國 立 交 通 大 學

經營管理研究所

博 士 論 文

No.142

風險傳染：從宏觀分析到微觀分析

Risk Contagion: From Macro to Micro Analysis

研 究 生：鄭乾臨

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研 究 生：鄭乾臨　　Student: Chien -Ling Cheng
指導教授：許和鈞　　Advisor: Dr. Her-Jiun Sheu

國 立 交 通 大 學
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中 華 民 國 一〇〇 年 十 二 月

風險傳染：從宏觀分析到微觀分析

研究生：鄭乾臨　　　　　　　　　　　　　　　指導教授：許和鈞博士

國立交通大學經營管理研究所博士班

摘要

財務風險是具有傳染性，會從一個個別公司擴散到一個產業（公司層級)、從一個產業擴散到一個國家（產業層級)，及一個國家擴散到其他國家。本論文主要探討台灣金融市場之國家層級及產業層級的風險傳染效果，前者是以宏觀之分析來探討“中國大陸與美國股票市場之波動性對台灣與香港之影響”、 後者是以微觀角度來研究“台灣股票市場之體係性風險”。

在國家層級方面，主要目的係比較中國大陸及美國股票市場對台灣及香港之風險傳遞效果，我們使用 VAR(vector autoregressive) 及 MGARCH (multivariate generalized autoregressive conditional heteroskedastic)模型來研究 1996-2005 及 2006-2009 二期間之資料。結果顯示，雖然中國大陸經濟快速成長並與香港台灣經濟整合，然而它的股票市場卻是相當獨立、與其他香港台灣市場共整合現象並不明顯。在產業層級方面，我們取用台灣股票市場從 2000 到 2010 年間資料，並運用 CoVaR 模型來探討個別產業的獨特風險對整個市場體系性風險之衝擊。結果發現，產業別之邊際 CoVaR 值（△CoVaR）可以解釋在 2001 網路泡沫及 2007-09 的金融危機期間，台灣股票市場受到各別產業衝擊之效果。

本研究顯示，財務風險具有感染性，一個股票市場不僅會受到市場內個別產業之衝擊，還會受到來自市場外其他國家之風險傳染。股票投資不僅應注意市場內個別產業及個別股票之獨特風險，還要關注來自特定國家或市場之風險衝擊。而因為風險傳染是最近財務危機的主要原因，因此說明風險之辨認與風險之衡量為未來必須進一步探討的重要議題。

關鍵詞：風險傳染、波動、擴散效果、條件風險值、個別風險、財務危機

Risk Contagion: From Macro to Micro Analysis

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Abstract

Financial risk is contagious, which spillovers from one company to industry (company level), from one industry to country (industry level), and from one country to another country (country level). In this dissertation, risk contagion of country level and industry level were discussed, the former discussed “China’s and U.S. volatility spillover effects on Hong Kong and Taiwan”, and the latter explored “systemic risk in Taiwan”.

In country level, the aim was to discuss the volatility effect across countries. Both vector autoregressive(VAR) and multivariate generalized autoregressive conditional heteroskedastic(MGARCH) model were employed. In industry level, CoVaR model was adopted to explore the impact of sector-specific idiosyncratic risk on the systemic risk of Taiwan stock market. Results indicated that while China’s rapid economic growth and integration with Taiwan and Hong Kong, its stock market was independent and its co-moments with other markets were not significant. In addition, sector-specific marginal CoVaR, i.e., △CoVaR, perfectly explained Taiwan stock market disturbance during the 2001 dot-com bubble and 2007-09 financial crises.

These findings indicate that risk is contagious, which means a stock market could be easily affected not only by idiosyncratic distress inside the market but also by risk contagion from other countries. Moreover, the fact that risk contagion is the source of recent financial crises highlights the issues of risk

identification and risk measurement to be further discussed.

Keywords: risk contagion, stock market, volatility, spillover, Conditional VaR, systemic risk, idiosyncratic risk, financial crisis

誌謝

生命是曲折的，有許多預料中的事，也有很多是意料之外。從小立志教書，卻一頭栽進金融業；五年以前的我，曾以為夢想難圓，但是，交大卻給我一把鑰匙、為我開啟了一扇窗，現在的我於完成本論文的同時，我的博士求學生涯即將畫上句點，但是我的下一段人生正要飛揚、我的圓夢之旅正要上場。

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乾臨

民國一○○年十二月于台北

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1. Introduction

Financial risk is contagious, which spillovers from one company to another, e.g. bank run spreads from a bank to others (company level), from one industry to its country , e.g. an industry distress spills over the interconnected industries (industry level), and from one country to another country, e.g. sovereign defaults, or stock market crashes spread across countries (country level).

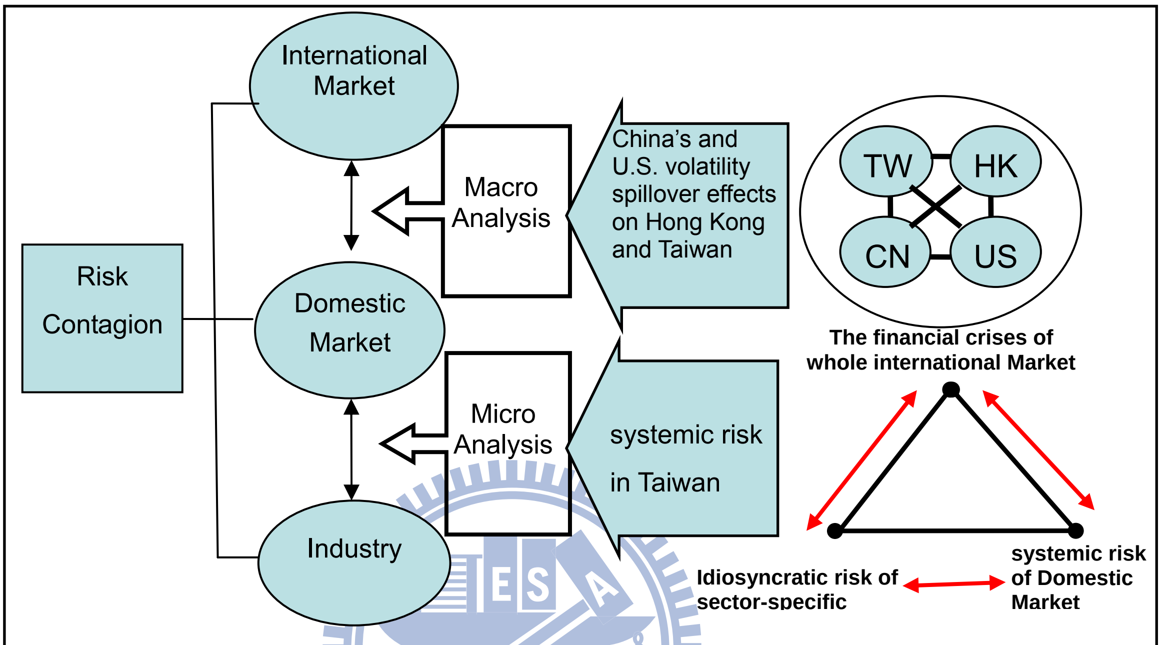
Most recent financial crises are caused by systemic risk, which describes an economic crisis that was triggered by entities failure in the financial system. Systemic risk is different from systematic risk. “Systemic risk” is defined as "financial system instability caused by idiosyncratic events in financial intermediaries". It is the risk of entire financial system collapse, as opposed to risk of any individual or group and it refers to the risks imposed by inter-linkages and interdependencies in a system, where the failure of an individual or group can cause a cascading failure. On the contrary, “systematic risk” happens due to the changes in macroeconomic parameters such as recessions, wars, and disadvantage movement of interest rates. It, usually called market risk, cannot be diversified and affects the entire market as a whole.

Due to high frequency of systemic risk, such as the 1987 equity market crash, the 2001 dot-com bubble, and the 2007-09 financial crisis, it is more important to clarify financial risk spill-over effects and assess systemic risk. Moreover, the economic costs of systemic crises are large if many banks fail together as a contagion causing the failure of the whole system. To ensure the financial stability of the system as a whole, the Bank of International Settlements (BIS) has improved many bank regulations after the global financial crisis of 2007–2009. Amongst which, a pressing policy is to implement a regulatory framework for systemic important financial institutions to have higher capital and liquidity requirements. Meeting these practical requirements calls for measures of systemic risk. Thus, systemic risk is a new issue that has been started to study most recently. Related researches include the measurement of systemic risk, the relationship between systemic risk and financial crises, the factors that contribute to systemic risk, etc.

Systemic risk involves country level contagion, such as sovereign defaults, or stock market crashes spreads across countries. According Markowitz (1952) Modern Portfolio Theory, asset correlation, which equals to risk contagion, is crucial component for the effects of asset risk management and asset diversification on probable investment portfolio returns. It is important to understand how financial markets correlate, how country-specific shocks are transmitted to other markets and how risk is contagious between stock markets because these factors affect their ability to hedge risk and manage risk via portfolio diversification.

Systemic risk also involves industry level contagion, which spreads from an industry distress to the interconnected industries. Amongst these three levels of risk contagion, industry level risk or sector-specific risk, caused by a group of interconnected institutions, is the main source of sudden increases in systemic risk. Many financial crises are initially caused by a “sector-specific” idiosyncratic distress of a country, then spill over across other sectors to increase systemic risk, consequently leading to worldwide crashes such as dot-com bubble, sub-prime crisis, etc. It is more crucial to accurately identify the true systemic risk caused by a group of interconnected institutions.

In this dissertation, country level and industry level of Taiwan financial risk contagion were discussed, the former studied “China’s and U.S. volatility spillover effects on Hong Kong and Taiwan” from macro analysis, and the latter explored “systemic risk in Taiwan” from micro analysis. The following demonstrates the research framework.



First, from macro analysis , the purpose of this study is to explore how the Taiwan and Hong Kong stock markets are affected by their regional stock market (China stock markets) and the U.S. stock market in order to analyze how financial risk spillovers from one country to other countries. Due to the economic integration, China’s economic has begun playing an important role on Taiwan and Hong Kong; on the contrary, as U.S. stock market traditionally is the most important international stock market and its return and volatility spill over the whole world. The issue whether China stock market has been increasing influence on Taiwan and Hong Kong after 2005 is interesting to be discussed. Both vector autoregressive(VAR) model and the multivariate generalized autoregressive conditional heteroskedastic(MGARCH) model were employed for two sub-periods: 1996-2005 and 2006-2009 respectively to examine the volatility transmission effect of China and U.S. stock markets on Taiwan’s and Hong

Kong's during two separate sub-periods. Second, due to recent financial crises resulted from systemic risk caused by idiosyncratic distress, the second part of this dissertation is from micro analysis to discus how the financial risk is contagious from one industry to the whole country (industry level). In this part, taking Taiwan's stock market as an example and collecting data from 2000 to 2010 which contained the 2001 dot-com bubble and the 2007-09 financial crisis, we adopt the CoVaR model to empirically explore the impact of sector-specific idiosyncratic risk on the systemic risk of the system and attempt to investigate the links between financial crises, systemic risk and the idiosyncratic risk of a sector-specific anomaly.

