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台股市場報酬率連結與波動率連結之測量與分析

MEASURING THE RETURN AND THE VOLATILITY CONNECTEDNESS OF TAIWAN'S EQUITY MARKET

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本論文係王元翰君（學號 R04323010）在國立臺灣大學經濟學系完成之碩士學位論文，於民國 106 年 7 月 4 日承下列考試委員審查通過及口試及格，特此證明

口試委員：

曾中閔 （指導教授）

曾中閔 陳宜廷

王泓仁 徐士勛

謝辭

還記得碩一上修了管中閔教授的計量經濟學，才上沒幾堂課我便決定要跟隨教授寫論文，當時還因為成績不夠好，不知道要如何開口，而如今論文已經完成，回首往事，真是恍如隔世。論文前後大約花了一年時間完成，這一年之中絕大部分的時間是在柏克萊交換，柏克萊課業繁重異常，因此這一年論文寫得甚是刻苦，更是憔悴，然而這一年中，在管教授細心指導之下所學習與經歷的一切，將是我此生中最重要的學術資產。

能夠順利完成碩士論文、並取得碩士學歷，首先要感謝三位口試委員：徐士勛教授、王泓仁教授、陳宜廷教授。謝謝三位教授對於論文的指正與建議，使我發現了很多不曾想過的問題，並且重新去認識自己研究方法與結論的缺陷。

再者，感謝吳惟小姐，論文寫作的一年期間，我們分隔兩地，過程充滿煎熬，時差、課業、再加上論文，以至於就算回了台灣，我們相聚之日依然難得，然古人所言不虛，「兩情若在長久時，又豈在朝朝暮暮」，儘管艱難，但妳堅定的支持、耐心、溫柔與愛，一直是我最堅強的後盾。

我還要感謝我的家人，謝謝我母親永遠無條件的支持，而此篇論文的完成，我更需要謝謝我的弟弟，王元睿先生。從論文的雛形，到第一版、第二版、以至於後來的好幾個版本，都是你從頭看到尾，並且花好幾個小時，一段一段的告訴我你對於論文的想法與疑慮，而因為你的建議所做出的許多重大修正，事後證明也都是關鍵且正確的。

最後，也是最重要的，我要謝謝我的指導教授，我的恩師，管中閔院士。

在論文寫作的初期，當時教授時常稱讚我，認為此論文所要探討的問題與想法十分有趣，而初步得到的結論也令人振奮，當時我胡亂地寫了一篇四十多面的初稿，因為速度快更是被教授讚譽為「跑車級」研究生。然而這初稿乃金玉其外、敗絮其中，不看則以，一看則問題層出不窮。學生本還志得意滿，自

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以為真有些天分，但後來才發現大從論文架構、行文邏輯、論事角度，小到用字遣詞、語句文法、標點符號，周身是病，無一處能讓人滿意。最終還是由教授如父親帶幼童寫字一般，手把手，一個字、一個標點地從頭改到尾。為此，我心中充滿無比的感恩，教授您如此用心對待學生，我將永誌不忘。在論文寫作的過程中，教授您給予了我無數的指正、建議、與勉勵，而這一切，也將成為我往後從事研究時最重要的基石。

謝謝管爺您的指導，能夠成為您的碩士指導學生，無疑是我在台大六年最幸運、亦是最開心的一件事。雖然學生現在資質能力依然平庸，但希望經過不斷的努力與奮鬥，未來我能達到您所有的期望，最終使您感到驕傲。

經過一年的掙扎與學習，我才了解以前一切的研究計畫、無數個大小報告只不過是自娛娛人，而我此生的研究，當以此篇為始。

“ Now this is not the end. It is not even the beginning of the end.
But it is, perhaps, the end of the beginning. “

— Sir Winston Churchill. After the victory in El Alamein, 1942.

王元翰 謹誌
于 國立臺灣大學經濟學研究所
2017 年 6 月

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中文摘要

本論文旨在測量與分析台灣股票市場內，九大類股自身之報酬率連結(return connectedness)與波動率連結(volatility connectedness)。論文結果顯示不同產業別之間的連結程度有很大的差異，其中金融業連結程度最高，而貿易百貨業、網路通訊業連結程度最低。另外本論文也針對各產業之報酬率連結與波動率連結做長達 17 年的動態追蹤，除了發現在所有產業中，此兩種連結的動態有顯著分歧，同時我們也可以觀察到，不同產業別自身連結程度之動態變化。最後，本論文對於影響連結程度的因子做了一些探討，並且發現即使是排除了 2008 金融海嘯的影響，經濟不景氣仍會顯著的使各產業之報酬率連結與波動率連結上升，另外，各產業之結構也會對其連結程度造成影響。

關鍵字: 經濟危機、系統風險、連結、向量自我回歸、變異數分解、市場結構

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Abstract

The empirical objective of this study is to measure the connectedness of stock prices in nine different market segments in Taiwan. For both the return and the volatility of stock prices, this research demonstrate that the connectedness level in different market segments significantly differs from one another. Moreover, the results suggest that the time-varying natures between the return and the volatility connectedness of stock prices are drastically different from each other. In addition, this paper aims to identify the key factors that strengthen or weaken the return and the volatility connectedness of stock prices. The findings suggest that both of them are profoundly influenced by economic downturns and the market structure of the industry.

Key Words: Financial Crises, Systemic Risk, Connectedness, Vector Autoregression, Variance Decomposition, Market Structure.

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1 Introduction

The collapse of the investment bank Lehman Brothers on September 15, 2008 leads to a full-blown international financial crisis, and has since created renewed interest in the nature of financial institutions' connectedness. Billio et al. (2012) track down the connectedness of hedge funds, banks, broker/dealers, and insurance companies in the United States. Using a different connectedness-measuring technique, Diebold and Yilmaz (2014) measure the connectedness for major US financial institutions, while Demirer et al. (2017) do the same thing for the top 150 global banks. Other related works include Diebold and Yilmaz (2009), Adrian and Brunnermeier (2011), and Acharya et al. (2017), among others.

The researches regarding the connectedness level among companies are important in multiple aspects: Allen et al. (2012), and Billio et al. (2012) argue that by exploiting the time-varying nature of the connectedness level among financial institutions, we can predict future economic downturns. Furthermore, from the viewpoint of company regulation, understanding the nature of a given industry is vital for effective policy making, and this cannot be done without the knowledge of the connectedness level in that industry. Moreover, the knowledge of connectedness is also valuable for portfolio management. For example, if the level of connectedness among certain companies are very high and one's portfolio is only constructed by those companies, then this could imply a poor ability to diversify the risk.

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The research on the connectedness among companies is vital. The existing empirical works, however, only focus on financial firms and rarely go beyond. Moreover, there is little research on identifying the forces that strengthen or weaken connectedness. Due to the lack of investigation and the importance of understanding connectedness, this research focuses on finding the system-wide connectedness level in the financial business industry, along with eight other industries that haven't been studied before. Furthermore, the fluctuation of the connectedness level in different industries over time is examined, and the key factors that strengthen or weaken the system-wide connectedness level in each industry are also identified.

Utilizing the connectedness measuring technique proposed by Diebold and Yilmaz (2009), this research measures the connectedness of stock return and stock volatility across nine different market segments classified by Taiwan Stock Exchange. The results show that, for both the stock return and volatility, different market segments have very different levels of connectedness. The financial business industry has the strongest connectedness in terms of both stock return and stock volatility; the wholesale and retail trade industry has the weakest connectedness in terms of stock return, while the telecommunication and internet service industry has the weakest connectedness in terms of stock volatility. In addition, in all nine market segments, when monitoring the return and the volatility connectedness level of stock prices over time, evidences of their distinct behavior are found. In particular, stock return connectedness changes slowly over time; in contrast, its volatility counterpart

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changes drastically within short periods.

This research also aims to identify the forces that influence connectedness of stock return and volatility. The results in this thesis suggest that in most market segments studied in this research, both the stock return and volatility connectedness tend to *increase* during economic downturns. Furthermore, the market structure plays a vital, but different role in determining the connectedness level in each market segments. To be specific, the results show that when the market becomes more concentrated (from perfect competition to oligopoly), the stock return and volatility connectedness will *increase* for financial business, plastic, and textile industry, while they will *decrease* for construction, transportation, and food industry.

This research proceed as follows. Section 2 presents the literature on connectedness, in particular, standard vector autoregressive (VAR) models and variance decomposition are reviewed. Section 3 describes the data that is used in the empirical study. Section 4 provides the empirical results, and Section 5 summarizes this research.

2 Measures of Connectedness

The concept of connectedness could be convoluted and elusive, as a result, a careful definition is required. The classical approach would be the correlation-based measurement of connectedness. It is evident that it captures certain aspects of con-

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nectedness in perhaps the most intuitive way. However, there are three major limitations in this approach. First of all, it only captures linear relations, which makes it of little value in some complex cases. Second of all, it only deals with pairwise relations. Lastly, it is symmetrical, that is, $corr(x, y) = corr(y, x)$. These limitations can become quite restrictive in certain situations. This research aims to measure the "overall level" of connectedness in multiple market segments, and hence needs some methods that can capture system-wide connectedness, which clearly can't be achieved by the traditional correlation-based method.

To measure connectedness, different authors developed various ways to go beyond the correlation-based approach. For example, the principal components analysis and pairwise Granger-causality tests proposed by of Billio et al. (2012), the conditional value at risk (CoVaR) approach proposed by Adrian and Brunnermeier (2011), and the marginal expected shortfall (MES) approach suggested by Acharay et al. (2010). These approaches are all distinct ways to define and measure connectedness, but unfortunately, they are *not* designed to measure system-wide connectedness, and hence cannot be utilized in this research. On the other hand, the equicorrelation approach proposed by Engle and Kelly (2012) are intended to measure system-wide connectedness, but it requires assumptions that are not suitable for this research.[1] As a result, this research follows the connectedness measuring framework originally developed in Diebold and Yilmaz (2009), and subsequently modified in Diebold and

[1]In order to apply the equicorrelation approach proposed by Engle and Kelly (2012), one has to assume, at every time period, *all pairs* of stocks within a given industry share the *same* correlation.

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Yilmaz (2012, 2013, 2014, 2015).

