



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

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ABSTRACT

This paper investigates 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. We distinguish volume trading before the Asia financial crisis from trading after the crisis. 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. Moreover, 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.

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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

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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 Kyrtsov (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 & 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.

2. Theoretical background

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 are 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

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).

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: $\text{Cov}(r_t^2, V_t) = \text{Cov}(r_t^2, V_t^{(L)}) + \text{Cov}(r_t^2, V_t^{(I)}) = cb\text{Var}(I_t) + \text{Cov}(r_t^2, V_t^{(L)})$.

In Andersen's framework $\text{Cov}(r_t^2, V_t^{(L)}) = 0$. 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 $\text{Cov}(r_t^2, V_t^{(L)})$ 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.

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 it does not affect volatility.

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.

3.1. 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. Fig. 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

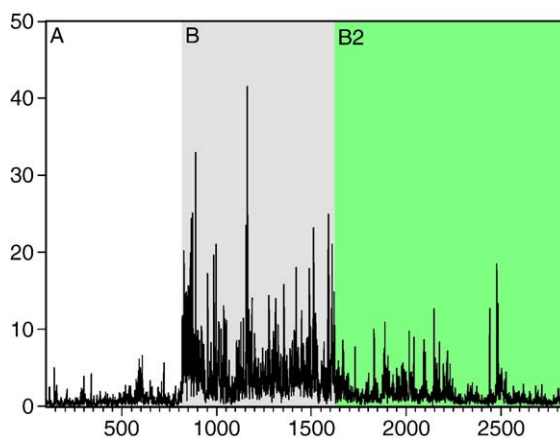


Fig. 1. Garman Klass volatility.

inherent biases induced 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 & Wiley, (1999), Fung & Patterson, (1999), Wang (2000), Kawaller et al. (2001), Wang (2002b) and Chen and Daigler (2004).²

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 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). 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

$$y_{vt} = \frac{VLM_t}{\frac{1}{100} \sum_{i=1}^{100} VLM_{t-i}},$$

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. Fig. 2 plots the turnover volume from January 1995 to October 2005.

3.3. Structural breaks

We choose the break points by employing the methodologies in Bai and Perron (1998, 2003a,b) and Lavielle and Moulines (2000) (hereafter LaMo).⁴ 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

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 & Wiley, 1999; Fung & Patterson, 1999, Kawaller et al., 2001, Wang, 2002a 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.

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.

⁴ These tests are performed on the raw data, one series at a time, prior to fitting the bivariate models. Details are available from the authors upon request.

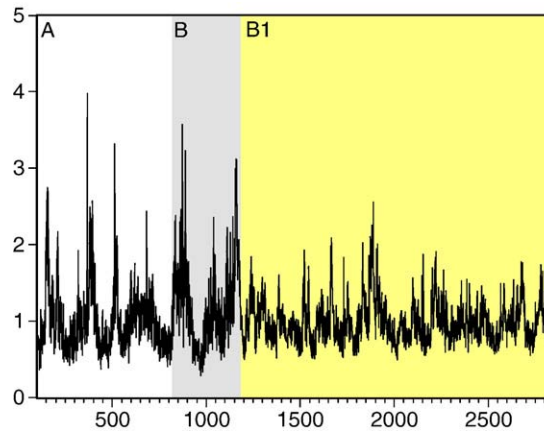


Fig. 2. Turnover volume.

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 (see Figs. 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).

3.4. 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 & 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).

4. Estimation procedures

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 $z_t \sim I(d_z)$, that is integrated of order d_z , and $x_t \sim I(d_x)$ they show that the corresponding t -statistic will be divergent provided that $d_z + d_x > 0.5$ even if the two series are independent.

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 heteroskedasticity 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.⁵

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.

Next 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 $\boldsymbol{\varepsilon}_t \triangleq (\varepsilon_{vt} \ \varepsilon_{gt})'$. That is in Eq. (1) below the subscripts v and g mean that the first expression represents the volume and the second one stands for the volatility. 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 $\rho \triangleq h_{vg,t} / \sqrt{h_{vt}h_{gt}} (-1 \leq \rho \leq 1)$.⁶

In order to make our analysis easier to understand we will introduce the following matrix notation. 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 $\Phi_{ij}(L) \triangleq \sum_{r=1}^{p_{ij}} \phi_{ij,r}L^r$, $i, j = v, g, j \neq i$. The structure of the ARFI (p_i, d_{mi}), mean equation is given by

$$\begin{aligned} (1-L)^{d_{mv}} \Phi_v(L) [y_{vt} - \Phi_{vg}(L)y_{gt} - \mu_v] &= \varepsilon_{vt}, \\ (1-L)^{d_{mg}} \Phi_g(L) [y_{gt} - \Phi_{gv}(L)y_{vt} - \mu_g] &= \varepsilon_{gt}, \end{aligned} \tag{1}$$

