ESSAYS ON SEGMENTATION OF CHINESE STOCK MARKETS: NONLINEAR ANALYSES

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Summary

As a mechanism for the development of the Chinese stock markets, the Chinese government has adopted a market segmentation policy that divides its stock market into a domestic board (A shares) and a foreign board (B shares and H shares, etc). Because of the isolation of Chinese currency from foreign currencies, different information environments, different regulatory policies, and different investors, the segmented markets have shown different patterns of evolution.

Though there is a vast literature on various issues related to Chinese segmented stock markets, their analyses are usually based on traditionally linear econometric models, while the nonlinearity property in market variables has been neglected. In recent years, researchers have demonstrated numerous evidences of the nonlinearity in economic and finance time series.Thus previous analyses solely depending on conventional linear methods may lead to incomplete and incorrect statistical inference.

The objective of this thesis is to adopt three different nonlinear econometric models to explore three issues which have been widely studied in recent years. The nonlinear modeling techniques adopted in the essays have different features and advantages, which enable us to capture three different types of nonlinearity: i.e. regime structure shift, long memory process and nonlinear causality in financial time series. With these techniques, we study three topics with different research emphases. Investigating these issues from a nonlinear point of view will shed more light on understanding of the segmentation of Chinese stock markets.

The first essay adopts a nonlinear Markov switching GARCH model (MS-GARCH) to examine the volatility structure switching across high-low regimes in A-share and B-share stock indices in mainland China over years. This chapter aims to provide more insightful information on the evolution of volatility characteristics of the segmented stock markets. We find evidence of a regime shift in the volatility of the four markets, and the MS-GARCH model appears to outperform the single regime GARCH model. The evidence suggests that B-share markets are more volatile and shift more frequently between high- and low-volatility regimes. B-share markets are found to be more sensitive to international shocks, while A-share markets seem immune to international spillovers of volatility. Finally, we find volatility linkage asymmetry across A-share and B-share stock markets.

The second essay adopts a nonlinear Fractionally Integrated VECM multivariate GARCH approach to examine the bilateral relationships among the A-share and B-share stock markets in mainland China and the H-share stock market in Hong Kong. Our evidence shows that these stock markets are fractionally cointegrated. In each of the six pairs, the H-share stock market adjusts to return to equilibrium with the two A-share stock markets as well as the two B-share markets, while two B-share markets adjust to return to equilibrium with the corresponding two A-share markets. We conclude that A-share markets have strongest power in the long run. Analyses of the spillover effects across these markets indicate that the H-share market plays a very influential role in influencing segmented stock markets in mainland China. Investigation of the dynamic path of correlation coefficients suggests the relaxation of government restrictions on the purchase of B shares by domestic residents accelerates the market integration process of A-share markets with the B-share and H-share markets. The effects of the Asian crisis on the stock-return dynamic correlations vary across these markets.

The third essay adopts both linear and nonlinear Granger causality tests to investigate the lead-lag relation among four Chinese segmented stock markets before and after Chinese government relaxed the restriction on the purchase of B shares by domestic investors. The evidences show that there exists strong nonlinear dependence among the four stock markets. Our findings reveal that the causality relation among China stock indices is more complicated than what the linear causality test reveals. More specifically, only linear causality from Shenzhen A index to Shenzhen B index is present after China implemented the policy, while our nonlinear Granger causality test reveal evidence of stronger bi-directional causal relationship between two A-share markets as well as between two B-share markets after the implementation of the policy. Furthermore, A-share markets tend to lead their B-share counterparts in the same stock exchange since the implementation of this new policy.

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Chapter 1: Introduction

1.1 Research Background

China has experienced dramatic economic growth in the past decade. Its average annual growth rate is about 9%, much higher than that of the world economy. As one important component of the Chinese economy, Chinese stock markets have also expanded rapidly. Within only 11 years, the number of listed companies traded in Mainland China has grown from 323 in 1995 to 1380 in December 2005, and its total market capitalization has increased from RMB 348 billion to RMB 3243 billion.

As a mechanism for developing its stock markets, the Chinese government has adopted a market segmentation policy, which has two implications. Firstly, each company's stock is restricted to one of the two exchanges, i.e. Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). In this way, the markets in these two exchanges remain distinct. In addition, the companies listed in SHSE are likely to be state-owned big companies, many of which monopolize supplies to the domestic market (Kim and Shin, 2000). Whereas those listed in the SZSE tend to be smaller export-oriented companies, many of which are joint ventures. Although cross listing is not permitted, the two exchanges are subject to the same macroeconomic and policy factors.

Secondly, to cater to the needs of different investors, Chinese companies can issue A shares to Chinese citizens living in mainland China and B shares to foreign investors, including Chinese investors residing in Hong Kong, Macau, or Taiwan[1]. Though investors trading A shares outnumber those trading B shares, the former group is composed mostly of individual investors without much experience or many resources to obtain and analyze new information, while the latter group is dominated by experienced foreign institutional investors (Tian and Wan, 2004). A and B shares are listed on the SHSE and the SZSE, namely, SHA, SHB, SZA, and SZB. A shares are denominated in the local currency (RMB), while B shares are denominated in U.S. dollars on the SHSE and Hong Kong dollars on the SZSE.

Besides A shares and B shares, the Chinese government also allows some companies to issue red chip, H, N, and S shares in accordance with different listing locations and investors. Interestingly, although mainland enterprises are allowed to issue two classes of shares in China-related stock markets, the shares are usually observed to trade at significantly different prices[2]. Among these types of shares, H and red-chip shares are traded on the Hong Kong Stock Exchange (HKSE) and are denominated in HK dollars. H-shares are usually the stocks of state-owned enterprises (SOEs) incorporated in mainland China. Red Chips are the stocks of companies controlled by mainland government or SOEs, but incorporated in Hong Kong. The Hong Kong entity is usually a shell corporation of mainland counterpart and is

[1] This restriction was relaxed on February 19, 2001, when it became permissible for domestic citizens to buy and sell B shares. Since then, Chinese citizens are allowed to hold B shares. Though they still cannot freely exchange foreign currency, they are allowed to exchange some quota of foreign currencies and put them in special accounts to invest in B shares. Due to this policy more and more Chinese investors are willing to trade in B-share stocks now.

[2] A listed company can issue shares on either the A- and B-share markets, or the A- and H-share markets.

capitalized through public offering. The so called N shares and S shares are the stocks of Chinese enterprises that have been chosen to be listed on the New York Stock Exchange (NYSE) as American Depository Receipts (ADRs)[3] and in Singapore Stock Exchange (SSE). They are denominated in U.S. dollars and Singapore dollars, respectively.

Information environment and regulatory policies are also different among segmented stock markets. Because foreign broad stocks, namely red-chip, B, H, N and S shares, are traded in other locations and subject to different groups of investors and market conditions, the information environment and regulatory policies of these shares are different from those of A-share (Abdel-khalik et al. (1999), Cheng (2000) and Sami and Zhou (2004)).

The information environment of A shares seems to be dominated by local regulations and customs at the time of offering or trading. In addition, the information environment of A shares appears to be relatively unstructured, underdeveloped and is affected by informal communication between various groups. In addition, the financial reporting of A-share stocks adheres to the Chinese local markets, which are prepared and audited, respectively under the Chinese Generally Accepted Accounting Principles (Chinese GAAP). As to external monitoring, other than the roles played by state officials and appointed managers, external monitoring of A shares appears to be

[3] Most non-U.S. issuers enter the U.S. markets by creating ADRs. ADRs are issued by a U.S. depository bank (e.g., Bank of New York, Citibank, J.P. Morgan) and represent shares of a foreign corporation. The U.S. bank is responsible for currency conversion between underlying foreign shares and ADRs, for dividend payments, and for information collection and dissemination. All China-backed companies listed on NYSE are in the form of ADRs.

limited. Independence and social acceptance of auditing appear to be making slow progress, especially when the majority of domestic CPA (Certificated Public Accountant) firms are government owned[4].

In contrast, the information environment for the foreign broad shares is more structured, developed and is not too different from information environment present in developed capital markets. Their financial reporting adheres to International Accounting Standards (IASs) and financial statements are audited by CPA firms with international practice. The information-release requirements for these shares are more stringent than those for the firms issuing A-share only. Finally, foreign investors, mainly large financial institutions, also act as external monitors.

There are reasons for issuing different types of stocks in Chinese markets. First, the traditional economic units were believed to lack the capacity to compete with modern corporate power. To insulate these units from the impact of external shocks, the domestic broad was artificially separated from foreign broad. Second, issuances of a variety of stocks are designed to cater to the needs of different financial environments that will help Chinese businesses to raise capital in order to facilitate their functioning. However, due to the existence of dual economic characteristics, accompanied by the restriction of foreign currency conversion, different regulations and different information environments, the segmented markets have shown different patterns of evolution. Figure 1.1 shows these patterns[5].

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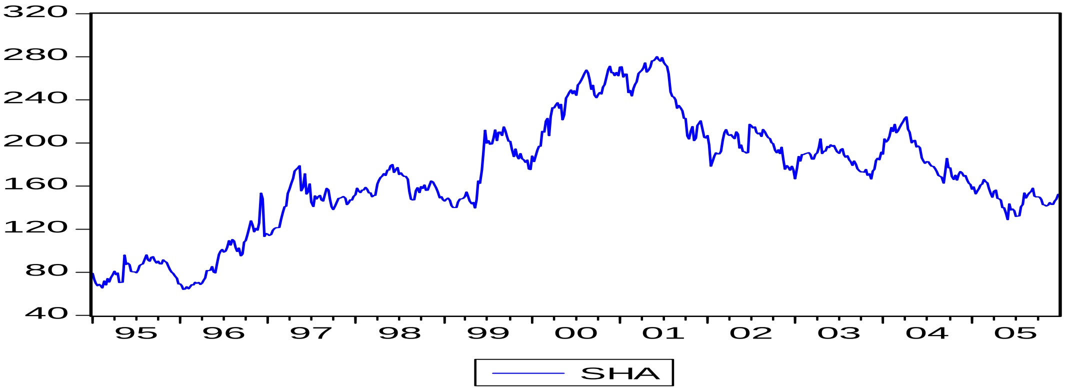
[4] For A-share, and the independence of the auditors is not guaranteed.

[5] As two A-share, two B-share and H-share are the focus of our research in this thesis, we present the price indices of these shares only.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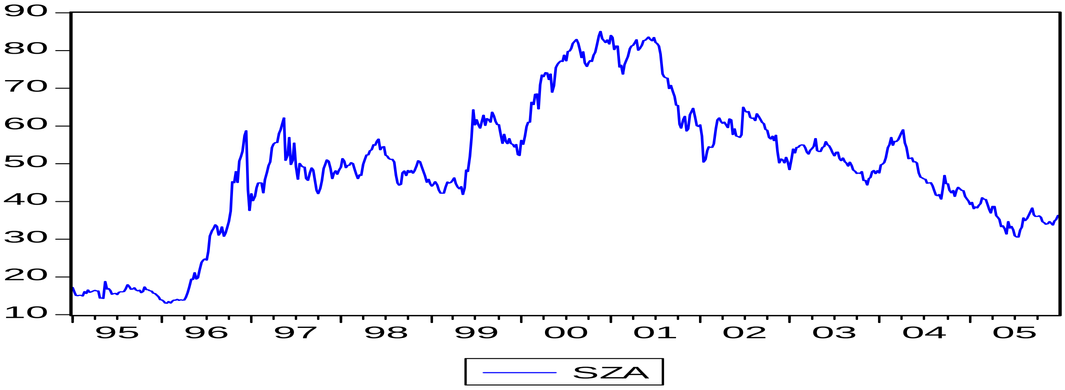
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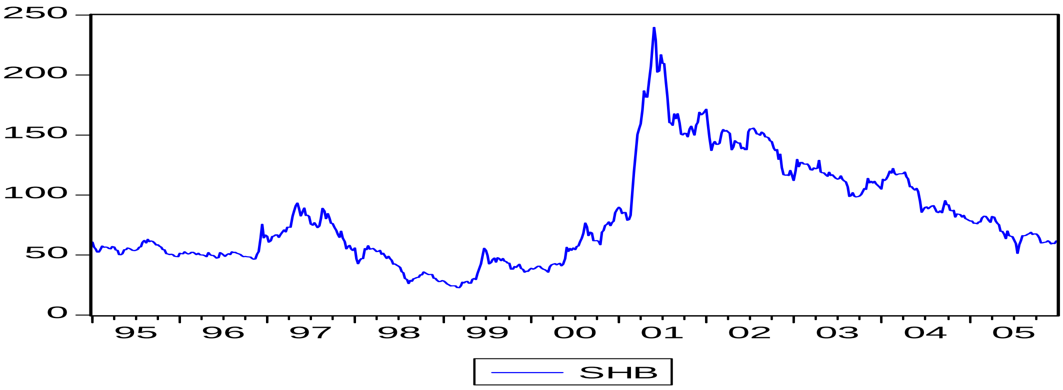
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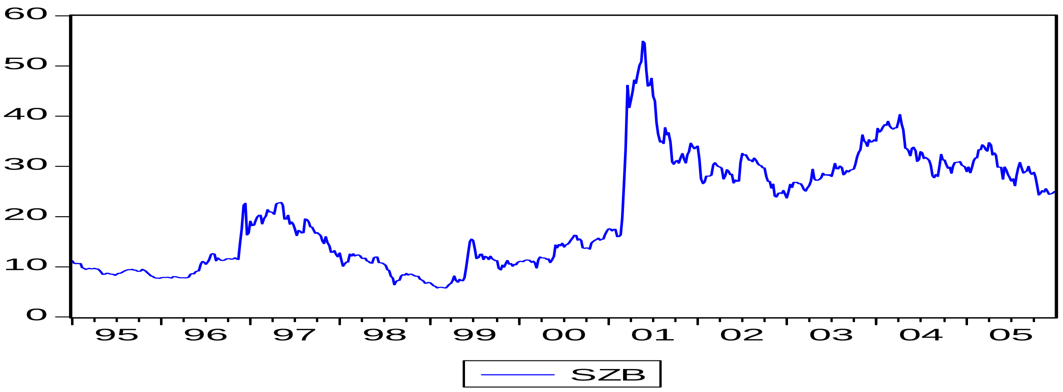
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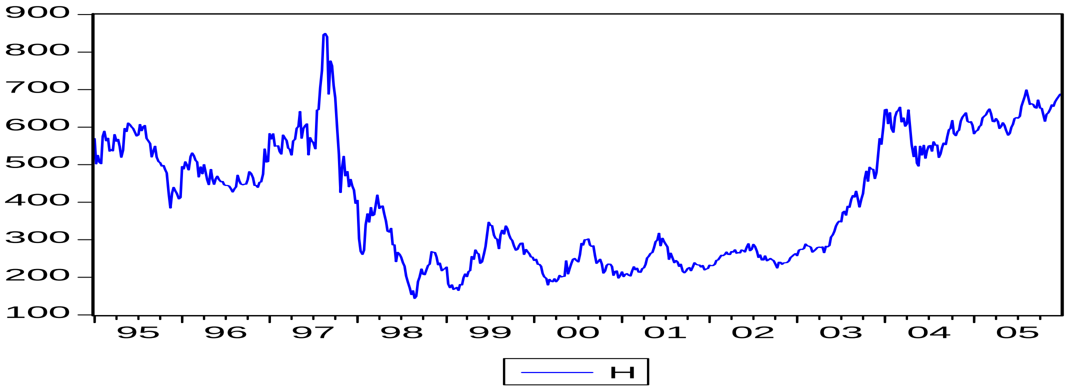

Figure 1.1

Price indices of Chinese stock markets

1.2 Objectives

Due to its rapid growth and unique features of market segmentation, Chinese stock markets have attracted great attention of investors and researchers. Many researchers have analyzed Chinese segmented stock markets and their research has focused on topics as diverse as, volatility behavior, volatility spillover, lead-lag relation in return, stock market efficiency, dynamic linkages with international financial markets, long run equilibrium relations among segmented stock markets, information asymmetry and price discount etc. However their analyses are usually based on traditionally linear econometric methodology while the nonlinearity property in market variables has been neglected.

In recent years, researchers have demonstrated numerous evidences of the nonlinearity in economic and finance time series.[6] Thus previous analyses solely

[6] For instance, there are reports of nonlinearity of the time series for exchange rates (Sarno, 2000; Baum *et al*., 2001; Liew *et al*. 2003, 2004, 2005; Baharumshah and Liew, 2006; among many others), interest rates (van Dijk and Franses, 2000; Shively, 2005; Baillie and Kilic, 2006), stock prices (Kanas, 2005; Lim and Liew, 2006), relative income (Liew and Lim, 2005), balancing items (Tang *et al*., 2006), etc..

depending on conventional linear methods may lead to incomplete and incorrect statistical inference.

The objective of this thesis is to adopt three different nonlinear econometric models to explore three issues which have been widely studied in recent years. The nonlinear modeling technique adopted in each essay has *different features and advantages*, which motivate us to study topics focusing on *different research emphases for each essay*[7]. Investigation of these issues from a nonlinear point of view will shed more light on understanding of the segmentation of Chinese stock markets. The empirical results derived from this thesis reveal more complicated nature of segmented stock markets, which, in turn, provides useful information to investors and fund managers for their investment decisions and strategy in these markets. Our findings are also useful for policy makers in setting regulations for these markets.

1.3 Survey of This Thesis

The first essay investigates volatility structure switching across high-low regimes in four stock indices in mainland China (SHA, SZA, SHB and SZB) over years. This chapter aims to provide broader and more insightful information on the evolution of volatility characteristics of segmented stock markets in China. The structure stability issue is particularly relevant to China, since the stock markets over recent years have experienced a sequence of policy innovations, reforms, "Asia disease," and "Russian crisis." All these shocks are likely to have a significant impact on return correlations

[7] There are many forms of nonlinearity. Each type of model can only address one specific form. In addition, three essays focus on different research issues in the Chinese segmented market.

and volatility covariances as is evident from Karolyi and Stulz's study (1996). To provide more insight into the volatility characteristics and evaluate how external shocks are affecting Chinese stocks, it is crucial to distinguish between the high-volatility state and the low-volatility state, since market behavior is expected to be different in different states. This motivates us to adopt the Markov switching GARCH (MS-GARCH) model (Gray, 1996), which allows stochastic regime shifts in both the conditional mean and conditional volatility, to analyze the volatility evolution in Chinese stock markets. More important, this model has the capacity to deal with abrupt changes. The by-product of the estimation of Markov switching GARCH model, estimates of the "smoothed probability," offers us a very powerful tool for studying the evolution of volatility switching behaviors in each of the segmented stock markets. In our first essay the features of MS-GARCH model produce interesting results.

The second essay investigates the bilateral relations among two A-share and two B-share stock markets in mainland China and the H-share stock market in Hong Kong. Within a multivariate system, this essay aims to explore the long-run equilibrium, short run dynamic and spillover effects among these markets. Another purpose of this essay is to evaluate the effects of changes in financial policy on the dynamic correlations between the markets. In particular, we examine the fractional cointegration mechanism with a nonlinear Fractionally Integrated VECM (FIVECM) model. As a generalization of the standard linear VECM, which allows only the first-order lag of the cointegration residual to affect the equilibrium relationship, the nonlinear fractional integrated VECM is superior because it not only enables investors to reveal the long-term equilibrium relationships and short-run adjustments among co-integrated variables but it also accounts for the possible long memory in the cointegration residual series that otherwise might distort the estimation. In addition, this chapter specifies the conditional variances of VECM residuals with the multivariate GARCH model (Yang, 2001, Giovannini and Grasso, 2004 and Chen et al., 2006). Within this framework, both long run relationships, short term adjustment and empirical relationships in the mean as well as volatility in a cross-market setting can be simultaneously estimated, which is expected to produce more consistent and accurate estimation. The empirical results derived from this essay reveal the nature of the complicated structure between two different markets, which, in turn, provides additional information to investors and fund managers for their investment decisions and strategy in these markets.

On February 19, 2001, Chinese government adopted a new policy which removes the previous restriction on trading B shares by domestic citizens. Due to foreign exchange restriction, they may exchange some quota of foreign currencies and put them in special accounts for investment in B shares. Since the implementation of this policy, more and more Chinese investors now are willing to trade in B-share stocks. The third essay thus focuses on analyzing the effect of change in the government policy concerning the lead-lag relations among segmented A-share and B-share markets. The unique features of A-share and B-share markets in mainland China provide a sound background to examine a few well-known finance theories on information transmission between different investors and between stocks of different sizes. The financial literature is rife with claims on lead-lag relationship among Chinese segmented stock market. However their methodology is based on traditional linear models such as Granger causality test, which is well known to possess a low power in detecting nonlinear causal relationships. To circumvent this problem, this essay contributes by utilizing a nonlinear Granger causality test developed by Hiemstra and Jones (1994) in order to investigate existence of any nonlinear lead-lag relationship among Chinese segmented stock markets. As this nonlinear test has very good power in detecting nonlinear relationships between economic and finance variables, it has been widely used by researchers especially in recent years. As indicated by our empirical results, nonlinear Granger causality test provides very different findings from those based on its linear counterpart. Therefore, this essay also recommends that nonlinear Granger causality test should be used in conjunction with the conventional linear Granger causality test in practice.

Chapter 2: Literature Review

Chinese stock markets have attracted great attention of investors and researchers for its rapid growth and unique features of market segmentation. The literature is filled with many research papers on Chinese segmented stock markets. The previous research related to this thesis can be categorized into following areas in this chapter.

2.1 Price Discount Puzzle[8]

Various papers have explored the distinct price behaviors of stocks that are simultaneously traded in Chinese segmented markets. Among these studies, one very interesting issue related to this thesis is the price differentials among different classes of shares.

Using one year of weekly data (March 1992 to March 1993) on eight stocks that have both A shares and B shares for that period, Baily (1994) first reports that B shares traded by foreign investors are sold at discounts relative to A shares traded by domestic investors, a phenomenon that is inconsistent with the price premiums commonly found in other countries (e.g., Bailey and Jagtiani, 1994; Domowitz et al., 1997; Stulz and Wasserfallen, 1995; Bailey et al., 1999).

Several explanations have been provided for this exception. Baily (1994) hypothesizes this could be due to a lower cost of capital in China, a perception that Chinese economic and political risk is not diversifiable, or unduly optimistic Chinese

[8] Although price discount puzzle is not the main focus of this thesis, the literature reviewed on this issue provides useful information to understand Chinese segmented stock markets, which is related to the three topics of this thesis.

investors as a source of high prices of A-share stocks. However, his results are based on a basic statistical analysis of one year's weekly data. In a later comprehensive study of 11 countries with similar stock market segmentation structures, Bailey et al. (1999) conclude that China is a "strange" case and "difficult to explain."

Applying both cross sectional and time series analysis, Ma (1996) extends Bailey's (1994) work with a larger data set (weekly data of 38 listed companies that have both A and B listed shares, with sample period from August 1992 to August 1994). Based on his analysis, he provides five possible explanations for the puzzle of B-share discounts. These are (1) a lower cost of capital in China; (2) the speculative behavior of Chinese investors; (3) low liquidity in the market for B-share stocks; (4) low demand for B-share stocks; (5) regulatory changes. He argues that the Chinese markets are highly speculative and are driven by the risk preferences of Chinese investors.

Fernald and Rogers (1998) argue that the lower return required by domestic investors, and little domestic investment opportunities in China contribute to the price discount. Gordan and Li (1999) argue that legal restrictions create the segmented market and limit investment opportunities. Thus, domestic investors have inelastic demands for equity due to insufficient supply, pushing up the price of class A shares.

Using data of 70 listed companies for the period January 1995 to August 1999, Bergstrom and Tang (2001) address the price discount issue with both cross-sectional analysis and time-series analysis. From the cross-sectional analysis, they find that information asymmetry between domestic investors and foreign investors, illiquid trading of B shares, diversification benefits from investing in B shares and clientele bias against stocks on SHSE are significant determinants in explaining the cross-sectional variations in the discount on B shares. In additional, the significance of information asymmetry and clientele bias confirms the findings of Chakravarty et al. (1998). Moreover, their time series analyses confirm the explanatory power of risk-free return difference and foreign exchange risk for the time-variations in the discount.

Chen et al. (2001) implement several tests to examine the price difference between A-share and B-share stocks. In their paper, they consider four hypotheses, i.e. asymmetry information hypothesis, differential demand hypothesis, liquidity hypothesis and differential risk hypothesis. Their panel data analysis indicates that price difference is mainly due to illiquid B-share markets: relative illiquid B-share stocks have a higher expected return and are priced lower to compensate foreign investors for increased trading cost. However, they find that between the two classes of shares, B-share prices tend to move more closely with the markets fundamentals than do A-share process. They conclude that there exist A-share premium rather than B-share discount in Chinese segmented stock markets.

Focusing on risk analyses, Zhang and Zhao (2003) develop an model to decompose the price differential into components attributable to the effects four different risks, such as political risk, exchange rate risk, interest rate risk and market risk. They attribute the price differentials between A- and B-, and B- and H-shares to the different responses of the respective investors to country-specific risk. Their empirical tests show there is a significant difference between the foreign investor's attitudes toward the political risk of China. Compared with domestic investors of A-shares, foreign investors would require a higher rate of return for B-shares to adjust for the country specific political risk of China. Interestingly, they find the valuation differential between A-shares and H-shares is more related to firm-specific risk and market risk premium differentials. They suggest that their finding implies that, because of the increasing integration between the Hong Kong and Chinese mainland markets ("one country and two systems"), Hong Kong investors, who have a greater tolerance of the political risk involved in H-shares, thus are willing to pay a higher price for H-shares relative to B-shares.

Li et al. (2006) conducts an exploratory study of price discounts on H-share relative to A-share. His approach is the conventional asset pricing theory. By studying the price behaviors of 13 firms both listed on mainland and Hong Kong stock markets over January 1997–March 2002, they find that A-share excess returns are primarily explained by the market risk premium from the mainland China. In contrast, their results show that H shares excess returns can be explained by risk premiums from both Hong Kong and mainland China's markets, with a larger portion pertaining to the former. These results indicate that the price differentials in the Chinese dual-listed A shares and H shares are mainly attributable to the deviation in the systemic risk premiums of the local markets. Further more, they find that the exchange rate change between the currencies of Hong Kong and mainland China does not have any significant effects on the price discounts of H shares below A shares.

2.2 Volatility Modeling

Modeling the volatility is an important part of a financial economist job in any financial market. Due to its importance, several scholars have examined the behavior of the volatility of Chinese segmented stock markets.

Bailey (1994) analyzes one year of weekly data (March 1992 to March 1993) on eight stocks that had both A shares and B shares for that period. He finds B shares to be more volatile than A shares.

Yu (1996) utilizes the ARCH/GARCH framework to study the volatility of the Chinese stock exchanges. He studies daily index return data for both the Shanghai and Shenzhen exchanges from their inception date (SHSE December 19, 1990; and SZSE, April 3, 1991) to 28 April 1994. He finds evidences in favor of an ARCH (2) model for the Shenzhen index returns and a GARCH (1,1) model for the Shanghai index returns.