Diebold and Yilmaz (2009) utilized VAR models to measure system-wide connectedness based on the share of forecast error variance. This is, in fact, the familiar economic notion of a variance decomposition that traces back to Sims (1980). To simplify notation, let's first consider a canonical example, a **covariance stationary, two-variable** VAR(p) model:

$$\mathbf{\Theta}_p(L)\mathbf{X}_t = \mathbf{V}_t,$$

where $\mathbf{X}_t = (x_{1,t}, x_{2,t})'$ and $\mathbf{\Theta}_p(L) = \mathbf{I}_2 - \mathbf{\Phi}_1 L - \mathbf{\Phi}_2 L^2 - \ldots - \mathbf{\Phi}_p L^p$, with L as the lag operator, $\mathbf{I}_2$ and $\mathbf{\Phi}_1 \ldots \mathbf{\Phi}_p$ as the 2×2 identity and parameter matrixes. By covariance stationarity, we can transform the above VAR(p) process as follow:

$$\mathbf{X}_t = \mathbf{\Psi}(L)\mathbf{V}_t = \mathbf{A}(L)\mathbf{U}_t,$$

where $\mathbf{\Psi}(L) = [\mathbf{\Theta}_p(L)]^{-1}$ and $\mathbf{A}(L) = \mathbf{\Psi}(L)\mathbf{Q}_0$, where $\mathbf{Q}_0$ is the unique lower triangular Cholesky factor of the variance-covariance matrix of $\mathbf{V}_t$. That is, $\mathbf{V}_t = \mathbf{Q}_0\mathbf{U}_t$ where $\mathbb{E}[\mathbf{U}_t\mathbf{U}_t^{'}] = \mathbf{I}_2$. Now, the error of forecasting this VAR(p) model **one period** ahead is:

$$\mathbf{X}_{t+1} - \mathbb{E}[\mathbf{X}_{t+1}|\mathbf{X}_t] = \mathbf{V}_{t+1} = \mathbf{Q}_0\mathbf{U}_{t+1} = \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

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and the variance of the forecast error yeilds:

$$\mathbb{E}[\mathbf{Q}_0\mathbf{U}_{t+1}\mathbf{U}_{t+1}^{'}\mathbf{Q}_0^{'}] = \mathbf{Q}_0\mathbf{Q}_0^{'} = \begin{bmatrix} q_{11}^2 + q_{12}^2 & q_{11}q_{21} + q_{12}q_{22} \\ q_{11}q_{21} + q_{12}q_{22} & q_{21}^2 + q_{22}^2 \end{bmatrix} \equiv \mathbb{V}_0 \ .$$

From the above calculation, we know that when forecasting $x_{1,t}$ one period ahead, its forecast error variance is $q_{11}^2 + q_{12}^2$. An interesting question to ask is: What proportion of this variance is due to the shocks from $x_{1,t}$ itself, and how much is from the shocks from $x_{2,t}$? Intuitively, If all of $x_{1,t}$'s forecast error variance comes from its own shock but not from the shock of $x_{2,t}$, then it seems like $x_{2,t}$ can't influence $x_{1,t}$ at all. Building on this interpretation, we can now define *"own connectedness"* as the fraction of the variance caused by the shocks from itself, and *"cross connectedness"* as the fraction caused by the shocks from others ($x_{2,t}$ in our example). Note that the error of forecasting $x_{1,t}$ one period ahead is: $q_{11} \cdot u_{1,t+1} + q_{12} \cdot u_{2,t+1} \equiv \mathbb{F}_{x_1}$, where $u_{1,t+1}$ and $u_{2,t+1}$ are orthogonal to each other by construction, hence we have:

$$\frac{\partial \mathbb{F}_{x_1}}{\partial u_{1,t+1}} = q_{11} \ , \text{ and } \ \frac{\partial \mathbb{F}_{x_1}}{\partial u_{2,t+1}} = q_{12} \ .$$

As a consequence, the own connectedness of $x_{1,t}$ is given by:

$$\frac{q_{11}^2}{q_{11}^2 + q_{12}^2} = \frac{q_{11}^2}{[\mathbb{V}_0]_{11}} \ ,$$

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while the cross connectedness equals:

$$\frac{q_{12}^2}{q_{11}^2 + q_{12}^2} = \frac{q_{12}^2}{[\mathbb{V}_0]_{11}} \ ,$$

where $[\mathbb{V}_0]_{ij}$ is the ij^{th} element of $\mathbb{V}_0$. Using this definition, we can answer the earlier posed question: For the forecast error variance in forecasting $x_{1,t}$ one period ahead, $(q_{11}^2/[\mathbb{V}_0]_{11}) \times 100$ percent of the variance is caused by the shocks from itself and $(q_{12}^2/[\mathbb{V}_0]_{11}) \times 100$ percent comes from the shocks from $x_{2,t}$. On the other hand, the own connectedness of $x_{2,t}$ is given by:

$$\frac{q_{22}^2}{q_{21}^2 + q_{22}^2} = \frac{q_{22}^2}{[\mathbb{V}_0]_{22}} \ ,$$

while the cross connectedness equals:[2]

$$\frac{q_{21}^2}{q_{21}^2 + q_{22}^2} = \frac{q_{21}^2}{[\mathbb{V}_0]_{22}} \ .$$

Having established the cross and the own connectedness, we now expand to the "overall" level of connectedness, which Diebold and Yilmaz (2009) referred to as "total spillover", or "total connectedness" in their subsequent works. Observe that, there are two types of connectedness in our model, the own connectedness of $x_{1,t}$

[2]Note that for both $x_{1,t}$ and $x_{2,t}$, own connectedness and cross connectedness will add to one, that is:

$$\frac{q_{11}^2}{[\mathbb{V}_0]_{11}} + \frac{q_{12}^2}{[\mathbb{V}_0]_{11}} = \frac{q_{22}^2}{[\mathbb{V}_0]_{22}} + \frac{q_{21}^2}{[\mathbb{V}_0]_{22}} = 1$$

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and $x_{2,t}$:

$$\frac{q_{11}^2}{[\mathbb{V}_0]_{11}}, \frac{q_{22}^2}{[\mathbb{V}_0]_{22}},$$

and the cross connectedness of $x_{1,t}$ and $x_{2,t}$:

$$\frac{q_{12}^2}{[\mathbb{V}_0]_{11}}, \frac{q_{21}^2}{[\mathbb{V}_0]_{22}}.$$

Now we can define the "total connectedness" of our model as follow:

$$\begin{aligned}
Total\ connectedness &= \frac{cross\ connectedness\ in\ the\ model}{cross + own\ connectedness\ in\ the\ model} \\
&= \frac{1}{\frac{q_{11}^2+q_{12}^2}{[\mathbb{V}_0]_{11}} + \frac{q_{21}^2+q_{22}^2}{[\mathbb{V}_0]_{22}}} \left(\frac{q_{12}^2}{[\mathbb{V}_0]_{11}} + \frac{q_{21}^2}{[\mathbb{V}_0]_{22}} \right) \\
&= \frac{1}{2} \left(\frac{q_{12}^2}{[\mathbb{V}_0]_{11}} + \frac{q_{21}^2}{[\mathbb{V}_0]_{22}} \right),
\end{aligned}$$

which is a measurement of the overall level of connectedness among different variables in the model. In this simple two-variable example, total connectedness is just the average of $x_{1,t}$ and $x_{2,t}$'s cross connectedness.

Having established the system-wide connectedness measurement for this simple 2-variable, 1-step ahead forecasting model, it is straightforward to generalize it to a more complex one. In a k-**variable** ($\mathbf{X}_t = (x_{1,t}, x_{2,t}, \ldots, x_{k,t})'$), 1-**step ahead** forecasting model, the total connectedness is given by:

$$\frac{1}{k} \sum_{i=1}^{k} \sum_{j \neq i} \frac{q_{ij}^2}{[\mathbb{V}_0]_{ii}}.$$

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Finally, recall that for a covariance stationary VAR(p) process,

$$\begin{aligned}\mathbf{X}_t &= \boldsymbol{\Psi}(L)\mathbf{V}_t = \boldsymbol{\Psi}(L)\mathbf{Q}_0\mathbf{U}_t \\ &= \mathbf{Q}_0\mathbf{U}_t + \boldsymbol{\Psi}_1\mathbf{Q}_0\mathbf{U}_{t-1} + \boldsymbol{\Psi}_2\mathbf{Q}_0\mathbf{U}_{t-2} + \ldots \quad ,\end{aligned}$$

where $\mathbf{Q}_0$ is the unique lower triangular Cholesky factor of the variance-covariance matrix of $\mathbf{V}_t$. Now, the error of forecasting a two-variable VAR(p) model H-step ahead is:

$$\begin{aligned}\mathbf{X}_{t+H} - \mathbb{E}[\mathbf{X}_{t+H}|\mathbf{X}_t] &= \mathbf{Q}_0\mathbf{U}_{t+H} + \boldsymbol{\Psi}_1\mathbf{Q}_0\mathbf{U}_{t+H-1} + \ldots + \boldsymbol{\Psi}_{H-1}\mathbf{Q}_0\mathbf{U}_{t+1} \\ &\equiv \begin{bmatrix} q_{0,11} & q_{0,12} \\ q_{0,21} & q_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+H} \\ u_{2,t+H} \end{bmatrix} + \begin{bmatrix} q_{1,11} & q_{1,12} \\ q_{1,21} & q_{1,22} \end{bmatrix} \begin{bmatrix} u_{1,t+H-1} \\ u_{2,t+H-1} \end{bmatrix} + \\ &\quad \ldots + \begin{bmatrix} q_{H-1,11} & q_{H-1,12} \\ q_{H-1,21} & q_{H-1,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},\end{aligned}$$

and the variance of the forecast error yeilds:

$$\begin{aligned}&\begin{bmatrix} q_{0,11}^2 + q_{0,12}^2 & q_{0,11}\cdot q_{0,21} + q_{0,12}\cdot q_{0,22} \\ q_{0,11}\cdot q_{0,21} + q_{0,12}\cdot q_{0,22} & q_{0,21}^2 + q_{0,22}^2 \end{bmatrix} + \ldots \\ &\quad + \begin{bmatrix} q_{H-1,11}^2 + q_{H-1,12}^2 & q_{H-1,11}\cdot q_{H-1,21} + q_{H-1,12}\cdot q_{H-1,22} \\ q_{H-1,11}\cdot q_{H-1,21} + q_{H-1,12}\cdot q_{H-1,22} & q_{H-1,21}^2 + q_{H-1,22}^2 \end{bmatrix} \\ &\equiv \mathbb{V}_0 + \ldots + \mathbb{V}_{H-1} \ .\end{aligned}$$

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As a consequence, the total connectedness in a k**-variable**, H**-step ahead** forecasting model is given by:

$$\frac{1}{k}\sum_{i=1}^{k}\sum_{j\neq i}\frac{\sum_{h=0}^{H-1} q_{h,ij}^2}{\sum_{h=0}^{H-1}[\mathbb{V}_h]_{ii}} ,$$

and this measurement is what we will use in the rest of this research. Note that it serves as a summary of the degree of connectedness that exists among x_1 through x_k. Since its value must lie between zero and unity by construction, we can actually view the total connectedness as a "percentage" of connectedness among x_1 through x_k.

To fully understand and interpret total connectedness, it's helpful to cut through the notation mess by using a simple example. In a k-variable, H-step ahead forecasting model, suppose the total connectedness equals to zero, this implies that for each x_i $(i = 1, ..., k)$, its H-step-ahead forecast error variance is 100% caused by its own shock. Thus there is absolutely no cross connection in this system. On the other hand, if total connectedness equals to 1, then for every x_i $(i = 1, ..., k)$, 100% of its H-step-ahead forecast error variance is caused by the shocks from other x_j $(j \neq i)$, implying a perfect cross connection within the system. Finally, if total connectedness equals to 0.5, then it implies that on average, for a given x_i $(i = 1, ..., k)$, 50% of its H-step-ahead forecast error variance is caused by the shocks from x_j $(j \neq i)$ and the other 50% is caused by its own shock.