Result of the macro analysis indicated that while China's rapid economic growth and integration with Taiwan and Hong Kong, its stock market was independent and its co-moments with other markets were not significant. The possible reason is that irrespective of the intensive economic integration of the three Chinese markets, there is no apparent stock spillover effect that could be transmitted from China to Taiwan and Hong Kong. In addition, result of the micro analysis showed sector-specific marginal CoVaR, i.e., $\triangle$CoVaR, perfectly explained Taiwan's stock market disturbance during the 2001 dot-com bubble and 2007-08 financial crises. Thus, by identifying the high $\triangle$CoVaR sectors and their risk indicators, investors could employ the sector-specific $\triangle$CoVaR measure to deepen the systemic risk scrutiny from a macro perspective into a micro prudential perspective.

2 Risk Contagion: Macro Analysis

2.1. A study of China's and U.S. volatility spillover effects on Hong Kong and Taiwan

Recently, due to the blooming economic development of Asia, many investors have taken an active interest in the Asia stock markets, heightening the need for more diversification beyond the mature markets to explore the opportunities of higher returns. Among the Asian areas, the Chinese three emerging stock markets, including Hong Kong, Taiwan, and China, attract a large number of investors' high attention owing to their rapid economic growth and increased link with international capital markets over the past decades. According Markowitz (1952) Modern Portfolio Theory, asset correlation is crucial component for the effects of asset risk management and asset diversification on probable investment portfolio returns. As asset pricing, risk controlling, and portfolio allocating are primary concerns for investors and researchers (De Santis and Gerard, 1997; Sarno and Valente, 2005), it is gradually essential to clarify the co-movement of these stock markets.

As U.S. stock market is the most important international stock market and its return and volatility spill over the whole world, it would be interesting to discuss the co-movement of these three Chinese and U.S. stock markets. The first purpose of this paper is to discuss the properties of the U.S and the three Chinese stock markets -Taiwan, Hong Kong and China. The secondary aim is to explore the returns and volatility spillover effect of the U.S and the three Chinese stock markets. Finally, this paper is to compare the effect of volatility of China and U.S. stock market respectively on the other two stock markets (i.e., Taiwan and Hong Kong stock markets) for two different sub-periods truncated on 2005 when China started taking economic reform policy. Does the influence of volatility spillover from China get beyond the one from the U.S.?

It is hoped that the co-movement information captured from this study may be useful in precisely asset pricing, portfolio allocating and risk controlling for both the investors having established portfolio and the potential investors of these stock markets.

International stock market transmission among different markets has been comprehensively studied. Many recent studies have discussed the volatility spillover effect of stock market returns. These papers have shown some typical characteristics that there are volatility spillover effect among different stock markets and that transmission spillovers from developed to developing stock markets and from major to minor stock markets (Martens and Poon, 2001; Goetzmann , Li and Rouwenhorst , 2001; Worthington and Higgs, 2004; Michelfelder RA, 2005; Scheicher M, 2001; Bekaert and Harvey, 1997; Gokcan S, 2000). Also, many research found out that when there is no restricted policy in stock investment, the stock market will co-move with international markets. Hassler(1999) found that increased international financial integration is likely to cause greater interdependence; King et al.(1994 a,b)said that during periods of high volatility there is a tendency for stronger international dependence between financial markets; Bertero & Mayer(1990) indicated that international co-movement increases in connection with the 1987 stock market crash.
In addition, few papers have discussed the volatility interdependence of Asian stock markets or spillover effects of U.S. stock market on Asian stock Markets. Worthington and Higgs (2004) discussed not only the mean and volatility spillover effects between the U.S. and Pacific-basin stock markets, but also the

transmission of returns and volatility among Asian developed and emerging markets. Li (2007), using data from 2000 to 2005, examined the linkages between China and U.S. stock markets and found no significant spillover effect between these two stock markets. Johansson and Ljungwall (2009) explored the spillover effects and linkages, solely focusing on interactions within China, Hong Kong and Taiwan these three Chinese stock markets. Lin et al. (2009) investigated the correlation between the China and world stock markets and demonstrated that there was no significant evidence of an increasing trend of correlation from 1993 to 2006. Wang and Wang (2010) examined the spillover effects between China stock markets and developed markets. Jian, Wang and Murray (2010) analysed the volatility spillover effect between primary developed stock markets and China before and after sub-prime crisis of 2007.

However, the limited previous studies in this discipline either have not concentrated on the co-movement of these three Chinese stock markets, or have been suffered from too elder data before 2005. In addition, there is no research surveyed the extent Taiwan and Hong Kong stock markets are influenced by China and U.S. especially in recent years and no studies discussed whether or not China's influence on Hong Kong and Taiwan stock markets is getting beyond U.S. owing to Greater China intensively economic integration. This paper attempts to compare the influence pre- and post- 2005 from China and U.S. on Taiwan and Hong Kong respectively.

While it is generally acknowledged that there is a variety of difference between these Chinese markets including the degree of market liquidity, transparency and openness, they share some common characteristics and possess high homogeneity through their intensive trades and close investment activities. It is evident that China's economic began playing an important role on

Taiwan and Hong Kong due to its large economic scale and their economic integration (Ash and Kueh, 1997). Is there any likelihood that China stock market would be highly related to Taiwan's and Hong Kong's after 2005?

Data of these four stock markets was collected from January 1997 through December 2009 and then was spilt into two sub-periods: 1996-2005 and 2006-2009, which was truncated according to research of Moon and Yu (2010) proposing that there would be a structural break date occurring on China stock market in December 2005 when the China government started taking a series of financial reform policy.

This research first used generalized autoregressive conditional heteroskedastic (GARCH) model to discuss the volatility transmission effect among these four stock markets for the entire period from 1997 through 2009, and then employed both vector autoregressive(VAR) model and the multivariate generalized autoregressive conditional heteroskedastic(MGARCH) model for two sub-periods: 1996-2005 and 2006-2009 respectively to examine the influence degree of China and U.S. stock markets on Taiwan's and Hong Kong's during two separate sub-periods.

The structure of this paper is organized as follows. Section 2.2 describes some statistic characteristics of these four stock markets. Section 2.3 presents the empirical specification, the implementation of the model which is designed to solve the research problems. Section 2.4 demonstrates the results of statistical and other computation analysis. Finally, section 2.5 summarizes some findings.

2.2. SAMPLE AND STATISTICAL PROPERTIES

2.2.1 Data description

The dataset used in this research is the daily closing price of stock indices of U.S.

Standard & Poor's 500(USX), Taiwan Composite Index(TWX), Hong Kong Hang Seng Index(HKX) and China Shanghai Stock Index(CNX) and it ranges from 1996, determined solely by data availability, to 2009. This data used is gathered from Bloomberg Information Network, a well known data warehouse company. Figure 1 and figure 2 show the index value and the index returns of these four markets in the whole sample period.

Figure 1：Daily index value

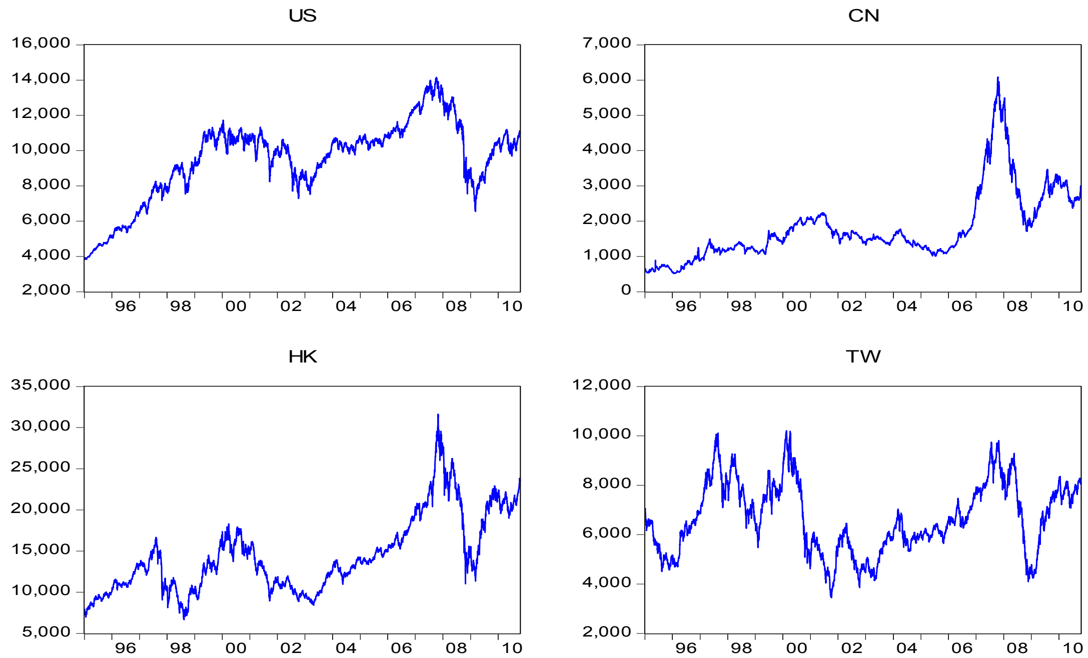
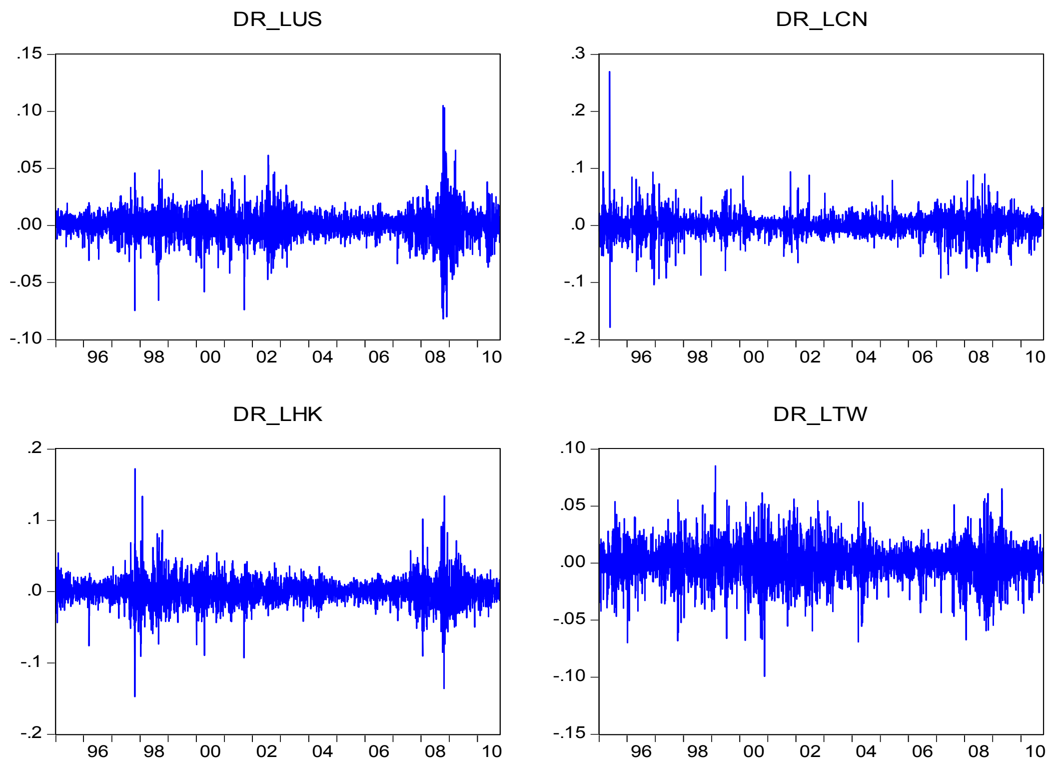


Figure 2： Daily return for log index returns



2.2.2 Statistical Properties

In this paper, returns are defined as first differences of log index prices ($\ln(y_t)$-$\ln(y_{t-1})$). Table 1 summarizes the statistical properties of the returns for these four stock indices including the first four order moments, the Jarque-Bera test statistic, the Augmented Dickey-Fuller test statistic and the Ljung and Box (1978) test statistic for autocorrelation in returns and squared returns. From table 1, it is indicated that the variability of Taiwan, Hong Kong and China stock markets is higher, and the variability of the US stock market is lower than those three Chinese stock markets. In addition, the returns of these four stock markets are significant to reject unit root hypothesis after the Augmented Dickey-Fuller test. Finally, two stylized facts for return series could be observed: first, the volatility of returns is time-varying which is indicated by the significant Ljung-Box

Q(24) test statistics showing autocorrelation in squared returns and the second stylized fact is nonnormality, suggested by the significant Jarque-Bera test statistics, of the unconditional distribution of returns in the form of leptokurtosis.