Su and Fleisher (1998) also adopt an ARCH/GARCH framework to study the volatility of the Chinese segmented stock markets. In this paper, they study the distributional assumptions underlying the ARCH/GARCH model with a view to explaining the fat-tailed property of Chinese stock returns. Three possible error distributions, i.e. Normal, Student-t and Stable are considered in their analyses. Their empirical results show Stable distribution is favored for all the markets. Finally, they report that the volatility changes can be linked to changes in the market regulation policies such as price limit policy.

Su and Fleisher (1999) find that A-shares are much more volatile than B-shares. They try to explain their finding with an assumption that the contemporaneous dependence of stock returns and trading volume on an underlying mixing variable represent unobserved intensity of information arrival. They estimate a dynamic model under a modified mixture of distribution hypothesis (MMDH). In this study, they offers three key findings to explain this question: (1) news enters the A-share market more intensively than the B-share market; (2) news is more highly correlated with trading for A-shares than for B-shares; and (3) news is more persistent for A-shares than for B-shares. Their results also indicate that cross-section variation in volatility-related expected intensity of information flows and the amount of informed trading are related to information correlates, namely number of investors, variation in profits, and firm size. They conclude that the MMDH provides useful insights into the underlying causes of A- and B-share volatility behavior in Chinese stock markets.

Yeh and Lee (2000) analyze the asymmetric reaction of return volatility to good and bad news by utilizing GARCH model. They report that the impact of bad news (negative unexpected return) on future volatility is greater than the impact of good news (positive unexpected return) of the same magnitude in Taiwan and H-share in Hong Kong However, just the opposite is found in the Shanghai and Shenzhen B-share stock markets, implying good-news-chasing behavior of the investors. They also find that the leverage and volatility feedback effects, although supported by Taiwan and H-share data, failed to capture the essence of investor behavior in

Mainland China. Moreover, the investors in the two B-share markets in mainland China tend to support the trading noise hypothesis.

Fredimann and Kohle (2003) analyze volatility clustering in two A-share and two B-share indices of the Chinese stock markets with an EGARCH model and a GJR GARCH model. They find that these two approaches perform quite similarly. They also examine the effect of reintroducing daily price change limits in December 1996 and find that it is successful in reducing the deterministic volatility component significantly in the stock indices.

2.3 Information Asymmetry and Information Transmission

Another interesting issue closely related to Chinese stock market segmentation is the information asymmetry pattern in Chinese stock markets. Some equilibrium pricing models of Chinese market segmentation (e.g., Chakravarty et al. 1998) are based on the assumption of the information asymmetry pattern in Chinese stock markets. Many other works concerning Chinese stock markets, such as return volatility (Su and Fleisher, 1999) and initial public offerings (Mok and Hui, 1998) have also produced important implications for the information asymmetry issue, regarding whether foreign or domestic investors are better informed in these markets. In this section, we review the key findings in the literature.

Chakravarty et al. (1998) develop a model, incorporating both information asymmetry and market segmentation, and derive a relative equilibrium pricing models for A shares and B shares. They find the prices of B-shares are sensitive only to

A-share prices and have little relationship to the foreign markets. However, they find the prices of A-shares are not sensitive to B-share prices. Based on this, they argue that, due to language barriers, different accounting standards and a lack of reliable information about the local economy and firms, foreign investors in B-share stock markets have less information on Chinese stocks than domestic investors[9].

By focusing on relationship between the differences in A- and B-share expected intensity of information flows and the average B-share discounts, Su and Fleisher (1999) hypothesize that the information asymmetry increases international investors' required risk premium for B-shares and reduces their incentives to trade. As a consequence, information-induced B-share trading volume is less than that of A-share. Their empirical result suggests that one of the reasons for B-shares discount, even though both share types are entitled to the same rights and dividends, is that the intensity of information arriving at B-share markets is smaller than for A-share markets, which lends support to their hypothesis that information asymmetry is important in explaining B-share discounts. Generally, their conclusion is consistent with that of Chakravarty et al. (1998), which supports foreign investors are less informed.

Using portfolio returns sorted by liquidity, Chui and Kwok (1998) find positive cross-autocorrelation between B- (A-) share stock returns on time t-1 and the corresponding A- (B-) share stock returns on time t. They conclude that both A-share and B-share affect each other through prior price movement. Further analysis show

[9] They believe that this is one reason for the large price discount of *B* shares.

that A-share traders condition much of their trading on the more informative B-share returns, implying A-share investors tends to gain more information from the trading of B-shares and information mainly flows from the price of B-shares to the price of A-shares. In all, they find foreign investors are better informed. They think this is because foreign investors may receive information faster than the domestic investors due to information barrier in Chinese stock markets created by local government. Their results, however, are based on an implicit assumption of a complete long-run segmentation between A- and B-shares. This is no basis on which to make such assumptions about the relationship between the prices of A- and B-shares (Sjoo and Zhang, 2000).

Focusing on the initial public offerings IPOs in SHSE, Mok and Hui (1998) find that A-share initial public offerings IPOs in SHSE are 289% under priced, against a mere 26% for B-share IPOs. Based on the theory of Rock (1986), who postulates that information about the issuing firm's value is distributed asymmetrically among the informed and the uninformed investors, they find information asymmetry are key determinants of this large underpricing discrepancy. They argue that the domestic A-share investors are inevitably naive both in the concepts and practices of stock investment. In contrast, company information disclosures to foreign investors are well provided in B-share IPOs markets. As a consequence, the foreign investors are much better informed than the domestic Chinese investors, which would increase the ex-ante uncertainty for A-share IPOs, and thus a higher underpricing for A-share IPOs than B-share IPOs is expected.

Recently, several groups have studied the information asymmetry and information transmission among these Chinese segmented stock markets by carrying out Granger causality tests.

Laurence et al. (1997) examine causality among the two A-share and two B-share stock markets in mainland China by applying bivariate causality tests. Their results suggest a causal relationship running from the SHB to all other markets and from SHA and SZB back to SHB. They argue that the causal relationships from the B-share markets to the A-share markets imply that foreign investors in B-share markets exert a significant influence on the markets open only to Chinese nationals.

Based on the returns of portfolios of individual stocks instead of stock indices, Sjoo and Zhang (2000) find that in the larger and more liquid SHSE, information flows from foreign to domestic investors, while in the smaller and less liquid SZSE, the information diffusion goes in the opposite way. Therefore, their study indicates that the direction of the information diffusion is determined by the choice of stock exchange. They argue that foreign investors drive the prices of A shares in SHSE because domestic investors have problems in acquiring relevant and trustworthy firm information from domestic and foreign media. Domestic investors therefore condition their investment decisions on observed B-share prices. However, in the smaller SZSE, this foreign information advantage might not exist and foreign investors rely on the domestic investors to obtain the information on the prospects of the listed companies.

Using four Chinese stock indices and applying Granger causality test, Kim and Shin (2000) find that stocks listed in Chinese stock exchanges, particularly B shares, tend to lead H-shares in Hong Kong after 1996. They argue that Chinese stocks listed in the two exchange of mainland China can incorporate Chinese information into the price more efficiently than H-share stocks in Hong Kong. Additionally, they find A-shares tended to lead B-shares before 1996, but such relationships either disappear or are reversed after 1996. They argue that A-share markets may reflect new information more efficiently into price through active trading. Finally, they find B shares listed in SHSE tend to lead those in SZSE before 1996. Since then, the situation has been reversed. They attribute this finding to a substantial increase in trading activities in Shenzhen B shares.

Focusing on risk premiums, Fung et al. (2000) apply Granger causality test for the cross-market relation between SHSE and SZSE. Their results suggest the latent risk premiums in SZA or SZB shares do not reflect information of the latent risk premiums in the SHA or SHB. In contrast, the latent risk premiums in SHA or SHB respond to information in the corresponding market on the Shenzhen stock exchange. However, the latent risk premiums in Shenzhen A or B shares do not reflect information of the latent risk premiums in SZA or SZB. Therefore, their study suggests the Shenzhen markets lead the Shanghai markets rather than the other way around.

Using daily time series and a new Granger causality testing procedure developed by Toda and Yamamoto (1995)[10], Tian and Wan (2004) investigate a causal relationship among A-, B- and H-shares. Their results suggest that there are

[10] This is still a linear econometric methodology.

bi-directional causal relations between two B-share markets during the entire period between 1993 and 1999 but this pattern does not exist within two A-share markets. Furthermore, they provide evidence of a Granger causality running from H-share market to two B-share markets and from SHB to all the rest Chinese markets for the post-1996 period. Overall, their results suggest that foreign investors in B-shares market particularly Shanghai market might more cost effectively acquire both market-wide and company-wide information than domestic traders and Hong Kong traders in turn have better information than these foreign institutional investors in B-share markets in Mainland China.

Yeh and Lee (2000) examine information transmission of contemporaneous and cross-period by exploring the interaction of unexpected returns among these four markets. The results of their VAR model reveal that the H-share market does not have impact on the Shanghai and Shenzhen composite indices, which are dominated by A-share. However, the unexpected shocks coming from the H-share stock market do have most influential contemporaneous and cross-period influence on the Taiwan, Shanghai, and Shenzhen B-share markets.

Several researchers have extended the research work from return linkages to volatility linkage among Chinese segmented stock markets.

Focusing on causal relationships in both stock return and return volatility, Chen et al. (2001) test the Granger causal relationship between A-share and B-share stocks. Their results show that, there is no causal relations between A-share return (volatility) and B-share (volatility). This implies that the changes in A-share returns are not informative for the change in B-share returns, and vice versa[11].

Li (2003) applies a TGARCH model and he finds that information transmission in return volatility, which is defined as the impact of volatility of one market on the volatility of the other market, is weak. His results indicate the existence of three groups of information linkages, respectively. He uses the symbol of arrow to indicate the direction of information transmission and summarizes his finding as: (1) no information transmission (SHA←SZA, SHB←SHA, SHB←SZB, SZB←SHA and SZB←SZA); (2) weak information transmission (SHA←SHB, SHA←SZB, SHB←SZA, SZA←SHB and SZA←SZB); and (3) strong information transmission (SZA←SHA and SZB←SHB).

Brooks and Ragunathan (2003) examine the Chinese stock volatility linkage with AR, VAR and univariate GARCH model. Unlike Chui and Kwok (1998) who find evidence of spillovers from B shares to A shares, bi-directional spillovers are found for stock return in their analysis. In contrast, no such spillovers are found for the volatility of returns: A-share market volatilities are driven by factors in A share markets themselves, while B market volatilities are driven by factors in B-share markets themselves. They conclude that their results may be consistent with Su and Fleisher's (1999) findings of news having impacts A-shares and B-shares in a different manner.

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[11] Their finding is not consistent with the asymmetric information hypothesis, which anticipates a one way causal direction between A-share return (volatility) and B-share (volatility).

A few researchers also try to investigate the information transmission mechanism within multivariate GARCH framework, which is believed can capture both return linkages and volatility linkages between any two segmented stock markets.

Pong and Fung (2000) apply multivariate EGARCH-in-mean model to examine the information flow between H-shares, red chips, Shanghai Composite and Shenzhen Composite. They find there is no linkage between the conditional mean and volatility in all index returns. Both current and future conditional returns and volatility in all indices can be predicted by past information with the exception of the return on the Shenzhen Composite Index. They provide evidences of significant return spillover effects from the red-chip to the Shenzhen Composite index, then from the Shenzhen Composite index to the Shanghai Composite index, and from the Shanghai Composite index to the H-share index. As to volatility spillovers, they find volatility spillovers running from the red-chip market to the Shanghai equity market and the H-share market; then from the H-share market to the Shanghai equity and the Shenzhen equity market; and finally from the Shenzhen equity market to the Shanghai equity market. Generally, this study demonstrates that red chips play a leading role in the flow of information among China-backed securities.

Adopting VAR and bivariate GARCH-M models, Yeh et al. (2002) analyze the information content in premiums of A shares over B shares. They find that the unexpected changes in the premium ratio of A-share price over B-share price contribute to the return volatility of both A and B shares.

Using weekly stock index data from the period 1992 through 2005, Zheng and Wong (2007) employ a two-stage bivariate GARCH model incorporating external shocks, to study spillover effect between price return of A-share and B-share and the impacts of US and Hong Kong on Chinese markets. Their empirical results show that overall, there are spillover effects between A-share and B-share but the evidence is not strong. In Shanghai markets, B-share is more influential in the information transmission. However, in Shenzhen markets, the spillover effect direction is more from A-share to B-share. Moreover, they provide evidence that external effects from US and Hong Kong market are much stronger after 1996 and that Hong Kong, as a neighbor of mainland China's economy, is more influential on Shanghai and Shenzhen stock markets than US -the superpower economy in the world.

2.4 Long Run Relationships

Ahlgren et al (2003) use a panel cointegration method to examine the cointegration between the A and B share prices on two Chinese stock exchanges. The data they use is the monthly data of 88 firms listing both A and B shares on either of two stock exchanges and sample period is from January 1993 to July 2002. They find that the A and B shares prices are cointegrated. They therefore conclude that domestic and foreign investors share information in the long run. Further more, their results show that cointegration is more likely to be found for firms in the service sector and for firms that listed their B shares recently.

Applying a recursive cointegration technique (Diamandis et al., 2000; Hansen and Johansen, 1993) and standard cointegration technique, Yang (2003) analyze the long run relationship between A-share markets and B-share markets and H-share and red-chip in Hong Kong. He finds that each of six markets is not linked with other markets in the long run.

Applying standard cointegration technique, Geng et al. (2005) find there are cointegration relations between two A-share markets as well as between two B-share markets. However, they do not find the evidence supporting A-share and B-share markets are cointegrated with each other.

Chapter 3: An empirical analysis of stock volatility under segmented Chinese stock markets: A Markov switching GARCH approach

3.1 Introduction

As a mechanism for the development of the Chinese stock markets, issues of Chinese stocks are mainly divided into A shares (SHA and SZA) and B shares (SHB and SZB); both A shares and B shares are listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) of mainland China.[12]

Researchers in international finance (Frankel and Schmukler, 2000; Yang 2003) recognize that the issue of market segmentation is closely tied to information asymmetry. Given the fact that rational B-share investors have relatively less knowledge about Chinese corporate structure and market fundamentals, they are unwilling to pay the same prices as the well-informed domestic investors do. Asymmetric information thus implies a discount on B-shares (See, for example, Bailey (1994), Su (1998) and Chen et al. (2001)).[13]

A separate line of research has been advanced by examining the linkage between Chinese stock markets and international stock markets (See, for example, Chakravarty et al. (1998), Lean and Wong (2004), Brooks and Ragunathan (2003), Wang and Firth

[12] As these four shares are the main components in the Chinese markets and they are all traded in mainland China, our investigation shall focus on these four markets.

[13] Following this line of reasoning, Chakravarty et al.(1998) and Su and Fleisher (1999) argue that domestic investors are better informed than foreign investors about the value of local assets because of the familiarity of the language, culture, and institutional setting. However, no supportive evidence is found by Chui and Kwok (1998) and Mok and Hui (1998).

(2004) and Zheng and Wong (2006)) or the linkages among four segmented markets (See, for example, Laurence et al. (1997), Sjoo and Zhang (2000), Kim and Shin (2000), Fung et al. (2000), Yeh and Lee (2000), Tian and Wan (2004), Li (2003) and Brooks and Ragunathan (2003)).[14]

Notice that the evidence on the stock return relationship between A- and B- share markets or their linkages with foreign markets is useful, since this information can be used to justify market efficiency or to construct an optimal, internationally diversifiable portfolio. The evidence of volatility spillover is also meaningful, since it provides information about checking for risk shifting. Despite the investment/financial significance of the stability of the stock return correlations and cross-market volatility covariances, very few attempts have been made to investigate volatility changes across regimes and markets in Chinese stock indices. This stability issue is particularly relevant to China, since the stock markets over recent years have experienced a sequence of policy innovations, reform, "Asia disease," and "Russian crisis." All these shocks are likely to have a significant impact on return correlations and volatility covariances as is evident from Karolyi and Stulz's study (1996). To provide more insight into the volatility characteristics and evaluate how external shocks are affecting Chinese stocks, it is crucial to distinguish between the high-volatility state and the low-volatility state, since market behavior is expected to be different in different states. This motivates us to adopt the Markov switching GARCH (MS-GARCH) model, which allows stochastic regime shifts in both the

[14] For detailed information about these papers, please refer to Chapter 2.

conditional mean and conditional volatility, to analyze the volatility behavior in Chinese stock markets[15]. More important, this model has the capacity to deal with abrupt changes; the by-product, estimates of the "smoothed probability," offers us a very powerful tool for studying the volatility of switching behaviors in each of the segmented stock markets.[16]

The remainder of this chapter is organized as follows. Section 3.2 briefly reviews the features of Markov switching models and discusses the MS-GARCH model specification as well as its estimation procedure. Section 3.3 presents the data used and their corresponding descriptive statistics. Section 3.4 provides empirical results of the MS-GARCH model and a discussion. Section 3.5 investigates volatility spillover effects among the four segmented markets. Section 3.6 contains concluding remarks.

3.2 Methodology

3.2.1 Brief Review of Markov Switching Models

Many economic and financial time series exhibits occasional structural breaks in their levels or volatility. Examples of those include the October 1987 crash of stock market and July 1997 Asia Financial Crisis. Regime shifts such as these extreme events induce substantial nonlinearities in the stochastic process. This has led to much interest among econometricians in models which have the ability to adequately

[15] A few researchers (see for example, Bailey (1994), Yu (1996), Su and Fleisher (1998, 1999), Yeh and Lee (2000) and Fredimann and Kohle (2003) have examined the volatility issue of Chinese stock markets, please refer to Chapter 2 for more information.

[16] The properties of the Markov switching GARCH model and its strengths will be discussed in more detail in the next section.

capture nonlinearities arising from the stochastic shift in regimes (or states). One such class of model is Markov switching model, which originally proposed by Hamilton (1989) in studying GNP of the USA.

In the Markov switching models, the mean and (or) variance of a time series can switch stochastically between a finite number of regimes where the regime could represent distinct phases such as economic expansion or contraction as in Hamilton (1989) or stages of high and low volatility in stock market associate with different states of the business cycle as in Hamilton and Susmel (1994). See also Cai (1994) and Fong (1997) for more information in this line. In all these models, the transition between regimes from one period to another is assumed to follow a finite-order Markov process (usually the first order).

Markov switching models are attractive to researchers for many reasons. Firstly, in Markov switching models, regimes are assumed to be endogenously decided. This feature enables regime shifts can be modeled as a systematic part of data generating process. Secondly, regimes are not assumed to be observable to the researchers. Instead, they are treated as latent variables which can nevertheless be inferred on the basis of observed data (i.e. data itself decides the regime characteristics). Thirdly, regime shifts are a source of nonlinearity in the data generation process. Markov switching models provide tractable approach for modeling these nonlinearies. Fourth, Markov switching models are appealing to diverse group of researchers. For example, economic historians and policy makers may wish to understand the timing, duration and causes behind regimes shifts. These issues can be analyzed with the aid of smoothed probability curve which is an output of the estimation process. This curve essentially summarizes the probability of each regime at any time t over sample period, conditional on the whole sample of data available. For example, probability curve has been used in the literature to "date" business cycle turning points (See for example, Hamilton 1989 and Filardo 1994).

All the features above, combined with the possibility this nonlinear models may deliver better forecasts than linear models, provided for a growing number of successful applications using the Markov switching models. The time series examined in these applications include interest rates (Hamilton 1988, Cai 1994 and Gray 1996), exchange rate (Engle and Hamilton 1990), stock returns (Turner et al. 1989, Schwert 1989a, 1989b, Hamilton and Susmel 1994, Fong 1997, 2003 and Scaller and Van Norden 1997), future market return (Fong 2001, 2002), stock index options (Duekker 1996), aggregate output (Hamilton 1989, Lam 1990) and arrogate consumption (Cechetti et al. 1990)[17].

3.2.2 Markov switching GARCH model

3.2.2.1 Structure of the model

The observed financial time series often undergo alternating periods of calm and turbulence with clusters of volatility. To model this phenomenon, a GARCH type model has been widely used (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Bollerslev et al., 1992). Schwert and Seguin (1990); Nelson (1991); Engle and Mustafa (1992)

[17] For detailed review of Markov switching models, please refer to Fong et al. (2003).

point out that GARCH models may be limited in their ability to model the volatility of financial time series if structural breaks, caused by certain dramatic evens such as the stock market crash in 1987, are present. This means that to obtain more robust estimates of conditional volatility would require a more general class of GARCH models, allowing for regime shifts as part of the data-generating process.[18]

The Markov switching ARCH/GARCH models introduced by Hamilton (1990), Hamilton and Susmel (1994), Cai (1994), and Gray (1996) help us to address this issue[19]. These models allow the conditional volatility process to switch between a discrete number of states, with the transitions between states governed by a hidden and finite order Markov chain. In addition, the transition probability of the Markov process determines the probability of volatility switching, thus indicating the expected duration of each regime. To examine the behavior of the conditional volatility of return of the four segmented Chinese stock markets by incorporating these dynamic features, in this paper, we apply a Markov Switching GARCH model (MS-GARCH) by first employing a Markov switching model proposed by Gray (1996) as a mixture-of-distributions representation such that:

$$R_t \mid \Omega_{t-1} \begin{cases} N[\mu_{1t}, h_{1t}] & with \quad probability \quad p_{1t} \\ N[\mu_{2t}, h_{2t}] & with \quad probability \quad (1-p_{1t}) \end{cases} \tag{3.1}$$

[18] Although the power ARCH model has been designed to take care of the long memory property of the stock return volatility, the regime shift issue has not been resolved (Ding et al., 1993).
[19] For bivariate Markov switching GARCH model, please refer to Edwards and Susmel (2001 and 2003), Fong (2003), Lee and Yoder (2006, 2007a and 2007b).

where R_t is the stock return for each series on the time t, μ_{it} and h_{it} are the conditional mean and conditional variance at time t, respectively. Both μ_{it} and h_{it} are allowed to switch between two regimes; for instance, regime probability $p_{1t} = \Pr(s_t = 1 \mid \Omega_{t-1})$ is probability for Regime 1 conditional on a past information set available up to time *t-1*. To construct the model, we further specify conditional mean by using an AR (1) process due to partial-price adjustment, limit-price policy, the existence of feedback trading, or other forms of market frictions (Kim and Rogers, 1995; Koutmos, 1998; Antoniou et al., 2005). The conditional estimate volatility is thereafter assumed to evolve by a GARCH (1, 1) process as popularized by (Bollerslev et al., 1992):

$$R_{i,t} = \phi_{i0} + \phi_{i1} R_{i,t-1} + \varepsilon_{it} \tag{3.2}$$

where $\varepsilon_{it} \left| \Omega_{t-1} \sim N(0, h_{it}) \right.$ with State i =1, 2

$$h_{it} = a_{i0} + a_{i1}\varepsilon_{t-1}^2 + b_{i1}h_{t-1} \tag{3.3}$$

where $a_{i0} > 0$, $a_{i1} \geq 0$ and $b_{i1} \geq 0$ to ensure that the conditional variance is positive. All variance and mean parameters are regime-dependent. Finally, Markov switching is assumed to be governed by a first-order Markov process with the following transition probability matrix:

$$\Pr(s_t = 1 | s_{t-1} = 1) = P$$

$$\Pr(s_t = 2 | s_{t-1} = 1) = 1 - P$$

$$\Pr(s_t = 2 | s_{t-1} = 2) = Q \tag{3.4}$$

$$\Pr(s_t = 1 | s_{t-1} = 2) = 1 - Q$$

where P (Q) is the transition probability for State s_t=1 (2) conditional on State 1 (2). A similar definition applies to Regime (*1-P*) and (*1-Q*).[20] Thus, the state variable depends on the previous realization of R_t through s_{t-1}. For example, if s_{t-1}=1， and P is high, then R_t is more likely to be drawn from the distribution 1. if s_{t-1}=1， and P is low, then R_t is more likely to be drawn from the distribution 2. This thus allows for some regimes to be more persistent than others. As stated earlier, a special feature of this model is that in addition to capturing the stochastic volatility, it allows us to estimate the probability of regime shifting and shed some light on the duration of volatility, which is one of the research interests of this study.

One important point is that even though this model has fixed transition probabilities, the mixing probability is still time-varying. For the regime probability of state 1, it can be written as follows:

[20] In his recent paper, Engle (2002) provides alternative stochastic volatility models. In SV models, variance is specified to follow some stochastic process. This specification makes SV models very attractive for theoretical finance. It has been found that the prices of options based on SV models are more accurate than those based on the Black-Scholes model (see, for example, Melino and Turnbull (1990)). Moreover, the SV model is more flexible and more powerful than GARCH-type models to explain the well documented time varying volatility. Empirical successes of the lognormal SV model relative to GARCH-type models are documented in Danielsson (1994), Geweke (1994), and Kim, Shephard and Chib (1998) in terms of in-sample fitting and Yu (2002) in terms of out-of-sample forecasting.

$$\Pr(s_t = 1 \mid \Omega_{t-1}) = \sum_{i=1}^{2} \Pr(s_t = 1 \mid s_{t-1} = i, \Omega_{t-1}) \times \Pr(s_{t-1} = i \mid \Omega_{t-1}) \tag{3.5}$$

Based on the Markov assumption:

$$\Pr(s_t = 1 \mid s_{t-1} = i, \Omega_{t-1}) = \Pr(s_t = 1 \mid s_{t-1} = i) \tag{3.6}$$

Therefore,

$$\Pr(s_t = 1 \mid \Omega_{t-1}) = P \Pr(s_{t-1} = 1 \mid \Omega_{t-1}) + (1-Q)[1 - \Pr(s_{t-1} = 1 \mid \Omega_{t-1})] \tag{3.7}$$

Clearly, even with fixed transition probabilities, the mixing probability of each state is time-varying. The special structure of the Markov switching models makes parameter estimation much more complicated than the standard models.

