Department of
Economics and Finance

Working Paper No. 19

during the GFC, when their total trading has affected volatility positively. Finally, the whole trading activity, as well as the foreign one, in the two pre-crisis periods has stabilized the market, whereas in the case of the GFC its impact on volatility has become positive after the crisis.

The remainder of the paper is structured as follows. Section 2 reviews the existing empirical evidence on the trading behaviour of institutional, individual and foreign investors, and allows us to develop our theoretical hypotheses on the volume - volatility link. Section 3 describes the data, while Section 4 outlines the econometric model and estimation procedure. Section 5 presents the empirical results for different investor categories around the Asian financial crisis. In Section 6, we apply the dual long-memory model of the volume - volatility link to the GFC of 2008. Section 7 offers some concluding remarks.

2 Theoretical Background

2.1 Hypotheses

In this Section we develop two hypotheses for the volume - volatility link. The first concerns the investment style (Hypothesis 1, H1) and the second is based on the investors'information advantage (Hypothesis 2, H2).

First, we look into the effect of active (insurance companies, mutual funds, and investment banks) vs. passive (commercial banks, savings banks, and other companies) institutional non-member investors based on a finer partition of trading volume data into the six different non-member categories. In line with the literature reviewed below, we assume that traders who use market orders to assure rapid execution (at the cost of large price impacts) and engage in herding and positive feedback trades (based on short-lived information) will exacerbate short-run volatility (H1a). By contrast, traders who use limit orders and pursue contrarian trades (based on long-term information) will reduce short-run volatility (H1b).

trading will be associated with less volatility in the Korean Stock Exchange (H2b). For investors with no access to order flow data (less informed) we expect a wider dispersion of beliefs since they cannot differentiate short-term liquidity demand from changes in overall fundamental supply and demand. As a result, less informed traders, here proxied by individual and foreign investors, are expected to buy and sell within a wider range of prices around the fair value of the asset. On the other hand, if investors have an information advantage due to access to market data, they are likely to form homogeneous expectations about market movements and the fundamental characteristics of an asset. If this is the case informed traders, proxied by member institutional investors in this study, are expected to buy and sell within a small range of prices around the fair value of the asset.

In this paper, we associate the trading of institutional member and individual (and foreign) investors with those of informed and uninformed traders, respectively. We do so, not by means of serial correlation tests (Campbell et al., 1993, Easley et al., 1997) or conditioning on past price changes (Avramov et al., 2006), but by taking into account the distinction made by the Korean Stock Exchange between institutional (member and non-member) and individual investors as in Daigler and Wiley (1999). Here, the latter are treated as uninformed (or less informed), because their orders are channeled through members' trading pits. Moreover, individual investors are significantly affected by psychological biases, which lead to increased levels of trading, systematic behaviour and high trading costs. Institutional member investors are treated as informed because members' direct access to the trading system provides them with short-term information such as trading activity at specific prices, and price trends. They also have specific information about their own customers' supply and demand in the cash and futures markets.

Institutional or large block trades are more informative than small trades and are more likely to cause permanent price changes (Easley and OHara, 1987, Easley et al., 1997). Daigler and Wiley (1999) find that the positive volume-volatility relation is driven by the (uninformed) general public (H2a), whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility (H2b). Kelley and Tetlock (2013) show that overconfidence (not hedging) explains nearly all uninformed trading. Abbes (2013) provides further evidence of the destabilizing effect of trading volume on volatility, which can be attributed to investors' overconfidence bias in both developed and emerging stock markets. In the multi-country context, several studies on the Asian stock markets also find a positive relationship between aggregate trading volume and volatility. For example, Pisedtasalasai and Gunasekarage (2007) and Chuang et al. (2012) report a positive volume-volatility link for the Philippines, Singapore, Hong Kong, Korea, China, Indonesia, and Thailand. Finally, Girard and Biswas (2007) find that volatility persistence decreases when the trading volume is decomposed into its expected and unexpected components in all markets under investigation, including most Asian developed and emerging ones.