Table 1 Statistics property of returns (1996-2009) for Taiwan, Hong Kong, China and U.S. stock markets

	Taiwan	Hong Kong	China	U.S.
Mean	0.0000348	0.000172	0.000387	0.000341
S.D.	0.017018	0.017997	0.017190	0.010845
Coefficient of Variation	0.002045	0.009557	0.022513	0.031443
Skewness	0.0256723	0.414914	-0.142786	-0.158067
Kurtosis	6.970485*	15.57036*	8.748058*	7.292847*
JB	1503.996*	14891.60*	3107.922*	1738.589*
ADF	-45.22121*	-48.21921*	-46.9318*	-45.23540*
$Q(24)r_t$	36.691*	44.921*	31.488	31.647
$Q(24)r_t^2$	614.66*	840.34*	384.53*	342.60*

Note: t-statistics are in parentheses.   5% significant level

Before discussion the purpose of this paper, the correlation of these four stock market returns was examined. Table 2 demonstrates the unconditional correlation matrix of these four countries including first moments of 1996-2005 (panel 1) , second moments of 1996-2005(panel 2) ,first moments of 2006-2009(panel 3) , second moments of 2006-2009(panel 4). From table 2, it is indicated that the highest correlation of 0.348566 is observed between Taiwan and Hong Kong stock markets. It also shows that U.S. stock market is middle correlated to Taiwan and Hong Kong stock markets. However, China stock market shows lower correlation with the other two Chinese stock markets and U.S. stock market. Turning to the result of squared returns in panel 2, it is substantial agreement with result of returns in panel 1.

From panel 3 and 4, the correlations among these four markets from 2006 to 2009 are discussed. As indicated from the correlation matrix, both the returns and the square returns of China stock market are increasingly correlated with the other two Chinese stock markets from period of 1996-2005 to period of 2006-2009 , however they are as usually low correlated with U.S. stock market. The correlation coefficients of returns of China with Taiwan and Hong Kong are 0.033769 and 0.088227 (during period of 1996-2005) to 0.099512 and 0.139747 (during period of 2006-2009) respectively.

Table 2 Unconditional correlations of Taiwan, Hong Kong, U.S. and China stock markets

	TWX	HKX	USX	CNX
Panel 1: Returns(1996-2005)				
TWX	1			
HKX	0.348566	1		
USX	0.144838	0.21648	1	
CNX	0.033769	0.088227	-0.03187	1
Panel 2: Squared returns(1996-2005)				
TWX	1			
HKX	0.242248	1		
USX	0.132296	0.229228	1	
CNX	0.004751	0.029667	0.038757	1
Panel 3: returns(2006-2009)				
TWX	1			
HKX	0.550006	1		
USX	0.206374	0.228294	1	
CNX	0.099512	0.139747	0.013742	1
Panel 4: squared returns(2006-2009)				
TWX	1			
HKX	0.331922	1		
USX	0.167196	0.612802	1	
CNX	0.090211	0.032899	0.017714	1

Where TWX, HKX, USX and CNX denote the stock index of Taiwan, Hong Kong, U.S., and China stock markets respectively.

2.3 MODEL SPECIFICATION

Being seen as a symptom of market disruption, volatility indicates the implications for uncertainty and variance risk. Changes in the volatility of stock market returns would have significant negative effects on risk averse investors and affects investment decision making. As mentioned earlier in the introduction, there has been a great deal of researches to address the importance of modeling the volatility effect in financial markets.

One of the most prominent stylized facts of returns on financial assets is that their volatility changes over time. This characteristic feature is referred to as volatility clustering. Engle (1982) introduced the class of AutoRegressive Conditionally heteroscedastic (ARCH) models to capture the volatility clustering of financial time series. Bollerslev (1986) suggested adding lagged conditional variance to the ARCH model and introduced Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. GARCH models are popular because they can describe not only the feature of volatility clustering, but also other characteristics of financial times series, such as excess kurtosis or fat-tailed. Bollerslev et al. (1992) evidenced that the GARCH model is adequate to capture the volatility of many financial time series. Presently, the GARCH family models have been one of the most popular econometric models being used in academic studies of this field.

Because of the test statistics in Section 2.2.2, including the characteristics of significant skewness, excess kurtosis, autocorrelations and cross-correlations, it is fairly rational to employ GARCH family models following Bollerslev (1986) et al. to investigate the volatilities properties of these four stock markets.

In addition, evidenced from a variety of academic literature, volatility is contagious and spills over from one market to other markets (Maana, Mwita and Odhiambo R 2010; Léon 2007). While the univariate GARCH models examines the time-varying nature of financial time series, multivariate GARCH (MGARCH) models analyses the time-varying conditional cross moments.

There are some MGARCH models available for financial time series to capture the volatility spillover effects and there have been several improvements applied for the MGARCH model to raise accurateness for model estimation with regard to the parameterization of cross-moments (Tse and Tsui, 2002, and Bae, Karolyi,and Stulz, 2003). In this paper, MGARCH models were employed to estimate the volatility co-movement effects in stock markets.

Finally, using Vector Autoregression (VAR) models to capture spillover effects, a variety of studies have proposed that the United States have profound influence on other stock markets (Bayoumi and Swiston, 2007). To investigate the spillover effects, this paper simultaneously estimates the co-movements of these four market indices: Taiwan, Hong Kong, China and US. The specification contains a vector autoregression (VAR) models for return and for volatility (MGARCH).

2.3.1 VAR model for returns:

A simple vector model used in modeling asset returns is the vector autoregressive (VAR) model. This paper uses VAR model with one lag to model returns. The following equation denotes the VAR model for returns:

$$r_t = \phi_0 + \Phi \cdot r_{t-1} + a_t$$

Where ϕ_0 is a k-dimensional vector, Φ is a k x k matrix, and a_t is a sequence of serially uncorrelated random vectors with mean zero and covariance matrix Σ. There are three processes used to build a VAR model: first, use some information criterion to identify the order, second, estimate the specified model by using the least squares method, and third, check the adequacy of a fitted model.

In our sample, the VAR model could be described as the following:

$$r_{it} = m_{i0} + \sum_{j=1}^{4} m_{ij} r_{jt-1} + u_{it} \qquad i = 1,2,3,4$$

It indicates that Taiwan, Hong Kong, China and U.S. stock market as series 1,2,3,4 respectively. Then the following VAR equations show the model for return of these four stock markets:

$$\begin{aligned}
r_{1t} &= m_{10} + m_{11} r_{1t-1} + m_{12} r_{2t-1} + m_{13} r_{3t-1} + m_{14} r_{4t-1} + u_{1t} \\
r_{2t} &= m_{20} + m_{22} r_{2t-1} + m_{21} r_{1t-1} + m_{23} r_{3t-1} + m_{24} r_{4t-1} + u_{2t} \\
r_{3t} &= m_{30} + m_{33} r_{1t-1} + m_{31} r_{1t-1} + m_{32} r_{2t-1} + m_{34} r_{4t-1} + u_{3t} \\
r_{4t} &= m_{40} + m_{44} r_{4t-1} + m_{41} r_{1t-1} + m_{42} r_{2t-1} + m_{43} r_{3t-1} + u_{4t}
\end{aligned}$$

2.3.2 VAR model for volatility (VAR-MGARCH Model)

It has been observed that U.S. stock market plays the price leader role of the world. That means that U.S. stock returns and volatility would affect the other countries' stock return and volatility. A variety of researchers, including Eun and Shim (1989), Hamao, Masulis, and Ng (1990), Engle, Ito and Lin (1994), Fatemi and Park (1993), and Theodossiou and Lee (1993), have found evidence that a shock from U.S. stock market would transmit to many other countries.

It is commonly accepted that MGARCH model could use to explain the volatility co-movement across markets. In this paper, we analyze the linkages between these four stock markets through vector autoregressive MGARCH models. In this research, to model this variance of VAR equation and to explore the volatility spillover effects for the four markets of the U.S., China, Taiwan, and HK, the VAR-MGARCH model was developed to examine the joint processes for the four markets by using two spilt period sub-sample:1996-2005 and 2006-2009. It analyses not only the linkages between first moments of return through VAR representation but also the volatility transmission between the stock markets through GARCH specifications.

The following Equation denotes the multivariate GARCH(1,4) model:

$$h_{it} = \alpha_{ii} + \beta_{ii} h_{it-1} + \sum_{j=1}^{4} \gamma_{ij} u_{jt-1}^{2} \qquad i = 1,2,3,4$$

$$h_{ijt} = \delta_{ij} \sqrt{h_{it} h_{jt}} \qquad i, j = 1,2,3,4$$

The parameterization for conditional variances is shown in the first equation and for covariance in the second equation. In equation h_{it} is the variance of these four stock markets. The coefficient γ_{ii} and $\gamma_{ij}(i \neq j)$ represent the shock to volatility from the previous day and the impacts of volatility shocks form other countries. The δ_{ij} accounts for the correlations of these four stock markets.

2.4 Empirical Results

2.4.1 Test of Heteroscedasticity

This paper starts from ARMA(p,q) Model to model these four stock market returns, and the AIC(Akaike information criterion) and BIC(Schwartz Bayesian information criterion) are use to help us to choose the fittest model. Under these two criteria, the best model for Hong Kong, Taiwan and China stock index returns is ARMA(2,2), and the best model for U.S. stock index return is ARMA(2,1) as show in Table 3. All the residuals of these models do not have autocorrelation after Ljung-Box Q test, but after Jarque-Bera test indicate they are not normal distributions.

However, Ljung-Box Q^2 test (as indicates in Table 4 shows that residuals of these 4 series is heteroscedastic , that is volatility changes over time.