3.2.2.2 Estimation

Conditional on Regime i, the normal density function of the stock return, R_t, defined in (3.1) is given by:

$$f_{it} = f(R_t \mid s_t = i, \Omega_{t-1}) = \frac{1}{\sqrt{2\pi} h_{it}} \exp[-\frac{1}{2} \frac{(R_t - \mu_{it})^2}{h_{it}^2}] \quad . \tag{3.8}$$

Following Gray (1996), regime probability p_{it} can be expressed as a nonlinear recursive function of the transition probabilities and the conditional distribution of the return innovation such that:

$$p_{1t} = P[\frac{f_{1t-1}p_{1t-1}}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}] + (1-Q)[\frac{f_{2t-1}(1-p_{1t-1})}{f_{1t-1}p_{1t-1} + f_{2t-1}(1-p_{1t-1})}] \qquad (3.9)$$

Thus, the log-likelihood function of this model can be written as:

$$L = \sum_{t=1}^{T} \log[p_{1t} f_{1t} + (1-p_{1t}) f_{2t}] \qquad (3.10)$$

where T is the number of observations. The above log-likelihood function can then be constructed recursively using the following expressions for ε_t and h_t:

$$\varepsilon_t = R_t - E[R_t \mid \Omega_{t-1}] = R_t - [p_{1t}\mu_{1t} + (1-p_{1t})\mu_{2t}] \qquad (3.11)$$

$$\begin{aligned} h_t &= E[R_t \mid \Omega_{t-1}]^2 - \{E[R_t \mid \Omega_{t-1}]\}^2 \\ &= p_{1t}(\mu_{1t}^2 + h_{1t}) + (1-p_{1t})(\mu_{2t}^2 + h_{2t}) - [p_{1t}\mu_{1t} + (1-p_{1t})\mu_{2t}]^2 \end{aligned} \qquad (3.12)$$

Equation (3.12) implies:

$$h_{t-1} = p_{1t-1}(\mu_{1t-1}^2 + h_{1t-1}) + (1-p_{1t-1})(\mu_{2t-1}^2 + h_{2t-1}) - [p_{1t-1}\mu_{1t-1} + (1-p_{1t-1})\mu_{2t-1}]^2 \qquad (3.13)$$

Apparently, Equation (3.13) is not path dependent, as it does not depend on the entire past history of conditional variance. Therefore, it can be used recursively to construct h_{it} via Equation (3.3).

In addition, the estimation of the model gives the "smoothed probability" $prob(s_t = i|\Phi_T)$, which provides information about the likelihood that the market is in a particular volatility state at time *t* based on the full sample of observations. Three different algorithms for computing the smoothed probabilities were proposed respectively by Hamilton (1989 and 1990), Kim (1994) and Gray (1996), respectively. All give identical inference. An *r*-lag smoothed probability can be constructed through a recursive procedure developed by Gray (1996)[21] as follows:

$$p(s_t = i \mid \Phi_{t+r}) = \frac{f(R_{t+r} \mid s_t = i, \Phi_{t+r-1})\, p(s_t = i \mid \Phi_{t+r-1})}{\sum_{j=1}^{k} f(R_{t+r} \mid s_t = j, \Phi_{t+r-1})\, p(s_t = j \mid \Phi_{t+r-1})} \tag{3.14}$$

where

$$f(R_{t+r} \mid s_t = i, \Phi_{t+r-1}) = \sum_{j=1}^{k} f(R_{t+r} \mid s_{t+r} = j, \Phi_{t+r-1})\, p(s_{t+r} = j \mid s_t = i, \Phi_{t+r-1}) \tag{3.15}$$

$$p(s_{t+r} = j \mid s_t = i, \Phi_{t+r-1}) = \sum_{m=1}^{k} p(s_{t+r} = j \mid s_{t+r-1} = m, \Phi_{t+r-1})\, p(s_{t+r-1} = m \mid s_{t+r-1} = i, \Phi_{t+r-1}) \tag{3.16}$$

[21] It is easy to calculate the r-lag smoothed probability as mentioned by Hamilton (1989), which uses the additional information of r sub-samples up to t-1.

$$p(s_{t+r-1}=m\mid s_{t+r-1}=i,\Phi_{t+r-1})=\frac{f(R_{t+r-1}\mid s_{t+r-1}=m,\Phi_{t+r-2})\,p(s_{t+r-1}=m\mid s_t=i,\Phi_{t+r-2})}{\sum_{j=1}^{k}f(R_{t+r-1}\mid s_{t+r-1}=j,\Phi_{t+r-2})\,p(s_{t+r-1}=j\mid s_t=i,\Phi_{t+r-2})} \tag{3.17}$$

The estimation is implemented with GAUSS computation software and its constrained maximum likelihood (CML) module. Initial values for the optimization are based on estimates from a standard GARCH (1, 1) model. To obtain the negative minimum likelihood function values as well as to reduce the possibility of hitting a local minimum, we conduct an experiment by employing several starting values. Here, we report the estimates with the highest likelihood. As indicated by Gray (1996), Fong and Kim (2001, 2002), Fong and Koh (2002) and Fong (2003) etc, some parameters might fall to the boundary during estimation process.

3.3 Data and Preliminary Analysis

3.3.1 Sample Data and Study Period

The weekly price indices in this study are Shanghai A-share (SHA), Shenzhen A-share (SZA), Shanghai B-share (SHB), and Shenzhen B-share (SZB) taken from DataStream International and our sample covers January 1995 through June 2005. Weekly indices are used to avoid representation bias from some thinly traded stocks.

3.3.2 Descriptive Statistics

Table 3.1 contains information on the mean, standard deviation, skewness coefficient, kurtosis coefficient, the Jarque-Bera normality test (JB) and ARCH –LM test. As may be seen from the skewness coefficients, all the returns except SZA are skewed to the right. The kurtosis coefficients are in excess of 3.0, implying that the distributions of the series have fat tails. The JB statistic suggests that all of the stock returns fail to be normally distributed, which is quite typical for financial time series. ARCH-LM test is adopted here to examine whether there is ARCH effect. The corresponding test statistics at lag 10 signify the presence of ARCH effects in our data.

Table 3.1
Descriptive Statistics for Chinese Stock Market Returns

	SHA	**SZA**	**SHB**	**SZB**
Mean	0.101	0.121	0.011	0.170
Median	0.071	-0.001	-0.229	-0.033
Maximum	30.485	27.372	19.501	32.306
Minimum	-26.874	-30.877	-17.819	-32.590
Std. Dev.	3.922	4.328	4.902	5.689
Skewness	0.497	-0.141	0.494	0.919
Kurtosis	14.639	12.005	5.391	10.575
Jarque-Bera	3115.460***	1853.540***	152.783***	1387.251***
ARCH-LM(10)	18.303**	34.270***	63.709***	34.270***

Note: *** and ** indicate significance at the 1% and 5% level, respectively. ARCH-LM (10) is the ARCH-LM test statistics up to the 10^{th} order.

With this evidence in hand, it is natural to inquire whether volatilities of stock returns in these segmented markets are time varying. Are the volatility patterns among the segmented stock markets different? What are the durations of volatility staying in the high versus the low regime for these markets? The following sections address these issues.

3.4 Empirical Results

3.4.1 Hansen Test for Multiple Regimes

We begin by testing whether there are indeed regime shifts in the four segmented Chinese stock markets by applying Hansen's (1992, 1996) modified likelihood ratio test. Tests of whether there is more than one regime using Markov switching models cannot be resolved using standard specification tests such as the likelihood ratio (*LR*) test or its asymptotic equivalent like the Lagrange Multiplier (*LM*) or Wald tests. This is because the asymptotic theory justifying the use of such tests is based on certain regularity conditions which are violated in the case of Markov switching models. One of these conditions is that all parameters must be identified under the null hypothesis of a single regime, in order that the information matrix is non-singular. However, under the null of a single regime, parameters related to the second regime cannot be identified. Thus, the classical likelihood surface is flat with respect to these unidentified "nuisance" parameters. Another regularity condition is that the score must not be identically zero under the null hypothesis (i.e. the score must have a positive variance). To satisfy the condition, the null hypothesis must not yield a local maximum or a point of refection. However, since a single regime model is nested within a model of multiple regimes, this regularity condition will be violated under the null.

To overcome this problem, Hansen (1992, 1996) developed a general but computationally demanding standardized likelihood ratio test procedure using empirical process theory that can be applied under non-standard conditions. The following is a brief description of the set-up of the Hansen test[22].

Suppose we have a sample of T observations and we write the log-likelihood function as follows:

$$L_T(\alpha,\theta) = \sum_{i=1}^{T} l_i(\alpha,\theta) \tag{3.18}$$

where θ denotes parameters identified under both the null and the alternative and $\alpha = (\beta'\gamma')$ where γ is a vector of nuisance parameters not identified under the null. To simplify the test, we concentrate the parameter vector θ out of the sample likelihood function. Let

$$\hat{\theta}(\alpha) = \arg\max_{\theta} L_T(\alpha,\theta) \tag{3.19}$$

denotes the maximum likelihood estimates of θ for fixed values of α. The concentrated likelihood function is

$$\hat{L}_T(\alpha) = L_T(\alpha,\hat{\theta}(\alpha)) \tag{3.20}$$

Next, define the following statistics which will be used to construct the likelihood

[22] A number of other papers have also attempted to address the problems of hypothesis testing under non-standard conditions (e.g. Davies, 1977, 1987; Garcia, 1992).

ratio LR statistic for testing the number of regimes:

$$LR_T(\alpha) = L_T(\alpha, \hat{\theta}(\alpha)) - L_T(0, \gamma, \hat{\theta}(0, \gamma)) \quad (3.21)$$

$$V_T(\alpha) = \sum_{i=1}^{T} q_i(\alpha, \hat{\theta}(\alpha))^2 \quad (3.22)$$

$$q_i(\alpha, \hat{\theta}(\alpha)) = l_i(\alpha, \hat{\theta}(\alpha)) - l_i(0, \gamma, \hat{\theta}(0, \gamma)) - \frac{1}{T} LR_T(\alpha) \quad (3.23)$$

The standardized likelihood ratio statistic is:

$$LR_T^* = \sup_{\alpha} \frac{LR_T(\alpha)}{\sqrt{V_T(\alpha)}} \quad (3.24)$$

Hansen proves that $\Pr(LR_T^* \geq x)$ is bounded by an asymptotic distribution $\Pr(\sup_{\alpha} Q_T^* \geq x) \to \Pr(\sup_{\alpha} Q^* \geq x)$ where the distribution Q_T^* is defined by:

$$Q_T^* = \frac{LR_T(\alpha) - E[LR_T(\alpha)]}{\sqrt{V_T(\alpha)}} \quad (3.25)$$

Under the null hypothesis, $E[LR_T(\alpha) \leq 0$, assuming an empirical Central Limit Theorem holds, $Q_T^*(\alpha) \to Q^*(\alpha)$ which is a Gaussian process with a known covariance function. The distribution $Q_T^*(\alpha)$ can be simulated and the supremum obtained by taking over all possible values of α. This explains why the test is computationally intensive for all but the simplest Markov switching models. In practice, the simulations are carried out over a finite grid of nuisance parameters.

We apply the Hansen's test to evaluate the null hypothesis of a geometric random walk against the alternative of a two-state Markov switching model with switches in mean and variance. In returns form, the single regime random walk model can be written as $R_t = \mu + \sigma\varepsilon_t$ while the Markov switching model can be written as $R_{it} = \mu(s_t) + \sigma(s_t)\varepsilon_t$ where $\varepsilon_t \sim i.i.d.N(0,1)$ and i =1, 2 denote two states. The law of motion governing switch is assumed to be a first-order Markov process specified in Equation (4). Let *P* and *Q* denote the Markov transition probabilities for states 1 and 2 respectively. We start the algorithm by using the stable probabilities for the first state, i.e. $P(s_t = 1) = (1-Q)/(2-P-Q)$. Under the null, all parameters γ associated with the second state are unidentified. For the Markov switching model, we have $\beta = P-1, \gamma = (\mu_{2,} \sigma_{2,} Q)$ and $\theta = (\mu_{1,} \sigma_1)$. Given the computationally intensive nature of the test, we consider three grids for $\alpha = (P, \mu_{1,} \sigma_1, Q)$. The grids are:

Grid 1	P = .75, .80, .85, .90, .95 μ_2 = -.10, -.08, -.06, -.04, -.02, .00, .02, .04, .06, .08 σ_2 = .10, .25, .40, .55, .70, .85, 1.00, 1.15, 1.30, 1.45 Q = .75, .80, .85, .90, .95

Grid 2	P = .75, .80, .85, .90, .95 μ_2 . = -.10, -.09, -.08, -.07, -.06, -.05, -.04, -.03, -.02, -.01, .00, .01, .02, .03, .04 σ_2 = .10, .20, .30, .40, .50, .60, .70, .80, .90, 1.00, 1.10, 1.20, 1.30, 1.40, 1.50 Q = .75, .80, .85, .90, .95

Grid 3	P = .40, .50, .60, .70, .80, .90 μ_2 . = -.10, -.09, -.08, -.07, -.06, -.05, -.04, -.03, -.02, -.01, .00, .01, .02, .03, .04 σ_2 = .10, .20, .30, .40, .50, .60, .70, .80, .90, 1.00, 1.10, 1.20, 1.30, 1.40, 1.50 Q = .40, .50, .60, .70, .80, .90

Grid 1 has 2500 points, grid 2 has 5625 points and grid 3 has 8100 points. Table 3.2 presents the results of the simulations. For each grid, we report the standardized LR statistic, the simulated *p*-value and the computation in Table 3.2. As indicated, the p-values are well below 1%, thus providing formal evidence that there are two volatility regimes in four Chinese segmented stock index returns. We conclude from the Hansen test that the regimes detected using the Markov switching model are not spurious.

Table 3.2
Results of Hansen Test

	Grid 1	**Grid 2**	**Grid 3**
SHA	6.940 (0.000)	6.894(0.000)	6.567(0.000)
SZA	9.185 (0.000)	9.015 (0.000)	8.482 (0.000)
SHB	8.735 (0.000)	8.698 (0.000)	8.112 (0.000)
SZB	10.92 (0.000)	10.97 (0.000)	10.43 (0.000)

Note: The standardized likelihood statistic is computed as $\sup_a LR_T(\alpha)/\sqrt{V_T(\alpha)}$ where T is sample size, α is the vector of nuisance parameters under the null, $LR_T(\alpha)$ is the sample likelihood ratio function and $\sqrt{V_T(\alpha)}$ is the sample variance function to ensure that all values of a yield the same variance for the likelihood ratio. Numbers in parentheses are asymptotic p-values obtained via 1000 Monte Carlo simulations for each grid.

3.4.2 Performance of MS-GARCH model VS. GARCH model

For illustrative purposes and to set a basis for comparison, it is convenient to start with an estimation of a standard GARCH (1, 1) model. The results for the four Chinese stock index returns are reported in Table 3.3. Consistent with most financial markets, the estimated coefficients of GARCH effects are highly significant for all of the markets.

Table 3.3
Estimates of the AR (1)-GARCH Model

Panel A	SHA	SZA	SHB	SZB
φ_0	-0.041(0.125)	-0.135 (0.135)	-0.153(0.192)	-0.037(0.215)
φ_1	0.047(0.048)	0.061(0.048)	0.099(0.049)**	0.134(0.051)***
a_0	0.650(0.164)***	0.426 (0.113) ***	1.535(0.367)***	5.511(1.046)***
a_1	0.141(0.024)***	0.116(0.017) ***	0.127(0.024)***	0.204(0.037)***
b_1	0.826(0.024)***	0.868(0.015) ***	0.812(0.028)***	0.601(0.063)***
Panel B	**Summary statistics and diagnostics**			
Log-likelihood	-1471.818	-1511.416	-1604.128	-1646.329
LB(10)	14.865	10.243	17.270	12.358
$LB^2(10)$	6.388	5.289	11.582	5.601

Note: *** and ** indicate significance at the 1% and 5% level, respectively. Numbers in parentheses are standard errors. LB (10) is the Ljung -Box statistics based on the standardized residuals up to the 10^{th} orders. LB^2 (10) are the Ljung-Box statistics based on the squared standardized residuals. Both statistics on the level and squared level are asymptotically distributed as $\chi^2(10)$, respectively.

To highlight the feature of stochastic volatility embodied in Chinese segmented markets, we estimate the MS-GARCH model and compare its performance with a standard GARCH model.

Table 3.4
Estimates of the Markov Switching AR (1)-GARCH Model

Panel A	SHA	SZA	SHB	SZB
φ_{10}	-0.156(0.141)	-0.263 (0.148)*	-0.539(0.198)***	0.463(0.235)**
φ_{20}	1.277(0.930)	1.732(1.005)*	0.551(0.477)	-0.152(0.648)
φ_{11}	0.056(0.055)	0.038(0.058)	-0.124(0.071)	-0.025(0.068)
φ_{21}	-0.093(0.184)	-0.022(0.117)	0.308(0.113)***	0.219(0.156)
a_{10}	6.977(0.651)***	7.203(0.664)***	5.467(1.292)***	9.458(1.553)***
a_{20}	26.073(11.815)**	40.289(14.581)***	29.556(9.893)***	27.660(6.453)***
a_{11}	0.031(0.064)	0.101(0.077)	0 @	0.019(0.041)
a_{21}	0.024(0.064)	0.001(0.063)	0.046((0.113)	0.526(0.341)
b_{11}	0 @	0 @	0.046(0.158)	0 @
b_{21}	0.749(0.344)**	0.593(0.296)**	0.564(0.281)**	0.365(0.172)**
P	0.973(0.012)***	0.976(0.011)***	0.822 (0.007)***	0.855(0.068)***
Q	0.890(0.043)***	0.896(0.043)***	0.736(0.092)***	0.740(0.091)***
d_1	37.037	41.667	5.618	6.897
d_2	9.091	9.615	3.788	3.846
Panel B	**Summary statistics and diagnostics**			
Log-likelihood	-1388.832	-1425.681	-1516.166	-1574.275
LB(10)	13.402	10.452	14.124	13.783
LB^2(10)	4.698	3.902	13.269	15.482

Note: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Numbers in parentheses are standard errors. @ indicates parameter fell to the boundary. *P* (*Q*) is the transition probability for State s_t =1 (2) conditional on State 1 (2). d_1 and d_2 are the duration of regimes 1 and 2, which equals 1/(1-P) and 1/ (1-Q), respectively. LB (10) is the Ljung -Box statistics based on the standardized residuals up to the 10^{th} orders. LB^2 (10) are the Ljung-Box statistics based on the squared standardized residuals. Both statistics on the level and squared level are asymptotically distributed as $\chi^2(10)$, respectively.

Table 3.4 reports the estimates of Markov switching GARCH models for four stock markets. Apparently, volatilities in the two states are sharply diverse, indicating the existence of two distinct volatility regimes. The unconditional volatility parameters (a_{10} and a_{20}) are statistically significant at the 5% and 1% levels, respectively. The evidence shows that the MS-GARCH models fit data much better than standard GARCH models. The log-likelihood values for all MS-GARCH (1, 1) models are larger compared to their counterparts of the single regime GARCH (1, 1) models. For example, the log-likelihood value of the MS-GARCH (1, 1) model for SHA in Table 3.4 is -1388.832, which is much larger than the value -1471.818 to be obtained from a single regime GARCH (1, 1) model in Table 3.3.

To test the difference in performance, we first calculate the standard likelihood ratio (*LR*) statistic for each pair of models. The likelihood ratio *LR* statistic is given by: λ_{LR} = 2*[(Log $L(\hat{\theta})$ - Log $L(\tilde{\theta})$], where ($\hat{\theta}$) is the unconstrained estimator, the MS-GARCH (1, 1) model, and ($\tilde{\theta}$) is the constrained model, GARCH (1, 1) model. Under the null hypothesis, the test statistic has a Chi-squared distribution with J degrees of freedom, where J is the number of restrictions. As may be seen in Column 4 in Table 3.5, the null hypothesis is decisively rejected and the results favor the Markov switching GARCH (1, 1) model for all markets.[23] To formally evaluate these two models, we further compute the statistics proposed by Schwartz (1978) and

[23] For example, the LR statistic for SHA is 165.972; its p-value is significant at the 1% level. Notice that the LR tests employed in the text should not be viewed as a formal diagnostic checking, since the two models are not strictly nested. The existence of unidentified parameters under the null of a single-regime model may cause the MS-GARCH model to violate the assumption for justifying the use of standard LR tests. Moreover, standard likelihood ratio (LR) statistic tests may be biased, since it no longer follows the standard χ^2 distribution. Following Gray (1996), we take this test results only for reference.

Akaike (1976). As shown in Table 3.5, the SBC and AIC values of MS-GARCH models are significantly higher than those of the standard GARCH models, supporting the data-fitting ability of the Markov switching GARCH (1, 1) model over the standard GARCH(1,1) model in all markets.

Table 3.5
The Summary Statistics for GARCH and MS-GARCH Models

Model	No. of Parameters	Log-likelihood	LR Statistics	SBC	AIC
Panel A: SHA					
GARCH (1,1)	5	-1471.818	/	-1487.584	-1476.818
MS-GARCH(1,1)	12	-1388.832	165.972 (0.000)***	-1426.670	-1400.832
Panel B: SZA					
GARCH (1,1)	5	-1511.416	/	-1527.182	-1511.416
MS-GARCH(1,1)	12	-1425.681	171.47 (0.000)***	-1463.519	-1437.681
Panel C: SHB					
GARCH (1,1)	5	-1604.128	/	-1619.894	-1609.128
MS-GARCH(1,1)	12	-1516.166	175.924 (0.000)***	-1554.004	-1528.166
Panel D: SZB					
GARCH (1,1)	5	-1646.329	/	-1662.095	-1651.329
MS-GARCH(1,1)	12	-1574.275	144.108 (0.000)***	-1612.113	-1586.275

Note: LR statistics refers to the likelihood ratio test statistic. Numbers in parentheses below the LR statistic are *p*-value. The likelihood ratio LR statistics is computed as follows: 2*(likelihood of H_1 – likelihood of H_0), where H_1 is the MS-GARCH (1, 1) model and H_0 is the GARCH (1, 1) model. *** and ** denote statistical significance at the 1% and 5% level, respectively. SBC is the Schwarz Bayesian criterion for testing model adequacy and it is calculated as likelihood function value-(k/2) ln (T). T is the number of samples. AIC is Akaike's information criterion and AIC is calculated as the likelihood function value-k, k is the model parameter number.

As part of the evaluation process, it is useful to compare the forecast abilities of MS-GARCH models and standard GARCH models. To this end, we evaluate the models based on their forecasting accuracy. The forecast errors of one-week-ahead forecasts are measured by MSE, RMSE, LES, and |LE|, which are defined as below:

$$MSE = T^{-1}\sum_{t=1}^{T}(e_t^2 - \sigma_t^2)^2 \tag{3.25}$$

$$RMSE = \sqrt{T^{-1}\sum_{t=1}^{T}(e_t^2 - \sigma_t^2)^2} \tag{3.26}$$

$$LES = T^{-1}\sum_{t=1}^{T}\{\ln(e_t^2) - \ln(\sigma_t^2)\}^2 \tag{3.27}$$

$$|LE| = T^{-1}\sum_{t=1}^{T}|\ln(e_t^2) - \ln(\sigma_t^2)| \tag{3.28}$$

Table 3.6 displays the results:

Table 3.6
One-week-ahead Forecast Errors of GARCH and MS-GARCH Models

Model	MSE	RMSE	LES	|LE|
Panel A: SHA				
GARCH (1,1)	3235.183	56.879	9.230	2.095
MS-GARCH (1,1)	3130.0466	55.947	9.3076	2.0782
Panel B: SZA				
GARCH (1,1)	3775.082	61.442	9.961	2.193
MS-GARCH (1,1)	3608.849	60.074	8.843	2.134
Panel C: SHB				
GARCH (1,1)	2187.573	46.771	9.186	2.204
MS-GARCH (1,1)	1983.374	44.535	8.840	2.189
Panel D: SZB				
GARCH (1,1)	6927.442	83.231	11.539	2.508
MS-GARCH (1,1)	6872.797	82.902	10.540	2.371

It consistently shows that the MS-GARCH models outperform the standard GARCH models in forecasting.

3.4.3 Empirical Evidence from the MS-GARCH model

Having demonstrated the relative performance, the next question is: what other empirical regularities can be derived from the estimates of the MS-GARCH models? We shall summarize our findings as follows: First, the estimated volatilities in four markets are distinguished from each other in two different states. It can be shown that regime one is a low-variance regime, while regime two is a turbulent state, as evidenced by the ratios (3.73, 5.59, 5.41 and 2.92, respectively) of high variance to low variance (a_{20}/a_{10}) for SHA, SZA, SHB, and SZB.

Second, the transition probabilities, *P* and *Q*, are highly statistical significant and close to one, suggesting the volatility regime is persistent (i.e. market switching between high volatility regime and low volatility regime is not so frequent). These probabilities measure the magnitude of persistence of each volatility state and a higher value suggests a longer length of stay. For instance, the duration of a low volatility state d_1 for SHA is about 37 [1/ (1-0.973)] weeks. As indicated in Table 4, the values of *P* (the probability of staying at low volatility) and *Q* (the probability of staying at high volatility) are close to one for all of the markets.[24] In contrast, (1-*P*) (the probability of shifting from a low volatility state to a high volatility state) and (1-*Q*) (the probability of shifting from a high volatility state to a low volatility state) is

[24] The fact that these probabilities are relatively large also suggests a meaningful decomposition of the time series in terms of volatility regimes.

small. This indicates that volatility clustering, i.e., low (high) volatility usually followed by low (high) volatility, exists in all segmented markets. Nevertheless, the evidence of *P* being larger than *Q* for all markets signifies that the low-volatility regime dominates the market.

Although there are some features commonly shared by the estimates of four markets, two different points deserve our attention. First, despite the fact that not all of the unconditional mean return parameters (φ_{10} and φ_{20}) are highly significantly different from zero in two regimes, it appears to have opposite signs among the four stock markets. For SHA, SZA, and SHB, we find that negative returns tend to be associated with a low variance regime, while positive returns are associated with turbulence. This phenomenon is different from Hamilton and Susmel's (1994) finding, which shows that higher volatility regimes tend to be associated with slumps in US stock market. Our results imply a rather interesting behavior of investors in Chinese stock markets: when stock returns are positive, investing activities vary dramatically, accelerating the stock volatility; when stock returns are negative, investors tend to be slowing down, rather than engaging in a short sell. This finding is consistent with the naïve, highly speculative, and information asymmetric behavior presented in the Chinese stock markets (Ma, 1996; Chen et al., 2001; Mei et al., 2004).[25] In sum, investors in Chinese markets focus more on the speculative profits when the market moves upward, whereas investors in the US market concentrate on minimizing losses

[25] It is widely recognized that China's stock market is a "policy oriented market," meaning that it is government policy, rather than economic fundamentals, that drives the stock market. Ma (1996) finds that the Chinese markets are highly speculative and are driven by the risk preferences (or risk seeking) of Chinese investors. Chen et al. (2001) and Mei et al. (2004) found that China's stock returns cannot be explained by fundamental factors.

as the market moves downward. It appears that US markets are dominated by risk-averse, rational investors, whereas investors in Chinese markets tend to assume excess risk.

Second, the evidence clearly indicates that the volatility switching behavior with A-share markets differs from that of B-share markets. In particular, the values of *P* and *Q* for B-share markets are much smaller than those of A-share markets, implying that B-share markets are more volatile and more apt to shift between a high-volatility state and a low-volatility state. The state duration indicators, d_1 and d_2, provide more straightforward evidence for illustration: for SHA and SZA, a low-volatility state lasts, on average, about 37-42 weeks, while a high-volatility state lasts, on average, 9-10 weeks; for B-share markets, however, both low-volatility and high-volatility states have much shorter "survival" times: for SHB and SZB, a low-volatility state lasts, on average, about 6-7 weeks, while a high-volatility state lasts only about 4 weeks.