The above expressions can be written in a matrix form as

$$\Delta^m(L) \Phi(L) [\mathbf{y}'_t - \boldsymbol{\mu}_t] = \boldsymbol{\varepsilon}_t, \tag{2}$$

where $\Delta^m(L)$ and $\Phi(L)$ are 2×2 diagonal polynomial matrices in the lag operator L with elements $(1-L)^{d_{mi}}$ and $\Phi_i(L)$, $i = v, g$, respectively; $\mathbf{y}'_t = \Phi'(L)\mathbf{y}_t$, with $\Phi'(L)$ a 2×2 matrix polynomial in the lag operator L with unit diagonal elements and off-diagonal elements $-\Phi_{ij}(L)$, $i, j = v, g$, for $j \neq i$; $\boldsymbol{\mu}$ is the 2×1 vector of constants: $\boldsymbol{\mu} \triangleq (\mu_v \ \mu_g)'$ ($|\mu_i| < \infty$). The process \mathbf{y}_t is covariance stationary if $d_{mi} < 0.5$ and the roots of $\Phi_i(L)$ lie outside the unit circle.

Further, to establish terminology and notation, the bivariate FIGARCH(1, d_{vi} , 1) process is defined by⁷

$$(1 - \beta_i L)(h_{it} - \varpi_i) = [(1 - \beta_i L) - (1 - L)^{d_{vi}}(1 - \alpha_i L)] \varepsilon_{it}^2, \quad i = v, g. \tag{3}$$

The above expressions can be written in a matrix form as

$$\mathbf{B}(L)(\mathbf{h}_t - \boldsymbol{\varpi}) = [\mathbf{B}(L) - \Delta^v(L)\mathbf{A}(L)] \boldsymbol{\varepsilon}_t^2, \tag{4}$$

⁵ 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 Teyssi re (1998). For applications to the inflation-growth link see (Karanasos & Zeng, 2006).

⁶ In Section 6.1 below, to check the sensitivity of our results to different error distributions, we reestimate our dual long-memory GARCH models using the skewed- t density.

⁷ 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.

Table 1
Mean equations: AR lags.

Samples:	Total	A	B	B1
Eq. (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
Eq. (2): Volatility				
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.

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; $\boldsymbol{\omega}$ is a 2×1 column vector given by $\boldsymbol{\omega} \triangleq (\boldsymbol{\omega}_v, \boldsymbol{\omega}_g)' [\boldsymbol{\omega}_i \in (0, \infty)]$; $\Delta^v(L)$ is a 2×2 diagonal matrix polynomial with diagonal elements $(1 - L)^{d_{vi}}$ and \wedge denotes elementwise exponentiation.⁸

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).⁹

5. Empirical analysis

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 (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.

The best fitting specification is chosen according to the minimum value of the information criteria (not reported). Recall that, in Table 1 below, the superscripts for volume, *T*, *D* and *F*, denote total, domestic and foreign volume respectively. For the conditional means of volumes, we choose an ARFI(12, d_{mv}) model for the whole sample. In particular, for total and domestic volumes, $\Phi_v(L) = 1 - \sum_{k=1}^{12} \phi_{vk} L^k$, with $\phi_{vk} = 0$ for $k = 3, 4, 5, 7, 9, 10, 11$. For these volumes we choose an ARFI(8, d_{mv}) for the pre- and post-crisis periods and an ARFI(9, d_{mv}) for the sample B1 (Fig. 3). For the conditional mean of foreign volume we choose an ARFI(6, d_{mv}) for sample A and an ARFI(5, d_{mv}) for the two post-crisis periods (see Table 1).¹⁰

Finally, for the conditional mean of volatility, we choose an ARFI(3, d_{mg}) for the pre-crisis period and an ARFI(1, d_{mg}) process for the other three samples. That is $\Phi_g(L) = 1 - \phi_{g3} L$ and $\Phi_g(L) = 1 - \phi_{g1} L$, respectively. We do not report the estimated AR coefficients for space considerations.

