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Network-based measures of systemic risk in Korea

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Abstract
The authors estimate systemic risk in the Korean economy using the econometric measures of commonality and connectedness applied to stock returns. To assess potential systemic risk concerns arising from the high concentration of the economy in large business groups and a few export-oriented sectors, the authors perform three levels of estimation using individual stocks, business groups, and industry returns. The results show that the measures perform well over the study's sample period by indicating heightened levels of commonality and interconnectedness during crisis periods. In out-of-sample tests, the measures can predict future losses in the stock market during the crises. The authors also provide the recent readings of their measures at the market, chaebol, and industry levels. Although the measures indicate systemic risk is not a major concern in Korea, as they tend to be at the lowest level since 1998, there is an increasing trend in commonality and connectedness since 2017. Samsung and SK exhibit increasing degrees of commonality and connectedness, perhaps because of their heavy dependence on a few major member firms. Commonality in the finance industry has not subsided since the financial crisis, suggesting that systemic risk is still a concern in the banking sector.

Keywords Systemic risk, Network analysis, Korean economy

Paper type Research paper

1. Introduction
How big is systemic risk in the Korean economy and how can we measure it? These are undoubtedly one of the most important questions for policymakers, regulators and academics alike. The concept of systemic risk stems originally from the banking literature, referring to the risk of a crisis in the banking system. Since the recent financial crisis of 2008, however, systemic risk is applied to a more broader sense, indicating an economy-wide shock that may or may not arise from the financial sector and regulators around the globe are increasingly concerned with assessing and moderating it.

A proper assessment of systemic risk in Korea is particularly an important issue, given the following considerations of the uniqueness of the Korean economy. First, Korea is an export-driven, relatively open economy that is highly vulnerable to shocks from abroad, particularly when the global economy takes a downturn. Any crisis situation that occurs during global economic downturn can pose a great threat to the economic stability of Korea. Second, the Korean economy is highly concentrated in a few large business groups (chaebols) and export-

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oriented manufacturing sectors (e.g. semiconductors and automobiles). As disproportionately large portion of the economy depends on a relatively fewer sectors and corporations, systemic risk concerns due to a possible collapse of too-big-to-fail corporations are all the more important. As such, a failure of a big industrial corporation can have a substantial ripple effect through the customer–supplier network and also through the banking system. Third, the economic crisis in late 90s – the Asian financial crisis – had everlasting impacts in Korea, not only economically, but also politically and socially, and preventing another crisis is perhaps is one of the most important issues to policymakers.

Measuring systemic risk, however, is not an easy task. As mentioned, systemic risk in a broad sense refers to market-wide risks that are crucial to the overall soundness of the economy. Practically, it is a concept that is elusive to measure. In a narrow sense, one can measure systemic risk of a banking system based on the exposure of the balance sheet of financial institutions to other financial institutions to see how interconnected those institutions are with each other. This approach might not be plausible to assess systemic risk that is not confined to the banking sector, as it is not entirely clear how firms in non-banking sectors are economically interconnected due to the lack of data availability. Thus, when applied in a broader sense, systemic risk is not straightforward to define and also difficult to quantify.

Our goal in this study is to propose a set of measures for systemic risk to take a first step toward understanding the degree of such risk in the Korean economy (not just in the banking sector). In particular, we focus on the commonality and connectedness of the Korean stock market through the following two econometric methods that are well-suited for our purposes: the principal component analysis (PCA) and the network analysis based on Granger-causality, following Billio *et al.* (2012). Applying these two econometric methods, we exploit the unique feature of the Korean stock market, that is, high concentration of economic power in both large chaebols and major export industries. Specifically, we examine the systemic risk of the stock market at the market, chaebol and industry levels by investigating returns on the largest 50 stocks, 30 chaebols and major industries, respectively. Note that we employ market prices to estimate systemic risk, instead of employing balance sheet data. By exploiting market data that are by construction forward-looking, our measures have advantages in that they can detect changes in risk levels much quicker than backward-looking balance sheet based measures.

The two econometric methods are particularly well designed to measure the commonality and connectedness of the stock market, which are arguably key characteristics of systemic risk. According to Reinhart and Rogoff (2009), linkage in the system is one of the four major elements (the four "L"s) of crises. Linkages among stocks will show up as commonality and connectedness in the stock market. In this regard, the PCA allows us to estimate the number of important common factors and thus can measure how important commonality in stock returns is over time. The Granger-causality network analysis measures will illuminate the complex network structure of the Korean stock market and thus allows us to identify the network structure and potential spillover and interconnectedness of the system.

Our results show that the systemic risk measures do a very good job in capturing system-wide risk in the stock market for our sample period from 1994 through 2018. The measures of commonality and connectedness in the system increase substantially during the past two crisis periods, that is, the Asian financial crisis and the 2008 financial crisis periods. In contrast, the systemic risk measure points to subsided levels of commonality and connectedness during post-crisis periods. Among the 50 largest stocks, for example, the fraction of linkages in the stock market peaks to 25% during the Asian crisis period, indicating one in four stocks are interlinked with one another, but it decreases to less than 5% in mid-2000s. We also find that systemic risk in the Korean stock market has never reached the same level as in the Asian financial crisis, although it increases during the financial crisis period. For example, the fraction of linkages again increases to over 7% during the 2008 crisis, but compared to the late 90s, it is at a modest level. We also find that these systemic risk measures have out-of-sample predictive power for future losses in the stock market. At the onset of the two crises, the network connectedness measures predict higher losses in the cross section of the largest 50 stocks. That is, the more connected a stock is with other stocks as measured by Granger-causality networks, we find bigger losses for the stock. Overall, these results show that our commonality and connectedness measures can be a useful tool for detecting systemic risk in the market.

We also examine the extent to which our measures signal cautions regarding increased systemic risk in the stock market. Overall, we find that the level of connectedness and commonality is at the lowest levels since early 2000. The largest principal component does not explain more than 20% of system-wide variance, while it used to explain more than 40% until mid-2010s. Although there is some evidence that interconnectedness is increasing in 2018, it does not show a strong trend. The other network measures also point to similar conclusion that systemic concern is not particularly high in the recent period, compared with prior to early 2010.

We further examine systemic risk in Korea, focusing on the recent periods. In particular, we search for any noticeable increases in commonality and interconnectedness within the major chaebols, that is, Samsung, Hyundai-Kia Motors, LG and SK corporations, as well as the major industries including electronics, automobile, and finance. Any build-up in systemic risk in these business groups and industries can have a large impact on the Korean economy, as it is heavily dependent on the economic soundness in them. In our within-chaebol analysis, we do not find a substantial increase in systemic risk, although Samsung and SK exhibit some increasing trend in both commonality and connectedness, perhaps due to their heavy dependence on the major member firms. In our industry-level analyses, we do not find a significant increase in commonality and connectedness in any of the three industries. However, the finance sector exhibit a relatively high level of commonality and connectedness throughout the period after 2010, suggesting that systemic risk in the finance sector is always a concern and has not subsided since the 2008 financial crisis.

This study contributes the literature on measuring systemic risk by extending the measures proposed in Billio *et al.* (2012). For example, Adrian and Brunnermeier (2016) propose CoVaR, which measures the change in value at risk of the financial system. Brownlees and Engle (2016) introduce SRISK that focuses on the contribution of a financial firm on systemic risk. Acharya *et al.* (2017) use SES, which measures the expected loss of a financial firm in case of financial market crisis. Huang *et al.* (2012) suggest DIP that estimate the marginal contribution of the financial firms to distress insurance premium of the financial system. Our study also contributes to the literature that measures the systemic risk of Korea, e.g. Lee (2015) and Seo (2014).

2. Measures of systemic risk

In this section, we provide two broad categories of commonality and connectedness measures that can represent the correlation and causality structure of the Korean stock market, which we argue can measure the systemic risk of Korea. The first type of measures is based on the PCA of the major stocks in Korea. The measure allows us to quantify the extent to which the largest components of common risk in stock returns explain account for the variance of the system. The main idea of the measure is that, when the systemic risk in the market is high, a larger portion of stock market risk should be driven by the common component. The second type of measures is based on the Granger-causality network analysis and thus enables us to assign directions of common risk among stocks. That is, we estimate pairwise Granger-causality among stock returns to model the network structure of Korean stock market among major companies.