Before finishing this section, there's still one important issue that needs to be ad-

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dressed. Recall that the Cholesky factorization method was used in order to identify the shocks. As a consequence, different "orderings" of the data *will* lead to different results. That is, whether x_1 = Company A, or x_2 = Company A in our model *will* make a difference. To solve this problem, Koop et al. (1996), and Pesaran and Shin (1998) propose an alternative method that is immune to this "ordering problem". One fundamental assumption in their procedure, however, is that they assume the shocks are Gaussian. This research trys to measure the return and the volatility connectedness among different stock prices. The Gaussian assumption is reasonable when measuring the connectedness of stock volatility, where the shocks are well-approximated as Gaussian. The same assumption is *not* appropriate for stock return (Diebold and Yilmaz, 2015). Furthermore, under the connectedness measuring framework introduced in this section (the Cholesky-based method), cross connectedness is very sensitive to a different ordering of the data; total connectedness, on the other hand, is *not* sensitive at all.[3] Since in this research, cross connectedness per se is not a concern, and this research only focus on total connectedness, hence it's more reasonable to use the Cholesky factorization-based measuring method. Finally, to demonstrate the fact that total connectedness is indeed not sensitive to the ordering of the data, a robustness check against the ordering problem

[3] In order to test the sensitivity of this approach against different VAR orderings, Diebold and Yilmaz (2009) construct sixty-eight different orderings and calculate their corresponding total connectedness. Their results show that the range of total connectedness measured across various orderings is very small, implying that the total connectedness is quite robust to different orderings of the data.

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will be provided in section 4.

3 Data

This research measures the return and the volatility total connectedness within nine different market segments in Taiwan's stock market, and monitor the fluctuations of the return and the volatility total connectedness over time. The market segments considered are:

1. Textile industry
2. Food industry
3. Wholesale and retail trade industry
4. Financial business industry
5. Construction and building materials industry
6. Telecommunication and internet service industry
7. Transportation and shipping industry
8. Semiconductor industry
9. Plastic industry

The daily stock prices of individual stocks (including open price, close price, daily high price, and daily low price) can be obtained from *Taiwan Economic Journal Data Bank*. For all market segments, the data ranges from Jan/04/2000 to Dec/01/2016, and there are 4213 data points for each stock (since there are 4213 trading dates during this period), with two exceptions: financial business industry, and telecommunication and internet service industry. Because some major players in those two market segments did not enter until 2003, so the data from those two

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segments spans between Jan/02/2003 and Dec/01/2016, with a total of 3450 trading dates for each stock.

For the daily stock return, this research follows the convention and use the change in daily log closing prices. As for the daily stock volatility, ideally, one could construct the daily realized volatility using high frequency (say, one minute) intra-day data. This data, however, is out of reach for the author. Hence this research follows the approach of Garman and Klass (1980), which obtain the estimator of the daily stock volatility by the following formula:

$$\begin{aligned}\hat{\sigma}_{i,t}^2 = 0.511(h_{i,t} - l_{i,t})^2 - 0.019[(c_{i,t} - o_{i,t})(h_{i,t} + l_{i,t} - 2o_{i,t}) \\ -2(h_{i,t} - o_{i,t})(l_{i,t} - o_{i,t})] - 0.383(c_{i,t} - o_{i,t})^2 ,\end{aligned}$$

where $h_{i,t}, l_{i,t}, o_{i,t}, c_{i,t}$ are, respectively, the natural log of daily high, low, opening and closing prices for company i at date t, $i = 1, \ldots, k$ and $t = 1, \ldots, 4213$. Alizadeh et al. (2002) show that this range-based estimator of volatility is approximately Gaussian and robust to microstructure noise. Moreover, it is highly efficient.

Until this point, we have yet to explain how to choose k, the number of companies we are going to estimate in each market segment. we want to choose k large enough so that the connectedness in each segment is well captured by these k companies, that is, these k companies in each market segment serve as a good proxy of the whole market segment itself. A trivial way is just to include all the companies in

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each market segment, but note that in a VAR(p) model, the number of parameters grows exponentially as k grows. So this research chooses $k = 10$, where these ten companies are, loosely speaking, the "largest 10" in their market segment, which are determined by the following steps:

Step 1: Drop all the companies that have less than five years of data. (So it is either a start-up or a company in the past that lives shortly, hence reasonable to assume that dropping these short-lived company will not lose valuable information).

Step 2: For the companies that remain, obtain its daily market value from Jan/04/2000 to Dec/01/2016 (or Jan/02/2003 to Dec/01/2016). These data can be obtained from *Taiwan Economic Journal Data Bank*.

Step 3: Calculate all companies' daily market share, which is obtained by dividing their individual market value by total market value

Step 4: Average out each company's market share over the years (4213/3450 days to be exact), obtain the "average market share", then choose 10 companies with the first 10 largest average market share in that market segment.

After choosing 10 companies in all nine market segments, we examine how well they represent the whole market. Table 1 shows the value of combined average market shares of the top 10 largest companies in each industry. As Table 1 shows, the

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Table 1: Combined Average Market Share Of The Top 10 Companies

Market Segment	Taiwan Stock Exchange Classification Code	Values
Plastic Industry	M1300	93%
Wholesale and Retail Trade	M2900	87%
Food Industry	M1200	85%
Transportation and Shipping	M2600	82%
Textile Industry	M1400	70%
Telecommunication and Internet Service	M2327	70%
Semiconductor Industry	M2324	62%
Financial Business	M2800	53%
Construction and Building Materials	M2500	47%

Note: The data spans between Jan/04/2000 and Dec/01/2016

percentage is quite high. Six out of nine market segments are more than 70%, one is around 60%, and two are around 50%. Hence it is not unreasonable to expect that the top 10 companies in each market segment can well represent that segment.[4]

Finally, among the 90 companies that are choosen (10 for each market segment), all of them have complete data during the time span of Jan/02/2005 - Dec/01/2016. In some cases when the data is missing from Jan/04/2000 to Dec/31/2004, the missing values are replaced by the data from the 11^{th} largest company in that segment. If there's still missing data, we then use the 12^{th} largest company and so on, until all missing values are replaced. The ticker numbers and the average market shares

[4]For interested readers, note that there are ways to deal with the situation when "k" gets very large under this variance decomposition based connectedness-measuring framewrok. Dees et al. (2007), and Pesaran et al. (2004) proposed a Global VAR approach to linearly combine the parameters; Demirer et al. (2017) use LASSO methods to shrink, select and estimate the high-dimensional network. Each procedure has their own assumptions and limitations. Since $k = 10$ seems suitable for this research, these methods won't be needed.

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of those companies are shown in Appendix (see Table A1).

4 Empirical Results

This section begins by analyzing connectedness using the full sample. In Subsection 4.2, the dynamics of connectedness is examined by using rolling samples. In Subsection 4.3, the key factors that strengthen or weaken the stock return and volatility connectedness are identified. Finally, Subsection 4.4 provides the robustness check against different VAR orderings of the data.

In this research, the VAR ordering of the data is organized from the largest company to the smallest company in each market segment with respect to its average market share. Also, when the data is fitted to a VAR(p) model for each market segment, one have to decide the value of the lag. These values are determined based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Lastly, this research measures connectedness using H-step-ahead forecast error variance where H equals two weeks ($H = 10$). This is because the data shows total connectedness quickly converge to a fixed value after $H = 3$ for return and $H = 7$ for volatility connectedness.

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4.1 Full-Sample Return and Volatility Total Connectedness

Table 2 lists the total connectedness of daily stock return and volatility for nine market segments in Taiwan Stock Exchange using the entire sample: Jan/04/2000 (or Jan/02/2003) to Dec/01/2016

First of all, for the nine market segments that are under investigation, Table 2 indicates that 10% to 50% of the forecast error variance comes from connectedness, both volatility and return. Now observe that for both the return and the volatility connectedness, financial business industry has the strongest connectedness among all market segments (50.79%, 43.72% respectively, around five times the amount of telecommunication and internet service industry). Wholesale and retail trade industry has the weakest return connectedness (10.84%), while telecommunication and internet service industry has the weakest volatility connectedness (9.55%). It's also worth noting that return connectedness is stronger than volatility connectedness in all market segments (with the only exception of wholesale and retail trade industry).

Full-sample total connectedness provides us a useful summary of the return and the volatility connectedness of different market segments in the Taiwan's stock market. However, it overlooks some exciting features of connectedness that vary over time. It's quite reasonable to suspect that given different time spans, the total connectedness measured here will take various values. There is no reason why connectedness should be constant across time. To this aspect, we now move from a

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Table 2: Total Connectedness - Entire Sample

Market Segment	Return Total Connectedness	Volatility Total Connectedness
Plastic Industry	39.33%	31.32%
Wholesale and Retail Trade	10.84%	11.62%
Food Industry	20.05%	15.24%
Transportation and Shipping	34.90%	26.66%
Textile Industry	21.60%	16.12%
Telecommunication and Internet Service	11.38%	9.55%
Semiconductor Industry	27.47%	24.11%
Financial Business	50.79%	43.72%
Construction and Building Materials	17.99%	13.64%

The lag p are chosen according to Bayesian Information Criterion (BIC) and are equal to 1 for return total connectedness and 2 for volatility total connectedness in all market segments.

static full-sample analysis to a dynamic rolling-sample analysis.

4.2 Dynamics of Return and Volatility Total Connectedness

To investigate the dynamics of the return and the volatility total connectedness in each market segment, we now use 200-day rolling samples. For each 200-day sample, we fit it to a VAR(p) model, recalculate its return/volatility total connectedness and plot them over time. AIC is used to determine the lag "p" for each rolling sample. The results are displayed in Figure 1. There are many insightful features in these figures. First, and perhaps the most surprising result, the return and the volatility total connectedness for almost all market segments tend to increase during the 2008 global financial crisis and the 2012 EU sovereign debt crisis.

