Long memory, structural breaks and the volatility-volume relationship

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D.Phil Thesis

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March 2008

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Abstract

The volatility-volume relationship and their own dynamic dependencies have been the subject of extensive economic and econometric research over the years. Two related types of theories explain the volatility-volume relation. The Mixture of Distributions Hypothesis uses information as the driving force to determine both volatility but no explanation is provided for the process through which information incorporates into market prices. From a market microstructure perspective, the volatility-volume relation depends on who is generating volume and why and/or on what information they are trading. For example, differences in traders' beliefs caused by different interpretation to common information and by the 'noisy' liquidity demand predict a positive association between abnormal volume and excess volatility. Empirical studies for various financial instruments show that a significant positive relation exists between the two variables while a negative is also possible. The main objective of this thesis is to investigate the volatility-volume (simultaneous and causal) relationship for an emerging market's stock and futures exchanges. In particular, we examine the impact of domestic and foreign as well as that of member and non member investors' trading on the volatility of the cash and futures markets. Primarily, we examine the case of Korea while additional evidence is provided for the Indian stock market. Our interest to Asian emerging markets stems from the outstanding economic growth

and strong trade performance experienced over that last thirty years resulting to increased portfolio flows and new capital markets. Our empirical analysis is conducted using up-to-date econometric techniques that can properly capture the commonly known stylized facts in volatility and volume such as ARCH effects, long run dependence and structural breaks. Moreover, using an extensive and detailed time series dataset for the spot and futures markets in Korea we can disentangle the impact of different types of traders on volatility. Several aspects of the volatility-volume relation arise over time and across traders. An important point that emerges is that the contemporaneous relation between volatility and volume is primarily positive while the causality effect from volume to volatility is sensitive to the different sample periods and types of traders considered. Our results are consistent with several theoretical and empirical studies in the literature. Finally, in the case of India the impact of the introduction of derivatives markets on the spot volatility-volume relation and their levels is examined.

Acknowledgements

I wish to express my gratitude to Professor Menelaos Karanasos for his supervision and encouragement during the preparation of this thesis. I am also grateful to Professor Huw Dixon and Dr. Marco Realdon for their helpful comments on earlier drafts of this study.

I would like also to thank seminar participants at the 4th Oxmetrics user conference (September 2006) and Financial Economics conference in Brunel University for helpful comments and suggestions. The thesis was also benefited from very useful comments by the editors of Asian Pacific Financial Markets and Journal of Business and Economic Statistics.

Special thanks are also due to Chrisostomos Florackis, Alex Kostakis and Dimitrios Kolovos for their helpful discussions.

I take the opportunity of this section to thank my friends Margaritis Voliotis, Giannis Klapaftis and Kostantinos Bletsas for their support during the inevitable difficult moments of a PhD.

Finally, there are not enough words to thank my family for helping me, in every sense, throughtout the PhD process. Above all, I would like to express my warmest gratitude to my parents. Their understanding, encouragement and support have been invaluable. This thesis is dedicated to them.

Declaration

A version of Chapter 2 has now been published in *Asian Pacific Financial Markets*, 2005, Vol. 12, pp. 245-271 (joint with Jinki Kim and Menelaos Karanasos)

Chapter 3 has been submitted to the *Journal of Empirical Finance* and is currently under revision . An earlier version of Chapter 3 was presented at the 4th Oxmetrics user conference in Cass Business School, London (September 2006) (joint with Menelaos Karanasos)

A version of Chapter 4 was deveopled in co-authorship with Menelaos Karanasos and presented at the Financial Economics conference in Brunel University, London (June 2006)

Chapter 5 is a sole authored study and has been submitted for presentation to the annual meeting of the European Finance Society (EFA) in Athens, Greece (August 2008)

A version of Chapter 6 has been accepted for presentation at the 2nd Emerging Markets Group Conference in Cass Business School, London (May 2008) (joint with Menelaos Karanasos)

Chapter 1

Introduction

An extensive amount of research has been developed for modelling volatility in financial markets. This interest stems from the fact that volatility is an important factor in many financial applications, such as option pricing and value at risk measures. It is also important in asset allocation under the mean-variance framework, in which expected returns are typically related to the joint second order moments of returns and other stochastic processes. Moreover, modelling the volatility of a time series can improve the efficiency in parameter estimation and testing procedures as well as the accuracy in interval forecasting. On the econometrics side, researchers proposed a variety of volatility models that try to capture some commonly seen characteristics in absolute or squared returns such as clustering (ARCH effects), leverage and long range dependence. In order to explore the sources of such stylized facts, univariate as well as multivariate models for the mean and variance of asset returns, conditional on previous returns, variances and other economic variables, were proposed. Bollerslev, Chou and Kroner (1992) and Ghysels, Harvey and Renault (1996) provide a review of the earliest studies in the literature using autoregressive conditional heteroscedasticity

(ARCH)-type and stochastic volatility models, respectively.

The empirical regularities experienced in financial markets have also attracted theoretical work in a more economic framework such as specifying the optimization problem, agent type and information structure. From a market microstructure viewpoint, price movements are caused mainly by the arrival of new information and the process that incorporates this information into market prices (Kyle, 1985, Glosten and Milgrom, 1985, Easley and O'Hara, 1987). Under this market framework, the arrival of news into the market is likely to provide an informational advantage to informed traders who try to exploit it in a sequence of trades and, thus, make prices to adjust to full information values. As long as the sequence of trades and transaction prices reveal the content of private information, a sequence of temporary intraday equilibria arises. As O'Hara (1995) argues, prices play the dual role of market clearing and information aggregation when information asymmetry is present. Another variable that can probably provide useful information to investors is trading volume (Blume, Easley and O'Hara, 1994). In market microstructure theory, variables such as the trading volume, the number of transactions, the bid-ask spread as well as issues of market liquidity are closely associated with the return volatility process.

A commonly-cited saying is that 'it takes volume to move prices ' or simply that volume and volatility are positively correlated. An early attempt to explain the volatility-volume relationship, without fully illustrating the information integration process, is the mixture of distributions hypothesis of Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983). According to the mixture of distribution model, price changes and trading volume are jointly determined by an information arrival process serving as a common mixing variable and a positive volatility-volume relationship is predicted. Li and Wu (2006) suggest a version of the mixture of distributions hypothesis which allows liquidity trading to affect price volatility. They find that the positive relationship between volatility and volume is primarily associated with information arrivals by informed trading. In addition controlling for the effect of informed trading, return volatility is negatively correlated with volume, which is consistent with the contention that liquidity trading increases market depth and lowers price volatility.

Several market microstructure studies describe the evolution of prices and volume by fully utilizing a market framework with market participants distinguished by the information they hold, the dispersion of beliefs they form based on this information and their trading motives. Harris and Raviv (1993) and Shalen (1993), find a positive relationship between absolute price changes and volume due to the dispersion of beliefs partly caused by different interpretation to common information and partly caused by the 'noisy' liquidity demand. However, Holthaussen and Verrecchia (1988) argue that the extent to which the information content (informedness) of an information signal makes investor revise their beliefs in the same (consensus) or opposite direction gives rise to different volume volatility relationships. Particularly the variance of price changes and trading volume tend to be positively related when informedness effect dominates the consensus effect and tend to be negatively related when the consensus effect dominates the informdness effect. The empirical evidence on the volatility-volume relationship reveals a positive association (see Karpoff, 1987, Bessembinder and Seguin, 1992, 1993) between these two variables while a negative one (Daigler and Wiley, 1999, Li and Wu, 2006) is also possible.

The main objective of this thesis is to investigate the volatility-volume (simultaneous and causal) relationship for an emerging market's stock and futures exchanges such as Korea. Although there have been numerous empirical studies that have examined the relationship between trading volume and stock returns (and volatility), these studies have focused almost exclusively on the well-developed financial markets, usually the US markets. Over the past three decades, Asian economies have experienced outstanding economic growth and strong trade performance. The developing and emerging market economies of Asia have not just been major exporters but they have also been an increasingly important market for other countries' exports. Moreover, emerging markets as an asset class have attracted a vast amount of investment capital due to the higher expected returns as a result of higher economic growth. Moreover, a portfolio of emerging markets is an excellent portfolio diversifier. Consequently, the developing and emerging market economies of Asia have been a major engine of growth in the world economy. Moreover, new capital markets have emerged and this has further stimulated research over emerging markets finance (see Bekaert and Harvey, 2003). As Bekaert and Harvey (2003) argue, portfolio flows (fixed income and equity) and foreign direct investment replaced commercial bank debt as the dominant sources of foreign capital. This could not have happened without these countries putting forward a financial liberalization process, relaxing restrictions on foreign ownership of assets, and taking other measures to develop their capital markets, often in tandem with macroeconomic and trade reforms. The case of Korea, among the Asian emerging economies, is particularly important as it has enjoyed increased economic performance and capital inflows until the hit of the Asian financial crisis in 1997. In particular, real GDP growth fell from levels which had been running in the positive 10% range before the crisis to a negative 6.7% rate in 1998. The crisis in 1997 seems to have brought changes in the Korean financial system under an IMF bailout program. One of the major features of the reformation was the financial opening to foreign investors. The opening included the abolition of the foreign ownership ceiling in the stock market, the free movement of the profit on investment, the provision of transparent financial reports and so on. All these developments in the Korean Stock Exchange raised a number of questions on how the volatility-volume relationship has evolved over time and across different types of traders.

Our study uses a uniquely constructed dataset that includes detailed and up-to-date information on the daily price range and trading volume of the KOSPI Composite and KOSPI200 cash and futures index. Specifically, daily data on high, low, open and closing prices are available from the 3rd of January 1995 to 26th of October 2005 and this allows us to use range based volatility estimators apart from the widely used absolute or squared returns. Furthermore, for the same period total daily trading volume, number and value of shares as well as number and value of futures contracts traded, is available. Additionally, in this study total trading volume is separated into the domestic investors' and the foreign investors' volume whereas all previous research investigated mainly total volume. We are able to conduct empirical analysis for different market participants as our trading volume data consists of domestic and foreign traders' buy and sell trading activity. In addition, domestic trading volume is divided into eight different types of domestic traders such as securities companies, insurance, investment, bank, merchant and mutual fund, pension fund, others and individuals. Therefore, this dataset enables us to examine the relationship between volatility and different types of domestic as well foreign investors trading volume as in Daigler and Wiley (1999).

Finally, to conduct our empirical investigation we put forward sophisticated time series econometric techniques that can mimic the stylized facts commonly found in volatility and trading volume such as ARCH effects and long run dependence. In particular we use univariate as well bivariate long memory models than capture effectively the long run dependence in the mean and the variance of both volatility and volume (Ding, Granger and Engle, 1993, Baillie, Bollerslev and Mikkelsen, 1996). In order to examine the relationship between volatility and trading activity we use either a two-step or a simultaneous estimation approach. In the two step approach we use the estimated conditional variance from the long memory GARCH model as our statistical measure of volatility and then we employ Granger methods to test for evidence on the bidirectional causality relationship between the two variables. Under the simultaneous approach, we estimate a univariate conditional variance model augmented by lags of trading volume, thus allowing simultaneous estimation and testing of the contemporaneous as wells as of the causal effect from volume to conditional volatility. Further, within the framework of the bivariate ccc AR-FI-GARCH model, we will analyze the dynamic adjustments of both the conditional means and variances of volume and volatility as well as the implications of these dynamics for the direction of causality between the two variables. Finally, we perform subsample analysis subject to prior investigation for structural breaks in the mean of volatility and trading volume as our sample spans over periods of increased turbulence such as the Asian Financial Crisis in 1997 and the Russian default in 1998. We use the Bai and Perron (1998, 2003a, b) testing procedure for multiple structural breaks as the problem has been addressed under very general conditions on the data and the errors. In addition, we use an extension of Bai and Perron's (1998) test by Lavielle and Moulines as it is valid under a wide class of strongly dependent processes, including long-memory, GARCH-type and non-linear models.

The thesis is organized as follows. Chapter 2 investigates the stock volatility–volume relation in the Korean market for the period 1995–2001. Previous research examined the impact of liberalization on the Korean stock market up to the period before the financial turmoil in 1997 although the crucial measures of the liberalization were introduced after the crisis under the International Monetary Fund program. One of the major features of the reformation was the financial opening to foreign investors. In this study the 'total' trading volume is separated into the domestic investors' and the foreign investors' volume. By doing this the information used by two different groups of traders can be separated. Further, as a complement to the absolute value of the returns and their squares we use the conditional volatility from a GARCH-type model as an alternative measure of stock volatility. The following observations, among other things, are noted about the volume–volatility causal relationship. First, for the entire period there is a strong bidirectional feedback between volume and volatility. In most cases this causal relationship is robust to the measures of volume and volatility used. Second, volatility is related only to domestic volume before the crisis whereas after the crisis a bidirectional feedback relation between foreign volume and volatility begins to exist.

Chapter 3 examines the issue of temporal ordering of the range-based volatility and turnover volume in the Korean market for the period 1995-2005. We examine the dynamics of the two variables and their respective uncertainties using a bivariate dual long-memory model. Additionally, we perform subsample analysis subject to properly identifying the change points in trading volume, especially around the Asian Financial Crisis, using structural break tests. We find that the impact of foreign volume on volatility is negative in the pre-crisis period but turns to positive after the crisis. This result is consistent with the view that foreign purchases tend to lower volatility in emerging markets-especially in the first few years after market liberalization when foreigners are buying into local markets- whereas foreign sales increase volatility. Before the crisis there is no causal effect for domestic volume on volatility whereas in the post-crisis period total and domestic volumes affect volatility positively. The former result is in line with the theoretical underpinnings that predict that trading within domestic investor groups does not affect volatility. The latter result is consistent with the theoretical argument that the positive relation between the two variables is driven by the uninformed general public.

Chapter 4 provides empirical evidence on the degree of long run dependence of volatility and trading volume in the Korean Stock Exchange. We employ the semiparametric estimators of the long memory parameter d proposed by Robinson (1994, 1995a), and results are also reported for subsamples once we first test for structural breaks. The results from testing for long memory support the argument for long run dependence in both Garman-Klass volatility and trading volume. Total and domestic trading volume show very similar long memory characteristics for all sample periods. The degree of long memory in foreign volume is significantly lower than that experienced in domestic volume. In addition, the results for all trading volume categories are not influenced by structural breaks in the mean of the series. On the other hand, the long range dependence in volatility is quite sensitive to the different sample periods considered. Moreover, the null hypothesis that volatility and volume share a common long memory parameter is only accepted for foreign volume and Garman-Klass volatility in all three subperiods. This result is consistent with a modified version of the mixture of distributions hypothesis in which volatility and volume have similar long memory characteristics as they are both influenced by an aggregate information arrival process displaying long range dependence. Finally, we find no evidence that foreign volume and volatility share a common long memory component.

Chapter 5 investigates whether different types of traders, distinguished by the information they possess, have a positive or negative effect upon volatility while the trader type volume is partitioned into expected and unexpected components. Our empirical results show that surprises in non member investors' trading volume are positively related with volatility in most of the cases. These results are more reinforcing in the case of log-volume and generally consistent with existing theoretical and empirical evidence. As regards member investors, we primarily find that unexpected volume is positively related to volatility, providing further support for the argument that informed rational speculators exacerbate volatility especially when noise traders follow positive feedback strategies. Another important result of our study is that the coefficients relating the unexpected component of open interest with volatility are uniformly negative, implying that an increase in open interest during the day lessens the impact of a volume shock in volatility. Moreover, the long run effect of non member investors trading seems to be important and stabilising over futures prices in the case of institutional and foreign trading but destabilising over futures prices in the case of individual trading, especially up to the end of the financial crisis. As regards member investors, their long run effect on futures prices is significant and negative in the case of log volume only and primarily for the period up to the end of the Asian Financial Crisis.

In Chapter 6 we attempt to complement the empirical findings on the volatility-volume relationship by considering the case of another Asian emerging economy such as India. In particular, within the framework of the bivariate ccc AR-FI-GARCH model, which can accurately capture the own dynamic dependencies of both the conditional means and variances of volume and volatility, we analyze the direction of causality between the two variables. In addition, the introduction of derivatives trading in the Indian stock exchange is very likely to course action away from the stock market, especially for discretionary liquidity traders (Subrahmanayan, 1991). Therefore, in order to investigate the effect of the introduction of derivatives trading on the constant of and the relationship between volatility and volume we introduce constant as well as slope dummies in our model, respectively. The empirical findings in this chapter point towards a negative relation between volatility and both measures of trading activity, the number of trades and the value of shares traded, for all three periods considered. This result is in line with a version of the MDH model in which the higher the intensity of liquidity trading the lower the price volatility. Another important finding of our study is that the introduction of futures trading leads to a decrease in spot volatility, a result consistent with the empirical finding of Bessembinder and Seguin (1992). Finally our results indicate that expirations of equity based derivatives have significant impact on the value of shares traded and on the range-based volatility on expirations days.

Chapter 7 presents the main conclusions of this work.

Chapter 2

The volume-volatility relationship and the opening of the Korean stock market to foreign investors after the financial turmoil in 1997

2.1 Introduction

Some researchers have carried out studies about the effect of capital controls introduced by emerging countries around the financial crisis in 1997 (see, for example, Edison and Reinhart, 2001). However, studies for countries which took further liberalization after the crisis are difficult to find. This research investigates the Korean stock market volatility after the crisis and hence contributes to the study of emerging markets' liberalization after the crisis. Although there is a warning from some researchers that the stock market development and liberalization in developing countries could dampen the country's long term economic growth[1] (see Singh 1997; Singh and Weisse, 1998; Stiglitz, 2002), most of the previous empirical studies found that the market opening was favorable to emerging countries' economies (e.g., Bekaert and Harvey, 2000; Henry, 2000; Kim and Singal, 2000).

In developing countries, the empirical research on financial liberalization suggested that the stock market opening to foreign investors did not increase the stock market volatility. However, these studies are limited when exploring the case of the Korean stock market because they analyzed data only for periods before the crisis. In fact the crucial measures of the liberalization were introduced after the crisis under the International Monetary Fund (IMF) program. In other words, the previous studies examined the impact of liberalization on the Korean stock market up to the period before the crisis although the Korean stock market abolished the foreign ownership limit right after the crisis and at the same time introduced measures to induce foreign capital. The IMF bailout program resulting from the financial crisis initiated the fundamental reformation of the Korean financial system. One of the major features of the reformation was the financial opening to foreign investors. The opening included the abolition of the foreign ownership ceiling in the stock market, the free movement of the profit on investment, the provision of transparent financial reports and so on. The crisis in 1997 seems to have brought in a different era in Korean stock market history. Four years after the crisis the stock market return series still showed much higher variability than ever before. The Korean economy has recovered rapidly after the financial turbulence, recording 10.7% and 8.8% of GDP growth rate in 1999 and

[1] Singh (1997) suggests several reasons, including excess stock market volatility.

2000 respectively over against -6.7% in 1998. However, the stock market volatility has not returned to the level that it had before the crisis.

This paper makes four contributions. First, it investigates the stock volatility-volume relation in the Korean market. In particular, we use Granger causality tests to examine the dynamic relation between daily stock price volatility and trading volume. Causality tests can provide useful information on whether knowledge of past trading volume movements improves short-run forecasts of current and future movements in stock price volatility, and vice versa (see Lee and Rui, 2002). Although there have been numerous empirical studies that have examined the relationship between trading volume and stock returns (and volatility), these studies have focused almost exclusively on the well-developed financial markets, usually the US markets. There is a relative scarcity of literature investigating the relation in fast-growing stock markets in emerging economies. Only Silvapulle and Choi (1999) and Pyun et al. (2000) attempt to examine the relation in the Korean market. However, both studies use data based on a time series of stock returns up to 1994.

Second, unlike all previous studies which used data only up to the period before the crisis, this study investigates the volume-volatility relationship for the period 1995 to 2001. We examine whether the financial crisis affects the dynamic interaction between volume and volatility by dividing the whole sample period into two sub-periods and conducting causality tests for each sub-period separately. Third, in this research the 'total' trading volume is separated into the domestic investors' and the foreign investors' volume (hereafter 'domestic' and 'foreign' volume respectively) whereas all previous research investigated 'total' volume. By doing this the information used by two different groups of traders can be separated. Daigler and Wiley (1999) examine the volume-volatility relation using volume data categorized by type of trader. They find that the positive volatility-volume relation is driven by the general public (a group of traders without precise information on order flow) whereas financial institutions and floor traders who observe order flow often decrease volatility.

Fourth, in addition to the two most commonly used measures of stock volatility- that is the absolute value of the returns and their squares- we use the conditional volatilities from a GARCH-type model. This fractional integrated asymmetric power ARCH (FIAPARCH) model can mimic three stylized empirical facts of stock market volatility: (i) volatilities are highly persistent, (ii) volatility responds to price movements asymmetrically, and (iii) the power of returns for which the predictable structure in the volatility pattern is the strongest should be determined by the data. To test for the relationship between volume and conditional volatility, hereafter 'FIAPARCH' volatility, one can use either the two-step or the simultaneous estimation approach. Under the former approach, we proceed in two steps. First, we use the estimated conditional variance from the FIAPARCH model as our statistical measure of volatility. Having constructed a time series of volatility in the second part we employ Granger methods to test for evidence on the bidirectional causality relationship between the two variables. Under the latter approach, we estimate: (i) a FIAPARCH specification augmented by lagged volume, thus allowing simultaneous estimation and testing the causal effect from volume to conditional volatility, and (ii) a bivariate FIAPARCH model of volume and stock returns with the mean equation for the volume incorporating lags of the conditional variance of the stock returns. This bivariate in mean model permits us to test the causal effect from 'FIAPARCH' volatility to volume.

This study provides strong empirical support for the argument made among others by Brooks (1998) that daily stock price volatility and trading volume are intertemporally related. Hence, instead of focusing only on the univariate dynamics of stock price volatility one should study the joint dynamics of stock price volatility and trading volume. Moreover, as Bessembinder and Seguin (1993) and Lee and Rui (2002) point out, an important distinction in investigating the trading volume and volatility relation is to distinguish between expected and unexpected trading volume. In addition, Daigler and Wiley (1999) show that the general public drives the positive volatility-volume relation. Conversely, trades by floor traders often exhibit an inverse relation between volatility and volume. Thus, they argued that using trader categories is a better way to describe the link between volatility and volume than is 'total' volume. In this paper we show that it is also important to distinguish between domestic and foreign investors' trading volume.

The following observations, among other things, are noted about the volume-volatility causal relationship. First, for the entire period there is a strong bidirectional feedback between volume and volatility. In most cases this causal relationship is robust to the measures of volume and volatility used. Second, before the crisis volatility is independent of changes in 'foreign' volume whereas after the crisis a negative feedback relation begins to exist. Daigler and Wiley (1999) point out that the relation between clearing members and other floor traders with volatility is often negative. This suggests that information about order flow from trading activities may actually help reduce risk and therefore enhance the value of holding a seat. Similarly, in the Korean stock market 'foreign' volume tends to have more information about volatility in recent years, which suggests the increased importance of 'foreign' volume as an information variable. It turns out that using any of the three alternative measures of volatility results in exactly the same causal relation between 'foreign' volume and volatility. Third, the effect of absolute/square returns on 'domestic' volume is positive in the pre-crisis period but turns to negative after the crisis. Further, in both sub-periods increased conditional volatility lowers 'domestic' volume. On the other hand, before the crisis 'domestic' volume has a positive impact on the conditional volatility whereas it affects absolute/squared returns negatively. In sharp contrast, after the crisis volatility is independent of changes in 'domestic' volume. Finally, the evidence obtained from the causality tests is reinforced by the parameter estimates provided by the augmented FIAPARCH processes and the bivariate FIAPARCH in mean models.

The remainder of this paper is organized as follows. Section 2 presents a brief description of the Korean market, and the next Section provides a summary of existing theories and empirical evidence. Section 4 outlines the data which are used in the empirical tests of this paper. Section 5 lays out our econometric model and reports our results. Section 6 discusses our results and proposes possible extensions. Section 7 contains summary remarks and conclusions.

2.2 The Korean market

The Korean market is classified as one of the emerging markets as it has experienced significant economic growth and development in the past few years. The economic growth and development of the Korean market has been accompanied by a series of important legislative and structural changes (Silvapulle and Choi, 1999). This section provides a brief description of the organizational and institutional factors of the Korean market.

2.2.1 Liberalization date

The decision on the liberalization date is important for understanding the effect of financial liberalization and capital inflow on an emerging stock market, because researchers compare the two periods before and after the liberalization date to study the effect. Various liberalization dates are suggested and examined, including the date of government announcement of the stock market opening to foreign investors. Bekaert and Harvey (2000) and Kim and Singal (2000) used the same liberalization date for Korea, i.e. January 1992. Authors generally agree that foreign capital flows do not increase emerging stock market volatility despite their differences in liberalization dates and sample periods. **Table 2.1** reports the sample period and the results of the previous research.

**TA-
BLE 2.1**

According to the above studies Asian emerging markets were liberalized mostly in the late 1980s and in the early 1990s. However, when emerging stock markets were liberalized the levels of foreign ownership were significantly different from country to country. Foreign ownership of domestic firms may not be a sufficient measure of stock market openness. Emerging countries have various barriers that hinder international portfolio investment. However, the lifting of the foreign investment ceiling is a necessary condition for the participation of foreign investors and therefore the foreign ownership limit is the crucial indicator of stock market openness.

Noticeably Korea had a strict limitation of foreign investment in its stock markets at the 10% level. Korea pledged to increase these ceilings step by step in the future. However, the speed of this process was remarkably slow. More than five years later the foreign ownership limit of the Korean stock market reached only 23% in May 1997 (see **Table 2.2**). The aforementioned studies did not take into account the slow pace of the Korean liberalization process properly when they simply investigated a period of three or five years after the liberalization date. Moreover, they missed the most important period of liberalization of Korea after the crisis. For example, the Korean stock market opened wide to foreign investors without any ownership ceiling in May 1998, eight months after the crisis (see **Table 2.2**).

TABLE 2.2

This radical financial reform was implemented owing to the IMF, which has had a great role in Korean financial liberalization after the crisis in 1997. The reform program of the Korean government under IMF supervision has managed to recover market confidence. The response of the Korean government to the IMF program had to be urgent. It abandoned step by step liberalization and opened the stock market immediately. The Korean authority altered the foreign ownership ceiling three times from 26% to 55% in the two months of October and November 1997 and finally removed the limit in May 1998. It only took 6 months to change the ceiling from 26% to 100%, whereas it had taken more than five and half years to move from 0% to 26%.

Because of the financial crisis all the stock markets in East Asia became highly volatile so it is difficult to parse what is due to the financial crisis and what is owing to the ongoing liberalization if the crisis period is included in the sample. This is a possible reason why the previous studies limited their sample periods to before the crisis. The current research may allow us to shed more light on this latter problem, which is indeed of major concern. Studying whether the financial liberalization caused the financial crisis is not the purpose of this paper.[2] The aim of this research is to study the effect of liberalization on the stock market volatility. Hence, even if it is true that the financial liberalization did not lead to the crisis it does not mean that the financial liberalization does not make the financial market more volatile at all because in the middle of and after the crisis the financial liberalization continued. Especially in Korea the liberalization was accelerated and reached close to its goal in the middle of and after the crisis. Therefore, an extension to the period after the crisis seems to be justified to evaluate the effect of the financial liberalization. This seems more appropriate when we consider that the IMF program not only brought the abolition of the foreign investment limit but more profoundly changed the financial system itself.

2.2.2 The informational change of the stock market after the crisis

One of the main features of the economic transformation after the crisis is that the Korean economy has created a climate favorable to foreign investors' activity. This was inevitable to attract foreign capital. The IMF led the Korean government to revise laws and regulations for further free capital inflow. The foreign investors' shareholding in the Korean Stock Exchange had increased to 30.1% of total market capitalization by the end of 2000 from 14.6% at the end of 1997. In manufacturing industries foreign controlling companies' sales grew to 18.5% of total revenue in 1999 from 5.5% in 1996. Also in the financial industry foreign capital advanced. At the end of 1999 the market share of banks in which foreign investors are the first majority shareholders amounted to 41.7% in terms of de-

[2]Unlike the aforementioned empirical research Stiglitz (2002, p. 99) argues that capital account liberalisation was 'the single most important factor' leading to the crisis.

posits and lendings. The securities companies of which the majority shareholders are foreigners increased their market share to 20.9% in 2000 from 3.9% in 1997. During the same period the market share of foreign insurance companies reached 9.6% from 1.3%. The number of listed companies that give stock options to their employees also increased to 105 in 2000 from only 2 in 1997 (Kim ed., 2001).

Table 2.3 reports the daily trading volumes of domestic and foreign investors in the Korean stock market. The third column shows the increase of the proportion of foreign investors' trading since 1995. Although the proportion of foreigners trading was under 11% in 2001 their shareholding was already over 30% at the end of 2000.

TABLE 2.3

The obvious increase in foreign shares in the Korean companies has been supported by government regulations and the practice of firms. Put differently, the tremendous increase in foreign investors' stock trading volume can also be explained by the investment information changes in the Korean stock market. Even after foreign investment was allowed in 1992, external investors may have been uncomfortable trading because they did not have proper investment 'information'. Providing a transparent financial status can induce foreign capital inflow and activate foreign investors' trading. To assess the effect of stock market liberalization the change in the informational environment should be considered. Therefore, the effect of Korean stock market liberalizations will be more clear when the period after the crisis is investigated.

2.3 Prior research

2.3.1 The stock volatility-trading volume relation

This section reviews previous research on the relation between stock price changes and trading volume. Karpoff (1987) gives four reasons why the price-volume relation is important: (i) it provides insight into the structure of financial markets, (ii) it is important for event studies that use a combination of price and volume data from which to draw inferences, (iii) it is critical to the debate over the empirical distribution of speculative prices and, (iv) it has significant implications for research into futures markets.

There are several explanations for the presence of a causal relation between stock price volatility and trading volume. According to various mixture of distributions models there is a positive relation between current stock return variance and trading volume. For example, Epps and Epps (1976) present a model which suggests a positive causal relation running from trading volume to absolute stock returns. The sequential information arrival models also suggest a positive causal relation between stock prices and trading volume in either direction. Due to the sequential information flow, lagged absolute stock returns could have predictive power for current trading volume and vice versa. These theoretical models imply bidirectional causality between volume and volatility and hence provide motivation for empirical research into this relationship (see Hiemstra and Jones, 1995; Brooks, 1998, and the references therein).

Karpoff (1987) proposes a model which links trading volume, returns and volatility and predicts a positive but asymmetric relationship between trading volume and the absolute value of returns. Other researchers have developed models that are based on information economics and link information arrival with trading, price changes and price volatility. One such model suggests that trading volume and the variance of price changes move together, while another one suggests that there is no relationship between stock price volatility and trading volume (see Brailsford, 1996, and the references therein). Harris and Raviv (1993) assume that traders receive common information but differ in the way in which they interpret it. Their model predicts that absolute price changes and trading volume are positively correlated. Wang (1994) develops an equilibrium model of stock trading in which investors are heterogeneous in their information and the positive correlation between trading volume and absolute price changes increases with information uncertainty.

Brock (1993) develops a heterogeneous agent trading model which implies a nonlinear stock price-volume relationship. Campbell et al. (1993) present a model of noninformational trading, which implies that the serial correlation in stock returns is a nonlinear function of the trading volume. Brailsford (1996) points out that a positive correlation between the trading volume, returns and variance may be inferred from the fact that the trading volume and both the level and variance of returns exhibit similar U-shaped patterns during the trading day.

Daigler and Wiley (1999) argue that clearing members have specific private information that allows them to better distinguish liquidity demand from fundamental information and to estimate current value more precisely, which translates into a smaller dispersion of beliefs and less price volatility. On the other hand, since the general public possesses less information it has difficulty in distinguishing liquidity demand from fundamental information and its behaviour is consistent with the noise literature. Researchers have examined how the unpredictability of noise traders' beliefs creates excess risk, causing prices to diverge significantly from fundamental values (see, Daigler and Wiley, 1999 and the references therein).

2.3.2 A brief survey of the empirical literature

This section summarizes several empirical studies that investigate the relationship between stock price and trading volume or between volatility and volume. In a survey paper Karpoff (1987) finds that 18 of the 19 empirical investigations that examine the relationship between absolute price change and volume report a positive correlation. Harris (1987) documents a positive correlation between changes in volume and changes in squared returns for individual NYSE stocks. Smirlock and Starks (1988) provide strong evidence for a positive lagged relation between volume and absolute price changes. Gallant et al. (1992) using nonlinear impulse response functions find evidence of a strong nonlinear impact from lagged S&P 500 stock returns to current and future NYSE trading volume but only weak evidence of a nonlinear impact from lagged trading volume to current and future stock returns. Campbell et al. (1993), using regression models, provide statistically significant evidence of nonlinear interactions between stock returns and trading volume in the US market. Subsequently, Hiemstra and Jones (1995) indicated the presence of bidirectional nonlinear Granger causality between daily Dow Jones stock returns and changes in the NYSE trading volume. After controlling for volatility effects, their modified Baek and Brock (1992) test continues to provide evidence of significant causality running from trading volume to stock returns. Bhagat and Bhatia (1996) test for causality in both the mean and the variance and demonstrate that price changes lead volume. Brooks (1998), employing both linear and non linear Granger causality tests, provides extensive evidence of bidirectional feedback between volume and gvolatility. He used the square of the day's return as a measure of the Dow Jones stock returns volatility. Lee and Rui (2002) show that there exists a positive feedback relationship between trading volume and return volatility in the three largest stock markets.

Daigler and Wiley (1999) find that the volume generated by clearing members and other floor traders indicates a volatility-reducing relation, which is consistent with these traders being more strongly associated with private information and less likely to trade on noise. In sharp contrast, the activity of the less-informed general public is directly and strongly associated with higher volatility.

At the same time a parallel literature has developed which employs GARCH models to describe stock return volatility. Lamoureux and Lastrapes (1990) find that the inclusion of contemporaneous trading volume in the conditional variance equation eliminates the persistence in the volatility. However, as noted by Lamoureux and Lastrapes (1990) if trading volume is not strictly exogenous, then there is possibly simultaneity bias. One potential solution to this problem is to use lagged measures of volume, which will be predetermined and therefore not subject to the simultaneity problem. Lamoureux and Lastrapes (1990) found that lagged volume was insignificant. Brooks (1998) uses various GARCH-type models to forecast volatility out-of-sample, and considers their augmentation to allow for lagged values of market volume as predictors of future volatility. Chen et al. (2001) find that the persistence in EGARCH volatility remains even after incorporating contemporaneous and lagged volume effects.

Although there has been extensive research into the empirical and theoretical aspects of the stock price volatility-volume relation, most of this research has focused on the well-developed financial markets, usually the US markets. However, some studies have examined the volatility-volume relation in markets outside of the United States. In particular, Tse (1991) examines the relations between volume and the absolute value of returns for different indices in the Tokyo Stock exchange and he finds mixed results. Brailsford (1996) uses both the squared returns and the absolute value of the returns as measures of volatility. He provides support for a positive relationship between trading volume and volatility for the Australian stock market. Saatcioglou and Starks (1998) employ Latin America stock data and document a positive relation between volume and both the price changes and their magnitude. Chen et al. (2001) find a positive correlation between trading volume and the absolute value of the stock price change for nine major stock markets.

Two recent studies have examined the price-volume relation in the Korean stock market. Silvapulle and Choi (1999) examine the dynamic relationship between daily aggregate Korean stock returns and trading volume. After controlling for volatility persistence in both series and filtering for linear dependence they find evidence of nonlinear bidirectional causality between stock returns and volume series. Pyun et al. (2000) examine the relationship between information flows and return volatility for individual companies actively traded in the Korean stock exchange. They find that adding the current trading volume to the conditional variance equation reduces the volatility persistence of returns and conclude that the Mixture of Distribution hypothesis is relevant in the Korean stock market. However, they also find that lagged volume has no effect on the conditional volatility of individual stocks (similar results have been reported by Brailsford, 1996, for the Australian stock market).

2.4 Measurement issues

2.4.1 Data and sample periods

The data set used in this study comprises 1844 daily trading volume and closing prices of the Korean Composite Stock Price Index (KOSPI), running from 3 January 1995 to 30 September 2001. The data were obtained from the Korean

Stock Exchange (KSE). The KOSPI is a market value weighted index for all listed common stocks in the KSE since 1980. Daily stock returns are measured by the daily difference of the log KOSPI [r_t =log($\frac{\mathrm{KOSPI}_t}{\mathrm{KOSPI}_{t-1}}$) $\times$ 100]. The whole sample is divided into two sub-samples to investigate informational change after the financial crisis in 1997. The first sub-sample covers the period between January 1995-which is the first month from which categorical volume data are available-and mid October 1997 with 816 observations (afterwards sample A). The second sub-sample covers the period mid October 1997-from which the KOSPI returns show dramatic change due to the crisis-to September 2001 with 1028 observations (afterwards sample B) (see **Figure** 2.1).

Figure 2.1

An alternative in choosing the break point approximately by looking at the graph is to employ a number of recently developed tests for structural breaks. In addition to testing for the presence of breaks, these statistics identify the number and location of multiple breaks. The change-point literature has recently dealt with the unknown multiple change points question in strongly dependent processes in a least squares context. In what follows we provide a brief discussion of the Lavielle and Moulines (2000) test (hereafter LM test). This recent work by Lavielle and Moulines has greatly increased the scope of testing for multiple breaks. The advantage of the LM test is that it is not model-specific. That is, it is valid under a wide class of strongly dependent processes, including long memory, GARCH-type and non-linear models. It is worth noting that the test simultaneously detects multiple breaks. The number of breaks is estimated via a penalised least-squares approach.

Consider the following generic process: $x_t = \mu_k + e_t$, $t_{k-1} \leq t \leq t_k$, $1 \leq k \leq r$, where we use the convention $t_0 = 1$ and $t_{r+1} = T$, T is the sample size. The indices of the breakpoint and mean values μ_k, $k = 1, \ldots, r$, are unknown. In practical applications, this generic model can be applied to absolute returns, their squares and the volatility estimates. The LM test is based on the following least-squares computation: $Q_T(t) = \sum_{k=1}^{r+1} \sum_{t=t_{k-1}+1}^{t_k} (x_t - \overline{x}(t_{k-1}, t_k))^2$, where for any sequence $\{u_t\}_{t \in \mathbb{Z}}$, we denote $\overline{u}(i,j)$ $(j > i)$ the average $\overline{u}(i,j) := (j-i)^{-1} \sum_{t=i+1}^{j} u_t$. A modified version of the Schwarz criterion, which yields a consistent estimator, is used. This consists of adding a penalty term to the least-square criterion in order to avoid over-segmentation. The penalty term is a linear function of the number of changes r with coefficient ξ_T. The coefficient of penalization is chosen in order to obtain approximately the same number of over- and under- estimations of the change-points. $\{\xi_T\}$ is a decreasing sequence of positive real numbers. If the disturbance term e_t is a fractional Gaussian noise, with fractional differencing parameter d, an upper bound of the regularization factor can be computed as $\xi_T = 4\log(T)/T^{1-2d}$.

The LM test can unmask the existence of multiple breaks. The results of the test do not support the null hypothesis of homogeneity in the absolute returns or their squares. The overall picture dates a single change point on the 14th of October 1997 for absolute and squared returns. The same change-point date, associated with the financial crisis in 1997, is revealed for the ‘FIAPARCH’ volatility as well. The latter result squares with the findings in choosing the break point approximately. The results of the LM test for the volume reveal the existence of a single change-point that is detected on the 3rd of December 1998. Thus there is not a common break in volume and absolute/squared returns or ‘FIAPARCH’ volatility.

2.4.2 Volume

The available measures of trading volume provided by the KSE are the daily number of shares traded and the daily total Korean won value of shares traded. The Korean won value of shares is used as the measure of trading volume in this study because the number of shares does not take into account the relative market value of the individual shares. Among others, Gallant et al. (1992) and Silvapulle and Choi (1999) also use value of shares as a measure of trading volume. Brailsford (1996) employs three different measures of trading volume (number of transactions, number of shares traded and value of shares traded) and argues that the number of shares traded is the least preferred measure of trading volume and should be avoided in future research. Other researchers use the turnover (the ratio of the number of shares traded to the number of shares outstanding) as a measure of trading volume (see Campbell et al., 1993; Brooks, 1998).

Since January of 1995 the Korean Stock Exchange has recorded the daily trading volume of foreign investors and of 8 different domestic investors, including financial institutions, pension funds, individuals and so on. The domestic investors' trading volume is constructed by adding all the different domestic investors' trading volumes.[3] **Figure** 2.2 plots the daily total Korean won value of traded shares while the shaded area covers the period from December 1998 to September 2001 with 691 observations (Sample B1) .[4]

Figure 2.2

[3] Due to the categorical trading volume records of the KSE one can use the different investors' trading volumes to study the relationship between the trading volume and the volatility of the stock market. Further research could be done using all 9 different investors' trading volumes to find out investors' trading behavior in the stock market.

[4] In order to ensure that the results of this study are not influenced by the financial crisis in 1997, we also examine the period from December 1998 to September 2001 (afterwards sample B1).