2.1 Measuring systemic risk in the Korean setting

Before we explain in greater detail how we measure systemic risk, we first provide a more formal discussion of the definition of systemic risk. Note that there is no accepted definition of systemic risk. Perhaps, the quote of U.S. Supreme Court Justice Potter Stewart's regarding pornography might describe it the best: "I know it when I see it." In other words, systemic risk is difficult to define in a formal way, but many academics, policymakers and regulators alike have been using the term as if they know it when they see it.

For the purpose of our study, however, such an informal, intuitive discussion of the true nature of systemic risk is not particularly helpful as we aim to provide measures of such risk so that they can be helpful in practice. Although the concept of systemic risk originally stems from the banking literature [1], after the onset of the 2008 financial crisis, it generally refers to the following in a broader sense, not confined to the banking risk: *any set of circumstances that threatens the stability of or public confidence in the financial system and also the entire economy* [2]. In the U.S. finance literature, systemic risk is mainly confined to the risk in the financial system, as its importance increased after the recent financial crisis, which was a major threat to the financial system.

Considering the unique characteristics of the Korean economy, the concept of systemic risk should be more generally applied to the economy, or to the manufacturing sector, not just to the finance sector. This is because the Korean economy is highly concentrated in the export-oriented manufacturing sector, for example, semiconductor, shipbuilding, automobile and steel industries, and also in a few large business groups, for example, Samsung, Hyundai and SK-Hynix that dominate the economy. A crisis in these manufacturing sectors or chaebols can easily spread into the banking sector, as Korean manufacturing firms are heavily dependent on bank financing rather than public equity and debt financing. A good example is the currency and economic crisis in the late 90s, during which period the crisis in the manufacturing sectors due to high debt burdens, combined with decreased profitability, spilled over to the banking sector, as major banks in Korea had very concentrated loan portfolios to the large business groups, which also can create the too-big-to-fail phenomenon and push the entire Korean economy to the crisis. For these reasons, it makes more sense to examine the risk of the system, including the manufacturing sectors as well, to better measure the real threat to the Korean economy. While these considerations that are unique to Korea make it more appealing to apply the concept of the systemic risk more broadly to the entire economy, it is still unclear how to measure the systemic risk of the economy, or risk to the stability and public confidence of the economy, according to the formal definition discussed above. After all, how can we measure stability and public confidence? We refer to Reinhart and Rogoff's (2009) narrative of economic and financial crises in this regard, that is, the four "L"s that characterizes crises: leverage, liquidity, losses and linkages. The literature on the financial crises already provides a long list of studies for the former three [3]. However, another defining characteristic of the Korean economy is tight linkage in the large business groups, that is, the connections and interactions among the member firms in the business groups. In this regard, a systemic risk measure that can capture the connections and linkages among firms is highly important. Thus, the main emphasis of our paper is on how to measure the linkages, that is, the fourth "L" of Reinhart and Rogoff (2009).

Among the recent literature that covers the measurement issue of U.S. systemic risk [4], it is rather well-established that systemic risk events are associated with the common holdings (and their return correlations) in financial institutions, how concentrated the risk of the financial system is, and how cross-linked the financial institutions are with one another. In this line of research, for example, there are already quite a few studies proposing measures of systemic risk [5]. Although these existing measures have broadened our understanding of systemic risk, their main shortfall is that it is ex-post. That is, they can capture systemic risk exposures only after they show up in data, as these measures mainly focus on the loss components of systemic risk. It would be too late from the point of view of regulators and policymakers, once systemic losses are realized.

In this study, we take a rather different approach, following the work of Billio *et al.* (2012), who measure the correlation structure of the major financial institutions in the U.S. such as banks, hedge funds and insurance companies. Their approach is to measure the correlation structure through PCAs and the Granger-causality tests, with which they estimate how deeply connected the financial system is. For example, it is possible that in good times average correlation declines, but in certain sectors, or in certain business groups, connectedness can increase, which can signal increased systemic risk to the economy. Thus, by examining the snapshots of the network linkages and connectedness, we can assess how vulnerable the Korean economy would be given unexpected shocks from the outside.

Based on the discussion above, we examine the network structure, as measured using the PCA and the Granger-causality tests and the extent to which the measures of the network linkages in the Korean stock market can predict losses in the stock market. In the next subsections, we provide a greater detail of our measures.

2.2 Principal component analysis

A heightened level of systemic risk leads to increased principal components, as stock returns of major companies should commove more strongly. We measure this increase in commovement in stock returns, using the PCA. Just as a brief review, we provide the basic PCA procedure here. Let R^I be the stock return of firm I, $I = 1, \ldots, N$, and the variance-covariance matrix of the stock returns is Σ. We use standardized stock returns to make sure that any single stock return with huge variance do not account for the largest component. Let λ_k be the kth largest eigenvalue and a_k be the corresponding eigenvector of the variance-covariance matrix. Then, the kth principal component is given as $\mathrm{Y_k} = a_k' R$ where R is the column vector of stock returns. The eigenvalue λ_k provides the variance of the kth principal component.

The PCA decomposes the variance-covariance matrix of the Korean stock market into a linear combination of stock returns that represent the maximal variation of the system. It is generally the case that the first few components explain the vast majority of the variation in the system. In particular, during the crisis period, the majority of stock returns tend to commove and the first few principal components account for the largest variation of stock returns in the system. In this sense, the PCA captures the connectedness of the stock market.

2.3 Network measures based on Granger-causality

Although the PCA presented above can explain time-variation in comovement of stock returns, it does not consider the propagation of shocks in the system. To address this issue, we use Granger-causality of stock returns and measure the directionality of links between stock returns.

Let R_t^i and R_t^j be stock returns for firm i and j. We have a system of two data generating processes to represent Granger-causality in the system:

$$R_{t+1}^i = a^i R_t^i + b^{ij} R_t^j + e_{t+1}^i,$$

$$R_{t+1}^j = a^j R_t^j + b^{ji} R_t^i + e_{t+1}^j,$$

where e_{t+1}^i and e_{t+1}^j are two error series that are not correlated with each other. Then, Granger-causality is defined as j Granger-causes i when b^{ij} is different from zero. Likewise, i Granger-causes j when b^{ji} is non-zero. Note that Granger-causality does not suggest any causal relationship between the two variables. Rather, it should be interpreted in a statistical sense.

In a frictionless, efficient market, one should not expect to see any Granger-causality links in the stock market. This is because all the pieces of information in the market should be reflected in stock prices immediately. However, there are plenty of reasons for why one would expect Granger-causal links in stock markets. Market frictions, for example, short sale constraints, borrowing and margin constraints, and any costs associated with information acquisition including limited attention of investors will preclude immediate response of stock returns to information. Therefore, any spillover effect among firms that arises from any underling economic links between firms, e.g. supplier–customer relationship, will show up as Granger-causality in stock return data. In other words, the degree of Granger-causal links in stock returns can be treated as a measure of spillover effects, financial or economic, among firms, as suggested by Daniellsson *et al.* (2011), Battiston *et al.* (2012), and Buraschi *et al.* (2010). The Granger-causal links can amplify when they form a highly connected network, which is also shown by Castiglionesi *et al.* (2009) and Battiston *et al.* (2012). Based the arguments of these studies, we use the Granger-causality measure of connectedness to model the spillover effects in a stock market network in Korea.