The weekly stock return series and smoothed probability for each market are displayed in Figures 3.1 through 3.4. In each figure, the upper panel plots the stock return series, the middle and bottom panels plot the smoothed probabilities for the market in State 1 (low volatility) and State 2 (high volatility), respectively. The plots follow Hamilton's (1989) procedure of dating regime switches, which classifies an observation as staying at State *i* if the smoothed probability $prob(s_t = i | R_T, R_{T-1}, \cdots)$ is greater than 0.5.

Fig. 3.1 AR (1)-MS-GARCH (1, 1) Estimation for SHA

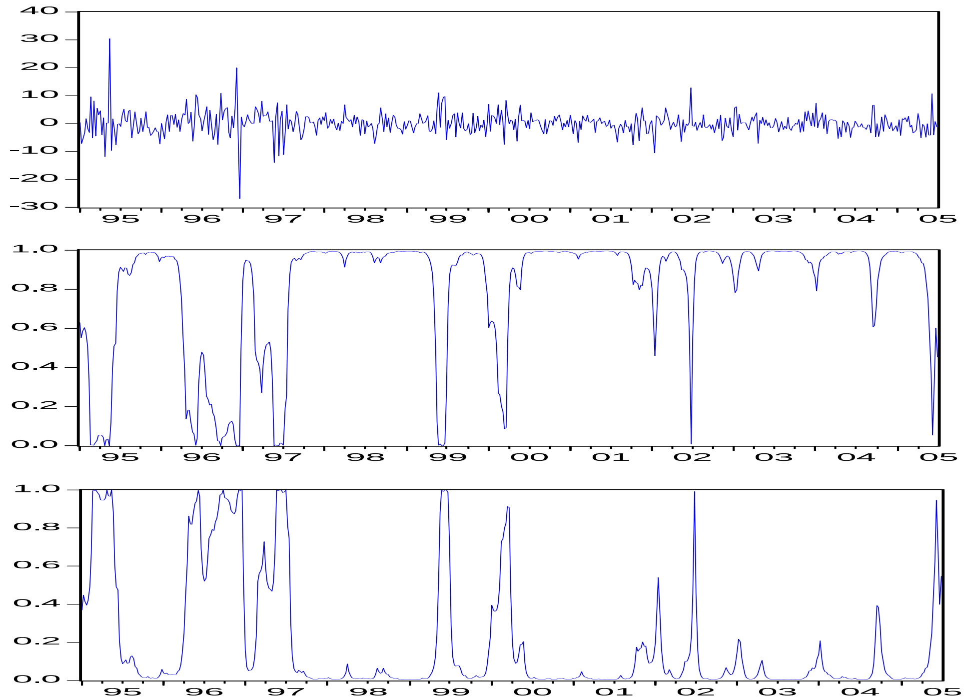


Fig. 3.2 AR (1)-MS-GARCH (1, 1) Estimation for SZA

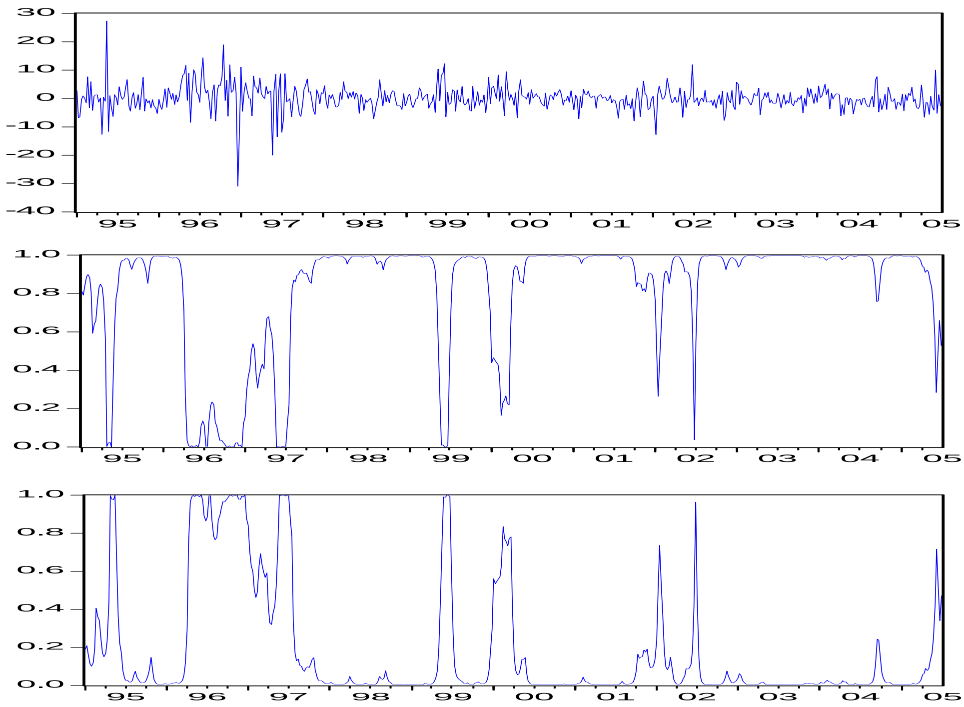


Fig. 3.3 AR (1)-MS-GARCH (1, 1) Estimation for SHB

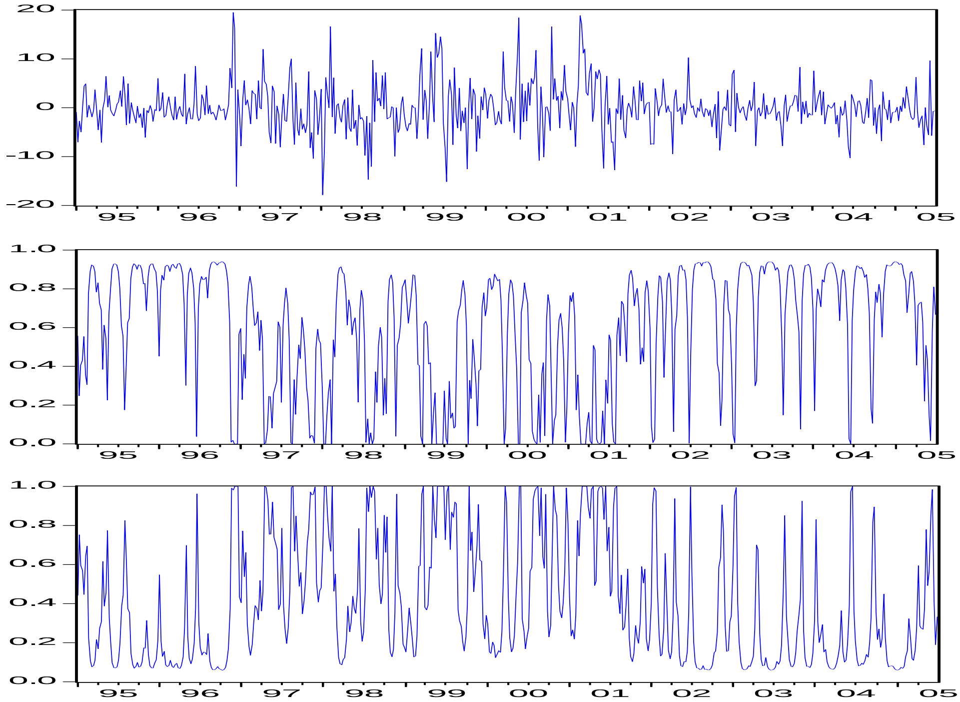
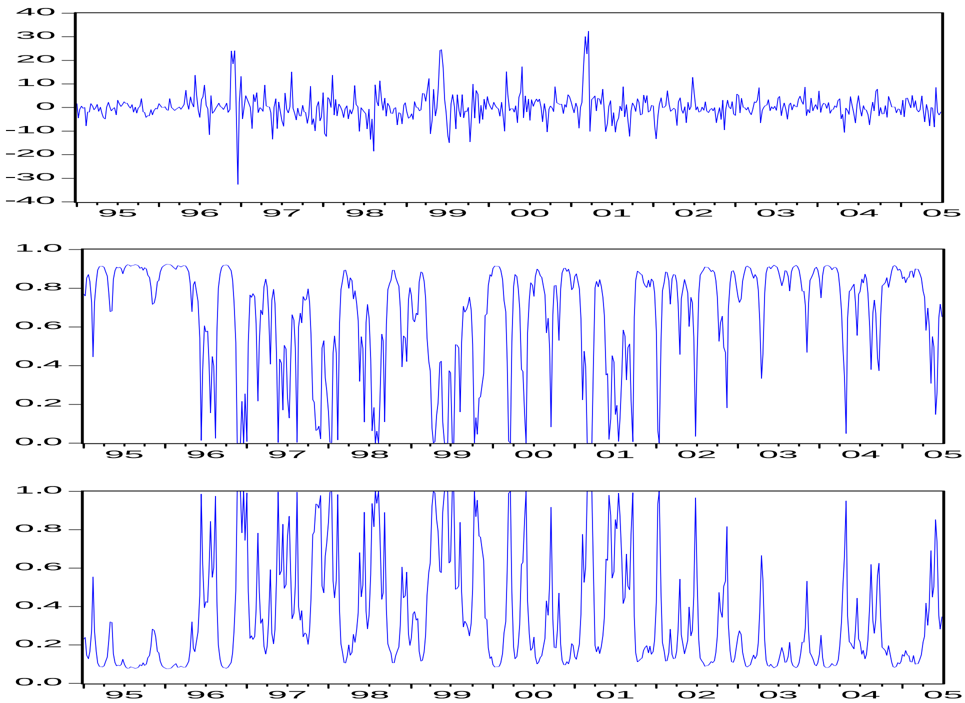


Fig. 3.4 AR (1)-MS-GARCH (1, 1) Estimation for SZB



These figures offer us a visual illustration of the volatility patterns presented in different markets. We observe that both SHA and SZA markets actually have a similar volatility pattern, especially for the period after October 1997. A similar volatility pattern also holds true for the two B-share series, although the stocks are traded in different currencies and in different places. Noticeably, the volatility patterns of the two A-share markets have quite contrasting dynamic variations as compared to those on the two B-share markets: the two A-share markets are relatively stable and dominated by a low-volatility state most of time, while the two B-share markets are much more volatile and switch very frequently between a high-volatility and a low-volatility state. This scenario is especially true before Feb 18, 2001[26], when Chinese government allows domestic citizens to buy and sell B-share stocks. One possible explanation for this is that the B-share holders are sophisticated foreign investors consisting of major international financial institutions. These investors hold more diversified international assets. It follows that their portfolio decisions and, hence, their adjustments are responsive to a broader set of global information. Any shock that disturbs international asset return parity conditions or risk comportment will lead them to adjust their portfolio allocation, generating market volatility. On the contrary, A-share investors do not have sufficient market information, nor do they have alternative investing instruments. These restrictions

[26] From February 19, 2001, Chinese citizens are allowed to hold B shares. As they still can not freely exchange foreign currency, they are allowed to exchange some quota of foreign currencies and put them in special accounts to invest in B shares.

prevent A-share investors from shuffling their portfolios and, hence, reducing the volatility switching.

Figure 3.1 through Figure 3.4 also provide us a very convenient instrument for tracking the regime switching in the segmented markets. Eyeballing these figures, the volatility switching of A-share and B-share markets is subject to major "domestic" events that have occurred in recent history. For instance, the adoption of "price limits" (12/16/1996) by SHSE and SZSE as a regulatory tool helped the markets shift to a low-volatility state effectively (This finding is consistent with the findings of Friedmann and Sanddorf-Kohle (2002). In contrast, the death of Chinese leader Den Xiaoping (02/19/1997), policy change to issue new stocks to the investors on secondary market (02/13/2000),[27] and suspension of the sale of state shares via stock markets (6/24/2002) pushed the markets to a high-volatility state.

With respect to the B-share market volatility switching, it appears that the spell of high-volatility states on two B-share markets corresponds closely to the major international financial crises, while the two A-share markets seem immune to these events: as international crises take place, these two A-share markets stay at a low-volatility state or switch to a low-volatility state rapidly. It is of interest to check some of the recent international events and their impact on volatility switching. As the Asian crisis started to transpire in early July 1997, the two B-share markets

[27] To improve the method of issuing new stocks, China Securities Regulatory Commission (CSRC) adopted a new policy that allows new shares to be purchased by the investors on secondary market. Before this date, new securities were only sold to some "special" investors, who can obtain much higher profit than investors on secondary market (security transaction market). This policy innovation has significant impact on fund flows, stimulating the transactions in two exchanges.

switched to a high-volatility state immediately, while the two A-share markets switched from high volatility to low volatility. During the Asian financial crisis, the two A-share markets stayed at a low-volatility state up to May 1999, while the two B-share markets remained sensitive to the volatility changes in the global markets. For example, during the global stock market collapse caused by the drastic change in Hong Kong's Hang Seng Index in late October 1997, the two A-share markets remained calm, while the two B-share markets switched to high volatility quickly and remained highly volatile for about 2 months. When the Russia financial crisis broke out in mid-July 1998, the two B-share markets also switched to a high-volatility regime and hung on there until early September 1998. The same scenario holds true for the incidence of global stock market collapses triggered when the IT bubble burst on April 14, 2000; both SHB and SZB moved to a high-volatility state on May 4 and May 11, 2000, respectively, and remained in a high-volatile state for about one month. However, the two A-share markets remained in a low-volatility state. All of these incidences provide strong support for the market segmentation argument that international volatility spillovers do affect the segmented stock markets profoundly and the sterilization policy in China has been an effective instrument for shielding the A-share markets from external turbulence. Nevertheless, it can be argued that A-share investors are insensitive to external shocks owing to a lack of investment sophistication or simply because they fail to switch to alternative investment instruments.

3.5 Volatility Spillover among Segmented Stock Markets

Although the above analyses offer some significant insight into the nature of volatility associated with different markets, the possibility of volatility linkages among the four segmented markets has been abstract. In this section, we fill in this gap[28]. As high volatility regime is what investors concern most, we investigate whether there is any markets linkage asymmetry across A-share and B-share stock markets. The way we handle it is to modify the variance equation by adding a conditional variance derived from a cross-market. More subtly, we shall investigate regime-dependency of the volatility linkages among the four segmented markets by introducing an indicator ID to the following specifications:

$$R_t = \phi_0 + \phi_1 R_{t-1} + \varepsilon_t$$

where $\varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + \delta \cdot h_{r,t} \cdot ID \tag{3.29}$$

where R_t is an index return of a particular stock market. $h_{r,t}$ is the conditional variance derived from the estimation of the MS-GARCH model based on a cross stock market. ID is an indicator variable, which takes the following forms:

[28] Different from the methodology adopted here and the multivariate GARCH framework adopted in Chapter 4, Hong (2000) proposed a class of asymptotic N (0, 1) tests, which based on the sample cross-correlation function between two squared standardized residual series, to examine volatility spillover. The simulation results show that this approach has strong power to test volatility spillover.

$$ID = 1, \text{ if } prob(s_t = 2 | R_T, R_{T-1}, \cdots) > 0.5$$

$$ID = 0, \text{ if } prob(s_t = 2 | R_T, R_{T-1}, \cdots) \leq 0.5 \quad (3.30)$$

Equation 3.30 states that when a cross stock market is in a high volatility regime, i.e., the smoothed probabilities are greater than 0.5, *ID* equals one; otherwise, it equals zero. It follows that conducting a significant test on parameter δ provides us a direct test for analyzing the volatility linkages among the four segmented stock markets. If δ is significantly different from zero, it suggests the existence of cross-market spillover; the sign, however, will signify the direction of impact. The estimates of volatility linkages under a high-volatility regime are reported in Table 3.7.

Table 3.7
Analyses of Volatility Linkages among Four Segmented Stock Markets at High Volatility Regime

	SHA	SZA	SHB	SZB
SHAIDHV	/	1.823(0.422)***	0.027(0.008)***	0.231 (0.049)***
SZAIDHV	1.647 (0.203)***	/	0.019(0.005)***	0.161(0.035)***
SHBIDHV	-0.005(0.008)	-0.005(0.006)	/	1.975(0.215)***
SZBIDHV	0.010(0.006)	0.003(0.004)	1.178(0.214)***	/

Note: This table contains regression coefficients of volatility linkages for Shanghai A shares (SHA), Shenzhen A shares (SZA), Shanghai B shares (SHB), and Shenzhen B shares (SZB). *** and ** indicate significance at the 1% and 5% level, respectively. Numbers in parentheses are standard errors.

The findings are interesting. As we inspect the impact of A-shares on other markets, the estimated values of the coefficient δ are positive in high-volatility regimes. More important, all of the coefficients from A-share markets are statistically significant. This suggests that the A-share markets' volatility has a spillover effect on all of the market. Specifically, when the highly volatile regime is prevailing, it provokes more volatility over other segmented markets. However, for two B-share markets, the findings are different. That is, the volatility coefficients are positive between the two B-share markets in the high-volatility regime. However, there is no impact from B-share markets to A-share markets in the high-volatility regime. One possible explanation is that in the high-volatility regime, the volatile movements in B-share markets are often more sensitive to the disturbances from international markets. The A-share markets, however, do not react in the same way owing to a lack of information or overconfidence. Generally speaking, we find volatility spillover asymmetry across A-share and B-share stock markets.

3.6 Conclusions of Chapter 3

This study adopts a Markov switching GARCH model to examine the volatile nature among the four major segmented Chinese stock indices. We also conduct statistical tests to examine the volatility spillover effects among these four segmented markets at high volatility regimes. Our empirical findings are consistent with the following notions. First, there is strong evidence of regime shift in the volatility of the four segmented markets, and the MS-GARCH model appears to outperform the single regime GARCH model in modeling the volatility of stock markets in China. Second, although there are some common features of volatility switch in A-share and B-share markets, B-share markets appear to be more volatile and shift more frequently between a high-volatility state and a low-volatility state, which implies comparatively higher investment risk in B-share stock market. Therefore, investors interested in B shares ought to be more careful and should pay more attention to the volatility changes in B-share market as this is highly related to their portfolio construction and risk diversification. Our estimated results on duration of high volatility regime and frequency of high-low volatility switching should be useful for their investment decisions. Third, for SHA, SZA, and SHB, we find that negative returns tend to be associated with a low variance regime, while positive returns are associated with a turbulent market. This phenomenon is different from Hamilton and Susmel's (1994) finding, which shows that higher volatility regimes tend to be associated with the slumps in the US stock market. Our finding suggests that investors' behavior in light of profit maximization between Chinese and US markets is quite diverse. US investors are more sensitive to the downside of the market due to risk aversion, while Chinese investors are more excited by the upside of the market because they are more apt to pursue a speculative opportunity. Four, the volatility switch of A-share markets and B-share markets is subject to different major events. The volatile movements in B-share markets are sensitive in reacting to international shocks. A-share markets seem to be immune to the volatility spillover from international financial markets. Our results show that the market segmentation policy imposed by the policy makers of Chinese authority is very helpful in protecting domestic A-share markets from external turbulence. Five, evidence strongly indicates that, in high volatility regime, A-share volatility has a positive and significant impact on all of the alternative markets. However, the volatility spillover of B-share markets occurs only between the B-share markets and has no impact on the A-share markets. We find volatility spillover asymmetry across A-share and B-share stock markets.

Chapter 4: Long-run equilibrium, short-term adjustment, and spillover effects across Chinese segmented stock markets

4.1 Introduction

As a mechanism for developing the Chinese stock market, the Chinese government has adopted a market segmentation policy that divides its stock market into a domestic board and a foreign board to cater to the needs of different investors. Companies can issue A shares, which only Chinese citizens living in mainland China can buy, and some companies are allowed to issue B shares and H shares, which can be bought by foreign investors[29]. A and B shares are listed on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), namely, SHA, SHB, SZA, and SZB, of mainland China.

Unlike A shares and B shares which are traded in the same stock exchanges within mainland China, A shares and H shares are segmented in terms of the stock ownership as well as the listing and trading locations (Li, et al., 2006). Since the RMB is not yet convertible to foreign currencies and the HKSE provides a stable and established system of stock market, many overseas investors prefer trading H-shares in Hong Kong rather than B-shares in mainland Chinese markets (Kim and Shin, 2000).

Whether stock markets are cointegrated with each other carries important implications for policy makers and investors. Cointegrated markets imply that there is

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[29] From February 19, 2001, Chinese citizens are allowed to hold B shares. However, due to foreign exchange restriction, they may exchange some quota of foreign currencies and put them in special accounts for investment in B shares.

a common force, such as market fundamentals, investors' preferences and government interventions, which bring the stock markets together in the long run. In theory, if stock markets are not cointegrated, this implies that there is no long run relationship between the markets.

Since China's stock market is relatively new, the long run relationship among China's segmented stock markets has not been investigated extensively. Ahlgren et al (2003) use a panel cointegration method to examine the cointegration between the A and B share prices on two Chinese stock exchanges. They find that the A and B shares prices are cointegrated. Applying a recursive cointegration technique (Diamandis et al., 2000; Hansen and Johansen, 1993) and standard cointegration technique, Yang (2003) analyzes the long run relationship between A-share markets and B-share markets and H-share and red-chip in Hong Kong. He finds that that each of six markets is not linked with other markets in the long run. Applying standard cointegration technique, Geng et al. (2005) find there are cointegration relations between two A-share markets as well as between two B-share markets. However, they do not find the evidence supporting A-share and B-share markets are cointegrated with each other.

A great number of researchers have examined the information transmission among Chinese segmented stock markets. However, most of them focus on the information transmission of stock return (i.e the first moment). See, for example, Laurence et al. (1997), Chakravarty et al. (1998), Chui and Kwok (1998), Sjoo and Zhang (2000), Kim and Shin (2000), Fung et al. (2000), Yeh and Lee (2000), Chen et al. (2001) and

Tian and Wan (2004) etc.. A few researchers also have examined the information transmission of stock return volatility (i.e the second moment), see, for example, Chen et al. (2001), Li (2003) and Brooks and Ragunathan (2003). Elucidating the advantages of multivariate GARCH model in modeling stock return linkage and return volatility linkage simultaneously, three recent papers adopt this approach to examine the short run dynamic relationships among the segmented Chinese stock markets. Pong and Fung (2000) apply multivariate EGARCH-in-mean model to examine the information flow between H-shares, red chips, Shanghai Composite and Shenzhen Composite. They provide some evidences of return and return volatility spillover effects among the markets. Generally, they argue that red chips play a leading role in the flow of information among China-backed securities. Adopting VAR and bivariate GARCH-M models, Yeh et al. (2002) find that the unexpected changes in the premium ratio of A-share price over B-share price contribute to the return volatility of both A and B shares. Zheng and Wong (2006) employ a two-stage bivariate GARCH model incorporating external shocks to study spillover effect between price return of A-share and B-share and the impacts of US and Hong Kong on Chinese A-share and B-share markets. Their empirical results show that overall, there are spillover effects between A-share and B-share but the evidence is not strong[30].

Different from previous research, in this study, we apply a nonlinear fractional integrated vector error correction model (FIVECM) multivariate GARCH framework

[30] For detailed information about these papers, please refer to Chapter 2.

to examine the bilateral relationships between any pair of the following six pairs of stock markets[31]: H-SHA, H-SHB, SHB-SHA; H-SZA, H-SZB and SZB-SZA. More specifically, instead of using a VAR model or a VAR model with exogenous variable (VARX) to examine the dynamic relationships between stock returns[32], we use a FIVECM to examine the fractional cointegration mechanism between these six pairs of stock markets. In particular, we shall explore whether there is fractional cointegration between stock markets. This finding will be very useful to investors because the presence of fractional cointegration implies the existence of both long-run co-memories and non-periodic long cycles between the two markets. As a result, it would affect investors' asset allocation strategies in the long and medium terms (Cheung and Lai, 1995). At the same time, the presence of a fractional cointegrating relationship between two stock markets has an important implication for their short-run linkages. As a generalization of the standard linear VECM, which allows only the first-order lag of the cointegration residual to affect the equilibrium relationship, the FIVECM is superior because it not only enables investors to reveal the long-term equilibrium relationships and short-run adjustments among co-integrated variables but it also accounts for the possible long memory in the cointegration residual series that otherwise might distort the estimation (Ding et al.,

[31] It should be fine to investigate the possibility that there is a third variable, which can influence the cointegration relationship between two series. For our analysis, we did not do this because: (i) It is not easy to identify the third variable. (ii) Compared with other markets, the impacts from international markets on our Chinese stock markets are small. For A-shares, it is isolated from outside. For B-share market, there are evidences to show that their correlation with the major international stock markets, such as USA and Japan, are very low and these markets do not have much influences to B-share markets.

[32] If two stock indices are cointegrated or (fractionally) cointegrated, it is improper to use simple VAR or VARX to model their dynamic relationships in returns. Instead, we should use VECM or FIVECM as shown in this paper.

1993). Therefore, our FIVECM approach is a more general specification because it incorporates both the traditional VECM and the effects of the long memory of the cointegrating relationship, which is important for revealing the true relationships among markets (Baillie, 1996). In addition, this chapter specifies the conditional variances of VECM residuals with the multivariate GARCH model (Yang, 2001, Giovannini and Grasso, 2004 and Chen et al., 2006). Within this framework, empirical long-run relation, short term adjustment and spillover relationships in the mean as well as volatility in a cross-market setting can be simultaneously estimated[33]. The empirical results derived from this research reveal the nature of the complicated structure between two different markets, which, in turn, provides additional information to investors and fund managers for their investment decisions and strategy in these markets. Findings from this chapter are also useful for policy makers in setting regulations for these markets.

The empirical results show that all six pairs of stock markets are fractionally cointegrated. In each of the six pairs, the H-share stock market adjusts to return to equilibrium with the two A-share stock markets as well as the two B-share markets, while two B-share markets adjust to return to equilibrium with the corresponding two A-share markets. We find that there are bidirectional volatility spillover effects between the H-share and two A-share markets and between H-share and the two B-share markets. However, we find only unidirectional mean spillover effects from H-share market to the two A-share and two B-share stock markets and from SZA to

[33] The specification of FIVECM-BEKK will be discussed in more detail in Section 4.3.

SZB market. We find that H-share market plays very influential role in influencing four segmented stock markets in mainland China. Investigation of the dynamic path of correlation coefficients suggests that relaxation of government restrictions on the purchase of B shares by domestic residents increased the correlation between the A- and B-share markets and accelerated the market integration process of the A-share markets with the H-share stock market. The results also disclose that the Asian crisis had a different effect on stock-return dynamic correlations across Chinese segmented markets.

The remainder of this chapter is organized as follows. Section 4.2 discusses the data and methodology. Section 4.3 provides empirical results, and Section 4.4 summarizes the conclusions and comments.

4.2 Data and Methodology

4.2.1 Data

The data used in this study are weekly price indices of Shanghai A-share (SHA), Shenzhen A-share (SZA), Shanghai B-share (SHB), Shenzhen B-share (SZB), and H-share (H). All data are taken from *DataStream International*, and the sample covers January 1994 through the most recent October 2006. Weekly indices are used to alleviate the effects of noise characterizing daily data and to avoid the day-of-the-week effect (Lo and MacKinlay, 1988). The total number of observations in our study is 669.

