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

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Abstract This paper 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, in addition 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. In other words, 'foreign' volume tends to have more information about volatility in recent years, which suggests the increased importance of 'foreign' volume as an information variable.

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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 & 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 & Weisse, 1998; Stiglitz, 2002), most of the previous empirical studies found that the market opening was favourable to emerging countries' economies (e.g., Bekaert and Harvey, 2000; Henry, 2000; Kim & 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 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

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

current and future movements in stock price volatility, and vice versa (see Lee & 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, Lee, and Nam (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 1995–2001. 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 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.

2.1 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 1 reports the sample period and the results of the previous research.

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 5 years later the foreign ownership limit of the Korean stock market reached only 23% in May 1997 (see Table 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 3 or 5 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).

Table 1 Impact of liberalization on emerging stock market volatility

Authors	Number of countries[a]	Sample data	Volatility after liberalization[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 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

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 2 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 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 favourable 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'

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

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 deposits 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, 2001).

Table 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.

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.

3 Prior research

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

Table 3 Average daily trading volumes in the Korean stock market

	'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 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

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 Brooks, 1998; Hiemstra and Jones, 1995, 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, Grossman, and Wang (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 behavior 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 & Wiley, 1999 and the references therein).

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, Rossi, and Tauchen (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 volatility. 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, Firth, and Rui (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).

4 Measurement issues

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 $\left[r_t = \log\left(\frac{\mathrm{KOSPI}_t}{\mathrm{KOSPI}_{t-1}}\right) \times 100\right]$. 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 Fig. 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

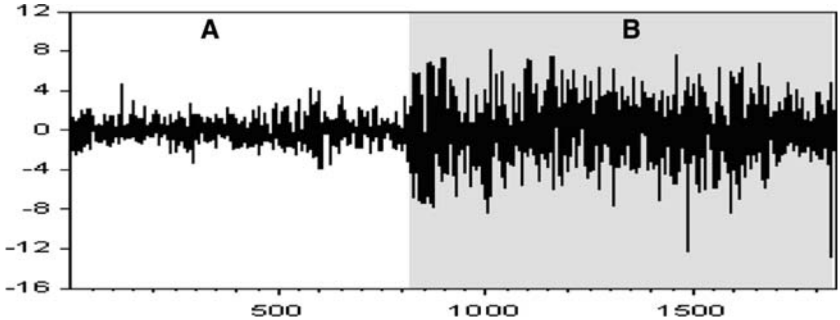

Fig. 1 The daily KOSPI return series from January 1995 to September 2001

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 penalized 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, $k = 1,...,r$, 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 $\overline{u}(i,j) := (j-i)^{-1} \sum_{t=i+1}^{j} u_t$. Here and in the remainder of the paper the symbol ':=' is used to indicate equality by definition. 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 $\xi_T = 4\log(T)/T^{1\text{-}2d}$.

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.

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.[3,4]

Figure 2 plots the daily total Korean won value of traded shares of the Korean stock market from January 1995 to September 2001. The unit of the vertical axis is trillion Korean Won. The shaded area covers the period from December 1998 to September 2001 with 691observations (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 4, imply that we can treat the stock returns and trading volume as stationary processes.

4.3 Volatility

The Korean stock market after the crisis is more volatile than it was before the crisis according to Fig. 1 and the standard deviation of returns series (see Table 5). This is probably due to the crisis. However, the standard deviation of stock return series and Fig. 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

[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 nine 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).

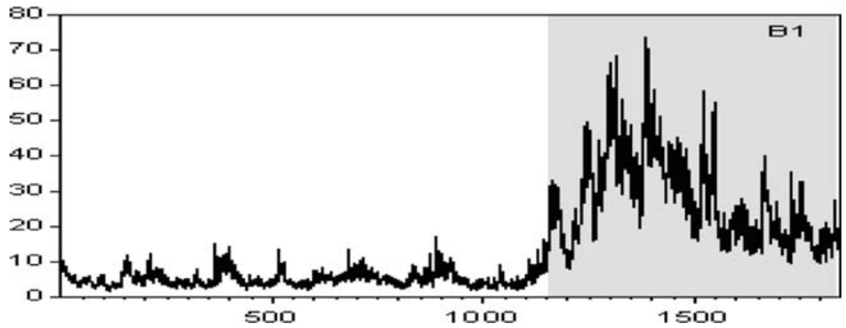

Fig. 2 The daily total Korean won value of shares traded in the KSE

Table 4 Unit root tests

	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 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

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 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.