We define the following notations of causality:

$(j \to i) = 1$ if j Granger-causes i, and $(j \to i) = 0$ otherwise.

and $(j \to j) = 0$. Using these indicator variables, we characterize the network structure of the stock market. Specifically, we define the following measures as in Billio *et al.* (2012):

Degree of Granger-causality (DGC) is the fraction of statistically significant Granger-causal links among all combinations of total of N stocks. Note that DGC is defined for the entire network unlike the other measures defined for each node. Specifically, DGC is given as

$$DGC \equiv \frac{1}{N(N-1)}\Sigma_i^N \Sigma_{j\neq i}(j \to i)$$

The number of in and out connections counts the number of directional Granger-causal links for in and out links, separately. S denotes the entire stock market (composed of the major stocks).

$$\#Out\ :(j \to S) = \frac{1}{N-1}\Sigma_{i\neq j}(j \to i)$$

$$\#In\ :(S \to j) = \frac{1}{N-1}\Sigma_{i\neq j}(i \to j)$$

$$\#In + Out\ :(j \leftrightarrow S) = \frac{1}{2(N-1)}\Sigma_{i\neq j}(i \to j) + (j \to i)$$

Closeness represents how close a firm is from all the other firms in the stock market. The first step is to calculate a monthly causal link from a stock j to i through all possible paths: $(\mathrm{j} \to \mathrm{k}_1) \times (k_1 \to k_2) \times \ldots \times (k_n \to i) \equiv (j \to \to i) = 1$. Then we denote using C_{ji} the distance of the shortest weak causal link from j to i: $\mathrm{C}_{\mathrm{ji}} \equiv \min\{C \in [1, N-1] : (j \to \to i) = 1\}$. The closeness measure is defined as

$$C_{jS} = \frac{1}{N-1}\Sigma\_(i \neq j)C_{ji}(j \to \to i)$$

Eigenvector centrality is a popular measure in network theory by calculating the average centrality measures surrounding a stock. The first step is to define the adjacency matrix A whose element is $[A]_{ji} = (j \to i)$. The centrality measure is the eigenvector v of the adjacency matrix. Among many eigenvectors, we choose the one whose eigenvalue is one:

$$Av = v$$

Intuitively, this measure is the average of all the centralities around a node.

3. Data description

Our focus is to examine systemic risk in the Korean economy, exploiting common movement and lead-lag relationship in stock returns rather than employing balance sheet information over the period from 1994 through 2018. We obtain monthly stock returns and the number of outstanding shares from FnGuide [6], corporate bond yields, 5-year government bond yields and CD rates from Kofiabond [7], and financial stability index from BOK [8].

Our sample covers the period from 1994 through 2018. The choice of this data frequency and also the sample period serve our purpose well. First, we work with monthly data instead of higher frequency data, i.e. weakly or daily, because of the tradeoff between microstructure issues and statistical power. On one hand, our statistical estimation can have stronger power if we employ higher frequency data. On the other hand, because of potential nonsynchronous trading in relatively smaller-sized stocks, estimation can be noisier with higher frequency returns, which will lead to overestimation of connectedness and underestimation of commonality (Scholes and Williams, 1977). To balance between statistical power and noise due to microstructure issues, we use monthly frequency data. Second, our sample period from 1994 through 2018 covers the major systemic crisis periods of Korea, namely, the late 90s Asian financial crisis, the 2008 financial crisis, and the recent stagnation in economic growth in late 2010s, thus allowing us to compare the performance of the systemic risk measures throughout the sample period.

In our main empirical analyses, we investigate systemic risk at the following levels: the stock market level [9], using the largest 50 [10] or 36 stocks; the business group level, using the largest 30 business groups; and the sector level, using the industry classification from the Korean stock exchange (KRX). To examine systemic risk at the business group and sector level, we also construct aggregate stock returns at the business group and sector levels, respectively, by value-weighting individual stock returns in the groups or sectors. As alternative proxies of systemic risks, we use credit spread, term spread and financial stability index: the credit spread is computed by the difference in BBB and AA corporate bond yields in Korea; the term spread is the difference between 5-year government bond yields and 3-month CD rates in Korea.

4. Empirical results

In Section 4.1, we first implement the connectedness and commonality measures introduced in the previous section. We estimate commonality using the PCA and connectedness using the Granger-causality network analysis, focusing particularly on the graphical illustration of how the measures change before and after the major crises in the Korean economy. In Section 4.2, we perform out-of-sample predictive regressions of maximal realized losses in the stock market using our measures in the regressions. The purpose of these analyses are to show that they are useful indicators of systemic risk. Lastly in Section 4.3, we provide the most recent readings of our measures in 2018, as compared with 2014, to have a better sense of potential risk that the Korean economy faces due to interconnectedness among firms.

The unique features of the Korean economy motivate us to examine the following three, related, but distinct analyses of stock returns. The first analysis is at the market level by analyzing the largest stocks in the market. This resembles the usual analysis of the value-weighted stock market return, or the broad market index, as is most often employed in asset pricing tests. We choose the large 50 (or 36 in the PCA) stocks instead of working with a broader set of, e.g. 200 stocks in the Korean market. By expanding the set of stocks, our network measures would put relative more weights on small-sized stocks. As systemic risk is more likely to originate in a few larger stocks, our choice of the 50 largest stocks suits our purpose better. In addition, given the high concentration of market capitalization in s relatively fewer number of stocks, our focus of the sample stocks has strong economic ground, based on the point of Gabaix (2011). The second analysis is based on chaebol returns that are constructed as value-weighted average of individual member firm returns. As the Korean economy is heavily concentrated on a few large chaebol groups and the commonality at the chaebol returns will also signal increased systemic risk. The third analysis employs industry returns. Given that the Korean economy is also highly concentrated in a few export-heavy industries, it is of particular interest to examine time-variation in commonalty at the industry level. We employ industry returns, which are value-weighted average of stock returns in the same industry, classified by the Korean stock exchange.

4.1 Systemic risk in Korea: full sample analysis from 1995 to 2018

4.1.1 Principal component analysis: graphical illustration. We first examine the commonality in the Korean stock market using the PCA. To the extent that heightened levels of systemic risk manifest as increased common movement in the largest stocks in the market, the PCA can provide an indication of increasing degrees of systemic risk. We perform the PCA using three-year rolling estimation windows (and thus we limit to the largest 36 stocks in the PCA).

In Figure 1, we plot the fraction of system variance explained by the largest principal components during our sample period as well as up to the tenth principal components, using the three sets of stock returns series (i.e. the largest 36 stocks, chaebols and industries).

Figure 1(a) plots the fraction of variance explained by the principal components, using the largest 36 stock returns. A few observations are in order. There is a pronounced downward trend in the first principal component over the period from 1995 through 2018, which might suggest a decreased level of systemic risk in Korea. In particular, since around 2015, the first principal component explain approximately 20% of total system variance, which contrasts with over 40% of total system variance in around 2010 and 1999, the periods following the 2008 financial crisis and Asian financial crisis, respectively. In sum, the figure from the PCA suggests that the level of systemic risk, as proxied by commonality in stock returns, has decreased to the lowest level since 1998.

Figure 1(b) and (c) provide similar plots that show the fraction of variance explained by the first 10 principal components, but using returns on the 30 largest chaebols and KRX industries, respectively. These analyses complements the previous analysis using the largest 36 stocks, by encompassing larger universe of the Korean stock market. Both the figures depict largely similar pictures to Figure 1(a). That is, systemic risk, as represented by commonality in stock returns, has decreased to the lowest levels since 1998. In Figure 1(b), chaebol returns show slight increases toward the end of the sample period, which can suggest that there is mounting systemic risk, particularly among chaebol groups. Other than this recent increase in systemic risk among chaebols, the cumulative PCA plots show that systemic risk in the Korean stock market is at the lowest level since 1998.

4.1.2 Network analysis. In Figure 2, we plot the graphical representation of the Granger-causal links of the Korean stock market. We perform Granger-causality tests using 36-months rolling window estimation and establish a Granger-causal link from stock i to j if the corresponding coefficient from the Granger-causality test is positive with a statistical significance at the 10% level. Similar to the PCA plots provided in the previous section, we also apply the causality tests for the largest 50 stocks, the largest 30 chaebols, and the industry groups classified by the Korean stock exchange. To highlight how network connectedness can covary with systemic risk in the stock market, we provide three graphical representations of the network structure for the following five periods: the Asian crisis 1997–1999, the pre-financial crisis 2002–2005, the financial crisis 2007–2009, the post-financial crisis 2010–2012, the recent period 2016–2018.

