effect of Centrality and Diversification on Bank Performance

To the extent that interbank networks in the United States have heterogeneous characteristics, we suggest that the strategic behaviors of banks and the central characteristics of banks have impacts on performance. We focus on two properties of banks: structural properties and strategic properties. We use the four measures of centrality as structural properties in the PMFG network. The relationships between lenders and borrowers are likely to mitigate the problem of information asymmetry because lending banks collect a considerable amount of information about the corporate management of their borrowers and have stable and long-term relationships with the managers of these organizations (Sufi 2007). Sometimes, banks place their directors on borrowers' boards of directors to improve the quantity and quality of information regarding operations that they receive (Omer et al. 2019). We found that capitalized banks tend to centralize their networks. Therefore, we assume that banks with a high level of centrality in their networks have the unique abilities of quickly obtaining resources through the members of their network and of reducing the level of information asymmetry between lenders and borrowers.

Based on our assumption, centralized banks would feel more secure when expanding their business. In this context, we would expect to see that these banks hold portfolios that are more diverse. Diversification in the syndicated loan market creates the potential advantage of reducing credit risk exposure (Cai et al. 2018). Banks become more resilient to common shocks such as exposure to risk when holding diversified portfolios. We estimate the following regression with pooled data:

$$\begin{aligned} ROA_{i,t} &= \alpha_{i,t} + \beta_1 DIV_{i,t} + \beta_2 Centrality_{i,t} + \beta_3 Centrality_{i,t} \times Dummy \\ &+ \beta_4 Marketsize_{i,t} + \beta_5 Marketshare_{i,t} + \beta_6 Banksize_{i,t} + \epsilon_{i,t} \end{aligned} \tag{15}$$

where the dependent variable $ROA_{i,t}$ is a financial indicator of profitability during month t. $DIV_{i,t}$ measures the diversification of bank i based on its syndicated loan portfolio during the twelve months prior to month t and dummy as an indicator variable is

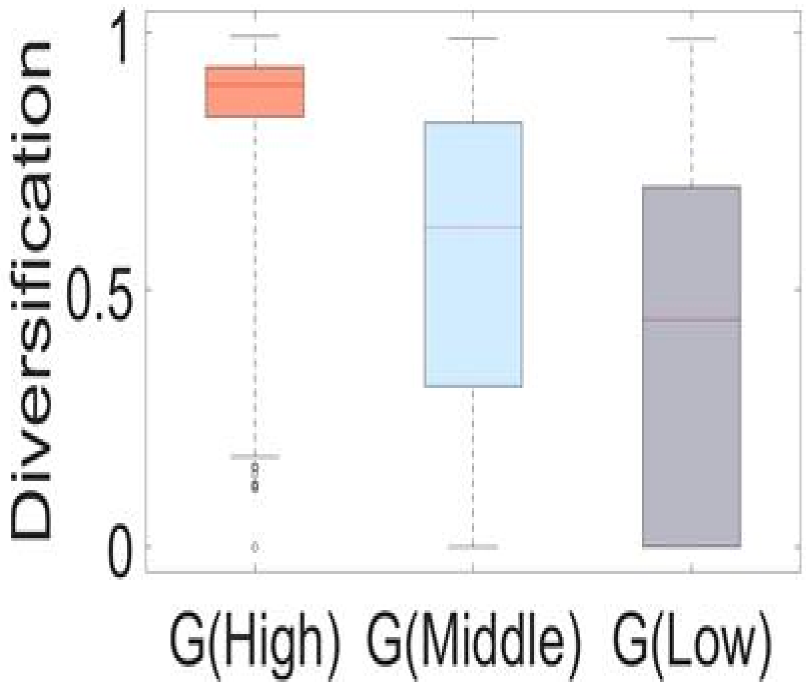
.as follow: Dummy is 1 if the observation is from financial crisis period, otherwise 0. As a proxy for structural importance in the PMFG network, centralityi,t is replaced by four representative types of centrality: degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality.

By including the variables market size, market share, and bank size in this regression, we control for the effects of systematic and idiosyncratic effects that we cannot directly observe. Market share is measured by the log of the amount of outstanding loans held by each bank. Gopalan et al. (2011) use that as a proxy for a lead arranger's reputation in terms of market participants' perceptions of its screening and monitoring of borrowers.

We control for market share to identify the effects of banks' reputations. Market size is calculated as the log of the sum of the loan amounts of newly originated syndicated loans in billions of U.S. dollars. To control high performance of bank with high asset, bank size is estimated by logarithm of total asset of each bank. In all the regressions, we include market size and year fixed effects to remove the time characteristics.