2.2 Trading Behaviour

Sentiment

Increased volatility in …nancial markets could also re‡ect sentiment-induced mispricing or time-varying risk (or risk aversion that causes time variation in expected stock returns). Baker and Wurgler (2006, 2007) argue that sentiment traders shift from safe to speculative securities when sentiment increases, and from speculative to safe securities when sentiment declines, and that these sentiment-induced demand shocks drive mispricing in …nancial markets. Moreover, market-wide sentiment should have a greater e¤ect on securities that are hard to arbitrage and di¢ cult to value. Consistently with this prediction, they …nd that when sentiment is low, subsequent returns are relatively high for small, young, high volatility, pro…table, non-dividend-paying, extreme growth, and distressed stocks. When sentiment is high, on the other hand, these categories of stocks have relatively low subsequent returns.[1]

DeVault et al. (2019) …nd that commonly used measures of investor sentiment capture the demand shocks of institutional, rather than individual, investors. In other words, the traders driving the sentiment-induced mispricing are institutional, rather than individual, investors (on aggregate). In particular, the level of institutional investors'speculative stock holdings, relative to that of their holdings of safe stocks, increases when sentiment is higher. More importantly, di¤erences in investment styles (risk management and reputation concerns, momentum, and herding trading) across types of ins across that8as, objectives (index tracking, value, growth), liquidity needs and tax-management purposes (Alexander et al., 2007). If active institutional traders use market orders and engage in herding and positive feedback trades, on the basis of short-lived information, this is likely to increase short-run volatility. De Long et al. (1990) argue that in the presence of positive feedback traders, rational speculation (or trading by institutional investors) can be destabilizing (H1a). On the other hand, passive institutional traders who use limit orders and engage in more contrarian or value-motivated trades are likely to reduce volatility in the short run (H1b). Lakonishok et al. (1992) use data on the holdings of tax-exempt (predominantly pension) funds to evaluate the potential effect of their trading on stock prices. Their evidence suggests that institutional herding moves prices, but not necessarily in a destabilizing way. For example, if all investors react to the same fundamental information prices will adjust faster to new fundamentals.

For the Chinese market, institutional trades are considered more informative and overall reduce market volatility (Li and Wang, 2010). Cai et al. (2010), using a unique dataset of the Chinese stock market, document how a higher proportion of trades initiated by institutional investors can be considered as informed (H2b) compared to trades initiated by individuals (H2a). This result is consistent with the argument that institutional investors are better informed and therefore can earn bigger profits than individuals.[2] By contrast, exploring the incentives of institutional trading, Basak and Pavlova (2013) develop an asset-pricing model with institutional investors' incentives to overperform their benchmarks and find that their trading increases market volatility.[3]

Individual Investors

Barber et al. (2009) show that the aggregate portfolio of individuals performs poorly and almost all individual trading losses can be traced to their aggressive orders. Behavioural biases such as overconfidence can possibly explain why retail investors trade so much and self-manage their portfolios (see Daniel et al., 1998; Odean, 1998; Gervais and Odean, 2001; Kelley and Tetlock, 2013). Barber et al. (2009a) construct portfolios that mimic the purchases and sales of each investor group in order to analyze who gains and loses from trade. Individual investors incur substantial losses, while institutional ones (corporations, attention (or which they are familiar with), under-diversify their stock portfolios and engage in naïve reinforcement learning by repeating past behaviours that coincided with pleasure, while avoiding past behaviours that generated pain (Barber and Odean, 2008, 2011). As a result, the buy and sell decisions of individual traders are likely to exacerbate volatility, unless the liquidity provided by individual traders is matched by increased levels of informed trading by institutional investors. Herding, feedback and/or un-informed trading have the potential to explain destabilizing stock prices or excess volatility (H1a, H2a). However, they have also been used to explain momentum and reversals in stock prices depending on who trades and on what type of information. Others also argue that individual traders overinvest in stocks because they are familiar with them (or love gambling), leading to under-diversification (Goetzmann and Kumar, 2008) and average or even below-par returns (Anderson, 2013). Barber et al. (2009b) provide evidence that the trading of individuals is highly correlated and persistent. This systematic trading of individual investors is not primarily driven by passive reactions to institutional herding, by systematic changes in risk-aversion or by taxes. Psychological biases contribute to the correlated trading of individuals, which leads investors to systematically buy stocks with strong recent performance, to refrain from selling stocks held at a loss, and to be net buyers of stocks with unusually high trading volume. Foucault et al. (2011) provide evidence based on French data that individual investors as noise traders exacerbate stock returns volatility, in line with (H2a). By contrast, the study by Che (2018) concludes that individuals reduce volatility in Norway, where they are shown to be contrarian traders (H1b).