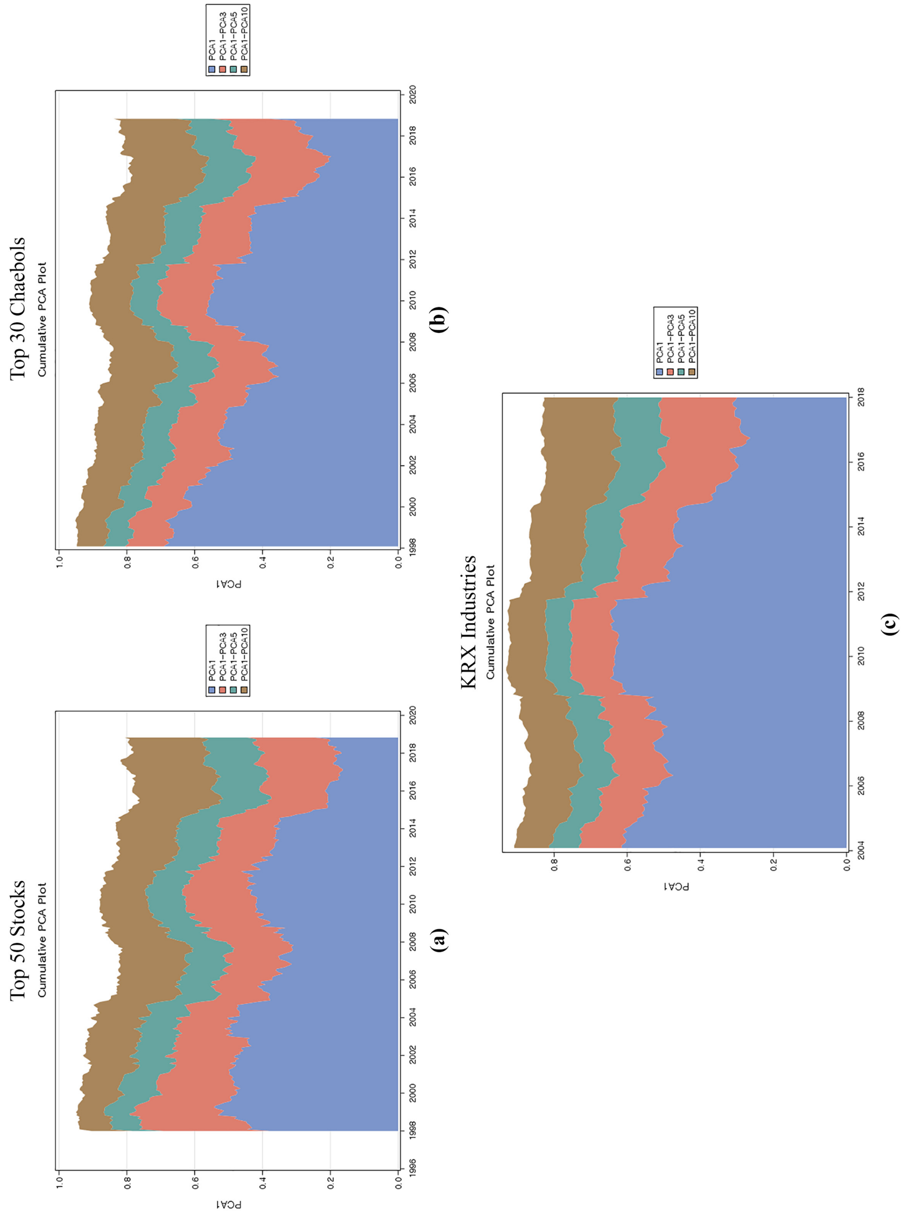


Figure 1.
Cumulative PCA plots

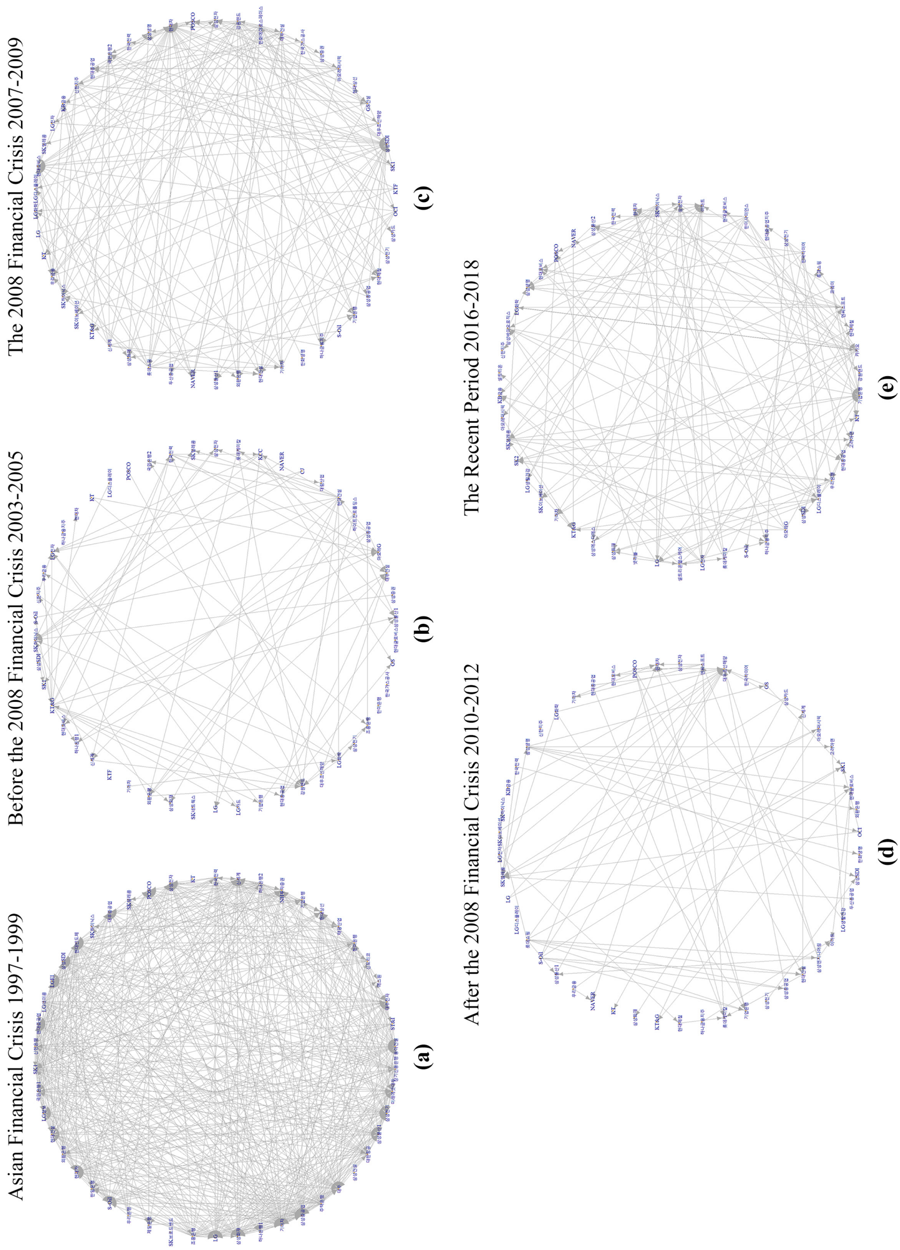


Figure 2.
Network diagram of
top 50 stocks

The evolution of the network diagrams over our sample period, as plotted in Figure 2, shows that the increased connectedness in the stock market coincides with the periods that are typically characterized by increased systemic risk. First, note that the network diagrams plotted in Figures 2(a) through 2(e) show the dynamic nature of connectedness in major Korean stocks, thus suggesting the importance of monitoring the network structure in understanding the degrees of systemic risk in the stock market. Second, and perhaps more importantly, the connectedness of the system increases significantly during the crisis periods. In Figure 2(a), for example, the network is highly connected, showing that systemic risk peaked during the Asian financial crisis. The connectedness of the system subsided significantly after the crisis, increased during the 2008 financial crisis shown in Figure 2(c), and decreased again during mid-2010s in Figure 2(d). We also plot the most recent network structure in Figure 2(f), which shows a slightly more congested network structure.