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 6). The somewhat high figure 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

Table 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 6 Standard deviation of KOSPI stock returns

	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

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 (2001, p. 33).

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

$$h_t^{\delta/2} = \omega + \Omega(L) f(\varepsilon_t), \tag{1}$$

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. 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: $\beta - d \le a \le (2 - d)(0.333)$, $d[a - (1 - d)(0.5)] \le \beta\,(a - \beta + d)$ are sufficient.

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

Table 7 FIAPARCH Models

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

Notes: For each of the three periods, Table 7 reports QML parameter estimates for the 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 parentheses are standard errors

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 subperiods (before and after the crisis) are shown in Table 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 estimated power term is very close to two. That is, the conditional variance is a linear function of lagged squared residuals.

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 statis-

[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.

tically significant evidence of misspecification. Generally speaking, the parameter estimates support the idea that long memory effects are present in stock volatility. The results also show strong evidence of asymmetry in the conditional variance.

5 Empirical methodology

5.1 Granger causality tests

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

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

where e_t and v_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 $b_i(c_i)$, $i = 1,..., m$, 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, $i = 1,..., m$, 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 W tests and in Table 8a we report the F statistics of Granger causality tests for the entire sample using the optimal-chosen by the AIC and SIC-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 values 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.

[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.

Table 8 Granger causality tests between trading volume and stock volatility

Volume	Volatility		
	$\lvert r_t \rvert$	r_t^2	FIAPARCH
a. *Entire sample*			
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]
b. *Sample A*			
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](–)
c. *Sample B*			
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**)
d. *Sample B1*			
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: The bold numbers indicate the optimal lag length chosen by the SIC and AIC. The figures are *F* statistics. The numbers in square brackets [·] are *P* values. A (-) or (+) sign indicates that the sum of the lagged coefficients is positive (negative)

5.1.1 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. Table 8b, c 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, 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 8b 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.

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, which is 3 years after the 'liberalization date' of the previous research (see Table 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 8c. The picture is different to that of the period before the crisis. which 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.

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 Fig. 3).

Figure 3 plots the daily KOSPI return series and total Korean won value of traded shares of the Korean stock market from January 1995 to September 2001. The unit of the vertical axis is trillion Korean Won. Sample A covers the period from January 1995 to mid October 1997 with 816 observations. Sample B covers the period from mid October 1997 to September 2001 with 1028 observations. Sample B1 covers the period from December 1998 to September 2001 with 691 observations.

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 8d). 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.