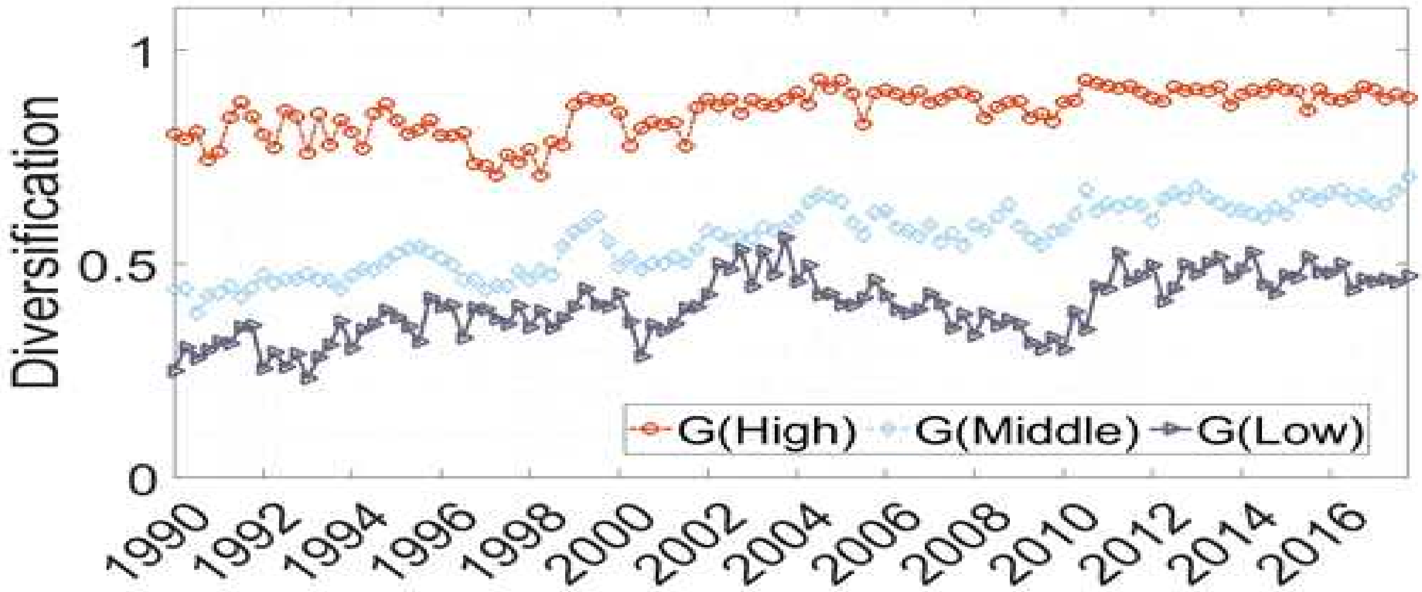
We report the results related to diversification and those of each of these models using four centrality measures of the interbank networks. In all the models, the regression coefficients of the measures of diversification are statistically highly significant, and they indicate a positive relationship (0.3970, $p < 0.01$; 22.2780, $p < 0.01$; 0.3078, $p < 0.01$; 0.0853, $p < 0.01$) in the Table 3.3. These findings are in line with the results of the descriptive studies by Hitt et al. (1997), who report that product-diversified firms have high levels of performance and innovation. There are simply too many results and perspectives about the agency theory of diversification to include them in this paper. Our results support the existing evidence regarding diversification and profitability in terms of lead arrangers' loan portfolios. Each type of centrality represents a different aspect of a bank's structural position in the network. These findings allow us to determine whether each type of centrality is able to represent a factor of composite centrality index (CCI) in the Table 4. Overall, our results suggest that higher levels of the individual dimensions of centrality based on loan portfolio similarities are related to increases in the profitability of banks.

Figure 3.5. Diversification level of subset of banks



Note: we divide banks into three groups: high-, middle-, and low-centrality. The banks corresponding to the highest (lowest) 10% in terms of degree centrality are designated as core (peripheral) of banks in this paper. The core banks have higher levels of diversification than middle- and low-centrality groups

Figure 3.6. Time series of diversification of subsets according to degree centrality



Note: this figure shows the time series of the monthly diversification of syndicated loan portfolios from January 1990 to December 2017. The diversification of the three groups is computed by using the entropy method based on their loan portfolios. We divided whole sample into three groups. The red circles, blue diamonds, and black triangles indicate the high-, middle-, and low-centrality groups, respectively.