We also test for the stationarity properties of our data using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The results of these tests, reported in **Table 2.4**, imply that we can treat the stock returns and trading volume as stationary processes.

TABLE 2.4

2.4.3 Volatility

The Korean stock market after the crisis is more volatile than it was before the crisis according to **Figure** 2.1 and the standard deviation of returns series (see **Table 2.5**). This is probably due to the crisis. However, the standard deviation of stock return series and **Figure** 2.1 indicate that this higher volatility had become a normal feature of the Korean stock market even in 2001. Does this higher volatility have no connection with the financial liberalization after the crisis? To answer this question we examine the causal relations between stock volatility and trading volume. If the external information through the foreign investors' trading affects the higher volatility after the liberalization the causality between volume and volatility can be demonstrated.

Table 2.5 presents summary statistics for the continuously compounded KOSPI return series. The return series shows non-normality with leptokurtosis. The standard deviation of the series in period B is almost 2.5 times as great as that of period A, indicating much higher return volatility in period B.

TABLE 2.5

The standard deviations of the KOSPI returns before the crisis are 1.021, 1.089 and 1.266 in 1995, 1996 and 1997 (excluding the period of the crisis) respectively (see **Table 2.6**). The somewhat high value 1.266 in the period before the crisis from January 1997 to September 1997 might be due to turmoil in other East Asian countries, which had already begun in April 1997. After the crisis all figures are far greater than those in the pre-crisis period. In 2001 the standard deviation recorded 2.171 and is still twice as large as those in 1995 and 1996 although other economic indicators show the recovery from the crisis as pointed out by Kim ed.(2001, p.33).

TABLE 2.6

In what follows, we use three different measures of stock volatility. The most commonly used measure is the squared return series (see Brooks, 1998, and the references therein). Second, we use the absolute value of the return series (see Saatcioglou and Starks, 1998). Brailsford (1996) uses both the absolute value of the returns and their squares as a measure of volatility. Lee and Rui (2002) point out that the results from their causality tests between trading volume and volatility measured by a GARCH(1,1) model were very similar to those with squared returns. Hence, as a third measure we use the estimated volatility from the fractional integrated asymmetric power ARCH (FIAPARCH) model proposed by Tse (1998).

Next, we denote the stock return by r_t and define its mean equation as

$$r_t = c + (1 + \theta L)\varepsilon_t.$$

That is stock returns follow an MA(1) specification.[5] We also assume that ε_t is conditionally normal with mean zero and variance h_t. Put differently, $\varepsilon_t|\Omega_{t-1} \sim$

[5]In order to carry out our analysis of stock returns, we have to select a form for the mean equation. Some researchers suggested an MA(1) specification for the mean whereas others used an AR(1) form. In practice, there is little to differentiate an AR(1) and an MA(1) model when the AR and the MA coefficients are small, and the autocorrelations at lag one are equal, since

$N(0, h_t)$, where Ω_{t-1} is the information set up to time $t-1$. Finally, we assume that the structure of the conditional variance is

$$h_t^{\delta/2} = \omega + \Omega(L) f(\varepsilon_t), \tag{2.1}$$

with

$$\Omega(L) := \left[1 - \frac{(1-aL)(1-L)^d}{(1-\beta L)}\right], \quad f(\varepsilon_t) := (|\varepsilon_t| + \gamma\varepsilon_t)^\delta,$$

where $\delta, \omega \in (0, \infty)$, $|\gamma| < 1$ and $a, \beta < 1$. Here and in the remainder of this paper, L stands for the lag operator and the symbol ':=' is used to indicate equality by definition. Conrad and Haag (2006) provide the necessary and sufficient conditions which ensure that the parameters in the infinite ARCH representation are all nonnegative. The simple inequality constraints: $\beta - d \leq a \leq (2-d)(0.333)$, $d[a - (1-d)(0.5)] \leq \beta(a - \beta + d)$ are sufficient.

We estimate the various GARCH models using quasi maximum likelihood estimation (QMLE) as implemented by Davidson (2006) in Time Series Modelling. Estimates of the GARCH parameters for the entire period and the two sub-periods (before and after the crisis) are shown in **Table 2.7**. Several findings emerge from this table. The value of the estimated long memory parameter ($\widehat{d}$) is higher in sample A (0.47) than in sample B (0.21). Further, negative shocks predict higher volatility than positive shocks, since in most cases the estimated asymmetry coefficient ($\widehat{\gamma}$) is significant and negative. In addition, in both samples the value of the power coefficient is less than but not significantly different from one. Thus, it seems that the conditional standard deviation is a linear function of lagged absolute residuals. In sharp contrast, for the whole sample the

the higher order autocorrelations die out very quickly in the AR model. We therefore model the stock returns as MA(1) processes.

estimated power term is very close to two. That is, the conditional variance is a linear function of lagged squared residuals.

TABLE 2.7

To test for the persistence of the conditional heteroscedasticity model and for asymmetry in the conditional variance, we examine the likelihood ratio (LR) tests and the Wald (W) statistics for the linear constraints $d = \gamma = 0$ (PARCH model). The LR tests and W statistics (not reported) clearly reject the PARCH null hypothesis against the FIAPARCH model. Thus, purely from the perspective of searching for a model that best describes the degree of persistence in the variance of the return series, the FIAPARCH model appears to be the most satisfactory representation.

Following the work of Conrad and Karanasos (2005) among others, the LR test can be used for model selection. Alternatively, the Akaike, Schwarz, Hannan-Quinn and Shibata information criteria (AIC, SIC, HQIC, SHIC respectively) can be applied to rank the various GARCH type models. These model selection criteria check the robustness of the LR and W testing results discussed above.[6] According to the four information criteria, in all cases the optimal GARCH type model is the FIAPARCH.[7] Hence, the model selection criteria are in accordance with the LR and W testing results.

Finally, in all three cases, the hypothesis of uncorrelated standardized and squared standardized residuals is well supported, indicating that there is no statistically significant evidence of misspecification. Generally speaking, the parameter estimates support the idea that long memory effects are present in stock

[6] The analysis in Caporin (2003) focuses on the identification problem of FIGARCH models. Caporin performs a detailed Monte Carlo simulation study and shows that the four information criteria can clearly distinguish between long and short memory data generating processes.

[7] We do not report the AIC, SIC, HQIC or SHIC values for space considerations.

volatility. The results also show strong evidence of asymmetry in the conditional variance.

2.5 Empirical methodology

2.5.1 Granger causality tests

The following bivariate autoregression is used to test for causality between the trading volume and stock return volatility

$$x_t = \sum_{i=1}^{m} a_i x_{t-i} + \sum_{i=1}^{m} b_i y_{t-i} + e_t,$$
$$y_t = \sum_{i=1}^{m} c_i x_{t-i} + \sum_{i=1}^{m} d_i y_{t-i} + \nu_t,$$

where e_t and ν_t are i.i.d processes with zero mean and constant variance. The test of whether $y(x)$ strictly Granger causes $x(y)$ is simply a test of the joint restriction that all the $b_i(c_i)$, $i = 1, \ldots, m$, are zero. In each case, the null hypothesis of no Granger causality is rejected if the exclusion restriction is rejected. Bidirectional feedback exists if some of the elements b_i, c_i, $i = 1, \ldots, m$, are jointly significantly different from zero.

Next we report the results of Granger causality tests to provide some statistical evidence on the nature of the relationship between trading volume and stock volatility. We first perform Wald tests and in **Table 2.8** we report the F statistics of Granger causality tests for the entire sample using the optimal-chosen by the Akaike and Schwarz information criteria (AIC and SIC, respectively)-lag length, as well as, the sign of the sums of the lagged coefficients in case of statistical significance. Panel A considers Granger causality from trading volume to stock volatility. We apply the F statistics and use the Newey-West heteroscedasticity and autocorrelation consistent standard errors. Panel B reports the results of the causality tests where causality runs from the stock volatility to the trading volume. The tests are performed under the assumption that the conditional variances follow GARCH-type processes.[8] There is strong evidence of a bidirectional feedback between volume and volatility. In particular, volume has a positive effect on volatility. In all cases this causal relationship is robust to the measures of volume and volatility used. In addition, the absolute value of the returns or their squares affect volume negatively. In contrast, 'FIAPARCH' volatility has a positive impact on 'foreign' volume, while either 'total' or 'domestic' volume are independent of changes in 'FIAPARCH' volatility

Table 2.8

Sub-sample analyses

In this section we examine whether the informational change after the crisis affects the dynamic interactions by dividing the whole sample period into two sub-periods and conducting causality tests for each sub-period separately. **Tables 2.9** and **2.10** report the results of the Granger causality tests between volume and volatility for the two sub-periods. Panels A and B correspond to the panels that report the results for the whole sample. When a break is known, the lag length of the VAR model is estimated by minimizing the AIC and SIC (Yang,

[8]In the presence of conditional heteroskedasticity Vilasuso (2001) investigates the reliability of causality tests based on least squares. He suggests that causality tests be carried out in the context of an empirical specification that models both the conditional means and conditional variances. However, if the conditional variances are unrelated, then there is only slight size distortion associated with least-squares tests, and the inconsistency of the least squares standard errors is unlikely to be problematic.

2002).

First, we discuss the results for the pre-crisis period. Not surprisingly, volatility is independent of changes in 'foreign' volume. Regarding the 'domestic' and 'total' volume, Panel A shows that they have a negative effect on either absolute returns or their squares. In sharp contrast, they affect 'FIAPARCH' volatility positively. Panel B shows a significant positive effect of either absolute returns or their squares on volume. The last column of **Table 2.9** considers Granger causality from 'FIAPARCH' volatility to volume. In particular, conditional volatility has a negative impact on volume. The results in Panel B are not qualitatively altered by changes in the measure of volume.

Table 2.9

The evidence from the Granger causality tests suggests that the causal effect from 'total' volume to volatility reflects the causal relation between 'domestic' volume and volatility. In other words, the statistical evidence suggests that volatility is affected only by the domestic investors' volume before the crisis, which is in line with the results of the previous work. Sample A covers the period from January 1995 to mid October 1997, that is three years after the 'liberalization date' of the previous research (see **Table 2.1**). Some part of this period overlaps with those in Bekaert and Harvey (2000) and Spyrou and Kassimatis (1999). Hence, their conclusion that the nature of volatility has not changed dramatically after the 'liberalization in 1992', is in the case of the Korean stock market, probably because there was no serious amount of information inflow from the outside world. That is, even after the 'liberalization in 1992' it was the domestic rather than foreign investors' information or trading that affected the stock market volatility as it had before.

The results of applying the Granger causality tests for the period after the financial crisis in 1997 are reported in **Table** 2.10. The picture is different to that of the period before the crisis. That is, there is extensive evidence of a negative bidirectional feedback between 'foreign' volume and volatility. This finding has an important implication. The evidence of causality running from 'foreign' volume to volatility suggests that it may be possible to use lagged values of 'foreign' volume to predict volatility. Regarding the 'domestic' and 'total' volume, Panel A shows that they do not have a significant causal effect on volatility, whereas according to Panel B, there is strong evidence that volatility has a negative effect on either the 'domestic' or the 'total' volume. These results are not qualitatively altered by changes in the measure of volatility.

Table 2.10

In sum, before the crisis the 'domestic'/'total' volume-volatility relationship is altered by changes in the measure of volatility. That is, volume has a positive impact on 'FIAPARCH' volatility, whereas there is a negative causal effect from volume to either the squares of the returns or their absolute value. In addition, 'FIAPARCH' volatility affects volume negatively, whereas the absolute value of the returns or their squares have a positive impact on volume. Moreover, after the crisis the 'domestic'/'total' volume-volatility relationship is robust to the measures of volatility used. There is strong evidence of causality running only from volatility to volume. In particular, increased volatility lowers volume. We should also mention that before (after) the crisis this causal effect is stronger (weaker) for 'domestic' volume than for 'total' volume. Finally, before the crisis volatility is independent of changes in 'foreign' volume, whereas after the crisis there is a strong negative bidirectional feedback between volatility and 'foreign' volume. These results are not qualitatively altered by changes in the measure of volatility.

Next, in order to ensure that the results of this study are not unduly influenced by the financial crisis in 1997, the Granger causality tests are recalculated disregarding all data from mid October 1997 to end of November 1998. This leaves sample B running from December 1998 to September 2001, hereafter sample B1 (see **Figure** 2.3). The following observations among other things, are noted about the volume-volatility relationship for the second sub-period that excludes the crisis period. In all the cases the results from the causality tests between volatility and 'total' volume are very similar to those between volatility and 'domestic' volume (see **Table** 2.11). In particular, the 'total' and 'domestic' volumes are independent of changes in volatility and vice versa. Moreover, there is a strong bidirectional feedback between 'foreign' volume and 'FIAPARCH' volatility. 'Foreign' volume has a positive impact on volatility whereas volatility affects volume negatively. There is also strong evidence of causality running only from absolute/squared returns to 'foreign' volume. In particular, increased absolute/squared returns lower 'foreign' volume. Comparing the results of sample B1 with those of sample B, the following observations are noted. In the entire after-crisis period the effect of 'foreign' volume on absolute/squared returns is negative but becomes negligible when we exclude the period mid October 1997-end of November 1998. In addition, 'foreign' volume affects 'FIAPARCH' volatility negatively whereas when we exclude the aforementioned period it has a positive impact on the conditional volatility. Finally, in sample B there is evidence of causality running from 'total'/'domestic' volatility to volume but it disappears in sample B1.

TABLE 2.11

Figures 2.4-2.7 plot (for the entire sample as well as for samples A, B and B1) the time profiles of squared returns due to shocks in 'domestic'/'foreign' volume and vice versa.[9] For the entire sample the maximum positive effect of 'domestic'/'foreign' volume on squared returns takes place after one day whereas the negative impact of squared returns on 'foreign' volume reaches its peak after six days. For sample A the maximum positive effect of squared returns on 'foreign' ('domestic') volume takes place after two (seven) days. In contrast, the negative impact of 'domestic' volume on squared returns reaches its peak after eight days. For sample B(B1) the maximum negative(positive) effect of squared returns on 'domestic' volume takes place after four(two) days. Moreover, for samples B and B1 the negative impact of 'foreign' volume on squared returns reaches its peak after four days whereas the maximum negative effect of squared returns on 'foreign' volume takes place after six days. Finally, for the entire period and for samples B and B1 the effect of squared returns on 'foreign' volume seems much smaller in size than the effect of 'foreign' volume on squared returns.

2.5.2 Simultaneous approach

Augmentation of FIAPARCH models using lagged volume

To test for the volume-(conditional)volatility relationship one can use either the two-step (Granger causality) or the simultaneous estimation approach. In this Section we test for the causal effect from volume to conditional volatility using the latter approach. That is, we estimate a FIAPARCH model with lagged volume included in the variance specification. In particular, **Table** 2.12 reports the estimation results of a model that includes the variance equation (2.1) augmented

[9] Generalised impulse response functions are calculated as suggested in Pesaran and Shin (1998). We do not report figures for the other cases for space considerations.

by the term $k_{jl}V_{j,t-l}$, where $V_{j,t-l}$ denotes the volume at time $t-l$ ($j = D, F, T$ for 'domestic', 'foreign' and 'total' volume, respectively; $l = 0, 1, 2$). In other words, the ω in equation (2.1) is replaced by $\varpi := \omega + k_{jl}V_{j,t-l}$. **Table** 2.12 reports only the estimated parameters of interest (k_{jl}'s).

First, an interesting feature of the estimated models is the significance and the sign of the coefficient estimates on the contemporaneous volume (V_{jt}). In all cases these parameters are positive and highly significant. These results are robust to either the sample periods or the measures of volume used. However, inferences from the augmented FIAPARCH model can be made only if volume is exogenous (Chen et al., 2001). Accordingly, since lagged volume ($V_{j,t-l}$, $l = 1, 2$) can be interpreted as a predetermined variable, we use lagged volume in the variance specification. In the expressions for the conditional variances only up to two lags are considered since it is likely that these will have the largest effect upon the current value of volatility (Brooks, 1998).

The first row of **Table** 2.12 reports the results for the entire sample. It shows a significant positive effect of volume on volatility. In all cases this causal relation is robust to the measures and lags of volume used. Strong evidence, the coefficients of lagged volume (k's) are significant at the 5% level or better, is reported in all cases. In sum, with all three volumes we find a positive association between lagged volume and volatility similar to that found with the causality tests. The results for the pre-crisis period are presented in the second row. As with the causality tests, we find that volatility is independent of changes in 'foreign' volume, whereas either 'total' or 'domestic' volume affect volatility positively. These results are not qualitatively altered by changes in the lag of volume. The estimated results for the periods after the financial crisis in 1997 are reported in the third and fourth rows. The picture is different to that of the period before the crisis. That is, the results indicate the lack of an effect of either 'total' or 'domestic' lagged volume on volatility. Moreover, in the entire-after crisis period the effect of 'foreign' lagged volume on the conditional volatility is negative. In sharp contrast, when we exclude the period mid October 1997-end of November 1998 it has a positive impact on volatility. These results square with the findings of the causality tests.

In sum, the evidence obtained from the causality tests is reinforced by the parameter estimates provided by the augmented FIAPARCH models. That is, the statistical evidence suggests that before the crisis the dynamic relation between 'total' volume and volatility reflects the relation between 'domestic' volume and volatility, whereas after the crisis volatility is related only to the foreign investor's volume.

**Ta-
ble 2.12**

Bivariate FIAPARCH-in-mean models

In this Section we test for the causal effect from conditional volatility to volume with the application of a bivariate FIAPARCH model with the mean equation for the volume incorporating lags of the conditional variance of the stock returns. Along these lines, we describe the time series model for volume and stock returns. Let us define the column vector of the two variables y_t as $y_t := (r_t\ V_{pt})'$, $p = T, D, F$, and the residual vector ε_t as $\varepsilon_t := (\varepsilon_{rt}\ \varepsilon_{vt})'$. Regarding ε_t we assume that it is conditionally normal with mean vector 0, variance vector $H_t := (h_{rt}\ h_{vt})'$ and constant correlation $\rho := h_{rv,t}/\sqrt{h_{rt}h_{vt}}$.

Next, we define the mean equation as

$$\Phi(L)[y_t - \Phi_0 - M_l H_{t-l}] = \varepsilon_t,$$

where $\Phi(L) := I - \sum_{i=1}^{p} \Phi_i L^i$, I is a 2×2 identity matrix, Φ_i are diagonal 2×2 matrices with diagonal elements $\phi_{j,i}$ ($j = r, v$, $\phi_{r,i} = 0$ for $i \geq 2$); Φ_0 is the 2×1 vector of constants: $\Phi_0 := (\phi_r \ \phi_v)'$; M_l ($l = 0, 1, 2$) is a lower triangular 2×2 matrix with the diagonal elements equal to zero and the 21st element denoted by m_l.

For notational convenience, in what follows we denote $H_t^{(\delta)} := (h_{rt}^{\delta_r/2} \ h_{vt}^{\delta_v/2})'$, $\varepsilon_t^{(\delta)} := (|\varepsilon_{rt}|^{\delta_r} \ |\varepsilon_{vt}|^{\delta_v})'$ and $\Delta^{(d)} := [(1-L)^{d_r} \ (1-L)^{d_v}]'$. Further, we impose the following structure on the conditional variance matrix:

$$B(L) H_t^{(\delta)} = \Omega + [B(L) - \Delta^{(d)} A(L)] \varepsilon_t^{(\delta)},$$

where $B(L) := I - BL$, $A(L) := I - AL$; I is 2×2 identity matrix, B and A are diagonal 2×2 matrices with diagonal elements β_j and α_j, respectively ($j = r, v$); Ω is is the 2×1 vector of constants: $\Omega := (\omega_r \ \omega_v)'$.

The bivariate FIAPARCH in mean model allows up to the second lag of the conditional variance of the stock returns to influence the volume. **Table** 2.13 reports only the estimated parameters of interest (m_l's). First, we discuss the results for the entire sample. **Table** 2.13 shows that all three measures of volume are independent of changes in volatility. Moreover, before the financial crisis in 1997 increased volatility lowers volume. The picture for the after-crisis period is similar to that of the first sub-period. That is, 'FIAPARCH' volatility has a negative impact on volume (see samples B and B1). These causal relationships are robust to the measures of volume used.

In sum, the results obtained from the estimation of the bivariate in mean models square with the findings of the causality tests. That is, the statistical evidence suggests that before and after the crisis volatility affects volume negatively.

These results are not qualitatively altered by changes in the measure of volume.

TABLE 2.13

2.6 Discussion and Possible Extensions

The Korean stock market after the crisis is more volatile than it was before it happened. This is probably due to the crisis itself. However, this higher volatility had become a normal feature of the Korean stock market even in 2001. This higher volatility might be connected to the Russian financial crisis in 1998 and to the boom in the international stock markets that took place in 2000.

In order to study the effect of the financial liberalization - which took place in the middle of, and after the financial crisis- on the volatility-volume relationship we choose to exclude the period from mid October 1997 to end of November 1998. In other words, we investigate whether or not the liberalization process affected the 'foreign'/'domestic' volume-volatility relationship. In doing this we can see if, one year after the crisis, foreign investors continue to play an influential role in the Korean stock market.

Although the ceiling on foreign ownership in the Korean stock exchange was lifted in full in May 1998, in order to trace the effect of financial liberalization, we choose to start our sample from December 1998, which coincides with the period when total trading volume seems to change regime. We thus allow for a period of six months for the full impact of the liberalization process to take place and at the same time we allow more than one year to pass from the financial crisis.

We do not expect the lifting of the foreign ceiling on investment to have taken its full effect immediately after it happened since it coincides with a period shortly after the financial crisis (7 months) and the majority of new foreign investors might have been somewhat reluctant to take investment action in the Korean stock market at that time. The foreign ceiling limit was already at 50 % in October 1997, and that is probably enough for those foreign investors who would like to exploit any arbitrage opportunities arising from the financial crisis. These assumptions make sense not only economically but also statistically since a large number of observations is needed for the econometric modeling that we use .

We found that some of the results in period B are influenced by the financial crisis in 1997. In addition, the liberalization process itself does not seem to play an important role at that period as volatility is independent of changes in 'foreign' volume. For example, in sample B there was evidence of causality running from 'foreign' volume to absolute/squared returns but it disappeared in sample B1. Finally, in the entire after-crisis period volatility had a negative effect on 'total' volume whereas when we excluded the period mid October 1997-end of November 1998 the effect became negligible.

Future research on the volume - volatility relationship by trader category in the Korean stock market will shed more light upon the type of investors dominating the market during the financial crisis. In this way we can be more accurate about the type of investors stabilizing or destabilizing the market or about other factors possibly causing this apparent turbulence. But it is not only the different kinds of investors that can cause excess stock market volatility. Our sample period is very challenging due to the numerous structural events that took place: the Asian financial crisis in 1997, the Russian crisis in 1998, and the International stock market boom in 2000. Another possible extension of our work is to perform a multi-country study so that we can trace out volatility spillovers or contagion effects from other stock markets as well as effects upon the 'foreign' and 'domestic' volume in the Korean stock market.

2.7 Conclusions

In this paper, we have examined the dynamic causal relations between stock volatility and trading volume for the Korean stock market. For the overall period from 1995 to 2001 we found a strong bidirectional feedback between volume and volatility. In general this causal relationship was robust to three alternative measures of volatility. However, either 'domestic' or 'total' volumes were independent of changes in 'FIAPARCH' volatility.

Our structural break test on volatility indicates one break in mid October 1997, which coincides with the Asian financial crisis. For this reason we conducted sub-sample analysis in order to check whether the volume-volatility relationship changed due to the financial turmoil in Asia in 1997.

We find that there are structural shifts in causal relations, and also that it is important to distinguish between domestic and foreign investors' volume. Specifically, before the financial crisis in 1997 there was no causal effect from foreign investors' volume to stock volatility whereas after the crisis a negative feedback relation began to exist. In other words, foreign investors play an influential role after the financial crisis. This might be because of the liberalization process which took place in the middle of, and after, the crisis or because of arbitrage opportunities spotted by foreign investors after the crisis.

In sharp contrast, the impact of 'domestic' volume on either absolute returns or their squares was negative in the pre-crisis period but disappeared after the crisis. Similarly, 'domestic' volume had a positive impact on 'FIAPARCH' volatility in sample A whereas in sample B conditional volatility was independent of changes in ‘domestic’ volume. Further, absolute/squared returns affected ‘domestic’ volume positively in the first sub-period but the effect turned to negative in the second sub-period.

Table 2.1: Impact of liberalization on emerging stock market volatility.

Authors	Number of countries[a]	Sample data	Volatility after liberalisation[b]
Bekaert and Harvey (2000)	20	1976:01-1996:09	Decreased
Kim and Singal (2000)	18	1976:01-1995:12	Unchanged
Spyrou and Kassimatis (1999)	8	1988:01-1998:02[c]	Decreased or unchanged
Grabel (1995)	6	1956-1990	Increased

Notes: [a] All these four studies include Korea. [b] There are some exceptions but this is the general conclusion of the research. [c] The financial crisis which covers the period 1997:09-1998:02 is excluded for Korea and Pakistan.

Table 2.2: Ceiling of foreign ownership in the Korean stock exchange

Date	03/01/92	01/12/94	01/07/95	01/04/96	01/10/96
Collective ceiling	10*	12	15	18	20
Individual investor	3	3	3	4	5
Date	**02/05/97**	**03/11/97**	**11/11/97**	**30/12/97**	**25/05/98**
Collective ceiling	23	26	50	55	100
Individual investor	6	7	50	50	100

Notes: * The numbers are percentage points.

Source: Korean Financial Supervisory Services.

Table 2.3: Average daily trading volume in the Korean stock market.

Year	'Foreign' Volume (Trillion won)	'Domestic' Volume (Trillion won)	$\frac{\text{'Foreign'}}{\text{'Total'}} \times 100$
1995	23.7	464.4	4.86[a]
1996	29.3	457.5	6.02
1997	37.2	518.6	6.69
1998	49.3	611.1	7.47
1999	179.5	3302.0	5.16
2000	238.5	2363.7	9.16
2001	198.9	1628.9	10.89

Notes: Table 2.3 presents the foreign and domestic investors' (average daily) trading volumes from January 1995 to September 2001. [a] The numbers are percentage points. Source: Korean Stock Exchange.

Table 2.4: Unit root tests

Series	ADF test statistic	PP test statistic	KPSS test statistic
KOSPI returns	−38.34	−38.34	0.09
'Total' trading volume	−4.24	−5.98	0.17
'Domestic' trading volume	−4.26	−5.81	0.16
'Foreign' trading volume	−4.70	−19.09	0.14

Notes: Table 2.4 reports the results of unit root tests on the stock returns and the volume series. The lag lengths used in the ADF tests are chosen with the Schwarz information criterion. For the PP and KPSS tests we use the bandwidth automatic selection according to Andrews (1991). An intercept and a time trend are included in the regression. Critical values at 1% significant level are -3.96 for the ADF and PP tests, and 0.22 for the KPSS test.

Table 2.5: Summary statistics for the KOSPI stock returns.

	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis
Sample A[a]	-0.063	4.660	-3.963	1.125	0.281	3.913
Sample B[b]	-0.022	8.161	-12.804	2.766	-0.143	3.957

Notes: [a] Sample A covers the period from January 1995 to mid October 1997.

[b] Sample B covers the period from mid October 1997 to September 2001.

Table 2.6: Standard deviation of the KOSPI stock returns

Stats	Year						
	1995	1996	1997	1998	1999	2000	2001
Standard deviation	1.021	1.089	2.218*	2.838	2.503	2.879	2.171
Mean	-0.047	-0.104	-0.188	0.138	0.242	-0.295	-0.027

Note: * The Standard deviation excluding the period of the crisis is 1.266.

Table 2.7: FIAPARCH Models.

	c	θ	ω	α	β	γ	d	δ
Entire Sample:	-0.05 (0.04)	0.14 (0.03)	0.02 (0.03)	0.13 (0.09)	0.53 (0.11)	-0.23 (0.08)	0.44 (0.06)	2 –
Sample A:	-0.07 (0.04)	0.19 (0.03)	0.17 (0.07)	-0.04 (0.08)	0.43 (0.15)	-0.51 0.13	0.47 (0.15)	1 –
Sample B:	-0.05 (0.03)	0.11 (0.03)	1.13 (0.22)	-0.16 (0.06)	– –	-0.38 (0.19)	0.21 (0.06)	1 –

Notes: For each of the three periods, Table 2.7 reports QML parameter estimates for MA(1)-FIAPARCH(1,1) model: $r_t = c + (1 + \theta L)\varepsilon_t$, $h_t^{\delta/2} = \omega + \Omega(L)f(\varepsilon_t)$. The numbers in $(\cdot)$ are standard errors.

Table 2.8: Granger causality tests between volatility and trading volume (Entire sample)

Volume	Volatility		
	$\lvert r_t \rvert$	r_t^2	FIAPARCH
Panel A. H_0: Trading volume does not Granger-cause stock volatility			
Domestic (**5**)	5.11[0.00](+)	1.65[0.14](+)	1.96[0.08](+)
Foreign (**5**)	4.92[0.00](+)	2.31[0.04](+)	3.05[0.01](+)
Total (**5**)	5.57[0.00](+)	1.68[0.14](+)	2.32[0.04](+)
Panel B. H_0: Stock volatility does not Granger-cause trading volume			
Domestic (**5**)	2.13[0.06](-)	2.26[0.04](-)	1.07[0.37]
Foreign (**5**)	3.18[0.01](-)	2.95[0.01](-)	2.58[0.02](+)
Total (**5**)	2.69[0.02](-)	2.79[0.02](-)	1.53[0.17]

Notes: The bold numbers indicate the optimal lag length chosen by the SIC and AIC. The figures are F statistics. The numbers in $[\cdot]$ are p-values. A +(-) indicates that the sum of the lagged coefficients is positive (negative).

Table 2.9: Granger causality tests between volatility and trading volume (Sample A)

Volume	Volatility		
	$\|r_t\|$	r_t^2	FIAPARCH
Panel A. H_0: Trading volume does not Granger-cause stock volatility			
Domestic (**7**)	1.41[0.19](-)	1.55[0.14](-)	3.54[0.00](+)
Foreign (**1**)	0.88[0.38]	0.36[0.54]	0.05[0.83] (**4**)
Total (**7**)	1.58[0.14](-)	1.59[0.14](-)	3.64[0.00](+)
Panel B. H_0: Stock volatility does not Granger-cause trading volume			
Domestic (**7**)	2.12[0.04](+)	2.40[0.02](+)	2.59[0.01](-)
Foreign (**1**)	4.23[0.04](+)	3.08[0.08](+)	2.71[0.09](-) (**4**)
Total (**7**)	2.04[0.05](+)	1.86[0.07](+)	2.18[0.03](-)

Notes: As in Table 2.8

Table 2.10: Granger causality tests between volatility and trading volume (Sample B)

Volume	Volatility		
	$\|r_t\|$	r_t^2	FIAPARCH
Panel A. H_0: Trading volume does not Granger-cause stock volatility			
Domestic (**3**)	1.26[0.28]	1.07[0.36]	0.99[0.39]
Foreign (**5**)	2.26[0.04](-)	2.15[0.06](-)	3.01[0.01](-)
Total (**4**)	0.87[0.48]	0.76[0.55]	3.58[0.62] (**3**)
Panel B. H_0: Stock volatility does not Granger-cause trading volume			
Domestic (**3**)	1.84[0.14](-)	2.58[0.05](-)	2.15[0.09](-)
Foreign (**5**)	3.57[0.00](-)	3.23[0.01](-)	4.17[0.00](-)
Total (**4**)	2.14[0.07](-)	2.37[0.05](-)	2.53[0.05](-) (**3**)

Notes: As in Table 2.8

Table 2.11: Granger causality tests between volatility and trading volume (Sample B1)

Volume	Volatility		
	$\lvert r_t \rvert$	r_t^2	FIAPARCH
Panel A. H_0: Trading volume does not Granger-cause stock volatility			
Domestic (**3**)	0.82[0.48]	0.40[0.75]	0.37[0.83]
Foreign (**5**)	1.21[0.30]	0.99[0.42]	2.12[0.06](+)
Total (**3**)	0.62[0.60]	0.29[0.83]	0.65[0.63]
Panel B. H_0: Stock volatility does not Granger-cause trading volume			
Domestic (**3**)	0.86[0.46]	1.45[0.22]	1.27[0.28]
Foreign (**5**)	3.52[0.00](-)	3.86[0.00](-)	2.49[0.03](-)
Total (**3**)	1.40[0.24]	1.69[0.17]	0.86[0.48]

Notes: As in Table 2.8

Table 2.12: FIAPARCH models augmented by the addition of volume lags

Volume (j):	Total			Foreign			Domestic		
Lag (l):	0	1	2	0	1	2	0	1	2
Entire Sample	0.07 (0.02)	0.02 (0.01)	0.02 (0.01)	0.93 (0.26)	0.24 (0.13)	0.17 (0.07)	0.07 (0.02)	0.02 (0.01)	0.02 (0.01)
Sample A	0.12 (0.02)	0.03 (0.01)	0.02 (0.01)	$-$	0.28 (0.31)	0.15 (0.15)	0.13 (0.03)	0.03 (0.01)	0.02 (0.01)
Sample B	0.01 ($4x10^{-3}$)	8×10^{-5} ($4x10^{-3}$)	1×10^{-4} ($4x10^{-3}$)	0.14 (0.06)	-0.02 (0.01)	-0.09 (0.06)	0.01 ($5x10^{-3}$)	2×10^{-4} ($4x10^{-3}$)	1×10^{-3} ($4x10^{-3}$)
Sample B1	0.04 (0.01)	0.01 (0.01)	0.01 (0.01)	0.37 (0.10)	1×10^{-3} (0.15)	0.12 (0.10)	0.04 (0.01)	0.01 (0.01)	0.01 (0.01)

Notes: For each of the four periods, Table 2.12 reports QML parameter estimates of the lags of volume (k_{jl}) for the FIAPARCH(1,1) model: $h_t^{(\delta/2)} = \omega + k_{jl}V_{j,t-l} + \Omega(L)f(\varepsilon_t)$ (j=T,F,D; l=0,1,2).

The numbers in ($\cdot$) are standard errors. A - indicates that there was no convergence.

Table 2.13: Bivariate FIAPARCH in mean models

Volume:	T	F	D		T	F	D
Lag (l):	1	0	1		0	0	0
Entire sample:	-0.01 [0.71]	0.01 [0.76]	0.01 [0.93]	A:	-0.35 [0.35]	-0.09 [0.38]	-0.18 [0.19]
Lag (l):	2	2	2		1	1	1
B:	-0.06 [0.35]	-0.01 [0.69]	-0.05 [0.40]	B1:	-0.36 [0.30]	-0.04 [0.16]	-0.54 [0.56]

Notes: For each of the 4 periods, Table 2.13 reports QML estimates of the in-mean parameters (m_l) (l=0,1,2) for the bivariate FIAPARCH in mean models. T, F and D denote'total', 'foreign' and 'domestic' respectively. The numbers in [$\cdot$] are p-values

Figure 2.1: The daily KOSPI return series from January 1995 to September 2001

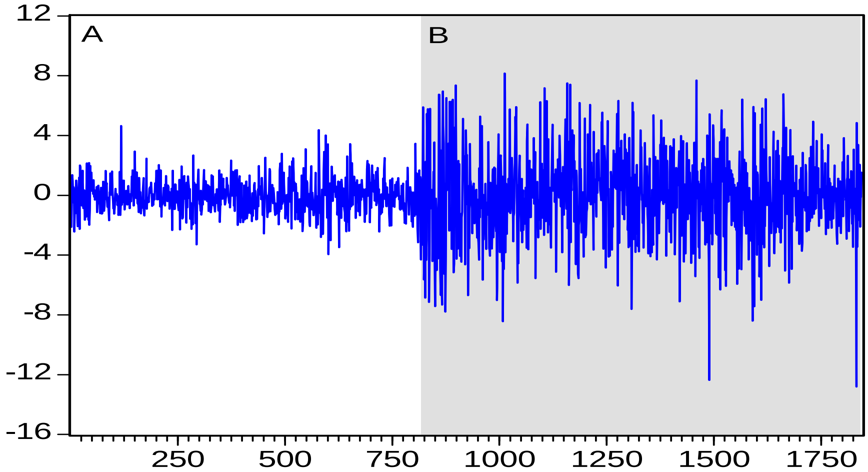


Figure 2.2: The daily total value of shares traded in Korean won

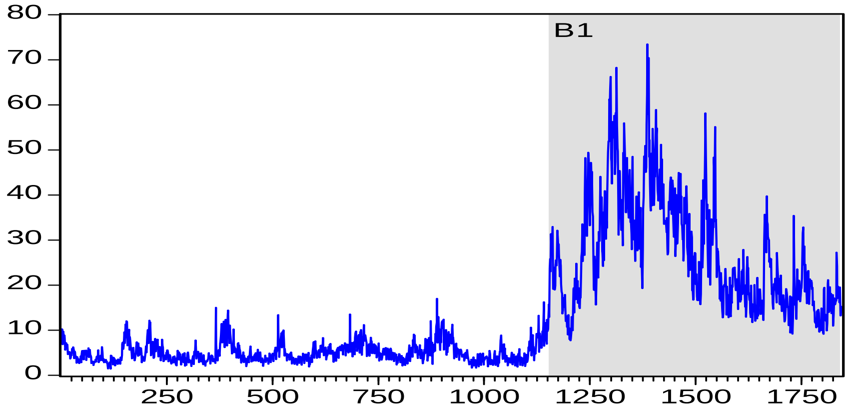


Figure 2.3: The daily KOSPI return series and total value of shares traded in Korean won

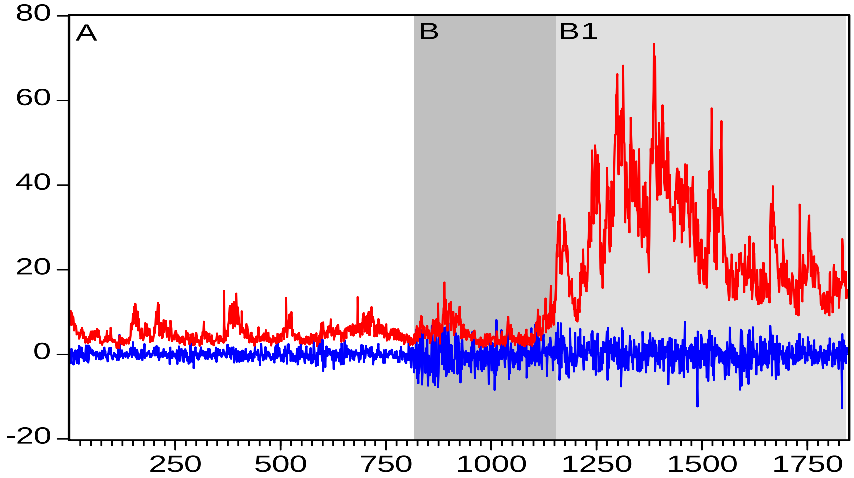


Figure 2.4: Impulse response graphs for Entire Sample

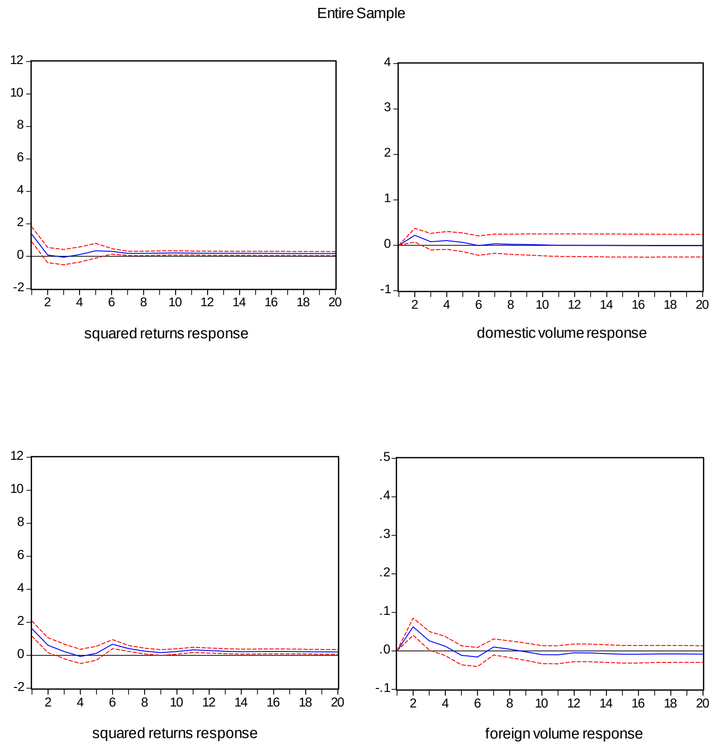
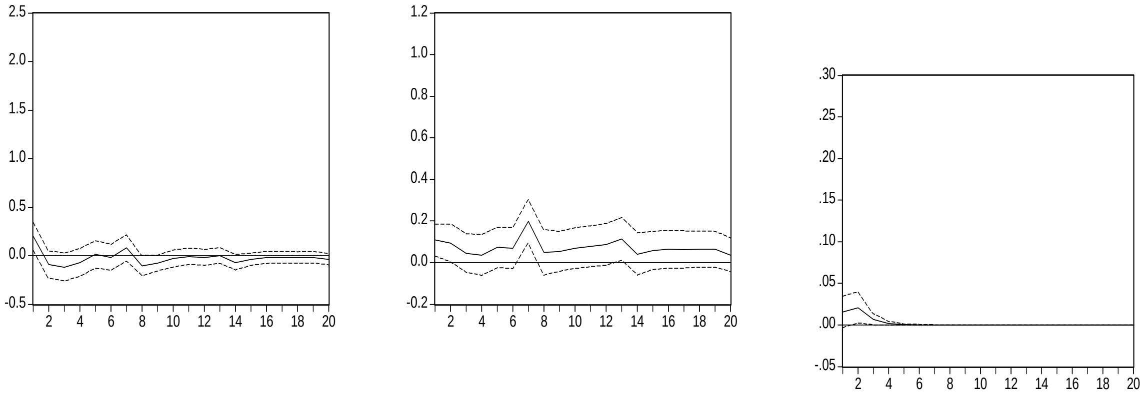


Figure 4 plots the effects of a one-time one-standard-deviation increase in 'domestic'/'foreign' volume on squared returns and vice versa for the entire sample. The dotted lines indicate $\pm$ two standard deviation bands computed by the asymptotic standard errors.