Table 3： ARMA(p,q) Model

Market	Model	AIC	BIC	DW	JB
HK	ARMA(2,2)	-5.202048	-5.189339	2.000411	1452.850*
TAIWAN	ARMA(2,2)	-5.302065	-5.291899	2.023368	12989.37*
CHINA	ARMA(2,2)	-5.299762	-5.289595	1.991147	2839.480*
U.S.	ARMA(2,1)	-6.213638	-6.206013	1.999042	1763.939*

Table 4：Ljung-Box Q^2 test of heteroscedasticity

	TAIWAN	HONG KONG	U.S.	CHINA
$Q(36)^2$	334.30*	1006.2*	586.81*	796.35*

Since these four return series are heteroscedastic, that is variance of residuals is not constant, but time varying, it can not be assumed that $u_t \sim N(0,\sigma^2)$ as in ARMA model. The GARCH model, introduced by Bollerslev (1986), is used to model the variance of the series and to capture the volatility clustering of financial time series.

2.4.2 Result of VAR Model & VAR-MGARCH Model

To explore the spillover effect of these four stock markets, both VAR(1) and VAR(1)-MGARCH(1,1) models were chose to model our sample returns and volatility. Table 5 and 6 displayed the estimation of VAR(1)-MGARCH(1,1) model for 1996-2005 and 2006-2009 respectively and they provided value of the maximum likelihood estimates of the models given by the above-mentioned equation. When 5% was taken as significance level, the results suggested that many coefficients were significantly different from zero. It was indicated that there were comprehensive spillover effects in returns and in volatilities among these four stock markets.

As indicated in Table 5 and 6, first, for return spillovers during 1997-2005 and 2006-2009, all of these four stock market returns（r_t） had a statistically significant lag-1 (r_{t-1}) autocorrelation. Second, for volatility spillovers during 1997-2005 and 2006-2009, the coefficient of lag conditional variance β_{ii} had significant large coefficient ,providing evidence for the heteroscedasticity of these four stock markets, and all of these four stock market returns (h_t) had a statistically significant lag-1 (h_{t-1}) autocorrelation. However, there were different levels of spillover in returns and in volatilities among these four stock markets.

Table 5：The result of VAR(1)-MGARCH(1,1) model for period of 1996-2005

Panel A: VAR(1) for return

	Taiwan	*Hong Kong*	*China*	*US*
m_{i0}	-0.0000782 [-0.22189]	-0.0000089 [-0.025151]	0.000366 [1.01001]	0.000329 [1.43924]
$m_{i1}(Taiwan(-1))$	-0.05312 [-2.25039]*	-0.05906 [-2.66888]*	0.029488 [1.30263]	0.010745 [0.75218]
$m_{i2}(HongKong(-1))$	0.059894 [2.81189]*	-0.073583 [-3.43745]*	0.025701 [1.17370]	-0.025195 [-1.82332]
$m_{i3}(China(-1))$	-0.003513 [-0.17063]	-0.039008 [-1.88511]	0.017083 [0.80704]	-0.002138 [-0.16006]
$m_{i4}(US(-1))$	0.314116 [9.40411]*	0.610451 [18.1854]*	0.046175 [1.34470]	0.053535 [2.47062]*

Note: t-statistics are in parentheses. 5% significant level

Panel B: MGARCH(1,1) for volatility

	Taiwan	*Hong Kong*	*China*	*US*
α_{ii} (intercept)	0.00000947 [3.639114]*	0.00000157 [1.409359]	0.00000527 [5.069756]*	0.00000328 [4.402489]*
β_{ii} (GARCH(-1))	0.72207 [29.15649]*	0.779315 [44.89307]*	0.874291 [204.5666]*	0.786771 [40.08283]*
$\gamma_{i1}(Taiwan(-1))$	0.129152 [8.029113]*	0.003827 [1.62542]	0.000899 [0.656818]	-
$\gamma_{i2}(HongKong(-1))$	0.047216 [4.493319]*	0.125996 [9.171628]*	0.002053 [1.527358]	-
$\gamma_{i3}(China(-1))$	0.000321 [0.113554]	0.002368 [1.427538]	0.114847 [18.07506]*	-
$\gamma_{i4}(US(-1))$	0.19808 [8.398591]*	0.086331 [6.637636]*	-0.00469 [-1.37129]	0.111635 [7.242763]*

Note: t-statistics are in parentheses. 5% significant level

Table 6: The result of VAR(1)-MGARCH(1,1) model for period of 2006-2009

Panel A: VAR(1) for return

	Taiwan	**Hong Kong**	**China**	**U.S.**
$m_{i1}(Taiwan(-1))$	-0.07218 [-2.20161]*	-0.092759 [-2.70958]*	0.055421 [1.48647]	0.017382 [0.50674]
$m_{i2}(HongKong(-1))$	-0.16929 [-3.33509]*	0.115052 [2.10759]*	-0.05414 [-1.01985]	0.044698 [0.91519]
$m_{i3}(China(-1))$	-0.03928 [-1.01557]	-0.013739 [-0.24519]	-0.07951 [-2.00542]*	0.006234 [0.15528]
$m_{i4}(US(-1))$	0.420468 [9.62555]*	0.373852 [5.90719]*	0.049602 [1.00643]	0.105535 [2.16316]*

Note: t-statistics are in parentheses.　5% significant level

Panel B: MGARCH(1,1) for volatility

	Taiwan	**Hong Kong**	**China**	**U.S.**
α_{ii} (intercept)	0.000209 [4.693436]*	0.0000204 [1.965792]*	0.0000211 [4.413392]*	0.0000427 [4.149677]*
β_{ii} （GARCH(-1)）	0.297801 [1.921640]*	0.562078 [2.211955]*	0.676973 [22.22297]*	0.495082 [5.770686]*
$\gamma_{i1}(Taiwan(-1))$	0.151418 [2.360975]*	0.098839 [4.0270]*	0.006581 [0.396621]	-
$\gamma_{i2}(HongKong(-1))$	-0.049866 [-4.336348]*	0.068925 [3.209832]*	0.005241 [0.629233]	-
$\gamma_{i3}(China(-1))$	-0.033137 [-1.753788]	0.009977 [1.069328]	0.266583 [8.413897]*	-
$\gamma_{i4}(US(-1))$	0.138426 [2.820019]*	0.059942 [2.655385]*	-0.009256 [-1.395652]	0.188415 [3.792212]*

Note: t-statistics are in parentheses.　5% significant level

Additionally, Table 5 and 6 showed that （1）the lag-1 return and volatility of Hong Kong and U.S. stock markets had significant effects on Taiwan’s return and volatility （2）the lag-1 return and volatility of Taiwan and U.S. stock markets had significant effects on Hong Kong's return and volatility（3）China stock market obtained spillover effect neither from Taiwan's and Hong Kong's nor from U.S.

Being as the most important global stock market, U.S. stock market would transmit its return and volatility to affect other regional and local stock markets, such as Hong Kong's and Taiwan's. On the contrary, though China's rapid economic growth and integration with international, its stock market was closed and independent as usual and its co-moments with other international markets were not statistically significant as before. But to our surprise, while these three Chinese areas had affinities in cultural and linguistic and had mutual investment and extensive trade, there was no evidence that China stock market illustrated return and volatility spillover effects on Taiwan's and Hong Kong's. However, Taiwan and Hong Kong, having been relatively open markets, demonstrated influence on each other not only in economic but also in stock market.

2.5 Concluding Remark

For international investors, the three Chinese stock markets (China, Hong Kong and Taiwan) amongst the emerging Asian stock markets have attracted increasing attention. Owing to the economic integration, intensive trade and close investment of the Chinese markets (China, Hong Kong and Taiwan) for recent decades, it was assumed that China's influence on Hong Kong and Taiwan stock markets would have been getting beyond that of U.S.

VAR and VAR-MGARCH models were used to examine the return and volatility spillover effects among U.S., Taiwan, Hong Kong and China stock markets. The results of our study from examining the data for period of 1996-2005 and 2006-2009 respectively may be summarized by pointing out the following: first, while China's rapid economic growth and its economic integration with two other Chinese markets, the spillover effect from U.S. stock market on Hong Kong and Taiwan was significantly stronger than that of China in recent years; Moreover, China stock market was considerably independent and isolated as usual and its co-moments with other (international) markets were still not significant, neither having influence on nor being influenced by other stock markets, including the two surrounding Chinese stock markets.

The results of this study are partially related to some recent papers. For example, Johansson (2009), using data during 1991-2008, found that China's stock market is fairly isolated from the rest of the world. Also, Johansson and Ljungwall (2009), looking at spillover effects among China, Hong Kong, and Taiwan stock markets, proposed that the relationship between Hong Kong and Taiwan is stronger. In addition, Yao and Yueh (2009), investigating the law, finance, and economic Growth in China, proposed that while China had experienced remarkable economic growth, its financial markets were still under-developed. Wang (2010) surveyed the relationship between stock market volatility and macroeconomic volatility of China and found that China's stock market was likely to be less efficient than those in the U.S. and other developed countries and was somewhat separated from the real economy of China.

Indicated as these previous researches, it is reasonable to explain the finding why these three Chinese areas are highly economic related but low stock market co-movement. The more open of the stock market, the more likely the market is integrated with the world market. Irrespective of the intensive economic integration of the three Chinese markets, there is no apparent stock spillover effect that could be transmitted from China to Taiwan and Hong Kong.

To sum up, international portfolio diversification has long been advocated which attempts to enhance expected returns while minimizing portfolio risk by deliberately selecting the proportions of investment assets. However, the validity of this proposition depends on the precise parameter estimation of returns and variances. Therefore, it appears that the correct capture of the return and volatility spillover effect would be beneficial to asset pricing, portfolio allocating, and risk controlling for investors. The results are important for investors that China stock market, with low co-moments with others, would be a good risk diversified investment and that U.S. stock market, with high co-moments with others, would be a good pricing indicator.

Compared with U.S., China stock market has no apparent spillover effect on Taiwan's and Hong Kong's stock markets recently. However, China has decided to open more stock market shares to qualified foreign institutional investors (QFII) and a variety of China's companies have been listed in overseas stock markets in recent years. Both will lead the China stock market to more interaction with international capital markets. It is likely that volatility spillover effects between China and international stock markets, including emerging stock market of Taiwan and Hong Kong, will become stronger in the future. Our approach of this research could be useful for further empirical study.

3 Risk Contagion: Micro Analysis

3.1 Systemic risk in Taiwan stock market

Many financial crises have resulted from systemic risk which is caused by idiosyncratic distress, leading to the crunch of the whole system. The interaction between financial distress and systemic risk due to the effect of idiosyncratic distress has been discussed recently (Fu, 2009; Campbell et al., 2008; Ang et. al., 2006). Amongst the idiosyncratic distress, sector-specific risk, which is caused by a group of interconnected institutions, has been given as the main reason for sudden increases in systemic risk, leading to the formalization of financial crises. In this research, taking Taiwan's stock market as an example and collecting data from 2000 to 2010 which contained the 2001 dot-com bubble and the 2007-09 financial crisis, we adopted the CoVaR model to empirically explore the impact of sector-specific idiosyncratic risk on the systemic risk of the whole financial system and attempt to investigate the links between financial crises, systemic risk, and the idiosyncratic risk of a sector-specific anomaly.