Table 3.3. Dimensions of connectedness and the likelihood of performance

Variable	(1)		(2)		(3)		(4)	
Intercept	-7.2×1010	(-0.1475)	-1.85×1011	(-0.3832)	-1.1×1011	(-0.2178)	-6.7×1010	(-0.1377)
DEGREE	0.3970***	(9.3934)						
DEGREE×Dummy	-1.1628***	(-9.1937)						
EIGEN			22.2780***	(10.6610)				
EIGEN×Dummy			-50.1001***	(-10.2535)				
CLOSE					0.3078***	(9.8138)		
CLOSE×Dummy					-0.8945***	(-10.9380)		
BTWN							0.0853***	(8.7560)
BTWN×Dummy							-0.1878***	(-5.1339)
DIV	0.0339***	(4.9161)	0.0196***	(2.7594)	0.0094	(1.2388)	0.0338***	(4.9143)
Market size	0.0920***	(4.8797)	0.0979***	(5.1879)	0.0927***	(4.9039)	0.085***	(4.5681)
Market share	-0.0193***	(-7.8407)	-0.0193***	(7.9123)	-0.0167***	(-6.9458)	-0.0180***	(-7.3890)
Bank size	-0.0622***	(-29.1980)	-0.0628***	(-29.5153)	-0.0623***	(-29.3096)	-0.0623***	(-29.2473)
Observations	33,289		33,289		33,289		33,289	
Year FEs	Yes		Yes		Yes		Yes	
Adj.R2	0.2256		0.2263		0.2244		0.2266	

Note: this table reports the regressions of four dimension connectedness and diversification on ROA: degree centrality (DEGREE), eigenvector centrality (EIGEN), closeness centrality (CLOSE). and betweenness centrality (BTWN). ROA is defined as net income divided by total assets. Consistent with Section 2.2, the centrality indices of the banks are measured for each month. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of the loans extended to ten industries by each bank. Market size is defined as the log of the sum of all outstanding loans. Market share is defined as the log of the amount of loans extended by each bank. Bank size is decided by log of total assets of each bank. Year fixed effects are included to account for time characteristics. The t-statistics are reported in brackets. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and, 1%, respectively.

Next, we use dummy variable with centrality indices to exclude the financial crisis effect in 2008- 2009. They are statistically significant with negative coefficients of DEGREE × Dummy, EIGEN × Dummy, CLOSE × Dummy, BTWN × Dummy (−1.1628, $p < 0.01$; −50.1001, $p < 0.01$; −0.8945, $p < 0.01$; −0.1878, $p < 0.01$) in Table 2.3. As shown in columns 1-4 of Table 2.3, although the dummy variable has a negative sign, the main effect for the dimension of centrality and diversification is positive and significant. It means that the impact of network centrality on performance is negative during 2008-2009 financial crisis and positive during the normal period. We then show the results of the regression using our composite centrality index (CCI) through principal component analysis, including degree centrality, eigenvector centrality, closeness centrality, and betweenness centrality based on the results shown in Table 3.3. The results of the regression including CCI are reported in Table 3.4 using equation model 3. Consistent with the preceding regressions, we use the dummy variable with CCI to remove the recession trends. We find a negative and significant coefficient for the CCI × Dummy(−0.0170, $p < 0.01$), whereas the coefficients of CCI and DIV are positive and significant (0.0084, $p < 0.01$; 0.0216; $p < 0.01$), consistent with the results in Table 2.3. Together, these results suggest that overall centrality consistently moderates the increases in a bank’s profitability when it holds a diversified portfolio.

Table 3.4. The effect of diversification and network centrality on bank performance

Variables	Coefficient	t-value	Coefficient	t-value
Intercept	-2.1× 1011	(-0.4797)	-1.3× 1011	(-0.2783)
CCI			0.0084***	(10.5008)
CCI×Dummy			-0.0170***	(-6.6791)
DIV	0.0344***	(5.0023)	0.0216***	(3.0677)
Market size	0.0820***	(4.3706)	0.0850***	(4.5429)
Market share	-0.0140***	(-5.8422)	-0.0197***	(-8.0319)
Bank size	-0.0623***	(-29.2561)	-0.0626***	(-29.3747)
Observations	33,289		33,289	
Year FEs	Yes		Yes	
Adj. R2	0.2224		0.2255	

Note: this table reports the regressions of diversification and centrality on ROA. ROA is defined as net income divided by total assets. DEGREE is the degree centrality. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of the loans extended to ten industries by each bank. Composite centrality index (CCI) is calculated by using principal component analysis of four centrality measures pertaining to the PMFG network, namely, degree centrality (DEGREE), eigenvector centrality (EIGEN), betweenness centrality (BTWN), and closeness centrality (CLOSE). Market size is defined as the log of the sum of all outstanding loans. Market share is defined as the log of the amount of loans extended by each bank. Bank size is decided by log of total assets of each bank. Year fixed effects are included to account for time characteristics. The t-statistics are reported in brackets. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and, 1%, respectively.