Before elaborating this result, let's first examine the economic environment of

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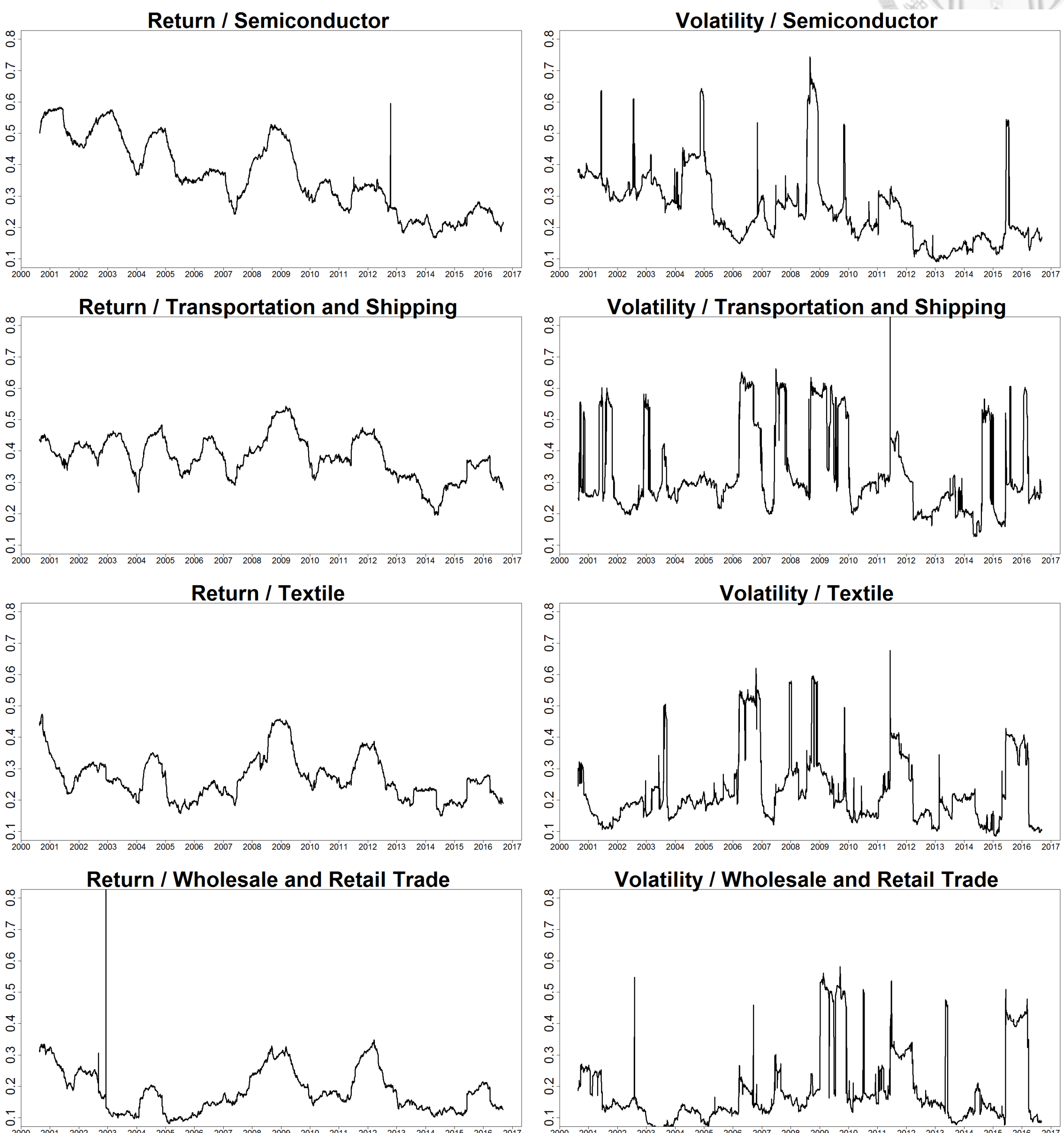
Figure 1: Total Connectedness - 200 Days Rolling-Sample



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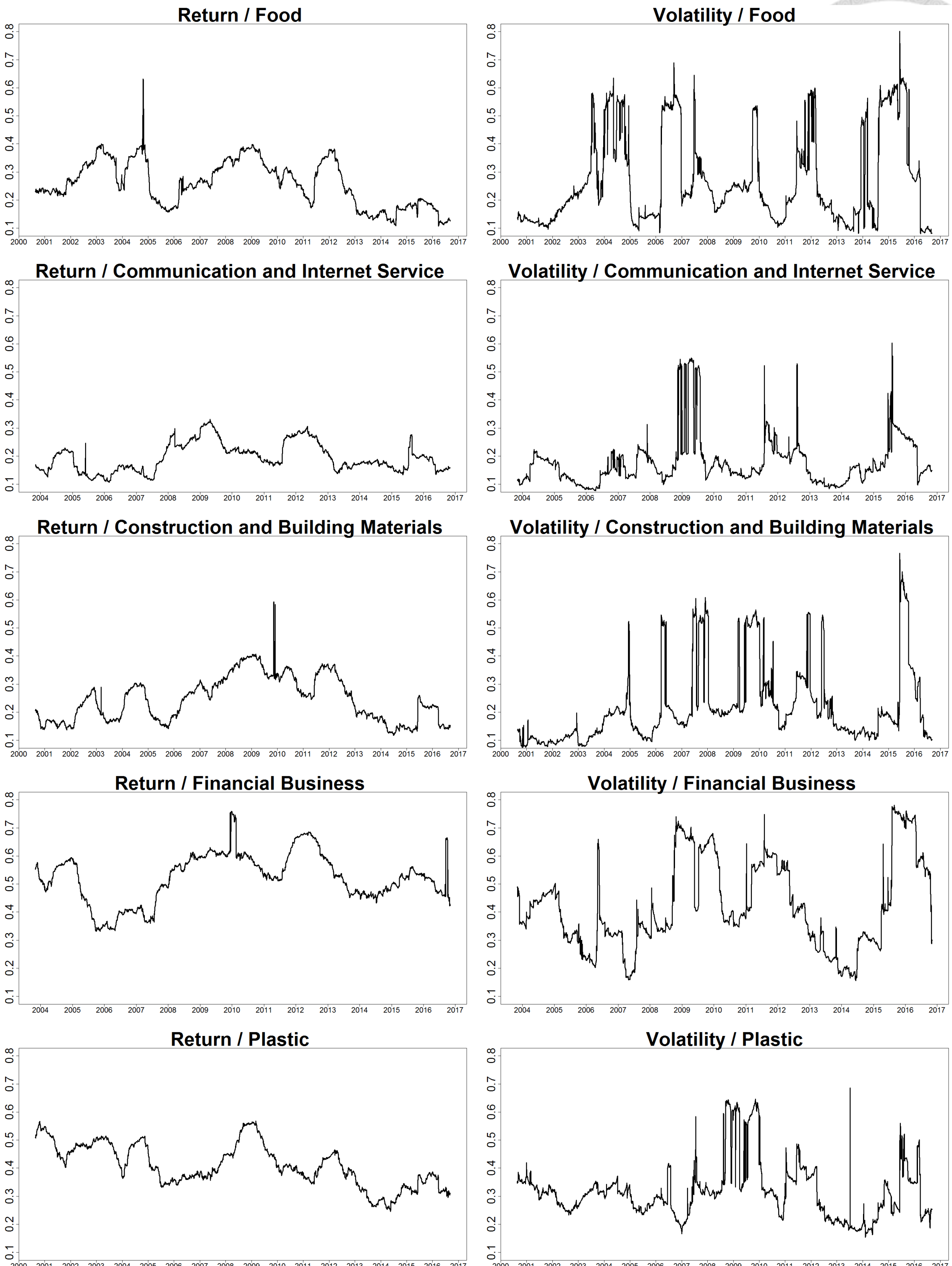

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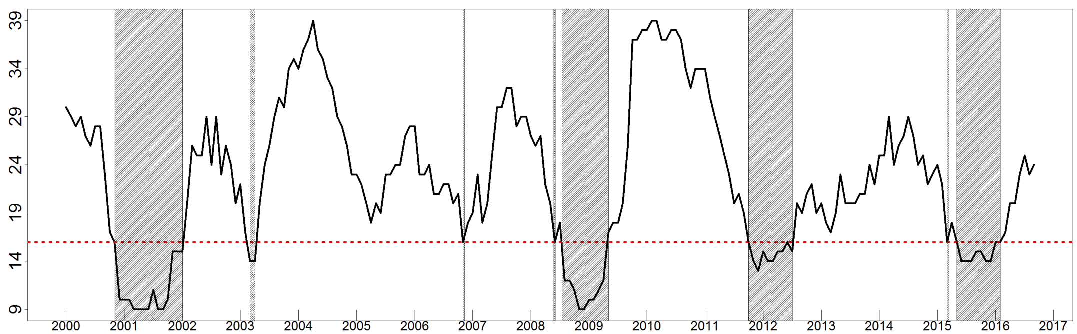
Figure 2: Business Cycle Indicator of Taiwan



Taiwan during the period this research studys. For a given month, the National Development Council of Taiwan considers the following indexes: Monetary Aggregate M1B, Nonagricultural Employment Rate, Taiwan Stock Exchange Average Closing Price, Industrial Production Index, along with five other indexes. After reviewing them, the council assigns a number to that month where the value ranges from 9 to 45. The months that take values between 9-16 are classified as the "economic sluggish period". Figure 2 shows the values that National Development Council of Taiwan assigned to each month starting from Jan 2000 to Nov 2016. The dotted line represents the value 16, there are eight economic sluggish periods (shaded area in Figure 2), and their duration is listed in Table 3. Finally, there are 203 months in our sample, and among them, there are 49 months that are labeled sluggish.

Now, observe the connection between these economic sluggish periods and the movements of the return/volatility total connectedness of the nine market segments. It is important to note that, despite many exceptions can be found, in general the

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Table 3: Economic Sluggish Periods

	Time Span	Duration (month)
1	Dec.2000 - Feb.2002	15
2	Apr.2003 - May.2003	2
3	Dec.2006	1
4	Jul.2008	1
5	Sep.2008 - May.2009	9
6	Nov.2011 - Aug.2012	10
7	Apr.2015	1
8	Jun.2015 - Mar.2016	10

return/volatility total connectedness in all nine market segments tend to increase during those eight economic sluggish periods: They typically start at a high value in 2000 - 2001 when the "dot-com bubble" occurred, decrease afterwards and sharply increase from mid-2008 to mid-2009 due to the effect of the global financial crisis. Then they decline after 2009, but due to the aftermath of the sovereign debt and banking sector problems in EU, they increase yet again during 2011. Finally, after a short period of tranquility, they rise from mid-2015 to mid-2016.

To better understand the relationship between connectedness and business cycle, Figure 3 and 4 present the stacked graph of them. In order not to confuse the reader with multiple graphs, only the outcomes of plastic industry and financial business industry are displayed. (For the complete results, see Figures A2 and A3 in Appendix). Solid lines represent the return/volatility total connectedness with their coordinates one the left axis, dotted lines are the business cycle with coordinates on the right. It's now clear from Figure 3 and 4 that, although some exceptions can be

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Figure 3: Return Total Connectedness and Business Cycle (selected)

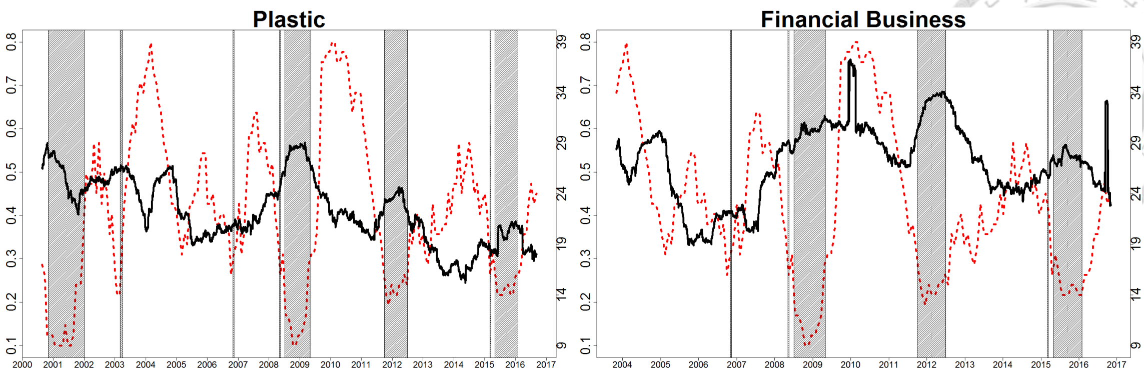
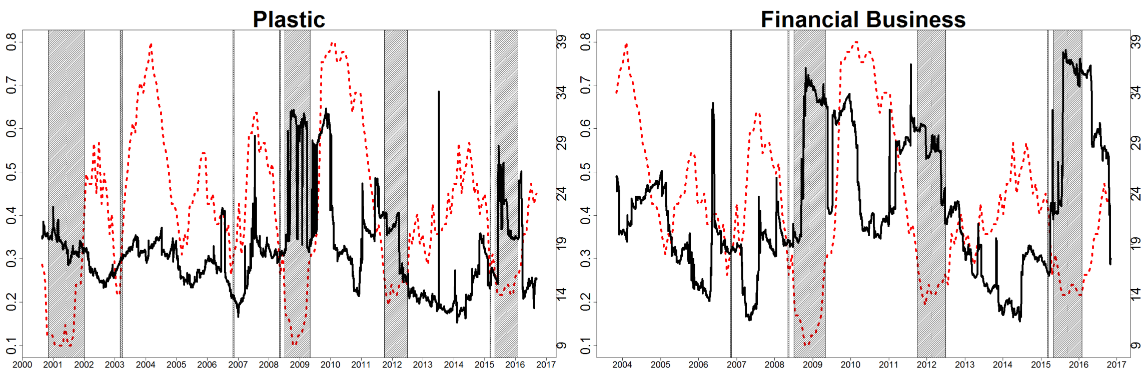


Figure 4: Volatility Total Connectedness and Business Cycle (selected)



found, the return and the volatility total connectedness increase drastically during economic sluggish periods.