4.2.2 Methodology

One of the principal tasks in this paper is to examine the stock-return behavior by exploring the short-run dynamics in relation to the long-run equilibrium in a cross-market setting. To achieve this end, we employ a cointegration test. The essence of the cointegration test is to examine whether two series that drifted apart in long-run equilibrium have a tendency to be brought back together again. Usually, the disequilibrium error used in the VECM framework is neither *I(1)* nor *I(0)* but follows a fractionally integrated process, *I(d)*[34], where $-0.5<d<0.5$ (Engle and Granger, 1987). Without accounting for the long memory (when $d<0.5$) feature of the disequilibrium error, the true relationships among cointegrated variables disclosed by traditional VECM may be misspecified. To circumvent this problem, we employ a fractionally integrated VECM (Engle, 1986) to study the nature of co-movements for each pair of stock-return series[35].

First we employ the Engle-Granger (1987) two-step approach. In the first step, following Saikkonen (1991), we fit a dynamic ordinary least squared model (*DOLS*) to the pairs of stock indices and thereafter obtain the estimated cointegrating residual $\hat{z}_t$ as follows:

$$y_{1t} = \alpha + \beta y_{2t} + \sum_{j=-p}^{p} \omega_j \Delta y_{2t-j} + v_t$$

$$\hat{z}_t = y_{1t} - \hat{\beta} y_{2t} \tag{4.1}$$

[34] A series, say y_t, that has a stationary, invertible, and stochastic ARMA representation after differencing *d* times is said to be integrated of order *d*, and denoted as $y_t = I(d)$.
[35] For more information on FIVECM, please refer to Baillie (1996)

Here, y_{1t} and y_{2t} are logarithm values of two stock indices; each could be SHA, SHB, SZA, SZB, and H; and Δy_{2t} is the differenced series of y_{2t}. This Regression is preferred to ordinary least squares, because it remove the deleterious effect of short-run dynamics in the equilibrium error v_t and the estimate $\hat{\beta}$ has been demonstrated by Stock and Watson (1993) to be super-consistent[36] as well as efficient. In the second step, we use both rescaled range (R/S) test and modified R/S test (Lo, 1991) to test for the existence of any long memory in the $\hat{z}_t$ series. If $\hat{z}_t$ is confirmed to follow an *I(d)* (-0.5<d<0.5) process, then y_{1t} and y_{2t} are said to be fractionally cointegrated and we proceed to estimate the fractional difference parameter *d* using each residual series.

A few methods have been proposed to estimate the parameter *d* based on either time domain or frequency domain, and the research in this line is still an active research field, say, for example, Shimotsu and Phillips (2005)[37]. In this study, we apply a robust R/S analysis shown by Taqqu and Teverovsky (1995, 1998) to estimate the fractional difference parameter *d.* Given the partial sums of a time series $Y(t)=\sum_{i=1}^{t} X(i)$ and its sample variance $S^2(n)$, the R/S statistics (Hurst, 1951) is defined as:

$$\frac{R}{S}(n)=\frac{1}{S(n)}\left[\max_{0\le t\le n}(Y(t)-\frac{t}{n}Y(n))-\min_{0\le t\le n}(Y(t)-\frac{t}{n}Y(n))\right] \tag{4.2a}$$

[36] This means that the estimate $\hat{\beta}$ converges to true value β at faster rate than usual OLS estimate.

[37] For other methods of estimating the parameter d, refer to Mandelbrot and Wallis(1969), Mandelbrot and Taqqu,(1979), Fox and Taqqu(1986), Beran (1994) Samorodnitsky and Taqqu(1994), Peng et al.(1994), Robinson (1995) and Kokoszka and Mikosch(1995, 1996b, 1996c) etc.

Lo (1991) pointed out that the R/S statistic above is not robust to short range dependence. Instead, Lo (1991) proposed a modified R/S statistic as follows:

$$\tilde{\frac{R}{S}}(n) = \frac{1}{\tilde{S}(n)}\left[\max_{0\le t\le n}(Y(t) - \frac{t}{n}Y(n)) - \min_{0\le t\le n}(Y(t) - \frac{t}{n}Y(n))\right] \qquad (4.2b)$$

Therefore, the sample standard deviation $S(n)$ in Equation (4.2a) is replaced by the square root of the Newey-West estimate of the long run variance $\tilde{S}(n)$ in Equation (4.2b).

Because of the asymptotic scaling property of $Y(t)$, $R(n)$ behaves like $n^H = n^{d+1/\alpha}$. Here α is a real number between 0 and 1 and H is known as the Hurst coefficient (see Hurst, 1951) to measure long memory. $S(n)$ is just the square root of the sample variance, which is proportional to $n^{2/\alpha-1}$. Thus, $S(n)$ behaves like $n^{1/\alpha-1/2}$. Since, in fact, one has joint convergence of ($R(n)$, $S(n)$), $\frac{R}{S}(n)$ behaves like $n^{d+1/\alpha}$, as $n \to \infty$. This provides a way of estimating *d*, whatever the value of α [38].

The actual method divides the original time series of length N into K blocks, each of size N/K. Then for each lag n, we compute $R(k_i, n)/S(k_i, n)$, starting at points $k_i = iN/K + 1$, $i = 1,2,...$ such that $k_i + n \le N$. As for large values of k_i, it is not robust to calculate R/S statistics. To mitigate this problem, we use least absolute deviation (LAD) method for robust estimation of *d*.

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[38] For more detailed discussion, please refer to Taqqu and Teverovsky (1998).

According to Engle and Granger (1987), if there is any cointegration relationship among the variables, a VECM representation can be established to adequately capture the relevant long-run and short-term relationships. Then VECM is extended to the FIVECM to account for the fractional integration property in $\hat{z}_t$ series. The bivariate FIVECM will then take the following form[39]:

$$\begin{aligned}\Delta y_{1t} &= c_1 + \alpha_1[(1-B)^d - (1-B)]\hat{z}_t + \sum_{i=1}^{m}\phi_{11}^{i}\Delta y_{1t-i} + \sum_{i=1}^{m}\phi_{12}^{i}\Delta y_{2t-i} + \varepsilon_{1t} \\ \Delta y_{2t} &= c_2 + \alpha_2[(1-B)^d - (1-B)]\hat{z}_t + \sum_{i=1}^{m}\phi_{21}^{i}\Delta y_{1t-i} + \sum_{i=1}^{m}\phi_{22}^{i}\Delta y_{2t-i} + \varepsilon_{2t}\end{aligned} \tag{4.3}$$

where

$$(1-B)^d = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)B^k}{\Gamma(-d)\Gamma(k+1)} \tag{4.4}$$

In the above equations[40], B is a backward shift operator and $\Gamma(.)$ is Gamma function taking the form:

$$\Gamma(x) = \int_0^{\infty} t^{x-1}e^{-t}dt \tag{4.5}$$

Here Δy_{1t} and Δy_{2t} denote the differenced series of y_{1t} and y_{2t}, respectively. They represent the return series for each pair of stock indices, namely, H-SHA, H-SHB, SHB-SHA; H-SZA, H-SZB and SZB-SZA. $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is the vector of

[39] For more discussion of the FIVECM framework, please refer to Davidson (2002).
[40] This fractional difference filter can be handled as an infinite order autoregressive process. In practice, we could use its truncated case of 200 lags here.

error terms; and the coefficients α_1 and α_2 indicate the short-run dynamic adjustments with their magnitudes representing the speeds of the adjustment. We employ a VAR (*m*) structure in the VECM model, in particular *m*=1, in this chapter. The lag terms in (4.3) account for the AR structure of the Δy_t series, with their coefficients reflecting the return transmissions between different stock markets.

To capture the heteroskedasticity in the VECM residuals, we follow the practice of a few papers to model it with a bivariate GARCH specification (Yang, 2001, Giovannini and Grasso, 2004 and Chen et al., 2006). To ensure that the variance matrix of error terms is positive definite, a bivariate BEKK (1, 1) model (Engle and Kroner, 1995) is adopted here such that[41]:

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \quad \text{for t=1, 2, ….. T;} \tag{4.6}$$

$$\Sigma_t = \begin{pmatrix} \sigma_t^{11} & \sigma_t^{12} \\ \sigma_t^{21} & \sigma_t^{22} \end{pmatrix} = C\,C' + A\,(\varepsilon_{t-1}\varepsilon_{t-1}')A' + B\,\Sigma_{t-1}\,B'; \tag{4.7}$$

Here, ε_t is assumed to follow a bivariate normal distribution conditional on the past information set Ω_{t-1}; Σ_t denotes the variance-covariance matrix of ε_t, which is symmetric and positive semi-definite; C is a lower triangular matrix; and A and B are unrestricted square matrices. Adopting this framework, the dynamics of Σ_t are fully displayed, since the dynamics of conditional variance and the conditional covariance are modeled directly. The volatility spillover effects across return series

[41] BEKK (1, 1) is usually sufficient to model volatility in financial time series. See, for example, Baba et al. (1990).

indicated by the off-diagonal entries of coefficient matrices A_1 and B_1 are also estimated. The expansion of BEKK (1, 1) into individual dynamic equations generates the following variance and covariance:

$$\begin{aligned}
\sigma_t^{11} &= (C^{11})^2 + \left[A^{11}\varepsilon_{1,t-1} + A^{12}\varepsilon_{2,t-1}\right]^2 + \left[(B^{11})^2\sigma_{t-1}^{11} + 2B^{11}B^{12}\sigma_{t-1}^{12} + (B^{12})^2\sigma_{t-1}^{22}\right] \\
\sigma_t^{22} &= (C^{21})^2 + (C^{22})^2 + \left[A^{21}\varepsilon_{1,t-1} + A^{22}\varepsilon_{2,t-1}\right]^2 + \left[(B^{21})^2\sigma_{t-1}^{11} + 2B^{21}B^{22}\sigma_{t-1}^{21} + (B^{22})^2\sigma_{t-1}^{22}\right] \\
\sigma_t^{12} &= C^{11}C^{21} + C^{11}C^{21}\varepsilon^2{}_{1,t-1} + (A^{11}A^{22} + A^{12}A^{21})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + A^{12}A^{22}\varepsilon^2{}_{2,t-1} + B^{11}B^{21}\sigma_{t-1}^{11} + \\
&\quad (B^{12}B^{21} + B^{11}B^{22})\sigma_{t-1}^{12} + B^{12}B^{22}\sigma_{t-1}^{22}
\end{aligned} \tag{4.8}$$

The conditional correlation between market 1 and 2 at any time t thus is defined as:

$$\rho_{1,2,t} = \frac{\sigma_t^{12}}{\sqrt{\sigma_t^{11}\sigma_t^{22}}} \tag{4.9}$$

One weakness of BEKK model is that it requires estimation of a large number of parameters, especially when the dimensions of the variance-covariance matrix increase. However, this weakness will not bother much in this study as our model is in a bivariate framework. Instead, we prefer to use BEKK specification in our study because of its advantage of generality and flexibility. In fact, the BEKK specification appears to be a more general and flexible multivariate GARCH model as there are no restrictions imposed on the coefficients. In this chapter, the FIVECM-BEKK model (i.e., systems (4.3) and (4.8) jointly) is estimated jointly and the coefficient estimates would be more efficient, and the relationships among the series would be delineated more accurately. The estimates of parameters, conditioning on the starting value of conditional variance; the popular optimization algorithm BHHH (Berndt, Hall, Hall & Hausman) is employed in maximizing likelihood.

4.3 Empirical Results[42]

4.3.1 Data Preliminary Analysis

We report the basic statistics of five stock indices[43] in Table 4.1. These statistics provide an overview on the five segmented stock markets.

Table 4.1
Descriptive Statistics for Chinese stock indices

	SHA	SHB	SZA	SZB	H
Mean	5.035	4.289	3.738	2.902	6.021
Median	5.126	4.291	3.878	2.863	6.122
Maximum	5.636	5.480	4.443	4.006	6.955
Minimum	3.663	3.124	2.403	1.753	4.969

Note: These are descriptive statistics of the logarithms of stock indices. Sample covers January 1994 through October 2006. The total number of observations is 669.

We then conduct augmented Dikey-Fuller (ADF) and Philips-Perron (PP) unit root tests to examine the stationary property for the five logarithm indices in this study: SHA, SZA, SHB, SZB, and H. The results presented in Table 4.2 above clearly indicate that all of the indices are I (1)[44] process by adopting both ADF and PP unit root testing procedures. The findings are consistent with the results widely reported in the literature.

[42] The empirical part is done with the S-Plus of Insightful Corporation.
[43] The indices in this paper are referred to as logarithm indices.
[44] For all series, we further test for I(2). Our findings reject the hypothesis that the series are I(2), inferring that the series are I(1). We skip the I(2) results, which are available on request.

Table 4.2
Unit Root Tests for Chinese Stock Index Series

Market \ Test	ADF		PP	
	t-statistic	p-value	t-statistic	p-value
SHA	-2.146	0.519	-2.238	0.467
SZA	-1.549	0.812	-1.640	0.776
SHB	-2.051	0.572	-2.225	0.474
SZB	-2.839	0.184	-2.602	0.280
H	-1.639	0.777	-1.742	0.732

Note: The null hypothesis of ADF test and PP test is that the series has unit root. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.3.2 Test for Long Memory

The next step is to estimate the six cointegration residuals $\hat{z}_t$ based on Equation (4.1) for the six pairs of stock indices of interest to us: H-SHA, H-SHB, SHB-SHA; H-SZA, H-SZB and SZB-SZA. This is done by performing a *DOLS* estimation with lag length *p*=2. The resulting error series are denoted by z_{SHA}^{H}, z_{SHB}^{H}, z_{SHA}^{SHB}, z_{SZA}^{H}, z_{SZB}^{H} and z_{SZA}^{SZB} respectively, where a superscript stands for a dependent variable and a subscript for an independent variable.

We then adopt both R/S test and Lo's modified R/S test (Lo, 1991) to examine the long memory behavior in the six residual series mentioned above and report the results in Table 4.3 below. The results indicate that all these six residual series have long memory.

Table 4.3

Long Memory Tests on Cointegration Residuals

Test / Residual series	R/S test	Modified R/S test
	Test statistic	**Test statistic**
z_{SHA}^{H}	9.039***	3.496***
z_{SHB}^{H}	11.674***	4.470***
z_{SHA}^{SHB}	9.436***	3.597***
z_{SZA}^{H}	8.539***	3.304***
z_{SZB}^{H}	11.687***	4.473***
z_{SZA}^{SZB}	11.249***	4.289***

Note: The residual series are constructed using Equation (4.1) in the text; superscript stands for a dependent variable and subscript for an independent variable. *** and ** indicate significance at the 1% and 5% level, respectively.

With these evidences of existence of long memory property in the six residual series, therefore, we proceed to apply robust R/S analysis (Taqqu and Teverovsky, 1998) to estimate the fractional difference parameter *d* for each of these six series. For the purpose of comparison, we also do the R/S analysis. We display the estimated results using the two methods in Table 4.4.

It can be seen that all of the estimated values of *d* fall into the range (0, 0.5). This evidence thus confirms that the cointegrating variables follow long memory stationary processes. We, therefore, conclude that the six pairs of stock markets are fractionally cointegrated with each other. This finding also carries important implication for the investors: when these stock markets are cointegrated, the potential for making supra-normal profits through portfolio diversification is limited in the long run.

Table 4.4

Estimation of fractional parameter *d* using R/S Analysis

Method / Residual	R/S Analysis	Robust R/S Analysis
	d	***d***
z_{SHA}^{H}	0.450	0.478
z_{SHB}^{H}	0.456	0.470
z_{SHA}^{SHB}	0.452	0.477
z_{SZA}^{H}	0.457	0.474
z_{SZB}^{H}	0.453	0.472
z_{SZA}^{SZB}	0.446	0.461

Note: The residual series are constructed using Equation (4.1) in the text; superscript stands for a dependent variable and subscript for an independent variable.

Having verified the feature of the long-term cointegration relationships between each pair of the stock indices, we proceed to employ the FIVECM-BEKK(1,1) model to model each pair of log-returns, including the pairs of log-returns for HK-SHA, H-SHB, SHB-SHA; H-SZA, H-SZB and SZB-SZA. The results are presented in Tables 4.5 and 4.6, respectively[45].

The statistical results shown in these tables allow us to analyze the short-term adjustment, the long-term equilibrium relationship, and the spillover effects between each pair of segmented Chinese stock market. For instance, the estimated coefficient ϕ_{12}^{1} for H-SHA pair measures the mean spillover effect from the Shanghai A-share

[45] When estimated FIVECM-BEKK in Table 4.5 and 4.6, we used the estimated *d* based on Robust R/S analysis reported in the second column of Table 4.4.

stock market to the H-share stock market, while ϕ_{21}^{1} measures the mean spillover effects from the H-share stock market to the Shanghai A-share stock market. Similarly, ARCH(1,2) and GARCH(1,2) measure the volatility spillover effects from the Shanghai A-share stock market to the H-share stock market, while ARCH (2,1) and GARCH(2,1) measure the volatility spillover effects from the H-share stock market to the Shanghai A-share stock market. Parameters α_1 and α_2 indicate short-term adjustments to the equilibrium of the H-share stock market and Shanghai A-share stock market, respectively.

Finally, we adopt Ljung-Box test of white noise for the purpose of model adequacy diagnostics. It is applied to both standardized residuals and squared standardized residuals to test for possible remaining serial correlation in the first and second moments of residuals. The number of lags employed in both Ljung-Box tests is 10, thus the test statistics follow Chi-square distribution with 10 degree of freedom. All the tests are applied to two individual residual series, separately. Insignificant Ljung-Box test statistics suggest that the fitted model is adequate and successful in capturing the dynamics in the first as well as second moments of index return series.

4.3.3 Relationships among H-share, Shanghai A- and B- Share Stock Markets

In Panel A of Table 4.5, we present the estimation results of FIVECM-BEKK (1, 1) bivariate GARCH models for three pairs of stock market: i.e., H-SHA, H-SHB and SHB-SHA.

Table 4.5
Estimates for FIVECM-BEKK (1, 1) Fitted on H-SHA, H-SHB and SHB-SHA

Markets / Estimates	**H**-SHA	**H**-SHB	**SHB**-SHA
Panel A: Estimated results			
c_1	0.008(0.003)***	0.008 (0.003)**	0.002 (0.002)
c_2	0.000 (0.002)	0.002 (0.003)	0.001 (0.001)
ϕ_{11}^1	-0.044 (0.039)	-0.010 (0.049)	0.162 (0.049)***
ϕ_{12}^1	0.024 (0.039)	-0.022 (0.046)	-0.006 (0.041)
ϕ_{21}^1	0.060 (0.024)***	0.075 (0.033)***	0.036 (0.032)
ϕ_{22}^1	-0.006 (0.040)	0.073 (0.050)	-0.003 (0.042)
α_1	-0.016 (0.006)***	-0.017 (0.008)**	-0.039 (0.016)**
α_2	-0.001 (0.003)	-0.010 (0.008)	-0.013 (0.011)
A(1,1)	0.006 (0.002)***	0.003 (0.004)	0.014 (0.001)***
A(2,1)	0.008 (0.002)***	0.016 (0.020)	0.008 (0.001)***
A(2,2)	0.005 (0.002)***	0.003 (0.096)	0.003 (0.001)***
ARCH(1,1)	0.220 (0.028)***	0.222 (0.037)***	0.346 (0.039)***
ARCH(1,2)	0.149 (0.040)***	0.106 (0.037)***	0.096 (0.034)***
ARCH(2,1)	-0.116 (0.024)***	-0.135 (0.040)***	-0.012 (0.028)
ARCH(2,2)	0.504 (0.029)***	0.374 (0.039)***	0.405 (0.022)***
GARCH(1,1)	0.966 (0.007)***	0.982 (0.012)***	0.892 (0.017)***
GARCH(1,2)	-0.072 (0.016)***	-0.071 (0.026)***	-0.032 (0.013)***
GARCH(2,1)	0.016 (0.007)**	0.052 (0.013)***	-0.024 (0.013)
GARCH(2,2)	0.851 (0.016)***	0.865 (0.022)***	0.919 (0.008)***

Panel B: Diagnostic tests			
LB (10)-H	11.510	10.919	NA
LBS (10)-H	9.418	7.581	NA
LB (10)-SHA	13.259	NA	16.34
LBS (10)-SHA	7.096	NA	7.837
LB (10)-SHB	NA	15.759	17.26
LBS (10)-SHB	NA	7.253	8.551
Jarque-Bera-H	18.38***	29.07***	NA
Jarque-Bera-SHA	354.58***	NA	431.6***
Jarque-Bera-SHB	NA	207.52***	138.3***

Note: The estimates are based on Equations (4.3) and (4.8) in the text. The dependent variable in each model is marked in bold. The first-order ARCH(i,j) and GARCH(i,j) terms are the elements of the ARCH and GARCH coefficient matrices A1 and B1 in Equations (4.6) and (4.7). Numbers in parentheses are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. LB (10) and LBS (10) are the Ljung-Box statistics based on the level and the squared level of the time series up to the 10th lag. Jarque-Bera is Jarque-Bera normality test statistics.

The first column of Table 4.5 report the estimates of FIVECM-BEKK (1,1) model for the H-SHA pair. For the estimates of mean equations, ϕ_{21}^{1} has a positive sign and is statistically significant, but ϕ_{12}^{1} is not significant. This suggests that there is a mean spillover effect from the H-share stock market in Hong Kong to the Shanghai A-share stock market but the reverse relationship does not hold. The value of the short-term adjustment parameter α_1 is -0.016, which is significant at the 1% level, suggesting that the H-share stock market makes a partial adjustment when it drifts away from long-run equilibrium. The α_2 bears a negative sign; however, it is not statistically significant. This suggests that the cointegrating relationship between the two markets does not reveal the movements on the part of the Shanghai A-share stock market. So the adjustment scheme is only unilateral. For the variance equation, we find that off-diagonal ARCH (1,2), ARCH (2,1), GARCH (1,2) and GARCH(2,1) are all significant, indicating the existence of a bidirectional volatility spillover effect between Shanghai A-share stock market and H-share stock market.

With respect to the estimates of the H-SHB pair market, the evidence reported in the second column of Table 4.5 shows that ϕ_{12}^{1} is not significant, but ϕ_{21}^{1} is, indicating a unidirectional mean spillover effect from the H-share to the Shanghai B-share stock market. In other words, H-share stock market Granger-causes or leads Shanghai B-share stock market in returns. The value of the short-term adjustment parameter α_1 is -0.017, which is significant at about 5% level, suggesting that the H-share market adjusts when it drifts away from long-run equilibrium. The non-significance of the α_2 estimate indicates that the Shanghai B-share stock market is not bound by the cointegration relationship. For the variance equation, the test results show that all off-diagonal ARCH terms and GARCH terms are significant and disclose a bidirectional volatility spillover effect between the H-share stock market and Shanghai B-share stock market, implying strong transmission of information between these two stock markets.

The third column of Table 4.5 provides the estimates for the SHB-SHA pair of stock returns. From the results, we find that neither ϕ_{12}^{1} nor ϕ_{21}^{1} is significant, concluding that there is no spillover effect in the first moment between the Shanghai B-share stock market and the Shanghai A-share stock market. The adjustment speed coefficient α_1 is significantly negative, while coefficient α_2 is insignificant, implying that the Shanghai A-share stock market is not bound by the cointegration relationship and Shanghai B-share stock market adjusts when it drifts away from long-run equilibrium. For the spillover effect of volatility, evidence shows that only ARCH (1, 2) and GARCH (1, 2) terms are significant, while ARCH(2,1) and GARCH(2,1) terms are insignificant. Thus, we conclude that there exists strong and unidirectional transmission of information from the Shanghai A-share stock market to the Shanghai B-share stock market.

To sum up, evidence shows that there are bi-directional volatility spillover effects between H-share stock market and Shanghai A-share stock market, between H-share stock market and Shanghai B-share stock market, but only a unidirectional volatility spillover effect from the Shanghai A-share stock market to the Shanghai B-share stock market. In addition, we find H-share market also pass mean spillover effect to both Shanghai A-share and Shanghai B-share stock markets. We conclude that the H market plays a very influential role among the three markets: it not only passes return realizations to the Shanghai A-share and Shanghai B-share stock markets, but it also leads in the transmission of their volatilities. We also find that among three pairs of stock markets, only one market is found to adjust to return to equilibrium: the H-share market adjusts disequilibrium conditions with the Shanghai A-share and Shanghai B-share stock markets, while the Shanghai B-share stock market adjusts in response to disequilibrium with the Shanghai B-share stock market. Among the three markets, we find Shanghai A-share stock market has strongest market power as other two segmented markets move to it in the long run.

The model diagnostics are reported in Panel B of Table 4.5. Ljung-Box tests of white noise are applied to both the standardized residuals and the squared standardized residual series to test joint significance for serial correlation in the first and second moments of residuals. As indicated, all Ljung-Box test statistics are not significant at conventional level, and we conclude that our fitted FIVECM-BEKK GARCH models are adequate and successful in capturing the dynamics in the first two moments of three index return series. The normality test shows the residuals are non-normal[46].

4.3.4 Relationships among H-share, Shenzhen A- and B- Share Stock Markets

We report the estimated results of FIVECM-BEKK for H-SZA, H-SZB and SZB-SZA in Table 4.6.

Table 4.6
Estimates for FIVECM-BEKK (1, 1) fitted on H-SZA, **H**-SZB and **SZB**-SZA

Markets / Estimates	**H**-SZA	**H**-SZB	**SZB**-SZA
Panel A: Estimated results			
c_1	0.008 (0.003)***	0.008 (0.003)***	0.004(0.002)*
c_2	-0.001 (0.002)	0.002 (0.004)	-0.001(0.002)

[46] In literature, it is reported that the distribution of the residuals sometime is different from the distribution assumption of the econometrics models. The reason to explain this issue is an open question for further research.