Before we discuss the estimation results we want to ensure that the models are well specified. First, we calculate Ljung–Box *Q* statistics at 12 lags for the levels, squares, and cross-equation products of the standardized residuals for the estimated bivariate dual long-memory GARCH systems. The results (not reported) show that the time-series models for the conditional means and the conditional variances adequately capture the joint distribution of the disturbances. Next we employ the tests for skewness, kurtosis and a joint test for normality proposed by Bai and Ng (2005). For the total sample only in the foreign volume, and for the pre-crisis period only in the volatility, we find asymmetry and excess kurtosis. For the pre-crisis period we fail to reject symmetry and to find evidence of excess kurtosis in the three volumes. For the post-crisis period we find excess kurtosis in the total and foreign volumes. In the rest of the cases the test statistics are marginally significant (results not reported).

Finally, we employ the diagnostic tests proposed by Engle and Ng (1993) which emphasize the asymmetry of the conditional variance to news. For the entire sample and before the crisis all the sign and the size bias test statistics (not reported) for asymmetries in the conditional variances of the total/domestic volume are insignificant. Similarly, for the pre-crisis period there is no indication of asymmetry in the conditional variance of the volatility. In sharp contrast, for the total sample in the volatility and foreign volume, for the pre-crisis period in the foreign volume, and for the post-crisis period in all the four series the results from the diagnostic tests point to the presence of a leverage effect in the conditional variances. To judge the sensitivity of our results to

⁸ Moreover, in Section 6.1 below to check the sensitivity of our results to the presence of asymmetries we reestimate our dual long-memory GARCH models by replacing ε_{it}^2 in Eq. (3) with $(1 + \varsigma_i D_{it}) \varepsilon_{it}^2$ where $D_{it} = 1$ if $\varepsilon_{it} < 0$ and 0 otherwise. That is, in Eq. (4) we replace ε_t^2 by $\mathbf{Z}_t \varepsilon_t^2$ where \mathbf{Z}_t is a 2×2 diagonal matrix with elements $(1 + \varsigma_i D_{it})$.

⁹ Baillie and Morana (2009) 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 (2009). This is undoubtedly a challenging yet worthwhile task.

¹⁰ 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 $(1 - \sum_{k=1}^6 D_k) y_{vt}^{(F)}$ where D_k is a dummy indicating the presence of outliers. That is, $D_k = 1$ if a particularly large outlier has been observed and $D_k = 0$ otherwise. Carnero et al. (2007) investigate the effects of outliers on the estimation of the underlying volatility when they are not taken into account.

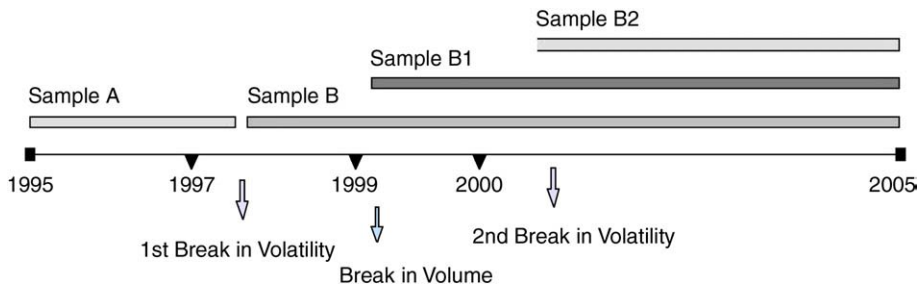


Fig. 3. Pre- and post-crisis periods.

the possible presence of asymmetries and/or skewness in the conditional variances of the four series, in Section 6.1 below, we reestimate our models using the skewed *t* density with asymmetries.

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 ($\phi_{ij,r}$, $i, j = v, g$, for $j \neq i$) of the polynomials $\Phi_{vg}(L)$ and $\Phi_{gv}(L)$, defined in Eq. (1), which capture the possible feedback between the two variables, are shown in Table 2. To test for the presence of a bidirectional link we examine the likelihood ratio statistic (not reported) for the linear constraints $\phi_{vgr,r} = \phi_{gvr,r} = 0$. In almost all cases only the first two lags, $r = 1, 2$, are significant.

Table 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 $\phi_{gv,r}$ 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 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

Table 2
Mean equations: cross effects.

	$y_t^{(T)} \triangleq (y_{vt}^{(T)} \ y_{gt}^{(T)})'$		$y_t^{(D)} \triangleq (y_{vt}^{(D)} \ y_{gt}^{(D)})'$		$y_t^{(F)} \triangleq (y_{vt}^{(F)} \ y_{gt}^{(F)})'$	
	$y_{vt}^{(T)}$	$y_{gt}^{(T)}$	$y_{vt}^{(D)}$	$y_{gt}^{(D)}$	$y_{vt}^{(F)}$	$y_{gt}^{(F)}$
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 $\phi_{ij,r}$, $r = 1, 2$. The $y_t^{(S)}$, $S = T, D, F$, and y_{gr} 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 ° denotes significance at the 0.01, 0.05, 0.10 and 0.15 levels respectively. The numbers in parentheses are standard errors.