In Table 1, we tabulate the two measures of connectedness (i.e. centrality and the number of connections in the network) as well as two relative principal components from the estimation of the PCA (i.e. the fractions of system variance explained by the first principal component and the sum of the second and third principal components, denoted as λ_1 and $\lambda_2 + \lambda_3$, respectively) over the major subperiods in our sample. We take average of node-level eigenvalue centrality to obtain network-level centrality. We report the results for the largest 50 stocks (the first lines in each panel), the top 30 chaebols (the second lines in each panel), and the KRX industries (the third lines in each panel). The industry classification is available only from 2000, and thus we do not have report industry-level results in Panels A and B.

The results in Table 1 show that our measures capture systemic risk capture in a timely manner. Focus first on the systemic risk measures using top 50 stocks (the first lines of each panel). Note that the measures already signal increased systemic risk even before the Asian financial crisis (see panel A for January 1995–December 1996): the network centrality was even higher at 0.124 than the Asian financial crisis period 0.116. The other measures, except

	λ_1	$\lambda_2 + \lambda_3$	# of links	Centrality
Panel A: January 1994–December 1996 (Before the Asian Financial Crisis)				
Top 50 firms	0.378	0.316	304	0.124
Top 30 chaebols	0.533	0.210	62	0.036
Industry sectors	NA	NA	NA	NA
Panel B: January 1997–December 1999 (During the Asian Financial Crisis)				
Top 50 firms	0.475	0.285	285	0.116
Top 30 chaebols	0.609	0.164	123	0.141
Industry sectors	NA	NA	NA	NA
Panel C: January 2004–December 2006 (Before Financial Crisis)				
Top 50 firms	0.332	0.240	120	0.049
Top 30 chaebols	0.366	0.225	56	0.064
Industry sectors	0.507	0.185	67	0.063
Panel D: January 2007–December 2009 (Financial Crisis)				
Top 50 firms	0.421	0.269	143	0.058
Top 30 chaebols	0.560	0.191	52	0.060
Industry sectors	0.636	0.154	121	0.108
Panel E: January 2010–December 2012 (Post-Financial Crisis)				
Top 50 firms	0.366	0.163	77	0.031
Top 30 chaebols	0.437	0.152	30	0.034
Industry sectors	0.484	0.139	42	0.042
Panel F: January 2016–December 2018 (Recent Period)				
Top 50 firms	0.324	0.281	137	0.056
Top 30 chaebols	0.459	0.242	39	0.045
Industry sectors	0.332	0.346	67	0.068

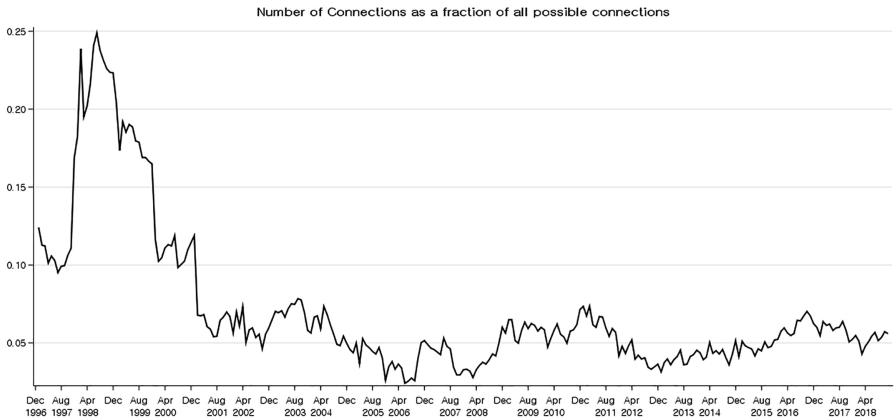
Table 1.
Commonality and connectedness measures for the six subperiods

for lambda1, also show that connectedness in the system has already peaked before the crisis, while lambda1 shows that commonality among stocks is at the highest during the Asian financial crisis period.

Table 1 also shows an interesting trend in the recent sample period. In particular, Panel F presents the results that suggest mounting systemic risk in the stock market in the recent period. Across all the measurers, except for the commonality measure based on the PCA shows increased values of network connectedness, compared with the early-2010 period. For example, the network centrality is 0.056 for the top 50 firms, a comparable level to the 2008 financial crisis (0.058), but a much higher value than the post-financial crisis period (0.031). We find similar results for other network measures. The only exception is the commonality measure (the fraction of the first principal component), which is lower than the post-financial crisis period. Given that the commonality measure tends to be the highest at peak of the crisis (see the results in panel A and panel B), these results in Panel F can suggest systemic risk has increased in the recent years and regulators might want to pay more attention to see whether this is a temporary spike or signals an early warning.

In Figure 3, we also plot the fraction of the number of connections in the network relative to all possible connections. The figure shows that since the Asian financial crisis, connectedness in the stock market has subsided significantly. Even during the peak of the 2008 financial crisis, connectedness in the system did not increase very much, around at 0.06, a much lower level compared with the Asian financial crisis. (Note that we use rolling 36-months windows. Apr, 2010 represent the fraction of connections estimated using data from May 2008 through Apr, 2010). Interestingly, there is increased connectedness in the later period of the sample, e.g. since 2016, almost to the level of the financial crisis period.

In sum, our empirical evidence shows that both the levels of commonality and connectedness have dramatically decreased since the period of the Asian financial crisis except for a slight increase during the period of the 2008 financial crisis. In comparing two crises, systemic risk in the Asian financial crisis is much higher than that of the 2008 financial crisis, consistent with the existing studies that the 2008 financial crisis, different from the events of the Asian financial crisis, has less impact on the Korean economy (Emmer and Ravenhill, 2011; Goldstein and Xie, 2009). This result can be interpreted that our measure tends to detect the risk from the insolvency of the corporate sector (i.e. Asian financial crisis) well rather than the risk from the collapse of the financial sector (i.e. the 2008 financial crisis).



Note(s): Until December 1997, the rolling period is not 36 months but used past data available

Figure 3. The fraction of network connections to the total possible connections: The top 50 stock analysis

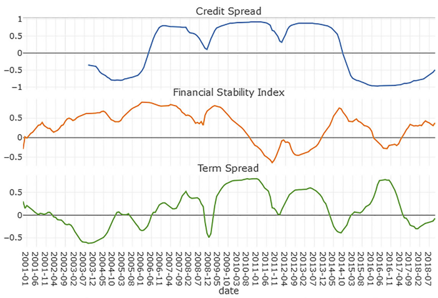
4.2 Correlations between systemic measures and alternative measures

In this section, we compare the patterns of our systemic measures with those of alternative measures that previous literature has commonly used (e.g. credit spread, financial stability index, and term spread).

Specifically, in Figure 4(a), we plot our PCA measure of the top 50 stocks with credit spreads, term spreads and the financial stability index, using rolling 36 months windows. Similarly, in Figure 4(b) we also plot correlations of our measure for the chaebol group's systemic risk with the three macroeconomic variables. In Figure 4(c), we also plot the correlations between the connection measure and the three macroeconomic variables. In the three plots, we find in general high levels of correlations but they also fluctuate over time. In particular, the correlations with the financial stability index tend to be high in the earlier part of the sample, which indicates that our measure and the financial stability index capture similar variation of systematic risk. At the same time, we also find that in the later part of the sample, the correlations are sometimes below zero, which also suggests that the two measures also represent somewhat distinct aspects of systemic risk.