3.4.2 The Effect of Centrality and Diversification on Bank Performance according to the Level of Centrality

In this section, we examine the different ways in which the structural importance of the PMFG network affects banks' strategic actions. We also consider the way in which the relationship between strategic actions and relative profitability identified in the full sample may vary based on banks' degree of centrality. Several papers have highlighted the likelihood that board interlocking between banks has more power and information in the market when they release financial risk (Mariolis, 1975; Gopalan et al., 2011; Berger et al., 2014; Newman, 2003). Because the importance of each bank in the network is not homogeneous, we group the banks by their degrees centrality into groups consisting of core banks and of peripheral banks. We designated the upper (lower) 10% of banks in terms of degree centrality as high (low) groups to define the cores and peripheral in the PMFG network. Table 3.5 represents the Pearson correlation of diversification between each subset of banks. The high- and middle-centrality groups have the positive correlations (0.7906), and the low-centrality groups also have the positive correlations with the other groups (0.5488, 0.7072). Additionally, we investigate a two-sample Kolmogorov-Smirnov test to assess the distribution of the two samples in brackets. This test implies a heterogeneous distribution of diversification among the three groups of banks. As a result, we conclude that the three groups classified by degree centrality could have investment strategies with differing characteristics. Our interpretation is consistent with the results in Figure 3.5 and Figure 3.6. Specifically, we run the following regression on two sets of banks; core and peripheral,

$$ROA_{i,t} = \alpha_{i,t} + \beta_1 DIV_{i,t} + \beta_2 Marketsize_{i,t} + \beta_3 Marketshare_{i,t} + \beta_4 Banksize_{i,t} + \epsilon_{i,t} \quad (16)$$

Table 3.6 shows the results of the linear regressions regarding bank diversification using the same explanatory variables we used for the subset of banks. These results indicate that core banks could obtain better private information than peripheral banks. This result is consistent with the study of Loutskina and Strahan (2011), who insist that concentrated lenders had higher profits than diversified lenders during the financial crisis. Additionally, Acharya et al. (2006) find that the diversification of bank assets is not guaranteed to produce superior return performances or greater safety for banks. These findings are different from the comprehensive perspectives of the market power view and the resource view in terms of profit maximization. Note, however, that these studies do not control for network centrality. Consistent with the systemic risk literature (Cai et al., 2018), we consider core banks to have high levels of risk exposure, and concentrated lenders have high levels of performance during our sample periods (−0.0635, $p < 0.1$). As shown in column 2 of Table 3.6, the group composed of peripheral banks has a statistically significant positive effect on performance (0.0651, $p < 0.01$). This means that the subsets of banks in the interbank network reflect the different risk cultures among banks.

Table 3.5. The relation of the diversification of the subsets of banks to degree centrality

	High	Middle	Low
High	1	0.7906**	0.5488***
		($7.82E^{-51}$)	($7.82E^{-51}$)
Middle		1	0.7072***
			($7.70E^{-22}$)
Low			1

Note: the table represents the Pearson correlations among the three groups of banks. We extract two groups of them from the sample bank. One is the hub as designated by High with highest 10% degree centrality and another is the ourlier as designated by Low with lowest 10% degree centrality. The other of group of banks is the Middle in the table. A two-sample Kolmogorov-Smirnov test asymptotic significance value (2-tailed) is shown in the bracket. P < 0.01 rejects the null hypothesis of the other population distributions.

Table 3.6. The effect of diversification on the bank performance of core and peripheral banks

	Core		Peripheral	
Intercept	-1.1×1012	(-0.5745)	-2.1×1012	(0.1175)
DIV	-0.0635*	(-1.7079)	0.0651***	(5.2336)
Market size	0.0735	(1.3409)	0.1548***	(4.0456)
Market share	0.0372**	(3.7565)	-0.0380***	(-8.1899)
Bank size	-0.1200***	(-15.6491)	-0.0650***	(-14.8352)
Observations	4,241		7,330	
Year FEs	Yes		Yes	
Adj. R2	0.2315		0.2427	

Note: the table investigates the effect of diversification on ROA for (1) core of banks and (2) peripheral of banks. ROA is defined as net income divided by total assets. Diversification (DIV) is measured by the Shannon entropy of bank portfolio calculated as the amount of the loans extended to ten industries by each bank. The control variable is consistent with equation 3. Year fixed effects are included to account for time characteristics. The t-statistics are reported in brackets. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and, 1%, respectively.

3.5 Summary and concluding remarks

Banks that are centrally located in a syndicated loan network have access to better information and more influence in the syndicated loan market. Adding to the previous studies on the role of network centrality among banks, we employ a network centrality measure to test the connection between bank performance and network structure. In terms of the diversification of loan portfolios, we show that banks with higher levels of network centrality are more likely to pursue diversification, and that this diversification is more likely to increase during periods of market instability. The evidence shows that the sample banks' lending strategies exhibited a significant relationship with these banks' degrees of network centrality, regardless of the market status. We further find that banks with a high level of centrality have higher returns than banks with a low level of centrality. We then test whether the diversification of the syndicated loan portfolios of individual banks is related to the performance of these banks according to their centrality position in the interbank network. Since a bank's centrality in the network plays an important role in its loan portfolio strategy, this centrality also plays a significant role for lending market participants. We found that in the core group, diversification showed a negative correlation with centrality; however, a positive relation was observed in the peripheral group.