ϕ_{11}^{1}	-0.029 (0.038)	-0.027 (0.042)	0.171 (0.045)***
ϕ_{12}^{1}	-0.033 (0.041)	0.030 (0.029)	0.071 (0.041)*
ϕ_{21}^{1}	0.044 (0.026)*	0.098 (0.034)***	0.028 (0.034)
ϕ_{22}^{1}	0.011 (0.039)	0.112 (0.049)**	0.081 (0.045)*
α_1	-0.016 (0.006)***	-0.021 (0.009)**	-0.044 (0.028)
α_2	0.001 (0.005)	-0.008 (0.014)	-0.004 (0.017)
A(1,1)	0.005 (0.002)***	0.006 (0.002)***	0.010 (0.001)***
A(2,1)	0.006 (0.002)***	0.023 (0.006)***	0.006 (0.001)***
A(2,2)	0.003 (0.002)	0.000 (0.501)	0.002 (0.001)***
ARCH(1,1)	0.217 (0.027)***	0.214 (0.032)***	0.381 (0.026)***
ARCH(1,2)	0.130 (0.029)***	0.099 (0.034)***	-0.020(0.029)
ARCH(2,1)	-0.070 (0.023)***	-0.188 (0.040)***	0.014 (0.016)
ARCH(2,2)	0.399 (0.027)***	0.466 (0.042)***	0.305 (0.023)***
GARCH(1,1)	0.969 (0.007)***	0.982 (0.010)***	0.915 (0.009)***
GARCH(1,2)	-0.053 (0.009)***	-0.096 (0.030)***	-0.002 (0.008)
GARCH(2,1)	0.015 (0.006)***	0.064 (0.016)***	-0.016 (0.056)
GARCH(2,2)	0.912 (0.010)***	0.748 (0.046)***	0.950 (0.006)***
Panel B: Model diagnostic statistics			
LB (10)-H	11.758	11.326	NA
LBS (10)-H	7.972	6.466	NA
LB (10)-SZA	11.542	NA	15.70
LBS (10)-SZA	4.745	NA	7.112
LB (10)-SZB	NA	16.122*	13.12

LBS (10)-SZB	NA	11.657	14.052
Jarque-Bera-H	16.56***	21.62***	NA
Jarque-Bera-SZA	644.59***	NA	600.20***
Jarque-Bera-SZB	NA	580.20***	550.30***

Note: The estimates are based on Equations (4.3) and (4.8) in the text. The dependent variable in each model is marked in bold. The first-order ARCH(i,j) and GARCH(i,j) terms are the elements of the ARCH and GARCH coefficient matrices A1 and B1 in Equations (4.6) and (4.7). Numbers in parentheses are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. LB (10) and LBS (10) are the Ljung-Box statistics based on the level and the squared level of the time series up to the 10^{th} lag. Jarque-Bera is Jarque-Bera normality test statistics.

In general, we find that the relationships are very similar to those of their counterparts presented in the sub-section above. For the H-SZA pair, which is reported in the first column of Table 4.6, we find that ϕ_{21}^{1} is positively significant, but the coefficient of ϕ_{12}^{1} is insignificant. This evidence is consistent with a unidirectional mean spillover from the H-share stock market to the Shenzhen A-share stock market. Next, the estimated parameter α_1 has a value of -0.016, which is statistically significant at 1%, suggesting that the H-share stock market adjusts as it diverges from its long-run equilibrium with the Shenzhen A-share stock market. On the other hand, the estimate of α_2 is found to be not significant, indicating that the movement of the Shenzhen A-share stock market is not governed by the cointegrating relationship between these two markets. By checking with the variance equations, results show that all off-diagonal ARCH terms and GARCH terms, ARCH (1,2), ARCH (2,1), GARCH (1,2) and GARCH(2,1), are significant, indicating that there are bidirectional volatility spillover effects between the two markets.

As we inspect the H-SZB pair relationship shown in the second column in Table 4.6, the estimate of ϕ_{21}^{1} is statistically significant and ϕ_{12}^{1} is not significant., showing a unidirectional mean spillover effect from H-share stock market to Shenzhen B-share stock market. Looking at the short-term adjustment parameter, we find α_1 to be -0.021 and statistically significant. The comparable coefficient, α_2, also shows a negative sign; however, it is insignificant, suggesting that the H-share market makes the adjustment when it deviates from a long-run equilibrium relationship. In contrast, no evidence indicates that the Shenzhen B-share stock market is bound by the cointegration relationship. On the basis of the conditional variance equations, we find that all off-diagonal ARCH terms and GARCH terms, ARCH (1,2), ARCH (2,1), GARCH (1,2) and GARCH(2,1), are significant. Therefore, we conclude that there are bidirectional volatility spillover effects between the H-share and Shenzhen B-share stock markets, implying strong transmission of information between the two stock markets.

Finally, we examine the SZB-SZA pair of markets. Since only ϕ_{12}^{1} is significant, there is evidence to indicate spillover effect in stock returns from the Shenzhen A-share stock market to Shenzhen B-share stock market. As far as the adjustment coefficient is concerned, the estimated α_1 is -0.044 and marginally significant at about 11% level, while α_2 is insignificant, revealing that the disequilibrium between the two markets will be corrected only by the Shenzhen B-share stock market. With respect to the spillover effect of volatility, evidence indicates there is no volatility spillover effect between the SZB and SZA markets.

The model diagnostics, as shown in Panel B of Table 4.6, demonstrate that none of the Ljung-Box test statistics is statistically significant for both the standardized residuals and the squared standardized residual series, implying no serial correlation in the first and second moments of residuals. This indicates the adequacy of our FIVECM-BEKK(1,1) bivariate GARCH model in modeling the dynamics of the conditional mean and conditional variance[47].

In short, interrelationships among these three markets are very similar to those among the H-share, Shanghai A-share and Shanghai B-share stock markets: there are bidirectional volatility spillover effects between H-share and Shenzhen A-share stock markets as well as between H-share and Shenzhen B-share stock markets and only a unidirectional mean spillover effect from the H-share stock market to these two stock markets in SZSE. It seems that H-share market is more influential in short run dynamic relationships among the three markets. Moreover, among the three pairs of stock markets, H-SZA, H-SZB and SZB-SZA, H-share market is characterized by a partial adjustment process to return to long-run equilibrium with Shenzhen A-share stock market and Shenzhen B-share stock market, respectively, while Shenzhen B-share stock market adjusts when it deviates from a long-run equilibrium relationship with Shenzhen A-share stock market. Generally speaking, we find Shenzhen A-share stock market has strongest market power in the long run as other

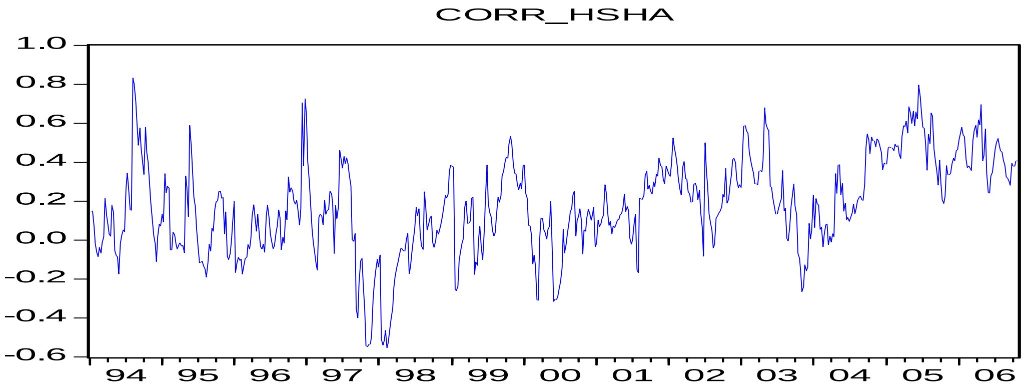
[47] Again, here the residuals are non-normal. In literature, it is reported that the distribution of the residuals sometime is different from the distribution assumption of the econometrics models. The reason to explain this issue is an open question for further research.

two markets will move to it when they deviate from a long-run equilibrium relationship with it, respectively[48].

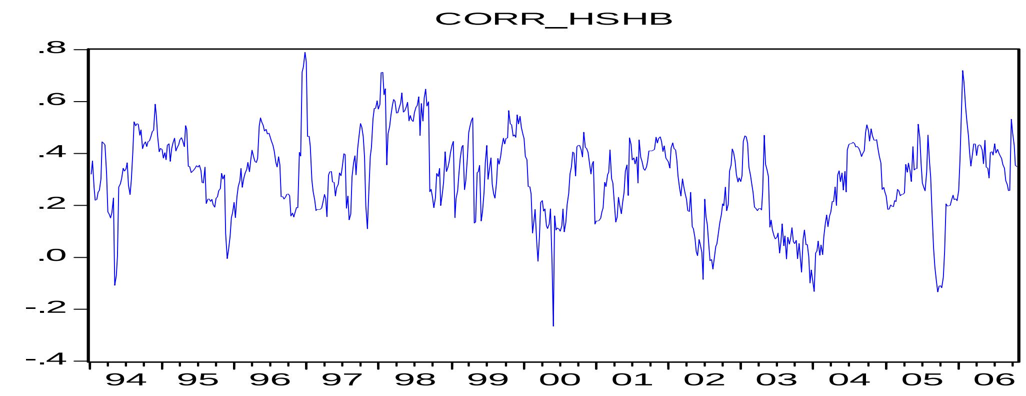
4.3.5 Analyses of Dynamic Correlations

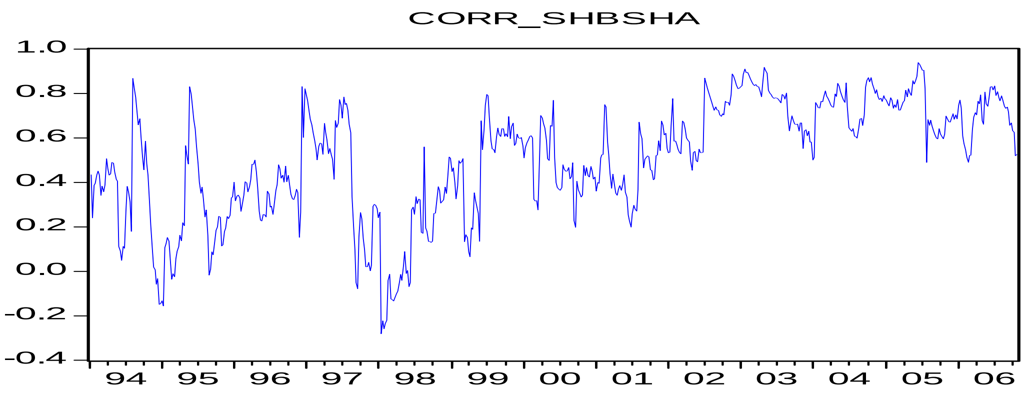
Having modeled the long-term equilibrium, short-term adjustment, and spillover effects across these markets, it is of interest to analyze the effects of changes in financial policy on the dynamic correlations between the markets. In Fig. 4.1, we plot the time-varying conditional correlation coefficients estimated from the FIVECM-BEKK model for each pair of markets.

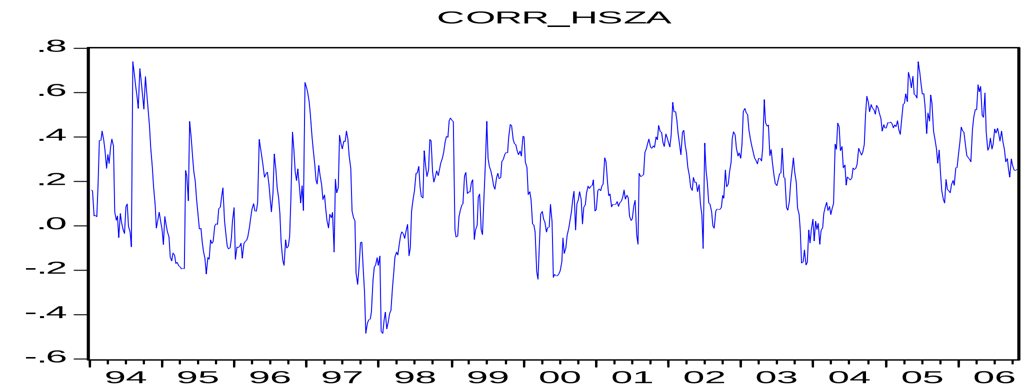
Figure 4.1 Conditional Correlations among the Markets

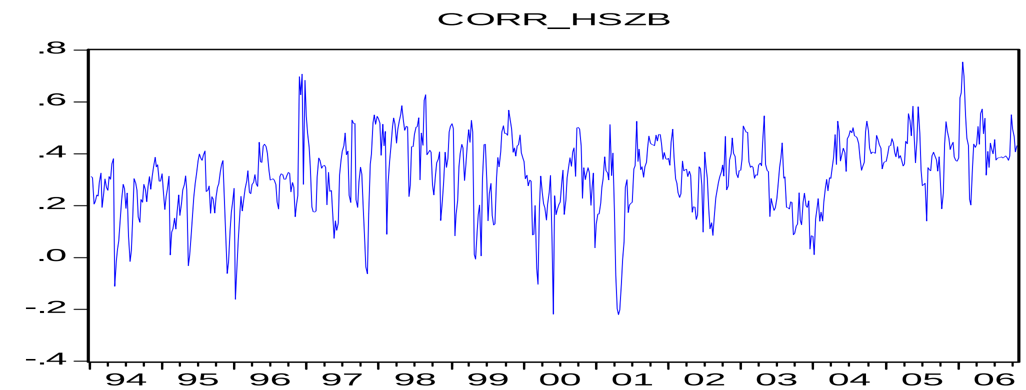


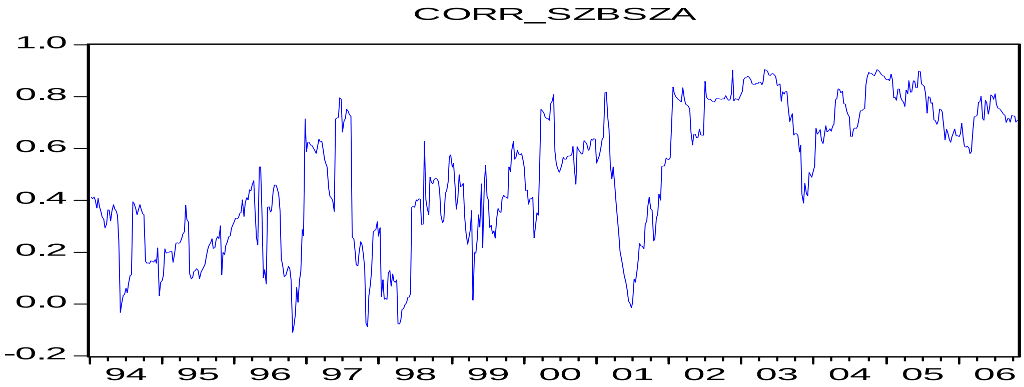
[48] Interesting enough, the results indicate that H-share stock market has a little bit faster speed of adjustment in response to disequilibrium with the Shenzhen B-share stock market than what it does with the Shanghai B-share stock market (for SHB, α_1=-0.017; for SZB, α_1=-0.021), implying its price discovery process of H-share stock market relative to Shenzhen B-share market is more efficient than its price discovery process relative to the Shanghai B-share. It might be due to the facts that same denominated currency of H-share and Shenzhen B-share (i.e. Hong Kong dollars) and their geographical proximity.


CORR_HSHB
.8
.6
.4
.2
.0
-.2
-.4
94 95 96 97 98 99 00 01 02 03 04 05 06


CORR_SHBSHA
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
94 95 96 97 98 99 00 01 02 03 04 05 06


CORR_HSZA
.8
.6
.4
.2
.0
-.2
-.4
-.6
94 95 96 97 98 99 00 01 02 03 04 05 06


CORR_HSZB
.8
.6
.4
.2
.0
-.2
-.4
94 95 96 97 98 99 00 01 02 03 04 05 06



Note: This figure shows the time-varying correlation coefficient of six pairs of stock markets: HSHA, HSHB, SHBSHA, HSZA, HSZB and SZBSZA for the period January 1994 through October 2006

By visual inspection of these figures above, we could identify two very interesting points. First, after February 2001, the correlations between the SHA-SHB and SZA-SZB markets show an upward trend over time. This pattern may be attributable to the more liberal governmental policy allowing domestic citizens who invest in A-share markets to invest in B-share markets.

Second, the time-varying correlation coefficients show different patterns of evolution during the Asian financial crisis, which started in early July 1997. For example, from late 1997 through early 1998, we find that the correlations between any of the A-share markets and the H or B-share markets decrease, but, in contrast, the correlations between any of the B-share markets and the H market increase.

In light of these observations, we proceed to examine the time-varying correlation coefficients between any two markets in response to unusual market conditions, such as a financial crisis and changes in regulation policy. Expressing this notion in a regression model, we write:

$$\rho_{ij,t} = d_0 + d_1 crisis1_t + d_2 crisis2_t + d_3 FP_t + \varepsilon_t \qquad (4.10)$$

where $\rho_{ij,t}$ are the conditional correlation coefficients between Markets i and j estimated from FIVECM-BEKK GARCH models based on Equation (4.9). $crisis1_t$ and $crisis2_t$ are dummy variables, denoting the early stage (7/2/1997 -10/15/1997) and the effective stage (10/22/1997-12/28/1998) of the Asian financial crisis, respectively. We select mid-October, 1997 as cutting date because: although the Asia financial crisis originated in Thailand and the market declined sharply in June 1997, followed by the collapse of the Indonesian market in August, no serious attention was given to these markets until the crisis hit the Hong Kong market in mid-October (between October 20 and October 23 the Hang Seng Index dipped by 23%). From the perspective of Chinese stock investors, the Hong Kong market crash in mid-October was a direct threat to their investments, since the portfolio performance in the B-share markets is perceived to be highly correlated with that of Hong Kong's market and Shenzhen B shares are measured in HK dollars. Furthermore, H-shares are traded in Hong Kong stock exchange. FP_t is a dummy to capture the impact of the removal of the restriction on investment in B shares in February 2001 by Chinese government (2/22/2001-12/28/2005). The dummy variables are set to unity to indicate the presence of an effect and are zero otherwise.

We display the estimated coefficients for Equation (4.9) in Table 4.7.

Table 4.7
Effects of Crisis and Policy Change on Conditional Correlation across Chinese Segmented Stock Markets

Markets / Estimates	H-SHA	H-SHB	SHB-SHA
d_0	0.111 (0.012)***	0.321 (0.009)***	0.412 (0.011)***
d_1	-0.033 (0.053)	0.031 (0.039)	-0.018 (0.048)
d_2	-0.213 (0.029)***	0.156 (0.021)***	-0.278 (0.026)***
d_3	0.194 (0.017)***	-0.056 (0.013)***	0.272 (0.015)***

Markets / Estimates	H-SZA	H-SZB	SZB-SZA
d_0	0.132 (0.012)***	0.272 (0.008)***	0.372 (0.012)***
d_1	-0.030 (0.054)	0.085 (0.036)**	0.060 (0.051)
d_2	-0.140 (0.029)***	0.133 (0.019)***	-0.134 (0.028)***
d_3	0.167 (0.017)***	0.072 (0.011)***	0.315 (0.016)***

Notes: The estimates are based on Equation (4.9) in the text. Numbers in parentheses are standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

From the above table, we find that the indicator of the effect of the early stage of Asian financial crisis, d_1, is insignificant for all pairs of markets except H-SZB[49].

[49] We think this is a reasonable finding as both of them are measured in HK dollars.

Thus, in the early stage of the crisis, 7/2/1997-10/15/1997, the effect was not fully hitting these six markets. However, from Hong Kong and Chinese investors' point of view, the crisis took effect on October 20, 1997. This led to the negative and highly significant d_2 for H-SHA, SHB-SHA, H-SZA, and SZB-SZA. In contrast**,** the contagion effect spread the crisis to the H- and two B-share markets, as evidenced by a positive correlation and significant d_2 on the H-SHB and H-SZB pair. Our findings are useful for the Chinese policy makers to evaluate their market segmentation policy. In all, we find this market segmentation policy is very successful to shield the A-share markets from the external shock.

The coefficient of the FP_t variable, d_3, is significantly positive for SHB-SHA and SZB-SZA, indicating that the correlations between A- and B-share markets increased after domestic investors in A-share markets were allowed to purchase B shares. Interestingly, we find that d_3 for H-SHA and H-SZA are also positive and highly significant, suggesting that even domestic investors in A-share markets are still not allowed to invest in the H market and their participation in B-share markets tends to stimulate active transmission of information between the A-share and the H-share markets. We conclude that this more relaxed policy on purchasing B shares helped to accelerate the market integration process of A-share markets with international financial markets. In contrast, we find that d_3 for H-SHB is negative and highly significant, suggesting that the participation of domestic citizens in Shanghai B-share stock market is less efficient in transmitting information between the Shanghai B-share market and the H-share market and, consequently, reduces the correlation between these two markets.

4.4 Conclusions of Chapter 4

In this chapter we apply a nonlinear FIVECM bivariate GARCH framework to examine the long-term equilibrium, short-term adjustment, and spillover effects among six pairs of stock markets, namely, H-SHA, H-SHB, SHB-SHA, H-SZA H-SZB and SZB-SZA. Our FIVECM approach is considered to be more general than the traditional linear VECM approach, since it can measure the effect of the long memory on the cointegrating relationship, which is important for revealing the true relationships between the relevant stock markets. Furthermore, augmenting the FIVECM with a bivariate GARCH formulation, we investigate the mean and volatility spillover effects across these markets simultaneously.

Our empirical results show that all six pairs of stock markets are fractionally cointegrated. In each of the six pairs, the H-share stock market adjusts to return to equilibrium with the two A-share stock markets as well as the two B-share markets, while two B-share markets adjust to return to equilibrium with the corresponding two A-share markets. We conclude that A-share markets have strongest market power in influencing other markets in the long run.

We find that there are bidirectional volatility spillover effects between the H-share and two A-share markets and between H-share and the two B-share markets. However, we find only unidirectional mean spillover effects from H-share market to the two A-share and two B-share stock markets and from Shenzhen A-share stock market to

Shenzhen B-share stock market. We conclude that H-share market plays a very influential role in influencing short-run dynamics of stock markets in mainland China. This may be due to the fact that: (1) H-share market are better managed and their management is more transparent as a result of their management style; and (2) investors are more conscious of economic content of news as Hong Kong market is subject to less manipulation vis-à-vis the China stock market.

Further investigation of the dynamic path of correlation coefficients suggests that relaxation of government restrictions on the purchase of B shares by domestic residents increased the correlation between the A- and B-share markets and accelerated the market integration process of the A-share markets with the H-share stock market. Our results also disclose that the Asian crisis had a different spillover effect on stock-return dynamic correlations across Chinese segmented markets. We conclude that the market segmentation policy imposed by the Chinese authority is an effective instrument for shielding the domestic A-share markets from external turbulence.

Chapter 5: Lead-lag relations among Chinese segmented stock markets

5.1 Introduction

China's stock markets, initiated in early 1990's, have been expending tremendously in the past decade. As a mechanism for developing its stock markets, the Chinese government has adopted a market segmentation policy[50]. Firstly, each company's stock is restricted to one of the two exchanges, i.e. Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). In this way, the markets in these two exchanges remain distinct. In addition, the companies listed in SHSE are likely to be state-owned big companies, many of which monopolize supplies to the domestic market (Kim and Shin, 2000). Whereas those listed in the SZSE tend to be smaller export-oriented companies, many of which are joint ventures. Although cross listing is not permitted, the two exchanges are subject to the same macroeconomic and policy factors. Depending on the nature of the companies listed in each exchange, the sensitivities of stock price movements caused to the common market factors might be different between the two stock exchanges (Kim and Shin, 2000).

Secondly, to cater to the needs of different investors, Chinese companies can issue A shares to Chinese citizens living in mainland China and B shares to foreign

[50] For detailed introduction on segmentation of Chinese stock markets, please refer to Chapter 1.

investors, including Chinese investors residing in Hong Kong, Macau, or Taiwan[51]. A and B shares are listed on the SHSE and the SZSE, i.e. SHA, SHB, SZA, and SZB.

Due to features of different type of shares (A- and B-share) and of different exchanges (SHSE and SZSE) dominated by stocks of different sizes, it is an interesting issue for both academic and practitioners to investigate the lead-lag relations among these stock markets. In the finance literature, it is a widespread assumption that foreign investors are less informed than domestic investors about the value of local assets (See, for example, Brennan and Cao, 1997; Kang and Stulz, 1997; Stulz and Wasserfallen, 1995). These authors think that this could be due to various factors such as language barriers, different accounting standards in the recipient and investing economies, and due to lack of reliable information about the local economy and firms. However, there are also evidences supporting foreign investors are better informed. For example, Froot, O'Connell, and Seasholes (2001) document that foreign investors' portfolio inflows have a noticeable ability to predict positive future returns in emerging markets but not in developed markets. Pan, Chan, and Wright (2001) also find that foreign investors are better informed than domestic investors in six East Asian emerging markets. Thus A detailed investigation of the dependence dynamics between A and B shares could lead to better understanding of the behaviors of domestic and foreign investors. If Chinese stock markets are efficient, any firm specific information should be reflected in prices of both A and B shares and also result in the same degree of price changes simultaneously as both A and B shares are

[51] Some companies are allowed to issue H, N, and S shares, which are traded on the Hong Kong Stock Exchange, New York Stock Exchange, and Singapore Stock Exchange.

issued by the same company. However, in practice, as the two shares are traded by distinct groups of investors, departure from the perfect dependence situation will reveal the existence of asymmetric information and different behaviors of domestic and foreign investors in Chinese stock markets.

As stated by Tian and Wan (2004), there could be four possible results on this issue between A- and B-share markets: (1) experienced foreign investors have information advantage, thus the prices of B shares would lead those A shares. (2) domestic investors can better acquire relevant news from local sources, resulting in the prices of A shares leading the prices of B shares. (3) different investor groups can have different comparative advantages in acquiring information so that price information can transmit in both directions. Finally, the markets for A and B shares might be completely segmented, showing no correlation among prices. Therefore, empirical work is required to identify the possible results in reality.

Furthermore, information transmission between same types of shares in two exchanges also deserves analyses. Research in financial economics suggests that market-wide information may impact the prices of large-capitalization stocks more quickly than small-capitalization stocks, thus information transmission is from stocks of large firm to stocks of small firms. The evidences supporting this assumption are numerous. See, for example, Lo and MacKinlay (1990), Conrad et al (1991), Brennan et al. (1993), Mech (1993), Badrinath et al (1995), McQueen et al (1996), and Chordia and Swaminathan (2000)). However, there are also evidences of bi-directional information transmission between the large and small firms, see, for example, Robert

(1996). Studies the lead-lag relation between A-(B-) shares in SHSE and SZSE may provide more empirical results to this issue.

The lead-lag relations among these segmented markets have been widely studied[52]. Several groups have applied Granger causality tests to determine the lead-lag relationships between the A-share and B-share markets, which in turn could also offer evidence on which group of investors is more efficient in obtaining and processing relevant information and trading upon it. For example, Laurence et al. (1997) observe a causal relationship from the SHB to all other Chinese markets and from SHA and SZB feedback to SHB. Kim and Shin (2000) find that the A-share markets lead the B-share markets before 1996, but the relationship either disappears or reverses after 1996. Sjoo and Zhang (2000) find that information flows from foreign to domestic investors in the SHSE, the direction is reversed in the smaller and less liquid SZSE. Chen et al. (2001) test the Granger causal relationship between A-share and B-share stocks. Their results show that, there is no causal relations between A-share return (volatility) and B-share (volatility). Tian and Wan (2004) find SHB and SZB exhibit causality relations with each other during the period from 1993 to 1999. However, this relationship does not exist within SHA and SZA.

On February 19, 2001, Chinese government adopts a new policy which removes the previous restriction on trading B shares by domestic citizens. From this date, domestic investors are allowed to exchange some quota of foreign currencies for the purpose of B-share investment and more and more domestic investors are interested in

[52] For detailed review on the information transmission among Chinese segmented stock markets, please refer to Chapter 2.

trading B-share stocks. Thus, it is of interest to explore the change in lead-lag relation among segmented stock markets caused by this liberal policy. Our findings will shed more light on understanding the dynamic interrelationships between the segmented markets, which are both useful in theoretical and empirical academic work.