4.3 Predicting stock market loss using the systemic risk measures

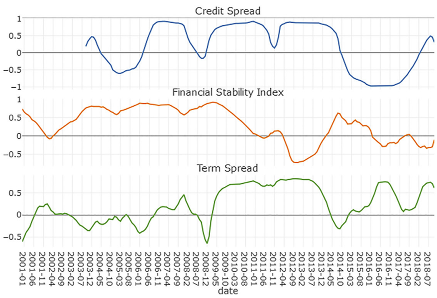
The previous analyses show that our measures of systemic risk capture the connectedness and commonality in advance of the crisis periods. An important check that we need to further



Note(s): We plot our PCA measure of the top 50 stocks with credit spreads, term spreads, and the financial stability index, using rolling 36 months windows

PCA of the Top 50 Stocks

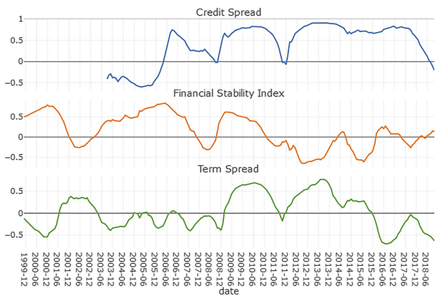
(a)



Note(s): We plot our PCA measure of the top 30 Chaebol stocks with credit spreads, term spreads, and the financial stability index, using rolling 36 months windows

PCA of the Top 30 Chaebols

(b)



Connection

(c)

Figure 4.
Correlations between our systemic risks and alternative measures

perform is whether these measures would have helped regulators detect potential risk in the system prior to the systemic events.

For this purpose, we examine whether our measures that are estimated before the crisis periods can predict losses in the stock market during the crises. Losses in the stock market are measured as maximum losses during our prediction periods. Specifically, we compute maximum percentage losses in market capitalization (*MaxLoss*) experienced by the 50 largest firms in the Korean stock market. The maximum percentage loss is defined as the difference between the market capitalizations of stocks at the beginning of the prediction period and their minimum market capitalizations during the next twelve months period from the beginning of the period, divided by the market capitalizations at the beginning of the prediction period. We calculate *MaxLoss* for the 50 largest stocks, separately.

To examine the predictive power of our systemic risk measures, we also calculate connectedness measures for the 50 stocks. In particular, we calculate the following five measures for each of the 50 stocks: eigenvector centrality, closeness, the number of out links, the number of in-links and the number of total links. The eigenvector centrality measure is the column vector item of the eigenvector of the adjacency matrix associated with the eigenvalue of one. The other four measures are based on the definition provided in Section 2. The measures are all calculated at the node-level to perform cross-sectional regression.

We explore the predictive power of these connectedness measures using the regressions of *MaxLoss*. We use the following two sample periods for the crises. The first crisis period is the one year period from September 1997, the onset of the Asian financial crisis. The second crisis period is the one year period from August 2008, the onset of the 2008 financial crisis. To avoid any look-ahead biases, we separate the network estimation period and the prediction period. The estimation period is the three-year periods preceding the beginning of these two prediction periods, that is, September 1997 and August 2008. In Table 2, we run the regressions of *MaxLoss* on the connectedness measures separately for the two sample periods.

The results provided in Table 2 show that our connectedness measures exhibit strong predictive power for future losses in the stock market during these subperiods of financial crisis. In panel A, for example, the coefficient estimates on the five systemic risk measures considered tend to be negative and statistically significant at the conventional levels. For example, the coefficient on centrality is −0.226 with a t-statistic of −2.11. The only measure that is not significantly associated with future *MaxLoss* is the number of in-connections. Panel B presents similar results. That is, the systemic risk measures are all negatively associated with future *MaxLoss*. Three of the five measures considered are statistically

	Coeff	t-statistic	R^2
Panel A: The Asian Financial Crisis Period			
Centrality	−0.226	−2.11	8.7%
Closeness	−0.419	−2.65	13.0%
# of Out Connections	−0.807	−2.02	8.0%
# of In-Connections	0.226	0.34	0.2%
# of All Connections	−0.761	−1.84	6.7%
Panel B: The 2008 Financial Crisis Period			
Centrality	−0.247	−3.39	10.6%
Closeness	−0.064	−1.08	1.2%
# of Out Connections	−0.441	−1.93	3.7%
# of In-Connections	−0.353	−1.11	1.3%
# of All Connections	−0.470	−2.40	5.6%

Table 2. Predicting stock market loss using network measures

significant at the conventional levels. In sum, the results in Table 2 show that increased values of these measures are associated with lower future market capitalization (i.e. greater maximum loss of market values), another evidence that suggests that the systemic risk measures based on the network analysis can be a helpful toolkit for regulators and policymakers.

4.4 Recent trend in systemic risk in Korea: within chaebol and industry analyses

The previous results show that although systemic risk has subsided substantially and tends to be at a much lower level than in early 2010, the most recent readings of the measures indicate a slight increase in systemic risk. We investigate further by focusing on chaebols and industries. First, we examine connectedness within the major chaebol groups (Samsung, Hyundai-Kia Automotive, LG Corporation and SK Groups) [11] to relate to any potential risk of too-big-to-fail. Third, we also examine within-industry connectedness in the major industry, that is, electronics, automobile and banking industries, as these are particularly important ones for their roles in the Korean economy.

4.4.1 Commonality and connectedness in the top chaebols. In Figure 5, we first provide the cumulative the PCA graphs during our sample period for Samsung, Hyundai-Kia, LG and SK. A few observations are made. First, overall commonality has decreased over time for all of the four chaebols, as indicated by the downward trend in the first principal component. Second, despite the common downward trend among the four, there is cross-sectional variation in the trend. Of the four, SK has the lowest level of commonality in the recent period, suggesting that their member firms do not covary with each other too much and thus SK has relatively lower level of common risk among their member firms. In comparison, Hyundai-Kia exhibits fairly highly level of commonality even in the most recent period. In fact, commonality has not decrease much since early 2010, unlike other chaebol groups, which might suggest that the member firms of Hyundai-Kia can be most vulnerable to chaebol-wide shocks. Considering the importance of Hyundai-Kia in the Korean economy, this trend in high commonality is noteworthy.

In Table 3, we tabulate changes in our measures of systemic risk between the two subperiods: 2012–2014 and 2015–2018. We report the fraction of system variance explained by the first principal component (λ_1), the number of connections in the Granger-causality network, and eigenvalue centrality for Samsung, Hyundai-Kia, LG and SK as well as the top 50 firms for a comparison. The table depicts a mixed picture. First, there is no strong evidence that within-chaebol systemic risk has increased in the recent period even for Hyundai-Kia. If any, Hyundai-Kia has lower centrality measures than before, although their commonality has increased. Thus, the chaebol is subject to high degrees of common shocks, but there does not exist strong causal links within the chaebol. In comparison, Samsung and SK exhibit increases in all measures of commonality and connectedness. For example, λ_1 increases from 0.228 to 0.286 and centrality increases from 0.026 to 0.044 for Samsung. These last pieces of results suggest increasing concentration and connectedness in the two chaebols, which can be driven by the relative importance of their key member firms in the semiconductor industry in the recent years.

4.4.2 Commonality and connectedness in industries: electronics, automobile and finance. We further search for any evidence of increased commonality and connectedness in the major industries. We choose electronics, automobile and finance, as these industries are arguably the basis of the Korean economy; the former two industries are among the most important export sectors in Korea and the finance industry is crucial in corporate financing given the heavy dependence of Korean firms on bank financing.