Figure 2.5: Impulse response graphs for Sample A



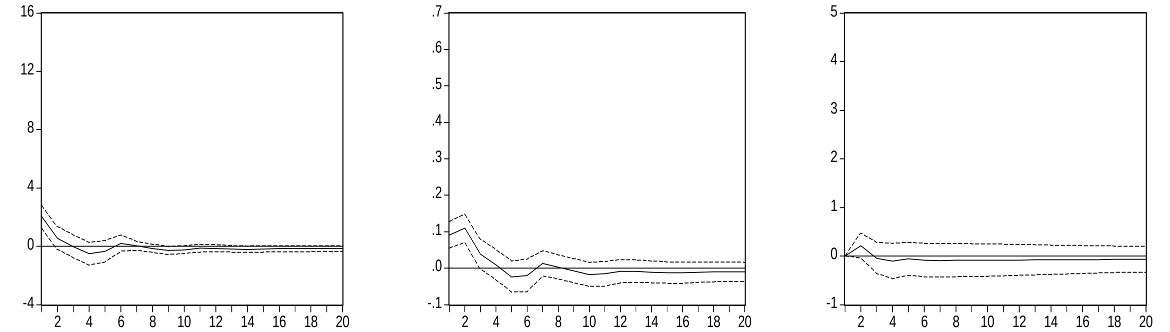
squared returns response to domestic volume

domestic volume response to squared returns

foreign volume response to squared ret.

Figure 5 plots, for sample A, the effects of a one-time one-standard-deviation increase in 'domestic' volume on squared returns and vice versa, as well as the effects of a one-time one-standard-deviation increase in squared returns on 'foreign' volume. The dotted lines indicate ± two standard deviation bands computed by the asymptotic standard errors.

Figure 2.6: Impulse response graphs for Sample B



squared returns response to foreign volume   foreign volume response to squared returns   domestic volume response to squared ret.

Figure 6 plots, for sample B, the effects of a one-time one-standard-deviation increase in 'foreign' volume on squared returns and vice versa, as well as the effects of a one-time one-standard-deviation increase in squared returns on 'domestic' volume. The dotted lines indicate $\pm$ two standard deviation bands computed by the asymptotic standard errors.

Figure 2.7: Impulse response graphs for Sample B1

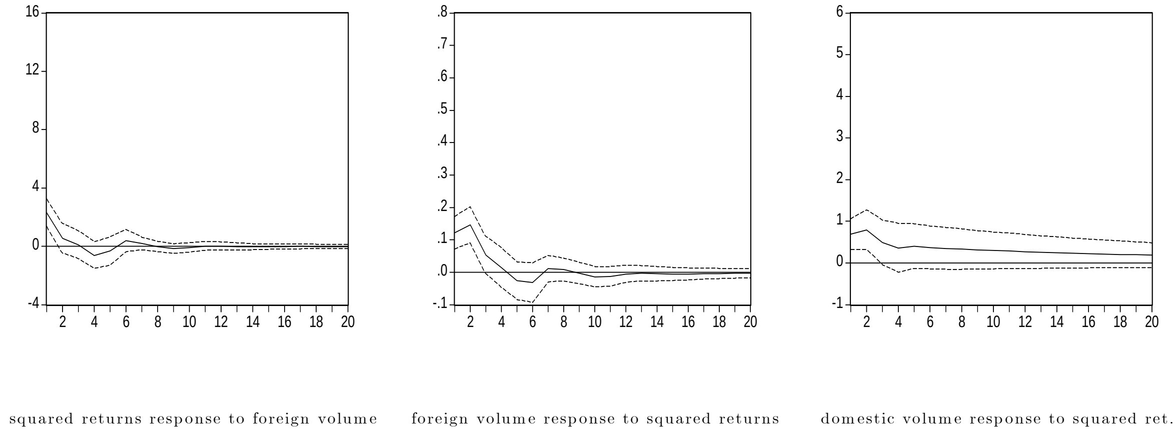


Figure 7 plots, for sample B1, the effects of a one-time one-standard-deviation increase in 'foreign' volume on squared returns and vice versa, as well as the effects of a one-time one-standard-deviation increase in squared returns on 'domestic' volume. The dotted lines indicate ± two standard deviation bands computed by the asymptotic standard errors.

Chapter 3

Dual long-memory, structural breaks and the link between turnover and range based volatility

3.1 Introduction

Korea's accession to the OECD in December 1996 represented the culmination of 35 years of extraordinary growth that transformed it from one of the poorest nations in the world to the 11th-largest economy and exporting country. Less than a year later, however, Korea was hit by one of the most severe financial crises ever experienced by an OECD member. The fact that this crisis occurred in the context of seemingly strong macroeconomic fundamentals made the crisis even more surprising (Visco, 1999).

Foreign investors were often blamed for the dramatic difficulties of the East

Asian countries and for the collapse of their currencies and stock markets (see, Choe et al., 1999). In recent years, some studies have examined the impact of foreign investors, often large financial institutions, on small emerging stock markets. It remains a highly contested issue among policymakers as well as researchers. Some academics point to the benefits of financial liberalization and foreign participation. Others have pointed out that foreign investors could have a destabilizing effect for a variety of reasons. It is therefore crucially important to understand whether this is the case.

This study has three primary objectives. First, it analyzes the volatility and volume dynamics of Korea. We estimate the two main parameters driving the degree of persistence in the two variables and their respective uncertainties using a bivariate constant conditional correlation (ccc) Generalized ARCH (GARCH) model that is Fractionally Integrated (FI) in both the Autoregressive (AR) and GARCH specifications. We refer to this model as the AR-FI-GARCH. It provides a general and flexible framework with which to study complicated processes like volume and volatility. Put differently, it is sufficiently flexible to handle the dual long-memory behavior encountered in the two series.

The second objective of this study is to shed more light on the issue of temporal ordering of volume and volatility. To do this we estimate the bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other variable. The empirical evidence on this link remains scant or nonexistent, as pertains, in particular, to Korean data after the Asian financial crisis (AFC). Only Kim et al. (2005) and Karanasos and Kyrtsou (2006) have attempted to examine the relation in the Korean market after 1997. However, both studies use data based on a time series of stock returns up to 2001 whereas this research investigates the aforementioned relationship for the period 1995-2005.

Following Kim et al. (2005) in this study the total volume is separated into domestic investors' and foreign investors' volume. However, Kim et al. (2005) employ Granger causality methods and estimate bivariate AR regressions to test for evidence on the relationship between the two variables. The most commonly used measures of volatility are the absolute values of the returns, their squares and conditional variances from a GARCH-type of model (see Kim et al., 2005). In this study we employ the classic range-based intraday estimator of Garman and Klass (1980) (hereafter GK). Chen and Daigler (2004) point out that the GK estimator is more efficient than the traditional close-to-close estimator and exhibits very little bias whereas the realized volatility constructed from high frequency data can possess inherent biases impounded by market microstructure factors (see also, Alizadeh et al., 2002).

As pointed out by Kawaller et al. (2001), empirical evidence of an inverse relation between the two variables is rare in the literature, and it contrasts sharply with the widely held perception that the two are positively related (see also Daigler and Wiley, 1999). Wang (2007) argues that foreign purchases tend to lower volatility, especially in the first few years after market liberalization when foreigners are buying into local markets. In sharp contrast foreign sales increase volatility. Therefore, we investigate the significance and the sign of the causal effect.

Our sample period from 1995 to 2005 includes the AFC. It is sensible to distinguish volume traded before the crisis from that traded after the crisis. To check the sensitivity of our results to the AFC we use three alternative sets of dates for the post-crisis period. Overall, we find that the apparent long-memory in all four variables is quite resistant to the presence of breaks. However, when we take into account structural breaks the order of integration of the conditional variance series decreases considerably. In particular, the long-memory in the variance of volatility reflects the post-crisis period. Similarly, the high values of the fractional parameters driving the degree of persistence in the variance of total/domestic volume are due to the financial crisis. In addition, when allowing for structural breaks the fractional integration in the foreign volume variance series disappears.

As regards causality, the results suggest that the feedback effects from volume to volatility are sensitive to structural changes. That is, the impact of foreign volume on volatility is negative in the pre-crisis period but turns to positive after the crisis. Before the crisis there is no causal effect from total/domestic volume to volatility whereas in the post-crisis period a positive one began to exist. In sharp contrast, the reverse causal effect (that is, from volatility to volume) is robust to structural breaks. Finally, the evidence for the entire period suggests that the (weak) negative influence of total volume on volatility reflects the causal relation between foreign volume and volatility. In sharp contrast, in the pre- and post- crisis periods the total volume-volatility link reflects the relationship between domestic volume and volatility.

The remainder of this article is organised as follows. Section 2 discusses the theory concerning the link between volume and volatility. Section 3 outlines the data which are used in the empirical tests of this paper. In Section 4 we describe the time series model for the two variables. Section 5 reports the empirical results and the next section performs sensitivity analysis. Section 7 contains summary remarks and conclusions. Some background information on the techniques used in the paper and additional technical results are contained in the appendix.

3.2 Theoretical background

3.2.1 Economic rationale for the negative impact of volume on volatility

Daigler and Wiley (1999) found empirical evidence indicating that the positive volume-volatility relation is driven by the (uninformed) general public whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility.

Moreover, the activity of market makers (liquidity providers) occurs independently of information arrival. Kawaller et al. (2001) argue that an increase in such noninformation-based trading mitigates the imbalances between liquidity suppliers and liquidity demanders by enhancing the market's capacity to absorb the information-induced trading. Accordingly, all else being equal, a marketplace with a larger population of liquidity providers (or a larger capacity to absorb demands for liquidity) will be less volatile than one with a smaller population, and vice versa (Kawaller et al., 2001).

In Andersen's (1996) Mixture of distribution hypothesis (MDH) model returns are composed of information ($I_t^{1/2}$) and non-information components (e_t) where e_t is assumed to be identically independently distributed (i.i.d). $N(0,\sigma^2)$.[1] In other words, we have $r_t = I_t^{1/2}e_t$. In addition volume contains informed ($V_t^{(I)}$) and liquidity ($V_t^{(L)}$) components. Implicit in Andersen's model is the assumption that each component is governed by a Poisson arrival process: $V_t^{(I)}|I_t \sim cP_o(bI_t)$, and $V_t^{(L)}|I_t \sim cP_o(a)$. The covariance between squared returns and volume is given by: $\text{Cov}(r_t^2, V_t)$=$\text{Cov}(r_t^2, V_t^{(I)})$+$\text{Cov}(r_t^2, V_t^{(L)}) = cb\text{Var}(I_t)$+$\text{Cov}(r_t^2, V_t^{(L)})$.

[1] Some studies examine whether the actual empirical dynamics of volatility and volume are consistent with the theoretical implications of the MDH (see, Luu and Martens, 2003; Karanasos and Kartsaklas, 2007 and the references therein).

In Andersen's framework $\mathrm{Cov}(r_t^2, V_t^{(L)}) = 0$. Li and Wu (2006) relax this assumption by postulating that liquidity trading can reduce price volatility. They employ Easley et al. (1996) set up that includes informed and uninformed traders and a risk-neutral competitive market maker. They show that in this sequential trade model the higher the intensity of liquidity trading, the lower the price volatility. They also highlight the fact that this negative relationship exists in any variant of the Bayesian learning model (see, for example, Easley et al., 2002). To incorporate the liquidity trading effect, Li and Wu (2006) allow $\mathrm{Cov}(r_t^2, V_t^{(L)})$ to be nonzero. In their empirical investigation they find that it is significantly negative. In other words, controlling for the information flow, they find that volatility is negatively related to volume.

3.2.2 Foreign and domestic investors

Bekaert and Harvey (2000) explore the impact of foreign speculative activity on returns volatility in 20 emerging markets. They measure increased foreign investment activity with the introduction of ADRs, country funds, the lifting of legal restrictions, and extent of net capital flows. They find that their measures of foreign activity have an insignificant effect on volatility. Another measure of foreign activity is the amount of foreign trading. In other words ADRs and country funds serve as vehicles for foreign speculators, but the actual volume of foreign trading is an alternative measure of foreign speculative activity (Dvořák, 2001).

Kim and Wei (2002) point out that in the context of the recent AFC, it has been argued that foreign portfolio investors may have been positive feedback traders so that they rush to buy when the market is booming and rush to sell when it is falling. Another popularly claimed behavior by foreign investors is herding.

That is the tendency for investors to mimic each other's trading. For at least two reasons, however, positive feedback trading and herding are not necessarily destabilizing. First, investors trading on fundamentals may be sufficiently powerful in the markets to prevent prices from moving away from fundamental values. Second, positive feedback traders may be trading in response to information about fundamentals, so that their trading does not drive prices away from fundamentals (Choe et al., 1999). Choe et al. (1999) examine the impact of foreign investors on stock returns in Korea over the period from November 30, 1996, to the end of 1997. They found evidence that, before the Korean crisis over the last months of 1997, foreign investors engage in positive feedback trading and herd. During the crisis, the evidence of positive feedback trading was much weaker. There was no evidence that herding was more important during the crisis period, and some evidence that it was less important. They concluded that neither positive feedback trading nor herding, however, were necessarily destabilizing.

Dvořák (2001) points out that even when foreigners are noisy and irrational, their activity does not necessarily have a destabilizing impact. Domestic investors may be powerful enough and the market as a whole sufficiently liquid to accommodate selling or buying pressures from noisy foreigners. It is also possible that, controlling for total volume, foreign trading has a negative effect on volatility. This may be the case if foreign trading activity supplies liquidity to local markets or that local investors destabilize markets more than foreign ones. In this case, foreign participation is highly beneficial (Dvořák, 2001).

Furthermore, in a market with partially informed investors, broadening the investor base increases risk sharing and stock prices. A simple extension of this analysis shows that broadening investor base improves the accuracy of market information and stabilises stock prices (see Wang, 2007 and the references therein).

Therefore foreign purchases tend to lower volatility by increasing the investor base in emerging markets. This is especially the case in the first few years after market liberalization when foreigners are buying into local markets, and is consistent with findings of stable stock markets after liberalization. In sharp contrast, foreign sales reduce investor base and increase volatility. Finally, Wang (2007) points out that trading within foreign and domestic investor groups does not change investor base, therefore does not affect volatility.

3.3 Data description and sub-periods

The data set used in this study comprises 2850 daily trading volume and prices of the Korean Composite Stock Price Index (KOSPI), running from 3rd of January 1995 to 26th of October 2005. The data were obtained from the Korean Stock Exchange (KSE). The KOSPI is a market value weighted index for all listed common stocks in the KSE since 1980.

3.3.1 Measurement of price volatility

Using data on the daily high, low, opening, and closing prices in the KOSPI index we generate a daily measure of price volatility. We can choose from among several alternative measures, each of which uses different information from the available daily price data. To avoid the microstructure biases introduced by high frequency data, and based on the conclusion of Chen et al. (2006) that the range-based and high-frequency integrated volatility provide essentially equivalent results, we employ the classic range-based estimator of Garman and Klass (1980) to construct the daily volatility (y_{gt}) as follows

$$y_{gt} = \frac{1}{2}u^2 - (2\ln 2 - 1)c^2, \quad t \in \mathbb{Z},$$

where u and c are the differences in the natural logarithms of the high and low, and of the closing and opening prices respectively. **Figure** 3.1 plots the GK volatility from January 1995 to October 2005.

Wiggins (1992) showed that the GK estimator exhibits very little bias and is more efficient than the traditional close-to-close estimator. In addition, Chen and Daigler (2004) point out that realized volatility constructed from high frequency data can possess inherent biases impounded by market microstructure factors, such as the uneven time spacing of trading, bid-ask bounce, and stale prices when cash index values are studied. The range-based GK estimator circumvents these problems. The details are covered in Alizadeh et al. (2002). Various measures of GK volatility have been employed by, among others, Daigler and Wiley (1999), Fung and Patterson (1999), Wang (2000), Kawaller et al. (2001), Wang (2002b) and Chen and Daigler (2004).[2]

3.3.2 Turnover volume

Since January of 1995 the KSE has recorded the daily trading volume of foreign investors and of 8 different domestic investors, including financial institutions, pension funds, individuals and so on. The domestic volume is constructed by adding all the different domestic investors' trading volumes. We use turnover

[2] Chou (2005) propose a Conditional Autoregressive Range (CARR) model for the range (defined as the difference of the high and low prices). In order to be in line with previous research (Daigler and Wiley, 1999, Fung and Patterson, 1999, Kawaller et al., 2001, Wang, 2000a, and Wang, 2007) in what follows we model GK volatility as an autoregressive type of process taking into account bidirectional feedback between volume and volatility, dual-long memory characteristics and GARCH effects.

as a measure of volume. This is the ratio of the value of shares traded to the value of shares outstanding (see, Campbell et al., 1993; Bollerlsev and Jubinski, 1999). Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (see, for details, Lobato and Velasco, 2000).[3] We form a trend-stationary time series of turnover (y_{vt}) by incorporating the procedure used by Campbell et al. (1993) that uses a 100-day backward moving average

$$y_{vt} = \frac{\mathrm{VLM}_t}{\frac{1}{100}\sum_{i=1}^{100}\mathrm{VLM}_{t-i}},$$

where VLM denotes volume. This metric produces a time series that captures the change in the long run movement in trading volume (see, Brooks, 1998; Fung and Patterson, 1999). The moving average procedure is deemed to provide a reasonable compromise between computational ease and effectiveness. We also extract a linear trend from the volume series. As detailed below, the results for the linearly detrended volume series are almost identical to those reported for the moving average detrending procedure.

In what follows, we will denote volume by $y_{vt}^{(s)}$ (s =total, domestic, foreign) respectively. **Figure** 3.2 plots the turnover volume from January 1995 to October 2005.

Figure 3.1

Figure 3.2

[3] Lobato and Velasco (2000) point out that the determination of a detrending mechanism that would allow for inference on the long-memory parameter of stock volume is still an unresolved problem. Therefore, they examine consistent estimation of the long-memory parameter of volume in the frequency domain by tapering the data instead of detrending them. However, Bollerslev and Jubinski (1999) find that neither the detrending method nor the actual process of detrending affected any of their qualitative findings.

3.3.3 Structural Breaks

We choose the break points by employing a number of recently developed tests for structural breaks. In addition to testing for the presence of breaks, these statistics identify the number and location of multiple breaks. The recent work by Bai and Perron (1998, 2003a,b) has greatly increased the scope of testing for multiple breaks. They addressed the problem of testing for multiple structural changes under very general conditions on the data and the errors. In particular, they constructed the tests allowing for different serial correlation in the errors and different distribution for the data and the errors across segments. Lavielle and Moulines (2000) (hereafter LaMo) dealt with the unknown multiple change-points question in strongly dependent processes in a least squares context. Their test is an extension of Bai and Perron's (1998) one and it is not model-specific. In particular, it is valid under a wide class of strongly dependent processes, including long-memory, GARCH-type and non-linear models. It is worth noting that these tests simultaneously detect multiple breaks.

The overall picture dates two change points for volatility. The first is detected on the 15th of October 1997. Accordingly, we break our entire sample into two sub-periods: 1st) 3rd January 1995– 15th October 1997 (sample A hereafter), and 2nd) 16th October 1997- 26th October 2005: the post-crisis period (sample B hereafter). The second change-point for volatility is detected on the 6th of October 2000. For the total/domestic volume they reveal the existence of a single change-point that is detected on the 20th of January 1999 whereas (see **Figure**s 1 and 2). That is, the results of the LaMo test do not support the null hypothesis of homogeneity in the two variables. In order to ensure that the results of this study are not influenced by the break in volume and the second break in volatility, we also examine the post-crisis period excluding the 16th October 1997-20th of

January 1999 period (afterwards sample B1).

3.3.4 Korean economy and sub-samples

The first change point in volatility is associated with the financial crisis in 1997. As mentioned earlier on, we break our entire sample into two sub-periods:

1st) 3rd January 1995– 15th October 1997 (the first break in volatility): the tranquil and pre-(currency) crisis period. This was the time when Korea was regarded as one of the miracle economies in East Asia, and foreign investors were enthusiastic about investing in Korea. While Korea's own currency crisis would come later in November of that year, the currency of Thailand, Baht (and maybe other currencies in Asia) was under several speculative attacks in June. The Thai Baht collapsed at the beginning of July, marking the beginning of what we now call the AFC. The Thai crisis sent repercussions throughout the region. 2nd) 16th October 1997- 26th October 2005: the post-crisis period (sample B hereafter).

Since there is not a common break in volume and volatility we break the post-crisis period into three sub-periods:

i) 16th October 1997- 20th January 1999 (the break in total/domestic volume): the in-crisis period. On November 18 1997, the Bank of Korea gave up defending the Korean Won. On November 21, the Korean government asked the International Monetary Fund (IMF) for a bail-out. There were also some instances of labor unrest and major bankruptcies during the period. The end of the crisis in Korea is set at the end of 1998. Even though in October 1998 there was significant uncertainty related to emerging markets in Russia and South America as well as in Asia, the worst of the Asian crisis was clearly over, the markets and the economies had begun to recover.

ii) 21st January 1999- 6th October 2000 (the second break in volatility): the economic recovery period. In 1999-2000 the Korean economy achieved an early and strong recovery from the severe recession.

iii) 7th October 2000- 26th October 2005: the world recession period. Since the end of 2000 the Korean economy faced many challenges, economically and politically, compounded by a global economic slow down with hesitant recovery, terrorist attacks, regional wars, avian flu outbreaks in Asia, and domestic and global uncertainty ahead. A 2005 World Bank research paper on Korea concluded that "the national economy is now suffering from weak investment, slow growth and slow job creation and rising unemployment" (Crotty and Lee, 2006).

The share of foreign trading activity in total stock market volume increased tremendously during the last few years. The internationalization of capital markets is reflected not only in the addition of foreign securities to otherwise domestic portfolios, but also in active trading in foreign markets (Dvořák, 2001). There is surprisingly little evidence, however, on the impact of foreign trading activity on local equity markets. In Korea foreign stock ownership increased dramatically in the post-crisis period. The share of foreign ownership of Korea's publicly held stock increased from 15% in 1997 to 22% in 1999, 37% in 2001 and 43% in early 2004 (see Chung, 2005). The foreign ownership share of the eight large urban banks grew from 12% in 1998 to 64% in late 2004. By mid-2005, Korea had higher foreign bank ownership than almost all Latin American and Asian countries. Korea's central bank issued a report underscoring a growing wariness in the country about the role of foreign investors.

Finally, in addition to sample B1, we also examine the post-crisis period excluding the world recession period (afterwards sample B2). **Figure** 2.3 illustrates the different sample periods considered.

FIGURE 2.3

3.4 Estimation procedures

3.4.1 Estimation methodology

Tsay and Chung (2000) have shown that regressions involving FI regressors can lead to spurious results. In particular, analyzing the bivariate regression of z_t on a constant and x_t where $z_t \sim I(d_z)$ and $x_t \sim I(d_x)$ they show that the corresponding t-statistic will be divergent provided $d_z + d_x > 0.5$.

Moreover, in the presence of conditional heteroskedasticity Vilasuso (2001) investigates the reliability of causality tests based on least squares. He demonstrates that when conditional heteroskedasticity is ignored, least squares causality tests exhibit considerable size distortion if the conditional variances are correlated. In addition, inference based on a heteroskedasticity and autocorrelation consistent covariance matrix constructed under the least squares framework offers only slight improvement. Therefore, he suggests that causality tests be carried out in the context of an empirical specification that models both the conditional means and conditional variances. Chen and Daigler (2004) explore the time-dependent heteroscedasticity in the second conditional moments of the volume and volatility processes. In particular, they employ a trivariate ccc AR-GARCH model. This methodology provides the dynamic ccc as a measure of non-linear dependence (see Chen and Daigler, 2004).

Furthermore, in many applications the sum of the estimated GARCH(1,1) parameters is often close to one, which implies integrated GARCH (IGARCH) behavior. For example, Chen and Daigler (2004) emphasize that in most cases both variables possess substantial persistence in their conditional variances. In particular, the sum of the GARCH parameters was at least 0.950. Most importantly, Baillie et al. (1996), using Monte Carlo simulations, show that data generated from a process exhibiting FIGARCH effects may be easily mistaken for IGARCH behavior. Therefore we focus our attention on the topic of long-memory and persistence in terms of the second moments of the two variables. Consequently, we utilize a bivariate ccc AR-FI-GARCH model to test for causality between volume and volatility.[4]

3.4.2 Dual long-memory

Along these lines we discuss the bivariate dual long-memory time series model for the two variables and discuss its merits and properties.

Let us define the column vector of the two variables $\mathbf{y}_t$ as $\mathbf{y}_t \triangleq (y_{vt}\ y_{gt})'$and the residual vector $\boldsymbol{\varepsilon}_t$ as $\boldsymbol{\varepsilon}_t \triangleq (\varepsilon_{vt}\ \varepsilon_{gt})'$. Here and in the remainder of this article, the symbol '$\triangleq$' is used to indicate equality by definition. Regarding $\boldsymbol{\varepsilon}_t$ we assume that it is conditionally normal with mean vector $\mathbf{0}$, variance vector $\mathbf{h}_t \triangleq (h_{vt}\ h_{gt})'$ and ccc $\rho \triangleq h_{vg,t}/\sqrt{h_{vt}h_{gt}}$ $(-1 \leq \rho \leq 1)$.

In order to make our analysis easier to understand we will introduce the following matrix notation. $\mathbf{\Phi}(L)$ is a 2×2 matrix polynomial in the lag operator L with diagonal elements $\Phi_i(L)$, $i = v, g$, and off-diagonal elements $\Phi_{ij}(L)$, $i, j = v, g$, $j \neq i$. The scalar finite polynomials $\Phi_i(L)$ and $\Phi_{ij}(L)$ are given by $\Phi_i(L) \triangleq 1 - \sum_{k=1}^{p_i} \phi_{ik} L^k \triangleq \prod_{k=1}^{p_i}(1 - \zeta_{ik}L)$ and $\Phi_{ij}(L) \triangleq -\sum_{s=1}^{p_{ij}} \phi_{ij,s} L^s$ respectively. The subscripts d and c will denote diagonal and cross diagonal matrices respectively. That is, $\mathbf{\Phi}^{(d)}(L) \triangleq \mathrm{diag}\{\Phi_v(L),\ \Phi_g(L)\}$ and $\mathbf{\Phi}^{(c)}(L) \triangleq \mathbf{\Phi}(L) - \mathbf{\Phi}^{(d)}(L)$.

Next, the structure of the ARFI (p, d_m), $p \triangleq \max(p_i, p_{ij})$, mean equation is

[4] An excellent survey of major econometric work on long-memory processes and their applications in economics and finance is given by Baillie (1996). Baillie et al. (2002) and Conrad and Karanasos (2005a,b) applied the univariate dual long-memory process to inflation, and Karanasos et al. (2006) to interest rates. The bivariate dual long-memory model was introduced by Teyssière (1998). For applications to the inflation-growth link see Karanasos and Zeng (2006).

given by

$$\mathbf{\Delta}(L)\mathbf{\Phi}^{(d)}(L)[\mathbf{y}_t' - \boldsymbol{\mu}] = \boldsymbol{\varepsilon}_t, \tag{3.1}$$

where $\mathbf{y}_t' \triangleq [\mathbf{I} + \mathbf{\Phi}^{(c)}(L)]\mathbf{y}_t$, $\mathbf{\Delta}(L)$ is a 2×2 diagonal matrix polynomial with diagonal elements $(1-L)^{d_{mi}}$ and $\boldsymbol{\mu}$ is the 2×1 vector of constants: $\boldsymbol{\mu} \triangleq (\mu_v\ \mu_g)'$ $[\mu_i \in (0, \infty)]$. The process $\mathbf{y}_t'$ is covariance stationary if $d_{mi} \leq 0.5$ and the roots of $\Phi_i(L)$ lie outside the unit circle.

Further, to establish terminology and notation, the bivariate FIGARCH$(1, d_v, 1)$ process is defined by

$$\mathbf{B}(L)(\mathbf{h}_t - \boldsymbol{\varpi}) = [\mathbf{B}(L) - \mathbf{\Delta}_{(v)}(L)\mathbf{A}(L)]\boldsymbol{\varepsilon}_t^2, \tag{3.2}$$

where $\mathbf{B}(L)$, $\mathbf{A}(L)$ are 2×2 diagonal polynomial matrices with elements $B_i(L) \triangleq 1 - \beta_i L$ and $A_i(L) \triangleq 1 - \alpha_i L$, $i = v, g$, respectively; $\boldsymbol{\varpi}$ is a 2×1 column vector given by $\boldsymbol{\varpi} \triangleq (\varpi_v\ \varpi_g)'$ $[\varpi_i \in (0, \infty)]$; $\mathbf{\Delta}_{(v)}(L)$ is a 2×2 diagonal matrix polynomial with diagonal elements $(1-L)^{d_{vi}}$ and $\wedge$ denotes elementwise exponentiation.[5]

Note that the FIGARCH model is not covariance stationary. The question whether it is strictly stationary or not is still open at present (see Conrad and Haag, 2006). In the FIGARCH model conditions on the parameters have to be imposed to ensure the non-negativity of the conditional variances (see appendix A).[6]

[5] Following Alizadeh et al. (2002), Brandt and Jones (2006) use the approximate result that if log returns are conditionally Gaussian with mean 0 and volatility h_t then the log range is a noisy linear proxy of log volatility. In this paper we model the GK volatility as an AR-FI-GARCH process.

[6] Baillie and Morana (2007) introduce a new long-memory volatility process, denoted by Adaptive FIGARCH which is designed to account for both long-memory and structural change in the conditional variance process. One could provide an enrichment of the bivariate dual long-memory model by allowing the intercepts of the two means and variances to follow a slowly varying function as in Baillie and Morana (2007). This is undoubtedly a challenging yet worthwhile task.

3.5 Empirical analysis

3.5.1 Bivariate Model

Within the framework of the bivariate ccc AR-FI-GARCH model we will analyze the dynamic adjustments of both the conditional means and variances of volume and volatility for all four sample periods, as well as the implications of these dynamics for the direction of causality between the two variables.

The estimates of the various formulations were obtained by quasi maximum likelihood estimation (QMLE) as implemented by James Davidson (2006) in Time Series Modelling (TSM). To check for the robustness of our estimates we used a range of starting values and hence ensured that the estimation procedure converged to a global maximum.

The best fitting specification is chosen according to the minimum value of the information criteria (not reported). For the conditional mean of volatility, we choose an ARFI(1) process for total sample and samples B and B1 and an ARFI(3) for the pre-crisis period. For the conditional means of total and domestic volumes, we choose an ARFI(12) model for the whole sample, an ARFI(8) for the pre- and post-crisis periods and an ARFI(9) for the sample B1. Finally, for the conditional mean of foreign volume we choose an ARFI(12) specification for the entire period, an ARFI(6) for sample A and an ARFI(5) for the two post-crisis periods (see **Table** 3.1).[7] We do not report the estimated AR coefficients for space considerations.

[7] The model with the foreign volume includes six dummy variables that take into account outliers. In particular, in the mean equation for the foreign volume instead of $y_{vt}^{(F)}$ we have $(1-\sum_{r=1}^{6} D_r)\, y_{vt}^{(F)}$ where D_r is a dummy indicating the presence of outliers. That is, $D_r = 1$ if a particularly large outlier has been observed and $D_r = 0$ otherwise. Carnero et al. (2007) investigate the effects of outliers on the estimation of the underlying volatility when they are not taken into account.

TABLE 3.1

3.5.2 Volume-Volatility link

We employ the bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other variable to test for bidirectional causality. The estimated coefficients ($\phi_{ij,s}$, $i, j = v, g,$ for $j \neq i$) of the polynomial matrix $\Phi^{(c)}(L)$, defined in equation (3.1), which capture the possible feedback between the two variables, are shown in **Table** 3.2. To test for the presence of a bidirectional link we examine the likelihood ratio statistic (not reported) for the linear constraints $\phi_{vg,s} = \phi_{gv,s} = 0$. In almost all cases only the first two lags, $s = 1, 2$, are significant.

TABLE 3.2

Table 3.2 reports parameter estimates of the cross effects. The likelihood ratio tests and the information criteria (not reported) choose the formulation with the bidirectional feedback between total/domestic volume and volatility for the whole sample and the two post-crisis periods whereas in the pre-crisis period causality runs only from the latter to the former. In most of the cases only the first lags are significant. In the entire sample for the total volume-volatility link the second lags are significant as well. Moreover, information criteria and likelihood ratio tests choose the specification with the bidirectional feedback between foreign volume and volatility for all four periods. In the entire period and in samples A and B1(B) the first and second(third) lags of $\phi_{gv,s}$ are significant. In addition, in the entire and two post-crisis periods only the second lag, $\phi_{vg,2}$, is significant whereas in the pre-crisis period only the third lag, $\phi_{vg,3}$, is significant.

As seen in **Table** 3.3 in the entire sample there is a negative bidirectional link between total volume and volatility. In addition, there is a bidirectional mixed feedback between domestic/foreign volume and volatility. In particular, domestic(foreign) volume affects volatility positively(negatively) whereas the reverse effect is of the opposite sign. In the pre-crisis period causality runs only from volatility to total/domestic volume and the impact is negative. In sharp contrast, foreign volume has a negative impact on volatility and there is positive causal effect in the opposite direction. In the two post-crisis periods there is a positive bidirectional feedback between foreign volume and volatility. There is also a bidirectional mixed relationship between total/domestic volume and volatility. In particular, the total/domestic volume(volatility) has a positive (negative) impact on the volatility(total/domestic volume).

TABLE 3.3

For the entire period total/foreign(domestic) volume has a negative(weak positive) effect on volatility. That is, the evidence for the whole sample suggests that the causal (weak) negative effect from total volume to volatility reflects the causal relation between foreign volume and volatility.

Moreover, before the crisis volatility is independent of changes in total/domestic volume whereas foreign volume has a negative impact on volatility. Recall that, according to Wang (2007) foreign purchases tend to stabilize stock markets-by increasing the investor base in emerging markets-especially in the first few years after market liberalization when foreigners are buying into local markets. The lack of an effect from total volume to volatility reflects the lack of a causal relation between domestic volume and volatility. It is noteworthy that the theoretical underpinnings (see Wang, 2007) predict that trading within domestic investor groups does not change investor base, therefore does not affect volatility.

In sharp contrast, after the crisis all three volumes affect volatility positively. It is interesting to highlight the theoretical arguments of Daigler and Wiley (1999) and Wang (2007). The former argue that the positive relation between the two variables is driven by the uninformed general public, whereas the latter states that foreign sales reduce investor base and destabilize the stock markets. Note that after the financial crisis the Korean stock market experienced large foreign outflows (see Chung, 2005).

For all four periods volatility affects total/domestic(foreign) volume negatively(positively). However, the positive impact of foreign volume is weak (see **Table** 2). That is, the evidence from the bivariate AR-FI-GARCH models suggests that the causal negative effect from volatility to total volume reflects the causal relation between volatility and domestic volume.

Finally, the results suggest that the causal effects from volume to volatility are sensitive to 'structural changes'. That is, the effect of foreign volume on volatility is negative in the pre-crisis period but turns to positive after the crisis. Before the crisis there is no causal effect from total/domestic volume to volatility whereas in the post-crisis period a positive impact began to exist. In sharp contrast, the reverse causal effect is robust to 'structural changes'.

3.5.3 Fractional mean parameters

Estimates of the fractional mean parameters are shown in **Table** 3.4.[8] Several findings emerge from this table. In all samples total and domestic volumes gen-

[8]Three tests aimed at distinguishing short and long-memory are implemented for the data. The statistical significance of the statistics indicates that the data are consistent with the long-memory hypothesis (see Karanasos and Kartsaklas, 2007). In addition, Karanasos and Kartsaklas (2007) test the hypothesis of long-memory following Robinson's (1995) semiparametric bivariate approach.

erated very similar fractional mean parameters: (0.61, 0.62), (0.54, 0.58), (0.54, 0.56) and (0.56, 0.56). In all the periods the estimated values of d_{mv} for foreign volume are lower than the corresponding values for total/domestic volume: 0.38, 0.42, 0.37 and 0.37.

TABLE 3.4

In all cases the estimated value of d_{mg} is robust to the measures of volume used. In other words, all three bivariate ARFI models generated very similar d_{mg} 's fractional parameters. For example, in the entire sample the three long-memory mean parameters are 0.45, 0.44 and 0.44. For the two post-crisis periods the estimated values of d_{mg} (0.42, 0.42, 0.41) are higher than the corresponding values for the pre-crisis period: 0.28, 0.28 and 0.27.

It is noteworthy that in all the samples the long-memory conditional mean parameters for total/domestic volume are higher than the corresponding values for volatility. In sharp contrast, in the entire sample and the two post-crisis periods, foreign volume and volatility generated very similar fractional parameters.[9] Generally speaking we find that the apparent long-memory in all variables is quite resistant to 'mean shifts'.[10]

[9]Karanasos and Kartsaklas (2007) although find that foreign volume and volatility exhibit the same degree of long-memory, they find no evidence that both processes share the same long-memory component.

[10]It is worth mentioning the empirical results in Granger and Hyung (2004). They suggest that there is a possibility that, at least, part of the long.-memory may be caused by the presence of neglected breaks in the series . However, the fractional integration parameters are estimated for the various sub-periods, after taking into account the 'presence of breaks', and the long-memory character of the series remain strongly evident.

3.5.4 FIGARCH specifications

Tables 3.5 and 3.6 present estimates of the FIGARCH model.[11] Note that in all cases the GARCH coefficients satisfy the necessary and sufficient conditions for the non-negativitiy of the conditional variances (see Appendix A).

TABLE 3.5

The estimates of d_{vi}'s govern the long-run dynamics of the conditional heteroscedasticity. In all samples total and domestic volumes generated very similar fractional variance parameters: (0.84, 0.87), (0,0), (0.90, 0.91) and (0.12, 0.13). In the two post-crisis periods the estimated values of d_{vv} for foreign volume are lower than the corresponding values for total/domestic volume: 0.11 and 0. However, in the total sample and the pre-crisis period, the fractional differencing parameters estimated for foreign volume (0.93, 0) are not different to the ones estimated for the total/domestic volume (see **Table** 3.6 below).

In all cases the estimated value of d_{vg} is robust to the measures of volume used. In other words, all three bivariate FIGARCH models generated very similar d_{vg} 's fractional parameters. For example, in the entire period all three long-memory variance parameters are 0.42. For sample B the estimated values of d_{vg} (0.57, 0.56, 0.59) are higher than the corresponding values for sample B1 (0.35, 0.34, 0.37).

The estimation of bivariate FIGARCH models for the pre-crisis period realized estimated values of d_{vi}, $i = v, g$, close to and not significantly different from zero. In other words, the conditional variances of the four variables are characterized by a GARCH behavior. Moreover, in sample B the value of the coefficient for

[11] Various tests for long-memory in volatility have been proposed in the literature (see, for details, Hurvich and Soulier, 2002).

foreign volume (0.11) is markedly lower than the corresponding value for the entire period (0.93). However, although the estimated value of d_{vv} is relatively small it is significantly different from zero. Furthermore, for total/domestic volume the fractional differencing parameters are similar to the ones for the entire period whereas for volatility the estimated values of d_{vg} are higher than the corresponding values for the whole sample.

TABLE 3.6

Overall, when 'allowing for structural breaks' the order of integration of the variance series decreases considerably. In the pre-crisis period the long-memory in variance for all four series disappears. In sample B the fractional differencing parameter for foreign volume is low whereas in sample B1 it is zero. Similarly, when we exclude the in-crisis period the long-memory in the variance of total/domestic volume (volatility) becomes negligible (much smaller in size).