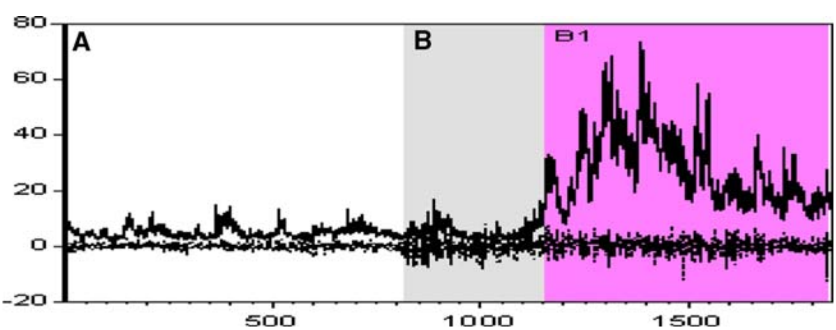

Fig. 3 The daily KOSPI return series and total Korean won value of traded shares

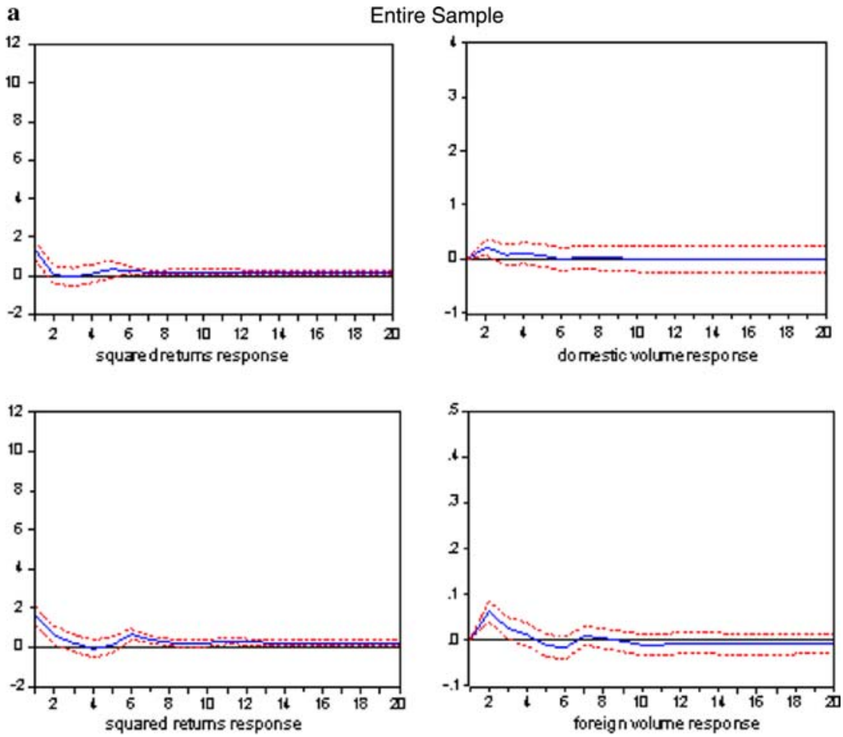

Fig. 4 (**a**) Plots the effects of a one-time one-standard-deviation increase in 'domestic'/'foreign' volume on squared returns and vice versa for the entire sample. The dotted lines indicate ±2 standard deviation bands computed by the asymptotic standard errors; (**b**) plots, for sample A (B and B1) the effects of a one-time one-standard-deviation increase in 'domestic' ('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 'foreign' ('domestic') volume. The dotted lines indicate ±2 standard deviation bands computed by the asymptotic standard errors

Figure 4 plots (for the entire sample as well as for samples A and B) 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 4 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