Table 3
The volume–volatility link.

Sample	Total	A	B	B1
<i>Panel A. The effect of volume on volatility</i>				
Total	Negative	Zero	Positive	Positive
Domestic	Positive	Zero	Positive	Positive
Foreign	Negative	Negative	Positive	Positive
<i>Panel B. The impact of Volatility on Volume</i>				
Total	Negative	Negative	Negative	Negative
Domestic	Negative	Negative	Negative	Negative
Foreign	Positive	Positive	Positive	Positive

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).

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'.

5.3. Fractional mean parameters

Estimates of the fractional mean parameters are shown in Table 4.¹¹ Several findings emerge from this table. In all samples total and domestic volumes generated 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.

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.¹² Generally speaking we find that the apparent long-memory in all variables is quite resistant to 'mean shifts'.¹³

¹¹ 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.

¹² 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.

¹³ 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.

Table 4

Mean equations: fractional parameters.

	$\mathbf{y}_t^{(T)} \triangleq (y_{vt}^{(T)} y_{gt}^{(T)})'$		$\mathbf{y}_t^{(D)} \triangleq (y_{vt}^{(D)} y_{gt}^{(D)})'$		$\mathbf{y}_t^{(F)} \triangleq (y_{vt}^{(F)} y_{gt}^{(F)})'$	
	$d_{mv}^{(T)}$	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. Recall that the superscripts T, D and F , denote total, domestic and foreign volume.

5.4. FIGARCH specifications

Tables 5 and 6 present estimates of the FIGARCH model.¹⁴ Note that in all cases the GARCH coefficients satisfy the necessary and sufficient conditions for the non-negativity of the conditional variances (see Conrad and Haag, 2006).

The estimates of d_{vi} 's govern the long-run dynamics of the conditional heteroskedasticity. 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 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 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.

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.¹⁵

6. Sensitivity analysis

6.1. Distributional assumptions and asymmetries

Many tests exist in the literature for multivariate normality (for a survey see Mecklin and Mundfrom 2004). However, as Bai and Chen (2008) point out, tests on multivariate t density are relatively scant. Bai and Chen (2008) propose a procedure for testing multivariate distributions which is applicable to time varying means and time varying covariance matrices. They construct an asymptotically distribution-free test statistic that takes a very simple form. In applications of multivariate GARCH models the most frequently used distributions are multivariate normal and t (see Bai and Chen, 2008 and the references therein).

Since asset returns may be skewed using a multivariate skewed t density may lead to improve empirical modeling and financial decision making. Bauwens and Laurent (2005) provide a brief literature review on skewed multivariate densities. They also propose a multivariate skewed- t distribution. They apply it on several portfolios of assets and currencies and find that in several cases it improved the quality of out-of-sample forecasts of Value at Risk forecasts. Thus, they argue that it may be more useful than its symmetric counterpart for modeling financial returns.

¹⁴ Various tests for long-memory in volatility have been proposed in the literature (see, for details, Hurvich & Soulier, 2002).

¹⁵ 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.

Table 5

Variance equations: GARCH coefficients.

	$\mathbf{h}_t^{(T)} \triangleq (h_{vt}^{(T)} \ h_{gt}^{(T)})'$		$\mathbf{h}_t^{(D)} \triangleq (h_{vt}^{(D)} \ h_{gt}^{(D)})'$		$\mathbf{h}_t^{(F)} \triangleq (h_{vt}^{(F)} \ h_{gt}^{(F)})'$	
	$h_{vt}^{(T)}$	$h_{gt}^{(T)}$	$h_{vt}^{(D)}$	$h_{gt}^{(D)}$	$h_{vt}^{(F)}$	$h_{gt}^{(F)}$
<i>Total sample</i>						
α_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)
<i>Sample A</i>						
α_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)
<i>Sample B</i>						
α_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)
<i>Sample B1</i>						
α_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 $h_{vt}^{(s)}$, $s = T, D, F$, and h_{gt} columns report results for the volume and volatility equations respectively.