We contribute to the literature on the bank-firm lending process in the field of finance by introducing the interbank network based on the syndicated loan market. Our findings extend the existing literature on the lending mechanisms between banks and firms and show that banks' centrality within the interbank network influences their portfolios in the syndicated loan market. Future studies can help to shed light on bank performance and lending mechanisms.

IV. Diversity of board network and corporate outcome

4.1 Motivation

The board of directors makes a vital contribution in corporate control and decision making, described in Fama and Jensen (1983) as "the apex of decision control systems". In contrast, considerable research has examined the relationship between the connectedness of the board members and the firm performance (see, Fich, Shivdasani 2006, Stuart, Yim 2010, Larcker et al. 2013, Omer et al. 2019), the question of how knowledge diversity from interlocking directorates affects the corporate outcomes has received less attention.

The CEO who owns part of the company's shares will match other shareholders' interests with his incentives (Jensen et al. 1976). The CEO's role is defining values, mission, vision, and overall decision of the firm, and the part of the board of directors is monitoring and advising top management (Mace 1971). Coles et al. (2014) suggested co-option to measure CEO power related to performance or his incentive. Adams et al. (2005) proposed firms with powerful CEO to have decision making should experience more performance fluctuations. In addition, Hirshleifer et al. (2012) insisted that firms with overconfident CEOs have greater return volatility, invest more in innovation, receive more patents and patent citations. This literature has highlighted the impact of CEO power related to operational performance.

In this paper, we focus on how information transfer of directors in different industrial groups impacts various aspects of decision making of corporate outcomes in the United States. We suggest a diversity measure of the board to investigate whether the diversity of board networks that comprise the director interlock affect Return of Asset (ROA) and Tobin's Q, used as the proxies for performance. To estimate our diversity, we merge the Investor Responsibility Research Center (IRRC) with the Centre for Research in Security Prices(CRSP) and Standard & Poor’s Compustat from 1996 through 2014. The sample contains stock return, accounting, director information, and interlocked firms' classification, where the same directors serve simultaneously. We use the Shannon entropy to calculate the diversity of each board within heterogeneous industries, which means the firms with higher diversity have the more valuable knowledge from the directors in other sectors than the firms with lower diversity (Shannon 1948, Jaynes 1957). Finally, the diversity captures that interlocking directorates have a significant role in operational performance after controlling several effects such as year-, industry- fixed effect, size, leverage, book-to-market ratio, etc. These results explain when a project initiates, the board with the directors among various industries is considered as a critical factor of decision making, in line with bridging the information gap (Dass et al. 2014).

In addition, we measure co-option as a proxy of CEO power in line with Coles et al.(2014). Co-option is estimated by the weight of the number of "co-opted" directors appointed after the CEO takes office, dividing by board size. When Co-option increase, board monitoring decreases. We then group firm-year observations into four subsets using the mean of co-option and diversity during sample periods. We predict that a CEO who has co-opted a greater fraction of board with high diversity will be likely to have good performance, and a CEO who has a low co-opted board with high diversity will have the best performance due to quality of information. The results of regression analyses are consistent with our predictions.

First, we find that the ROA and Tobin q have a statistically significant positive coefficient in the firm of CEO with low co-opted board with high diversity. Second, we find that ROA has a negative coefficient in the firm of CEO with high co-option with low diversity. These results represent the groups divided by the quality of information and board monitoring. Our results could help us understand the mechanism of choice to assess the skills that board members require and identify the factors affecting firm performance in a behavioral framework.

The paper proceeds as follows. We describe the data and regression variable in Section 2. In Section 3.1, we examine the association between diversity and performance, while in Section 3.2, we test the relation between co-opted CEO according to the level of diversity and firm performance. We conclude in Section 4.

4.2 Methodology

4.2.1 Data Description

We use several databases to build our sample of information on financial variables and the board of directors in the United States. The information on CEOs and compensation is provided at Standard and Poor's Execucomp database. Stock returns are from CRSP, and accounting information is from Compustat. The story of the director and board meeting is from the Investor Responsibility Research Centre (IRRC). To solve the problem of dual-class shares, we designate one share per firm with several directors.

To construct a sample, we exclude utility and financial industry in line with previous literature and exclude firms with assets under 10 million dollars, and sales under 10 million dollars, and book value under 1 million dollars. We only use firms listed on the S&P 500, S&P MidCap, and S&P SmallCap from 1996 to 2015 in the United States. Finally, we employ 7,956 firm-year observations with 24,679 director members. We gather 48 industrial classifications from the Fama-French website.

4.2.2 Main Variables and Regression Model

The main idea of our paper is measuring the quality of information by diversity measure. We use the Shannon entropy to measure each firm's diversity and define diversity as the weight of the number of interlocked boards with firms from other industries. The firm with low diversity tends to receive information from firms in the same industry. On the contrary, a firm with high diversity promotes technology and feedback on recent performance among firms with different industry fields. This is because corporate boards use interlocking directorates to access the private information of the firm. To our knowledge, this study is the first attempt to measure diversity in terms of quality of information, and even board diversity has already tried to measure educational experience, gender, race, or ethnicity.