International stock market transmission across different markets has been comprehensively studied. Many recent studies have discussed the volatility spillover effect of stock market returns. These papers have shown some typical characteristics of the volatility spillover effect among different stock markets (Martens and Poon, 2001; Goetzmann , Li and Rouwenhorst , 2001; Worthington and Higgs, 2004; Michelfelder RA, 2005; Scheicher M, 2001; Bekaert and Harvey, 1997; Gokcan S, 2000; Sheu and Cheng , 2011). In addition, within a stock market, during times of financial crisis, losses tend to spread from a single sector across other sectors, leading to increased system-wide risk and probable deterioration of the whole stock market system. This financial system instability or potential catastrophe, caused by idiosyncratic events and resulting in risk to the entire financial system, is defined as systemic risk. Many financial crises are initially caused by a “sector-specific” idiosyncratic distress of a country, then spill over across other sectors to increase systemic risk, consequently leading to worldwide crashes. These crises result from systemic risk, caused by idiosyncratic distress, which cannot be reduced through portfolio diversification. Several reasons might lead to systemic risk and there are two commonly used assessments for measuring systemic risk, i.e. the “too big to fail” and “too interconnected to fail” test. The “too big to fail” test considers an asset size relative to the marketplace, i.e. market share concentration and the “too interconnected to fail” measures the likelihood and extent of negative impact to the overall economic system from the failure of a group of correlated institutions. Traditionally, Value-at-Risk (VaR) is widely used to assess the risk of loss of specific financial assets and provides a measure to manage the market risk of assets. However, VaR focuses on these assets in isolation and does not consider external impacts. Using value-at-risk(VaR) to assess assets, it seems negligible to capture the systemic risk and the true risk is often underestimated when other assets come under stress. For investors to control the risk for underlying assets, the appropriate risk measure could not only assess the risk of a sector’s economic activities itself, but also consider the impact to systemic risk from the idiosyncratic distress. Thus, to supplement the drawback of VaR for estimating market risk, it is necessary to employ more interdependent and comprehensive measures that could consider the interconnected nature of the financial system and gauge the increased systemic risk due to the distress of other financial assets. However, it was not until the financial crisis of 1998 that some researches begun to discuss systemic risk and develop approaches to measure it. Among these approaches, the “CoVaR” method, proposed by Adrian and Brummermeier (2008), is a more interdependent and comprehensive method and has been successfully employed to capture systemic risk.

Following this CoVaR method, the Taiwan stock market during periods of 2000-2010 was taken as an example to explore systemic risk caused by “sector-specific” distress for some reason. First, Taiwan rose to second in the world for global IT competitiveness through its strengths in R&D and nurturing technology talent（Business Software Alliance, 2008）. Second, given the economic success of Taiwan in the last several decades, many global investors have taken an active interest and hold an index investment position in this stock market. Finally, the technology industry and financial industry rank as the top two important industries in Taiwan’s stock market. Thus, it is an appropriate objective to measure and backtest the systemic risk during the 2001 dot-com bubble and the 2007-09 financial crisis.

The purpose of this paper is to empirically explore the impact of “sector-specific” idiosyncratic risk on the systemic risk of the whole financial system. First, this paper examines the magnitude of systemic risk and the marginal risk contribution caused by sectors to the overall systemic risk on the Taiwan stock market. Further, the differences, between VaR of sectors and sector-specific marginal systemic risks, were also compared. Finally, we endeavored to investigate the links between marginal systemic risk caused by a sector-specific anomaly and the impact of global financial crises on Taiwan stock market. It is hoped the results of this study will be a useful tool for those stock investors to accurately identify the true systemic risk of Taiwan’s stock market and to properly allocate their investment portfolios across sectors according to their true risk contributions.

The structure of this paper is as follows. Section 3.2 discusses risk contagion theory. Section 3.3 describes the methodology used to measure the systemic risk of Taiwan's stock market and the implementation of the model, which is designed to solve the research problems. Section 3.4 demonstrates the results of the research and other computation analysis. Finally, section 3.5 summarizes some findings and conclusions.

3.2 Risk contagion theory and literature with regarding to sector contribution to the whole system

3.2.1 Drawbacks of VaR

Value-at-Risk (VaR) converts the downside risk of a portfolio into a single number, making it an easy to understand and widely used measure of the risk of financial assets. However, it has been challenged by many recent literatures. Artzner et al. (1999) suggested because VaR was not sub-additive[1], meaning the VaR of a combined portfolio can be larger than the sum of the VaRs of its components, it was not only incompatible with Markowitz portfolio theory (Markowitz, 1952), but also did not suggest diversification reduces risk. Besides, Wong and Fong (2010) proposed since VaR focused on the asset itself on isolation, the real risk of this asset might be underestimated, especially when other assets came under stress. Moreover, Brunnermeier, Crocket, Goodhart, Perssaud, and Shin (2009) suggested because VaR measured a single asset's

[1] A risk measure ρ ( ) is subadditive, if, for any two financial assets A and B, ρ (A+B) is no greater than ρ (A)+ ρ (B). Sub-additivity: $\rho(X + Y) \leqq \rho(X) + \rho(Y)$, for any risks X, Y , lack of sub–additivity [Artzner et al. (1999, Mathematical Finance)]

risk in isolation and did not consider the interconnected effect among assets, it might not necessarily reflect systemic risk, which is the risk when the stability of the whole financial system is threatened. Based on these criticisms, it is doubtful whether VaR is a good risk measure.

Nowadays, many international investors have major stakes in overseas markets to pursue higher profit opportunities. Given the economic success in the last two decades, Taiwan's stock market has attracted considerable global investments and the most used instrument is investment in Taiwan's stock index, such as the MSCI Taiwan Index. Measuring and monitoring the true risk of Taiwan's stock market has become a critical issue for investors. VaR, focusing on the risk of an individual exposure in isolation, is the most commonly used measure of risk. However, it does not necessarily reflect how much risk a single exposure contributes to the whole system, i.e. systemic risk, when the stability of the whole system is destroyed. It is necessary to employ more interdependent and comprehensive risk measures to capture the true risk of assets, including systemic risk, which is the main cause of financial crises.

3.2.2 Risk contagion during the crisis

Groups of interdependent institutions, defined as sectors, can contribute to systemic risk in two ways, the common exposure effects, and inter-linkages effects. First, a shock from a sector could become systemic because of direct common exposure, meaning a downward shock could affect most of the institutions within the sector simultaneously and thus trigger a systemic crisis in the sector (De Nicolò and Kwast, 2002; Hawkesby, Marsh, and Stevens, 2007). Financial globalization assists the capital and financial assets to flow across various markets, which increases systemic risk and links all markets together exposing them to common risk. Second, due to the markedly increased industry integration nowadays, a more and more complicated web of economy activities and transactions implies this integration enhances the inter-linkage effects and exposes the entities of the web to the same risk factors, and that a shock hitting one institution could spread to the others connected to it.

Many financial crises begin with sector-specific distress that then spills over into other sectors. These “sector-specific” caused crises comprise those before 2000 , such as the 1987 Black Monday stock market crash and the 1998 Russian crisis, as well as those after 2000 of (1) the 2001 dot-com bubble, resulting in a financial bubble centered on internet-based companies, the so-called burst of the dot-com companies, and finally affecting most markets in the world, and (2) the 2007-09 financial crisis, which spread from failures of financial institutions in the United States, due primarily to exposure to subprime securities and credit default swaps(CDS), rapidly devolving into a global crisis which led to many bank failures in Europe and sharp value reductions in equities and commodities worldwide (Brady ,1988; Rubin, Greenspan, Levitt, and Born, 1999; Brunnermeier, 2009; Adrian and Shin, 2010a,b; Junior et al., 2010; Allen, Babus and Carletti, 2009; Embrechts, 2000).

Apparently, these cases resulted from a “sector-specific” anomaly and then this “sector-specific” anomaly transmitted to increase systemic risk, which not only led to the crisis of the local financial system, but also spilled over across most financial markets and harmed the worldwide financial system. Further, as these global financial crises have shown, common exposure effects and inter-linkages effects have played an important role in international systemic risk that could not be diversified away. It highlights the interconnectedness of financial markets nowadays and demonstrates the importance to employ more interdependent and holistic measures that can take into account the interconnected nature of the financial system and evaluate how much the risk of the asset may deteriorate when other related assets become distressed.

3.2.3 CoVaR model

Systemic risk, as defined, is the risk of collapse of a whole market where the failure of an idiosyncratic distress could cause a cascading failure of the entire system, as opposed to risk only associated with any one individual entity, a group of entities, or a component of the system. Although systemic risk is the most important formal reason for financial crises, it was not until the financial crisis of 1998 that a few studies began to discuss the measures of systemic risk. These studies can be divided into two types, one adopts a top-down approach exploring systemic risk by attributing it to individual contributors, and the other adopts a bottom-up approach gauging marginal systemic risk that an individual entity contributes to the whole system, not decomposing systemic risk into individual contributors and not attempting to add components up to find total systemic risk (Tarashev, Borio and Tsatsaronis, 2010).