Another interesting result that we can observe from these figures is that, without any exception, return total connectedness is much "smoother" than its volatility counterpart - volatility total connectedness fluctuates drastically almost all the time, with only a few short periods it becomes relatively calm. In contrast, return total connectedness is mainly tranquil, with only a few periods of drastic changes. Moreover, while both the return and the volatility connectedness tend to increase during

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economic crises, the return connectedness does so in a milder way. On the other hand, volatility connectedness experiences discrete jumps when entering crisis periods, and afterward, they jump back to its pre-crisis level.

Last but not least, in order to compare the return and the volatility total connectedness across nine different market segments, the plot of them are combined into one figure which is displayed in Figure 5. In this massive figure, the individual plots of the return and the volatility total connectedness of all nine market segments are first combined, the economic sluggish periods are then added to the plot. From Figure 5, we can observe some salient features: For return total connectedness (top in Figure 5), all market segments tend to move together with clear pattern. Furthermore, the financial business industry has the highest level of connection among all market segments almost throughout the period of this study, while telecommunication industry, along with wholesale and retail trade industry have the weakest connectedness during this period. Moreover, despite the fact that return total connectedness of all nine market segments differ in level, they all seem to increase by a similar amount during economic sluggish periods. Finally, prior to the 2008 global financial crisis, the return total connectedness of financial, transportation and shipping, semiconductor, and plastic industries are very close to each other. But right after the crisis, the return total connectedness of financial industry diverges, leaving a huge gap between it and other industries.

Now let's focus on volatility total connectedness (bottom in Figure 5). By inspec-

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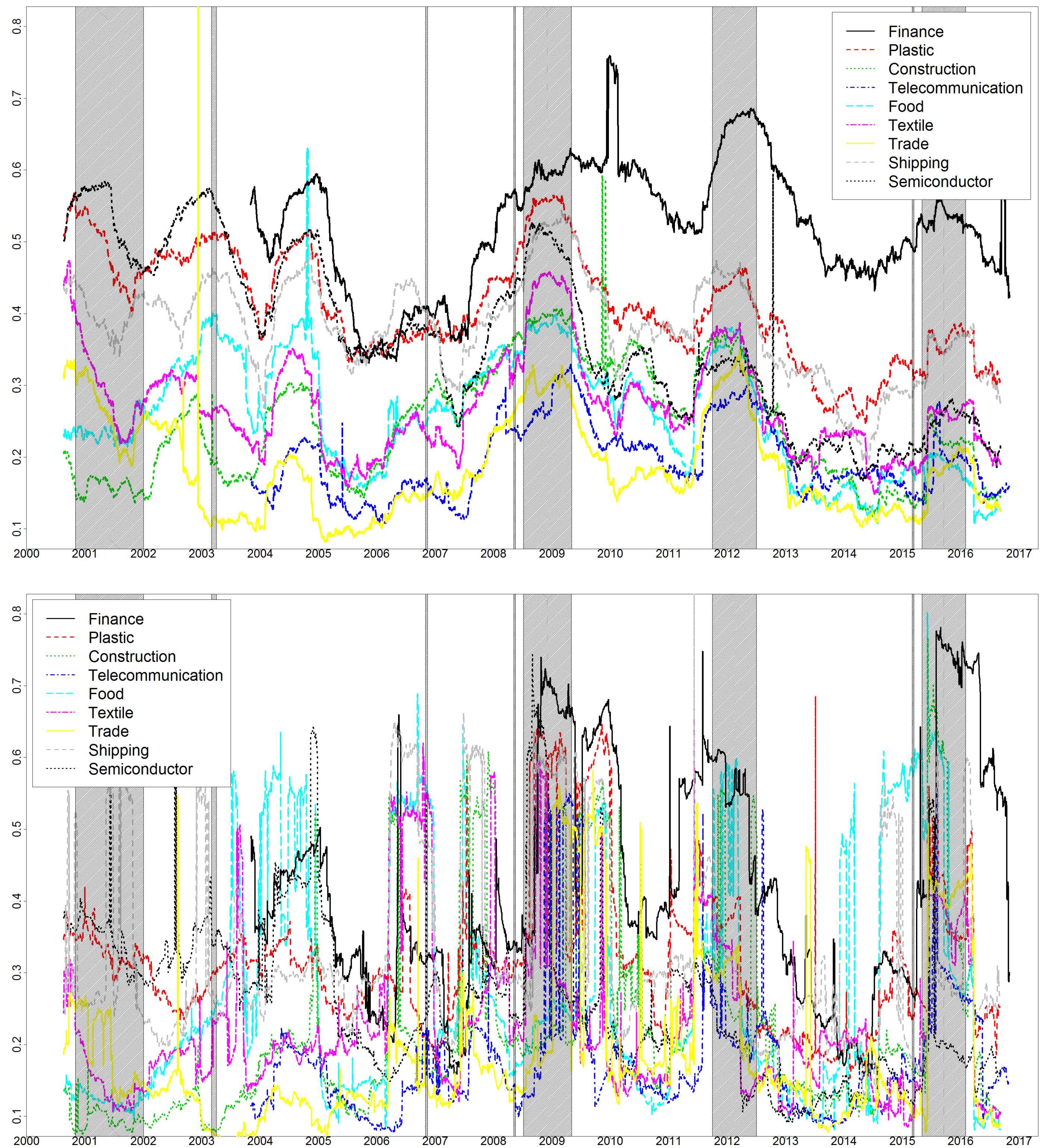
Figure 5: Combined Return and Volatility Total Connectedness



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tion, it is evident that volatility total connectedness for different market segments displays no consistency at all. Also, regarding the level of connectedness, no single industry is consistently higher (or lower) than others during the period we study. And while volatility total connectedness also tends to increase during economic sluggish periods like their return counterpart, the amount of increment is different from one industry to the next.

4.3 Regression Results

We have found many interesting features about the return and the volatility total connectedness in the last two subsections. In this subsection, the key factors that strengthen or weaken the return and the volatility total connectedness are identified. First, it's already very clear from previous analysis that economic sluggish periods have a sizable impact on the return and the volatility total connectedness, but still, we will put this statement to test and find out exactly how strong the impact is. Another possible factor that can influence return/volatility total connectedness may be the "degree of concentration" in each market segment. That is, within a market segment, if some major players continue to increase in size and gradually turn the market into an oligopoly, will this change affect connectedness in this market segment? On the other hand, if the major players decrease in size, what will happen to return/volatility connectedness?

To find out what forces strengthen or weaken connectedness, the following regres-

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sion is run for each market segment.

$$Y_t = \beta_0 + \beta_1 t + \beta_2 D_t^{2008} + \beta_3 D_t + \beta_4 C_t + \epsilon_t \ ,$$

where Y_t is the daily return/volatility total connectedness of the nine market segments, which is plotted in Figure 1. D_t^{2008} is a daily dummy variable that equals unity during the 2008 global financial crisis (Sep. 2008 - May. 2009), D_t is a daily dummy variable that equals unity during economic sluggish periods (shaded area in Figure 2), and C_t is a daily time series data that captures the degree of concentration for each market segments. Note that due to the uniqueness of the 2008 global financial crisis, we use D_t^{2008} to extract its effect from D_t in our regression. Also note that C_t is obtained by summing the market share of the top 10 companies in each industry each day. If this value is very low, then the market segment tends to be close to perfect competition. Figure 6 shows the market structure of plastic industry and transportation and shipping industry. The combined market share of the top 10 companies in the plastic industry doesn't fluctuate much over the years, while for transportation and shipping industry, it decreases over the years from around 95% in the year 2000 to 75% in the year 2016. The complete results are shown in Appendix (see Figure A4). Finally, note that we include a linear time trend in our regression, and all the variables are daily time series data, where t goes from 1 to 4013 for all market segments except for financial and telecommunication industry

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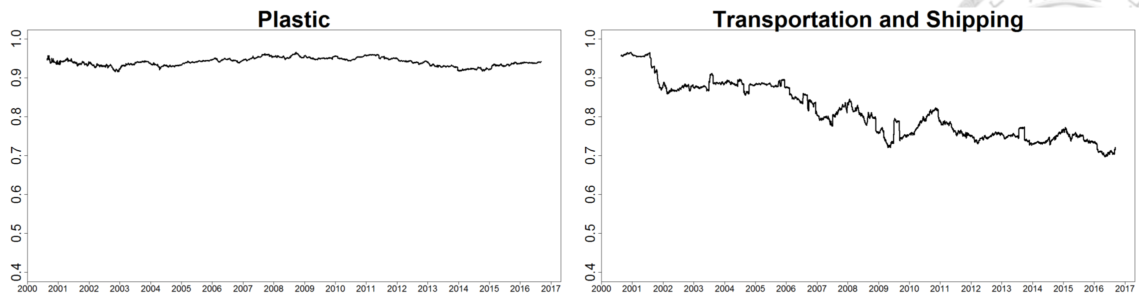
Figure 6: Market Structure (selected)



(where t goes from 1 to 3250).

For both the return and the volatility total connectedness, there are nine different market segments to be considered, hence a total of 18 regressions to run. Table 4 summarizes the estimated coefficients of D_t^{2008}, D_t, and C_t ($\hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4$) for return total connectedness, while Table 5 does the same thing for volatility total connectedness. For inference purposes, this research uses the Newey-West standard error (Newey and West, 1987) with Quadratic Spectral kernel and the automatic bandwidth selection procedure proposed by Newey and West (1994).