To estimate CEO power to make an excellent decision for stockholders and his incentive, we use co-option variable consistent with Coles et al. (2014). The definition of co-opted directors is directors who joined the board after the CEO assumed office. The co-option is defined as the ratio of the number of co-opted directors dividing by board size. When co-option is one, board monitoring decreases, and when co-option is zero, board monitoring increases.

The operational performance of the firm is estimated by ROA and Tobin q. ROA is defined by net income divided by total assets. Tobin q is the ratio of the market value of a firm's assets to the replacement cost of the firm's assets (Tobin 1969). The use of ROA as the dependent variable is ROA is the best measure of firm performance within the same industry. Furthermore, Tobin q is stable over time, and both variables are promising in the previous literature.

To control the CEO's impact, we use CEO duality, one if the CEO is also the chairman and zero otherwise. Similarly, the CEO president is one if the CEO is also the president and zero otherwise. Other control variables related to the board are CEO compensation, board independence, outside directors, and board size. We also use firm size, leverage to control variables related to firm characteristics. CEO compensation is defined as the natural logarithm of total annual pay. Board independence is defined as the number of independent directors divided by board size. Outside directors is measured by the number of outside directors. Board size is calculated by total number of directors on the board. In addition, firm size is defined by the natural logarithm of sale, and leverage is defined by the ratio of debt to assets. We also use year fixed effect and industry fixed effect in the regression model as follows:

$$\begin{aligned} Performance_{i,t} &= \alpha_{i,t} + \beta_1 Diversity_{i,t} + \beta_2 CEOduality_{i,t} + \beta_3 CEOpresident_{i,t} \\ &+ \beta_4 CEOcompensation_{i,t} + \beta_5 BoardSize_{i,t} + \beta_6 Independence_{i,t} \\ &+ \beta_7 OutsideDirectors_{i,t} + \beta_8 FirmSize_{i,t} + \beta_9 Leverage_{i,t} + \epsilon_{i,t} \end{aligned} \tag{17}$$

Table 4.1 provides the summary statistics of regression variables. The average of diversity is 0.56 means that the board of directors usually has more connections with other industries than those with the same industry. The average of co-option is 0.66, representing that more than half of board members are selected after the CEO assumed office.

Table 4.1. Summary statistics of main variables

	Obs.	Mean	Median	Std. Dev.
Diversity	6,919	0.56	0.6	0.33
Co-option	7,049	0.66	0.7	0.29
ROA	7,877	0.12	0.12	0.11
Tobin q	7,876	1.78	1.41	1.29
CEO duality	7,956	0.70	1.00	0.46
CEO president	7,956	0.62	1.00	0.48
CEO compensation	7,956	3.03	3.00	0.45
Board size	7,956	9.64	9.00	2.32
Independence	7,956	0.18	0.14	0.11
Outside directors	7,943	0.29	0.25	0.17
Firm size	7,953	3.40	3.35	0.69
Leverage	7,937	0.25	0.24	0.18

Note: The table shows summary statistics of regression variables of U.S. firms between 1996 and 2015. The sample consists of firms that have board of director information and accounting information in the IRRC, CRSP, and Compustat. Diversify is estimated by the Shannon entropy of interlocked industries. Co-option is the percentage of directors who have been appointed current CEO.

4.3 Empirical Results

In this section, we examine the effect of diversity and co-option using board members on operational performance. Our key explanatory variable is diversity, which takes high if a board is composed of directors from different industries and low others. Another variable is co-option, which is the value of one if board members are selected after occurring CEO and zero otherwise.

4.3.1 The Effect of Diversity on Performance

We hypothesize that firms with high diversity have good performance to access private information from different industries. Therefore, we examine the relation between board diversity and operational performance in Table 4.2. For each of the performance measures, we use the same control variables using equation 17. Our control variables are CEO related-, firm related variables: CEO duality, CEO president, CEO compensation, the board size, board independence, outside directors, firm size, and leverage. These control variables is consistent with previous studies related to firm performance. In the regression models, we also include year fixed effect and industry fixed effect.

We measure board diversity as the Shannon entropy using the ratio of interlocked firms with different industries. Table 4.2 shows the result that model (1) use ROA, and model (2) use Tobin q as operational performance. In all tests, board diversity is associated with the higher performance of a firm. The coefficient in the model (1) shows that having diversified directors with different industries significantly increases ROA at 90% of statistically significant levels. This result means information, which can access interlocked boards, is valuable to manage firm performance in ROA. In other words, we show evidence related to information quality estimated diversity using directorates interlocks. It contributes to future studies on board networks and governance mechanisms.