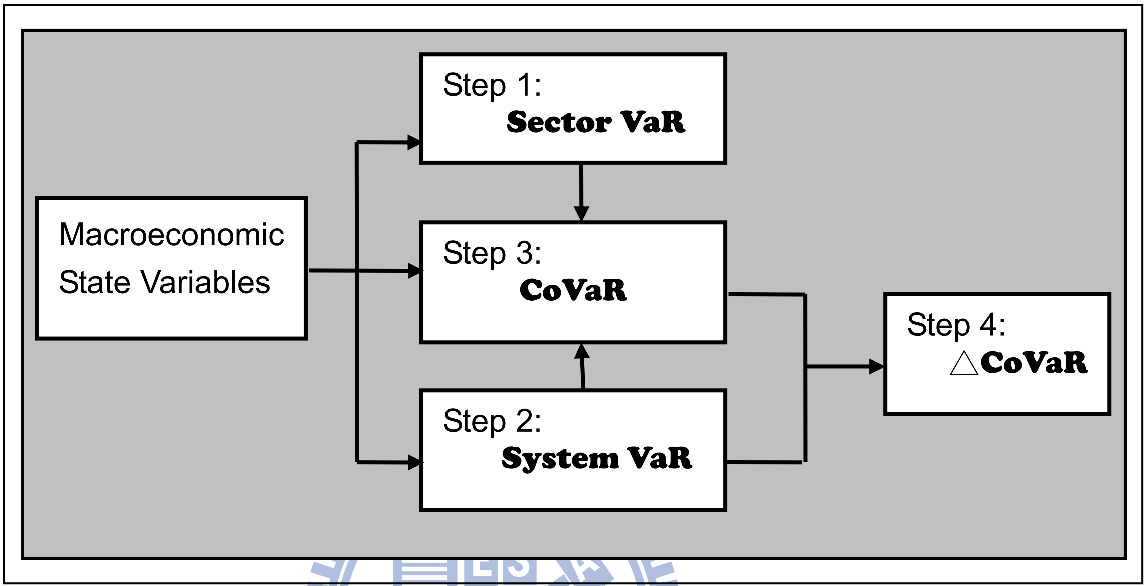
Several studies have used the top-down approach, decomposing the aggregate systemic risk and allocating it to individual contributors according to their expected loss in the event of distress (Praschnik et al, 2001; Hallerbach, 2002; Koyluoglu and Stoker, 2002; Kurth and Tasche, 2003; Glasserman, 2005; Acharya et al, 2009; Huang et al, 2009; Tarashev, Borio, and Tsatsaronis, 2010). The advantage of this top-down approach is the sum of the risk attributed to individual risk contributors will exactly equal the overall systemic risk. However, the disadvantage of this approach is it cannot be employed for the conditions where systemic risk is not measured by a fixed set of failure events. Conquering the disadvantage of the top-down approach, few researches have recently begun to employ the bottom-up approach to measure systemic risk. Adrian and Brummermeier (2008) proposed the concept of “CoVaR”, defined as the VaR of an asset conditional on some other assets being in distress, to measure the severity of the systemic risk, which is the whole system failure or potential catastrophe conditional on the negative effects caused by an institution-specific or a sector-specific severe calamity. Acharya, Pedersen, Philippon and Richardson (2009, 2010) measured the contributions of individual banks to systemic risk and proposed a “tax charge” based on the contribution to systemic risk. Chan-Lau (2008) used a similar approach to study the spillover effects of the CDS spreads of financial institutions in the US, Europe and Japan. Fong, et al. (2009) estimated CoVaRs to evaluate the interdependence of financial institutions in Hong Kong. However, these papers emphasized measuring the systemic risk caused by individual institution’s anomaly, i.e. “institution-specific” distress, and proposed institutions that were too large to fail were likely to cause risk spillover effects on the system, as well as transmit more systemic risk to the whole system. Nevertheless, according to the definition and the classification of Brunnermeier, Crocket, Goodhart, Perssaud, and Shin (2009), systemic risk includes the risk caused not only by “individual institutions”, which are so large (“too big to fail”) that they could negatively affect others, but also by a group of institutions, which are so interdependent (“too interconnected to fail”) that they are “systemic as part of a herd” which possess similar characteristics and could be affected by common risk factors. The previous studies of “institution-specific” CoVaR only emphasized the “too big to fail” effect, rather than the “too interconnected to fail" effect. However, due to the above mentioned inter-linkage effect and common exposure effect, the failure of a group of interconnected institutions, i.e., "sector-specific" distress, would bring down more severely negative effects on the whole system and would be the primary risk contributor of financial crises. However, there is a lack of research discussing the systemic risk caused by the "sector-specific" disaster. This paper focuses on the Taiwan stock market's systemic risk, conditional on "sector-specific" idiosyncratic risk.

3.3 Properties of the conditional VaR methodology

As indicated in the introduction, there are two types of systemic risk measures, the top-down approach estimates systemic risk by attributing it to individuals, while the bottom-up approach focuses directly on the marginal systemic risk which individual contributors attribute to. Amongst the bottom-up approach, the CoVaR model has been proved by Boyson, Stahel and Stulz (2008) and Jorion and Zhang (2009) to be a good method to measure systemic risk using quantile regressions. There are many advantages of using the CoVaR method. First, it provides a method to explore the comprehensive risk spillovers across the entire financial system. Second, it can decompose the marginal risk, $\Delta CoVaR$, from the total systemic risk. Then, it can help investors pay more attention to the important marginal risk contributory sectors instead of overall systemic risk, i.e., from the macro prudential perspective to micro prudential perspective. Finally, by exploring the risk factors of important marginal contributory sectors on systemic risk, it can help investors monitor the movement of these important risk factors as an early warning signal of overall systemic risk.

This paper adopts the CoVaR method to gauge systemic risk, both

CoVaR and $\Delta CoVaR$, of Taiwan's stock market. For the purpose of this study, VaR and CoVaR were generated from functions of a vector of macroeconomic state variables and were estimated by quantile regressions. To clarify, the framework of this study is depicted as follows:



3.3.1 VaR, CoVaR and △CoVaR model

For a given probability and time horizon, VaR is defined as a threshold value such that the probability that the market loss on the portfolio over the given time horizon exceeds this value is exactly the given probability level (Jin and Jorion, 2006; Suhobokov, 2007). The first step of this paper is to measure the VaRs of the whole Taiwan stock market (denoted as "system VaR") and its component sectors (denoted as "sector VaR") using the historical simulation method because this method provides a simple and straightforward implementation of valuation, as well as no distribution assumption and no complicated calculations being required (Suhobokov, 2007). In the second step, following the study of Adrian and Brunnermeier (2009), the CoVaR method is employed to evaluate the systemic risk of Taiwan's stock market conditional on sector-specific distress.

In the following section, $CoVaR_i$ is defined as the system (whole Taiwan stock market, hereafter) *VaR* conditional on specific sector *i* being in distress and $\Delta CoVaR_i$ was defined as the marginal contribution of sector *i* to the overall systemic risk which is generated from the difference between the $CoVaR_i$ and the VaR of the whole system.

The distinction between $CoVaR_i$ and $\Delta CoVaR^i$ is the former allows us to study how much the systemic risk will be when conditional on sector-specific's distress, while the latter quantifies how much marginal risk a sector contributes to overall systemic risk. Both VaR and CoVaR measures were computed using the Quantile Regression approach, which was suggested by Koenker and Bassett (1978) to estimate the coefficients. This approach could estimate a specific quantile under a conditional distribution and recently has been successfully used in the analysis of VaR and CoVaR (Chen, 2002; Gaglianone et al. 2009; Schaumburg, 2010; Coroneo and Veredas, 2008; Ou and Yi, 2010; Chernozhukov and Umantsev, 2001; Chernozhukov and Du, 2008).

3.3.2 Estimation CoVaR with macroeconomic state variables

Four steps were used to estimate △CoVaR with macroeconomic state variables. First, to capture time variation in the joint distribution of a sector's return (X^i) and the whole Taiwan stock market index return (X_t^{system}), the conditional distribution as a function of state variables is estimated. Subscripted with t , the time-varying X_t^i and X_t^{system} were estimated by conditioning on a vector of 1-month lagged time series for macroeconomic state variables M_{t-1} . The following regressions (1) and (2) were run in the monthly data (where " i " denotes a specific sector and " $system$ " denotes the whole system):

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \qquad (1)$$

$$X_t^{system} = \alpha^{system} + \gamma^{system} M_{t-1} + \varepsilon_t^{system} \qquad (2)$$

Second, to generate the CoVaR conditional on an individual sector, the whole Taiwan stock market index return (X_t^{system}), regressed as a function of its lag 1 return (X_{t-1}^{system}), an individual sector's return (X_t^i) and a vector of 1-month lagged time series for macroeconomic state variables M_{t-1}, was also estimated in the monthly data :

$$X_t^{system} = \alpha_0^{system|i} + \alpha_1^{system|i} X_{t-1}^{system} + \alpha_2^{system|i} X_t^i + \alpha_3^{system|i} M_{t-1} + \varepsilon_t^{system|i} \qquad (3)$$

Third, using the coefficients of the quantile approach from the first step, the predicted values, VaR_t and $CoVaR_t$, were generated from the regressions (4), (5), and (6). In equation 6, CoVaR, which denoted VaR of the whole market conditional on individual sector being at distress, was calculated by substituting VaR_t^i for X_t^i and VaR_{t-1}^{system} for X_{t-1}^{system} into the equation 3.

$$VaR_t^i = \alpha^i + \gamma^i M_{t-1} \qquad (4)$$

$$VaR_t^{system} = \alpha^{system} + \gamma^{system} M_{t-1} \qquad (5)$$

$$CoVaR_t^i = \alpha_0^{system|i} + \alpha_1^{system|i} VaR_{t-1}^{system} + \alpha_2^{system|i} VaR_t^i + \alpha_3^{system|i} M_{t-1} \qquad (6)$$

Finally, a panel of monthly $\Delta CoVaR_t^i$, conditional on a sector "i", was obtained by subtracting VaR_t^{system} from $CoVaR_t^i$:

$$\Delta CoVaR_t^i = CoVaR_t^i - VaR_t^{system} \qquad (7)$$

△CoVaR means the marginal systemic risk of the whole market, which happened when an individual sector being at distress and △CoVaR^i is the marginal systemic risk to the whole system when sector " i " distresses.

When estimating the above-mentioned time-varying $CoVaR_t$ and VaR_t, the set of lagged macroeconomic state variables M_{t-1} was used as controlling variables to remove variation which was not directly related to the risk of the financial system

(Aktan, Korsakienė, and Smaliukiene, 2010). These macroeconomic state variables were usually used to describe the "state" of the dynamic system and to forecast the future behavior of the system. Many studies have suggested the aggregate stock market return predictability is highly related to macroeconomic state variables that could reflect the business cycle (Chen, Roll and Ross, 1986; Fama and French, 1993; Vassalou, 2003; Petkova, 2006; Ludvigson and Ng, 2007; Birz and Lott, 2008; Cenesizoglu and Timmermann, 2008; Li and Liu, 2010; Festic, Repina and Kavkler, 2009). In reference to these researches, the selected macroeconomic state variables and reasons to be chosen are listed as below:

(1)Short term “Credit spread”：which was defined as the difference between the rate of a government bond and the rate of commercial paper in Taiwan’s money market.

(2)Monetary Aggregate M1B：which equaled M1A plus Passbook savings deposits of Individuals and non-profit organizations in banks and community financial institutions.

(3)Unemployment rate：the unemployment rate and Taiwan’s stock return were found to be stable time series after difference and to have a long-term equilibrium.

(4)The GDP leading index：which is composed of seven sub-indicators and is widely used in the financial field, because it is a significant indicator of Taiwan’s stock market returns.

(5)Exchange rate movement：which plays an important role in Taiwan economic performance and in the short run has significantly negative influences on Taiwan’s stock returns.

(6)The Crude Oil price movements：which has similar impacts as exchange rate movements and in the short run has a significantly negative influence on Taiwan's Stock returns.

(7)NASDAQ index return：which has been proved to be the most influential external source on Taiwan's stock market.

Besides, Taiwan is one of the Four Asian Dragons and its stock market has attracted a large number of investors' attention owing to its rapid economic growth over the past decades. Since it is highly correlated with international capital markets and other Asian stock markets, Taiwan's stock market could provide pricing predication or hedging tools for other Asian stock markets (Sheu and Cheng, 2011). This analysis, taking Taiwan's stock market as example, focused on the VaR and ΔCoVaR of this stock market index and its components of 18 sector indices, which are denoted as follows:

Whole stock market VaR：		
X^{system}: Taiwan stock index		
Sector VaR:		
X^1: cement sector	X^7 :medical technique sector	X^{13}: electronic sector
X^2: food sector	X^8: ceramic sector	X^{14}: building sector
X^3: plastic sector	X^9: papermaking sector	X^{15}: shipping sector
X^4: textile fiber sector	X^{10}: steel sector	X^{16} :sightseeing sector
X^5: electrical machinery sector	X^{11}: rubber sector	X^{17}: banking sector
X^6: electric appliance sector	X^{12}: automobile sector	X^{18}: trade sector

Data was collected from January 2001 through September 2010, covering the dot-com bubble of 2001 as well as the financial crisis of 2007-09, containing a whole economic cycle of Taiwan.