We begin from Table 4. First of all, by observing the coefficients for D_t^{2008} (the $\hat{\beta}_2$), it is evident that the economic crisis in 2008 has a significant influence on the return total connectedness. The coefficients in eight out of nine market segments are statistically significant under 1% confidence level, and all of them have positive signs, meaning the 2008 crisis increases the return total connectedness for all those market segments, as we suspect from the previous analysis. Moreover, five of them increase more than 10% during the 2008 crisis, with the highest increment in textile

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Table 4: Return Total Connectedness Regression Results

Industry	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
Financial Business	4.87%	4.94%**	2.200***
	(0.0367)	(0.0212)	(0.5365)
Plastic	10.66%***	3.50%***	0.898**
	(0.0214)	(0.0096)	(0.4019)
Wholesale and Retail	8.00%***	6.11%***	0.171
	(0.0250)	(0.0122)	(0.1356)
Textile	14.20%***	3.46%***	0.081
	(0.0250)	(0.0114)	(0.1431)
Semiconductor	11.94%***	4.09%***	0.033
	(0.0214)	(0.0100)	(0.0736)
Telecommunication	6.08%***	4.72%***	−0.058
	(0.0207)	(0.0118)	(0.0760)
Construction	14.20%***	−0.08%	−0.726***
	(0.0289)	(0.0136)	(0.1195)
Transportation	8.25%***	3.68%***	−0.781***
	(0.0229)	(0.0104)	(0.1745)
Food	13.69%***	2.00%	−1.109***
	(0.0297)	(0.0141)	(0.4185)

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$
Standard errors are in the parenthesis

and construction industries (14.20%). Finally, it is important to note that the only industry that is not statistically significant is, surprisingly, the financial business industry. This might be the consequence of the fact that, as we can see in Figure 3, although the return total connectedness for financial business industry increases sharply during the 2008 global financial crisis, but after the crisis (after May. 2009), it is still at a very high level, comparing to other industries (see Figure 5).

As for the coefficients for economic sluggish periods ($\hat{\beta}_3$), first and foremost, even

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after excluding the effect of the 2008 recession, seven out of nine industries are significant, with six of them being significant under 1% confidence level. This provides us evidence that economic sluggish periods indeed have strong influences over return total connectedness (even after excluding the 2008 crisis). Second of all, among the statistically significant coefficients, all of them have positive signs, which means that the return total connectedness tends to increase under economic sluggish periods. Third of all, when entering economic sluggish periods, wholesale and retail trade industry has the largest amount of increase in return total connectedness (6.11%), followed by financial industry (4.94%) and telecommunication (4.72%). Recall that when using the full sample, financial business industry has the highest level of return total connectedness (Table 2), thus perhaps not very surprising to see its return connectedness intensify drastically during crisis periods. What perhaps is peculiar is that when the full sample is used, both the telecommunication and the wholesale and retail trade industry have the lowest level of return total connectedness among all market segments. Yet when entering economic sluggish periods, they have the largest increment. Last but not least, the coefficients of return total connectedness are similar across market segments (around 3% to 4%), except for the wholesale and retail trade industry. This result again coincides with what we've observed from Figure 5, where the return total connectedness plot looks somewhat like vertical shifts of one another.

As for the coefficients for C_t ($\hat{\beta}_4$), recall that both Y_t and C_t are percentages

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and take values between zero and one, so the coefficient for C_t in financial industry (2.200) means that when the combined market share of the top 10 companies increase 1%, return total connectedness for financial business industry will increase by 2.2%. It is very important to note that, among the statistically significant coefficients, some have positive signs while the others are negative. This again gives us evidence of the distinctive nature of different market segments. That is, for financial business and plastic industry, return total connectedness will *increase* when the market becomes more concentrated. However, they will *decrease* for construction, transportation, and food industry. Note that these results imply that, in the financial business and plastic industry, if a company continues to grow, then the connectedness will increase and causes higher systemic risk when this company fails. On the other hand, in construction, transportation, and food industry, connectedness declines when a company grows and reduces the risk of a contagion.

Table 5 shows the estimated coefficients of D_t^{2008}, D_t, and C_t $(\hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4)$ for volatility total connectedness. First of all, for the coefficients of D_t^{2008} (the $\hat{\beta}_2$), six out of nine are statistically significant with positive signs, meaning the 2008 crisis increases the volatility total connectedness, with the highest increment in semiconductor industry (21.88%). Note that the magnitude of the increments (the $\hat{\beta}_2$) here is much stronger than in Table 4.

For the coefficients of economic sluggish periods ($\hat{\beta}_3$), similar to its return counterpart (Table 4), even after excluding the effect of the 2008 recession, six out of

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Table 5: Volatility Total Connectedness Regression Results

Industry	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
Financial Business	15.71%***	10.44%***	5.286***
	(0.0547)	(0.0316)	(0.7999)
Plastic	14.19%***	4.09%**	3.454***
	(0.0356)	(0.0160)	(0.6702)
Wholesale and Retail	3.96%	7.53%***	-0.252
	(0.0462)	(0.0226)	(0.2513)
Textile	8.47%*	2.66%	0.789***
	(0.0461)	(0.0211)	(0.2641)
Semiconductor	21.88%***	1.81%	0.134
	(0.0345)	(0.0160)	(0.1183)
Telecommunication	11.17%***	7.91%***	-0.015
	(0.0312)	(0.0179)	(0.1147)
Construction	-3.65%	4.46%*	-0.786^{***}
	(0.0540)	(0.0254)	(0.2236)
Transportation	17.86%***	-0.20%	-0.531
	(0.0557)	(0.0254)	(0.4241)
Food	-4.50%	6.52%**	-2.364^{**}
	(0.0695)	(0.0330)	(0.9788)

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$
Standard errors are in the parenthesis

nine industries are significant. This leads us to conclude that economic sluggish periods, even after excluding the 2008 crisis, indeed have strong influences over both the return and the volatility total connectedness. Moreover, when entering economic sluggish periods, financial business industry has the largest growth in volatility total connectedness (10.44%), followed by telecommunication (7.91%) and wholesale and retail trade (7.53%) industry. Similar to what we have discovered, when using the full sample, both the telecommunication and the wholesale and retail trade industry

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have the lowest level of volatility total connectedness. Yet when entering economic sluggish periods, they have the largest increment. Finally, recall that the coefficients of return total connectedness are similar across market segments (around 3% to 4%). The coefficients of volatility total connectedness, on the other hand, differ a lot from one another (from 4% to 10%). This conclusion is in line with what we've observed from Figure 5, where the return total connectedness plot has a clear pattern while its volatility counterpart exhibits no such consistency at all.

As for the coefficients of C_t ($\hat{\beta}_4$), just like Table 4, more than half of them are statistically significant, and among those coefficients, some have positive signs while the others are negative. As a consequence, for the financial business, textile and plastic industry, volatility total connectedness will *increase* when the market becomes more concentrated. However, they will *decrease* for construction and food industry.

4.4 Robustness Check

When choosing the VAR ordering, although it is reasonable to order companies in each market segment according to their average market share, it is still unknown to us whether the results obtained are sensitive to the choice of ordering or not. Hence this research chooses the reversed ordering (from the smallest to the largest) and four other random orderings (generated by computer) to construct the robustness test. Figure A1 in Appendix display the results, the solid line represents the original plot,

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and the dotted lines represent the reversed and four other random ordering plots. As shown from the figure, the results are extremely robust to the changes of ordering. This conclusion is in line with Deibold and Yilmaz (2009), where they found total connectedness is robust to different orderings.

5 Concluding Remarks

This research measures the return and the volatility total connectedness across different industries in Taiwan's stock market, both static and dynamic, then tests their relationships with the economic sluggish periods and the market structure.

For the full-sample return and volatility connectedness, we have found from 10% (telecommunication industry) to 50% (financial business industry) of the forecast error variance comes from connectedness. Also, eight out of nine market segments have their return connectedness stronger than volatility connectedness.

As for the dynamics of the return and the volatility connectedness, using the 200-day rolling samples, we have discovered that, in general, both the return and the volatility total connectedness for all market segments tend to increase during financial crises, where return total connectedness do so in small steps and its volatility counterpart experiences discrete jumps. Moreover, without any exception, return total connectedness is much "smoother" than volatility total connectedness. Finally, from Figure 5 we can see very clear that for return total connectedness, all the mar-

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ket segments tend to move in a similar pattern, while volatility total connectedness displays no such consistency.

As for the reasons that cause changes in connectedness, the 2008 global financial crisis has a significant influence on both the return and the volatility total connectedness for all market segments. Moreover, even after excluding the effect of the 2008 recession, we still find the return total connectedness for most market segments to increase 3% to 4% during economic sluggish periods while their volatility counterpart increase from 4% to 10%. Finally, for a different market segment, the changes in market structure concentration will have a different effect on its level of connectedness. In particular, when the market becomes more concentrated, the return and the volatility total connectedness will increase for financial business, plastic, and textile industry, while they will decrease for construction, transportation, and food industry.

We have obtained various interesting results in this research, and the possible applications of these results could be enlightening, which includes:

1. **Profolio Management**: Time-varying diversification opportunities have been studied by numerous researchers (see Fleming et al. 2001, Kirby and Ostdiek 2012 for example). This research obtains the level of connectedness for nine market segments using the full sample. And in the dynamic analysis, we know how much they will rise during crisis periods. Since the ability to diversify is inversely related to the level of connectedness, all these information would be

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valuable to achieve skillful portfolio managing.

2. **Company Regulation**: The 2008 global financial crisis has created renewed interest in company regulation. But for a given industry, how big can a company grow without being labeled as "too big"? The answer to this question not only depends on how well connected this market segment is (which by now we know), but also on what will happen when the company gets large. Regression results (Table 4 and 5) have shown us that for certain industry (e.g., financial industry), when a company becomes larger, the connectedness will increase, causing more risk when this company fails. On the contrary, connectedness declines when a company grows in some other industry (e.g., food industry), which reduces the risk of a contagion when it fails. Hence, policy maker should have very different regulations when facing companies from different industries.

3. **Economic Downturns Identification/Prediction**: The results show that connectedness have intimate relation with the economic downturns, volatility total connectedness exhibits jumps when entering a recession, then it jumps back to its original level after crises, for instance. As a result, we can at least try to identify, if not predict, economic downturns using return/volatility total connectedness. Notice that there is literature on predicting financial crisis by exploiting the time-varying nature of connectedness. See Allen et al. (2012),

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and Billio et al. (2012) for example.

As for future studies, there are still several intriguing questions not yet answered in this research. First of all, In the static analysis in Section 4.1, Table 2 shows that return connectedness is stronger than volatility connectedness in eight out of nine market segments. The reasons behind this result are still unknown. Second of all, as mentioned repeatedly, return total connectedness is much smoother than its volatility counterpart. Why this should be so is puzzling. Thirdly, on a more technical level, using VAR based variance decomposition is not the only way to capture "total connectedness". For example, Jorda (2005) suggests using local projection instead of a VAR model to construct impulse response functions. By using a different impulse response function, we'll get a different measurement of total connectedness.

This list of questions is by no means exhaustive. The profound implication and potential application of the results in this research are exciting. Base on these findings, I hope future researchers can eventually find out new theories and results that explain the distinct behavior of the return and the volatility total connectedness. Moreover, I wish this research can help explore new territories in portfolio management, recession prediction, company regulations, and others.