Because the coefficient of diversity in Table 4.2 is insignificantly related to Tobin q, we would like to investigate the effect of the combination of diversity and co-option on Tobin q. That is why Cole et al. (2014) revealed the evidence that co-option is related to pay-performance sensitivity and investment.

Table 4.2. The association between diversity and performance (1)ROA (2)Tobin q

	(1)		(2)	
Diversity	0.0009*	(1.7065)	0.0407	(0.7104)
CEO duality	-0.0128***	(-3.1778)	-0.0182	(-0.4462)
CEO president	0.0043	(1.3476)	-0.0601*	(-1.8559)
CEO compensation	0.0019	(0.5726)	0.0611*	(1.8117)
Board size	0.0000	(0.0085)	0.0227***	(2.7624)
Independence	0.0241	(1.0864)	0.4640**	(2.0797)
Outside directors	-0.0203	(-1.4973)	-0.5092***	(-3.6569)
Firm size	0.03446***	(14.8402)	0.0017	(0.0722)
Leverage	-0.0928***	(-11.1795)	-1.2791***	(-14.7752)
Fixed	Year-,industry-,		Year-,industry-,	
Obs.	6,060		6,059	

Note: The table shows empirical results using regression equation 17 of U.S. firms between 1996 and 2015. The sample consists of firms that have board of director information and accounting information in the IRRC, CRSP, and Compustat. Diversify is estimated by the Shannon entropy of interlocked industries. Co-option is the percentage of directors who have been appointed current CEO.

Table 4.3. The association between diversity and ROA according to sub-groups

	(1)		(2)		(3)		(4)	
Diversity	0.0143	(0.9104)	0.0481**	(2.1263)	-0.0327**	(-2.1022)	0.0248	(1.4232)
CEO duality	-0.0115*	(-1.6285)	0.0039	(0.3829)	-0.0044	(-0.5763)	-0.0153*	(-1.9072)
CEO president	-0.0081	(-1.3142)	-0.0069	(-1.0581)	0.0099	(1.4012)	0.0032	(0.4265)
CEO compensation	0.0151***	(2.7964)	-0.0013	(-0.2279)	-0.0047	(-0.7202)	0.0089	(0.8350)
Board size	0.0022**	(2.0229)	-0.0016	(-0.9368)	-0.0003	(-0.1930)	-0.0017	(-0.7817)
Independence	0.0330	(0.9760)	0.0331	(0.6149)	0.0197	(0.4913)	-0.0187	(-0.3523)
Outside directors	-0.0236	(-1.2340)	-0.0414	(-1.4336)	0.0063	(0.2194)	0.0131	(0.41773)
Firm size	0.0046	(1.3324)	0.0390***	(8.6147)	0.5323***	(10.8933)	0.0375***	(6.4981)
Leverage	-0.0733***	(-6.0668)	-0.0308*	(-1.8384)	-0.1160***	(-6.7057)	0.0089***	(-6.9481)
Fixed	Year-,		Year-,		Year-,		Year-,	
Obs.	1,549		1,554		1,563		1,394	

Note: (1) High diversity, high co-option (2) High diversity, low co-option (3) low diversity, high co-option (4) low diversity, low co-option

Table 4.4. The association between diversity and Tobin q according to sub-groups

	(1)		(2)		(3)		(4)	
Diversity	0.4125*	(1.8351)	1.1167**	(4.8813)	-0.1994	(-1.3540)	0.0040	(0.0277)
CEO duality	-0.1254	(-1.2214)	0.0842	(0.8294)	0.0047	(0.0712)	-0.0610	(-0.9169)
CEO president	-0.0270	(-0.3025)	-0.1124*	(-1.7162)	-0.0882	(-1.3178)	-0.0263	(-0.4224)
CEO compensation	0.2085***	(2.6643)	0.0070	(0.1223)	0.0593	(0.9647)	-0.0079	(-0.0889)
Board size	0.0344**	(2.2302)	-0.0228	(-1.3419)	0.0274*	(1.6377)	0.0319*	(1.7838)
Independence	0.4258	(0.8782)	0.4242	(0.7825)	1.2090***	(3.2096)	-0.0898	(-0.2038)
Outside directors	-0.2045	(-0.7427)	-0.3739	(-1.2729)	-0.7948***	(-3.0432)	-0.1188	(-0.4460)
Firm size	-0.0567	(-1.1342)	-0.0377	(0.7938)	-0.0968**	(-2.1700)	0.0837*	(1.7937)
Leverage	-1.7471***	(-10.0386)	-1.4752***	(-7.9582)	-1.2889***	(-7.7249)	-0.3560***	(-2.1859)
Fixed	Year-,		Year-,		Year-,		Year-,	
Obs.	1,549		1,554		1,563		1,394	

Note: (1) High diversity, high co-option (2) High diversity, low co-option (3) low diversity, high co-option (4) low diversity, low co-option