In Figure 6, we plot the cumulative the PCA graphs during our sample period for the three industries. The two manufacturing industries exhibit similar patterns that we observe the

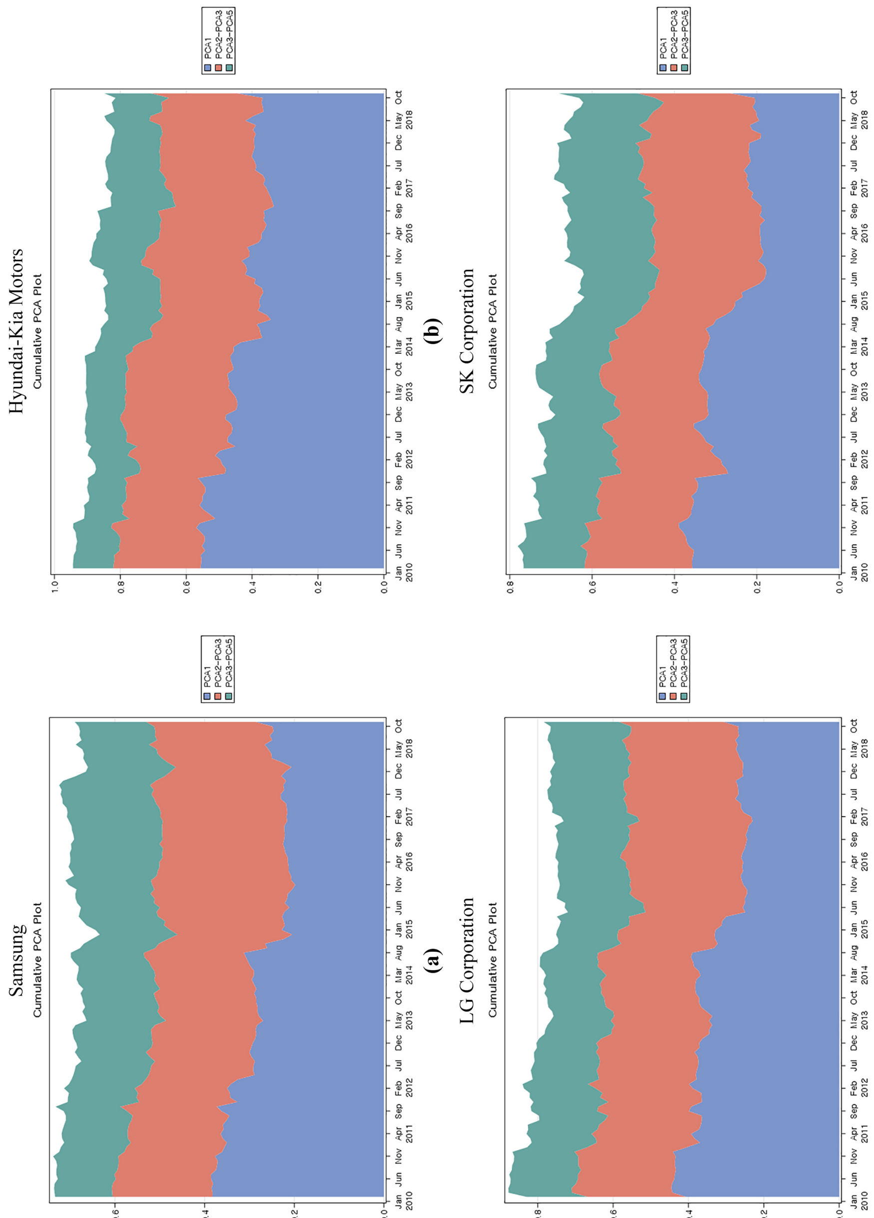


Figure 5.
Cumulative PCA plots
of top chaebols

previous sections: there is a downward trend in commonality and it does not seem particularly high. In Figure 6(c) for the finance industry, however, we find a unique pattern that we do not observe in previous sections. First, we find that commonality stays relative flat over time. In other words, the banking sector in Korea does not show downward trend in commonality. Second, the level of commonality is relatively high at the 40% level throughout the period from 2010 to 2018. Given that 2010 is the year with heightened systemic risk due to the financial crisis, we interpret that systemic risk in the finance sector in Korea has remained fairly high, at least from the perception of market participants.

To investigate further, in Table 4 we tabulate changes in our measures of systemic risk between the two subperiods: 2012–2014 and 2015–2018. As before, we report the fraction of system variance explained by the first principal component (λ_1), the number of connections in the Granger-causality network, and eigenvalue centrality for the three sectors. The table shows that there is no big changes in the measures across the two periods among the sectors. For the finance industry, we find that the centrality and commonality are high relative to the other two sectors, suggesting that connectedness and commonality can amplify system-wide shocks in the banking sector.

5. Conclusion

In this study, we provide econometric measures of systemic risk based on commonality and connectedness that are adapted to the settings of the Korean market. We estimate relative contributions of system variance using the PCA and the Granger-causality network, following Billio *et al.* (2012) by exploiting the unique features of the Korean stock market: high concentration in large business groups and manufacturing-driven export sectors. In particular, we employ stock returns at the individual firm (including manufacturing firms), chaebol and industry levels. We also provide within-chaebol and within-sector analyses of interconnectedness, thus examining how they are linked with each other.

Our results show that these econometric measures perform relatively well over our sample period. Our measures indicate heightened levels of commonality and interconnectedness during such periods. In out-of-sample tests, we also show that the measures can predict future losses in the stock markets, particularly during the crisis periods. We also provide the recent readings of our measures, both at the market, chaebol, and industry levels. Although the measures indicate systemic risk is not a major concern in Korea, as they tend to be lowest since 1998, there is an increasing trend in commonality and connectedness since 2017. Samsung and SK exhibit increasing degrees of commonality and connectedness, perhaps because of their heavy dependence on a few major member firms. Commonality in the finance

Table 3.
Current readings of commonality and connectedness in the Korean stock market: Top chaebols

	λ_1	# of connections	Centrality
Panel A: January 2012–December 2014			
Top 50 firms	0.251	101	0.041
Samsung	0.228	10	0.026
Hyundai Motors	0.379	7	0.064
LG	0.328	7	0.053
SK	0.252	26	0.076
Panel B: November 2015–October 2018			
Top 50 firms	0.249	137	0.056
Samsung	0.286	12	0.044
Hyundai Motors	0.446	2	0.018
LG	0.308	12	0.091
SK	0.264	23	0.061