3.4 Empirical results

This section presents the empirical results of applying the CoVaR method using the quantile approach introduced in the previous section to explore the systemic risk measures of Taiwan's stock market. First, the results of quantile regressions for sector's returns(X^i) and whole system return(X^{system}) on the macroeconomic state variables were calculated. Second, VaRs of the whole Taiwan stock market (system VaR, VaR^{system}) and individual sectors (sector VaR, VaR^i) on isolation were estimated. Third, systemic CoVaR measures conditional on individual sectors, $CoVaR^i$, were generated. In addition, two risk measures of unconditional and conditional on sectors' being in distress, i.e., VaR^{system} and $CoVaR^i$, were compared. Further, the difference between these two risk measures, denoted as $\triangle CoVaR^i$, was generated to capture the marginal contribution of an individual sector to overall systemic risk. Finally, the links between $\triangle CoVaR^i$ of some important sectors and the recent global financial crises were also investigated.

3.4.1 VaR estimation

The coefficients of quantile regressions for sector returns (X^i) and whole system return (X^{system}) of Taiwan's stock market on macroeconomic state variables were estimated. Using these equations, the VaR of Taiwan Stock Index(VaR^{system}) and VaRs of 18 sector indices(VaR^1 to VaR^{18}), were shown in Table 7, calculated by the Historical Simulation Method at 1%, 5%, and 10% maximum loss probability and denoted as VaR 1%, VaR 5%, and VaR 10%, respectively.

As seen in table 7, VaR increased when the maximum loss probability decreased. The trade sector, building sector, electric appliance sector, electronic sector, and electrical machinery sector had the top 5 VaR measures at any confidence level. For example, at 1% maximum loss probability, the VaR of electronic sector and

Taiwan stock index were -0.06697 and -0.06026, respectively, and the sector indices with the largest and smallest VaR were trade sector of -0.11382, and food sector of -0.04110.

The sector VaR is a risk measure representing the loss due to the sector's being in distress in isolation. However, the question of whether a sector with bigger VaR could mean it would contribute more marginal risk to the whole system needed to be further investigated and is discussed in the following.

Table 7 VaR of stock index & sector index at 1%, 5% and 10% respectively

	VaR 1%	VaR 5%	VaR 10%
Whole stock market VaR :			
X^{system} : Taiwan stock index	-0.06026	-0.05220	-0.04500
Sector VaR:			
X^{1} : cement sector	-0.04618	-0.04035	-0.03358
X^{2} : food sector	-0.04110	-0.03454	-0.02745
X^{3} : plastic sector	-0.04990	-0.04423	-0.03759
X^{4} : textile fiber sector	-0.05595	-0.05107	-0.04493
X^{5} : electrical machinery sector	-0.06359	-0.05619	-0.04484
X^{6} : electric appliance sector	-0.07182	-0.06500	-0.05835
X^{7} : medical technique sector	-0.05791	-0.04820	-0.03707
X^{8} : ceramic sector	-0.05585	-0.04868	-0.03653
X^{9} : papermaking sector	-0.05870	-0.05285	-0.04754
X^{10} : steel sector	-0.04850	-0.04401	-0.03587
X^{11} : rubber sector	-0.04465	-0.03902	-0.02971
X^{12} : automobile sector	-0.04603	-0.04406	-0.03886
X^{13} : electronic sector	-0.06697	-0.05941	-0.05006
X^{14} : building sector	-0.10082	-0.08487	-0.07066
X^{15} : shipping sector	-0.05516	-0.04740	-0.04014
X^{16} : sightseeing sector	-0.04912	-0.04529	-0.03626
X^{17} : banking sector	-0.05932	-0.05204	-0.04604
X^{18} : trade sector	-0.11382	-0.09169	-0.05992

3.4.2 CoVaR estimation

To generate the CoVaR measures, the quantile CoVaR regressions, as shown in equation (6) of section 3.2, conditional on individual sectors were established and the coefficients of regressions were estimated under the OLS method, 10th quantile method, and 5th quantile method respectively. Under these estimated equations, the CoVaRs for the whole system conditional on 18 sectors ($CoVaR^{1}$ to $CoVaR^{18}$) at 1%, 5%, and 10% maximum loss probability were then generated independently. To simplify the discussion, CoVaR at 5% maximum loss probability was chosen to be shown in table 8, because 5% was commonly accepted maximum loss level. As indicated in the table, CoVaRs measured using the OLS method were significantly larger than those estimated by the quantile model. Besides, regardless of what model was used, the two highest CoVaRs of Taiwan stock market could occur when it was conditional on the electronic sector and banking sector being at their VaR levels.

Table 8 Predicted CoVaR(5%) of Taiwan stock sector index using OLS and Quantile 5%

CoVaR（5%）when conditional on：	Method	
	OLS	Quantile 5^{th}
X^1 : cement sector	-0.0324	-0.07347
X^2 : food sector	-0.0307	-0.07365
X^3 : plastic sector	-0.0259	-0.07395
X^4 : textile fiber sector	-0.0318	-0.07313
X^5 : electrical machinery sector	-0.0286	-0.07932
X^6 : electric appliance sector	-0.0306	-0.07558
X^7 : medical technique sector	-0.033	-0.06575
X^8 : ceramic sector	-0.0204	-0.0545
X^9 : papermaking sector	-0.0311	-0.07268
X^{10} : steel sector	-0.0224	-0.06374
X^{11} : rubber sector	-0.0326	-0.0702
X^{12} : automobile sector	-0.026	-0.05916
X^{13} : electronic sector	-0.035	-0.09508
X^{14} : building sector	-0.033	-0.07175
X^{15} : shipping sector	-0.0227	-0.06337
X^{16} : sightseeing sector	-0.0306	-0.06782
X^{17} : banking sector	-0.0316	-0.07999
X^{18} : trade sector	-0.0147	-0.06475

Combining table 7 and 8, the top 5 highest VaR sectors (trade sector, building sector, electric appliance sector, electronic sector, and electrical machinery sector) did not completely equal the top 5 highest risk contributory sectors to the system CoVaR (electronic sector, banking sector, electrical machinery sector, electric appliance sector, plastic sector). Amongst these sectors, the electronic sector had the highest sector VaR and the highest systemic CoVaR, however, the banking sector did not have relatively substantial sector VaR, but did have the 2nd highest systemic CoVaR. On the contrary, the trade sector and building sector possessed the two highest sector VaRs, but they did not have relatively high systemic CoVaR. It appears sector VaR is not necessarily correlated with systemic CoVaR, with a Pearson's correlation of only 0.2715. The reason for this mismatch could be the probability sector VaR is not the only risk that transmits to the system and these two risk measures apparently capture different risks of the system. Thus, merely using VaR to measure risk would be insufficient and might underestimate its true risk. Up to this point, these results are consistent with those of Adrian, Tobias and Markus Brunnermeier (2008).

Correlation between VaR^i and $CoVaR^i$:

	VaR^i
$CoVaR^i$	0.2715

Fig. 3 depicts the measures of sector VaR(solid line) and systemic CoVaR(dotted line) of all 18 sectors. Clearly, most conditional CoVaRs were larger than the sector's VaR, except for a few sectors. In addition, it showed a sector with higher VaR did not necessarily contribute more systemic risk to the whole system or lead to a higher CoVaR.

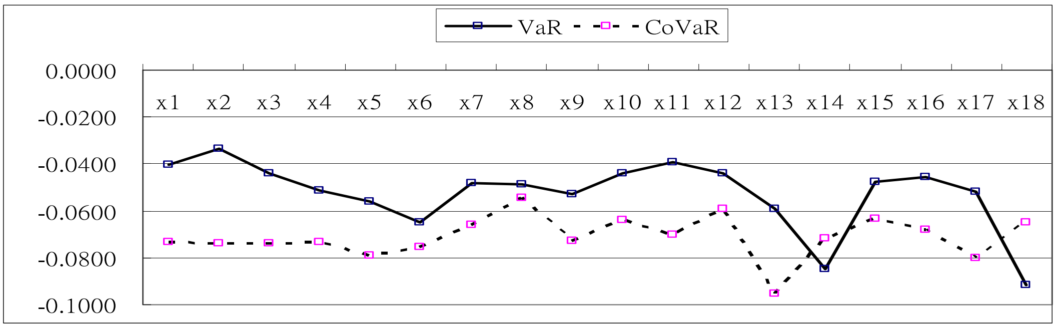


Fig. 3 Sector VaR and CoVaR conditional on 18 sectors

In addition, as the electronic sector and banking sector rank as the top two CoVaR sectors, their time series CoVaRs for the sample period needed to be thoroughly explored, with this being presented in Fig. 4. The CoVaRs of these two sectors was apparently spilt at 2007, matching the time of the global financial crises. Owing to the 2001 dot-com bubble, the electronic sector (as dotted line) had a larger CoVaR than the banking sector (solid line) from 2003 to 2007. On the contrary, for the 2007-09 financial crisis, the banking sector has had a higher CoVaR measure than electronic sector from 2007 till now, particularly in 2007.

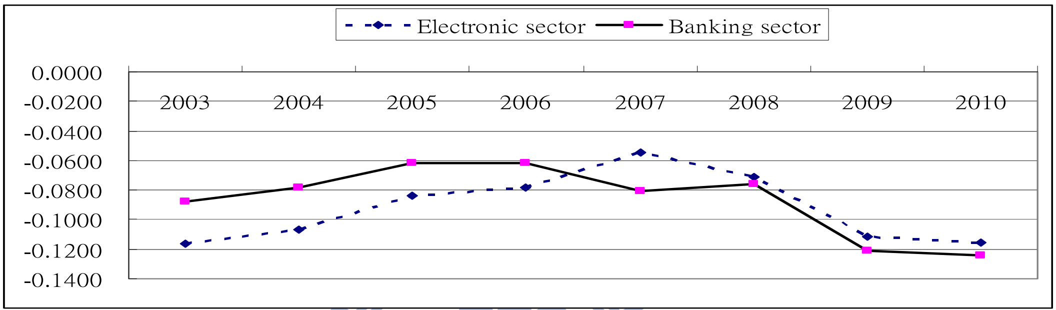


Fig. 4 Sector CoVaR of electronic sector and banking sector during 2003-2010

3.4.3 Marginal contribution to systemic risk, △CoVaR

The difference between CoVaR and VaR measures, denoted as △CoVaR, was generated to capture the marginal contribution of an individual sector to overall systemic risk. The △CoVaR of Taiwan's stock index using OLS, Quantile 5^{th} and Quantile 10^{th} at 1%, 5%, and 10% maximum loss probability were calculated corresponsively and only the △CoVaR at 5% maximum loss probability and under the 5^{th} quantile percentile was listed on table 9 and depicted in Fig. 5. Similar to the result of CoVaR, ranking as the top 2 largest transaction volume sectors in Taiwan's stock market, the electronic sector and banking sector also possessed the top 2 highest marginal risk contribution, △CoVaR, for Taiwan's stock market, indicating conditional on the crisis of these two sectors, the systemic risk of the whole Taiwan stock market could dramatically increase. This result could simultaneously prove the “too big to fail” and “too interconnected to fail” effects of the financial system characteristics which could not be fully obtained from the result of the VaR measure.