Further, in all samples the variances of total and domestic volumes generated very similar conditional correlations with the variance of volatility: (0.41, 0.41), (0.31, 0.32), (0.45, 0.44) and (0.36, 0.34). In the two post-crisis periods and the entire sample the estimated values of ρ for foreign volume-volatility are lower than the corresponding values for total/domestic volume-volatility.[12]

[12]Karanasos and Kartsaklas (2007), employ the methodology of Conrad and Karanasos (2006), and compare the short-run dynamics of the means and variances of the three volumes and the volatility.

3.6 Sensitivity analysis

3.6.1 Structural dynamics

The model in (3.1) can be thought of as exhibiting 'error dynamics', since a transformation allows it to be rewritten with only the error terms entering in the infinite moving average representation (see equation D1). To check the robustness of the aforementioned specification, we also estimate the following model

$$\boldsymbol{\Delta}(L)\boldsymbol{\Phi}(L)(\mathbf{y}_t - \boldsymbol{\mu}) = \boldsymbol{\varepsilon}_t.$$

In the above expression the lagged values of the y_{it}, $i = v, g$, variable in the equation of the y_{jt} ($j = v, g$, $j \neq i$) variable, exhibit 'structural dynamics', since they have a distributed lag representation. Overall, the new results (not reported) are in broad agreement with those reported in **Table**s 3.2 and 3.4-3.6.

In addition, the results appear to be robust to the choice of the FIGARCH lag length. Moreover, in order to ensure that the results of the previous section are not unduly influenced by the second change-point for volatility, which is detected on the 6th of October 2000, the bivariate models for the post-crisis period are reestimated disregarding all data from 15th of October 1997 to 6th of October 2000. That is, for the world recession period. In almost all cases the results (not reported) are very similar to those for samples B1 and B. Finally, to check the sensitivity of our results to the presence of outliers in foreign volume we reestimate our bivariate dual long-memory model excluding the dummy variables. It turns out that using any of the two alternative measures results in exactly the same causal relation between foreign volume and volatility.

3.6.2 Detrending

In this section in order to ensure that our results are not unduly influenced by the detrending procedure we also extract a linear trend from the volume series, taking into account the structural break on the 20th of January 1999, using the methodology of Bai and Perron (1998, 2003a) (see appendix B1). Overall the results appear very robust and are generally insensitive to fundamental changes in the detrending technique. Specifically, as seen in **Table** 3.7, in the entire sample there is a negative bidirectional link between total volume and volatility. In addition, there is a bidirectional mixed feedback between domestic/foreign volume and volatility. That is, the results for the linearly detrended volume series are almost identical to those reported for the moving average detrending procedure.

TABLE 3.7

Baxter and King (1999) develop an approach of filtering economic and financial time series that is fast, flexible, and easy to implement (see appendix B2). They show that their approximate filters can be used in a wide range of economic applications and produces a good approximation of the ideal filter. They also mention that these filters may be readily used by a researcher and applied to data at any observation frequency. We leave further work on these detrending techniques for future research.

3.7 Conclusions

In this study, we have investigated the volume-volatility link. The variables under consideration are inextricably linked. There are few theoretical models that come to grips with the main relationships. In addition, as a result of many econometric difficulties much of the empirical evidence is dubious. We know from the previous literature how hard it is to arrive at definitive conclusions on this topic. Some of the empirical studies which have been carried out in this area concentrated on the impact of volume on volatility and did not examine the effects in the opposite direction. The 'one-sidedness' of these methodologies is an important caveat and any such attempts to analyze the link between the two variables are doomed to imperfection. In our analysis, we show that not only does volume affect volatility but the latter influences the former as well. Finally, our methodology allowed for either a positive or a negative bidirectional feedback between the two variables, and so no restriction was imposed in their relationship.

This paper has examined simultaneously the long-run dynamics and the interactions of the two variables. In doing so we were able to highlight some key behavioral features that are present across the various bivariate formulations. One of the objectives of our analysis was to consider several changes and discuss how these changes would affect the interlinkages among the two variables. In particular, we took into account structural breaks. That is, we distinguished trading before the AFC from periods after the crisis and we chose three alternative sets of dates for the post-crisis period. In addition, we employed various specifications of the bivariate dual long-memory model and we used three different measures of volume: total, domestic and foreign.

We find that the apparent long-memory in all four variables is quite resistant to 'mean shifts'. However, when we allow for 'structural breaks' the order of integration of the conditional variance series decreases considerably. The following observations, among other things, were noted about the interlinkages. The causality effects are found to be 'fragile' in the sense that either their statistical significance or their sign changes when a different sample period is used. Finding that some results are fragile could in itself be valuable information. Thus our analysis suggests that the behavior of volatility depends upon volume, but also that the nature of this dependence varies with time and the measure of volume used. In particular, of significant importance is that in the pre-crisis period volatility is independent of changes in total/domestic volume whereas foreign volume affects it negatively. The former result is in line with the theoretical underpinnings predicting that trading within domestic investor groups does not affect volatility. The latter result is consistent with the view that foreign purchases tend to stabilize emerging stock markets, especially in the first few years after market liberalization when foreigners are buying into local markets. In sharp contrast, in the post-crisis period increased volume leads to higher volatility. This result is in line with the theoretical arguments that the positive impact of volume on volatility is driven by the uninformed general public and that foreign sales reduce investor base and destabilize stock markets. Another useful piece of evidence is that volatility tends to increase foreign volume and lower total/domestic volume. This finding is robust to the choice of the sample period.

Finally, we also draw attention to one particularly interesting finding. Most of the effects are found to be quite robust to the dynamics of the bivariate model, the presence of outliers in foreign volume, the choice of the FIGARCH lag length and the second break in volatility.

Table 3.1: Mean equations: Autoregressive (AR) lags

Samples:	Total	A	B	B1
Equation 1: Trading Volume				
Total $y_{vt}^{(T)}$	$1, 2, 6, 8, 12$	$1, 4, 6, 8$	$4, 5, 6, 8$	$2, 4, 5, 8, 9$
Domestic $y_{vt}^{(D)}$	$1, 2, 6, 8, 12$	$1, 4, 6, 8$	$4, 5, 6, 8$	$3, 4, 5, 8, 9$
Foreign $y_{vt}^{(F)}$	$2, 3, 5, 6, 8, 12$	$2, 3, 5, 6$	$2, 3, 5$	$2, 3, 5$
Equation 2: Volatility				
Garman-Klass y_{gt}	1	3	1	1

Notes: The numbers represent the AR lags used in the mean equations of the bivariate model. The superscripts T, D and F denote total, domestic and foreign volume respectively.

Table 3.2: Mean Equations: cross effects

	$\mathbf{y}_t^{(T)} \triangleq (y_{vt}^{(T)}\ y_{gt})'$		$\mathbf{y}_t^{(D)} \triangleq (y_{vt}^{(D)}\ y_{gt})'$		$\mathbf{y}_t^{(F)} \triangleq (y_{vt}^{(F)}\ y_{gt})'$	
	$y_{vt}^{(T)}$	y_{gt}	$y_{vt}^{(D)}$	y_{gt}	$y_{vt}^{(F)}$	y_{gt}
Total Sample						
$\phi_{ij,1}$	-0.01^{***} (0.002)	$-$	-0.01^{***} (0.002)	0.13° (0.08)	$-$	-0.02^{**} (0.01)
$\phi_{ij,2}$	0.01^{*} (0.002)	-0.08° (0.05)	$-$	$-$	0.001° (0.004)	-0.03^{***} (0.01)
Sample A						
$\phi_{ij,1}$	-0.03^{***} (0.01)	$-$	-0.03^{***} (0.01)	$-$	$-$	-0.03° (0.02)
$\phi_{ij,2}$	$-$	$-$	$-$	$-$	0.05^{**a} (0.03)	-0.02^{**} (0.01)
Sample B						
$\phi_{ij,1}$	-0.01^{***} (0.002)	0.80^{***} (0.29)	-0.01^{***} (0.002)	0.80^{***} (0.27)	$-$	0.42^{**} (0.22)
$\phi_{ij,2}$	$-$	$-$	$-$	$-$	0.01° (0.003)	0.22^{**b} (0.13)
Sample B1						
$\phi_{ij,1}$	-0.01^{*} (0.003)	0.67^{**} (0.30)	-0.01° (0.003)	0.68^{***} (0.26)	$-$	0.29 (0.22)
$\phi_{ij,2}$	$-$	$-$	$-$	$-$	0.01^{**} (0.004)	0.30° (0.21)

Notes: The table reports parameter estimates of the cross effects $\phi_{ij,s}$, $s = 1, 2$. The y_{vt} and y_{gt} columns report results for the volume and volatility equations respectively. [a]This is a $\phi_{vg,3}$ coefficient. [b]This is a $\phi_{gv,3}$ coefficient. * and $^{\circ}$ denotes significance at the 0.10 and 0.15 levels respectively. The numbers in parentheses are standard errors.

Table 3.3: The volatility-volume link

Sample:	Total	A	B	B1
Panel A. The effect of Volume on Volatility				
Total	negative	zero	positive	positive
Domestic	positive	zero	positive	positive
Foreign	negative	negative	positive	positive
Panel B. The impact of Volatility on Volume				
Total	negative	negative	negative	negative
Domestic	negative	negative	negative	negative
Foreign	positive	positive	positive	positive

Table 3.4: Mean equations: Fractional parameters

Sample	$\mathbf{y}_t^{(T)} \triangleq (y_{vt}^{(T)}\ y_{gt})'$		$\mathbf{y}_t^{(D)} \triangleq (y_{vt}^{(D)}\ y_{gt})'$		$\mathbf{y}_t^{(F)} \triangleq (y_{vt}^{(F)}\ y_{gt})'$	
	$d_{mv}^{(T)}$	d_{mg}	$d_{mv}^{(D)}$	d_{mg}	$d_{mv}^{(F)}$	d_{mg}
Total Sample	0.61*** (0.05)	0.45*** (0.05)	0.62*** (0.04)	0.44*** (0.05)	0.38*** (0.02)	0.44*** (0.05)
Sample A	0.54*** (0.05)	0.28*** (0.09)	0.58*** (0.05)	0.28*** (0.09)	0.42*** (0.09)	0.27*** (0.09)
Sample B	0.54*** (0.02)	0.42*** (0.03)	0.56*** (0.02)	0.42*** (0.03)	0.37*** (0.03)	0.41*** (0.03)
Sample B1	0.56*** (0.03)	0.42*** (0.04)	0.56*** (0.03)	0.42*** (0.04)	0.37*** (0.03)	0.41*** (0.04)

Notes: The table reports estimates of the long-memory parameter d_{mi}, $i = v, g$, for the three bivariate models.

Table 3.5: Variance equations: GARCH coefficients

	$\mathbf{h}_t^{(T)} \triangleq (h_{vt}^{(T)}\ h_{gt})'$		$\mathbf{h}_t^{(D)} \triangleq (h_{vt}^{(D)}\ h_{gt})'$		$\mathbf{h}_t^{(F)} \triangleq (h_{vt}^{(F)}\ h_{gt})'$	
	$h_{vt}^{(T)}$	h_{gt}	$h_{vt}^{(D)}$	h_{gt}	$h_{vt}^{(F)}$	h_{gt}
Total Sample						
a_i	-0.72^{***} (0.07)	-0.15 (0.15)	-0.72^{***} (0.10)	-0.16 (0.15)	-0.67^{**} (0.29)	-0.15 (0.15)
β_i	0.87^{***} (0.04)	0.60^{***} (0.22)	0.86^{***} (0.04)	0.59^{***} (0.23)	0.87^{***} (0.11)	0.58^{***} (0.23)
Sample A						
a_i	0.04 (0.03)	0.16 (0.27)	0.07^{*} (0.04)	0.16 (0.27)	0.72^{**} (0.36)	0.13 (0.25)
β_i	0.87^{***} (0.04)	0.71^{*} (0.40)	0.85^{***} (0.05)	0.72^{*} (0.41)	0.17 (0.14)	0.74^{*} (0.41)
Sample B						
a_i	-0.77^{***} (0.10)	-0.25^{*} (0.15)	-0.77^{***} (0.10)	-0.25^{*} (0.15)	-0.01 (0.04)	-0.26 (0.16)
β_i	0.87^{***} (0.03)	0.73^{***} (0.21)	0.87^{***} (0.04)	0.72^{***} (0.21)	0.26^{**} (0.11)	0.72^{***} (0.20)
Sample B1						
a_i	–	–	–	–	0.08^{***} (0.03)	–
β_i	–	–	–	–	0.76^{***} (0.08)	–

Notes: The table reports estimates of the ARCH (α_i) and GARCH (β_i) parameters. The h_{vt} and h_{gt} columns report results for the volume and volatility equations respectively.

Table 3.6: Variance equations: Fractional and ccc parameters

-

	$\mathbf{h}_t^{(T)} \triangleq (h_{vt}^{(T)}\ h_{gt})'$		$\mathbf{h}_t^{(D)} \triangleq (h_{vt}^{(T)}\ h_{gt})'$		$\mathbf{h}_t^{(F)} \triangleq (h_{vt}^{(T)}\ h_{gt})'$	
	$h_{vt}^{(T)}$	h_{gt}	$h_{vt}^{(D)}$	h_{gt}	$h_{vt}^{(F)}$	h_{gt}
Total Sample						
d_{vi}	0.84^{***} (0.06)	0.42^{**} (0.16)	0.87^{***} (0.09)	0.42^{***} (0.15)	0.93^{**} (0.44)	0.42^{***} (0.16)
ρ	0.41^{***} (0.04)		0.41^{***} (0.04)		0.34^{***} (0.04)	
Sample A						
d_{vi}	–	–	–	–	–	–
ρ	0.31^{***} (0.07)		0.32^{***} (0.07)		0.30^{***} (0.06)	
Sample B						
d_{vi}	0.90^{***} (0.10)	0.57^{***} (0.17)	0.91^{***} (0.11)	0.56^{***} (0.17)	0.11^{***} (0.03)	0.59^{***} (0.19)
ρ	0.45^{***} (0.06)		0.44^{***} (0.06)		0.33^{***} (0.04)	
Sample B1						
d_{vi}	0.12^{***} (0.03)	0.35^{***} (0.11)	0.13^{***} (0.03)	0.34^{***} (0.11)	–	0.37^{***} (0.11)
ρ	0.36^{***} (0.06)		0.34^{***} (0.06)		0.28^{***} (0.04)	

Notes: The table reports estimates of the long-memory (d_{vi}) and ccc (ρ) parameters.

Table 3.7: Mean equations: Cross effects (Linear Detrending)

-

	$\mathbf{y}_t^{(T)} \triangleq (y_{vt}^{(T)}\ y_{gt})'$		$\mathbf{y}_t^{(D)} \triangleq (y_{vt}^{(D)}\ y_{gt})'$		$\mathbf{y}_t^{(F)} \triangleq (y_{vt}^{(F)}\ y_{gt})'$	
	$y_{vt}^{(T)}$	y_{gt}	$y_{vt}^{(D)}$	y_{gt}	$y_{vt}^{(F)}$	y_{gt}
Total Sample						
$\phi_{ij,1}$	-0.01^{***} (0.002)	$-$	-0.01^{***} (0.002)	0.43° (0.27)	$-$	0.002 (0.14)
$\phi_{ij,2}$	0.002 (002)	-0.15 (0.19)	$-$	$-$	0.003° (0.003)	-0.01 (0.12)

Figure 3.1: Garman-Klass volatility

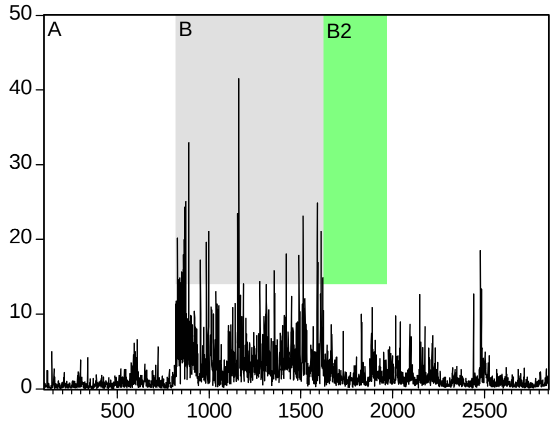


Figure 3.2: Turnover volume

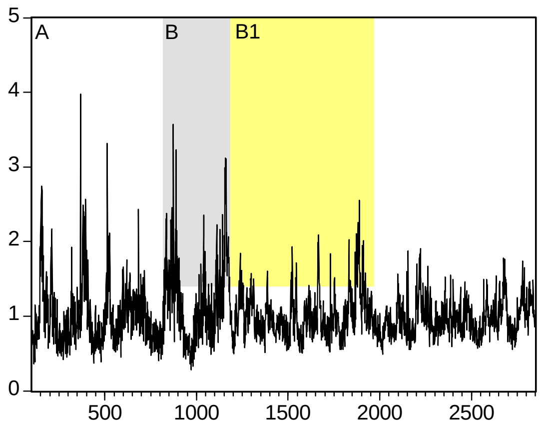
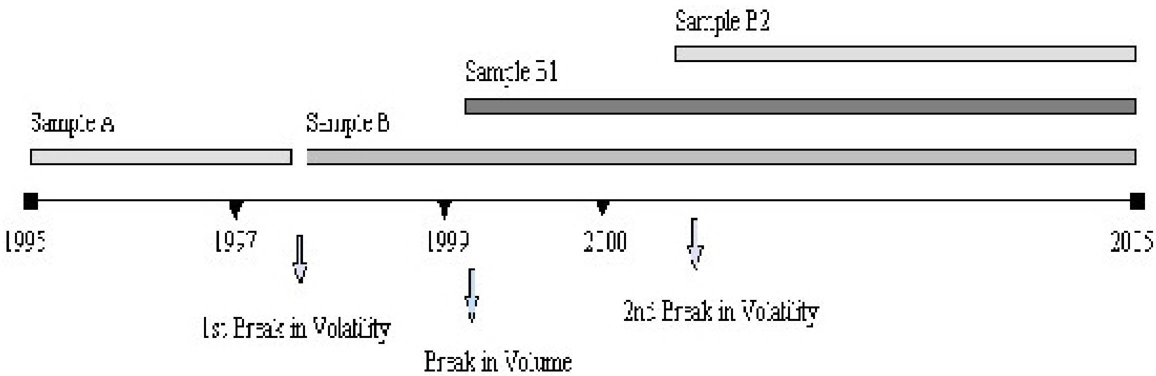


Figure 3.3: Pre- and post-crisis periods



3.8 Appendix

To keep this article relatively self-contained, we briefly review in the Appendix the main theoretical results of Conrad and Karanasos(2006), Bai and Perron (2003a) and Baxter and King(1999).

3.8.1 Non-negativity constraints

Conrad and Haag (2006) by investigating the ARCH(∞) representation of the process derive necessary and sufficient conditions for the FIGARCH(p, d_v, q) model with $p = 1$ or 2 and sufficient conditions for the general model.

$\mathbf{h}_t$ has an ARCH(∞) representation, i.e. it can be expressed as an infinite distributed lag of $\boldsymbol{\varepsilon}_{t-j}^2$ terms as

$$\mathbf{h}_t - \boldsymbol{\varpi} = \boldsymbol{\Psi}(L)\boldsymbol{\varepsilon}_t^{\wedge 2},$$

where $\boldsymbol{\Psi}(L) \triangleq \text{diag}\{\Psi_v(L), \Psi_g(L)\} \triangleq \mathbf{I} - [\mathbf{B}(L)]^{-1}\boldsymbol{\Delta}_{(d_v)}(L)\mathbf{A}(L)$ with

$$\Psi_i(L) \triangleq \sum_{l=1}^{\infty} \psi_{il} L^l \triangleq 1 - \frac{(1-L)^{d_{vi}}(1-\alpha_i L)}{(1-\beta_i L)}, \ i = v, g.$$

For any $0 < d_{vi} < 1$ the ψ_{il} coefficients will be characterized by a slow hyperbolic decay. Next the coefficients $g_{-vi,l} \triangleq \frac{\Gamma(l-d_{vi})}{\Gamma(l+1)\Gamma(-d_{vi})}$ are given by $g_{-vi,l} = f_l g_{-vi,l-1}$ with $f_l \triangleq \frac{l-1-d_{vi}}{l}$ for $l = 1, 2, \ldots$ and $g_{-vi,0} \triangleq 1$. The conditional variances of the bivariate FIGARCH($1, d_{vi}, 1$) model are non-negative a.s. iff

Case 1: $0 < \beta_i < 1$

either $\psi_{i1} \geq 0$ *and* $\alpha_i \leq f_2$ *or for* $l > 2$ *with* $f_{l-1} < \alpha_i \leq f_l$ *it holds that* $\psi_{i,l-1} \geq 0$.

Case 2: $-1 < \beta_i < 0$

either $\psi_{i1} \geq 0$, $\psi_{i2} \geq 0$ *and* $\alpha_i \leq f_2(\beta_i + f_3)/(\beta_i + f_2)$ *or for* $l > 3$ *with* $f_{l-2}(\beta_i + f_{l-1})/(\beta_i + f_{l-2}) < \alpha_i \leq f_{l-1}(\beta_i + f_l)/(\beta_i + f_{l-1})$ *it holds that* $\psi_{i,l-1} \geq 0$, $\psi_{i,l-2} \geq 0$.

(See Conrad and Haag, 2006).

3.8.2 Linear Detrending

We consider the linear regression with m breaks $(m+1)$ regimes:

$$y_{vt} = \mu_{vj} + \gamma t + u_t, \qquad t = T_{j-1}, \ldots, T_j,$$

where $j = 1, \ldots, m+1$ and the indices $(T_1, \ldots, T_m)$, or the break points, are explicitly treated as unknown (we use the convention $T_0 = 0$ and $T_{m+1} = T$). Bai and Perron (2003a) consider a method of estimation based on the least-squares principle. For each m-partition the associated least-squares estimates of the parameters are obtained by minimizing the sum of squared residuals. Substituting these estimates in the objective function and denoting the resulting sum of squared residuals as $S_T(T_1, \ldots, T_m)$, the estimated break points $(\widehat{T}_1, \ldots, \widehat{T}_m)$ are such that $(\widehat{T}_1, \ldots, \widehat{T}_m)$=argmin$_{T_1,\ldots,T_m} S_T(T_1, \ldots, T_m)$, where the minimization takes over all partitions $(T_1, \ldots, T_m)$. Once the sums of squared residuals of the relevant segments have been computed and stored, a dynamic programming approach can be used to evaluate which partition achieves a global minimization of the overall sum of squared residuals. Since a covariance matrix robust to heteroscedasticity and serial correlation is needed, we use Andrews's (1991) data dependent method with the quadratic Spectral Kernel and an AR(1) approximation to select the bandwidth (see Bai and Perron, 2003a, for details). In order to deal with the case of trending regressor we use the modifications in Bai and Perron (2003a) and we also obtain consistent estimates of the parameters $(T_1, \ldots, T_m)$ using the dynamic programming algorithm.

3.8.3 Moving Average Detrending

Applying a moving average to a time series, y_t, produces a new time series y_t^d, with $y_t^d = \sum_{m=-\varphi}^{\varphi} a_m y_{t-m}$. Baxter and King (1999) prove that symmetric moving averages (i.e., those for which the weights are such that $a_m = -a_m$ for $m = 1, \ldots, \varphi$) with weights that sum to zero ($\sum_{m=-\varphi}^{\varphi} a_m = 0$) will render stationary series that contain quadratic deterministic trends (i.e., components of the form $\tau_t = \gamma_0 + \gamma_1 t + \gamma_2 t^2$). One example, is the case where $a_0 = 1 - 1/2\varphi + 1$, and $a_m = a_{-m} = 1/2\varphi + 1$ for $m = 1, \ldots, \varphi$. Further, these moving averages can also make stationary the stochastic trends that arise when a time series is a realization of an integrated stochastic process (see Baxter and King, 1999).

Next, consider the filter weights $a_0 = r/\pi$ and a_m =sin$(mr)/m\pi$ for $m = 1, 2, \ldots$. While the weights tend to zero as m becomes large, notice that an infinite moving average is necessary to construct the ideal filter. Hence, one should consider approximation of the ideal filter with a finite moving average $\sum_{m=-\varphi}^{\varphi} a_m L^m$. Let a'_m be the filter weights with cutoffs r' $(r' > r)$. Baxter and King (1999) develop the band-pass filter that has weights $a_m - a'_m$. They denote their approximate band-pass filter that passes cycles between n and n' periods in length (periodicity is related to frequency via $n = 2\pi/r$), for given truncation point φ, by $\mathrm{BP}_{\varphi}(n, n')$.

Chapter 4

Long run dependencies in stock volatility and trading volume: the Korean experience

4.1 Introduction

The analysis of long-run dependence in time series has provided a wealth of statistical tools, parametric and non parametric, in order to test and measure the persistence of macroeconomic and financial processes. One of the most popular statistics used to describe long run dependence is the long memory parameter d, which allows for several persistence patterns in both stationary and non stationary time series apart from the known $I(0)$ and $I(1)$ cases. For covariance stationary processes, long memory is concerned with the behaviour of the autocovariance function at long lags or with the behavior of the spectral density function in a neighborhood close to zero frequency (Robinson 1994a. 1995a,b). Moreover, for non stationary data consistent estimators of the long memory parameter d

have been proposed by Velasco (1999a,b) and Robinson and Marrinucci (2003). In addition, it is often practice to first difference non stationary economic time series so that stationarity is imposed and the semi-parametric estimators can be applied.

An extensive amount of empirical research on financial market volatility strongly supports the finding that absolute or squared returns exhibit long memory characteristics. This has further stimulated research over estimating volatility processes of GARCH or stochastic volatility type that can better capture the slow hyperbolic rate of decay in the autocorrelation function of absolute or squared returns (Ding, Engle and Granger 1993, Baillie, Bollerslev and Mikkelsen1997, Robinson and Zaffaroni 1997, Breidt, Crato and de Lima 1997). Despite the empirical evidence over the long run dependence on volatility, little theoretical work has tried to explain the determinants that give rise to such dynamic dependencies. The information based (market microstructure) and mixture of distributions theories predict a positive contemporaneous relationship between volatility and volume, and provide only short run information about the dynamics of the two variables themselves. Andersen's (1996) model provides an overall reasonable fit for the joint return and volume moments of the individual stocks but there is a considerable decay in the estimated volatility persistence. Andersen and Bollerslev (1997) consider a modified version of the mixture of distributions hypothesis under which the similar long term dependence in volatility and trading volume are due to the aggregate impact of N distinct information arrival processes. Moreover, Bollerslev and Jubinski (1999) and Lobato and Velasco (2000) find that the daily volatility and trading volume for the majority of the individual companies examined are best described by mean-reverting long memory type processes. Moreover, Kirman and Teyserrie (2002) show that a class of microeconomic models with stochastically interacting agents can replicate the empirical long memory properties of the first two conditional moments of financial time series.

In this study, we aim to investigate the long run dependence of stock index volatility and trading volume in the Korean Stock Exchange. We employ semi-parametric analysis in the frequency domain and estimates of the long memory parameter are reported for the whole sample as well as for subsamples subject to prior investigation for structural break in the mean of the two series. The same analysis is performed for domestic and foreign investors' trading volume. Moreover, we test whether volatility and trading volume have the same degree of long memory as some modified versions of the mixture of distributions hypothesis suggest. Finally we examine if both processes are driven by the same long-memory component in case both volume and volatility possess the same long-memory parameter.

Our results support the argument that long run dependence is evident in both Garman-Klass volatility and trading volume. The degree of long memory in total and domestic trading volume ranges from 0.55 to 0.65 while across different sample periods similar long memory characteristics are experienced. The degree of long range dependence in foreign volume is significantly lower (almost half) than that experienced in domestic volume and no significant change is evident for the different periods considered. The long range dependence in Garman-Klass volatility for the whole sample is 0.50 and diminishes to 0.25 for the pre-crisis period and 0.38 for the post crisis one. As we can see, neglecting the structural break in the mean of Garman-Klass volatility may overestimate the degree of long memory. This result is consistent with Granger and Hyung (2004) who find that the volatility series may show the long memory property because of the presence of neglected breaks. Moreover, when we test for a common long memory parameter the null hypothesis is only accepted for foreign volume and Garman-Klass volatility in all three subperiods. Therefore, it appears that there is a close correspondence between the estimated degrees of fractional integration as predicted by the modified MDH (see Andersen and Bollerslev, 1997, Bollerslev and Jubinksi, 1999). Finally, we find no evidence that foreign volume and volatility share a common long memory component.

Section 2 reviews the several versions of the mixture of distributionss hypothesis that give rise to common long run dependencies in volatility and volume. Moreover, some empirical evidence is provided. Section 3 discusses the semiparametric estimators in the frequency domain developed by Robinson (1994, 1995a) and used here to estimate and test for a common degree of long range dependence. Section 4 summarizes the data and provides the empirical results. Section 5 presents the conclusion of the paper.

4.2 Volatility and volume dynamics

According to the mixture of distributionss model of Clark (1973), the variance of daily price changes is affected by the arrival of price-relevant new information which also serves as a mixing variable. Moreover, he finds that trading volume, used as a proxy for the latent information variable, contains significant explanatory power for return volatility while his inference is mainly univariate and based on the assumption that trading volume is exogenous. Tauchen and Pitts (1983) suggest that price changes and trading volume are jointly determined by an information arrival process functioning as a common mixing variable. Both of the studies mentioned above assume that the information process is serially independent, and as a result this argument cannot explain the well known empirical fact that return volatility exhibits highly persistent autoregressive behavior.

Andersen (1996) suggest a mixture of distributionss model that studies the joint distribution for return volatility and trading volume under the market microstructure setting of Glosten and Milgrom (1985). Under this market framework, informed and uninformed investors strategically interact with a risk neutral market maker resulting in a sequence of temporary intraday equilibria as long as the sequence of trades and transaction prices reveal the content of private information. The bivariate distribution of price change and trading volume conditional on the intensity of information arrivals, K_t, is given by

$R_t|K_t \sim N(0, \sigma^2 K_t)$

and

$V_t|K_t \sim P(\mu_0 + \mu_1 K_t)$

where μ_0 reflects the liquidity or noise component of trading volume and $\mu_1 K_t$ represents trading volume induced by the arrival of new information. The constant term μ_0 and the imposition of a conditional Poisson rather than a normal distribution are the main contributions of the modified mixture of distributions model proposed by Andersen (1996). In addition, a full dynamic representation of the model is provided assuming a specific stochastic volatility process for the information arrivals and the results point towards a low degree of volatility persistence when volume and volatility are jointly considered. This fact is in contrast with the empirical result that volatility either modeled as a GARCH type or stochastic volatility process is highly persistent. However, Andersen (1996) suggest that different types of information arrival processes may have different implications for volume and return volatility persistence as the information content carried over some types of news or events has an asymmetric impact on volume and volatility. Although the short run responses of volatility and volume to certain types of news arrivals are not necessarily the same, common long run dependencies may arise as illustrated in a study by Andersen and Bollerslev (1997).

Andersen and Bollerslev (1997) formulate a version of the mixture of distributions hypothesis for returns that explicitly acommodates numerous heterogeneous information arrival processes. According to Andersen (1994,1996) and the mixture of distributions hypothesis, they find that each information component, expressed in terms of stochastic volatility process, has an effect on the aggregate latent volatility process which is characterised by a highly persistent, though stationary, autocorrelation function $\rho(v_t, j) \sim j^{2d-1}$. In this way Andersen and Bollerslev (1997) show that persistence in volatility can arise naturally as the interaction of N distinct information processes. Additionally, they argue that the degree of volatility persistence should be invariant to temporal aggregation and to correlation between information processes. A direct extension of their result and of the mixture of distributions hypothesis as expressed above, is that trading volume and volatility may share the same dynamic properties with the aggregate latent (information arrival) volatility process. In such case

$\operatorname{cor}\left(|R_t|, |R_{t-j}|\right) \sim j^{2d-1}$

and

$\operatorname{cor}\left(|V_t|, |V_{t-j}|\right) \sim j^{2d-1}$

Bollerslev and Jubinski (1999) find that the daily volatility and trading volume for the majority of the individual companies in the S&P100 composite index are best described by mean-reverting long memory type processes. Moreover, Lobato and Velasco (2000) find that volatility and volume exhibit the same degree of long memory for most of the stocks in the Dow Jones Industrial Average Index. These empirical findings are consistent with a modified version of the MDH, in which the dynamics of volatility and volume are determined by a latent informational arrival structure characterised by long range dependence. However, Lobato and Velasco (2000) find no evidence that equity volatility and trading volume share a common long memory component.

Kirman and Teyssiere (2002) suggest a sequential trade model with two groups of interacting agents which differ in regard to the rule that they use to forecast prices. The two groups are not fixed in size and their forecasts are based on economic fundamentals for group1 and on technical analysis for group 2. They find that the degree of long memory in volatility of asset prices depends on the probability ξ of an agent independently changing his opinion (e.g from fundamentalist to chartist) and the accuracy of observation from agents regarding the proportion of fundamentalists. The essence of these models is that the forecasts and thus the desired trades of the individuals in the markets are influenced, directly or indirectly, by those of other participants. This interdependence generates herding behavior that affects the structure of the asset price dynamics.

4.3 Long memory and fractional integration

4.3.1 Definition of long memory

In the time domain, a covariance stationary sequence X_t with long memory is described by the following asymptotic relation

$\gamma(j) = Cov(X_t, X_{t+j}) \sim c_x \; j^{2d-1}$

where c_x is a slowly varying function at infinity and positive and ‘ ˜ ’ indicates that the ratio of left and right hand sides tends to 1. The parameter d governs the intensity at which the autocorrelation function decays and summarizes the degree of long range dependence of the series X_t.

In the frequency domain long range dependence is replicated in the spectral density $f_x(\lambda)$ of X_t, defined by

$\gamma(j) = \int_{-\pi}^{\pi} f_x(\lambda) e^{ij\lambda} d\lambda \quad , \quad j = 0, \pm 1, ... ,$

where $f_x(\lambda)$ asymptotically converges to $G_x |\lambda|^{-2d}$ as $\lambda \to 0$ for some finite constant $G_x > 0$. The spectral density has a pole at zero frequency when $d > 0$,

$f_X(0) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_x(j) = \infty$

and this indicates the increasing contribution of low frequency components to the variance decomposition of X_t. When $d = 0$, the series is weakly dependent and $f_x(\lambda)$ is bounded and positive. In addition, the above asymptotic relations do not provide any information about the short run, seasonal or cyclical behavior of X_t. Robinson (2003) argues that semiparametric definitions of the long range dependence indicates that short-run modeling is almost irrelevant at very low frequencies and very long lags, where d dominates.

4.3.2 Estimation of long memory parameter d

To test the hypothesis of long-memory we follow Robinson's (1995) semiparametric bivariate approach. To this end, let the sample periodogram for y_{it}, $i = v, g$, at the r-th Fourier frequency, $\delta_r \triangleq 2\pi r/T$, $r = \gamma + \varphi, \gamma + 2\varphi, \ldots, n$, be denoted $I_i(\delta_r)$. Note that the trimming and truncation parameters, γ and n tend to infinity at a slower rate than the sample size T. Next let d_{mi}, $i = v, g$, denote the two fractional parameters and define the $[(n-\gamma)/\varphi] \times 2$ matrix $\mathbf{\Lambda}$, with the ri-th element equal to the log-periodogram $\log[I_i(\delta_r)]$. Robinson (1995) suggested the following least squares estimator for $\mathbf{d} \triangleq (d_{mv}, d_{mg})'$

$$\widehat{d} = \mathbf{\Lambda}'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2, \tag{B1}$$

where $\mathbf{e}_2 \triangleq (0,1)'$ and the $r1$-th and $r2$-th elements in the $[(n-\gamma)/\varphi] \times 2$ matrix of explanatory variables, $\mathbf{Z}$, are defined by 1 and $-2\log(\delta_r)$ respectively. For $\gamma = 0$ and $\varphi = 1$ the two estimates for d_{mi} correspond directly to the univariate estimates obtained by Geweke and Porter-Hudak (1983).

Next, let $\psi(\cdot)$ denote the digamma function, c_i a scaling constant, and the $i1$-th element of the 2×1 vector of the residuals $\mathbf{u}_r$ be given by

$$u_{ir} = I_i(\delta_r) - \log(c_i) + \psi(\varphi) + \widehat{d}_{mi}[2\log(\delta_r)],$$

with estimated variance-covariance matrix

$$\mathbf{\Xi} = \varphi(n-\gamma)^{-1} \sum_{r=\gamma+\varphi}^{n} \mathbf{u}_r \mathbf{u}_r'.$$

A test of whether the two variables, $d_{mv,}$ d_{mg}, have the same degree of fractional integration, d_m, is given by

$$\mathbf{W} = (\widehat{\mathbf{d}}'\mathbf{f})^2 \mathbf{e}_2'(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{e}_2 \mathbf{f}'\mathbf{\Xi}\mathbf{f} \overset{a}{\sim} \chi_1^2, \tag{B2}$$

where $\mathbf{f}$ denotes the 2×1 vector $(1,-1)'$.

Finally, the corresponding restricted least squares estimator that imposes this commonality on the fractional orders of integration is expressed as

$$\mathbf{d}_m = \frac{\sum_{r=\gamma+\varphi}^{n} \eta_r \varkappa' \mathbf{\Xi}^{-1} \mathbf{\Lambda}_r}{2\varkappa'\mathbf{\Xi}^{-1}\varkappa \sum_{r=\gamma+\varphi}^{n} \eta_r^2}, \tag{B3}$$

where $\varkappa$ is a 2×1 vector of ones, $\mathbf{\Lambda}_r$ is the r-th row of $\mathbf{\Lambda}$ and $\eta_r \triangleq -2\log(\delta_r) - [\varphi/(n-\gamma)] \sum_{r=\gamma+\varphi}^{n} [-2\log(\delta_r)]$.

4.4 Data and Empirical Results

4.4.1 Data description and tests for long memory

Our data set consists of daily trading volume and prices of the Korean Composite Stock Price Index (KOSPI) from the 3rd of January 1995 to the 26th of October 2005. The KOSPI Index is a market value weighted index for all listed common stocks in the KSE since 1980. Using data on the daily high, low, opening, and closing prices in the KOSPI index we generate a daily measure of price volatility. We can choose from among several alternative measures, each of which uses different information from the available daily price data. To avoid the microstructure biases introduced by high frequency data, and based on the conclusion of Chen et al. (2004) that the range-based and high-frequency integrated volatility provide essentially equivalent results, we employ the classic range-based estimator of Garman and Klass (1980) to construct the daily volatility (y_{gt}) as follows

$$y_{gt} = \frac{1}{2}u^2 - (2\ln 2 - 1)c^2, \quad t \in \mathbb{Z},$$

where u and c are the differences in the natural logarithms of the high and low, and of the closing and opening prices respectively. Garman-Klass (1980) show that their volatility estimator is about eight times more efficient than using the close to close prices to measure volatility. Moreover, Alizadeh et al. (2002) and Chen and Daigler (2004) argue in favor of using range based volatility measures due the bias introduced by microstructure effects.

As regards trading volume disaggregated data concerning domestic and foreign investors' trading activity is also available. We use turnover as a measure of volume. This is the ratio of the value of shares traded to the value of shares outstanding (see, Campbell et al., 1993; Bollerslev and Jubinski, 1999; Lo and Wang, 2000). Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (see, for details, Lobato and Velasco, 2000).[1] We form a trend-stationary time series of turnover (y_{vt}) by incorporating the procedure used by Campbell et al. (1993) that uses a 100-day backward moving average

$$y_{vt} = \frac{\mathrm{VLM}_t}{\frac{1}{100}\sum_{i=1}^{100}\mathrm{VLM}_{t-i}},$$

where VLM denotes volume. This metric produces a time series that captures the change in the long run movement in trading volume (see, Brooks, 1998; Fung and Patterson, 1999). The moving average procedure is deemed to provide a reasonable compromise between computational ease and effectiveness. We also extract a linear trend from the volume series. As detailed below, the results for the linearly detrended volume series are very similar to those reported for the moving average detrending procedure. In what follows, we will denote volume by $y_{vt}^{(s)}$ ($s =$ total, domestic, foreign) respectively.

Granger and Hyung (2004) find that absolute returns series may show the long memory property because of the presence of neglected breaks. For this reason we investigate whether the long memory property is inherent to the volatility and volume processes once we account for structural breaks in the mean. We use the Bai and Perron (1998, 2003a,b) testing procedure for multiple structural breaks as the problem has been addressed under very general conditions on the data

[1] Lobato and Velasco (2000) point out that the determination of a detrending mechanism that would allow for inference on the long-memory parameter of stock volume is still an unresolved problem. Therefore, they examine consistent estimation of the long-memory parameter of volume in the frequency domain by tapering the data instead of detrending them. However, Bollerslev and Jubinski (1999) find that neither the detrending method nor the actual process of detrending affected any of their qualitative findings.

and the errors. In addition, we use an extension of Bai and Perron's (1998) test by Lavielle and Moulines as it is valid under a wide class of strongly dependent processes, including long-memory, GARCH-type and non-linear models.