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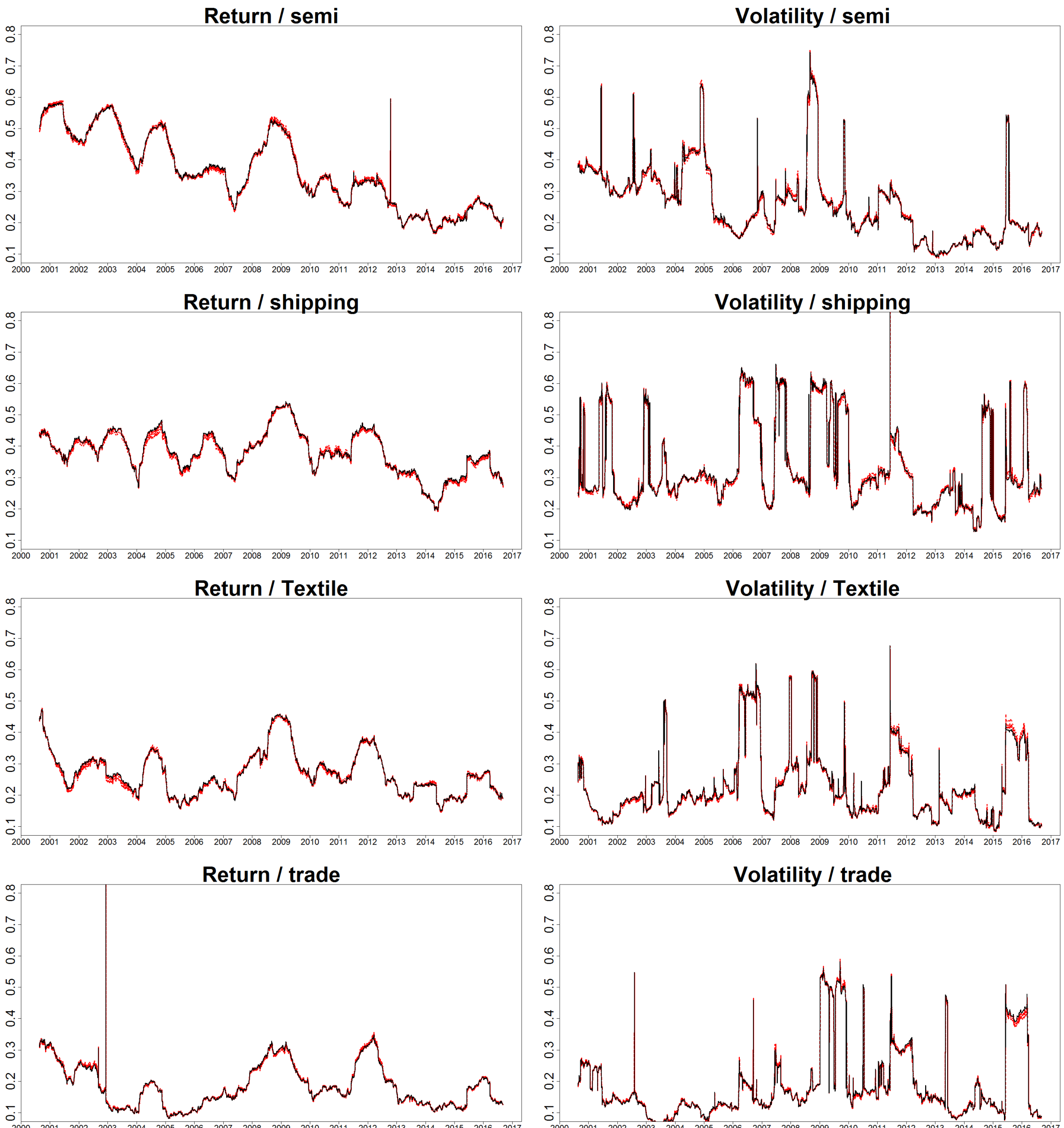
APPENDIX

Figure A1: Robustness Check - Reversed and Random Ordering



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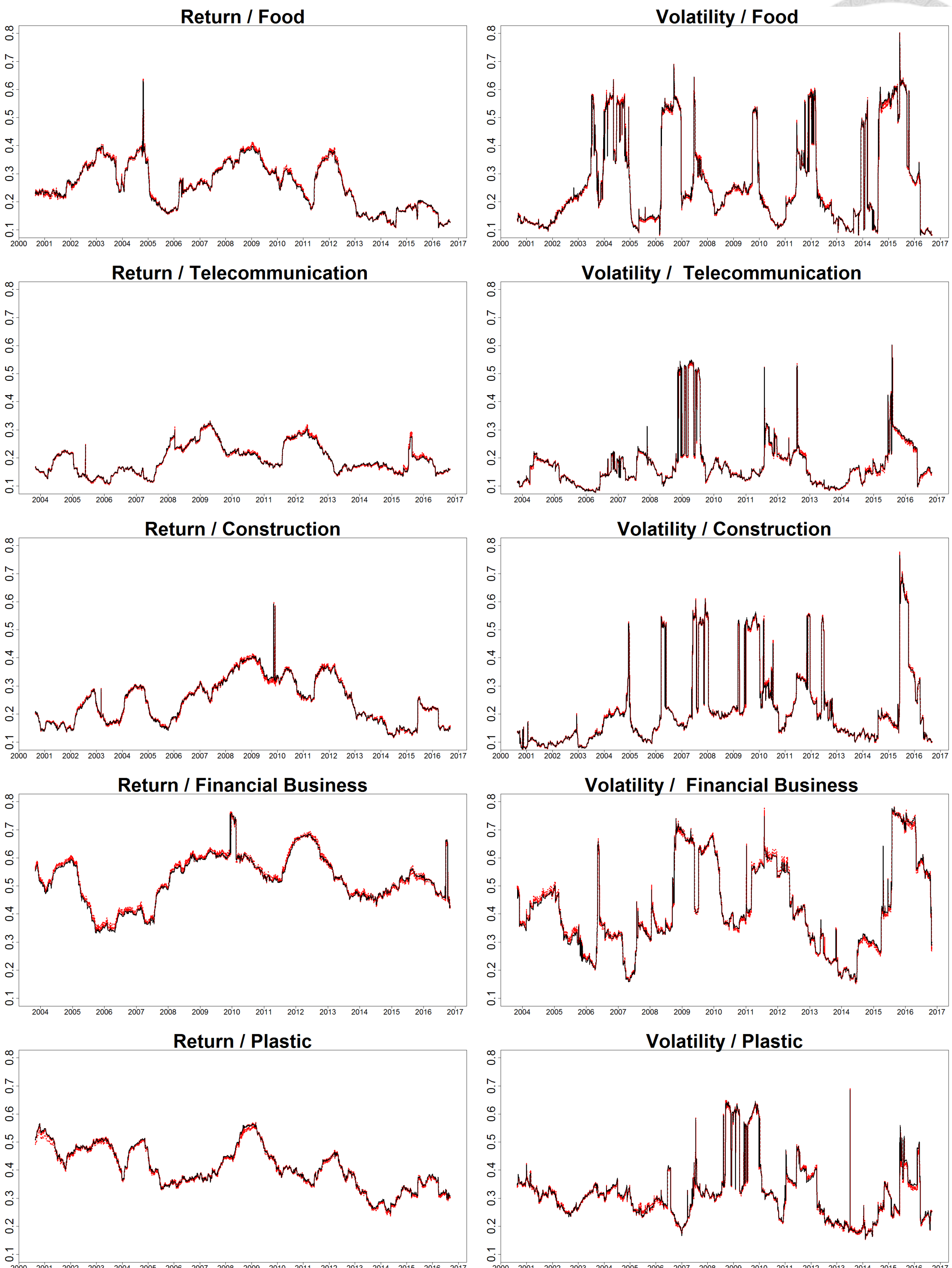

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Figure A2: Return Total Connectedness and Business Cycle

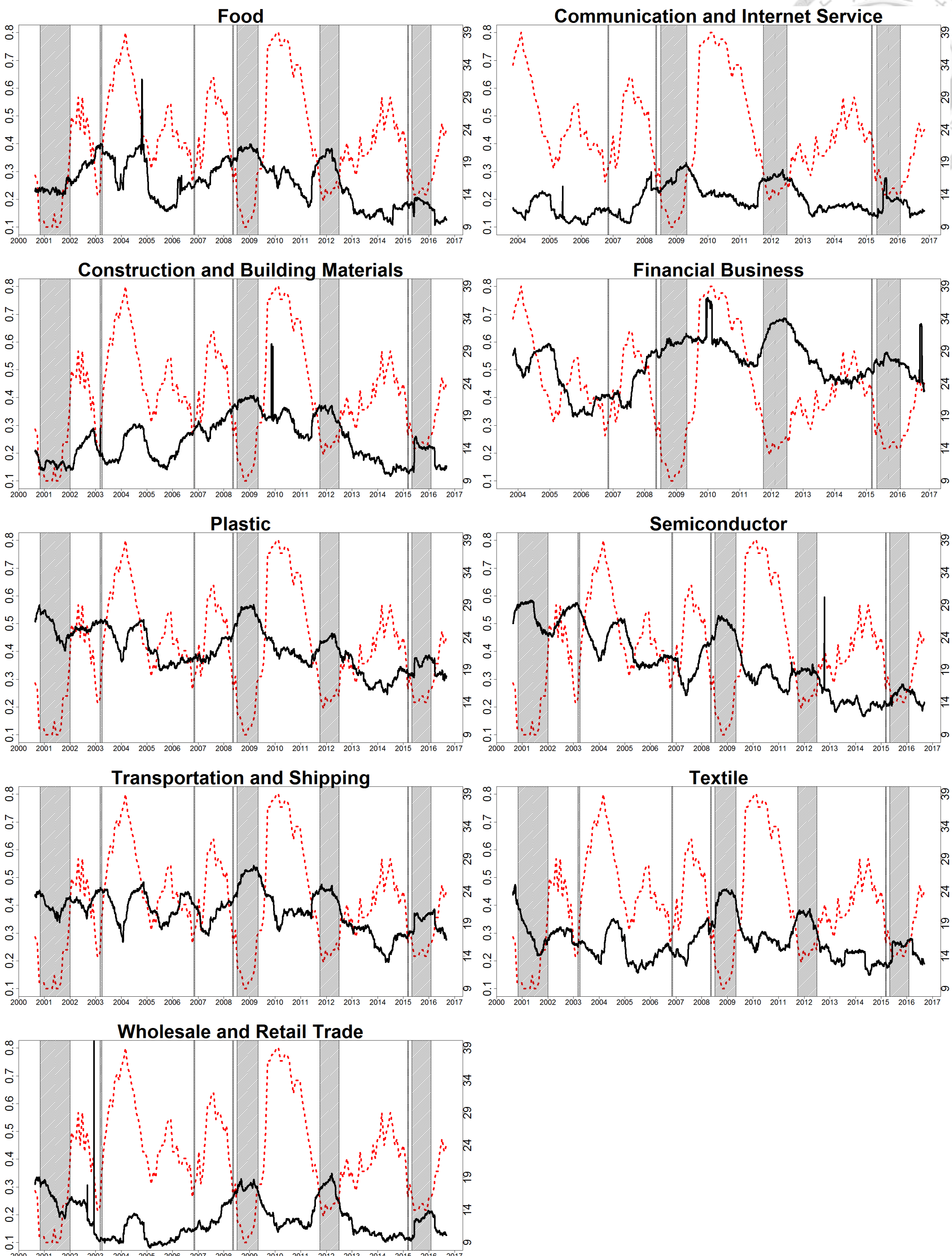

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Figure A3: Volatility Total Connectedness and Business Cycle