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

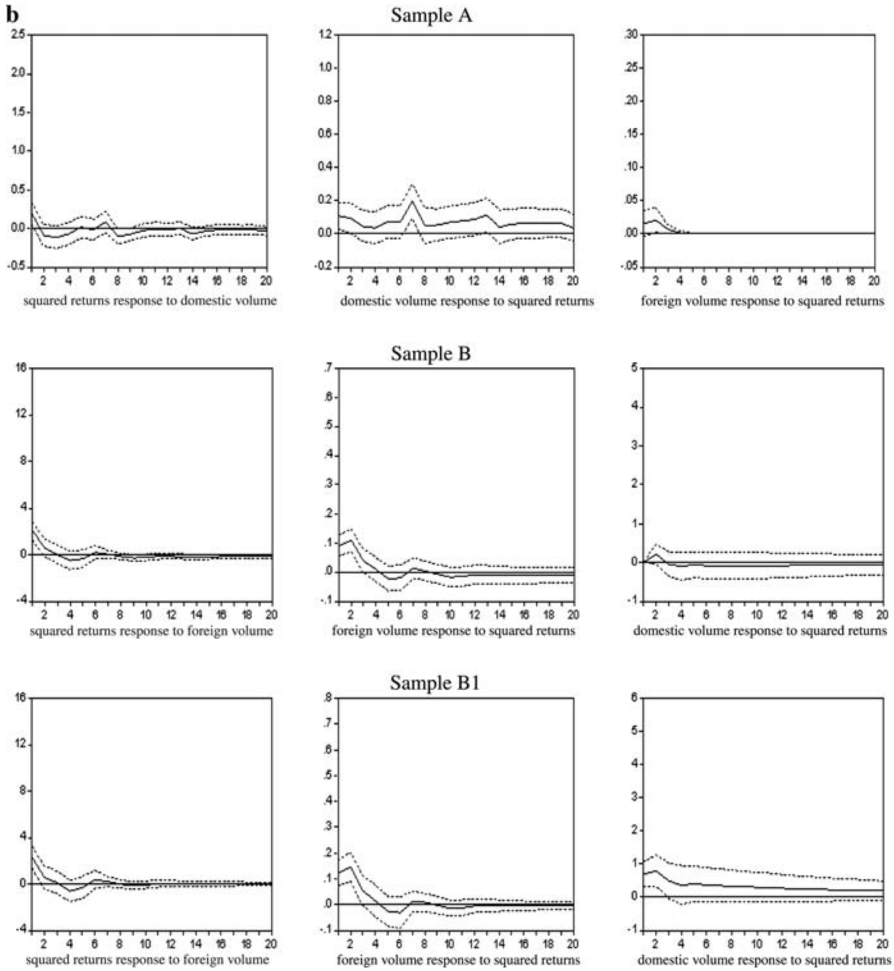

Fig. 4 continued

squared returns on 'foreign' volume seems much smaller in size than the effect of 'foreign' volume on squared returns.

5.2 Simultaneous approach

5.2.1 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 9 reports the estimation results of a model that includes the variance Eq. (1) augmented 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 Eq. (1) is replaced by $\varpi := \omega + k_{jl}V_{j,t-l}$. Table 9 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 9 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.

Table 9 FIAPARCH models augmented by the addition of lags of volume

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

Notes: For each of the four periods, Table 9 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 parentheses are standard errors. A-indicates that there was no convergence

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.

5.2.2 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 10 reports only the estimated parameters of interest (m_l's). First, we discuss the results for the entire sample. Table 10 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

Table 10 Bivariate FIAPARCH in mean models

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

Notes: For each of the four periods, Table 10 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 square brackets are *P* values

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

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, 1 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 6 months for the full impact of the liberalization process to take place and at the same time we allow more than 1 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.

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 subsample 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.

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References

Andrews, D. W. K. (1991). Heteroscedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica, 59*, 817–858.

Baek, E., & Brock, W. (1992). *A general test for nonlinear Granger causality: bivariate model.* Working paper, Madison: University of Wisconsin.

Bekaert, G., & Harvey, C. R. (2000). Foreign speculators and emerging equity markets. *Journal of Finance, 55*, 565–613.

Bessembinder, H., & Seguin, P. J. (1993). Price volatility, trading volume, and market depth: Evidence from futures markets. *Journal of Financial and Quantitative Analysis, 28*, 21–39.

Bhagat, S., & Bhatia, S. (1996). *Trading volume and price variability: Evidence on lead-lag relations from granger-causality tests*. Working paper, University of Colorado at Boulder.

Brailsford, T. J. (1996). The empirical relationship between trading volume, returns and volatility. *Accounting and Finance, 35*, 89–111.

Brock, W. (1993). Pathways to randomness in economy: Emergent nonlinearity and chaos in economics and finance. *Estudios Economicos, 8*, 3–28.

Brooks, C. (1998). Predicting stock index volatility: Can market volume help? *Journal of Forecasting, 17*, 59–80.

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993). Trading volume and serial correlation in stock returns. *Quarterly Journal of Economics, 108*, 905–939.

Caporin, M. (2003). Identification of long memory in GARCH models. *Statistical Methods and Applications, 12*, 133–151.

Chen, G., Firth, M., & Rui, O. M. (2001). The dynamic relation between stock returns, trading volume, and volatility. *The Financial Review, 38*, 153–174.

Conrad, C., & Haag, B. (2006). Inequality constraints in the fractionally integrated GARCH model. *Journal of Financial Econometrics, 3*, 413–449.

Conrad, C., & Karanasos, M. (2005). Dual long memory in inflation dynamics across countries of the Euro area and the link between inflation uncertainty and macroeconomic performance. *Studies in Nonlinear Dynamics and Econometrics*, 9(4).

Daigler, R., & Wiley, M. (1999). The impact of trader type on the futures volatility–volume relation. *Journal of Finance, 6*, 2297–2316.

Davidson, J. (2006). Time Series Modelling 4.19, http://www.timeseriesmodelling.com.