The structural break tests for volatility reveal two change points. The first break is detected on the 15th of October 1997 and thus we break our entire sample into two sub-periods: 1st) 3rd January 1995– 15th October 1997 (sample A hereafter), and 2nd) 16th October 1997- 26th October 2005: the post-crisis period (sample B hereafter). The second change-point for volatility is detected on the 6th of October 2000. For total/domestic volume the testing procedure reveals the existence of a single change-point that is detected on the 20th of January 1999. A single structural break is also detected for foreign volume and it coincides with the first break in volatility. That is, the results of the structural break tests do not support the null hypothesis of homogeneity in the two variables. In order to ensure that the results of this study are not influenced by the break in volume and the second break in volatility, we also examine the post-crisis period excluding the 16th October 1997-20th of January 1999 period (afterwards sample B1).

In this paragraph we analyze the results of the long-memory tests applied to the volatility and volume variables. Three tests aimed at distinguishing short from long-memory are implemented on the data. These are the KPSS test (Kwiatkowski et al., 1992), Lo's (1991) modified rescaled range statistic (R/S) and the "HML" test (see Harris et al., 2008). Some background information on the long memory tests used in this paper is contained in the appendix. The null hypothesis of the tests proposed is that of $I(0)$ against fractionally integrated alternatives $I(d)$. **Table** 4.1 reports results for the three volumes and volatility. The statistical significance of the test statistics indicates that the data are consistent with the long-memory hypothesis. [2]

TABLE 4.1

4.4.2 Long run dependence in volatility and volume

In this section we are interested in exploring the long run dependence of Garman-Klass volatility as well as that of domestic and foreign investors' trading volume. We employ semiparametric analysis in the frequency domain and estimates of the long memory parameter are reported for the series under study. Results are also reported for subsamples of the time series subject to prior investigation for structural break in the mean of the two series. This analysis is motivated by Granger and Hyung (2004) who find that infrequent structural breaks processes show long memory characteristics. In addition, Perron and Qu (2004) find that the autocorrelations and the path of the log periodogram estimates clearly follows patterns that would obtain if the true underlying process was one of short-memory contaminated by level shifts instead of a pure fractionally integrated process.

Next, we summarize the unrestricted semiparametric estimates of d_{mi}, $i = v, g$, based on Robinson's (1995) bivariate approach. All of the estimates are based on $\gamma = 0$ and $\varphi = 2$ and the results are reported in **Table** 4.2. The simulation results in Hurvich et al. (1998) suggest the use of $n = T^{.8}$ and this is utilized in Luu and Martens (2003) (see equation B1). In the present study for the two post-crisis periods we also use $n = T^{.8}$. For the entire (pre-crisis) period we use

[2] Andersen et al. (2001), among others, used the log periodogram estimator of Geweke and Porter-Hudak (1983) (hereafter, GPH) to construct a test for long-memory in volatility. Hurvich and Soulier (2002) justify the use of an ordinary Wald test for long-memory in volatility based on the log periodogram of the log squared returns. Various tests for long-memory in volatility have been proposed in the literature (see, for details, Hurvich and Soulier, 2002).

$n = T^{.7}(T^{.85})$. [3]In all four samples the estimates for the fractional parameter d_{mv} are remarkably close for total and domestic volumes: (0.64, 0.65), (0.57, 0.60), (0.59, 0.62) and (0.55, 0.59). All of the four estimates of $d_{mv}^{(T)}$ and $d_{mv}^{(D)}$ lie within the range 0.55 to 0.64 and 0.59 to 0.65 respectively. For the pre- and post-crisis periods foreign volume and volatility generated very similar fractional parameters: (0.26, 0.28) and (0.36, 0.38) respectively. For samples Total and B1 the long-memory parameters of the volatility (0.50, 0.39) are higher than the corresponding values of foreign investors' trading volume (0.34, 0.30). These empirical findings are consistent with a modified version of the MDH, in which the volume-volatility relationship is determined by a latent information arrival structure possessing long-memory characteristics.

TABLE 4.2

It is worth mentioning the empirical results in Granger and Hyung (2004). They suggest that there is a possibility that, at least, part of the long.-memory may be caused by the presence of neglected breaks in the series (see also Diebold and Inoue, 2001). However, the fractional integration parameters are estimated for the various sub-periods, after taking into account the presence of breaks. The long-memory character of the different volume series remains strongly evident while in the case of volatility there is a significant reduction in the long memory parameter d for the pre and post crisis periods.

[3]Practical optimality criteria for choosing both the trimming (γ) and truncation (n) parameters have proven elusive (see Bollerslev and Jubinski, 1999).

We perform a sensitivity analysis (not reported) of our results with respect to different values of the tuning parameters. Our empirical results do not appear overly sensitive to the specific values chosen for the γ, ϕ and n. Although the quantitative results vary slightly from case to case, the qualitative results do not.

4.4.3 Common long run dependence in volatility and volume

In this section we test whether the Garman-Klass volatility and trading volume have the same degree of long memory as the mixture of distribution hypothesis suggests. Empirical results in favour of this common long memory property are reported in Bollerslev and Jubinski (1999) and Lobato and Velasco (2000) for individual stocks. It is very appealing to see whether this property holds for an emerging market's stock index volatility and its trading volume. Additionally, we are interested in investigating whether different types of investors' trading volume show quite similar long memory characteristics.

Because it has been repeatedly shown that a main feature of return volatility and volume is the presence of long-memory, it is of interest to test if the two variables share the same stochastic properties. The results of Robinson's χ^2 test for a common long-memory parameter in volatility and any of the three volumes are reported in **Table** 4.3. A formal test of this hypothesis is available in equation (A2). In all four samples the total and domestic volumes produce chi-squared statistics that are higher than the 5% chi-squared critical value of 3.841. In sharp contrast, in all three sub-periods, the null hypothesis that the volatility and foreign volume share a common long-memory parameter cannot be rejected at any conventional significance level. Therefore, it appears that there is a close correspondence between the estimated degrees of fractional integration for the two series as predicted by the MDH (see Bollerslev and Jubinski, 1999). Restricting the value of the d_m to be the same across the volatility and the foreign volume, as in equation (A3), results in estimates of d_m: 0.42, 0.27, 0.37 and 0.35 (see the last column of **Table** 4.3).

TABLE 4.3

These results are in line with those obtained from the bivariate ccc AR-FI-GARCH model. That is, the semiparametric estimates and test statistics also point toward a remarkable commonality in the degree of fractional integration for foreign volume and volatility.

4.4.4 Fractional Cointegration and a common long-memory component

Because it appears that both foreign volume and volatility possess the same long-memory parameter, it is of interest to examine if both processes are driven by the same long-memory component. One way of doing that is to examine whether the two variables are fractionally cointegrated. Fractional cointegration has received much attention lately. Following Davidson (2002) we attempt a fractional bivariate analysis. We employ two versions (the generalised and the regular one) of the fractionally cointegrating vector error correction model (FVECM). General cointegration as defined in Davidson et al. (2006) is the case where the cointegrating variables may be fractional differences of the observed series. The generalised FVECM is given by

$$[\mathbf{\Phi}(L) - \mathbf{\Theta\Pi\Delta}^{*}(L)]\mathbf{\Delta}(L)(\mathbf{y}_t - \boldsymbol{\mu}) = \boldsymbol{\varepsilon}_t,$$

where Θ is a 2×1 vector given by $\Theta' \triangleq [\theta_1 \ \theta_2]$, Π is a 1×2 vector given by $\Pi \triangleq [1 \ \pi]$, and $\Delta^{*}(L)$ is a $2{\times}2$ diagonal matrix polynomial with diagonal elements $(1-L)^{d^{*}_{mi}}$, $i = v, g$, with $0 \leq d^{*}_{mi} \leq d_{mi}$. $\varepsilon_t \sim i.i.d.$ $(0, \Sigma)$ with $\Sigma \triangleq [\sigma_1 \ \sigma_2]$. In the case of regular cointegration linear combinations of fractionally integrated variables are integrated to lower order. Since there are just two variables in the system their order of integration must be equal: $d_{m1} = d_{m2} = d_m$. This implies that the orders of integration of the error correction terms must also match to ensure cointegration: $d^*_{m1} = d^*_{m2} = d^*_m$. In the generalised cointegration there is no requirement for any of the cointegration order to match across variables (see, Davidson et al., 2006). The models are of course identical if the orders of integration are the same.

The Lagrange Multiplier statistic can not reject the null of equality restriction and the IC also favour the restrictive model. Although the estimated d^*_m is significantly positive and also significantly smaller than the estimated d_m, it appears that cointegration does not exist, in the sense that π, $\theta_1 < 0$ and $\theta_2 > 0$ are all insignificant. In other words, there appears to be no fractional cointegration. [4] These results are robust to the choice of the sample period apart from sample A (see **Table** 4.4). Thus although foreign volume and volatility exhibit the same degree of long-memory, we find no evidence that both processes share the same long-memory component for all the sample periods considered.

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4.5 Conclusion

This study provides empirical evidence on the degree of long run dependence of volatility and trading volume in the Korean Stock Exchange. Our motivation stems from the fact that a modified mixture of distributions model with a fractionally integrated latent volatility process, due to the aggregate impact of N distinct

[4] **To interpret our results we assume that cointegration exists, in the sense that $d_m > 0$, and either $\theta_1 < 0$, or $\theta_2 > 0$, or both. To straightforwardly test the existence of cointegration one should use the residual-based bootstrap tests developed in Davidson (2004). We leave further work on these formal tests for future research.**

information arrival processes, predicts very similar long memory characteristics in volume and volatility.

The results of testing for long memory support the argument for long run dependence in both Garman-Klass volatility and trading volume. In order to estimate the degree of long memory we employ the semiparametric estimators suggested by Geweke and Porter-Hudak (1983) and Robinson (1994, 1995a). As regards trading volume, total and domestic show very similar long memory characteristics for all sample periods. The long memory parameters range from 0.55 to 0.64 for total volume and from 0.59 to 0.65 for domestic volume. The degree of long memory in foreign volume is significantly lower (almost half) than that experienced in domestic volume and it ranges from 0.26 to 0.34. In addition, the results for foreign volume reveal no significant change on the degree of long run dependence for the different samples considered. The long range dependence in Garman-Klass volatility for the whole sample is 0.50 and diminishes to 0.25 for the pre-crisis and to 0.38 for the post crisis period. As we can see neglecting the structural break in the mean of Garman-Klass volatility may overestimate the degree of long memory. This result is consistent with Granger and Hyung (2004) who find that the volatility series may show the long memory property because of the presence of neglected breaks.

We further proceed to test the implications of the modified mixture of distributions model concerning the common degree of long run dependence in volatility and trading volume. The null hypothesis that volatility and volume share a common long memory parameter is only accepted for foreign volume and Garman-Klass volatility in all three subperiods. Therefore, it appears that there is a close correspondence between the estimated degrees of fractional integration as predicted by the modified MDH (see Andersen and Bollerslev, 1997, Bollerslev and

Jubinksi, 1999). Finally, we find no evidence that foreign volume and volatility share a common long memory component. Our results are consistent with the results of Lobato and Velasco (2000) who find that volatility and volume share a common long memory parameter while there is no evidence that both processes share the same long memory component.

The results for the raw volume data as wells as for a linear detrending method are almost identical to those reported for the 100-day moving average detrending. Further work using Gaussian semiparametric estimators and fractional cointegration analysis as suggested by Robinson (1995b) and Robinson and Marrinucci (2001, 2003) for an Index as well as its constituent individual securities is a subject of future research.

Table 4.1: Testing for long memory

Long memory tests	Volume			Volatility
	Total	Domestic	Foreign	Garman-Klass
KPSS	0.94***	0.97***	0.51***	5.79***
R/S	2.55***	2.64***	1.62**	7.98***
HML	-2.03 [0.04]	-1.85 [0.06]	-3.13 [0.00]	4.68 [0.00]

Notes: *** and ** denote significance at the 0.01 and 0.05 levels respectively. The numbers in $[\cdot]$ are p values.

Table 4.2: Semiparametric estimates of the long memory parameter d

Sample	Volume			Volatility
	Total	Domestic	Foreign	Garman-Klass
Total Sample	0.64 (0.04)	0.65 (0.04)	0.34 (0.04)	0.50 (0.04)
Sample A	0.57 (0.04)	0.60 (0.04)	0.26 (0.03)	0.28 (0.04)
Sample B	0.59 (0.03)	0.62 (0.03)	0.36 (0.03)	0.38 (0.03)
Sample B1	0.55 (0.03)	0.59 (0.03)	0.30 (0.04)	0.39 (0.03)

Notes: In all cases $\gamma = 0$ and $\varphi = 2$. For sample Total (A) we use $n = T^{.7}(T^{.85})$. For the two post-crisis periods we use $n = T^{.8}$.

The numbers in parentheses are standard errors.

Table 4.3: Test for equality of the long memory parameter d

Sample	$d_{mv}^{(T)} \overset{?}{=} d_{mg}$	$d_{mv}^{(D)} \overset{?}{=} d_{mg}$	$d_{mv}^{(F)} \overset{?}{=} d_{mg}$	$d_{mv}^{(F)} = d_{mg}$
Total Sample	5.59 [0.02]	6.21 [0.01]	6.84 [0.01]	0.42 (0.03)
Sample A	24.47 [0.00]	29.94 [0.00]	0.13 [0.72]	0.27 (0.02)
Sample B	23.85 [0.00]	30.66 [0.00]	0.25 [0.62]	0.37 (0.02)
Sample B1	13.92 [0.00]	22.14 [0.00]	3.12 [0.08]	0.35 (0.02)

Notes: The table reports Robinson's (1995) χ^2 test statistic for the null hypothesis that volume and volatility have the same long-memory meanparameter d_m. The last column reports the restricted long-memory parameter d_m for foreign volume and volatility. The numbers in [·] are p-values. The numbers in parentheses are standard errors.

Table 4.4: Fractional vector error correction model (FVECM)

	d_m	d_m^*	π	θ_i	σ_i
Total Sample					
Foreign volume	0.43^{***} (0.04)	0.41^{***} (0.09)	0.04 (0.10)	0.001 (0.003)	0.39^{***} (0.01)
Volatility	-	-	-	-0.001 (0.003)	2.35^{***} (0.15)
Sample A					
Foreign volume	0.48^{***} (0.09)	0.14^{**} (0.06)	0.004^{***} (0.01)	-0.004 (0.03)	0.46 (0.04)
Volatility	-	-	-	-1.14^{***} (0.11)	0.72 (0.05)
Sample B					
Foreign volume	0.42^{***} (0.05)	0.31^{***} (0.09)	0.001 (0.002)	0.002 (0.003)	0.37 (0.01)
Volatility	-	-	-	-0.002 (0.004)	2.69 (0.16)

4.6 Appendix

4.6.1 Testing for Long Memory

In order to test for long memory we use the Lo's modified R/S test (Lo, 1991), the $KPSS$ test (Kwiatkowski et al., 1992), and the 'HML' test (Harris et al.. 2008). Lo (1991) proposed a modified version Hurst's (1951) 'rescaled range' or 'R/S ' statistic. The 'R/S ' statistic is the range of partial sums, S_k, of deviations of a time series from its mean, $S_k = \sum_{j=1}^{k}(Y_j - \bar{Y}_n)$, rescaled by its standard deviation, σ_n, and is defined as

$R/S = \frac{1}{\sigma_n}[\max\limits_{1\leq k\leq n} S_k - \min\limits_{1\leq k\leq n} S_k]$.

Lo's modified version of the 'rescaled range' statistic differs from the 'R/S ' defined above only in its denominator, which is the square root of a consistent estimator of the partial sum's variance. The reason for this is that if the time series under study is subject to short-range dependence, the variance of the partial sum is not simply the sum of the variances of the individual terms, but also includes the autocovariances. Under the null hypothesis of no long memory, the statistic $n^{-1/2}R/S$ converges to a distribution equal to the range of a Brownian bridge on the unit interval.The $KPSS$ test, proposed by Kwiatkowski, Phillips, Schmidt, and Shin, (1992), is based on the second moment of the partial sums, S_t, and is defined as

$$KPSS(q) = \frac{1}{n^2\hat{\sigma}^2(q)}\sum_{k=1}^{n} S_k^2$$

where $\sigma^2(q)$ is the Newey and West (1987) consistent estimator of the partial sum's variance and under the null hypothesis of stationarity the 'long-run variance' $\sigma^2(q)$ is proportional to the spectral density at zero frequency, which is required to be neither zero nor infinite or equivalently $\sigma^2(q) = \lim_{n\to\infty} n^{-1}E(S_n^2)$ which exists and is non zero. Lee and Schmidt (1996) shows that the $KPSS$ test is consistent against stationary long memory alternatives, such as $I(d)$ processes for $d \in (-1/2, 1/2)$, $d \neq 0$. Moreover, the power of the $KPSS$ test in finite samples is found to be comparable to that of Lo's modified rescaled range test.

As regards the test for long memory proposed by Harris, McCabe, and Leybourne (2008) consider the linear regression model

$$y_t = x_t'\beta + z_t, \tag{A1}$$

where the disturbances satisfy the $I(d)$ process $(1-L)^d z_t = u_t$ and u_t is a zero mean stationary short-memory process. Let $\widehat{z}_t$ be the ordinary least squares residuals from the above equation with sample autocovariances

$$\widehat{\vartheta}_j = T^{-1} \textstyle\sum_{t=\max(j,0)+1}^{T-\min(j,0)} \widehat{z}_t \widehat{z}_{t-j}.$$

HTL(2007) concerned with the hypothesis testing problem $H_0 : d = 0$, $H_1 : d > 0$. Their test statistic is given by

$$\widehat{S}_\gamma^* = \frac{\widehat{N}_\gamma}{\widehat{\varrho}_\varphi},$$

with

$$\begin{aligned} \widehat{N}_\gamma &\triangleq (T-\gamma)^{1/2} \textstyle\sum_{\tau=\gamma}^{T-1} \frac{1}{\tau - \gamma + 1} \widehat{\vartheta}_\tau, \\ \widehat{\varrho}_\varphi^2 &\triangleq \textstyle\sum_{m=-\varphi}^{\varphi} h_m \sum_{k=-\varphi}^{\varphi} \widehat{\vartheta}_k \widehat{\vartheta}_{k+m}, \end{aligned}$$

where $h_0 \triangleq \pi^2/6$, $h_m \triangleq \mathbb{H}_{|m|}/|m|$ for $m = \pm 1, \pm 2, \ldots$and $\mathbb{H}_{|m|}$ are the harmonic numbers $\sum_{k=1}^{m} k^{-1}$.

The effect of estimating the regression (A.1) can have a significant effect in finite samples. A bias corrected statistic is then defined to be

$$\widehat{S}_{\gamma} = \frac{\widehat{N}_{\gamma} + \widehat{b}}{\widehat{\varrho}_{\varphi}},$$

with

$$\begin{aligned}
\widehat{b} &\triangleq \widehat{\eta}(T-\gamma)^{1/2} \textstyle\sum_{\tau=\gamma}^{T-1} \dfrac{1}{\tau-\gamma+1}, \\
\widehat{\eta} &\triangleq (T-\gamma)^{-1} \mathrm{tr}[(\textstyle\sum_{t=1}^{T} x_t x_t')^{-1} \widehat{\Sigma}(x_t \widehat{z}_t)],
\end{aligned}$$

where $\widehat{\Sigma}(\cdot)$ is any standard long run variance matrix estimator.

HTL(2007) show that if some conditions hold (see theorem 1 in HTL) then under the null hypothesis the distribution of $\widehat{S}_{\gamma}$ is asymptotically standard normal. As regards the supplementary user-supplied items we use a bandwidth of $\varphi = [(2/3)T]^{12/25}$ and for $\widehat{\Sigma}(\cdot)$ we employ the QS kernel with Newey and West (1994) automatic bandwidth selection, using a nonstochastic prior bandwidth of $[4(T/100)^{2/25}]$ (see HTL, 2008). The finite sample performance of $\widehat{S}_{\gamma}$ will inherently depend on the specific value of the trancation parameter γ selected by the user. The Monte Carlo simulation results in HTL (2008) show that when $\gamma = (2T)^{1/2}$ there are no notable size distortions.

Chapter 5

Trader type effects on the volatility-volume relationship. Evidence from the KOSPI200 index futures market

5.1 Introduction

In their 1999 study Daigler and Wiley found that using trader categories is a better way to describe the link between volatility and volume than total volume. Their empirical results for the futures market show that the general public drives the positive volatility volume relationship whereas trading by clearing members and floor traders often exhibits an inverse relationship between volatility and volume. The intuition behind Daigler and Wiley's empirical study follows from models that associate price with private information and different traders distinguished by either the quality of information they hold or the dispersion of expectations they form based on that information (See O'Hara (1995) for a survey of the relevant literature). Shalen (1993) examines a two period rational expectations model of a futures market and shows that the dispersion of past and current beliefs helps to explain a number of stylised facts regarding price volatility and the volume of trade. For example, a positive correlation is found in most of the theoretical market microstructure models which involve strategically interacting traders with asymmetric information and rationally formed expectations. Another type of theory attempting to explain the volatility-volume relationship is the Mixture of Distributions Hypothesis (MDH) in which information is used as the driving force that determines both volatility and volume (Clark, 1973, Epps and Epps, 1976, and Tauchen and Pitts, 1983). A modified version of the Mixture of Distributions Hypothesis proposed by Andersen (1996) is based on Glosten and Milgrom's (1985) competitive setting and on a stochastic volatility latent information arrival process. The author finds that this alternative representation of the MDH provides an overall acceptable characterisation of several features of the volatility and volume variables found in common stocks.

This study investigates whether different types of traders, distinguished by the information they possess, have a positive or negative effect upon volatility. In addition we investigate whether the effect of trader type volume on volatility is uniform by separating volume into its expected and unexpected components. This work aims to provide empirical evidence on the volatility-volume relationship implied by theoretical models which associate movements in prices and trading volume with information, dispersion of beliefs and trading motives. Another objective of this paper is to investigate which groups of traders dominate the Index futures market in Korea in terms of significant association with its volatility. Bessembinder and Seguin (1993) suggest that the volatility volume relationship might depend on the type of trader after finding that trades causing changes in open interest have a larger effect on volatility than do trades that leave the open interest intact. In this study we have a dataset consisting of trading volume for eight different types of domestic investors, foreign investors and open interest. We distinguish trading volume into four categories based on the information they posses and their access to the trading system. Additionally, the range (high, low, open, close) of daily prices for the KOSPI200 Index futures contract is available, which allows us to test the volatility-volume relationships over different and usually more efficient volatility proxies.

Our empirical results show that surprises in non-member investors' trading volume are positively related with volatility in most of the cases. These results are more reinforcing in the case of log-volume and generally consistent with the empirical findings of Daigler and Wiley (1999). Moreover, this finding is consistent with the theoretical models of Harris and Raviv (1993) and Shalen (1993), who find a positive relationship between absolute price changes and volume due to the dispersion of beliefs partly caused by different interpretation of common information and partly caused by the 'noisy' liquidity demand. As regards member investors, we primarily find that unexpected volume is positively related to volatility and this further supports the argument of Delong et al (1990b), that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders.

Although for the whole sample we report very significant relations between long run changes in non-member investors' trading volume and volatility, after the financial crisis, all these relations become insignificant. Surprisingly, as regards the low frequency component, the results for the whole sample reveal a stabilising role for non-member institutional and foreign investors while a destabilising one for non-member individuals especially up to the period of the financial crisis. More interestingly, in the case of log volume, the moving average component of member institutional investors also turns to negative, indicating a stabilising role for these types of traders, at least up to the end of the crisis period. Further, it is worth mentioning the uniformly positive and significant relationship between volatility and the expected component of non-member individuals as well as the negative and significant relationship between volatility and the moving average component of non-member of foreign investors trading volume.

Another important result of our study is that the coefficients relating the unexpected component of open interest with volatility are uniformly negative, meaning that an increase in open interest during the day lessens the impact of a volume shock in volatility. This is consistent with the Bessembinder and Seguin (1993) results, who also report a negative relation between surprises in open interest and volatility. However, when we allow for time to maturity effects, surprises in open interest are associated with more volatility around the futures contract expiration probably due to the wider price range over which less informed investors trade as the contract rolls to its expiration and information asymmetry rises. Finally, the trading volume slope dummies reveal that non-member institutional investors are not associated with any movement in volatility towards the end of the contract life while surprises in the trading activity of non-member individual, foreign and member institutional investors are still positively associated with volatility over the same period.

Section 2 of this study reviews the volatility-volume relation implied by market microstructure and trader behaviour models and provides some empirical evidence. Section 3 briefly describes some microstructure issues regarding the Korean Index Futures Market. Section 4 summarizes the data while section 5 outlines the estimation procedure that we use. Section 6 provides the empirical results, and Section 7 presents the conclusion of the paper.

5.2 Information, Volatility and Trading Activity

5.2.1 Mixture of Distributions Hypothesis

The relation between volatility and volume has attracted a vast amount of theoretical and empirical research over the years. An early attempt to explain the volatility-volume relationship, without fully illustrating the information integration process, is due to Clark (1973), Epps and Epps (1976) and Tauchen and Pitts (1983). The mixture of distribution model posits a joint dependence of returns and volume on an underlying latent event or information flow variable such as the number of trades. Tauchen and Pitts (1983) find that the variance of the daily price change and the mean daily trading volume depend upon three factors: the average daily rate at which new information flows to the market, the extent to which traders disagree when they respond to new information and the number of active traders in the market. Their model predicts a positive volatility-volume relationship when the number of traders is fixed while a negative relation is predicted when the number of traders is growing, such as the case of T-bills futures market. Tauchen and Pitts (1983) do not consider how traders form their reservation prices or what they learn from the market price, issues subsequently explored by Hindy (1994).

Andersen (1996) suggested a modified version of the mixture of distribution hypothesis under a competitive market framework in which informational asymmetries and liquidity needs motivate trade in response to the arrival of new information. In Andersen's model trading volume differs from standard specifications due to microstructure effects as well as a Poisson, rather than normal, approximation to the limiting distribution of the binomial process that drives trading volume. Despite the overall satisfactory fit the simultaneous incorporation of returns and volume data results in a significant reduction in the estimated volatility persistence. The author also suggests that two or more information arrival processes may have different implications for volume and return volatility persistence an idea further pursued to Andersen and Bollerslev (1997). The authors demonstrate that by interpreting the volatility as a mixture of heterogeneous short run information arrivals, the observed volatility process may exhibit long run dependence. Li and Wu (2006) suggest a version of the mixture of distributions hypothesis which allows liquidity trading to affect price volatility. They find that the positive relationship between volatility and volume is primarily associated with information arrivals by informed trading. In addition controlling for the effect of informed trading, return volatility is negatively correlated with volume, which is consistent with the contention that liquidity trading increases market depth and lowers price volatility.

5.2.2 Information, Rational Expectations and Dispersion of Beliefs

Market microstructure theory has associated price changes and trading volume with the arrival of new information in the markets. French and Roll (1986) examine three potential explanations contributing to high trading time volatility. They find that the large difference in trading and non trading variances is caused by differences in the arrival and incorporation of information during trading and non trading periods. Easley, Kiefer and O'Hara (1997) try to identify the information content in the trading process. They find that large and small trades have different information content but this varies across stocks. Moreover, they find that uninformed trades are positively correlated and that reversals of trades are more informative than sequences of trades in the order flow. Ederington and Lee (1993, 1995) examine the impact of scheduled macroeconomic news announcements on futures prices and they find that most of the price change occurs within one minute while volatility remains considerably higher than normal for another fifteen minutes and slightly higher for several hours. A possible explanation provided is that investors continue to trade on the initial information as the implications for market prices are worked out and as the details of the information release become available.

The theoretical models that have been proposed try to explain the process of price discovery and information assimilation that occurs under a market setting that allows for different types of traders distinguished by the quality of information they hold, the dispersion of expectations they form based on this information and their trading motives. Additionally, the intertemporal setting of some of these models makes it possible to explore the dynamic implications for prices and trading volume. In the Glosten and Milgrom (1985) model the process over which new information integrates into prices requires an understanding of how the specialist and other uninformed investors learn from observing market information (see appendix A). For example, individual trades are not observable in batch systems but are observable in continuous auctions. Also the sequence of trades and their timing may be observable in some trading systems but not in others. Therefore, the trading process itself generates information which might be related to information on the underlying asset value.

Much of the literature on how information is incorporated into prices as well as its signaling role focuses on rational expectations and dispersion of beliefs models. In rational expectations models, prices are affected both by private information and supply uncertainty (Grossman and Stiglitz, 1980). Supply uncertainty is incorporated to capture transitory effects on price that are not related to information. The role of supply uncertainty is that with multiple sources of uncertainty, traders cannot immediately sort out the information from the supply effects on price. In such cases prices only reveal some of the informed trader's information to the uninformed traders. Brown and Jennings (1989) and Grundy and McNichols (1989) find that the sequence of prices is jointly fully revealing, meaning that they provide information to traders and hence affect the adjustment of prices to full information values. As O'Hara (1995) argues, prices play the dual role of market clearing and information aggregation when information asymmetry is present. Another variable that can probably provide useful information to investors is trading volume. Blume, Easley and O'Hara (1994) analyse the learning problem that arises when traders are allowed to condition on the information contained in volume and demonstrate how the volume statistic itself affects the adjustment of prices to information. The authors show that volume provides information about the quality of trader's information that cannot be deduced from the price statistic. Moreover, because the volume statistic is not normally distributed, if traders condition on volume they can sort out the information implicit in volume from that implicit in price. As regards the price-volume relationship, a V-shape is reported, meaning that large price changes (negative or positive) tend to be associated with large volume. Hence, it is the case that absolute price movements and volume are positively correlated.

Models of heterogeneous trader behavior can arise either because informed traders have different private information or because they simply interpret commonly known data in a different way. As some traders may obtain information, it is not always clear how that information relates to the ultimate value of the firm and hence not immediately apparent how unbiased or how valuable the information is. One example of this is that financial analysts often have different opinions regarding future movements of interest rates and stock prices, despite the fact that all these analysts have access to the same economic data. Harris and Raviv (1993) consider a model of trading in speculative markets assuming that traders share common prior beliefs, receive common information but differ in the way in which they interpret this information. Their main results are that absolute price changes and volume are positively correlated and volume is positively autocorrelated. In addition, if speculators overestimate (underestimate) the true quality of the signal, then consecutive price changes exhibit negative (positive) serial correlation. Hindy (1994) suggests a model in the futures market which includes only informed traders who disagree in the interpretation of the private signals. He shows, using examples, that this model is capable of producing expected volumes and price changes that are 'positively related, negatively related for all time periods, or have a relation that changes from positive to negative or vice versa over time'.

In contrast to the above model, in rational expectations models disagreement is the result of private information. Shalen (1993) developed a two period noisy rational expectations model of a futures market and showed that the dispersion of beliefs measures both the excess volatility and excess volume of trade induced by the 'noisy' liquidity demand of futures hedgers. The intuition behind this is that when liquidity demand is uncertain speculators' estimates of future prices are dispersed since they cannot isolate private information, embedded in current prices, from hedging demands. This creates excess price volatility because equilibrium prices are linear combinations of average estimates of future prices and liquidity demand. Moreover, Shalen (1993) shows that the dispersion of expectations based on current information also contributes to the positive correlation between volume and absolute price changes. Pfleiderer (1984) shows a positive contemporaneous relation between volume and price changes; however, this result is entirely due to non speculative trading because the correlation between speculative trading volume and absolute price changes is zero. Wang (1994) suggested a model in which the uninformed investors cannot perfectly identify the informed investors' motive behind their trade and they face the risk of trading against informed investors' private information. The risk of information based trading also dictates that volume and absolute value of excess returns are positively correlated, reflecting the price movement necessary to induce uninformed traders to take the other side of the trade. Furthermore, Wang (1994) finds that the greater the information asymmetry the larger the abnormal trading volume when public news arrives. He and Wang (1995) find that volume generated by new private signals and public announcements is always accompanied by large price changes while volume generated by existing private information is not.

Holthaussen and Verrecchia (1988) propose a partially revealing rational expectations model of competitive trading in which a heterogeneous interpretation of a public information release results in price and volume reactions. The extent to which the information content (informedness) of an information signal makes investors revise their beliefs in the same (consensus) or opposite direction gives rise to different volume volatility relationships. More specifically, the variance of price changes and trading volume tend to be positively related when the informedness effect dominates the consensus effect and tend to be negatively related when the consensus effect dominates the informdness effect. Schneider (2006) provides a closed form solution for a rational expectations equilibrium where all investors infer information about the state of the economy from private signals, the market price and aggregate trading volume. In this model investors use volume to decide how they should weight the market price relative to their own private signals when they update their beliefs. Specifically, when trading volume is high investors weight the market price more heavily while when volume is low, investors weight their private signals more heavily. This is happening because obtaining trading volume reduces uncertainty regarding the correlation of private signals among investors.

The models reviewed above provide a wealth of volatility-volume relationships depending on information, expectations formed based on this information and trading motives. If investors have an information advantage (informed) due to access to market economic data it is relatively likely to form homogenous expectations about the market movements as well as the fundamental characteristics of an asset. In such cases we would expect informed traders to buy and sell within a small range of prices around the fair value of the asset. Certainly this is not always true, as in the case of public news announcements expectations can be quite dispersed even among investors who have access to market economic data as well as in the case of informed investors' trading when noise traders follow positive feedback strategies (see next section). Moreover investors who do not have access to order flow data (less informed) cannot interpret with precision the noisy signals from volume and price changes, resulting in a wider dispersion of beliefs. Consequently, less informed investors are likely to react to all changes in volume and price as it is difficult to differentiate short term liquidity (hedging) demand from changes in overall fundamental supply and demand. Despite this information asymmetry that arises, we will argue in the next section that less informed traders not only survive the market but they can also dominate it. Additionally uninformed investors' frequent revision of their beliefs can also cause the price fluctuations resulting from their trading to persist more than those of informed investors after the new information is revealed.

5.2.3 Noise Trading and Information

In this study, the member financial institutions characterised as securities companies represent the informed traders due to their direct access to the trading system. By comparison we define the non-member financial institutions, individual and foreign investors as uninformed or less informed as their orders are channeled through members' trading pits. Clearing members of the exchange enjoy lower trading costs and information advantages. Their direct access to the trading system provides them with short term information about pit dynamics such as trading activity at specific prices and price trends. In addition they have specific information about their own customers' supply and demand in the cash and futures markets. Furthermore, they benefit from increased information in the cash markets because of their access to trading screens and in house knowledge in these markets. As Daigler and Wiley (1999) argue this access to private information allows clearing members to better distinguish liquidity demand from fundamental information and to estimate current value more precisely, which translates into smaller dispersion of beliefs and less price volatility. The non-member investors do not enjoy such information advantages as member investors since they do not have direct access to the trading system. If they receive some information this happens on a delayed or a second hand basis. Since the non-member investors hold less information, we would expect them to have a greater dispersion of beliefs and to trade over a wider range of prices around the fair value of the futures contract. The trading behavior associated with non-member investors is consistent with the noise literature (Black, 1986, DeLong, Shleifer, Summers and Waldman (1990, 1991). Black (1986) argues that noise trading increases liquidity in the markets and also puts noise into the prices as they reflect both information and noise induced trading. DeLong et al. (1990a) show that the unpredictability of noise traders' beliefs creates excess risk and significantly reduces the attractiveness of arbitrage. In cases where arbitrageurs have short horizons noise trading can lead to a large divergence between market prices and fundamental values. DeLong et al. (1991) find that noise traders who form incorrect expectations about asset price variance can not only earn higher returns than do rational investors but also survive and dominate the market in terms of wealth in the long run. DeLong et al (1990b) argue, despite the fact that rational speculation stabilizes prices, that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders. The key point is that, although part of the price rise is rational, part of it results from rational speculators' anticipatory trades and from positive feedback traders' reaction to such trades. In such cases we would expect to find a positive relationship between informed investors' trading volume and volatility.

5.2.4 Empirical Evidence

A plethora of empirical studies have examined the relationship between volatility and volume in cash and futures markets and a positive contemporaneous relationship between the two variables is often documented (see Karpoff (1987) for empirical evidence up to 1987). Gallant, Rossi and Tauchen (1992) find a positive contemporaneous volatility-volume relationship robust to non-normalities, stochastic volatility, and other forms of conditional heterogeneity. Bessembinder and Seguin (1992) find that equity volatility covaries positively with spot equity and futures equity trading volume with the unexpected component of spot trading volume being more effective. In a similar way, Bessembinder and Seguin (1993) examine the relationship between trading activity and volatility in eight futures markets. They find a strong positive relationship between contemporaneous volume (expected and unexpected) and volatility and that the impact of an unexpected volume shock is between 2 and 13 times greater than the effect of changes in expected volume. Moreover, they find that the expected open interest is negatively related to volatility in all markets, a result consistent with the belief that variations in open interest reflect changes in market depth. Furthermore, Bessembinder and Seguin (1993) suggest that the volatility-volume relationship might also depend on the class of traders after finding that trades resulting in changes in open interest appear to have a larger impact on prices than do trades that leave the open interest unaltered. Daigler and Wiley (1999), in line with Bessembinder and Seguin's (1993) suggestion, try to investigate the impact of trader type on the futures volatility-volume relationship. They find that the positive volume volatility relationship is driven by the general public, a group of traders distant from the trading floor, less informed and with greater dispersion of beliefs. On the other hand clearing members and floor traders often decrease volatility and this is attributed mainly to the informational advantage from holding a seat in the futures market.

5.3 The KOSPI200 Index Futures Market

The KOSPI 200, which is used as an underlying index for the futures contracts, is a market capitalization weighted index composed of 200 major stocks listed on the Korean Stock Exchange (KSE) and it represents about 80% of the total market capitalization of the KSE stock market. The KOSPI 200 is calculated using real time stock prices and is published every 10 seconds. The selection criteria for the 200 underlying stocks, which include both market capitalization and liquidity, is devised to have the KOSPI 200 index closely track the movement of the whole Korean stock market. Foreigners who want to become a member of the KSE have to establish an office in Korea that is licensed as a securities company by the Financial Supervisory Commission.

As of September 2002, the total number of KSE members stood at 52 while of all the members 15 are foreign brokerage firms. All transactions in the KSE market are automatically processed and executed by the computerized trading system without the intervention of market makers. Access to the trading system is granted to the member firms only. Any members who have their own system, which is a client server interface for customers or multi-functioning system, can access the KSE system directly. Overseas brokers or dealers cannot access the KSE system directly, but they can connect to a member's system located in Korea through international securities companies' global network (see KOSPI 200 Futures and Options booklet, published by the Korean Stock Exchange, for an illustrative diagram of the information dissemination process as well as the market participants during a trading day in the futures market).

During the trading hour, all orders are continuously matched at a satisfactory level to both the selling and buying parties according to price and time priority.

At the time of market opening and closing, however, orders are pooled over a fixed period of time and matched at a single price that minimizes any imbalance between the buying and selling parties. All trading on the KSE is processed automatically by computer system.

The contract months for futures are March, June, September and December, and the longest maturity period is one year. The last trading day of each contract is the second Thursday of each expiration month.

5.4 Data description

Our database consists of daily data on high, low, open and closing prices of the KOSPI 200 Futures Index of the Korean stock exchange from the 3rd of May 1996 to 30th of September 2005 (2308 observations). Furthermore, for the same period, daily trading volume of futures contracts bought and sold by eight different types of domestic investors and total open interest is available. The different types of domestic investors consist of Securities, Insurance, Investment, Bank, Merchant and Mutual Fund, Pension Fund, Others and Individuals. Finally, daily trading volume data is also available for foreign investors not members of the Korean stock exchange.

5.4.1 Index futures volatility

The returns for the futures contracts traded on the KOSPI200 index are defined as $R_{F,t} = 100 * Ln(F_t/F_{t-1})$. The most widely used proxies for daily volatility using close to close prices are squared and absolute returns. Other volatility measures utilising range based data have been suggested in the academic literature due to their higher efficiency compared to the aforementioned ones. The intuition behind range based volatility estimators is that in case, just by chance, the open and closing prices are close to each other when the security price has fluctuated substantially throughout the day, then the absolute or squared return will indicate low volatility. Parkinson (1980) proposed the use of the range for estimating volatility while Garman and Klass (1980) combine the range with opening and closing prices to produce highly efficient volatility estimators. Further studies that try to improve the range based volatility estimators include Beckers (1983), Rogers and Satchell (1991), Yang and Zhang (2000). Garman-Klass (1980) show that their volatility estimator is about eight times more efficient than using the close-to-close prices to measure volatility. The Garman-Klass estimator that we use in this study is defined as

$$\hat{\sigma}_t^{gk} = \frac{1}{2}\left[\mathrm{Ln}(High) - \mathrm{Ln}(Low)\right]^2 - 2\left[2Ln(2) - 1\right]\left[\mathrm{Ln}(Open) - \mathrm{Ln}(Close)\right]^2$$

where $\hat{\sigma}_t^{gk}$ is the Garman-Klass volatility, Ln is the natural logarithm and *High*, *Low*, *Open*, *Close* are the high, low, open and closing prices of the KOSPI200 Futures Index in the interval of a trading day. Brown (1990) argues that the opening and closing prices are highly influenced by microstructure effects and opposes their inclusion in estimators of volatility. Moreover, Alizadeh (1998) reveals little theoretical efficiency gain from combining the range with the opening and closing prices. For this reason, we estimate the range as

$$\hat{\sigma}_t^{range} = \max \ln(F_\tau) - \min \ln(F_\tau)$$

where $\tau = t-1, t-1+\frac{1}{n}, t-1+\frac{2}{n}, ..., t$ and n denotes the number trades within a single trading day. The properties of the range based estimator depend on the level of trading activity. This means that the smaller the sampling interval of the price path is, the more accurate the range based volatility estimator will be. Alizadeh et al (2002) argue in favor of using the range as volatility estimator as the return interval shrinks and discuss the very good performance of range based volatility in the presence of microstructure noise. **Figure**s 5.1-5.3 plot the different volatility estimators over time.