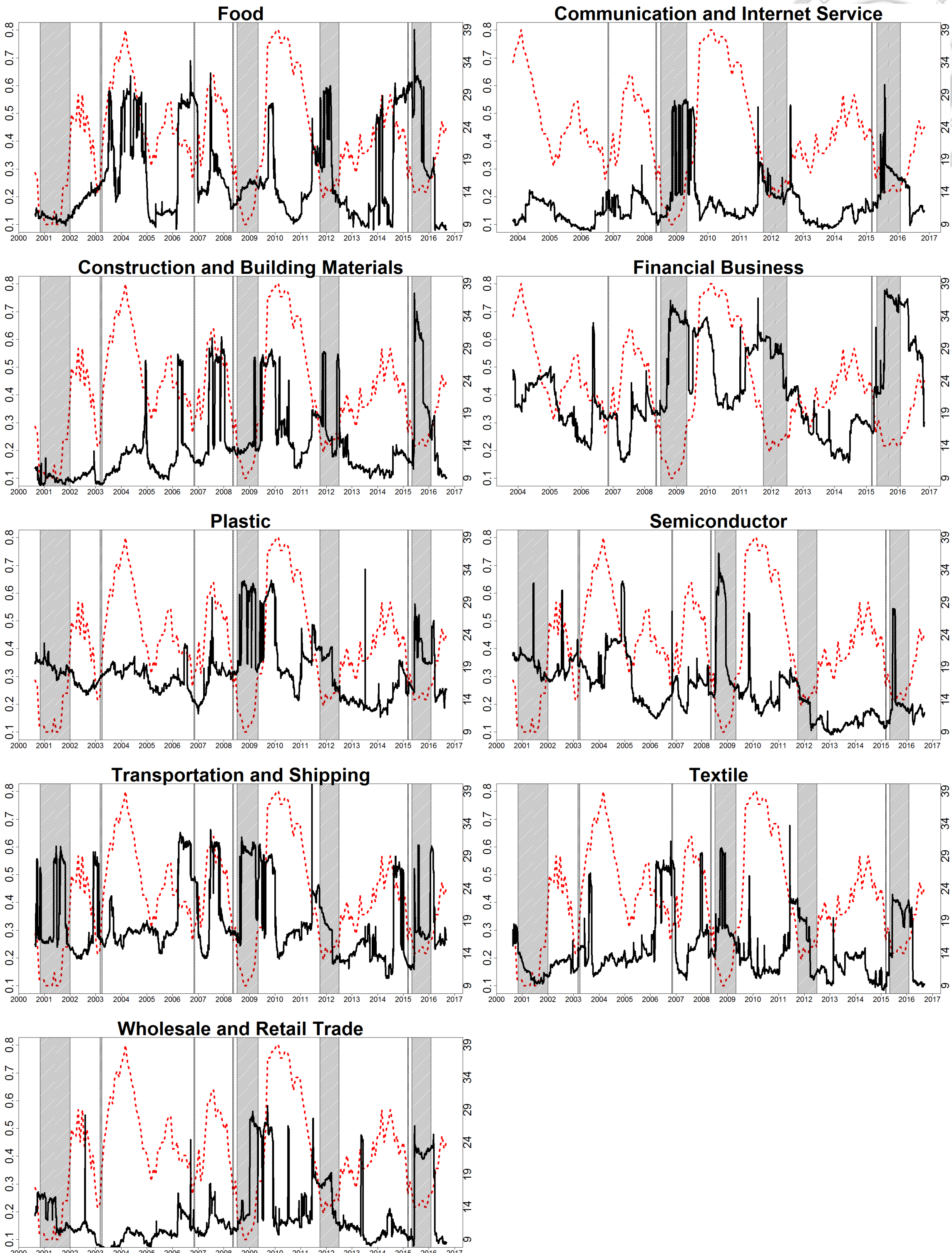

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Figure A4: Market Structure

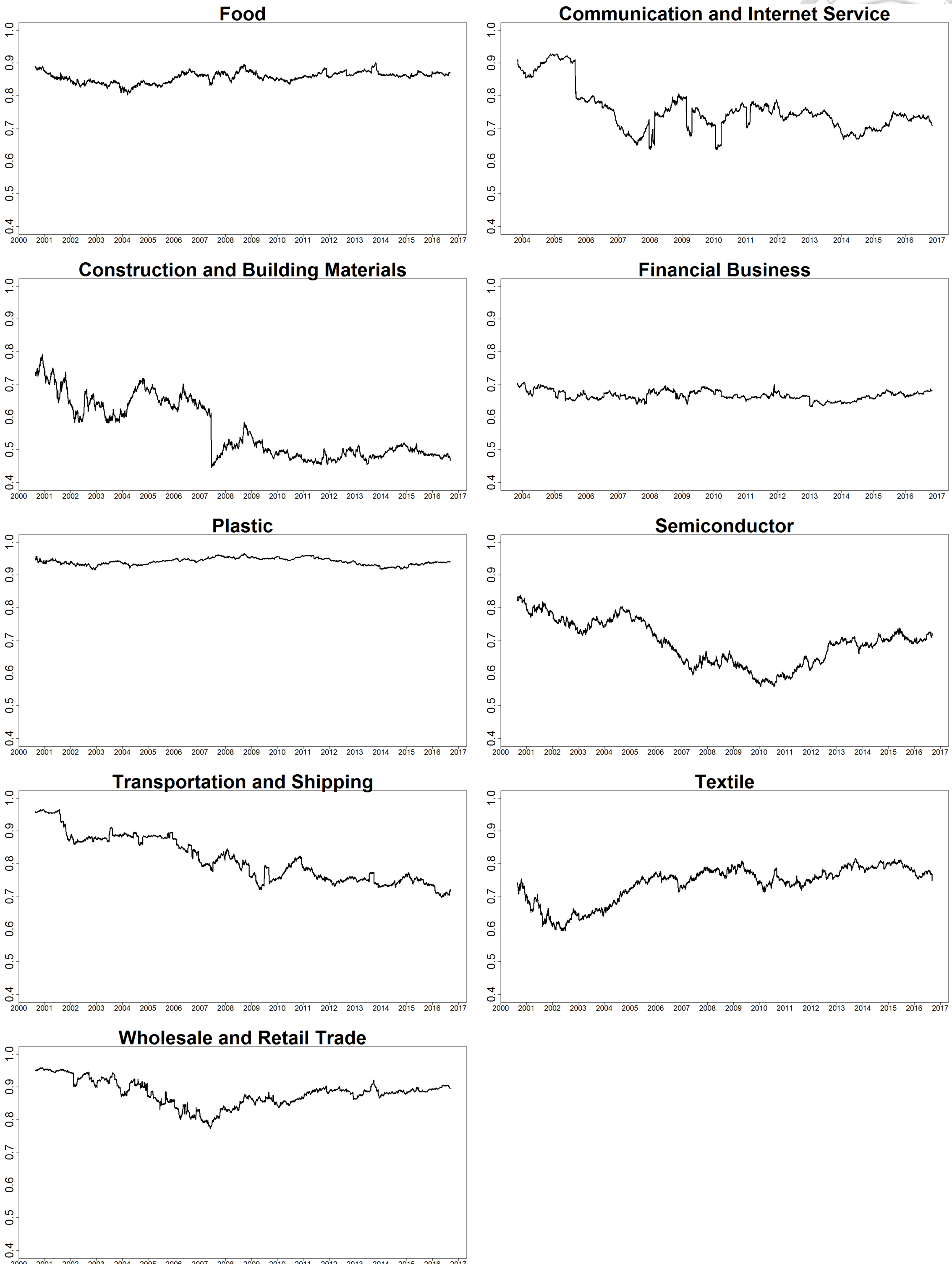

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Table A1: Ticker Numbers and Average Market Shares of the Companies Selected

Market Segment	Taiwan Stock Exchange Ticker Number (Average Market Share)					Replacement for Missing Values		
Plastic	1303	1301	1326	1314	1319			
	(31.46%)	(28.61%)	(25.09%)	(1.70%)	(1.33%)			
	1304	1313	1310	1312	1307			
	(1.13%)	(1.00%)	(0.90%)	(0.87%)	(0.57%)			
Wholesale and Retail	5903†	2912	5904†	8941†	2915	2913	2908	2614
	(33.74%)	(16.93%)	(10.00%)	(6.44%)	(4.62%)	(1.63%)	(1.54%)	(1.50%)
	5905†	2903	6195†	5902	2905	2910	2601	
	(4.27%)	(4.23%)	(2.44%)	(2.31%)	(1.72%)	(1.11%)	(1.05%)	
Food	1216	1227	4205	4207†	1229	1702	1232	
	(47.28%)	(6.56%)	(5.72%)	(4.42%)	(4.14%)	(2.01%)	(1.96%)	
	1201	4712	1234	1210	1737†			
	(3.86%)	(3.83%)	(3.70%)	(3.67%)	(2.14%)			
Transportation	2618	2603	2610	2609	2615	5601		
	(16.44%)	(12.32%)	(11.64%)	(8.58%)	(8.54%)	(2.25%)		
	5604	2606	5609†	2607	2605			
	(7.12%)	(6.62%)	(5.17%)	(3.25%)	(2.71%)			
Textile	1402	1434	4401	1440	1409	1444	1447	1460
	(30.06%)	(8.98%)	(7.87%)	(4.10%)	(3.01%)	(1.53%)	(1.37%)	(1.02%)
	1476†	1451	1477†	4417†	1419			
	(4.33%)	(3.82%)	(2.97%)	(2.79%)	(1.81%)			
Telecommunication	2412	4904	3045	2498	3152†	5388	4908	
	(25.71%)	(17.58%)	(9.05%)	(9.03%)	(3.30%)	(0.80%)	(0.79%)	
	3095†	4909	6143	6152	6170			
	(1.65%)	(1.23%)	(1.17%)	(0.89%)	(0.80%)			
Semiconductor	2330	5346	5387	5347	2303	5326		
	(22.98%)	(9.99%)	(9.52%)	(5.37%)	(5.15%)	(0.69%)		
	2454†	2311	2325	5351	2344			
	(4.23%)	(1.93%)	(1.21%)	(1.07%)	(0.94%)			
Financial Business	2882	2881	5820	2886	2891			
	(12.32%)	(7.48%)	(6.08%)	(5.85%)	(5.27%)			
	2883	2892	2880	2885	2801			
	(3.59%)	(3.49%)	(3.45%)	(2.62%)	(2.57%)			
Construction	5522	5508	5512	5213	4416	5514	2504	
	(13.87%)	(7.79%)	(6.42%)	(3.86%)	(3.74%)	(1.80%)	(1.53%)	
	2501	5521	2542	5511	5520			
	(2.80%)	(2.73%)	(2.13%)	(1.87%)	(1.83%)			

[†] represent the campanies with missing data during the time span of Jan/04/2000 to Dec/31/2004.

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