Edison, H., & Reinhart, C. M. (2001). Stopping hot money. *Journal of Development Economics, 66*, 533–553.

Epps, T., & Epps, M. L. (1976). The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis. *Econometrica, 44*, 305–321.

Gallant, A. R., Rossi, P., & Tauchen, G. (1992). Stock prices and volume. *Review of Financial Studies, 5*, 199–242.

Grabel, I. (1995). Assessing the impact of financial liberalization on stock market volatility in selected developing countries. *The Journal of Development Studies, 31*, 903–917.

Harris, L. (1987). Transaction data tests of the mixture of distributions hypothesis. *Journal of Financial and Quantitative Analysis, 22*, 127–141.

Harris, M., & Raviv, A. (1993). Differences of opinion make a horse race. *Review of Financial Studies, 6*, 473–506.
Henry, P. B. (2000). Stock market liberalization, economic reform, and emerging market equity prices. *Journal of Finance, 55*, 529–564.
Hiemstra, C., & Jones, J. D. (1995). Testing for linear and nonlinear Granger causality in the stock–volume relation. *Journal of Finance, 49*, 1639–1664.
Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis, 22*, 109–126.
Kim, E. H., & Singal, V. (2000). Stock market openings: experience of emerging economics. *Journal of Business, 73*, 25–66.
Kim, K. W. (Ed.) (2001). *Three years after the IMF bailout: A review of the Korean economy transformation since 1998*. Seoul: Sam-Sung Research Economic Institution Report.
Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: volume versus GARCH effects. *Journal of Finance, 45*, 221–229.
Lavielle, M., & Moulines, E. (2000). Least-squares estimation of an unknown number of shifts in a time series. *Journal of Time Series Analysis, 21*, 33–59.
Lee, B. S., & Rui, O. M. (2002). The dynamic relationship between stock returns and trading volume: domestic and cross-country evidence. *Journal of Banking and Finance, 26*, 51–78.
Pesaran, M. H., & Shin, Y. (1998). Impulse response analysis in linear multivariate models. *Economics Letters, 58*, 165–193.
Pyun, C. S., Lee, S. Y., & Nam, K. (2000). Volatility and information flows in emerging equity market: A case of the Korean stock exchange. *International Review of Financial Analysis, 9*, 405–420.
Saatcioglu, K., & Starks, L. T. (1998). The stock price–volume relationship in emerging stock markets: the case of Latin America. *International Journal of Forecasting, 14*, 215–225.
Silvapulle, P., & Choi, J. (1999). Testing for linear and nonlinear Granger causality in the stock price–volume relation: Korean evidence. *The Quarterly of Economics and Finance, 39*, 59–76.
Singh, A. (1997). Financial liberalization, stock markets and economic development. *The Economic Journal, 107*, 771–782.
Singh, A., & Weisse, B. A. (1998). Emerging stock markets, portfolio capital flows and long-term economic growth: Micro and macroeconomic perspectives. *World Development, 26*, 607–622.
Smirlock, M., & Starks, L. T. (1988). An empirical analysis of the stock price–volume relationship. *Journal of Banking and Finance, 12*, 31–41.
Spyrou, S. I., & Kassimatis, K. (1999). Did equity market volatility increase following the opening of emerging markets to foreign investors? *Journal of Economic Development, 24*, 30–51.
Stiglitz, J. (2002). *Globalization and its discontents*. London: Penguin Books.
Tse, Y. K. (1991). Price and volume in the Tokyo stock exchange. In: Ziemba, W. T., Bailey, W., & Hamao, Y. (Eds.), *Japanese financial market research*. Amsterdam: Elsevier Science.
Tse, Y. K. (1998). The conditional heteroscedasticity of the Yen–Dollar exchange rates. *Journal of Applied Econometrics, 13*, 49–55.
Vilasuso, J. (2001). Causality tests and conditional heteroscedasticity: Monte Carlo evidence. *Journal of Econometrics, 1*, 25–35.
Wang, J. (1994). A model of competitive stock trading volume. *Journal of Political Economy, 102*, 127–168.
Yang, M. (2002). Lag length and mean break in stationary VAR models. *Econometrics Journal, 5*, 374–386.