5.4.2 Trading volume

As regards trading volume of the KOSPI 200 futures index, the Korean Stock Exchange publishes the daily amount of contracts traded by eight types of domestic investors and the total amount by foreign Investors. Domestic investors are categorized as institutional and individual investors. Moreover domestic institutional investors consist of securities and non securities companies. The latter are divided into Insurance, Investment, Bank, Merchant and Mutual Fund, Pension Fund and Others. In this study we use total trading volume as well as disaggregated data of four different types of investors, namely member institutional (securities companies), non-member institutional (non securities), non-member individual and non-member foreign investors. We select these trader type volume categories according to their proximity and access to the trading system. **Figure**s 5.4-5.7 plot trading volume over time for the different trader types considered in this study.

As we mentioned above, membership is granted only to the securities companies licensed by the Financial Supervisory Commission to conduct securities business. Moreover, no individual members are accepted. Members of the Korean Stock Exchange have the right to trade and the responsibility of clearing the trade. Moreover access to the trading system is granted to the member firms only. Any members who have their own system, which is a client server interface for customers or multi-functioning system, can access the KSE system directly. Overseas brokers or dealers cannot access the Korean Stock Exchange system directly, but they can connect to a member's system located in Korea through international securities companies' global network.

Securities companies are members of the Korean Stock Exchange and as highlighted above they have direct access to the trading system. This gives an information advantage to this type of investors as they have up to the minute information about the supply and demand orders of the futures and cash markets. Daigler and Wiley (1999) argue that clearing members trade to benefit from mispricing of the futures contracts as well as for long term hedging and arbitrage purposes. Additionally, Kodres and Pritsker (1997) show that many smaller insurance companies and pension funds are not members of the exchange they trade in, as their trading activity is insufficient to justify a seat. In this study we have a volume category matching closely this type of institutional investors and this is an aggregation of the trading volume generated by Insurance, Investment, Bank, Merchant banks and Mutual Fund, Pension Fund and Other non-member institutional investors. Their share of trading volume is small compared to member institutional investors and they intend to trade for hedging and speculative purposes. The amount of information available for non-member investors in the Korean futures market is limited as anyone wishing to place an order is required to open an account for futures and options trading with a member firm. non-member institutional, foreign and individual traders are those least likely to have access to temporary private information such as trader's risk aversion, trading constraints and the supply and distribution of the underlying asset which affect prices in these markets (see Ito, Lyons and Melvin ,1998, Philips and Weiner,1994). Based on the information available as well as the different trading motives we would expect to find volatility-volume relationships that are not uniform over the different type of investors trading in the KSE futures market.

Wiley and Daigler (1998) examine the characteristics and relations among four categories of traders. They find that after scalpers, the general public trades most frequently and there are strong coincident correlations between pairs of groups such as scalpers, clearing members and the general public. Furthermore, they find that any information about prior days trading volume, both within and across trader categories, is useful for only a few days. A similar statistical analysis is followed in this study to identify the statistical characteristics of trading volume and measure volume relationships across trader categories. In **Table** 5.1 we report descriptive statistics regarding the percentage breakdown of total volume into the four trader categories mentioned above and the cross correlations between the identified trader categories. Average total trading volume was 0.62 trillion Korean won for the two years ending in 1997 and increased to 23.41 trillion won for the two years ending in 2005. This immense increase in trading volume over the years is not shared evenly across the different type of traders. Member institutional investors' average percentage of trading was 69.60 percent for the two years ending in 1997 and thereafter decreases gradually to 23.97 percent for the two years ending in 2005. As regards non-member investors, individuals' percentage of trading volume doubled after the financial crisis and remains almost at the same levels over the end of 2005. The presence of foreign investors in the index futures market almost doubles every two year period after the Asian financial crisis to match the performance of member institutional investors from the beginning of 2004. As regards non-member institutional investors' trading, their participation gradually increases until the end of 2001, reaching a level of 10 percent, while towards the end of the sample their participation fell to 6.37 percent.

TABLE 5.1

As regards cross correlations between traders, amongst the non-member investors, individuals show the highest correlation with member investors over all trading volume components. Moreover, the pair correlations between non-member investors reveal that the total and moving average components of institutional and individual investors are highly correlated but the correlations concerning the expected and unexpected components are the highest among institutional and foreigner investors.

Several studies in the volume-volatility literature suggest detrending trading volume into expected and unexpected components. This separation allows us to examine the extent to which surprises versus trend activity affect the volatility-volume relationship. Various detrending methods have been suggested depending on whether the underlying process is trend or stochastic stationary (See Appendix 2). As is evident from **Table** 5.1, the assumption of a constant growth rate for trader type volume seems quite restrictive. For this reason we employ a detrending procedure that allows for a stochastic trend component in volume as well as an autocorrelated disturbance term (see Andersen, 1996). In other words, we filter out the trend in volume while at the same time retaining the correlated deviations around this trend, which are often associated with increased information arrival intensity in market microstructure theory. We first construct a detrended activity series[1] by deducting an equally weighted moving average of length 200 days, centered on the estimated trend component, from the original series. Standard one-sided (weighted) averages are used for the start and end of the sample as suggested by Brockwell and Davis (1987). Further we partition the detrended activity series into expected and unexpected components using an ARIMA(0,0,10) model. The ARIMA (0,0,10)[2] model estimates the expected value using the 10-day moving average of the change in detrended volume. This is

[1] The detrended trading activity series are stationary for all trader types and open interest.

[2] We use 10 lags in the ARMA specification so that we are consistent with previous studies while further investigation into alternative lag structures gives rise to expected and unexpected components highly correlated with the ones arising from the 10 lag structure.

in line with the Bessembinder and Seguin (1993) empirical study, who interpret the unexpected component of the detrended series as the daily activity shock and the expected component as activity that is forecastable but highly variable across days. The moving average component of length 200 days captures the long run changes in the trading activity. Finally, we include open interest as a trading activity variable due to its association with the number of active informed traders. Bessembinder and Seguin (1993) argue in favor of using open interest in conjunction with volume data as it may provide insights into the price effects of market activity generated by informed versus uninformed traders or hedgers versus speculators. Open interest is also partitioned into expected and unexpected components once we first deduct the moving average component.

5.5 Estimation procedures

The econometric techniques that we use in this paper are mainly parametric and consistent with previous studies that investigate the impact of trading volume on volatility (see, Daigler and Wiley (1999), Bessembinder and Seguin (1992, 1993) and Schwert (1990). This procedure allows for unbiased estimation of the conditional daily return volatility while at the same accounting for effects such as the day of the week, the persistence of volatility, and lagged returns. In this model equation (1) estimates the conditional return based on lagged returns, the day of the week and lagged volatility. Equation (2) estimates conditional volatility using transformations of past volatility, day of the week, and trading activity variables. Equation (3) transforms the lagged unexpected returns. The equations are:

$$R_t = a+\sum_{i=1}^{4} \rho_j d_i+\sum_{j=1}^{n} \gamma_j R_{t-j}+\sum_{j=1}^{n} \pi_j \hat{\sigma}_{t-j}+U_t \ ,$$

$$\hat{\sigma}_t = \delta+\sum_{i=1}^{4} \eta_j d_i+\sum_{j=1}^{n} \beta_j \hat{\sigma}_{t-j}+\sum_{j=1}^{n} \omega_j \hat{U}_{t-j}+\sum_{k=1}^{m} \mu_k A_k+e_t \ ,$$

$$\hat{\sigma}_t = \left|\hat{U}_t\right| \sqrt{\pi/2} \,,$$

where R_t is the percent change in the futures price on day t; d_i represent the four dummy variables for the days of the week; $\hat{\sigma}_t$ is the volatility on day t and A_k are the activity variables of volume, change in open interest. The residual U_t represents unexpected returns.

In order to estimate the conditional volatility of the Korean Index futures market, equations (1) and (2) are estimated using an iterative procedure. First, we use the series of close to close returns on KOSPI200 index futures contract to estimate equation (1) without lagged volatility estimates. Second, the volatility transformation defined in equation (3) is applied to the residuals of equation (1) and using these transformed values we estimate equation (2). Third, the fitted volatility values from equation (2) are used to re-estimate equation (1). Finally, we re-estimate equation (2) with the residuals from the consistent estimation obtained from the second pass of equation (1).

Lags of the estimated standard deviation series are included in equation (2) in order to measure the effect of volatility persistence over time. Additionally, lagged raw residuals from (1) are included in equation (2) as it is evident from previous studies (Karpoff, 1987, Schwert, 1990) that they have explanatory power and they also allow for possible effects of recent realized returns on volatility. To be consistent with previous studies and incorporate the range of significant lags for each variable we set the number of lags n equal to 10 in both equations. Further examination of different lag structures using information criteria leaves the results unaltered.

The trading activity variables A_k in equation (2) are the expected and unexpected values of both the trader type volumes and the change in the contract's open interest. Trading activity variables are partitioned so we can investigate whether surprises in trading volume pass on more information and therefore have a larger effect on futures prices than forecastable volumes. Further, including expected and unexpected components of open interest in equation (2) allows us to measure the sensitivity of volatility on a volume shock especially when a change in open interest occurs at the same time. For example, if the unexpected component of volume and open interest are positive and negative respectively, a trade that increases both volume and open interest has a smaller effect on volatility than a trade that increases volume but decreases open interest or leaves it unchanged.

Moreover, we re-examine the volatility-volume relationship by individually substituting the Garman-Klass (1980) and High-Low range based measures of volatility for $\hat{\sigma}_t$ in equations (1) and (2). Since these measures calculate volatility independent of the return equation, we generate one pass estimation of equations (1) and (2) to fit the volatility-volume relation using these intraday estimators or proxies of volatility.

5.6 Empirical Results

5.6.1 Volatility-volume relationship by trader category

Raw volume results

Table 5.2 shows the results of regressing different measures of Index futures volatility on the volume for member institutional and non-member institutional, individuals and foreign investors as well as open interest. We also include variables such as lagged returns, lagged volatility and days of the week. The first column of Table 2 reports the results of running a regression of the daily return standard deviation on each trader type volume. As regards member institutional investors their unexpected component of trading volume is significant and positively associated with volatility. The same qualitative relationship is evident for non-member institutional investors over all volatility estimators and for non-member individuals over the range based estimators, namely the Garman-Klass and High-Low volatility. On the other hand, the unexpected component of non-member individual investors is negative and highly significant in the case of return volatility. In addition, surprises in non-member foreign investors' volume are positively and negatively associated with Return and Garman-Klass volatility respectively.

TABLE 5.2

The above results indicate that unanticipated trading volume generated by member institutional, non-member institutional and individual investors are positively related with range based volatility with the largest effect shared between member institutional and non-member individual investors. Interestingly, surprises in non-member foreign investors trading volume exert a stabilising effect on futures daily price range although they are insignificant for High-Low volatility. As regards return standard deviation, the positive effect over volatility is now shared over member institutional, non-member institutional and foreign investors with member institutional investors' coefficient being the most significant. On the other hand, in the case of return volatility, it is the non-member individuals unexpected component which affects volatility negatively. Moreover, the expected component of trading activity is insignificant over all trader types as well as over all volatility estimators and for this reason we do not analyse further the corresponding results.

An interesting result arises by looking at the moving average components of investors trading volume. The moving average component of non-member institutional and foreign investors is significant and negatively related to return volatility, indicating a stabilization effect over the long run for these trader types. In addition, the low frequency component of non-member individual investors trading volume is significant and positively associated with return volatility, exhibiting a destabilisation force on volatility over the long run. These results are robust over all volatility estimators as can be seen in **Table** 5.2. The inclusion of open interest as an activity variable in the volatility regressions is supported by significant coefficients on the moving average and unexpected components. The low frequency component of open interest is positively associated with volatility while surprises in open interest are often associated with lower volatility (negative relation). It is interesting to note here that unexpected changes in open interest reduce the sensitivity of volatility to volume, especially when a trade increases both trading volume and open interest. These results are robust across the different volatility proxies that we have used. However, their significance changes slightly as we move from one volatility estimator to the other.

An interesting exercise in our analysis is to check whether our results are robust to the Asian Financial Crisis that hit the major Asian Economies in the summer of 1997 and lasted over the end of the same year. Another reason for investigating the period after the financial crisis is that non-member investors significantly increased their participation in futures trading with non-member individual investors almost doubling their trading in the two year period following the Asian Financial Crisis (see descriptive statistics in **Table** 5.1). **Table** 5.3 reports the results of regressing volatility on volume excluding the period from the start of the sample until the end of 1997 (388 observations).

As is evident in **Table** 5.3 the unexpected components of trading volume remain highly significant and of the same sign as for the whole sample. More specifically surprises in trading activity are positively associated with range based volatility in the case of member institutional, non-member institutional and individual investors with the non-member individual being the most dominant players. Surprises in non-member foreign investors' volume no longer affect range based volatility. Results for the return standard deviation regression remain the same with member institutional investors being the most dominant among those who share a positive effect over return volatility and non-member individuals affecting volatility negatively, although somewhat less significantly. The expected components of trading volume and open interest remain insignificant. An important change is experienced concerning the moving average component of all investors trading activity after the Asian Financial Crisis. All the coefficients become insignificant and non-member individual and foreign investors' coefficients exchange sign. Another change is documented in the moving average component of open interest where the effect turns from positive to negative while unexpected changes in open interest remain negative and significant.

TABLE 3

The results after the financial crisis leave the unexpected and expected components of trading volume and open interest intact across different types of investors and volatility estimators. The moving average component of all non-member investors becomes insignificant after the financial crisis while being significant for the whole period. Moreover the moving average component of open interest turns to negative and is still significant, indicating that long run changes in open interest are often associated with increased informativeness and lower volatility.

Overall we find that unexpected levels of volume and open interest are more important in explaining volatility than expected and moving average components. This property is quite robust across the different trader types, volatility estimators as well as across different sample periods (whole sample and after crisis period).

In particular we find that surprises in non-member investors' trading volume are positively associated with volatility in most of the cases. This result is consistent with Daigler and Wiley's (1999) finding that the positive volatility volume relationship is driven by the general public or less informed investors. In this study we consider non-member investors as less informed due to the fact that they do not have direct access to the trading system. Moreover, we find that member investors' unexpected trading volume also exhibits a positive relation with volatility, a result consistent with Delong et al (1990b), who argue that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders. The coefficients relating the unexpected component of open interest with volatility are uniformly negative, implying that an increase in open interest during the day lessens the impact of a volume shock in volatility. This is consistent with the Bessembinder and Seguin (1993) results, who also find a negative relation between surprises in open interest and volatility. Furthermore, the after crisis period has a significant impact on the low frequency components of non-member investors and open interest. Although non-member institutional and foreign investors trading volume seems to play a stabilization role for volatility over the long run, when we exclude the Asian Financial Crisis period all moving average coefficients become insignificant. As regards the other variables that we include in the volatility regressions, lagged volatilities are significant and range from 0.69 to 0.76 for the whole sample and from 0.41 to 0.61 for the after crisis period. Lagged unexpected returns are negative and significant in four out of six cases. Finally, the explanatory power of the volatility-volume regressions are substantially higher for the High-Low (0.46, 0.49) and Garman-Klass volatility (0.34, 0.39) estimators than the return volatility ones (0.24, 0.20).

Log volume results

In this section we try to evaluate whether the number of active value-motivated traders can have a significant impact on the volatility volume relationship (Kyle (1985), Admati and Pfleiderer (1988). We repeat the prior analysis using the natural logarithm of each trader type volume and open interest. By taking the log differences of the original trading volume series and its 200 day centered moving average, we get a detrended series interpreted as percentage deviations from trend. The approach is motivated by the fact that log differences of volume series are approximately stationary, as argued by Andersen (1996). Further we decompose the resulting correlated detrended series into expected and unexpected components using an ARIMA(0,0,10). Trading volume shocks now represent deviations of volume from its expectation (the 10-day moving average of the change in percentage deviation from trend). Thus the unexpected log volume series is unaffected by trend growth in volume.

Table 5.4 shows the results of regressing volatility on the natural logarithm of member and non-member investors' trading volume. The results for this alternative specification of trading volume support some of the conclusions reached on the raw volume regressions. The unexpected trading activity of all non-member investors (institutional, individual and foreign) is significant and positively associated with all volatility estimators (Return VLT, Garman-Klass VLT and High-Low VLT). The effect of non-member individuals is the highest on the range based volatility (Garman-Klass, High-Low) but negligible on the return volatility. Also surprises on member institutional investors trading volume are positively associated with range based volatility and negatively associated with return volatility.

The expected component of trading volume is significant for the two major players of the Korean Stock Exchange, namely the member institutional and non-member individual investors. The effect of member institutional investors is negative and significant while the effect of non-member individuals in positive and significant over all volatility estimators. The expected components of non-member institutional and foreign investors as well as of open interest are positive but very insignificant.

TABLE 5.4

Interestingly the moving average component appears to be quite significant over all types of traders. Among the non-member investors, institutional and foreigners seem to play a stabilising role (negative) over volatility with the effect of foreign investors more significant over all volatility estimators. However, the long run effect of non-member individual investors is positive and very significant. Moreover, the moving average component of member institutional investors is negative over all volatility estimators while somewhat less significant for the range based volatility estimators (Garman-Klass VLT, High-Low VLT). Finally, the moving average component of open interest is positive over all different measures of volatility while the unexpected component is significant and negatively associated with the range based volatility estimators. These results also are quite consistent with the raw volume results.

As in the previous section we investigate whether our results are robust to the Asian Financial Crisis that hit the major Asian Economies in the summer of 1997 and lasted until the end of the same year, for this alternative volume specification. **Table** 5.5 below reports the results of regressing volatility on the natural logarithm of volume excluding the period from the start of the sample until the end of 1997 (388 observations).

The results for the after crisis period reveal that the unexpected component of all non-member investors remains positive and significant for most of the cases.

The strongest effect on volatility is imposed by individuals in the case of range based volatility while their effect remains still negligible in the case of return standard deviation. As regards surprises in the trading activity of member institutional investors, the mixed and significant effect on volatility evidenced for the whole sample becomes insignificant after the crisis. Moreover, activity forecastable across days (expected component) remains highly significant and of the same sign (positive) only for non-member individual investors. So after the crisis, the expected component of non-member individuals' trading volume continues to fluctuate in the same direction as volatility. The expected trading activity of member investors is still negative in sign; however, it becomes insignificant after the crisis.

Among the non-member investors, institutional and foreigners' slowly changing component (moving average) of trading volume is still negatively associated with volatility with the effect of foreigners remaining highly significant for the after crisis period. The long run changes in individuals' trading volume continue to be positively associated with volatility while again the after crisis results become of much less significance especially for the case of return and Garman-Klass volatility. Overall, the moving average component of non-member investors remains identical in sign but their effect after the crisis seems to be less significant. As regards the effect of member investors' long run changes in trading activity on volatility it remains negative and slightly less significant.

TABLE 5.5

Furthermore, the moving average component of open interest remains positive over all measures of volatility but highly significant only for the case of High-Low proxy. More importantly, the unexpected component of open interest is negative in sign and more significant after the crisis. This result provides further evidence on the negative relation between unexpected open interest and volatility. It is consistent with the results found using raw volume as well as with the results in other studies such as Bessembinder and Seguin (1993) and Daigler and Wiley (1999).

Overall, in the case of log volume, we find again that unexpected levels of log volume and open interest are more important in explaining volatility than expected and moving average components. This property is quite robust across different trader types, volatility estimators as well as across different periods. Again we find that surprises in non-member investors' trading volume are positively associated with volatility in most of the cases. This result is consistent with Daigler and Wiley's (1999) finding that the positive volatility-volume relationship is driven by the general public or less informed investors. In this study we consider non-member investors as less informed due to the fact that they do not have direct access to the trading system. Moreover, we find that member investors' unexpected trading volume also exhibits a mixed relation with volatility, a result partly consistent with Delong et al (1990b) who argue that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders and partly consistent with Daigler and Wiley (1999), who find that the relation between clearing members and other floor traders with volatility is often negative, suggesting that information about futures pit trading and order flow from trading activities may actually help reduce risk and therefore enhance the value of holding a seat.

Moreover, forecastable activity across days (expected component) is negatively related to volatility for member institutional and positively related to volatility for non-member individuals. After the financial crisis only non-member individuals coefficients are highly significant and of the same sign as of the whole sample.

The after crisis period has a significant impact on the low frequency components of member and non-member investors and open interest. Although the sign of the coefficients remain the same, the significance of them diminishes significantly in some cases. Among the non-member individual and foreign investors affecting volatility negatively over the long run, only the effect of non-member foreign investors remains highly significant after the crisis. As regards the moving average component of non-member individuals, it remains still positive and significant only for the High-Low volatility regression. In addition the low frequency component of member institutional investors retains its negative sign and importance (although less) after the crisis.

As regards the other variables included in the volatility regressions lagged volatilities are significant and range from 0.48 to 0.54 for the whole sample and from 0.29 to 0.47 for the after crisis period. Lagged unexpected returns are negative and significant in five out of six cases. Finally, the explanatory power of the volatility-volume regressions are substantially higher for the High-Low (0.58, 0.59) and Garman-Klass volatility (0.43, 0.48) estimators than the return volatility ones (0.28, 0.26).

Time-to-maturity effects

In this section we try to investigate whether the trader type behavior around the expiration of the futures contracts has a different impact on the volatility-volume relationship evidenced over the whole sample. For this reason we perform the same regression analysis as in the previous sections while we introduce a constant and trading volume slope dummies around the expiration of the futures contracts. The constant dummy in the volatility regression would allow us to test whether a pattern known as the 'Samuelson' effect is evident. Samuelson (1965) shows that the return volatility of a futures contract monotonically rises as the contract expires. This is mainly a price elasticity effect because when the futures contract approaches its expiration, its price elasticity to market shocks increases and therefore its volatility rises. In contrast to the "Samuelson effect" alternative theories such as the state variable effect (see Richard and Sundaresan (1981), Andersen and Danthine (1983) and the speculative effect (see, Hong (2000)) allow for more rich time-to-maturity patterns in futures return volatility. Hong (2000), allowing for differently informed investors and nonmarketed risks, argues that as the futures contract rolls to its expiration date, its sensitivity to the non marketed risks increases and uninformed investors can learn less about the fundamental, so information asymmetry rises. Therefore, less private information is impounded into the futures price and so, all else being equal, the futures price moves less as the contract expires. In line with Hong's (2000) argument it is interesting to investigate if uninformed investor's trading volume is less associated with volatility changes, especially near the futures contract expiration.

Moreover, the variation in information asymmetry that affects the term structure of futures return volatility is also an important determinant of open interest according to Hong (2000). The author shows that open interest can take on rich time-to-maturity patterns based on the fact that the higher the adverse selection cost taken by uninformed investors, when they trade with informed investors, the lower the open interest will be. Additionally, Milonas (1986) examines the time- to-maturity pattern of open interest for different futures markets with the very distant and the nearest contracts having the least open interest, probably due to their high illiquidity. Further, he finds that for the liquid contracts of intermediate maturities, different time-to-maturity patterns can also arise, with more distant contracts having more or less open interest than those nearer to the expiration. So, the effect of changes in open interest, near the contract expiration, on futures volatility will provide some evidence of the ability of the market to absorb trading volume shocks by the different types of trader.

As we see from **Table** 5.6, and in comparison with the results from **Table** 5.2, the qualitative relations between volatility and volume remain almost the same over all types of trader and volatility estimators for the whole period. Among the most notable differences, in terms of significance, is that for non-member institutional investors' unexpected trading volume. The t-statistics become much more significant when we add the trading volume dummy variables in the volatility regression. The dummy variables take the value of 1 near (two weeks before the expiration week as well as the days until the expiration of the contract) the expiration of the futures contract and the value of zero otherwise. The same effect is evident for non-member individuals and foreigners in the case of return volatility while the same traders' effect diminishes slightly in the case of range based volatilities. In the case of member institutional investors, the volatility-volume relationship continues to be highly significant and positive. Finally the unexpected component of open interest continues to affect volatility negatively over the sample.

Moreover, the expected component of trading volume is insignificant in most of the cases, a result consistent with evidence from **Table** 5.2. However, there are some significant values in the case of return volatility for non-member investors trading volume. Additionally, the moving average component of member investors is still insignificant despite adding the trading volume dummy variables. In addition, non-member investors' significance reduces a little rendering the effect of non-member investors still influential over all volatility estimators. The same result does not hold for the moving average component of the open interest, which, although still positive, becomes insignificant.

TABLE 5.6

TABLE 5.7

It is now worth looking at the second panel of **Table** 5.6 in order to compare the behavior of member and non-member investors near the expiration of the futures contracts with that over the whole sample. As regards non-member investors, the estimated coefficient for the slope dummy on institutional investors' unexpected volume is negative and significant, implying a reduction in the magnitude of the relation between volume and volatility towards the end of the contract life. In other words, the combined effect reveals a less significant role for non-member institutional investors as the futures contract rolls to its expiration. Moreover, the slope dummy coefficient for non-member individual and foreign investors' unexpected volume is insignificant, thus indicating no change in the behavior of these trader types near contract expiration. The same result is evident for member institutional investors. Further, an important result of this analysis is that the slope coefficient associated with unanticipated open interest is positive and highly significant, showing that open interest shocks are associated with bigger price movements towards the end of the contract life. Additionally, the slope dummy on expected volume becomes significant and negative for non-member institutional and foreign investors but significant and negative for member institutional investors. This result indicates that trading volume forecastable across days, for these types of trader, is much more associated with volatility as the contract rolls to its expiration. Finally, the estimated coefficient for the shift in the regression intercept near the futures expiration is negative and significant, showing reduced futures volatility near contract expiration.

Overall, when we include the trading volume dummies in order to capture time to maturity effects, the volatility-volume relationships across trader categories do not change sign while their significance in most cases changes a little. We conclude that, despite adding the slope dummies on trading activity, there is no evidence that trading activity across different types of traders affects volatility in a different way apart from the case of non-member institutional investors. In general we find small changes in significance among different investors with the most apparent difference concerning the non-member institutional trading becoming much less associated with volatility as the contract rolls to its expiration. In addition, surprises in open interest during the day are associated with much bigger price movements near the expiration of the contract, meaning that volatility becomes more sensitive to volume shocks especially when trades result in an increase on open interest as well. Moreover, the expected component of investors' volume becomes more significant near contract expiration while the level of volatility decreases slightly for the same period. The other variables included in the volatility regressions such as lagged volatilities and lagged unexpected returns are also very significant and of the same sign and magnitude compared to the values in **Table** 5.2. Finally, when the slope dummies on trading activity are added, the explanatory power of the trading activity and other variables in the volatility regressions is almost the same and consistent with the evidence in **Table** 5.2.

5.7 Conclusions

This study provides empirical evidence on the volume volatility relationship implied by theoretical models which associate movements in prices and trading volume with information, dispersion of beliefs and trading motives. We have examined the impact of different trader types on volatility in the Korean index futures market since its inception in the 2nd of May 1996. The different types of traders have been selected according to the information they possess and their access to the trading system. Moreover, the trading activity variables are partitioned into expected and unexpected components and the econometric techniques that we use allow for an unbiased estimation of daily standard deviations conditional on the trading activity variables, day of the week, lagged volatilities and lagged unexpected returns.

An important finding of this study is that surprises in volume and open interest are more important in explaining volatility than expected and moving average components. This result is robust across different types of traders, volatility estimators and sample periods. Also this result is consistent with the studies of Bessembinder and Seguin (1993), Daigler and Wiley (1999) and provides further support for the hypothesis that traders who lack information about the order flow and pit dynamics are unable to distinguish the liquidity demand of large hedgers from the volume associated with change in fundamental value.

In the case of raw volume we find, among the non-member investors, that institutional and individuals affect range based volatility positively while the same effect is shared between institutional and foreigners in the case of return volatility. When we consider the after crisis period we only find one significant case out of nine where non-member investors affect volatility negatively. Overall we find that surprises in non-member investors' trading volume are positively associated with volatility in most of the cases. This result is consistent with Daigler and Wiley's (1999) finding that the positive volatility volume relationship is driven by the general public or less informed investors. Moreover, we find that member investors' unexpected trading volume also exhibits a positive relation with volatility, a result consistent with Delong et al. (1990b), who argue that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders. The coefficients relating the unexpected component of open interest with volatility are uniformly negative implying that an increase in open interest during the day lessens the impact of a volume shock in volatility. This is consistent with the Bessembider and Seguin (1993) results, who also report a negative relation between surprises in open interest and volatility.

Although for the whole sample we report very significant relations between long run changes in non-member investors' trading volume and volatility, after the financial crisis, all these relations become insignificant. Surprisingly, the results for the whole sample reveal a stabilising role for non-member institutional and foreign investors but a destabilising one for non-member individuals, especially up to the period of the financial crisis.

Further, we have investigated the effect of the number of active value motivated traders by considering the natural logarithm of trader type volume. This alternative specification of trading volume helps interpret surprises in trading activity in terms of percentage deviations from trend so that the unexpected log volume series is unaffected by trend growth in volume. The positive relationship between volatility and surprises in non-member investors' trading volume is further reinforced, with individuals being the most active in the case of range based volatility and foreigners in the case of return volatility. These results are also consistent with those of Jones, Kaul, and Lipson (1994a), who find that public, rather than private, information is the major source of short-term volatility. Interestingly, the effect of member investors becomes much less significant and of changing sign over the different volatility estimators. Moreover, it is worth mentioning the uniformly positive and significant relationship between volatility and the expected component of non-member individuals as well as the negative and significant relationship between volatility and the moving average component of non-member of foreign investors trading volume. Interestingly, the slowly changing components of non-member individual and member institutional investors exert a strong destabilising and stabilising effect, respectively, over volatility up to the period of the financial crisis. As regards the unexpected component of open interest its effect on volatility remains negative and significant.

We also investigated the volatility-volume relationship as the futures contract roll to its expiration by adding trading volume slope dummies near the expiration date. Our results reveal a less significant role for non-member institutional investors as the futures contract moves towards expiration while we do not experience any change in trading behavior for the remaining trader types. Another important result of this exercise is that surprises in open interest during the day are associated with much bigger price movements near the expiration of the contract, indicating that volatility becomes more sensitive to volume shocks especially when trades result in an increase on open interest as well. This result is consistent with the argument of Hong (2000) that as the futures contract rolls to its expiration date, its sensitivity to nonmarketed risk shocks increases and uninformed investors can learn less about the fundamental by looking at prices. Therefore information asymmetry rises and less informed investors face a higher adverse selection cost in trading with informed investors near the futures contract expiration. As a result those uninformed traders who choose to trade with informed investors near the futures contract expiration will probably cause wider price movements so as to induce them to take the other side of the trade.

The inclusion of variables such as lagged volatilities and unexpected returns in the volatility regressions are significant in most of the cases, with the effect of lagged unexpected returns being consistently negative. Further, we find that when the high-low volatility measure is used, models that incorporate trader type volume, lagged volatilities and unexpected returns can explain up to 59 percent of the variability in volatility. In future work we aim to investigate the trader type effect on volatility using alternative detrending methods (see Appendix 2) for trading volume, such as the band pass filtering and non parametric regressions. Finally, an interesting exercise is to use nonparametric and semi-parametric techniques for analysig the trader type effect on volatility as we could capture simultaneously the long memory characteristics often evidenced in trading volume and volatility.

Table 5.1: Descriptive statistics

This table presents daily volume descriptive statistics for four categories of investors. The categories are: Member Institutional Investors (MFI), Non-member Institutional (NMFI), Non member Individual Investors (NMI) and Non-member Foreign Investors (NMF). Panel A shows the breakdown in percent of volume by category of traders and the total daily volume (in trillion Korean won). Percentages sum to 100 over each period. Panel B provides the cross correlations between each pair of volume variables. An ARIMA(0,0,10) model calculates the expected (predicted) value using the 10-day moving average of the change in volume. The unexpected volume is detrended volume minus expected volume.

Panel A: Average Trader Category Volume as a percentage of Total Volume

Investor Type	MFI	NMFI	NMI	NMF	Total
1996-97	69.60%	4.33%	23.19%	2.88%	0.6158
1998-99	41.63%	7.13%	48.59%	2.65%	4.8226
2000-01	33.49%	10.09%	49.76%	6.66%	8.1794
2002-03	24.42%	8.39%	53.69%	13.5%	19.0362
2004-05	23.97%	6.37%	47.11%	22.55%	23.4083

Panel B: Cross - Correlations between Trader Categories

Series	MFI - NMFI	MFI - NMI	MFI - NMF	NMFI - NMI	NMFI - NMF	NMI-NMF
Total	0.828	0.858	0.769	0.821	0.739	0.804
Moving Av.	0.935	0.925	0.873	0.933	0.793	0.898
Expected	0.521	0.656	0.388	0.414	0.579	0.320
Unexpected	0.502	0.608	0.458	0.380	0.593	0.397

Table 5.2: Regressions of volatility on expected and unexpected trader type volume (Entire Period)

Values in brackets are t-statistics for the hypothesis that the coefficient is zero using White (1980) heteroscedasticity consistent standard errors. Test statistics for 10 lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. Coefficients on raw volumes are scaled so the underlying unit is one trillion of Korean Won. Time series means are deducted from each volume series. VLT stands for volatility.

Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	0.6912 (4.21)***	0.0858 (2.71)***	0.0711 (6.55)***
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	0.1244 (0.60)	0.0393 (1.08)	0.0161 (1.33)
Expected	0.1259 (0.64)	0.0305 (0.67)	0.0075 (0.48)
Unexpected	0.4495 (2.12)***	0.1775 (4.75)***	0.0886 (7.07)***
Non-member Institutional Inv.			
Moving average	-0.5486 (-1.83)**	-0.1247 (-2.30)***	-0.0371 (-2.32)***
Expected	0.378 (1.23)	0.0021 (0.04)	0.0161 (0.94)
Unexpected	0.3124 (2.10)***	0.0496 (2.01)***	0.0309 (3.39)***
Non-member Individuals Inv.			
Moving average	0.3425 (1.44)*	0.0656 (1.62)**	0.0250 (1.91)***
Expected	-0.2363 (-0.68)	0.0111 (0.18)	-0.0071 (-0.38)
Unexpected	-0.4176 (-1.92)***	0.2705 (7.04)***	0.0859 (6.35)***
Non-member Foreign Inv.			
Moving average	-0.4247 (-2.24)***	-0.0892 (-2.18)***	-0.0401 (-3.62)***
Expected	-0.0475 (-0.43)	-0.0133 (-0.64)	-0.0086 (-1.23)
Unexpected	0.2333 (2.44)***	-0.0334 (-1.79)**	-0.0014 (-0.22)
KOSPI200 open interest			
Moving average	0.4305 (1.45)*	0.1163 (1.89)***	0.0397 (2.29)***
Expected	0.1666 (0.41)	0.0848 (0.99)	0.0046 (0.19)
Unexpected	-0.3690 (-0.69)	-0.2140 (-1.75)**	-0.0789 (-2.27)***
Sum of 10 lagged volatilities	0.6938 (128)***	0.7397 (84.2)***	0.7609 (427.5)***
Sum of 10 lagged unex. returns	-0.1919 (6.89)***	-0.0444 (5.75)***	-0.0088 (3.83)***
Regression $\bar{R}^2$	0.239	0.347	0.463

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Table 5.3: Regressions of volatility on expected and unexpected trader type volume (After Crisis Period)

Values in brackets are t-statistics for the hypothesis that the coefficient is zero using White (1980) heteroscedasticity consistent standard errors. Test statistics for 10 lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. Coefficients on raw volumes are scaled so the underlying unit is one trillion of Korean Won. Time series means are deducted from each volume series. VLT stands for volatility.

Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	1.6087 (7.19)***	0.1905 (6.04)***	0.1285 (8.59)***
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	-0.1267 (-0.59)	-0.0033 (-0.09)	0.0018 (0.15)
Expected	0.2338 (0.89)	0.0304 (0.71)	0.0125 (0.81)
Unexpected	0.4795 (2.29)***	0.1486 (4.30)***	0.0792 (6.51)***
Non-member Institutional Inv.			
Moving average	-0.2311 (-0.81)	-0.0542 (-1.17)	-0.0132 (-0.85)
Expected	0.4402 (1.45)*	0.0093 (0.19)	0.0191 (1.13)
Unexpected	0.3133 (2.10)***	0.0666 (2.89)***	0.0332 (3.66)***
Non-member Individuals Inv.			
Moving average	-0.1569 (-0.65)	-0.0469 (-1.26)	-0.0149 (-1.08)
Expected	0.1316 (0.38)	0.0484 (0.91)	0.0155 (0.84)
Unexpected	-0.3145 (-1.43)*	0.2523 (6.91)***	0.0864 (6.52)***
Non-member Foreign Inv.			
Moving average	0.1536 (0.75)	0.0298 (0.84)	0.0041 (0.34)
Expected	-0.0704 (-0.64)	-0.0219 (-1.06)	-0.0115 (-1.67)**
Unexpected	0.2491 (2.64)***	-0.0177 (-0.99)	0.0013 (0.23)
KOSPI200 open interest			
Moving average	-0.5886 (-1.85)**	-0.0871 (-1.67)**	-0.0344 (-1.81)**
Expected	-0.1321 (-0.33)	0.0407 (0.55)	-0.0041(-0.17)
Unexpected	-0.4723 (-0.92)	-0.2848 (-2.61)***	-0.0896 (-2.67)***
Sum of 10 lagged volatilities	0.4072 (28.2)***	0.5910 (82.9)***	0.6142 (183.3)***
Sum of 10 lagged unex. returns	-0.0918 (1.55)	-0.0209 (1.79)	-0.0081 (3.36)**
Regression $\bar{R}^2$	0.202	0.393	0.492

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Table 5.4: Regressions of volatility on expected and unexpected trader type log-volume (Entire Period)

Values in brackets are t-statistics for the hypothesis that the coefficient is zero using White (1980) heteroscedasticity consistent standard errors. Test statistics for 10 lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. Coefficients on raw volumes are scaled so the underlying unit is one trillion of Korean Won. Time series means are deducted from each volume series. VLT stands for volatility.

Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	1.2479 (6.15)***	0.1709 (4.72)***	0.1389 (9.86)***
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	-0.8917 (-2.18)***	-0.0731 (-0.94)	-0.0295 (-1.40)*
Expected	-1.4987 (-2.44)***	-0.3371 (-2.76)***	-0.0465 (-1.75)**
Unexpected	-0.5425 (-2.21)***	0.0721 (0.92)	0.0283 (1.44)*
Non-member Institutional Inv.			
Moving average	-0.0313 (-0.15)	-0.067 (-1.81)**	-0.0053 (-0.49)
Expected	0.3609 (0.87)	0.1179 (1.27)	0.0239 (1.13)
Unexpected	0.6122 (2.69)***	0.0663 (1.35)*	0.0417 (3.81)***
Non-member Individuals Inv.			
Moving average	0.8677 (3.73)***	0.1986 (4.39)***	0.0731 (6.57)***
Expected	0.9464 (1.75)**	0.1851 (1.69)**	0.0792 (2.97)***
Unexpected	0.0408 (0.12)	0.4845 (6.68)***	0.1705 (9.38)***
Non-member Foreign Inv.			
Moving average	-0.7505 (-5.19)***	-0.1640 (-4.89)***	-0.0680 (-8.50)***
Expected	0.2015 (1.12)	0.0678 (1.74)**	0.0054 (0.54)
Unexpected	0.7950 (6.31)***	0.1293 (6.04)***	0.0553 (8.73)***
KOSPI200 open interest			
Moving average	0.8411 (2.73)***	0.1448 (2.47)***	0.0443 (2.71)***
Expected	-0.2979 (-0.74)	0.0301 (0.36)	0.0003 (0.01)
Unexpected	0.2592 (0.42)	-0.2126 (-1.43)*	-0.0867 (-2.41)***
Sum of 10 lagged volatilities	0.4835 (45.3)***	0.5721 (41.8)***	0.5446 (147.8)***
Sum of 10 lagged unex. returns	-0.127 (3.12)**	-0.0468 (7.38)***	-0.0131 (10.1)***
Regression $\bar{R}^2$	0.275	0.428	0.579

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Table 5.5: Regressions of volatility on expected and unexpected trader type log-volume (After Crisis Period)

Values in brackets are t-statistics for the hypothesis that the coefficient is zero using White (1980) heteroscedasticity consistent standard errors. Test statistics for 10 lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. Coefficients on raw volumes are scaled so the underlying unit is one trillion of Korean Won. Time series means are deducted from each volume series. VLT stands for volatility.

Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	2.0531 (7.25)***	0.2436 (6.42)***	0.1735 (9.49)***
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	-0.7084 (-1.82)**	-0.0308 (-0.46)	-0.0285 (-1.39)
Expected	-0.2734 (-0.61)	-0.0578 (-0.58)	-0.0088 (-0.30)
Unexpected	-0.4232 (-1.35)	-0.0149 (-0.18)	0.0214 (0.81)
Non-member Institutional Inv.			
Moving average	-0.0594 (-0.26)	-0.0514 (-1.33)	-0.0008 (-0.07)
Expected	0.3241 (0.69)	-0.0193 (-0.25)	0.0063 (0.26)
Unexpected	0.6689 (2.62)***	0.0977 (2.47)***	0.0401 (3.07)***
Non-member Individuals Inv.			
Moving average	0.4117 (1.03)	0.0790 (1.04)	0.0527 (2.35)***
Expected	1.3498 (2.07)***	0.1625 (1.52)*	0.096 (2.85)***
Unexpected	-0.4341 (-1.02)	0.5456 (7.01)***	0.1613 (6.91)***
Non-member Foreign Inv.			
Moving average	-0.5379 (-2.27)***	-0.1096 (-2.34)***	-0.0631 (-4.46)***
Expected	-0.1020 (-0.40)	0.0832 (1.60)*	0.0098 (0.67)
Unexpected	1.5347 (8.03)***	0.1971 (5.94)***	0.0939 (9.20)***
KOSPI200 open interest			
Moving average	0.4434 (1.25)	0.0752 (1.22)	0.0368 (1.89)***
Expected	-0.5550 (-1.27)	-0.0458 (-0.59)	-0.0274 (-1.23)
Unexpected	-0.8534 (-1.36)	-0.4341 (-2.85)***	-0.1298 (-3.13)***
Sum of 10 lagged volatilities	0.2910 (10.5)***	0.5071 (52.1)***	0.4697 (67.8)***
Sum of 10 lagged unex. returns	-0.0918 (1.54)	-0.0275 (3.15)**	-0.0127 (8.37)***
Regression $\bar{R}^2$	0.256	0.482	0.592

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Table 5.6: Regressions of volatility on expected and unexpected trader type volume (Time-to-maturity effects)

Values in brackets are t-statistics for the hypothesis that the coefficient is zero using White (1980) heteroscedasticity consistent standard errors. Test statistics for 10 lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. Coefficients on raw volumes are scaled so the underlying unit is one trillion of Korean Won. Time series means are deducted from each volume series. VLT stands for volatility.

Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	0.7175 (4.36)***	0.0883 (2.91)***	0.0724 (6.62)***
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	0.1242 (0.52)	0.0553 (1.21)	0.0238 (1.63)**
Expected	-0.1511 (-0.53)	-0.0207 (-0.42)	-0.0158 (-0.93)
Unexpected	0.4708 (2.02)***	0.1679 (3.79)***	0.0864 (6.13)***
non-member Institutional Inv.			
Moving average	-0.4433 (-1.28)	-0.1026 (-1.67)**	-0.0326 (-1.76)**
Expected	0.8186 (2.31)**	0.0338 (0.59)	0.0380 (1.96)***
Unexpected	0.9105 (4.37)***	0.1110 (3.43)***	0.0604 (5.24)***
non-member Individuals Inv.			
Moving average	0.3595 (1.26)	0.0363 (0.76)	0.0205 (1.36)
Expected	-0.6399 (-1.67)**	0.0059 (0.09)	-0.0168 (-0.81)
Unexpected	-0.8209 (-3.18)***	0.2544 (5.74)***	0.0709 (4.74)***
non-member Foreign Inv.			
Moving average	-0.2919 (-1.29)	-0.0741 (-1.41)*	-0.0319 (-2.43)***
Expected	0.2486 (1.75)**	0.0276 (0.85)	0.0098 (0.99)
Unexpected	0.2930 (2.43)***	-0.0229 (-0.82)	0.0021 (0.25)
KOSPI200 open interest			
Moving average	0.2319 (0.64)	0.0839 (1.12)	0.0265 (1.23)
Expected	0.0877 (0.17)	0.0575 (0.51)	0.0010 (0.03)
Unexpected	-0.5032 (-0.84)	-0.2791 (-1.82)**	-0.0945 (-2.33)***
Sum of 10 lagged volatilities	0.6959 (127.1)***	0.7403 (83.3)***	0.7618 (423.1)***
Sum of 10 lagged unex. returns	-0.1884 (6.67)***	-0.0449 (5.83)***	-0.0087 (3.78)***
Regression $\bar{R}^2$	0.249	0.352	0.472

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Table 5.7: Regressions of volatility on expected and unexpected trader type volume (Time-to-maturity effects)

Time-to-maturity effects			
Regression coefficients	Volatility measures		
	Return VLT	Garman-Klass VLT	High-Low VLT
Intercept	-0.1647 (-1.23)	-0.0371 (-1.62)**	-0.0122 (-1.61)**
KOSPI200 futures volume			
Member Institutional Inv.			
Moving average	0.2265 (0.47)	-0.0132 (-0.19)	-0.0134 (-0.52)
Expected	1.1051(1.53)*	0.2767 (2.48)***	0.1141 (2.87)***
Unexpected	-0.1111 (-0.22)	0.0632 (0.81)	0.0138 (0.47)
Non-member Institutional Inv.			
Moving average	-0.6337 (-0.90)	-0.1266 (-0.99)	-0.0274 (-0.72)
Expected	-1.3453 (-1.74)*	-0.1129 (0.98)	-0.0987 (-2.27)***
Unexpected	-0.9509 (-3.25)***	-0.1150 (-2.44)***	-0.0438 (-2.58)***
Non-member Individuals Inv.			
Moving average	0.1648 (0.29)	0.1313 (-1.25)	0.0211 (0.63)
Expected	0.7464 (0.90)	-0.0679 (-0.54)	0.0059 (0.12)
Unexpected	0.4643 (0.91)	-0.0657 (0.65)	-0.0045 (-0.12)
Non-member Foreign Inv.			
Moving average	-0.3517 (-0.92)	-0.0519 (-0.82)	-0.0163 (-0.78)
Expected	-0.5367 (-2.07)***	-0.1079 (-2.38)***	-0.0446 (-2.79)***
Unexpected	0.0628 (0.35)	-0.0007 (-0.01)	0.0051 (0.42)
KOSPI200 open interest			
Moving average	0.3614 (0.58)	0.0423 (0.43)	0.0211 (0.58)
Expected	0.0089 (0.01)	0.0519 (0.25)	-0.0238 (-0.35)
Unexpected	3.7989 (2.68)***	0.7545 (2.96)***	0.3161 (3.82)***

*,**,*** Denotes statistical significance at 0.15, 0.10, 0.05 level.

Figure 5.1: Absolute returns

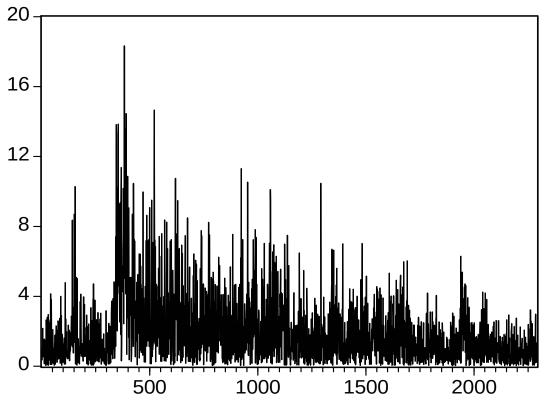


Figure 5.2: Garman-Klass volatility

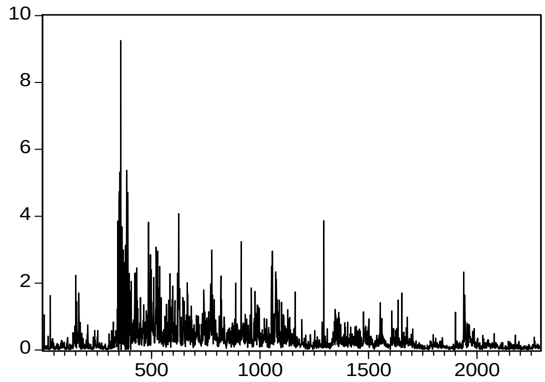


Figure 5.3: High-Low volatility

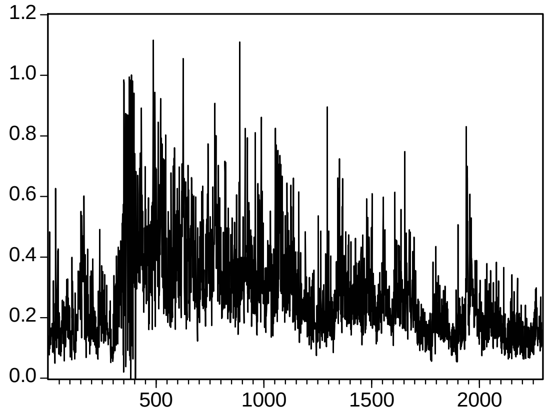


Figure 5.4: Member institutional investors

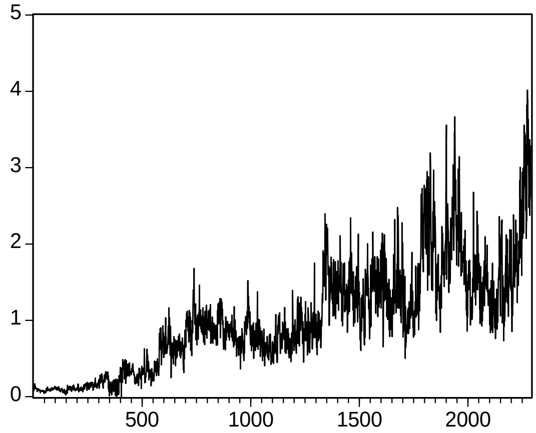


Figure 5.5: Non-member institutional investors

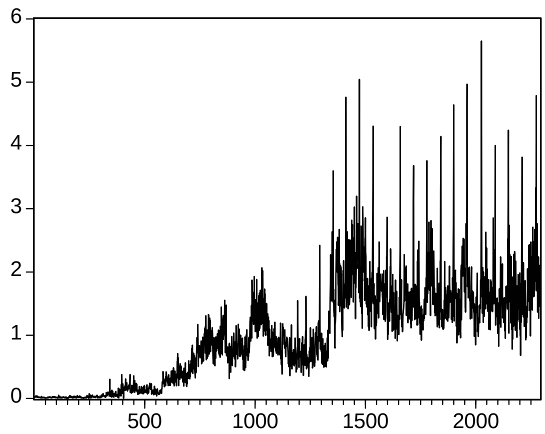


Figure 5.6: Non-member individual investors

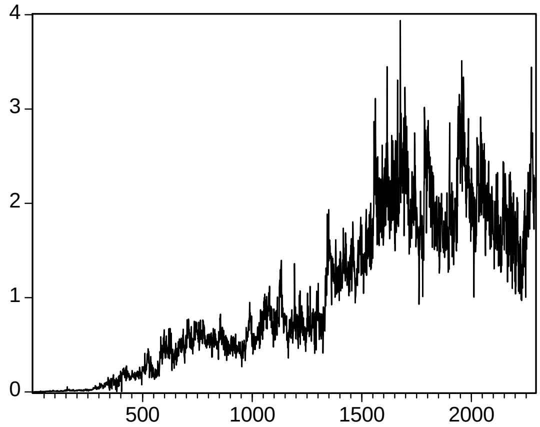
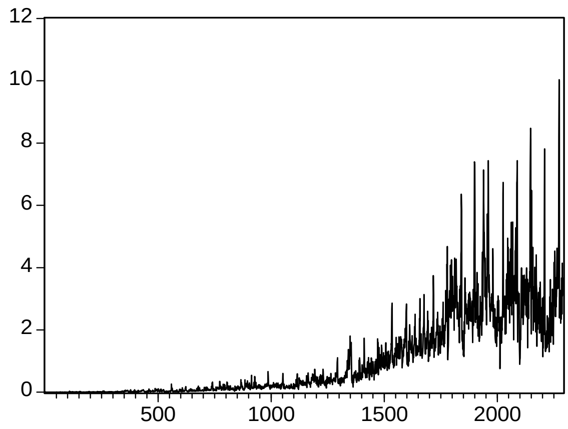


Figure 5.7: Non-member foreign investors



5.8 Appendix

5.8.1 Information assimilation process

Glosten and Milgrom (1985) suggest a framework in which informed and uninformed investors trade sequentially a unit of the risky asset at the bid or ask prices quoted by the market maker. Informed investors trade to make a profit when they obtain private signals that the quoted prices are not at full information levels while uninformed investors mainly trade for pure liquidity purposes. Since the market maker cannot distinguish between informed and uninformed investors he adjusts prices conditional on the type of trade that occurs. An important finding is that over time the sequence of trades reveals informed trader's information and the market maker's prices converge to the expected value of the asset given this information. The period over which the dynamic learning process takes place is referred to as the price discovery or information assimilation phase and is followed by a temporary market equilibrium phase when all agents agree on the price. Easley and O'Hara (1987), in a spirit similar to that of Glosten and Milgrom suggest a sequential trade model in which traders are allowed to transact different trade sizes and the market maker's learning problem involves determining both the existence and direction of new information. In case the informed trader is allowed to transact at different trade sizes a simple strategic element is introduced into the market making problem. The ability of informed traders to act strategically in order to maximize their profits leads to equilibrium outcomes that are difficult to analyse in a competitive sequential trade framework. A review of strategic trader models under a rational expectations framework is provided by O'Hara (1995). In rational expectations models, an important feature of an agent's decision problem is the inference he makes from market statistics about others' information. As O'Hara (1995) argues, it is the informed agent's conjecture about the market maker's pricing policy as well as the market maker's inference about the informed agent's information that plays a crucial role in determining the nature (and even the existence) of the equilibrium.

An extensive number of studies solve for a competitive rational market equilibrium price that reflects information contained in the order flow arising from strategically acting informed and uninformed investors (Kyle 1985, Admati and Pfleiderer (1988), Foster and Viswanathan (1990). Under the Kyle (1985) batch trading model, the market maker sets a market clearing price conditional on the aggregate net order flow arising from a strategic informed investor and noise traders. Admati and Pfleiderer (1988) focus on the timing decisions of uninformed traders transacting within a single day when informed investors' information is released immediately. Moreover, Foster and Viswanathan (1990), based on the Kyle (1985) model, consider the trading pattern arising when informed investors' information advantage fades out slowly and uninformed investors are allowed to time their trades.

5.8.2 Detrending procedures

Differencing and detrending are most often used when the series are non stationary and stationary respectively. Using terminology from frequency domain analysis we would say that differencing is a high pass filter and detrending is a low pass filter. Trend estimation in the frequency domain entails concentrating on the lowest frequencies and especially on zero frequency since a polynomial in t is non periodic or has 'period' of infinity. Granger (1964) argues that removing the trend factor by filtering merely multiplies the spectrum of the original series by a known function whereas removing the trend factor by regression methods will have a more complex effect on the spectrum of the original series. The idea of filtering was pursued further by Baxter and King (1999), who design filters that isolate the periodic components of an economic time series that lie in a specific band of frequencies. Specifically, they use frequency domain analysis to design a moving average that emphasizes specified frequency bands and also has trend elimination properties. Christiano and Fitzgerald (1999, 2003), in the same spirit as Baxter and King (1999), develop finite sample approximations to the band pass filter minimizing a slightly different objective function, which involves estimation of the spectral density of the original series. Also the assumption that the weights sum to zero at zero frequency is never imposed as a constraint and the weights are not constant at each t since at all times all data are used towards the edges of the sample. Furthermore, an alternative way for trend estimation is the adaptation of non parametric regression estimators. The intuition behind this estimator is to fit the response variable y on a k-th order polynomial of the explanatory variable x, in the neighborhood of each value of x where the nearby observations are weighted according to a kernel function. Kernel smoothing (Muller, 1988), LOESS (Cleveland, 1979) and locally weighted polynomial regression (Fan and Gijbels, 1996) are very powerful and widely used non parametric estimators. In this study we try different detrending estimators and we find that the correlation between expected and unexpected components across different estimators is very high. We choose to report the results for the expected and unexpected component arising from the band pass filters as we are able to extract the cyclical component of the futures trading volume due to the expiration of the contacts in March, June, September and December.

Chapter 6

Derivatives trading and the volatility-volume link in India.

6.1 Introduction

With the rapid growth in the market for financial derivatives, and given the prior that they are responsible for more volatile financial markets, perhaps even responsible for the financial crash of 1987, research since the crash has explored their impact on volatility in the spot equity (or cash) market. The impact of futures trading on cash market volatility is theoretically ambiguous and depends on the specific assumptions of the model (see Mayhew 2000). In keeping with this, the empirical evidence is also mixed. While some researchers have found that the introduction of futures and options trading has not had any impact on stock volatility, others have found evidence of a positive effect in a number of countries including Australia, Hong Kong, Japan, the UK and the USA. The balance of evidence suggests that introduction of derivatives trading may have increased volatility in the cash market in Japan and the US, but it had no impact on the other markets (Gulen and Mayhew, 2001).

Even as the sophistication of financial markets improves around the world and trading in financial derivatives spreads across emerging markets, the aforementioned literature is entirely restricted to developed country contexts. It is only recently that the development and financial literature have started exploring the impact of phenomena like market participation by foreign portfolio investors and expiration of derivatives contracts (see, for example, Vipul, 2005; Kim et al., 2005; Karanasos and Kartsaklas, 2007a; Wang, 2007). To the best of our knowledge, none of these papers examine the impact of the introduction of financial derivatives on cash market volatility, even though the market risk associated with such volatility is likely to have a greater economic impact on market participation by investors (and hence cost of capital) in emerging markets than in developed financial markets.

We address the lacuna in the literature about the impact of derivatives trading on the volatility of cash markets in emerging market economies by examining how the introduction of futures and options affected the volume-volatility link at the National Stock Exchange (NSE), the largest stock exchange in India. Using both daily and intra-day data from the NSE, we first analyze the volatility and volume dynamics in the cash market. We estimate the two main parameters driving the degree of persistence in the two variables and their respective uncertainties using a bivariate constant conditional correlation (ccc) Generalized ARCH (GARCH) model that is Fractionally Integrated (FI) in both the Autoregressive (AR) and variance specifications. We refer to this model as the AR-FI-GARCH. It provides a general and flexible framework with which to study complicated processes like volume and volatility. Put differently, it is sufficiently flexible to handle the dual long-memory behavior encountered in the two series.

Next we attempt to shed more light on the issue of temporal ordering of volume and volatility. To do this we estimate the bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other variable. The empirical evidence on this link remains scant or nonexistent, as pertains, in particular, to Indian data after the introduction of derivatives trading. The most commonly used measures of volatility are the absolute values of the returns, their squares and conditional variances from a GARCH-type model (see Kim et al., 2005). In this study we employ the classic range-based intra-day estimator of Garman and Klass (1980) (hereafter GK). The GK estimator is more efficient than the traditional close-to-close estimator and exhibits very little bias whereas the realized volatility constructed from high frequency data can possess inherent biases impounded by market microstructure factors (see Karanasos and Kartsaklas, 2007a and the references therein). We also use number of trades and value of shares traded as two alternative measures of volume. As pointed out by Kawaller et al. (2001), empirical evidence of an inverse relation between the two variables is rare in the literature, and it contrasts sharply with the widely held perception that the two are positively related (see also Daigler and Wiley, 1999). Wang (2007) argues that foreign purchases tend to lower volatility, especially in the first few years after market liberalization when foreigners are buying into local markets. Therefore, we investigate the significance and the sign of the causal effect.

Our sample period from November 3, 1995 to January 25, 2007 includes the introduction of (index) futures and (index) options trading. Our structural break tests results reveal that it is sensible to perform the empirical analysis for periods before and after the introduction of each of these financial instruments. In other words, we have three distinct sub-periods in our data. The results suggest that the impact of the number of trades on volatility is negative in all three periods. Similarly, the effects from the value of shares traded to volatility are negative in all three periods considered. This observation is consistent with the view that the activity of informed traders is often inversely related to volatility. This result is also in line with the theoretical arguments in Wang (2007). However, in the period from the introduction of options contracts until the end of the sample, the impact of the value of shares traded on volatility although still significantly negative is much smaller in size. Our intuition is that the introduction of derivative securities is very likely to make informed and discretionary liquidity traders to change the composition as well as the number of stocks traded and, consequently, change the informational role of the value of shares traded in terms of predicting volatility. In sharp contrast, both measures of volume are independent from changes in volatility. Another important finding of our study is that the introduction of futures trading leads to a decrease in spot volatility, a result consistent with the empirical finding of Bessembinder and Seguin (1992).

We also use both stylized non-parametric tests and the bivariate ccc AR-FI-GARCH model to analyse the impact of expiration of derivatives contracts on the cash market at the NSE. Our results indicate that expiration of equity based derivatives have a significant positive impact on the value of shares traded on expiration days and a negative one on the range-based volatility.

The remainder of this article is organised as follows. In Section 2, we trace the post-reforms evolution of the secondary market for equities in India. Section 3 discusses the theory concerning the link between volume and volatility. Section 4 outlines the data which are used in the empirical tests of this paper. In Section 5 we describe the time series model for the two variables. Section 6 reports the empirical results. Section 7 contains summary remarks and conclusions.

6.2 The Indian Equity Market

The reform of India's capital market was initiated in 1994, with the establishment of the NSE that pioneered nationwide electronic trading at its inception, a neutral counterparty for all trades in the form of a clearing corporation and paperless settlement of trades at the depository (in 1996). The consequence was greater transparency, lower settlement costs and fraud mitigation, and one-way transactions costs declined by 90% from an estimated 5% to 0.5%.

However, important structural problems persisted. Perhaps the most important of these problems was the existence of leveraged futures-type trading within the spot or cash market. This was facilitated by the existence of trading cycles and, correspondingly, the absence of rolling settlement. Given a Wednesday-Tuesday trading cycle, for example, a trader could take a position on a stock at the beginning of the cycle, reverse her position towards the end of the cycle, and net out her position towards during the long-drawn settlement period. In addition, the market allowed traders to carry forward trades into following trading cycles, with financiers holding the stocks in their own names until the trader was able to pay for the securities and the intermediation cost which was linked to money market interest rates (for details, see Gupta, 1995, 1997). The Securities and Exchange Board of India (SEBI) banned the use of carry forward (or badla) trades in March 1994, following a major stock market crash. However, in response to worries about decline in market liquidity and stock prices, stemming from the crash in the price of stocks of MS Shoes, carry forward was reintroduced in July 1995.

However, the crisis of 1994 had initiated a policy debate that resulted in significant structural changes in the Indian equity market by the turn of the century. On January 10, 2000, rolling settlement was introduced for the first time, initially for ten stocks. By July 2, 2001, rolling settlement had expanded to include 200 stocks, and badla or carry forward trading was banned. In the interim, in June 2000, the NSE (as well as its main rival, the Bombay Stock Exchange) introduced trading in stock index futures, based on its 50-stock market capitalisation weighted index, the Nifty (and, correspondingly, the 30-stock Sensex). Index options on the Nifty and individual stocks were introduced in 2001, on June 4 and July 2, respectively. Finally, on November 9, 2001, trading was initiated in futures contracts based on the prices of 41 NSE-listed companies. Prior to the introduction of derivatives trading in India, the SEBI banned short sales of stocks listed on the exchanges.

Some details about the derivatives contracts are presented next. Contracts of three different durations, expiring in one, two and three months, respectively, are traded simultaneously. On each trading day, they are traded simultaneously with the underlying stocks, between 8.55 am and 3.30 pm. The closing price for a trading day is the weighted-average of prices during the last half and hour of the day, and this price is the basis for the settlement of these contracts. The futures and options contracts on the indices as well as those on individual stocks expire on the last Thursday of every month, resulting in a quadruple witching hour.

FIGURES 6.1, 6.2, 6.3

The choice of NSE as the basis for our analysis can easily be justified. Since its inception in 1994, the market capitalisation at the NSE has grown by 828%; growth since the turn of the century has been 412%. The growth in the derivatives segment of the exchange has kept pace with the growth in the cash market. Between April 2002 and March 2006, the total turnover of the derivatives segment increased by 4,633%, while the average daily turnover increased by 4,587%. At the end of November 2006, 1098 companies were listed on the exchange, and

1014 of these stocks were regularly traded. The meteoric growth of the cash and derivatives segments of the NSE is graphically highlighted in **Figure**s 6.1-6.3. Of the 1098 listed securities, 123 act as underlying assets for futures and options contracts. In addition, three indices are used as the underlying assets for futures and options trading at the exchange. In November 2006, the latest month for which figures are available, the turnover in the derivatives segment of the equity market was 342% of the corresponding turnover in the underlying cash market.

6.3 Theoretical Background

6.3.1 Economic rationale for a negative volume-volatility link

Several theoretical models try to explain the volatility-volume relation either by describing the full process by which information integrates into prices or by using a less structural approach such as the Mixture of Distributions Hypothesis (MDH). According to various mixture of distributions models there is a positive relation between current stock return variance and trading volume (see Kim et al., 2005, and the references therein). Andersen (1996) suggests a modified MDH model in which the process of price discovery is fully described and a specific stochastic volatility process is assumed, such that the dynamic properties of volume and volatility are explored. Under this market framework, the arrival of news into the market is likely to provide an informational advantage to informed traders who try to exploit it in a sequence of trades and, thus, make prices to adjust to full information values. In Andersen's model prices are affected by informed traders' decisions in response to arrival of new information while volume is generated by information ($V_t^{(I)}$) as well as liquidity ($V_t^{(L)}$) induced trading. In

Andersen's framework $\mathrm{Cov}(r_t^2, V_t^{(L)}) = 0$. Moreover, Daigler and Wiley (1999) found empirical evidence indicating that the positive volume-volatility relation is driven by the (uninformed) general public whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility. In addition, the activity of market makers (liquidity providers) occurs independently of information arrival.

In addition, the activity of market makers (liquidity providers) occurs independently of information arrival. Kawaller et al. (2001) argue that an increase in such noninformation-based trading mitigates the imbalances between liquidity suppliers and liquidity demanders by enhancing the market's capacity to absorb the information-induced trading. Accordingly, all else being equal, a marketplace with a larger population of liquidity providers (or a larger capacity to absorb demands for liquidity) will be less volatile than one with a smaller population, and vice versa (Kawaller et al., 2001). Li and Wu (2006) employ Easley et al. (1996) set up that includes informed and uninformed traders and a risk-neutral competitive market maker. They show that in this sequential trade model the higher the intensity of liquidity trading, the lower the price volatility. They also highlight the fact that this negative relationship exists in any variant of the Bayesian learning model (see, for example, Easley et al., 2002). In their empirical investigation they find that $\mathrm{Cov}(r_t^2, V_t^{(L)})$ is significantly negative.

Furthermore, in a market with partially informed investors, broadening the investor base increases risk sharing and stock prices. A simple extension of this analysis shows that broadening investor base improves the accuracy of market information and stabilises stock prices (see Wang, 2007 and the references therein). Therefore foreign purchases tend to lower volatility by increasing the investor base in emerging markets. This is especially the case in the first few years after market liberalization when foreigners are buying into local markets, and is consistent with findings of stable stock markets after liberalization. In sharp contrast, foreign sales reduce investor base and increase volatility.

As pointed out by Karanasos and Kartsaklas (2007), empirical evidence of an inverse relation between the two variables is also possible apart form the widely held perception that the two variables are positively correlated.

6.3.2 The impact of futures trading on spot market volatility

The impact of opening a futures market on spot price volatility has received considerable attention in the finance literature. Gammill and Marsh (1988) and Ghysels and Seon (2005) argue over the important role played by futures trading during the stock market crash of 1987 in the US and the Asian Financial Crisis of 1997, respectively.

Several researchers study the level of the spot market volatility before and after the introduction of futures contracts. Theoretical studies on the impact of futures trading on spot market volatility have produced ambiguous results. Stein (1987) demonstrates the fact that opening a futures market is exactly equivalent to allowing more speculators to participate in the spot market. He focuses on two aspects of speculative behavior, risk sharing and information transmission. Stein argues that when the addition of speculators just raises the number of perfectly informed participants in the market and, hence, has no informational effect at all, then the opening of a futures market is stabilizing and welfare improving. In other words, in this case we are left with only the beneficial effect of pure risk sharing. Even when secondary traders have no private information and must rely solely on market prices to make their judgments, increases in the number of uniformed traders are stabilizing if these traders do not inflict any negative informational externality on the informed traders. However, if there is a muddling of the spot traders information then destabilizing speculation occurs.

Subrahmanayan (1991) proposes a model with strategically acting informed and uninformed (discretionary and nondiscretionary) traders. Discretionary liquidity traders try to minimize their losses to informed traders by either trading in individual securities or a basket of these securities. The author demonstrates that markets for basket of securities allow liquidity traders to realize their trades more efficiently since their losses to informed traders are usually lower than in the individual securities. Moreover, the basket tends to serve as the lowest transaction cost market for discretionary liquidity traders under a wide range of parameter values even when both security specific and systemic components of adverse selection exist. Although it has been argued that the introduction of index futures contracts may destabilize prices by encouraging irrational speculation (noise trading), the author finds that an increase in noise trading actually makes prices more informative by increasing the returns to being informed and thereby facilitating the entry of more informed traders. Hong (2000) develops an equilibrium model of competitive futures markets in which investors trade to hedge positions and to speculate on their private information. He finds that when a futures market is opened investors are able to better hedge spot price risk and hence are more willing to take on larger spot positions. As a result the introduction of futures contracts reduces spot price volatility.

Regarding the empirical evidence Damodaran and Subrahmanayan (1992) survey a number of studies. They conclude that there is a consensus that listing futures on commodities reduces the variances of the latter. Edwards (1988) and Bessembinder and Seguin (1992) find that S&P 500 futures trading affects spot volatility negatively. Brown-Hruska and Kuserk (1995) also provide evidence, for the S&P 500 index, that an increase in futures volume (relative to spot volume) reduces spot volatility. Dennis and Sim (1999) document that the introduction of futures trading does not affect spot market volatility significantly in Australia and three other nations. Gulen and Mayhew (2000) find that spot volatility is independent of changes in futures trading in eighteen countries and that informationless futures volume has a negative impact on spot volatility in Austria and the UK. The analysis in Board et al. (2001) suggests that in the UK futures trading does not destabilize the spot market. In general, mixed evidence is provided by studies that examine non-US markets. For example, Bae et al. (2004) find that the introduction of futures contracts in Korea is associated with greater spot price volatility. Overall, the impact of futures trading on the volatility of spot markets varies according to sample, data set and methodology chosen.

In what follows we will examine, within the context of a bivariate long-memory model, the effect of the opening of futures markets on spot price volatility and volume at the NSE.

6.4 Data and Estimation Procedure

The data set used in this study comprises 2814 daily trading volume and prices of the NSE index, running from 3rd of November 1995 to 25th of January 2007. The data were obtained from the Indian NSE. The NSE index is a market value weighted index for the 50 more liquid stocks.

6.4.1 Price Volatility

Using data on the daily high, low, opening, and closing prices in the index we generate a daily measure of price volatility. We can choose from among several alternative measures, each of which uses different information from the available daily price data. To avoid the microstructure biases introduced by high frequency data, and based on the conclusion of Chen et al. (2006) that the range-based and high-frequency integrated volatility provide essentially equivalent results, we employ the classic range-based estimator of Garman and Klass (1980) to construct the daily volatility ($y_t^{(g)}$) as follows

$$y_t^{(g)} = \frac{1}{2}u^2 - (2\ln 2 - 1)c^2, \quad t \in \mathbb{Z},$$

where u and c are the differences in the natural logarithms of the high and low, and of the closing and opening prices respectively. **Figure** 6.4 plots the GK volatility from 1995 to 2007.

Figure 6.4

Various measures of GK volatility have been employed by, among others, Daigler and Wiley (1999), Kawaller et al. (2001), Wang (2002), Chen and Daigler (2004) and Chen et al. (2006) (see Karanasos and Kartsaklas, 2007a, and the references therein). [1]

We also use an outlier reduced series for Garman-Klass volatility. In particular, the variance of the raw data is estimated, and any value outside four standard deviations is replaced by four standard deviations. Chebyshev's inequality is used as it i) gives a bound of what percentage ($1/k^2$) of the data falls outside of k standard deviations from the mean, ii) holds no asssumption about the distribution of the data, and iii) provides a good description of the closeness to the mean especially when the data are known to be unimodal as in our case.[2]

[1] Chou (2005) propose a Conditional Autoregressive Range (CARR) model for the range (defined as the difference of the high and low prices). In order to be in line with previous research (Daigler and Wiley, 1999, Kawaller et al., 2001, and Wang, 2007) in what follows we model GK volatility as an autoregressive type of process taking into account bidirectional feedback between volume and volatility, dual-long memory characteristics and GARCH effects.

[2] **Carnero et al. (2007) investigate the effects of outliers on the estimation of the underlying volatility when they are not taken into account.**

6.4.2 Trading Activity

We use the value of shares traded and the number of trades as two alternative measures of volume. Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (see, for details, Karanasos and Kartsaklas, 2007a). We form a trend-stationary time series of volume ($y_t^{(v)}$) by fitting a linear trend (t) and subtracting the fitted values for the original series ($\widetilde{y}_t^{(v)}$) as follows

$$y_t^{(v)} = \widetilde{y}_t^{(v)} - (\hat{a} - \hat{b}t), \; t \in \mathbb{N},$$

where v denotes volume. The linear detrending procedure is deemed to provide a reasonable compromise between computational ease and effectiveness. We also extract a moving average trend from the volume series. As detailed below, the results (not reported) for the moving average detrending procedure are very similar to those reported for the linearly detrended volume series.[3]

In what follows, we will denote value of shares traded by vs and number of trades by n. **Figure**s 6.5 plot the number of trades and value of shares traded from November 1995 to January 2007.

Figure 6.5

6.4.3 Breaks and the introduction of financial derivatives

We also examine whether there are any structural breaks in both volume and volatility and, if there are, whether they are associated with the introduction of futures and options contracts. We test for structural breaks by employing

[3]Bollerslev and Jubinski (1999) find that neither the detrending method nor the actual process of detrending affected any of their qualitative findings (see also, Karanasos and Kartsaklas, 2007a and the references therein).

the methodology in Bai and Perron (2003) who address the problem of testing for multiple structural changes under very general conditions on the data and the errors. In addition to testing for the presence of breaks, these statistics identify the number and location of multiple breaks. In this study we use a partial structural change model where we test for a structural break in the mean while at same time allowing for a linear trend of the form t/T.

The overall picture dates two change points for volatility. The first is detected on the 27th of July 2000 (recall that the index futures trading started on 12 June 2000) and the next one is on 12th of May 2006. As regards trading volume, both value of shares traded and number of trades, have a common break dated on the 7th of March 2001. This is almost three months before the introduction of options contracts. Accordingly, we break our entire sample into three sub-periods. 1st period (the period up to the introduction of futures trading): 3rd November 1995 – 12th June 2000; 2nd: 13th June 2000 - 2nd July 2001 that is, the period from the introduction of futures contracts until the introduction of options trading; 3rd period is the one which starts with the introduction of option contracts: 3rd July 2001 - 25th January 2007.

6.4.4 Expiration effects

We first examine the impact of the expiration of the derivatives contracts on the volumes of trade in the spot market at the NSE. The total number of trades executed in the cash segment of the exchange, and the ratio of the trades concluded on expiration (Thurs) days to the trades concluded on a control category of non-expiration days are highlighted in Panel A of **Figure** 6.6. The control category is the average of concluded trades on Thursdays one and two weeks prior to the expiration Thursday. Three things are evident from the figure: First, the numbers of trades on expiration days and the control category are closely correlated; the correlation coefficient is 0.91. Second, as noted earlier in the paper, there was a significant increase in the number of trades executed in the cash segment of the market over time. Not surprisingly, therefore, the ratio of number of trades on the expiration day to the number of trades included in the control category average (r) is close to unity, namely, 1.07. However, the null hypothesis that r = 1 is rejected at the 1 percent level, the alternative hypothesis being r > 1. In other words, in the cash market, the number of trades on the expiration day, on average, significantly exceeds the average number of trades on the Thursdays of the previous two weeks of trading.

Figure 6.6

Panel B reports the impact of expiration of derivatives contracts on the volume of trade that is measured in Indian rupees (INR or Rs.) billion. It is evident that the patterns and trends reported in Panel B are very similar to those reported in Panel A. As in the case of number of trades, the volume of trade increases significantly over time, and the volume of trade on expiration days is highly correlated (0.92) with the volume of trade on the control days. The ratio of the volume of trade on expiration days to the volume of trade on control days has an average of 1.13, and the null hypothesis that this ratio equals 1 is rejected at the 1 percent level, when the alternative hypothesis is that the ratio exceeds 1.

6.5 Model and Empirical Results

6.5.1 Bivariate long-memory process

Tsay and Chung (2000) have shown that regressions involving FI regressors can lead to spurious results. Moreover, in the presence of conditional heteroskedasticity Vilasuso (2001) suggests that causality tests be carried out in the context of an empirical specification that models both the conditional means and conditional variances.

Furthermore, in many applications the sum of the estimated variance parameters is often close to one, which implies integrated GARCH (IGARCH) behavior. For example, Chen and Daigler (2004) emphasize that in most cases both variables possess substantial persistence in their conditional variances. In particular, the sum of the variance parameters was at least 0.950. Most importantly, Baillie et al. (1996), using Monte Carlo simulations, show that data generated from a process exhibiting FIGARCH effects may be easily mistaken for IGARCH behavior. Therefore we focus our attention on the topic of long-memory and persistence in terms of the second moments of the two variables. Consequently, we utilize a bivariate ccc AR-FI-GARCH model to test for causality between volume and volatility.[4]

Within the framework of the bivariate ccc AR-FI-GARCH model we will analyze the dynamic adjustments of both the conditional means and variances of volume and volatility, as well as the implications of these dynamics for the direction of causality between the two variables. The estimates of the various formulations were obtained by quasi maximum likelihood estimation (QMLE) as implemented by James Davidson (2007) in Time Series Modelling (TSM). To check for the robustness of our estimates we used a range of starting values and hence ensured that the estimation procedure converged to a global maximum.

Next let us define the column vector of the two variables $\mathbf{y}_t$ as $\mathbf{y}_t = (y_t^{(g)}\ y_t^{(v)})'$and the residual vector $\boldsymbol{\varepsilon}_t$ as $\boldsymbol{\varepsilon}_t = (\varepsilon_t^{(g)}\ \varepsilon_t^{(v)})'$. In order to make our analysis easier to understand we will introduce the following notation. $D_t^{(f)}$ is a dummy

[4]Kim et al. (2005) and Karanasos and Kartsaklas (2007a) applied the bivariate dual long-memory process to model the volume-volatility link in Korea.

defined as: $D_t^{(f)} = 1$ during the period from the introduction of futures trading (that is 13th June 2000) until the end of the sample and $D_t^{(f)} = 0$ otherwise; similarly $D_t^{(o)}$ is a dummy indicating approximately the period which starts with the introduction of option contracts. That is, $D_t^{(o)} = 1$ in the period between 3rd July 2001 and 25th January 2007 and $D_t^{(o)} = 0$ otherwise. In addition, $D_t^{(e)}$ is a dummy defined as: $D_t^{(e)} = 1$ the last Thursday of every month -starting from the introduction of futures trading- and $D_t^{(e)} = 0$ otherwise.

In the expression below the superscripts g and v mean that the first equation represents the volatility and the second one stands for the volume. When the value of shares traded is used as a measure of volume, that is when $v = vs$, we will refer to the above expression as model 1. Similarly, when we use the number of trades, that is when $v = n$, we will have model 2.

The best fitting specification (see equation 6.1 below) is chosen according to the minimum value of the information criteria (not reported). For the conditional mean of volatility (g), we choose an ARFI(0) process for both model 1 and model 2. For the conditional means of value of shares traded (vs) and number of trades (n), we choose an ARFI(10) process. That is, $\Phi^{(v)}(L) = 1 - \sum_{k=1}^{10} \phi_k^{(v)} L^k$, $v = vs, n$, with $\phi_4^{(vs)} = \phi_6^{(vs)} = \phi_7^{(vs)} = \phi_9^{(vs)} = 0$, for the value of shares traded, and only $\phi_4^{(n)} \neq \phi_5^{(n)} \neq \phi_9^{(n)} \neq \phi_{10}^{(n)} \neq 0$ for the number of trades. We do not report the estimated AR coefficients for space considerations.