Table 9 △CoVaR(5%) of Taiwan stock index using Quantile 5th

Conditional on:	$\Delta CoVaR^i$	Conditional on:	$\Delta CoVaR^i$
X^1 : cement sector	-0.0213	X^{10} : steel sector	-0.0115
X^2 : food sector	-0.0215	X^{11} : rubber sector	-0.0180
X^3 : plastic sector	-0.0217	X^{12} : automobile sector	-0.0070
X^4 : textile fiber sector	-0.0209	X^{13} : electronic sector	-0.0429
X^5 : electrical machinery sector	-0.0271	X^{14} : building sector	-0.0195
X^6 : electric appliance sector	-0.0234	X^{15} : shipping sector	-0.0112
X^7 : medical technique sector	-0.0136	X^{16} : sightseeing sector	-0.0156
X^8 : ceramic sector	-0.0023	X^{17} : banking sector	-0.0278
X^9 : papermaking sector	-0.0205	X^{18} : trade sector	-0.0126

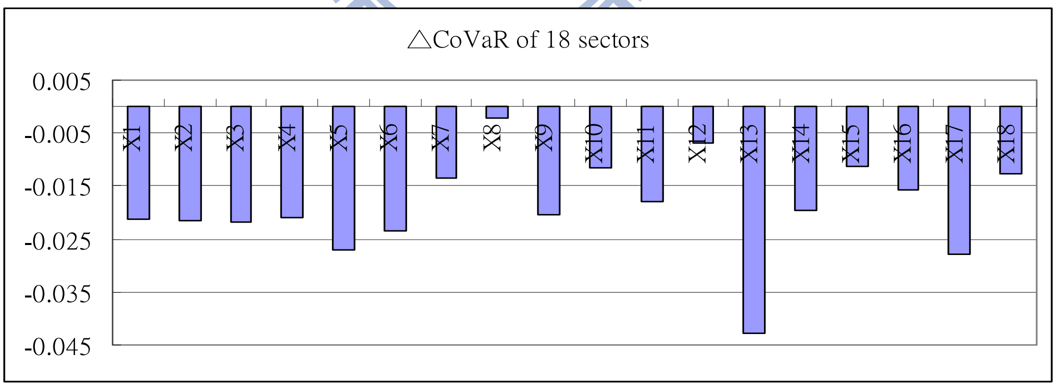


Fig. 5 △ CoVaR of 18 sectors

To clearly compare VaR^i with $\Delta CoVaR^i$, Table 10 lists the paired value of these two risk measures for 18 sectors. From the table, while the trade sector, building sector, electrical appliance sector, electronic sector, and electrical machinery sector ranked as the top 5 highest VaR sectors, the electronic sector and banking sector were the 2 most marginal risk contributing sectors for Taiwan's stock market. The main conclusions here are sectors might have a low VaR but a high △CoVaR, and △CoVaR could capture not only systemic risk but also the individual sector risk.

Table 10 yearly pairs of VaR^i and $\Delta CoVaR^i$ for 18 sectors

sector	VaR^i	$\Delta CoVaR^i$	sector	VaR^i	$\Delta CoVaR^i$
X^1 : cement sector	-0.04035	-0.0213	X^{10} : steel sector	-0.04401	-0.0115
X^2 : food sector	-0.03454	-0.0215	X^{11} : rubber sector	-0.03902	-0.0180
X^3 : plastic sector	-0.04423	-0.0217	X^{12} : automobile sector	-0.04406	-0.0070
X^4 : textile fiber sector	-0.05107	-0.0209	X^{13} : electronic sector	-0.05941	-0.0429
X^5 : electrical machinery sector	-0.05619	-0.0271	X^{14} : building sector	-0.08487	-0.0195
X^6 : electric appliance sector	-0.06500	-0.0234	X^{15} : shipping sector	-0.04740	-0.0112
X^7 : medical technique sector	-0.04820	-0.0136	X^{16} : sightseeing sector	-0.04529	-0.0156
X^8 : ceramic sector	-0.04868	-0.0023	X^{17} : banking sector	-0.05204	-0.0278
X^9 : papermaking sector	-0.05285	-0.0205	X^{18} : trade sector	-0.09169	-0.0126

The financial crises of the 2001 dot-com bubble and 2007-09 financial crisis resulted from systemic risk which not only led to the crisis of the local financial system, but also damaged the world-wide financial system. Taiwan is a primary electronic product factory of the world and its banking sector plays an important role in Pacific Asia. Thus, these two global financial crises might affect the electronic and banking sectors of Taiwan's stock market. Is there any link between the global financial crises and $\Delta CoVaR$? The time series $\Delta CoVaR^i$ of electronic sector, banking sector and market average during 2003 to 2010 was depicted as Fig. 6. For the recovery from the 2001 dot-com bubble, the $\Delta CoVaR$ of the electronic sector (blue line) is getting smaller from 2003 to 2010. However, the banking sector was seriously affected by the 2007-2008 financial crisis, and its $\Delta CoVaR$ was largest during these periods. The market average $\Delta CoVaR$ of the 18 sectors was largest at the beginning of the sample period and 2007, indicating Taiwan's stock market deteriorated during the dot-com bubble and the 2007-2008 financial crisis, and △CoVaR could capture these characteristics.

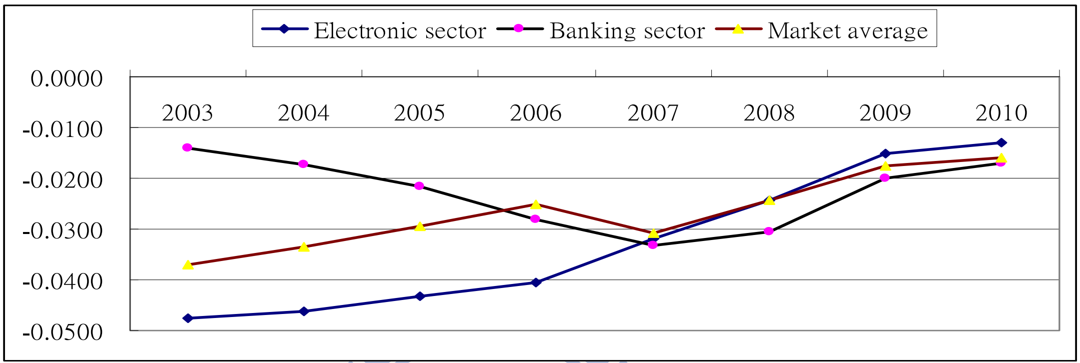


Fig. 6 △$CoVaR^i$ of electronic sector, banking sector and market average during 2003 to 2010

3.5 Concluding Remark

Many financial crises have resulted from systemic risk that was initially brought by idiosyncratic distress, spilling over across the related entities and finally causing a crunch of the entire system. The interaction between financial distress and systemic risk from the effect of idiosyncratic distress has been discussed recently. Amongst the idiosyncratic distress, sector-specific risk caused by a group of interconnected institutions has been accused of being the main reason for the increase in systemic risk, which led to the formalization of financial crises. In this research, Taiwan's stock market was taken as an example and data were collected from 2000 to 2010, which contained the 2001 dot-com bubble and the

2007-09 financial crisis. Following the CoVaR method of Adrian, Tobias, and Markus Brunnermeier (2010), this research attempted to empirically explore the impact of sector-specific idiosyncratic risk on the systemic risk of the entire financial system and tried to examine the link between financial crises, systemic risk, and the idiosyncratic risk of a sector-specific anomaly.

The results of the present study might be summarized by pointing out the following. First, the top 5 highest VaR sectors did not completely equal the top 5 highest risk contributory sectors to the system CoVaR. This showed there was no significant correlation between sector VaR and CoVaR, which was proved by a low correlation coefficient of 0.2715. The reason could be sector VaR and CoVaR captured different risk characteristics. The former assessed the risk of a sector in isolation, however, the latter appraised the systemic risk conditional on a specific sector being at its VaR level. Second, ranking as the top 2 largest transaction volume sectors in Taiwan's stock market, the electronic sector and banking sector also possessed the top 2 highest marginal risk contributions, $\triangle$CoVaR. This result could simultaneously prove the "too big to fail" and "too interconnected to fail" effects of financial system characteristics, which could not be fully obtained from the result of the VaR measure. Finally, linking the $\triangle$CoVaR measure to the global financial crises, $\triangle$CoVaR perfectly explained Taiwan's stock market disturbance during the 2001 dot-com bubble and 2007-08 financial crisis, both of which were resulted from systemic risk initially brought by a sector-specific idiosyncratic distress, finally causing the crunch of the whole system. This showed the financial crises, systemic risk, and the idiosyncratic risk of sector-specific anomaly are all linked.

This study has taken a successful step in the direction of measuring the marginal contribution risk of sector-specific effects on Taiwan's stock market. The finding is important for investors since it suggests the marginal risk contribution, △CoVaR, is more essential as an estimator of the risk of financial assets and could be a useful measure for investors to monitor financial risk. △CoVaR could help investors deepen systemic risk monitoring from a macro perspective into a micro prudential perspective. First, by integrating the monitoring of system VaR with sector-specific △CoVaR, the investors could shift attention from the VaR of overall system risk to the marginal risk contribution of the individual sector. Second, by identifying the influential risk indicators in risky and high △CoVaR sectors, the investors could focus on the important sectors and scrutinize their risk indicators, which can be regarded as early warning signals for sectors and for the entire financial system.

4 Conclusion

Financial risk is contagious. There are three-level risk contagions: company level, industry level, and country level. Systemic risk, defined as financial system instability caused by idiosyncratic events in financial intermediaries, is effect of risk contagion. Most recent financial crises are caused by systemic risk, especially at the beginning triggered by sector-specific failure, then spreading across countries, and finally leasing to worldwide financial crisis, such as the 1987 equity market crash, the 2001 dot-com bubble, and the 2007-09 financial crisis.

In this dissertation, country level of macro analysis and industry level of micro analysis centered on Taiwan financial risk contagion were discussed, the former studied "China's and U.S. volatility spillover effects on Hong Kong and Taiwan", and the latter explored "systemic risk in Taiwan". The result of the macro analysis indicated that while China's rapid economic growth and integration with Taiwan and Hong Kong, its stock market was independent and its co-moments with other markets were not significant. Risk contagion does not spread from China stock market to Taiwan or Hong Kong. A possible reason is that irrespective of the intensive economic integration of the three Chinese markets, China stock market is still very isolated and independent. The result is important because China stock market, with low co-moments with others, would be a good risk diversified investment and because U.S. stock market, with high co-moments with others, would be a good pricing indicator. In addition, result of the micro analysis showed sector-specific marginal CoVaR, i.e., $\triangle$CoVaR, perfectly explained Taiwan's stock market disturbance during the 2001 dot-com bubble and 2007-08 financial crises. It shows that risk contagion does spread from an industry to domestic market. Thus, by identifying the high △CoVaR sectors and their risk indicators, investors could employ the sector-specific △CoVaR measure to implement the systemic risk scrutiny from a macro perspective into a micro prudential perspective.

This study has taken a step in the direction of analyzing financial risk contagion from macro to micro and from internal to external. It is recommended the approaches outlined in this study be replicated in other stock markets or other financial assets. Moreover, it would be increasingly crucial to explore the influential indicators of the ΔCoVaR to predict in advance the marginal risk contribution based on the movement of the risk factors. However, because our sample market is very small compared with international stock markets, and the data period is relatively short, it is possible other stock markets may produce different results.

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