To take into account the points raised by Bai and Chen (2008) and Bauwens and Laurent (2005) and to check the sensitivity of our results to different error distributions we reestimate our dual long-memory GARCH models using the skewed t density with asymmetries.¹⁶

A comparison of these results with those obtained when a bivariate normal distribution without asymmetries is used reveals that the results are qualitatively very similar (see Tables 3 and 7). In particular, the evidence for the total sample and the pre-crisis period suggests that there is a causal negative effect from foreign volume to volatility.¹⁷ This 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 entire sample and the post-crisis period increased total/domestic 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. The results for the skewed t density with asymmetries, regarding the impact of volatility on volume, are almost identical to those reported for the normal distribution. That is, volatility tends to increase foreign volume and lower total/domestic volume. This finding is robust to the choice of the sample period.¹⁸ We also examine how the presence of skewness and asymmetry in the t density affects the volume–volatility relation. Overall the results appear very robust and are generally insensitive to the presence of skewness and/or asymmetry. We do not report the estimated results for space considerations.

6.2. Structural dynamics

The model in Eq. (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. To check the robustness of the aforementioned specification, we also estimate the following model

$$\Delta^m(L)\Phi^*(L)(\mathbf{y}_t - \boldsymbol{\mu}) = \boldsymbol{\varepsilon}_t, \quad (5)$$

where $\Phi^*(L)$ is a 2×2 matrix polynomial in the lag operator L with diagonal elements $\Phi_i(L)$, and off-diagonal elements $-\Phi_{ij}(L)$, $i, j = v, g, j \neq i$. 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 Tables 2–6.

¹⁶ Due to space limitations, we have not reported the estimated equations for the conditional means and variances. They are available upon request from the authors.

¹⁷ Interestingly, in the pre-crisis period all three volumes have a negative effect on volatility.

¹⁸ With the exception of sample A where the positive effect of volatility on foreign volume is insignificant.

Table 6

Variance equations: fractional and ccc parameters.

	$\mathbf{h}_t^{(T)} \triangleq (h_{vt}^{(T)} \ h_{gt}^{(T)})'$		$\mathbf{h}_t^{(D)} \triangleq (h_{vt}^{(D)} \ h_{gt}^{(D)})'$		$\mathbf{h}_t^{(F)} \triangleq (h_{vt}^{(F)} \ h_{gt}^{(F)})'$	
	$h_{vt}^{(T)}$	$h_{gt}^{(T)}$	$h_{vt}^{(D)}$	$h_{gt}^{(D)}$	$h_{vt}^{(F)}$	$h_{gt}^{(F)}$
<i>Total sample</i>						
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)	
<i>Sample A</i>						
d_{vi}	–	–	–	–	–	–
ρ	0.31*** (0.07)		0.32*** (0.07)		0.30*** (0.06)	
<i>Sample B</i>						
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)	
<i>Sample B1</i>						
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}), $i = v, g$ and ccc (ρ) parameters.**Table 7**The volume–volatility link skewed t density with asymmetries.

Sample	Total	A	B
Panel A. The effect of volume on volatility			
Total	Positive	Negative	Positive
Domestic	Positive	Negative	Positive
Foreign	Negative	Negative	Zero
Panel B. The impact of Volatility on Volume			
Total	Negative	Negative	Negative
Domestic	Negative	Negative	Negative
Foreign	Positive	Zero	Positive

Notes: Bold indicates that the result is different than the one in Table 3.

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.

6.3. 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)¹⁹. Overall the results appear robust and are generally insensitive to fundamental changes in the detrending technique. Specifically, as seen in Table 8, 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 similar to those reported for the moving average detrending procedure.²⁰

¹⁹ Details of the methodology are available from the authors upon request.

²⁰ Baxter and King (1999) develop an approach of filtering economic and financial time series that is fast, flexible, and easy to implement. 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.

Table 8

Mean equations: cross effects (linear detrending).

	$\mathbf{y}_t^{(T)} \triangleq (\mathbf{y}_{vt}^{(T)} \mathbf{y}_{gt}^{(T)})'$		$\mathbf{y}_t^{(D)} \triangleq (h_{vt}^{(D)} h_{gt}^{(D)})'$		$\mathbf{y}_t^{(F)} \triangleq (h_{vt}^{(F)} h_{gt}^{(F)})'$	
	$\mathbf{y}_{vt}^{(T)}$	$\mathbf{y}_{gt}^{(T)}$	$\mathbf{y}_{vt}^{(D)}$	$\mathbf{y}_{gt}^{(D)}$	$\mathbf{y}_{vt}^{(F)}$	$\mathbf{y}_{gt}^{(F)}$
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 (0.002)	-0.15 (0.19)	-	-	0.003° (0.003)	-0.01 (0.12)

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.

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