In this paper, we aim to explore the lead-lag relationships among Chinese segmented stock markets before and after the relaxation of government restrictions on the purchase of B shares by domestic investors. Our work extends the existing literature in the following two ways. Firstly, besides standard linear Granger causality test which have been applied extensively in analyzing the linear lead-lag relations between stock markets, we apply a nonlinear Granger causality test developed by Hiemstra and Jones (1994) (hereafter refered as HJ test) to investigate existence of any nonlinear lead-lag relationship among Chinese segmented stock markets. Many studies have reported that financial time series exhibit nonlinear dependence (e.g., Hsieh, 1991; Scheinkman and LeBaron, 1989 et al), thus nonlinear Granger causality test is more suitable than traditional linear Granger causality tests, which generally have low power against nonlinear relationships (Baek and Brock, 1992). There have been some research works applying HJ test to explore the nonlinear causal relation in the literature, for instance, between trading volume and stock/futures returns (Hiemstra and Jones, 1994; Ciner, 2002), between volume and volatility in stock market and futures markets (Brooks ,1998; Abhyankar, 1998; Silvapulla and Moosa, 1999), between exchange rates (Ma and Kanas, 2000), among real estate prices and stock markets (Okunev et al., 2000) , between GDP growth and the composite leading index (Huh, 2002) and between London Metal Exchange cash prices and some of its possible predictors (Chen and Lin, 2004), etc. To our knowledge, there has no research applying this test to explore the causal relation between stock markets. Our work thus aims to fill in this literature gap by applying this test to study the information transmission among Chinese segmented stock markets.

Secondly, we use more recent data to comparatively analyze the Granger causality relations among Chinese segmented stock markets before and after Chinese government relax the restriction on the purchase of B shares by domestic investors, to study the impact of the China government's policy on the lead-lag relations among segmented stock markets. This issue has not been analyzed by other researchers.

Our findings reveal that the causality relation among China's stock indices is more complicated than what the linear causality test reveals. We find that the linear causal relations diminish whereas the nonlinear causality relations strengthen after China adopted this more liberal policy. More specifically, our results show that there exists nonlinear dependence among the four stock markets. Contrast sharply with those of the linear causality test in which only the causality relation from SZA to SZB is present after the adoption of this liberal policy, nonlinear Granger causality test provides evidence of bi-directional causal relationship between two A-share markets as well as between two B-share markets. Further more, we find that SHA tends to lead SHB and SZA tends to lead SZB after this new policy has been implemented on February 19, 2001.

The remainder of this chapter proceeds as follows. Section 5.2 discusses the data and methodology. Section 5.3 provides empirical results, and Section 5.4 summarizes our conclusions and comments.

5.2 Data and Methodology

5.2.1 Data

The data used in this study are daily price indices of Shanghai A-share (SHA), Shenzhen A-share (SZA), Shanghai B-share (SHB) and Shenzhen B-share (SZB). All data are taken from *DataStream International.* Our sample covers January 1996 through December 2005. To study the possible change in the lead-lag relation among segmented stock markets, the sample is divided into two sub-samples which roughly have same number of observations. The first sub-sample covers the period from 1 January 1996 to 16 February 2001 and the second covers the period from 19 February 2001 to 30 December 2005[53]. All of these indices are based on closing prices in US dollars and stock index returns are continuously compounded.

5.2.2 Methodology

This section presents the methodologies used to investigate the causal relations among segmented Chinese stock markets by first introducing the linear Granger causality test and thereafter presenting the nonlinear Granger causality test in detail.

[53] As February 17 and 18, 2001 are weekend, the stock markets are closed. We choose February 19, 2001 as a cut-off point as since this date, Chinese government adopts a new policy to remove the restriction on trading B shares by domestic citizens.

5.2.2.1 Cointegration and Linear Granger Causality

In order to test for linear causal linkages between segmented stock markets, we proceed in the following steps. First, we apply augmented Dikey-Fuller (ADF) and Philips-Perron (PP) unit root tests to examine the stationary property for the four logarithm indices being studied in the paper to ensure these indices to be integrated of the same order before further examination. Second, if, as expected, these indices are found to be $I(1)$, then we apply well-known Johansen procedure to test possible cointegration between any two series. Third, if any pair of series is not cointegrated, we will adopt the following bivariate VAR model to test for the Granger causality[54]:

$$
\begin{aligned}
\Delta y_{1t} &= c_1 + \sum_{i=1}^{m} \phi_{11}^{i} \Delta y_{1,\,t-i} + \sum_{i=1}^{m} \phi_{12}^{i} \Delta y_{2,\,t-i} + \varepsilon_{1t} \\
\Delta y_{2t} &= c_2 + \sum_{i=1}^{m} \phi_{21}^{i} \Delta y_{1,\,t-i} + \sum_{i=1}^{m} \phi_{22}^{i} \Delta y_{2,\,t-i} + \varepsilon_{2t}
\end{aligned}
\tag{5.1}
$$

where Δy_{1t} and Δy_{2t} denote the return series for any two stock markets being examined, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t})'$ is the vector of the corresponding error terms[55], m is the optimal lag lengths which is obtained using AIC criterion.

On the other hand, if two series are cointegrated, we follow Granger (1981, 1988) and Sims et al. (1990) to impose the error-correction mechanism (ECM) on the VAR to test for the Granger causality between these variables. The ECM-VAR framework is as follows:

---

[54] The shortcoming of usual Granger causality test is that it might produce spurious causal relationship if the third variable is involved. However, as it is not easy to be clear about what other variables should be included in the Granger causality test framework. In this paper, we adopted the usual bivariate framework to do this analysis.

[55] We assume the error term follows the normal distribution.

$$
\begin{aligned}
\Delta y_{1t} &= c_1 + \alpha_1 ect_{t-1} + \sum_{i=1}^{m} \phi_{11}^{i} \Delta y_{1,\,t-i} + \sum_{i=1}^{m} \phi_{12}^{i} \Delta y_{2,\,t-i} + \varepsilon_{1t} \\
\Delta y_{2t} &= c_2 + \alpha_2 ect_{t-1} + \sum_{i=1}^{m} \phi_{2,1}^{i} \Delta y_{1t-i} + \sum_{i=1}^{m} \phi_{22}^{i} \Delta y_{2,\,t-i} + \varepsilon_{2t}
\end{aligned}
\tag{5.2}
$$

Here, the term ect_t is the error correction term, the coefficients α_1 and α_2 indicate the short-run dynamic adjustments with their magnitudes representing the speeds of the adjustment. Thereafter, the Granger causality test is conducted on the null hypotheses $\phi_{12}^{i} = 0$ or $\phi_{21}^{i} = 0$, for all *i* (i=1,2, . . . , *m*), in an usual manner[56].

5.2.2.2 Nonlinear Granger Causality[57]

The linear Granger causality test is known to possess a low power in detecting nonlinear causal relationships (Baek and Brock, 1992). To circumvent this problem, we utilize a nonlinear Granger causality test on the residuals from the linear VAR (ECM-VAR) model as discussed above. This approach enables us to detect the existence of any strictly nonlinear causality relations among the variables being studied as the VAR (ECM-VAR) has already purged the residuals of linear causality.

The nonlinear Granger causality test developed by of Baek and Brock (1992) has further been modified by Hiemstra and Jones (1994). This modified approach enables us to examine whether, by removing all the linear predictive power, any remaining incremental predictive power of one residual series for another can be considered nonlinear predictive power. A nonparametric statistical method is then proposed

---

[56] When the coefficient for error correction term, i.e. α_1 and α_2, is statistically significant, some researchers refer this as “long run” causality in literature. Here we focus on usual “short run” causality, which capture the lead lag relation in stock return in the short run.
[57] The nonlinear Granger causality test is done with C++.

employing the correlation integral (a measure of spatial dependence across time) to uncover any nonlinear causal relation between two time series.

Consider two strictly stationary and weakly dependent time series $\{X_t\}$ and $\{Y_t\}$, t=1,2,.... Let X_t^m be the m-length lead vector of X_t, and let $X_{t-L_X}^{L_X}$ and $Y_{t-L_y}^{L_y}$ be the L_x-length and L_y-length lag vectors of X_t and Y_t respectively. For given values of *m*, L_x, and L_y and for any distance *e*, $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ if:

$$\Pr(\left\|X_t^m - X_s^m\right\| < e \mid \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e)$$
$$= \Pr(\left\|X_t^m - X_s^m\right\| < e \mid \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e) \qquad (5.3)$$

where $\Pr(\cdot)$ and $\|\cdot\|$ denote probability and maximum norm respectively[58].

In the above equation, the left-hand side is the conditional probability that two arbitrary *m*-length lead vectors of $\{X_t\}$ are within a distance *e* of each other, given that the corresponding L_x-length and L_y-length lag vectors of $\{X_t\}$ and $\{Y_t\}$ are within a distance *e* of each other. The right-hand side is the conditional probability that two arbitrary *m*-length lead vectors of $\{X_t\}$ are within a distance *e* of each other, given that the corresponding L_x-length lag vectors of X_t are within a distance *e* of each other. The strict Granger noncausality condition in Equation (5.3) can be

58 The maximum norm for $Z = (Z_1, Z_2, \cdots Z_K) \in R^K$ is defined as $\max(Z_i)$, *i*=1,2…K.

implemented by expressing it in terms of the corresponding ratios of joint probabilities as follows:

$$\frac{C_1(m+L_x, L_y, e)}{C_2(L_x, L_y, e)} = \frac{C_3(m+L_x, e)}{C_4(L_x, e)} \quad (5.4)$$

where C_1, C_2, C_3 and C_4 are the correlation-integral estimators of the joint probabilities, which have been discussed in detail by Hiemstra and Jones (1994).

$$C_1(m+L_x, L_y, e) \equiv \Pr(\left\| X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx} \right\| < e, \ \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e)$$

$$C_2(L_x, L_y, e) \equiv \Pr(\left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e, \ \left\| Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly} \right\| < e)$$

$$C_3(m+L_x, e) \equiv \Pr(\left\| X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx} \right\| < e)$$

$$C_4(L_x, e) \equiv \Pr(\left\| X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx} \right\| < e) \quad (5.5)$$

Correlation-integral estimators of the joint probabilities are used to test the non-causality condition. Let $I(Z_1, Z_2, e)$ denote a kernel that equals 1 when two vectors Z_1 and Z_2 are within the maximum-norm distance *e* of each other and 0 otherwise. Then we have:

$$C_1(m+L_x, L_y, e, n) \equiv \frac{2}{n(n-1)} \sum_{t<s}\sum I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e) I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)$$

$$C_2(L_x, L_y, e, n) \equiv \frac{2}{n(n-1)} \sum_{t<s}\sum I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e) I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)$$

$$C_3(m+L_x, e, n) \equiv \frac{2}{n(n-1)} \sum_{t<s}\sum I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e)$$

$$C_4(L_x, e, n) \equiv \frac{2}{n(n-1)} \sum_{t<s}\sum I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e) \tag{5.6}$$

For given values of m, L_x and $L_y \geq 1$ and $e > 0$, under the assumptions that $\{X_t\}$ and $\{Y_t\}$ are strictly stationary and weakly dependent, if $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$, then

$$\sqrt{n}\left(\frac{C_1(m+L_x, L_y, e, n)}{C_2(L_x, L_y, e, n)} - \frac{C_3(m+L_x, e, n)}{C_4(L_x, e, n)}\right) \xrightarrow{a} N(0, \sigma^2(m, L_x, L_y, e)) \tag{5.7}$$

where n=T+ 1-m-max(L_x, L_y) and $t, s = \max(L_x, L_y)+1, \cdots, \mathrm{T-m+1}$.

Following Hiemstra and Jones (1994), $\sigma^2(m, L_x, L_y, e)$ can be estimated as follows. Defining the joint probabilities $h_{C1}(X_{t-Lx}^{m+Lx}, Y_{t-Ly}^{Ly}, e)$, $h_{C2}(X_{t-Lx}^{Lx}, Y_{t-Ly}^{Ly}, e)$, $h_{C3}(X_{t-Lx}^{m+Lx}, e)$ and $h_{C4}(X_{t-Lx}^{Lx}, e)$, which are conditioned on combinations of the realizations X_t^m, X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly} as:

$$h_{C1}(X_{t-Lx}^{m+Lx}, Y_{t-Ly}^{Ly}, e) \equiv \Pr(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < e,\ \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e)$$

$$h_{C2}(X_{t-Lx}^{Lx}, Y_{t-Ly}^{Ly}, e) \equiv \Pr(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e,\ \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < e)$$

$$h_{C3}(X_{t-Lx}^{m+Lx}, e) \equiv \Pr(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < e)$$

$$h_{C4}(X_{t-Lx}^{Lx}, e) \equiv \Pr(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < e) \tag{5.8}$$

Using above equation and the delta method (Serfling, 1980, pp.122-125), under the assumption that the underlying series are strictly stationary, weakly dependent, and satidy the mixing condition of Denker and Keller (1983), an expression for the variance in equation (5.7) is given by:

$$\sigma^2(m, L_x, L_y, e) = d\sum d' \tag{5.9}$$

where

$$d = [d_i],\ i = 1,\cdots 4$$

$$=[1/C_2(L_x, L_y, e), -C_1(m+L_x, L_y, e)/C_2{}^2(L_x, L_y, e), -1/C_4(L_x, e), C_3(m+L_x, e)/C_4{}^2(L_x, e)] \tag{5.10}$$

$$\sum = [\sum{}_{i,j}],\ i, j = 1,\cdots 4$$

$$= \left[4\cdot\sum_{k\geq 1} w_k E(A_{i,t}\cdot A_{j,t+k-1}\right], w_k = \begin{cases} 1, & if\ k=1 \\ 2, & otherwise \end{cases} \tag{5.11}$$

$$A_{1,t} = h_{C1}(X_{t-Lx}^{m+Lx}, Y_{t-Ly}^{Ly}, e) - C_1(m+L_x, L_y, e)$$

$$A_{2,t} = h_{C2}(X_{t-Lx}^{Lx}, Y_{t-Ly}^{Ly}, e) - C_2(L_x, L_y, e)$$

$$A_{3,t} = h_{C3}(X_{t-Lx}^{m+Lx}, e) - C_3(m+L_x, e)$$

$$A_{4,t} = h_{C4}(X_{t-Lx}^{Lx}, e) - C_4(L_x, e, n) \tag{5.12}$$

and where E in Equation (5.11) denotes expected value and the $C_i(\cdot)$ terms are defined in Equation (5.5).

Using the results of Denker and Keller (1983) and Newey and West (1987), a consistent estimator of the $\sum_{i,j}$ elements in Equation (5.9) is given by

$$\hat{\sum}_{i,j} = 4 \cdot \sum_{k=1}^{K(n)} w_k(n) \left[\frac{1}{2(n-k+1)} \sum_t (\hat{A}_{i,t}(n) \cdot \hat{A}_{j,t-k+1}(n) + \hat{A}_{i,t-k+1}(n) \cdot \hat{A}_{j,t}(n) \right]$$

$$K(n) = (\text{int}) n^{1/4}$$

$$w_k(n) = \begin{cases} 1, & if\ k=1 \\ 2(1-[(k-1)/K(n)]), & otherwise \end{cases} \tag{5.13}$$

where

$$\hat{A}_{1,t}(n) = \frac{1}{n-1} (\sum_{s \neq t} I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e) \cdot I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)) - C_1(m+L_x, L_y, e, n)$$

$$\hat{A}_{2,t}(n) = \frac{1}{n-1} (\sum_{s \neq t} I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e) \cdot I(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, e)) - C_2(L_x, L_y, e, n)$$

$$\hat{A}_{3,t}(n) = \frac{1}{n-1} (\sum_{s \neq t} I(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, e)) - C_3(m+L_x, e, n)$$

$$\hat{A}_{4,t}(n) = \frac{1}{n-1} (\sum_{s \neq t} I(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, e)) - C_4(L_x, e, n)$$

$$t, s = \max(L_x, L_y) + 1, \cdots, \mathrm{T} - \mathrm{m} + 1 \tag{5.14}$$

and where $C_i(\cdot, n)$ correlation integrals are defined in Equation (5.5). The $C_i(\cdot, n)$ correlation integrals provide a consistent estimator of d in Equation (5.10), namely,

$$\hat{d}(n) = [1/C_2(L_x, L_y, e), -C_1(m+L_x, L_y, e)/C_2^{\,2}(L_x, L_y, e), -1/C_4(L_x, e), \\ C_3(m+L_x, e)/C_4^{\,2}(L_x, e)] \tag{5.15}$$

A consistent estimator for $\sigma^2(m, L_x, L_y, e)$ in Equation (5.7) can then be expressed as follows:

$$\hat{\sigma}^2(m, L_x, L_y, e) = \hat{d}(n) \hat{\sum} \hat{d}(n)' \tag{5.16}$$

A significant positive value of the test statistic implies that lagged values of $\{Y_t\}$

help to predict $\{X_t\}$, whereas significant negative value suggests that lagged values of $\{Y_t\}$ rather confuse the prediction of $\{X_t\}$. This test has very good power properties against a variety of nonlinear Granger causal and non-causal relations, and its asymptotic distribution is the same if the test is applied to the estimated residuals from a VAR model (Hiemstra and Jones, 1994).

5.3 Empirical Results

We summarize the basic statistics of the natural logarithm values of price indices for each sub-period in Table 5.1.

Table 5.1
Descriptive Statistics for Chinese Stock Indices of Two Sub-samples

Index	SHA	SHB	SZA	SZB
Sub sample period 1: January 1, 1996 to February 16, 2001				
Mean	5.057	3.908	3.868	2.471
Median	5.058	3.921	3.919	2.457
Maximum	5.604	4.587	4.443	3.243
Minimum	4.157	3.063	2.563	1.680
Std. Dev.	0.342	0.332	0.425	0.331
Skewness	-0.642	-0.220	-1.465	-0.057
Kurtosis	3.212	2.449	5.178	2.307
Observations	1236	1236	1236	1236
Sub sample period 2: February 19, 2001 to December 30, 2005				
Mean	5.239	4.709	3.932	3.436
Median	5.242	4.749	3.952	3.408
Maximum	5.643	5.480	4.434	4.023
Minimum	4.855	3.939	3.387	2.796
Std. Dev.	0.177	0.334	0.250	0.165

Skewness	0.226	-0.161	0.003	0.924
Kurtosis	2.824	2.285	2.452	4.463
Observations	1173	1173	1173	1173

Note: These are descriptive statistics of the stock indices. Sample covers January 1996 through December 2005. The total number of observations is 2408.

We then conduct both ADF and PP unit root tests to reveal the stationary property for each logarithm index. The results in Table 5.2 indicate that all of the indices are I(1), which are consistent with the results found in the literature.

Table 5.2
Unit Root Test Results

Panel A: Unit root test results for the stock indices				
	SHA	**SHB**	**SZA**	**SZB**
Sub sample period 1: January 1, 1996 to February 16, 2001				
ADF Statistic	-2.727	-1.176	-2.502	-1.825
PP Statistic	-2.832	-1.121	-2.564	-1.900
Sub sample period 2: February 19, 2001 to December 30, 2005				
ADF Statistic	-2.582	-0.474	-2.756	-0.409
PP Statistic	-2.610	-0.765	-2.872	-0.207
Panel B: Unit root test results for the stock index returns				
	△SHA	**△SHB**	**△SZA**	**△SZB**
Sub sample period 1: January 1, 1996 to February 16, 2001				
ADF Statistic	-35.106***	-29.810***	-34.477***	-30.111***
PP Statistic	-35.123***	-29.810***	-34.635***	-30.359***
Sub sample period 2: February 19, 2001 to December 30, 2005				
ADF Statistic	-33.734***	-31.105***	-33.068***	-30.600***
PP Statistic	-33.731***	-31.316***	-33.069***	-32.284***

Note: The null hypothesis of the ADF test and PP test is that the variable has a unit root. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Upon confirmation of possessing unit roots of the same order by these results, we apply the Johansen procedure to look for evidence of cointegration for any pair of indices, i.e. SHA-SHB, SZA-SZB, SHA-SZA and SHB-SZB, in each sub-period[59]. We find evidence of one cointegration relation in SHB-SZB for the first sub-period whereas another cointegration relation in SHA-SHB for the second sub-period with their p-values smaller than conventional levels. Thus, for these two pairs, we further utilize the linear Granger causality test to examine their relationships in the ECM-VAR framework as shown in Equation (5.2). For other pairs of markets, instead, the usual VAR displayed in Equation (5.1) is adopted[60]. We conduct the conventional linear Granger causality test and report the results in Table 5.3.

The results in the Table 5.3 indicate that before Chinese government relaxed the restrictions on the purchase of B shares by domestic investors, A-share markets in Shanghai and Shenzhen exhibit strong causality relations with each other. For B-share stock markets, we find strong causal relation from SZB to SHB, while the causal relation running from SHB to SZB is very weak (significant only at the 8% level). This result suggests that there are bi-directional information transmission between the big stocks and small stocks for A shares, which is consistent with the finding of Robert (1998). However, for B shares, our finding supports small stocks lead big stocks. As to interaction between A-share and B-share markets, we only find the evidence that SZB weakly leads SZA, implying foreign experienced institutional

[59] We only report the lead-lag relations between different types of shares in the same exchange and display relations between same types of shares in different exchanges. Nevertheless, the results for SHA-SZB and SZA-SHB, though not being reported, are available upon request.
[60] Johansen cointegration test results and complete estimation results for VAR and ECM-VAR are not reported here but available upon request.

investors have some information advantage against domestic individual investors in SZSE.

Table 5.3
Testing for Linear Granger Causality

Markets \ Test	Wald statistics	LB(6)
Panel A: January 1, 1996 to February 16, 2001		
SHA→SHB	1.081(0.356)	1.061(0.983)
SHB→SHA	0.684(0.562)	3.114(0.794)
SZA→SZB	1.362(0.227)	0.111(1.000)
SZB→SZA	2.040(0.058)*	0.536(0.997)
SHA→SZA	2.961(0.000) ***	0.101(1.000)
SZA→SHA	2.419(0.002) ***	0.238(1.000)
SHB→SZB	9.801(0.081)*	0.422(0.999)
SZB→SHB	14.560(0.012)**	0.072(1.000)
Panel B: February 19, 2001 to December 30, 2005		
SHA→SHB	1.658(0.437)	4.853(0.563)
SHB→SHA	3.122(0.210)	2.801(0.833)
SZA→SZB	5.340(0.000) ***	4.495(0.610)
SZB→SZA	0.569(0.685)	0.679(0.995)
SHA→SZA	0.089(0.765)	3.350(0.764)
SZA→SHA	0.412(0.521)	3.962(0.682)
SHB→SZB	1.364(0.208)	2.797(0.834)
SZB→SHB	1.615(0.116)	1.716(0.944)

Note: Numbers in parentheses are p-values. LB (6) is the Ljung-Box statistics based on the level of the residual series of dependent variables in Equation (5.1), or (5.2) when cointegration relation exists, up to the 6^{th} lag. The results of the Ljung-Box, however, are robust to other lag length specification. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

In contrast, for the sub-sample period 2, after Chinese government adopts more liberal policy allowing domestic investors to invest in B-share markets, linear Granger causality test shows that there only exists a causality relation from SZA to SZB and there is no lead-lag relation between other pairs of markets at all. This suggests that after Feb 19, 2001, the information transmission among these four markets becomes much weaker.

Before testing for nonlinear Granger causality in the residuals from the linear VAR (ECM-VAR), two sets of diagnostic tests are conducted on the residuals from the VAR models. First, the Ljung–Box Q-test is used to determine whether any linear dependency remains in the residuals.

$$Q(T) = T(T+2)\sum_{i=1}^{k}\frac{r_i^2}{T-i} \tag{5.17}$$

where T is the size of the sample and r_i is the simple i-order correlation coefficient. In this null of no serial correlation (5.17) follows χ^2 distribution with k degrees of freedom.

Secondly, we perform a formal nonlinear dependence test, known as the Brock, Dechert, and Scheinkman (BDS) test (1987 and 1996), on the residuals. The BDS test is a portmanteau test for time based dependence in a series. The BDS approach essentially tests for deviations from identically and independently distributed (*i.i.d*) behavior in the time series of residuals. This test can be used to validate estimated models, since it detects any structure in the error term, be it linear, nonlinear or chaotic.

Given x_t (t=1,...,T), they are considered segments of the same size, called *m*-stories and form the *m*-dimensional vector, $x(m)_t = (x_{t,}\ x_{t+1,}\ x_{t+2,}\ \cdots x_{t+m-1})$. The

BDS test computes the correlation integral $C_{m,T}(l)$ of *m* dimension and *l* distance as:

$$C_{m,T}(l) = \frac{2}{(T-m+1)(T-m)} \sum_{I \le i \le j \le T-m+1} I_l(x(m)_i, x(m)_j) \tag{5.18}$$

where $I_l(\cdot)$ is the indicator function:

$$I_l(x(m)_i, x(m)_j) = \begin{cases} 1 & if \quad \left\| x(m)_i, x(m)_j \right\| < l \\ \\ 0 & if \quad \left\| x(m)_i, x(m)_j \right\| \ge l \end{cases} \tag{5.19}$$

The BDS test for an *m* fix dimension, an *l* distance and a T sample size is:

$$BDS(m,l,T) = \frac{\sqrt{T}(C_{m,T}(l) - C_{1,T}(l)^m)}{\sigma_{m,T}(l)} \tag{5.20}$$

where $\sigma_{m,T}(l)$ is the asymptotic standard deviation of $\sqrt{T}(C_{m,T}(l) - C_{1,T}(l)^m)$, which can be consistently estimated by:

$$\sigma^2_{m,T}(l) = 4\left[k^m + 2\sum_{j=1}^{m-1} k^{m-j} C^{2j} + (m-1)^2 C^{2m} - m^2 k C^{2m-2} \right] \tag{5.21}$$

where $C = E(C_{1,T}(l))$, and $k = f(F(z+l) - F(z-l))^2$. C is consistently estimated by $C_{1,T}(l)$, and *k* can be estimated by

$$k_n(l) = \frac{6}{n(n-1)(n-2)} \sum_{t=1}^{n} \sum_{s=t+1}^{n} \sum_{r=s+1}^{n} b_l(X_t, X_s, X_r) \tag{5.22}$$

$$b_l(i,j,k) = \frac{1}{3}(I_l(i,j)I_l(j,k) + I_l(i,k)I_l(k,j) + I_l(j,i)I_l(i,k) \qquad (5.23)$$

We reject the null hypothesis of a random *iid* series if the probability that any two *m*-dimensional vectors are close together exceeds the m^{th} power of the probability of any two points being close together. The properties of this test on finite samples were studied by Brock *et al.*(1987), Brock *et al.* (1996), Brock *et al.* (1991) or Lee *et al.* (1993), among others. Brock *et al.* (1987) showed that, under the null of *iid* series, the BDS statistic follows a normal distribution. However, for series with unusual distributions, the test may not be normal. For this reason, and given the high non normality of the corresponding residual series, p-values are calculated through bootstrap with 1000 replications. The test is applied for common lag lengths of 2–10 lags and a common scale parameter of $e = 1.5\sigma$ are used, where $\sigma = 1$ denotes the standard deviation of standardized series.