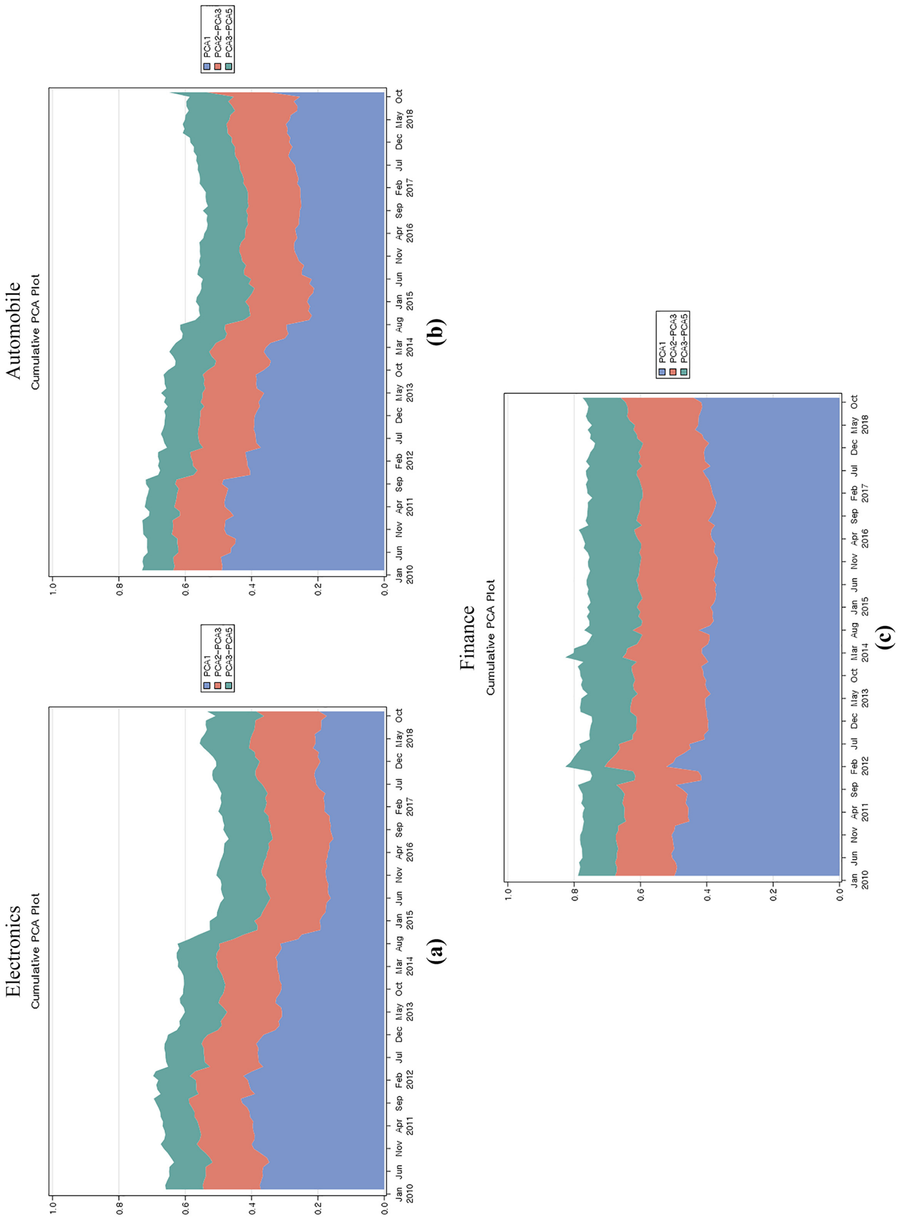


Figure 6.
Cumulative PCA plots
of major industries

Table 4.
Current readings of commonality and connectedness in the Korean stock market: Major industries

	λ_1	# of connections	Centrality
Panel A: January 2012–December 2014			
Electronics	0.195	50	0.057
Automobile	0.233	31	0.036
Finance	0.389	34	0.074
Panel B: November 2015–October 2018			
Electronics	0.197	47	0.054
Automobile	0.346	33	0.038
Finance	0.440	30	0.084

industry has not subsided to a lower level since the financial crisis, suggesting that systemic risk is always a concern to the industry. It is interesting future research to further examine the extent to which network-based systemic risk measures can be used as early warning signal of future crises.

Notes

1. Several survey papers on systemic risk in banking have summarized the details on various issues (i.e. systemic risk-taking, contagion and amplification and bank runs). See Borio and Drehmann (2009) for the definitions and Benoit *et al.* (2017) for the more recent papers. Recently, Adrian and Brunnermeier (2016) and Acharaya *et al.* (2017) define system risk based on bank tail risk and the connection of the bank with the system in financial distress.

2. See also De Bandt and Hartmann's (2000) review of the systemic risk literature, which provides the following alternative view:

   "*A systemic crisis can be defined as a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. While the "special" character of banks plays a major role, we stress that systemic risk goes beyond the traditional view of single banks' vulnerability to depositor runs. At the heart of the concept is the notion of "contagion," a particularly strong propagation of failures from one institution, market or system to another.*

   In a similar vein, Daniel Tarullo, the former Federal Reserve Governor, mention that "*A systemic risks is defined as the potential for an event or shock triggering a loss of economic value or confidence in a substantial portion of the financial system, with resulting major adverse effects on the real economy*." Modernizing Bank Supervision and Regulation Testimony before the Committee on Banking, Housing, and Urban Affairs, US Senate, Washington, DC, 19 March, 2009.

3. Among many others, see, for example, Amihud and Mendelson (1986), Brennan *et al.* (1998), Chordia *et al.* (2000, 2001, 2002), Glosten and Harris (1988), Lillo *et al.* (2003), Lo *et al.* (2001), Lo and Wang (2000), Pastor and Stambaugh (2003), Sadka (2006), Lo (2001), Getmansky *et al.* (2004), Billio *et al.* (2011), and Acharya *et al.* (2017).

4. A variety of systemic risk measures has been proposed in the wake of the 2008 global financial crisis. Bissias *et al.* (2012) and Benoit *et al.* (2017) provide comprehensive survey papers regarding systemic risk in banking and financial institutions covering more than 40 systemic risk measures and they highlight that no single measures can be used as the proxy of systemic risk that can fully detect crises.

5. For example, Adrian and Brunnermeier (2016), Acharya *et al.* (2017) and Huang *et al.* (2012), among many others.
6. FnGuide is a local data provider similar to the Center for Research in Security Prices.
7. http://kofiabond.or.kr
8. Financial stability index is obtained from the Financial Stability Report (2018), published by the Bank of Korea.
9. We measure size based on the market capitalization, multiplying the current stock price (closing price) by the number of total outstanding shares.
10. At the end of 2018, the top 50 firms account for 58.54% of the total market capitalization in the KRX.
11. See Appendix to descriptive statistics of the selected chaebol's asset, sales and profits. The ratio of four major chaebol group's asset to GDP has been increased from 30% to 52% over the period from 2001 to 2018.

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Appendix

Table A1. Characteristics of the major business groups (Unit: Billion)

Year	Samsung Asset	Samsung Sales	Samsung Profit	Hyundai-Kia motors Asset	Hyundai-Kia motors Sales	Hyundai-Kia motors Profit	LG corporation Asset	LG corporation Sales	LG corporation Profit	SK corporation Asset	SK corporation Sales	SK corporation Profit	GDP	$\frac{\text{SUM(ASSET)}}{\text{GDP}}$ (%)
2001	47,379	47,596	969	36,136	36,446	1,232	51,965	75,287	2,037	69,873	130,337	8,327	688,164.9	29.8
2002	46,754	50,319	1,157	41,266	45,904	2,859	54,484	79,966	1,627	72,351	128,739	5,320	761,938.9	28.2
2003	47,463	53,415	1,862	44,060	55,381	2,767	58,571	85,045	2,911	83,492	144,410	10,744	810,915.3	28.8
2004	47,180	49,847	3,845	52,345	56,610	2,797	61,648	70,940	3,557	91,946	120,998	7,418	876,033.1	28.9
2005	47,961	56,137	4,564	56,039	67,008	3,364	50,880	63,116	5,498	107,617	139,175	13,274	919,797.3	28.5
2006	54,808	64,520	4,562	62,235	73,769	5,797	54,432	64,033	3,338	115,924	142,570	9,449	966,054.6	29.7
2007	60,376	70,479	4,278	66,225	77,555	3,771	52,371	66,493	1,209	129,078	150,455	12,356	1,043,258	29.5
2008	71,998	69,067	4,897	73,987	84,351	3,908	57,136	72,686	5,120	144,449	160,658	12,363	1,104,492	31.5
2009	85,889	105,171	2,904	86,945	96,304	4,370	68,289	83,911	4,309	174,886	188,960	11,774	1,151,708	36.1
2010	87,522	95,118	2,625	100,775	94,652	8,429	78,918	94,638	7,332	192,850	220,120	17,664	1,265,308	36.4
2011	97,042	112,003	4,969	126,689	129,643	13,540	90,592	107,113	4,639	230,928	254,562	24,498	1,332,681	40.9
2012	136,474	155,252	6,431	154,659	156,255	11,804	100,777	111,804	2,094	255,704	273,001	20,243	1,377,457	47.0
2013	140,621	158,530	3,765	166,694	163,801	13,396	102,360	115,884	2,410	306,092	302,940	29,537	1,429,445	50.1
2014	145,171	156,868	4,547	180,945	158,798	14,725	102,060	116,468	2,155	331,444	333,892	24,150	1,486,079	51.1
2015	152,388	165,469	5,757	194,093	165,631	12,677	105,519	115,926	2,882	351,533	302,897	20,999	1,564,124	51.4
2016	160,848	137,798	13,626	209,694	171,409	12,227	105,849	114,290	3,285	348,226	271,880	18,779	1,641,786	50.2
2017	170,697	125,920	6,838	218,625	170,203	11,376	112,326	114,610	3,963	363,218	279,652	15,575	1,730,399	50.0
2018	189,531	158,080	17,355	222,654	171,033	7,731	123,135	127,396	7,124	399,479	315,852	35,538	1,782,269	52.4