4.3.2 The Effect of Diversity on Performance according to sub-groups

We also hypothesize that firms with low co-opted boards with high diversity have high performance in order to low monitoring and high quality of information. Those could help top management to have the best decision making. To prove our hypothesis, we use a regression model with four sub-groups. We divided our firm-year observations into four groups using the mean of diversity and co-option. Consistent with our expectation, model (2) in Table 4.3 and Table 4.4 shows that the firms with low co-opted boards with high diversity have statistically significant positive coefficients (0.0481; $p>0.05$, 1.1167; $p>0.01$). Model (1) in Table 4.3 and Table 4.4 shows that firms with high co-opted boards with high diversity have positive coefficients. These findings mean that firms with high diversity have access to private information on different industries. In that case, the key to performance is the level of board monitoring. Increasing board monitoring less likely to give an incentive to the CEO. On the contrary, model (3) in Table 4.3 and Table 4.4 shows the negative coefficients (-0.037; $p>0.01$, -0.1994). It represents that the firms with a high co-opted board with low diversity have the worst performance. Consistent Coles et al. (2014), decreasing board monitoring makes the CEO will be less likely to be fired following poor performance.

4.4 Summary and concluding remarks

Using proxies for board diversity and CEO power based on interlocking directorates and co-option, we find that, over the 1996-2015 period, board diversity is associated with higher operational performance. High board diversity and low co-opted board contributed to the best performance than other subsets in the previous section. The results of this study mean diversity is an appropriate proxy for estimating the quality of information.

Overall, our results highlight the importance of board structure to performance and CEO’s decision making. The results therefore lend support to the perspective that directors are monitors the CEO when they have the great quality of information. For further research, our paper could contribute to the literature on electing directors (Cai et al. 2009), firm performance, or corporate governance.

V. Conclusion

Firm-level interconnection plays an indispensable role in propagating economic shocks across countries and industries and the effectiveness of government policies. Interconnections between different firms and investors could become an important determinant of how societies and economies function. Network analysis could describe particular economic phenomena, such as the financial crisis and the collective behavior of agents. We propose firms' perspective with access to knowledge, resources, markets, or technologies via networks in line with behavior frameworks. As a result, this thesis has concluded how networks contribute to understanding microfinance and different relationships.

Chapter II proved that the interconnections embed systemic risk induced by heterogeneous investors' trading activity because investor strategies incorporate information into stock prices. Retail investors play a detrimental role in financial stability. Consistent with Ang et al. (2006), we uncover that stocks with high sensitivities to total connectedness innovations have low average returns. This evidence provides essential insight into future research.

Chapter III suggested that network centrality constructed by syndicated loans can allow banks to gather and transfer valuable information and thus facilitate profit-making acquisitions in loan investment decisions. We show that the syndicated loan portfolio of high-centrality banks exhibits a higher portfolio diversification level than those of low-centrality banks. We also documented that our composite centrality measure of the bank network showed statistical significance in bank performance even after controlling for the financial variables of market size, loan allocation, total asset, and loan diversification. Our findings suggest that a bank's performance in a syndicated loan hierarchy is related to its position in this hierarchy.

Chapter IV presented that the board of directors has decided on an investment strategy, determining a firm's performance through an information channel. The directorate interlocking enables them to gather valuable information, manifesting the investment. We showed that the effects of connections amongst firms are positive for firm performance. The positive impact also implies that directorate interlocking's information channel plays a vital role in future investment decisions. Moreover, we grouped observations into four using diversification and a CEO related variable.

In summary, this thesis makes the following four contributions. First, this thesis recommended how to make financial networks via indirect or direct connections at the level of investor, financial institution, and manager of firms. Variance decomposition has been actively studied using the stock volatility of financial institutions. In contrast, this thesis has a meaningful insight in that it utilizes the only database grouped as investors in South Korea. This study is the first attempt to create a bank network using a Planar Maximally Filtered Graph through loan portfolios, not the correlation coefficient of stock return.

Second, the evidence related to the association between connectedness and stock returns helped us to make a great understanding of the risk-return trade off. This thesis argued that total connectedness by variance decomposition is a new cross-sectional and systematic factor of stock return. Consequently, the pattern of cross-section expected returns sorting by the sensitivity of total connectedness represents ambiguity in the asset pricing theory.

Third, this thesis could contribute to research related to lending mechanisms that have been proposed to explain the occurrence of syndicated loans (Sufi, 2007; Schwert, 2018). In the perspective of network structure, hub and outlier banks follow different strategies of investment to industries. It is a finding which will be valuable to future works.

Finally, this thesis showed that co-option measured by Coles et al. (2014) has a negative impact on a firm’s operational performance. This finding remains a possibility of extension of CEO power in line with Adams et al. (2005) and Baldenius et al. (2014). When it comes to diversity, we offered meaningful incentives for a manager to improve performance. These findings make a significant insight for a director selection mechanism (Cai et al. 2009) and governance mechanism (Khanna et al. (2015); Ferreira et al. 2007).

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