The results of Ljung–Box Q-test as reported in the last column of Table 5.3 point out that the VAR (ECM-VAR) models successfully account for linear dependency, as indicated by insignificant values of Q-test. In Table 5.4, we report the BDS test results. As indicated, all the residual series from VAR (ECM-VAR) models are nonlinear dependent.

Table 5.4 BDS Test Results for the VAR (ECM-VAR) Residuals

Sub sample period 1: January 1, 1996 to February 16, 2001		
Dimension	**SHA→SHB**	**SHB→SHA**
2	9.597 (0.000) ***	9.751 (0.000) ***
3	11.623 (0.000) ***	11.708 (0.000) ***
4	13.304 (0.000) ***	13.239 (0.000) ***
5	14.394 (0.000) ***	14.031 (0.000) ***
6	15.620 (0.000) ***	14.789 (0.000) ***
7	16.710 (0.000) ***	15.612 (0.000) ***
8	17.724 (0.000) ***	16.452 (0.000) ***
9	19.042 (0.000) ***	17.359 (0.000) ***
10	20.383 (0.000) ***	18.410 (0.000) ***
Dimension	**SZA→SZB**	**SZB→SZA**
2	12.540 (0.000) ***	12.814 (0.000) ***
3	14.523 (0.000) ***	15.577 (0.000) ***
4	16.212 (0.000) ***	17.355 (0.000) ***
5	17.343 (0.000) ***	18.910 (0.000) ***
6	18.103 (0.000) ***	20.277 (0.000) ***
7	18.800 (0.000) ***	21.588 (0.000) ***
8	19.562 (0.000) ***	22.954 (0.000) ***
9	20.453 (0.000) ***	24.630 (0.000) ***
10	21.349 (0.000) ***	26.364 (0.000) ***
Dimension	**SHA→SZA**	**SZA→SHA**
2	13.153 (0.000) ***	9.074 (0.000) ***
3	15.435 (0.000) ***	10.849 (0.000) ***
4	17.213 (0.000) ***	12.370 (0.000) ***
5	18.798 (0.000) ***	13.250 (0.000) ***
6	20.203 (0.000) ***	14.020 (0.000) ***
7	21.579 (0.000) ***	14.788 (0.000) ***
8	22.981 (0.000) ***	15.667 (0.000) ***
9	24.673 (0.000) ***	16.681 (0.000) ***
10	26.456 (0.000) ***	17.877 (0.000) ***
Dimension	**SHB→SZB**	**SZB→SHB**
2	12.698 (0.000) ***	9.454 (0.000) ***
3	14.660 (0.000) ***	11.271 (0.000) ***
4	16.320 (0.000) ***	12.917 (0.000) ***
5	17.543 (0.000) ***	13.995 (0.000) ***
6	18.418 (0.000) ***	15.164 (0.000) ***
7	19.250 (0.000) ***	16.216 (0.000) ***
8	20.107 (0.000) ***	17.218 (0.000) ***
9	21.090 (0.000) ***	18.529 (0.000) ***
10	22.076 (0.000) ***	19.870 (0.000) ***

Panel B: February 19, 2001 to December 30, 2005		
Dimension	**SHA→SHB**	**SHB→SHA**
2	7.552 (0.000) ***	2.618 (0.009) ***
3	9.759 (0.000) ***	4.622 (0.000) ***
4	11.265 (0.000) ***	6.028 (0.000) ***
5	12.050 (0.000) ***	6.879 (0.000) ***
6	12.487 (0.000) ***	7.472 (0.000) ***
7	12.937 (0.000) ***	7.870 (0.000) ***
8	13.498 (0.000) ***	8.204 (0.000) ***
9	14.072 (0.000) ***	8.820 (0.000) ***
10	14.681 (0.000) ***	9.527 (0.000) ***
Dimension	**SZA→SZB**	**SZB→SZA**
2	6.526 (0.000) ***	3.365 (0.001) ***
3	9.333 (0.000) ***	5.946 (0.000) ***
4	11.018 (0.000) ***	7.478 (0.000) ***
5	11.873 (0.000) ***	8.408 (0.000) ***
6	12.420 (0.000) ***	9.054 (0.000) ***
7	13.012 (0.000) ***	9.626 (0.000) ***
8	13.711 (0.000) ***	10.087 (0.000) ***
9	14.278 (0.000) ***	10.728 (0.000) ***
10	14.895 (0.000) ***	11.541 (0.000) ***
Dimension	**SHA→SZA**	**SZA→SHA**
2	3.364 (0.001) ***	2.586 (0.010) ***
3	5.892 (0.000) ***	4.527 (0.000) ***
4	7.529 (0.000) ***	5.838 (0.000) ***
5	8.526 (0.000) ***	6.617 (0.000) ***
6	9.221 (0.000) ***	7.162 (0.000) ***
7	9.834 (0.000) ***	7.535 (0.000) ***
8	10.367 (0.000) ***	7.830 (0.000) ***
9	11.070 (0.000) ***	8.405 (0.000) ***
10	11.931 (0.000) ***	9.057 (0.000) ***
Dimension	**SHB→SZB**	**SZB→SHB**
2	5.160 (0.000) ***	6.235 (0.000) ***
3	8.025 (0.000) ***	8.488 (0.000) ***
4	9.803 (0.000) ***	9.957 (0.000) ***
5	10.685 (0.000) ***	10.858 (0.000) ***
6	11.212 (0.000) ***	11.485 (0.000) ***
7	11.743 (0.000) ***	12.074 (0.000) ***
8	12.406 (0.000) ***	12.824 (0.000) ***
9	12.945 (0.000) ***	13.537 (0.000) ***
10	13.406 (0.000) ***	14.292 (0.000) ***

Notes: This table reports the results of the normalized BDS test statistics proposed by Brock et al (1987 and 1996). Each cell contains two numbers: numbers without parenthesis are the standardized BDS test statistics based on the level of the residual series of dependent variable in Equation (5.1) or (5.2); numbers in parenthesis are the corresponding p-values, which are simulated using bootstrap with 1000 replications. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Considering the low power of conventional linear Granger causality against nonlinear relationships, we apply the HJ nonlinear Granger causality test to the residuals from the above linear VAR (ECM-VAR) model. To implement the HJ test, values for the lead length, *m*, the lag lengths, L_x and L_y, and the scale parameter, *e*, have to be selected. Following Hiemstra and Jones (1994), we set lead length m=1 and $L_x = L_y$ for all cases. Also, common lag lengths of 1–10 lags and a common scale parameter of $e = 1.5\sigma$ are used, where σ =1 denotes the standard deviation of standardized series. The results of nonlinear causality tests are displayed in Table 5.5.

Different from its linear counterpart test for the first sub-sample, nonlinear Granger causality test reported in Panel A of Table 5.5 indicates there are not only strong bi-directional information transmission between two A-share markets, there are also strong bi-directional information transmission between two B-share markets. This provides strong support to Robert's argument (1998) that information transmission between the large and small firms is bi-directional[61]. Further more, nonlinear Granger causality test shows that SZB strongly leads SZA for the first sub-sample, suggesting more sophisticated institutional investors in B-shares market in SZSE might more cost effectively acquire both market-wide and company-wide information than corresponding domestic traders[62].

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61 It implies that investors can use the information of one market to forecast the movement of another market, which also suggests both markets are not efficient.

62 We do not find evidence of information exchange between SHA and SHB, implying no information asymmetry between foreign investors and domestic investors in SHSE (Chen et al., 2001). The exact reason for this deserves

Table 5.5
Testing for Nonlinear Granger Causality

Sub sample period 1: January 1, 1996 to February 16, 2001		
Lx=Ly	**SHA→SHB**	**SHB→SHA**
1	0.447 (0.327)	0.631 (0.264)
2	-0.759 (0.224)	0.072 (0.471)
3	-1.022 (0.153)	-0.626 (0.266)
4	-1.192 (0.117)	-1.424 (0.077)
5	-1.416 (0.078)	-2.158 (0.015)
6	-1.799 (0.036)	-2.768 (0.003)
7	-1.804 (0.036)	-3.474 (0.000)
8	-1.979 (0.024)	-3.237 (0.001)
9	-2.033 (0.021)	-2.920 (0.002)
10	-1.880 (0.030)	-2.687 (0.004)
Lx=Ly	**SZA→SZB**	**SZB→SZA**
1	1.372 (0.085)*	2.385 (0.009)***
2	0.900 (0.184)	2.189 (0.014)**
3	-0.423 (0.336)	1.837 (0.033)**
4	-1.298 (0.097)	1.183 (0.118)
5	-1.182 (0.119)	0.869 (0.192)
6	-0.798 (0.212)	0.789 (0.215)
7	-0.664 (0.253)	0.553 (0.290)
8	-0.251 (0.401)	0.340 (0.367)
9	-0.068 (0.473)	-0.120 (0.452)
10	0.092 (0.463)	0.038 (0.485)
Lx=Ly	**SHA→SZA**	**SZA→SHA**
1	3.606 (0.000) ***	4.037 (0.000) ***
2	3.808 (0.000) ***	4.482 (0.000) ***
3	4.402 (0.000) ***	4.661 (0.000) ***
4	4.342 (0.000) ***	4.758 (0.000) ***
5	3.811 (0.000) ***	4.956 (0.000) ***
6	4.184 (0.000) ***	4.687 (0.000) ***
7	4.020 (0.000) ***	4.328 (0.000) ***
8	3.756 (0.000) ***	4.091 (0.000) ***
9	4.007 (0.000) ***	3.439 (0.000) ***
10	4.241 (0.000) ***	3.230 (0.000) ***
Lx=Ly	**SHB→SZB**	**SZB→SHB**
1	3.320 (0.000) ***	3.397 (0.000) ***
2	4.355 (0.000) ***	2.741 (0.003) ***
3	4.879 (0.000) ***	3.568 (0.000) ***
4	4.442 (0.000) ***	3.326 (0.000) ***

further investigation.

5	4.412 (0.000) ***	3.304 (0.000) ***
6	4.015 (0.000) ***	2.922 (0.002) ***
7	3.230 (0.001) ***	2.778 (0.003) ***
8	3.308 (0.000) ***	2.201 (0.014) **
9	2.922 (0.002) ***	1.935 (0.027)**
10	2.799 (0.003) ***	2.144 (0.016)**
Panel B: February 19, 2001 to December 30, 2005		
Lx=Ly	**SHA→SHB**	**SHB→SHA**
1	0.108 (0.457)	0.711 (0.239)
2	0.707 (0.240)	0.483 (0.315)
3	0.915 (0.180)	-0.108 (0.457)
4	0.966 (0.167)	-0.144 (0.443)
5	0.649 (0.258)	-0.302 (0.381)
6	1.051 (0.147)	-0.491 (0.312)
7	1.299 (0.097)*	-0.391 (0.348)
8	1.922 (0.027)**	-0.279 (0.390)
9	1.756 (0.040)**	-0.033 (0.487)
10	1.999 (0.023)**	0.519 (0.302)
Lx=Ly	**SZA→SZB**	**SZB→SZA**
1	0.519 (0.302)	-0.900 (0.184)
2	0.507 (0.306)	-0.538 (0.295)
3	-0.257 (0.398)	-1.059 (0.145)
4	0.191 (0.424)	-1.465 (0.071)
5	-0.012 (0.495)	-1.385 (0.083)
6	1.097 (0.136)	-1.450 (0.074)
7	1.156 (0.124)	-1.393 (0.082)
8	1.694 (0.045)**	-1.438 (0.075)
9	1.984 (0.024)**	-0.771 (0.220)
10	2.024 (0.022)**	-0.485 (0.314)
Lx=Ly	**SHA→SZA**	**SZA→SHA**
1	0.395 (0.347)	0.842 (0.200)
2	0.438 (0.331)	3.707 (0.000) ***
3	1.100 (0.136)	4.071 (0.000) ***
4	1.108 (0.134)	4.815 (0.000) ***
5	1.428 (0.077)*	4.397 (0.000) ***
6	1.427 (0.077)*	4.425 (0.000) ***
7	1.244 (0.107)	4.329 (0.000) ***
8	1.837 (0.033)**	4.073 (0.000) ***
9	2.166 (0.015)**	4.657 (0.000) ***
10	1.658 (0.049)**	4.846 (0.000) ***

Lx=Ly	SHB→SZB	SZB→SHB
1	2.946 (0.002) ***	0.881 (0.189)
2	2.941 (0.002) ***	2.316 (0.010) ***
3	2.660 (0.004) ***	2.575 (0.005) ***
4	1.768 (0.039)**	2.344 (0.010) ***
5	1.606 (0.054)*	1.676 (0.047)**
6	1.854 (0.032)**	2.416 (0.008) ***
7	2.473 (0.007) ***	2.296 (0.011)**
8	2.611 (0.005) ***	2.048 (0.020)**
9	2.837 (0.002) ***	1.892 (0.029)**
10	2.769 (0.003) ***	1.868 (0.031)**

Notes: This table reports the results of the nonlinear Granger causality test proposed by Hiemstra and Jones (1994). Each cell contains two numbers: numbers without parenthesis are the standardized HJ test statistics as per Equation (5.7) and numbers in parenthesis are the corresponding p-values. Under the null hypothesis of nonlinear Granger noncausality, the test statistics is asymptotically distributed N (0, 1) and is a one-tail test. A significant positive test statistic implies that lagged values of $\{Y_t\}$ nonlinear Granger causes $\{X_t\}$. ***, ** and * indicate positive significance at the 1% (critical value=2.326), 5% (critical value=1.645) and 10% (critical value=1.280) level, respectively.

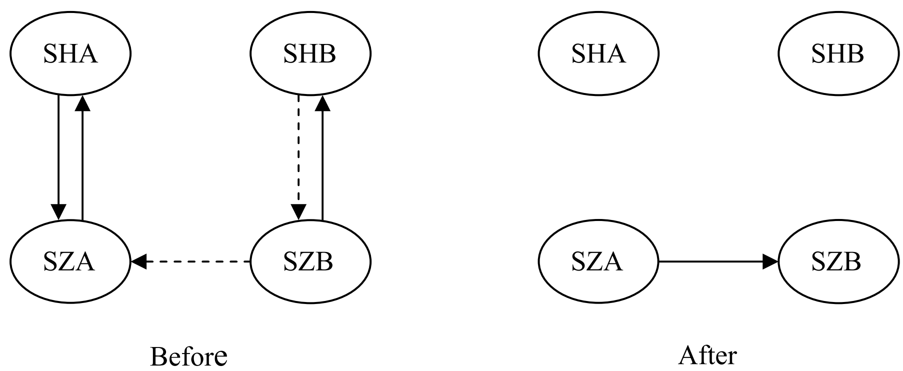
In the second sub-sample when more relaxed policy on purchasing B shares are implemented, nonlinear Granger causality reports very different scenario: there is evidence of a strong bi-directional causal relations between two A-share markets as well as between two B-share markets. Overall, our findings derived from both linear and nonlinear Granger causality tests contradicts the findings of Lo and MacKinlay (1990), Conrad et al (1991), Brennan et al. (1993), Mech (1993), Badrinath et al (1995), McQueen et al (1996), and Chordia and Swaminathan (2000)), while support that of Robert (1996). We find there are bi-directional information transmission between large stocks and small stocks in two sub samples.

Further more, we find some evidence that SHA leads SHB and SZA leads SZB.

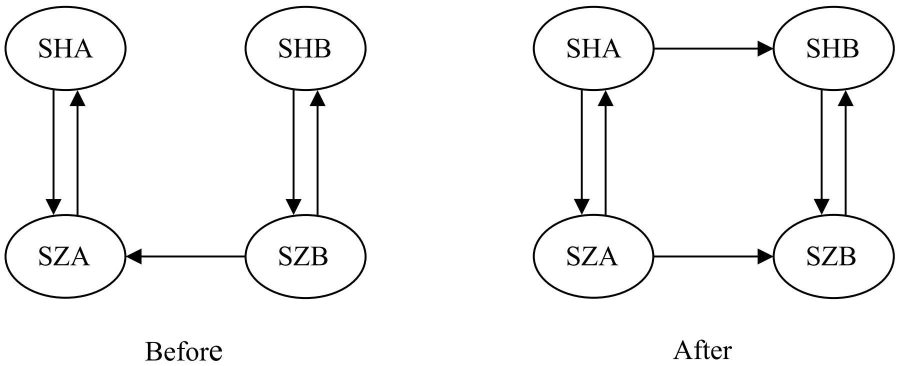
Thus, since Feb. 19, 2001, the information transmission among the four segmented markets becomes stronger in that A-share markets tend to lead their B-share counterparts in the same stock exchange. We think this is a valid conclusion. As the number of domestic investors participating in the transaction of B-share stocks increases, previous possible factors causing B-share stock markets to lead A-share stock markets, such as foreign investors in B-share markets having much more advanced technology for processing and analyzing information than domestic investors, become comparatively less important than before. Since A-share markets have much larger market capitalization, faster growth rate and higher liquidity, it is logical that they would attract more attentions from investors, and thus information is more likely to flow from A-share to B-share stock markets, resulting in A-share markets leading B-share stock markets. In Figure 5.1, we summarize the findings of this chapter.

Figure 5.1 Summary of Granger Causalities among Four Chinese Stock Indices

A: Granger causal relations based on linear Granger causality test



B: Granger causal relations based on nonlinear Granger causality test



Note: This figure demonstrates the Granger causal relations among our Chinese stock indices based on linear and nonlinear Granger causality tests before and after Chinese government relaxed the restriction on the purchase of B shares by domestic investors. Solid line indicates the Granger causal relation is significant at 5% or above, while dash line indicates the Granger causal relation is significant at 10%.

5.4 Conclusions of Chapter 5

The unique features of Chinese segmented stock markets provide a sound background to examine information transmission between different investors and between stocks of different sizes. Many researchers have investigate the lead-lag relations among Chinese segmented stock markets, however, their methodology is based on traditional linear models such as Granger causality test, which is well known to possess a low power in detecting nonlinear causal relationships.

This chapter paper has set out to examine the lead-lag relationships among four Chinese stock markets before and after Chinese government relaxed the restriction on the purchase of B shares by domestic investors. Besides linear Granger causality test, we apply a nonlinear Granger causality test to investigate existence of any nonlinear information transmission among Chinese segmented stock markets. Our findings reveal that the causality relation among China stock indices is more complicated than what linear causality test reveals. More specifically, our analyses show that there exists strong nonlinear dependence among the four stock markets.

In a sharp contrast with the results of the linear causality test, nonlinear Granger causality test provides evidence of strong bi-directional causal relations between two A-share markets as well as between two B-share markets both before and after the adoption of the more liberal governmental policy allowing domestic citizens who invest in A-share markets to invest in B-share markets. This contradicts the widely reported evidences in finance literature which concludes that large stocks lead small stocks (Lo and MacKinlay (1990), Conrad et al (1991), Brennan et al. (1993), Mech (1993), Badrinath et al (1995), McQueen et al (1996), and Chordia and Swaminathan (2000)). Our finding challenges a widespread assumption that information transmission is from big stocks to small stocks in the literature and supports the finding of bi-direction information transmission between these two types of stocks.

Furthermore, different from the results of linear Granger causality test indicating little lead-lag relation between A-share and B-share stock markets, our nonlinear causality test shows that before the adoption of the new policy, SZB leads SZA, while after the adoption of the new policy, A share stock markets tend to lead B-share stock markets in the same exchange. Our findings in this chapter are useful to regulators, investors, speculators, and hedgers. We also recommend that nonlinear Granger causality test should be used in conjunction with the conventional linear Granger causality test in practice.

Chapter 6 Concluding Remarks

The rapid growth and unique features of market segmentation in China have attracted great attention of researchers to study Chinese stock markets. The finance literature is rife with many papers analyzing various topics on Chinese segmented stock markets such as: volatility behavior, long run equilibrium relations and information transmission among segmented stock market etc. However these analyses are usually based on linear econometric methodology while the nonlinearity property in market variables has been neglected.

In recent years, researchers have demonstrated numerous evidences of the nonlinearity in economic and finance time series. Thus previous analyses solely depending on conventional linear methods may lead to incomplete and incorrect statistical inference. This thesis studies three widely investigated issues on Chinese segmented stock markets and contributes to the literature by focusing on the nonlinear property in the market variables. In particular, the three essays examine three different types of nonlinearity: i.e. structural breaks, long memory process and nonlinear causality, respectively. The nonlinear modeling techniques adopted in the essays have different features and advantages, which enable us to capture the above mentioned nonlinearities in a parsimonious way[63]. Our analyses from a nonlinear point of view will shed more light on understanding of the segmentation of Chinese stock markets,

[63] This thesis aims to contribute the literature by doing nonlinear analyses to study three topics which have been extensively studied in the literature. However, I find that there are many types of nonlinearity and so far each econometric model can only handle one type of nonlinearities. Therefore, I have to adopt three different models to focus on three types of nonlinearity respectively in these three chapters. These three types of nonlinearity are the common features of the market variables and it should be more parsimonious to study them and their relations within one system. Developing more powerful and flexible econometric models could be an important further work for econometricians.

which, in turn, provides useful information to investors and fund managers for their investment decisions and strategy in these markets. Our findings are also useful for policy makers in setting regulations for these markets.

The first essay adopts a nonlinear MS-GARCH model to examine the volatility nature in A-share and B-share stock indices in mainland China over the years. It also conducts statistical tests to examine the volatility spillover effects among these four segmented markets at high volatility regimes. This essay reaches following conclusions. First, there is strong evidence of volatility regime shift in the four segmented markets, and the MS-GARCH model appears to outperform the single regime GARCH model in modeling the volatility of stock markets in China. Second, B-share markets is more volatile and to shift more frequently between a high-volatility state and a low-volatility state. Third, for SHA, SZA, and SHB, we find that positive returns are associated with a turbulent market, which is different from Hamilton and Susmel's (1994) finding. Our finding suggests that Chinese investors are more excited by the upside of the market because they are more apt to pursue a speculative opportunity. Four, the volatility switch of A-share markets and B-share markets is subject to different major events. The volatile movements in B-share markets are sensitive in reacting to international shocks. Five, evidence strongly indicates volatility spillover asymmetry across A-share and B-share stock markets.

The second essay applies a nonlinear FIVECM bivariate GARCH framework to examine the long-term equilibrium, short-term adjustment, and spillover effects among H-SHA, H-SHB, SHB-SHA, H-SZA H-SZB and SZB-SZA. It shows that all these pairs of stock markets are fractionally cointegrated. In each of the six pairs, the H-share stock market adjusts to return to equilibrium with the two A-share stock markets as well as the two B-share markets, while two B-share markets adjust to return to equilibrium with the corresponding two A-share markets. We conclude that A-share markets have strongest market power in influencing other markets in the long run. As to short run dynamic relations, we find that H-share market in Hong Kong plays a very influential role in influencing stock markets in mainland China. The explanations on this are addressed in this essay as well. Finally, this essay also evaluates the effects of changes in financial policy and economic conditions on the dynamic correlations between the markets. We find that relaxation of government restrictions on the purchase of B shares by domestic residents increased the correlation between the A- and B-share markets and accelerated the market integration process of the A-share markets with the H-share stock market. Our results also disclose that the Asian crisis had a different spillover effect on stock-return dynamic correlations across Chinese segmented markets. We conclude that the market segmentation policy imposed by the Chinese authority is an effective instrument for shielding the domestic A-share markets from external turbulence.

The third essay examines the lead-lag relationships among four Chinese stock markets before and after Chinese government relaxed the restriction on the purchase of B shares by domestic investors. Besides linear Granger causality test, we apply a nonlinear Granger causality test in our analyses. Our analyses show that there exists strong nonlinear dependence among the four stock markets. In a sharp contrast with the results of the linear causality test, nonlinear Granger causality test provides evidence of strong bi-directional causal relations between two A-share markets as well as between two B-share markets both before and after the adoption of the more liberal governmental policy allowing domestic citizens who invest in A-share markets to invest in B-share markets. This contradicts the widely reported evidences in finance literature which concludes that large stocks lead small stocks and supports the finding of bi-direction information transmission between these two types of stocks. Finally, different from the results of linear Granger causality test indicating little lead-lag relation between A-share and B-share stock markets, our nonlinear causality test shows that before the adoption of the new policy, SZB leads SZA, while after the adoption of the new policy, A-share stock markets tend to lead B-share stock markets in the same exchange. The explanations of our findings are also provided in this essay.

Although three different nonlinear econometric models are adopted to study three different issues on Chinese segmented stock markets in this thesis, we can draw following conclusions on Chinese segmented stock markets.

First, two A-share stock markets are the major components of Chinese stock markets. Not only do they have the largest market capitalization, but they also have a significant impact on other segmented stock markets. They play the dominant role in Chinese stock markets in the long run and their evolution pattern could be taken as the development trend of Chinese stock markets. Furthermore, compared with B-share markets, the volatility of A-share stock markets, especially when they move to high volatility state, deserves more attention of investors.

Second, compared with the investors in more developed market, such as USA, Chinese domestic investors have more risk preference. Chinese domestic investors focus more on the speculative profits when the market moves upward, whereas investors in the US market concentrate more on minimizing losses as the market moves downward. Generally speaking, Chinese stock markets are highly speculative.

Third, B-share markets have become less and less important in Chinese stock markets. This is especially true after Chinese government allowed domestic investors to purchase B-share stocks in 2001. After the adoption of the more liberal policy, the B-share markets have moved very closely with A-share markets. Complete merger of A-share and B-share markets is anticipated in the near future.

Fourth, the market segmentation policy and the more liberal policy allowing domestic citizens to invest in B-share markets adopted by Chinese government are very successful. The latter is an effective step to merge A-share and B-share stock markets, while the former protects the domestic A-share stock markets from the external turbulence such as Asian financial crisis of 1997 and other unexpected events in the international financial markets. Considering the current developing stage of Chinese financial markets, it is suggested that the Chinese government should keep this policy instead of rushing to open A-share stock markets completely to foreign investors. The methodology applied in this thesis will also be useful for government policy makers to evaluate the effectiveness of their similar policies in the future.

Finally, the empirical findings of this thesis are also helpful to investors. For example, the existence of Granger causality implies that investors could use the information of one market to predict the future movement of another market, by which they could make profit in the short run. In reality, the Granger causal relationship could be both linear and nonlinear. Therefore, investors should not focus only on linear causal relationship, which has been widely acknowledged by public. Instead, more sophisticated investors could use the nonlinear Granger causality relationships disclosed by our nonlinear causality test of this thesis in practice to get additional investment profit, at least in the short run. In addition, the dominant role played by A-share markets as showed in our analyses suggests that investors in other segmented stock markets should be more careful about the movements of A-share markets, especially when they move to high volatility regime.

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