The chosen estimated bivariate ARFI model is given by

$$
\begin{bmatrix} (1-L)^{d_m^{(g)}}\Phi^{(g)}(L) & 0 \\ 0 & (1-L)^{d_m^{(v)}} \end{bmatrix} \times \tag{6.1}
$$
$$
\left\{ \begin{bmatrix} y_t^{(g)} \\ y_t^{(v)} \end{bmatrix} - \begin{bmatrix} \phi_1^{(gv)} L y_t^{(v)} + \phi_1^{(gv,f)} L D_t^{(f)} y_t^{(v)} + \phi_1^{(gv,o)} L D_t^{(o)} y_t^{(v)} \\ \phi_3^{(vg)} L^3 y_t^{(g)} + \phi_3^{(vg,f)} L^3 D_t^{(f,o)} y_t^{(g)} + \phi_3^{(vg,o)} L^3 D_t^{(o)} y_t^{(g)} \end{bmatrix} \right.
$$
$$
\left. - \begin{bmatrix} \mu^{(g)} + \mu^{(g,f)} D_t^{(f)} + \mu^{(g,o)} D_t^{(o)} + \mu^{(g,e)} D_t^{(e)} \\ \mu^{(v)} + \mu^{(v,f)} D_t^{(f)} + \mu^{(v,o)} D_t^{(o)} + \mu^{(v,e)} D_t^{(e)} \end{bmatrix} \right\} = \begin{bmatrix} \varepsilon_t^{(g)} \\ \varepsilon_t^{(v)} \end{bmatrix},
$$

where L is the lag operator, $0 < d_m^{(i)} < 1$ and $\mu^{(i)}, \mu^{(i,e)}, \mu^{(i,f)}, \mu^{(i,o)} \in (0, \infty)$ for $i = g, v$. The coefficients $\mu^{(g,e)}$,$\mu^{(v,e)}$ capture the impact of the expiration of derivatives contracts on the two variables.

The information criteria (not reported) choose the model with the third lag of $\phi_s^{(gv)}$ and the first lag of $\phi_s^{(vg)}$. The $\phi_s^{(gv)}$ coefficient captures the effect from volume on volatility while $\phi_s^{(vg)}$ represents the impact on the opposite direction. Similarly, $\phi_1^{(gv,f)}$, $\phi_3^{(vg,f)}$ correspond to the cross effects[5] from the introduction of futures contracts onwards while $\phi_1^{(gv,o)}$, $\phi_3^{(vg,o)}$ stand for the volume-volatility feedback after the introduction of options trading. Thus, the link between the two variables is captured by $\phi_1^{(gv)}$, $\phi_3^{(vg)}$, in the period up to the introduction of futures trading, by $\phi_1^{(gv)} + \phi_1^{(gv,f)}$, $\phi_3^{(vg)} + \phi_3^{(vg,f)}$ in the second period, and by $\phi_1^{(gv)} + \phi_1^{(gv,f)} + \phi_1^{(gv,o)}$, $\phi_3^{(vg)} + \phi_3^{(vg,f)} + \phi_3^{(vg,o)}$ in the period which starts with the introduction of options contracts.

Regarding $\boldsymbol{\varepsilon}_t$ we assume that it is conditionally normal with mean vector $\mathbf{0}$, variance vector $\mathbf{h}_t = (h_t^{(g)}\ h_t^{(v)})'$ and ccc $\rho = h_t^{(gv)}/\sqrt{h_t^{(g)} h_t^{(v)}}$ $(-1 \leq \rho \leq 1)$. We also choose an ARCH(1) process for the volume and a FIGARCH$(0, d, 0)$ one for

[5] Cross effects enter as exogenous variables to the bivariate model used. Futher, we estimate the bivariate long memory model with endogenous cross effects and the results are very similar to the results reported in this study.

the volatility:

$$\begin{bmatrix} h_t^{(g)} - \omega^{(g)} \\ h_t^{(v)} - \omega^{(v)} \end{bmatrix} = \begin{bmatrix} 1-(1-L)^{d_v^{(g)}} & 0 \\ 0 & \alpha^{(v)} L \end{bmatrix} \begin{bmatrix} [\varepsilon_t^{(g)}]^2 \\ [\varepsilon_t^{(v)}]^2 \end{bmatrix},$$

where $\omega^{(i)} \in (0, \infty)$ for $i = g, v$, and $0 < d_v^{(g)} < 1$.[6] Note that the FIGARCH model is not covariance stationary. The question whether it is strictly stationary or not is still open at present (see Conrad and Haag, 2006). In the FIGARCH model conditions on the parameters have to be imposed to ensure the non-negativity of the conditional variances (see Conrad and Haag, 2006).[7]

Estimates of the fractional mean parameters are shown in **Table** 6.1.[8] Several findings emerge from this **Table**. Number of trades and volatility generated very similar long-memory parameters, 0.47 and 0.43 respectively. The estimated value of $d_m^{(vs)}$, 0.60, is greater than the corresponding values for number of trades and volatility. In the mean equation for the volatility the long-memory coefficient $d_m^{(g)}$ is robust to the measures of volume used. In other words, the bivariate ARFI models 1 and 2 generated very similar $d_m^{(g)}$'s fractional parameters, 0.47 and 0.43.[9]

[6] Brandt and Jones (2006) use the approximate result that if log returns are conditionally Gaussian with mean 0 and volatility h_t then the log range is a noisy linear proxy of log volatility. In this paper we model the GK volatility as an AR-FI-GARCH process.

[7] Baillie and Morana (2007) introduce a new long-memory volatility process, denoted by Adaptive FIGARCH which is designed to account for both long-memory and structural change in the conditional variance process. One could provide an enrichment of the bivariate dual long-memory model by allowing the intercepts of the two means and variances to follow a slowly varying function as in Baillie and Morana (2007). This is undoubtedly a challenging yet worthwhile task.

[8] **Three tests aimed at distinguishing short and long-memory are implemented for the data. The statistical significance of the statistics (not reported) indicates that the data are consistent with the long-memory hypothesis. In addition, we test the hypothesis of long-memory following Robinson's (1995) semiparametric bivariate approach (see, also, Karanasos and Kartsaklas, 2007b).**

[9] **It is worth mentioning that there is a possibility that, at least, part of the long-memory may be caused by the presence of neglected breaks in the series (see, for example, Granger and Hyung, 2004). Therefore, the fractional integration parameters are estimated taking into account the 'presence of breaks' by including the dummy variables for introduction of futures and option trading. Interestingly enough, the long-memory character of the series remain strongly evident.**

Moreover, $d_v^{(g)}$'s govern the long-run dynamics of the conditional heteroscedasticity of volatility. The fractional parameter $d_v^{(g)}$ is robust to the measures of volume used. In other words, the two bivariate FIGARCH models generated very similar estimates of $d_v^{(g)}$: 0.57 and 0.58. All four mean long-memory coefficients are robust to the presence of outliers in volatility. When we take into account these outliers the estimated value of $d_v^{(g)}$ reduces from 0.57 to 0.44 but remains highly significant.[10]

TABLE 6.1

The variances of the two measures of volume generated very similar conditional correlations with the variance of volatility: 0.28, 0.30. Finally, the estimated values of the ARCH coefficients (not reported here) in the conditional variances of the value of shares and number of trades are 0.12 and 0.13 respectively. Note that in all cases the necessary and sufficient conditions for the non-negativitiy of the conditional variances are satisfied (see Conrad and Haag, 2006).

6.5.2 The relationship between volume and volatility

We employ the bivariate ccc AR-FI-GARCH model with lagged values of one variable included in the mean equation of the other variable to test for bidirectional causality. The estimated coefficients $\phi_s^{(ij)}$**,** $(\phi_3^{(gv)}, \phi_1^{(vg)})$ respectively defined in equation **(6.1),** which capture the possible feedback between the two variables, are shown in the first column of **Table** 6.2. All four $\phi_3^{(gv)}$ estimates are significant and negative. Note that both volume series have a similar impact on GK volatility (-0.013, -0.014). This result is in line with the theoretical underpinnings

[10] **Carnero et al. (2007) investigate the effects of outliers on the estimation of the underlying volatility when they are not taken into account.**

predicting that, all else being equal, a marketplace with a larger capacity to absorb demands for liquidity will be less volatile than one with a smaller capacity. On the other hand, in all cases the $\phi_1^{(vg)}$ coefficients are insignificant indicating that lagged volatility is not associated with currrent volume. Therefore in the period before the introduction of futures trading volatility affects volume negatively whereas there is no effect in the opposite direction.

TABLE 6.2

Estimated values of the dummy coefficients for the cross effects are presented in the last two columns of **Table** 6.2. Recall that the relationship between the two variables in the second period is captured by the sum of the coefficients in the first two columns while $(\phi_s^{(ij)} + \phi_s^{(ij,f)} + \phi_s^{(ij,o)})$ captures the link commencing with the introduction of options contracts. All $\phi_s^{(ij,f)}$ $(\phi_3^{(vg,f)}, \phi_1^{(gv,f)})$, estimates are insignificant. Thus it appears that the introduction of futures trading does not influence the volume-volatility link.

As far as the introduction of options contracts is concerned, there seems to be a change in the influence of the value of shares traded on volatility. In partcular, when $v = vs$, the estimated $\phi_3^{(gv,o)}$ coefficient is positive and significant (0.009). However, it is less than the estimate of $|\phi_3^{(gv)}|$ (0.013). Thus in the period which starts with the introduction of options trading the impact of the value of shares traded on volatility is still negative but much smaller in size $\phi_3^{(gv,o)} + \phi_3^{(gv)} = -.004$. As can be seen from Panels A and B of **Table** 6.3 the volume-volatility link is, in general, robust to the presence of outliers in volatility.

Overall, in all cases volume is independent of changes in volatility. In other words, causality runs only from volume-either value of shares traded or number of trades-to volatility (see **Table** 6.3). In particular, in all three periods the number of trades affects volatility negatively with the introduction of derivatives trading leaving the sign and the magnitude of this relationship unaltered. In other words, the introduction of the two financial instruments is not affecting the information role of the number of trades in terms of predicting future volatility. One possible explanation is that the use of number of trades as a proxy for volume does not reflect the fact that traders might take larger spot positions after the introduction of derivatives trading due to increased risk sharing opportunities.

Similarly, in all three periods the value of shares traded has a negative effect on volatility. However, in the period from the introduction of options trading until the end of the sample its impact on volatility although still significantly negative is much smaller in size. This result is consistent with the view that foreign purchases tend to lower volatility-especially in the first few years after 1995 when foreigners are buying into local markets. The fact that surprises in the value of shares are less influential on volatility in the third period indicates a change in its informational role. A possible explanation of this empirical finding may be related with the following arguments. Gammill and Perold (1989) raise the concern that the introduction of markets in baskets can decrease the informativeness of stock prices by decreasing liquidity trading in individual stock markets. Subrahmanayan (1991) finds that the price informativeness in the security specific component of stocks that are heavily weighted in the basket may increase because of the increased profits from security-specific information trading for such stocks after the introduction of the basket. Moreover, for less heavily weighted stocks in the basket, he finds that the introduction of derivatives can reduce the returns to trading on stock specific information by causing migration of liquidity traders to the basket and, consequently, decrease the price informativeness in the security specific component. According to the findings above, the introduction of derivative securities is very likely to make informed and discretionary liquidity traders to change the composition as well as the number of stocks traded and, consequently, change the informational role of the value of shares traded. It is true that there may have been other changes in the financial system of India during the period examined in this study and for this reason we cannot solely attribute the reduction in the informational role in the value of shares traded to the introduction of derivatives trading. **Table** 6.3 gives an overview of the volume-volatility link over the three different periods considered.

TABLE 6.3

6.5.3 Expiration effects and derivatives trading

By its very nature, arbitrage between the cash and (especially) futures markets require investors to unwind positions in the latter market on the day of expiration of contracts, in order to realize arbitrage profits. The consequent increase in the number of large buy and sell orders, and the temporary mismatch between these orders, can significantly affect prices and volatility in the underlying cash market. Not surprisingly, regulators around the world have responded with a number of measures aimed at reducing price volatility on account of the so-called expiration effect of index derivatives.

The importance of expiration day effects on the cash market to regulators has, in turn, generated interest on such effects within the research community. As a consequence, the impact of expiration of futures and options contracts on the underlying cash market has been examined in a number of contexts (see, e.g., Corredor et al., 2001, Chow et al., 2003, and Alkeback and Hagelin, 2004). The empirical evidence is not unequivocal, and the nature of the influence of expiration of derivatives on underlying cash prices remains an open question (see, Bose and Bhaumik, 2007, and the references therein).

In section 4 we explored the effect of the expiration of derivatives contracts on some aspects of the underlying cash market using simple parametric and non-parametric tests. Next, we pursue a more careful examination of the likely impact of derivatives contracts expiration on trading volume and range-based volatility. When the value of shares traded is used as a measure of volume the model indicates that there is a significant expiration day effect. In both equations of model 1 the estimates of $\mu^{(i,e)}$, $i = vs, g$, are statistically significant, albeit with opposite signs (see **Table** 6.4). The value of shares traded on expiration days is higher, on average, than their value on non-expiration days, while volatility is lower on expiration days, than on other days. This is in line with the results in Bose and Bhaumik (2007). In sharp contrast there is no evidence that the expiration of derivatives contract affects the number of trades. That is, the estimated value of $\mu^{(n,e)}$ is insignificant.

Next we investigate whether the opening of the futures and options markets affects spot price volatility and trading volume. Recall that the coefficients $\mu^{(i,f)}$, $\mu^{(i,o)}$, $i = g, v$, capture the effects of derivatives trading on spot volatility and volume. The estimate $\mu^{(g,f)}$ is negative and significant, indicating that the introduction of futures trading leads to a decrease in spot volatility. One possible explanation is provided by Stein (1987). Once futures are introduced increases in the number of uniformed traders are beneficial even though such increases lower the average informedness of market participants. The latter is mitigated by the increase in risk sharing and the fact that spot traders tend to offset any mistakes the secondary traders make. The above result also supports the Hong (1995) theory that stock volatility is negatively related to futures trading activity. The reason being that, when a futures market is opened, investors are able to better hedge their nonmarketed risks and therefore are willing to absorb more of the nonmarketed risk shocks in their spot holdings. It is also in line with the empirical findings in Bessembinder and Seguin (1992). On the other hand, options trading has no significant impact on spot volatility since the coefficient $\mu^{(g,o)}$ is insignificant in all cases.

TABLE 6.4

In sharp contrast, since the estimates $\mu^{(v,f)}$ $(v = vs, n)$ are insignificant, it appears that the average levels of value of shares traded and of number of trades remain the same before and after the introduction of futures trading. However, the negative and significant estimated values of $\mu^{(v,o)}$ indicate that on average the value of shares traded and the number of trades decreases after the introduction of option contracts. Probably the lower cost of entering an option contract induces traders to take positions in the derivatives markets while leaving their positions in the spot unaltered relative to constant growth rate implied for the spot log trading volume in this study.

These results are quite robust across models 1 and 2 and across panels A and B. In other words, in all cases the results are not qualitatively altered by changes in the measures of volume and they are not sensitive to the presence of outliers in volatility.

6.6 Conclusions

This paper has investigated the issue of temporal ordering of the range-based volatility and trading volume in the NSE, the largest cash and derivatives exchange in India, for the period 1995-2007. We examine the dynamics of the two variables and their respective uncertainties using a bivariate dual long-memory model. We distinguish volume traded before and after the introduction of futures and options trading.

Our main finding is that in all three periods the impact of number of trades on volatility is negative. Similarly, in all three periods the value of shares traded has a negative effect on volatility. This result is in line with a version of the MDH model in which the higher the intensity of liquidity trading the lower the price volatility. However, in the period from the introduction of options contracts until the end of the sample the impact although still significantly negative is much smaller in size. A possible explanation for the change in the informational role of the value of shares traded is following the arguments of Gammill and Perold (1989) and Subrahmnayan (1991). According to these studies, the introduction of derivative securities is very likely to make informed and discretionary liquidity traders to change the composition as well as the number of stocks traded and, consequently, change the informational role of the value of shares traded in terms of predicting volatility. In sharp contrast, volume is independent from changes in volatility.

Another important finding of our study is that the introduction of futures trading leads to a decrease in spot volatility, a result consistent with the empirical finding of Bessembinder and Seguin (1992). This result is also consistent with the theoretical finding of Stein (1987) when the 'risk sharing' effect dominates the 'misinformation' effect and that of Subrahmanayan (1991) when the increase in informativeness in the systematic component dominates the decrease in informativeness in the security-specific component.

Our results also indicate that expirations of equity based derivatives have significant impact on the value of shares traded on expirations days and on the range-based volatility. Finally, our analysis suggests that it might be useful to undertake an analysis of expiration day effects (and other events) using an approach that models the underlying data generating process, rather than one which depends on comparison of means and medians alone.

Table 6.1: Long memory in volatility and levels

Panel A. Garman-Klass volatility			
Long memory & ccc	$d_m^{(i)}$	$d_v^{(i)}$	ρ
Model 1 (Vale of shares traded)			
Eq. 1 Volatility $y^{(g)}$	0.47 (0.10)	0.57 (0.08)	-
Eq. 2 Volume $y_t^{(vs)}$	0.60 (0.04)	-	0.28 (0.03)
Model 2 (Number of trades)			
Eq. 1 Volatility $y^{(g)}$	0.43 (0.09)	0.58 (0.09)	-
Eq. 2 Volume $y_t^{(n)}$	0.47 (0.03)	-	0.30 (0.03)
Panel B. Outlier reduced Garman-Klass volatility			
Long memory & ccc	$d_m^{(i)}$	$d_v^{(i)}$	ρ
Model 1 (Value of shares traded)			
Eq. 1 Volatility $y^{(g)}$	0.42 (0.04)	0.44 (0.08)	-
Eq. 2 Volume $y_t^{(vs)}$	0.60 (0.04)	-	0.30 (0.03)
Model 2 (Number of trades)			
Eq. 1 Volatility $y^{(g)}$	0.39 (0.04)	0.44 (0.08)	-
Eq. 2 Volume $y_t^{(n)}$	0.48 (0.03)	-	0.31 (0.03)

Notes: The table reports parameter estimates of the long-memory and the ccc coefficients. $d_m^{(i)}$, $d_v^{(i)}$, $i= v, g$ and ρ are defined in equation (6.1).*,**,*** denote significance at the 0.15, 0.10 and 0.05 level respectively. The numbers in parenteses are standard errors.

Table 6.2: Mean equation: Cross effects

Panel A. Garman-Klass volatility			
Cross Effects	$\phi_s^{(ij)}$	$\phi_s^{(ij,f)}$	$\phi_s^{(ij,o)}$
Model 1 (Value of shares traded)			
Eq. 1 Volatility $y^{(g)}$	-0.013 (0.006)***	0.003 (0.008)	0.009 (0.006)*
Eq. 2 Volume $y_t^{(vs)}$	-0.110 (0.259)	-0.161 (0.507)	0.117 (0.461)
Model 2 (Number of Trades)			
Eq. 1 Volatility $y^{(g)}$	-0.014 (0.008)***	0.006 (0.010)	0.008 (0.007)
Eq. 2 Volume $y_t^{(n)}$	0.120 (0.177)	-0.006 (0.330)	-0.255 (0.317)
Panel B. Outlier reduced Garman-Klass volatility			
Cross Effects	$\phi_s^{(ij)}$	$\phi_s^{(ij,f)}$	$\phi_s^{(ij,o)}$
Model 1 (Value of shares traded)			
Eq. 1 Volatility $y^{(g)}$	-0.008 (0.004)**	-0.001 (0.006)	0.009 (0.005)**
Eq. 2 Volume $y_t^{(vs)}$	-0.065 (0.302)	-0.340 (0.586)	-0.558 (0.694)
Model 2 (Number of Trades)			
Eq. 1 Volatility $y^{(g)}$	-0.009 (0.005)**	0.001 (0.008)	0.008 (0.007)
Eq. 2 Volume $y_t^{(n)}$	0.195 (0.201)	-0.031 (0.365)	-1.006 (0.523)***

Notes: The table reports parameter estimates of the cross effects. $\phi_s^{(ij)}$ $\phi_s^{(ij,f)}$, and $\phi_s^{(ij,o)}$, $i= vg, gv$ are defined in equation (6.1).

*,**,*** denote significance at the 0.15, 0.10, and 0.05 level respectively.

The numbers in parentheses are standard errors.

Table 6.3: The volatility-volume link

Panel A. The effect of Volume on Volatility			
	Period 1	Period 2	Period 3
Value of shares traded	negative	negative	negative (smaller)
Number of trades	negative	negative	negative
Panel B. The impact of Volatility on Volume			
	Period 1	Period 2	Period 3
Value of shares traded	insignificant	insignificant	insignificant
Number of trades	insignificant	insignificant	insignificant

Table 6.4: Mean equations: Dummy effects for constants

Panel A. Garman-Klass volatility			
Constant Effects	$\mu^{(i,e)}$	$\mu^{(i,f)}$	$\mu^{(i,o)}$
Model 1 (Value of shares traded)			
Eq. 1 Volatility $y^{(g)}$	-0.003 (0.002)**	-0.12 (0.009)*	-0.003 (0.005)
Eq. 2 Volume $y_t^{(vs)}$	0.108 (0.022)***	-0.030 (0.154)	-0.746 (0.344)***
Model 2 (Number of trades)			
Eq. 1 Volatility $y^{(g)}$	-0.003 (0.002)**	-0.014 (0.009)*	-0.003 (0.002)
Eq. 2 Volume $y_t^{(n)}$	0.004 (0.015)	-0.073 (0.106)	-0.503 (0.295)**
Panel B. Outlier reduced Garman-Klass volatility			
Constant Effects	$\mu^{(i,e)}$	$\mu^{(i,f)}$	$\mu^{(i,o)}$
Model 1 (Values of shares traded)			
Eq. 1 Volatility $y^{(g)}$	-0.003 (0.002)**	-0.013 (0.007)***	-0.004 (0.005)
Eq. 2 Volume $y_t^{(vs)}$	0.105 (0.022)***	-0.033 (0.154)	-0.743 (0.342)***
Model 2 (Number of trades)			
Eq. 1 Volatility $y^{(g)}$	-0.003 (0.002)**	-0.014 (0.006)***	-0.004 (0.005)
Eq. 2 Volume $y_t^{(n)}$	0.001 (0.016)	0.065 (0.105)	-0.505 (0.299)**

Notes: The table reports parameter estimates of the constant dummy effects.

$\mu^{(i,e)}$, $\mu^{(i,f)}$ and $\mu^{(i,o)}$, $i = v, g$ are defined in equation (6.1).

*,**,*** denote significance at the 0.15, 0.10, 0.05 level. The numbers in parentheses are standard errors.

Figure 6.1: Daily trading volume of the NSE (Spot Market)

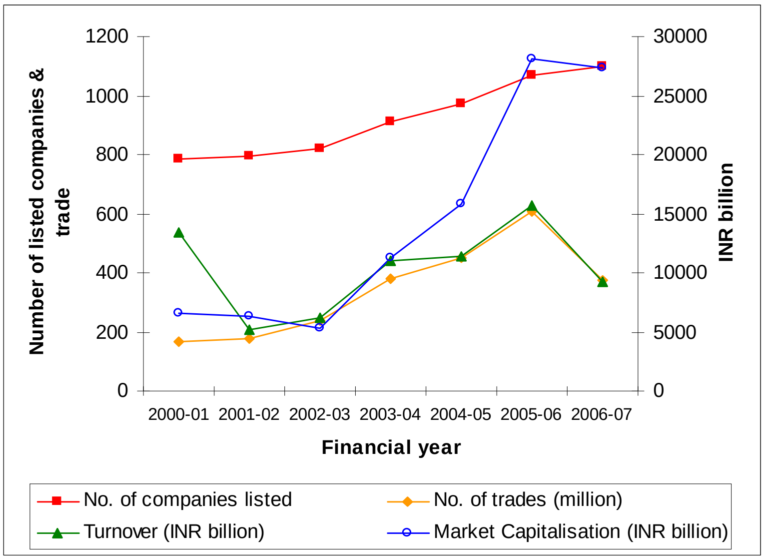


Figure 6.2: Daily closing prices and returns of the NSE (Spot Market)

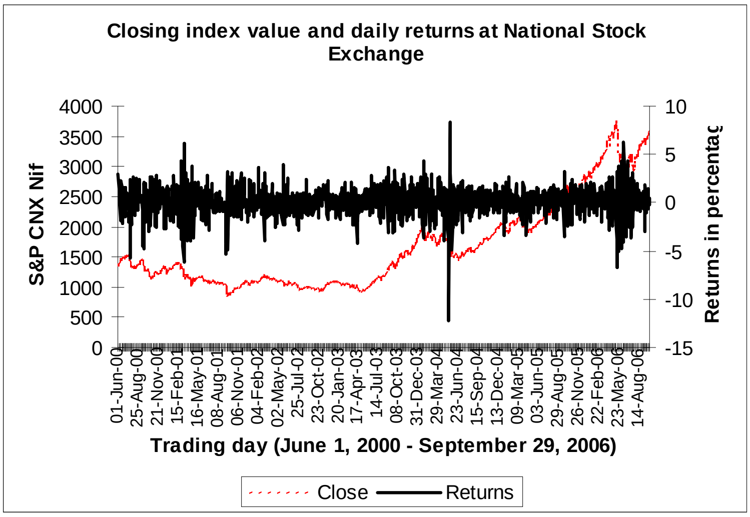
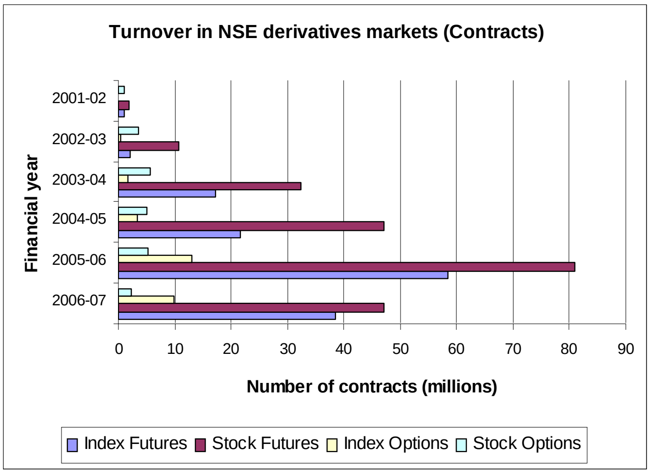


Figure 6.3: Daily turnover of the NSE (Deivatives Market)



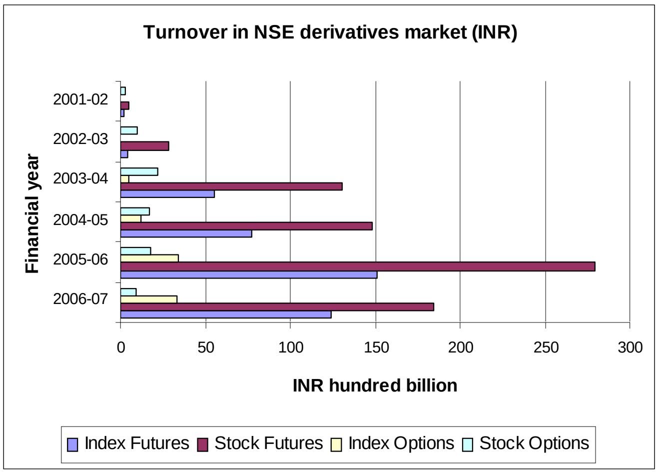
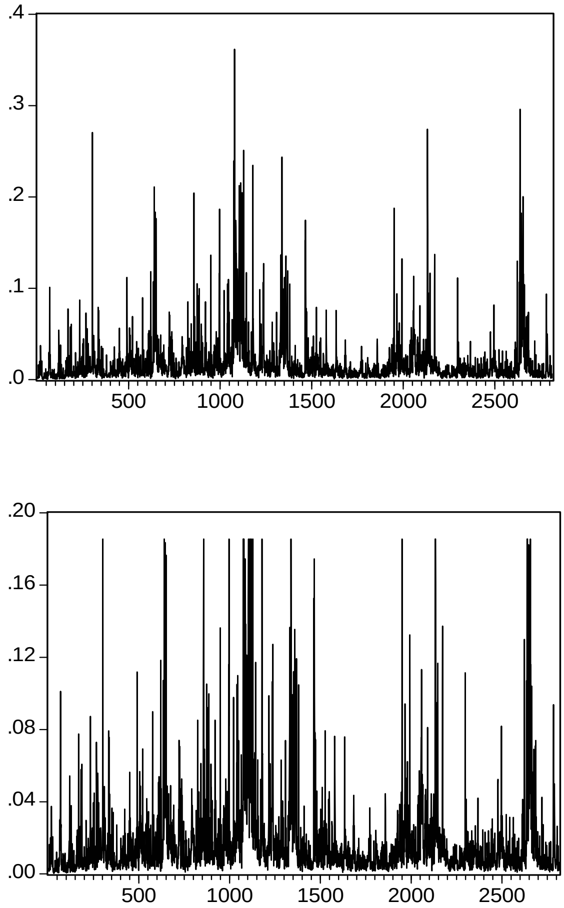


Figure 6.4: Garman-Klass and outlier reduced Garman-Klass volatility



Outlier reduced Garman-Klass volatility

Figure 6.5: Value of shares traded and number of trades of the NSE (Spot Market)

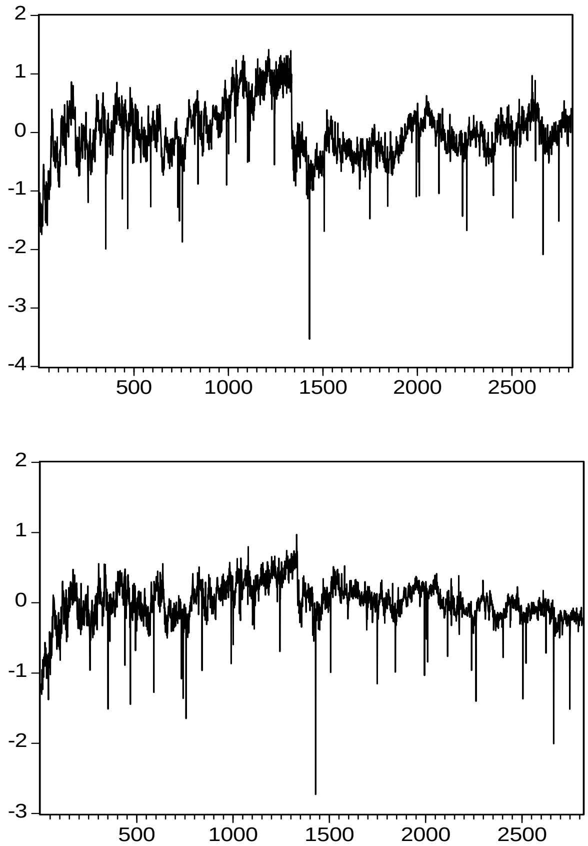
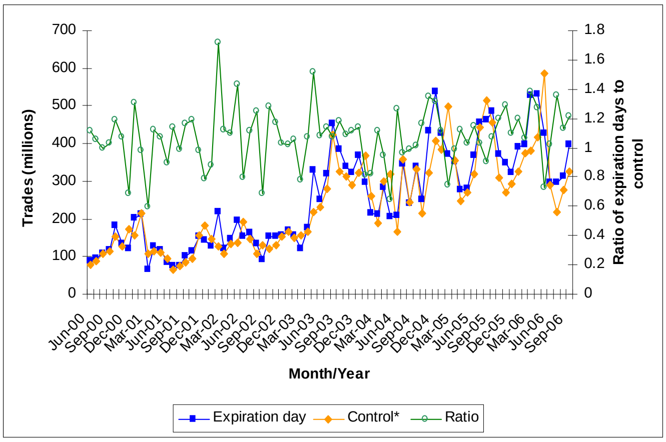
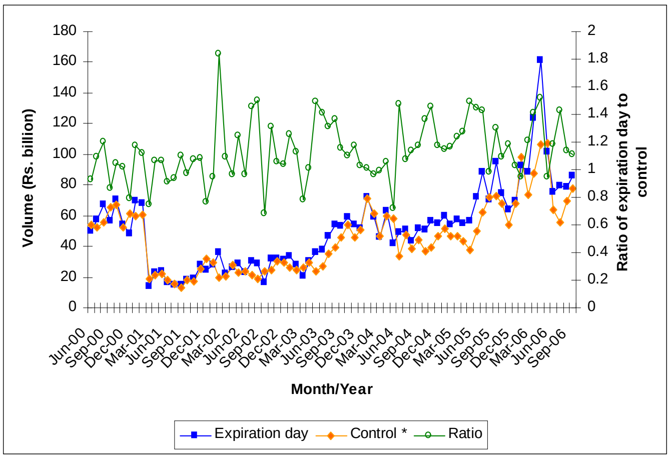


Figure 6.6: Comparative trading: Expiration day vs. control



A



B

Chapter 7

Conclusions

The objective of this thesis is to investigate the volatility-volume (simultaneous and causal) relationship for an emerging market's stock and futures exchanges. Primarily, we examine the case of Korea while additional evidence is provided for the Indian stock market. In addition, our unique database allows us to examine whether different types of traders have a positive or negative effect upon volatility. We derive our intuition from market microstructure models that associate price with private information and different types of traders distinguished by the quality of information they hold, the dispersion of expectations they form based on that information and their trading motives (See O'Hara (1995) for a review of the relevant literature).

In chapter 2 we examine the dynamic causal relations between stock volatility and trading volume for the Korean stock market. For the entire sample period we find a strong bidirectional feedback between volume and volatility while this causal relationship was robust to three alternative measures of volatility used. Moreover, we provide evidence that there are structural shifts in causal relations, and also that it is important to distinguish between domestic and foreign investors' volume. Specifically, before the financial crisis in 1997 there was no causal effect from foreign investors' volume to stock volatility whereas after the crisis a negative feedback relation began to exist. This might be due to the liberalization process which took place in the middle of, and after, the crisis or due to arbitrage opportunities spotted by foreign investors after the crisis. In sharp contrast, the impact of 'domestic' volume on either absolute returns or their squares was negative in the pre-crisis period but disappeared after the crisis. Similarly, 'domestic' volume had a positive impact on 'FIAPARCH' volatility in sample A whereas in sample B conditional volatility was independent of changes in 'domestic' volume. Overall, 'foreign' volume tends to have more information about volatility in recent years, which suggests the increased importance of 'foreign' volume as an information variable.

In chapter 3 we study the relationship between range-based volatility and turnover using a bivariate dual long-memory model. Our methodology allows for either a positive or a negative bidirectional feedback between the two variables, and so no restriction is imposed in their relationship. We find that the apparent long-memory in the variables is quite resistant to the presence of breaks. However, when we take into account structural breaks the order of integration of the conditional variance series decreases considerably. Additionally, our results show that the causal effects from volume to volatility are sensitive, in terms of statistical significance or sign changes, to the different samples considered. In particular, the impact of foreign volume on volatility is negative in the pre-crisis period but turns to positive after the crisis. This result is consistent with the view that foreign purchases tend to lower volatility in emerging markets-especially in the first few years after market liberalization when foreigners are buying into local markets- whereas foreign sales increase volatility. Before the crisis there is no causal effect for domestic volume on volatility whereas in the post-crisis period total and domestic volumes affect volatility positively. The former result is in line with the theoretical underpinnings that predict that trading within domestic investor groups does not affect volatility. The latter result is consistent with the theoretical argument that the positive relation between the two variables is driven by the uninformed general public.

Our results in chapter 4 provide empirical evidence on the degree of long run dependence of volatility and trading volume in the Korean Stock Exchange using the semiparametric estimators of Robinson (1994, 1995a). The results of testing for long memory support the argument for long run dependence in both Garman-Klass volatility and trading volume (turnover). Total and domestic trading volume exhibit very similar long memory characteristics for all sample periods. The degree of long memory in foreign volume is significantly lower than that experienced in domestic volume. Interestingly, the results for trading volume are not influenced by structural breaks in the mean of the series. On the other hand, the long range dependence in volatility is quite sensitive to the different sample periods considered and comparable to foreign volume. Furthermore, the null hypothesis that volatility and volume share a common long memory parameter is only accepted for foreign volume and Garman-Klass volatility in all three subperiods. This result is consistent with a modified version of the mixture of distributions hypothesis in which volatility and volume have similar long memory characteristics as they are both influenced by an aggregate information arrival process displaying long range dependence. Finally, we find no evidence that foreign volume and volatility share a common long memory component.

In chapter 5 we investigate whether different types of traders, distinguished by the information they possess, have a positive or negative effect upon volatility. This work aims to provide empirical evidence on the volatility-volume relationship implied by theoretical models which associate movements in prices and trading volume with information, dispersion of beliefs and trading motives. Our empirical results show that surprises in non-member investors' trading volume are positively related with volatility in most of the cases. These results are more reinforcing in the case of log-volume and generally consistent with the empirical findings of Daigler and Wiley (1999). Moreover, this finding is consistent with the theoretical models of Harris and Raviv (1993) and Shalen (1993), who find a positive relationship between absolute price changes and volume due to the dispersion of beliefs partly caused by different interpretation of common information and partly caused by the 'noisy' liquidity demand. As regards member investors, we primarily find that unexpected volume is positively related to volatility and this further supports the argument of Delong et al (1990b), that trading by informed rational speculators can drive prices further away from fundamentals if it triggers positive feedback strategies by noise traders. As regards the long run effect of non-member investors trading, it seems to be important and stabilising over futures prices in the case of institutional and foreign trading but destabilising over futures prices in the case of individual trading, especially up to the end of the financial crisis. As regards member investors, their long run effect on futures prices is significant and negative in the case of log volume only and primarily for the period up to the end of the Asian Financial Crisis.

Another important result of our study is that the coefficients relating the unexpected component of open interest with volatility are uniformly negative, meaning that an increase in open interest during the day lessens the impact of a volume shock in volatility. This is consistent with the Bessembinder and Seguin (1993) results, who also report a negative relation between surprises in open interest and volatility. However, when we allow for time to maturity effects, surprises in open interest are associated with more volatility around the futures contract expiration, probably due to the wider price range over which less informed investors trade as the contract rolls to its expiration and information asymmetry rises. Finally, the trading volume slope dummies reveal that non-member institutional investors are not associated with any movement in volatility towards the end of the contract life while surprises in the trading activity of non-member individual, foreign and member institutional investors are still positively associated with volatility over the same period.

Finally, in chapter 6 we examine the volatility-volume relationship in the Indian Stock Exchange from 1995 to 2007. The empirical findings in this chapter point towards a negative relation between volatility and both measures of trading activity, the number of trades and the value of shares traded, for all three periods considered. This result is in line with a version of the MDH model in which the higher the intensity of liquidity trading the lower the price volatility. This result is in line with a version of the MDH model in which the higher the intensity of liquidity trading the lower the price volatility. However, for the period spanning from the introduction of options trading until the end of the sample the impact is much smaller in size, though still significantly negative. A possible explanation of this effect is that the introduction of derivative securities is very likely to induce informed and discretionary liquidity traders to change the composition as well as the number of stocks traded and, consequently, changing the informational role of the value of shares traded in terms of predicting volatility. In sharp contrast, volume is independent from changes in volatility. Another important finding of our study is that the introduction of futures trading leads to a decrease in spot volatility. This result is consistent with the theoretical findings of Stein (1987) when the 'risk sharing' effect dominates the 'misinformation' effect and that of Subrahmanayan (1991) when the increase in informativeness in the systematic component dominates the decrease in informativeness in the security-specific component. Finally our results indicate that expirations of equity based derivatives have significant impact on the value of shares traded and on the range-based volatility on expirations days.

Several lines for future research can be suggested. Firstly, a natural extension of our work would be to investigate whether different types of domestic traders have a heterogeneous impact on volatility of the spot market especially after the introduction of futures trading. The introduction of stock index futures is very likely to induce trading in both individual securities and a basket composed of those securities, thus, making index products important components of many trading strategies. Gammill and Perold (1989) raise the concern that the introduction of markets in baskets can decrease the informativeness of stock prices by decreasing liquidity trading in individual stock markets while Subrahmanayan (1991) finds that the price informativeness in the security specific component may increase only for stocks that are heavily weighted in the basket. Consequently, our results on chapter 5 can provide the basis for a very interesting comparison concerning the behavior of various types of investors in the spot and futures markets.

Secondly, the fact that volume may predict short run movements in prices is consistent with microstructure effects arising from the adjustment of prices to public and private information (Blume, Easley and O'Hara, 1994). However, the informative role of volume in terms of predicting long term price movements is an interesting subject for future research. Gervais, Kaniel and Mingelgrin (2001) find that stock experiencing unusually high trading volume over a period of one day to a week tend to appreciate over the next month and continue to generate significant returns for horizons as long as 20 weeks. Moreover, recent advances in the frequency domain analysis allow us to measure contemporaneous as well as causal relationships for different frequency bands. In this way we can estimate simultaneously any medium or long term relationship between volatility and volume.

Finally, in Chapter 5, the high explanatory power of trading volume in the volatility regression when a range based estimator is used as a volatility proxy, indicate that there is a close correspondence between trading activity and volatility. If prices and volume are subordinated to the same latent information arrival process, range based volatility proxies may be well suited for volatility-volume studies as they contain sample path information. Moreover, Alizadeh et al. (2002) argue that the range is an attractive volatility proxy for Gaussian quasi-maximum likelihood estimation of stochastic volatility models while Lildholt (2002) argues in favor of using intraday data to estimate GARCH type volatility models. Further work using range based estimation of stochastic volatility and GARCH type models in conjunction with trading volume is a subject of future research.

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