Foreign Investors

Brennan and Cao (1997) present a theoretical model and empirical evidence that supports the view that foreign investors in the US have to pursue momentum strategies and achieve inferior performance because they are less informed than domestic investors (H1a, H2a).[4] Grinblatt and Keloharju (2001) also find that foreign investors, and often professionally managed funds or investment banking houses, pursue momentum strategies and achieve superior performance. Chen et al. (2013) shed further light on the positive relationship of foreign institutional ownership on Chinese equities with stock return volatility. After removing momentum investing's contribution to performance, they find that the momentum-adjusted performance of foreigners is still highly significant (H2a). Similarly, Che (2018) finds that foreign trading activity in Norway increases volatility because foreign investors are momentum traders while domestic institutions' trading is mostly associated with lower volatility (H2b).

Wang (2007) documents a strong contemporaneous relationship between foreign equity trading and market volatility in Indonesia and Thailand. Trading within foreign and local investor groups is often negatively related to market volatility in Indonesia. This is consistent with the view that within each

[4] Likewise, Choe et al. (1999) and Froot et al. (2001) find that foreign investors tend to be momentum investors.

group, investors are relatively homogeneous in terms of capital endowments and information. In particular, in Thailand foreign net purchases are negatively associated with market volatility, therefore they provided liquidity when local investors were under stress to sell and helped to reduce volatility during the Asian crisis by preventing the local markets from dropping further than they actually did.

Turning next to studies on Korea, Choe et al. (1999) find no evidence that trades by foreign investors had a destabilizing effect on Korea's stock market over the 1996-1997 subsample. In particular, the market adjusted quickly and efficiently to large sales by foreign investors, and these sales were not followed by negative abnormal returns. Jeon and Moffett (2010) show that foreign investors in Korea are involved in herding and positive feedback strategies (H1a).[5] Likewise, Bae et al. (2011) provide evidence that foreign and domestic institutional investors trade like momentum traders (H1a, H2a) while individuals behave like contrarians (H1b). Interestingly, Umutlu and Shackleton (2015) point out that uninformed individuals' trading exerts a positive influence on equities volatility (H2a), whereas trading by informed domestic institutional investors reduces volatility (H2b). They also find that foreign trading mostly drives volatility higher (H2a). According to a more recent study on investor sentiment in the Korean Stock Exchange by Yang et al. (2017), foreign and domestic institutional investors are more informed (H2b) than individuals, who are mostly affected by psychological biases and act as noise traders (H2a). Table A3 in the Appendix summarizes the main papers presented in this Section.

3 Data and Sub-periods

We first investigate the trader-type effect of buy and sell trades on volatility for the KOSPI 200 index from 1995 until 2005. This period seems suitable to capture changes in the trading activity across investors. As the market expands and traders become aware of the market's potential, the impact of different investors' trading on volatility becomes very important. In this study, the trading of individual and foreign investors changed significantly in the aftermath of the AFC. The dataset consists of daily data on high, low, open and closing prices of the KOSPI 200 index of the Korean Stock Exchange from the 3rd of January 1995 to the 26th of October 2005 (2850 observations). For the same period, daily buy and sell trades by eight different types of domestic investors are also available. Specifically, the Korean Stock Exchange publishes the daily buy and sell value (and volume) traded by eight types of domestic investors. Domestic investors are also split into institutionals and individuals, and institutionals are further divided into members and non-members based on their access to the trading system and its information. Non-member institutional investors consist of insurance companies, mutual funds, investment banks, commercial banks, savings banks, and other companies. Finally, daily trading volume data are also available for (non-member) foreign investors of the Korean Stock Exchange. The first part of our empirical analysis focuses on the decade around the AFC. In Section 6, we will use data from the decade around the GFC, in order to investigate the volume - volatility link during the most recent financial turmoil and compare the two crises in terms of the trader-type effects stabilizing or destabilizing the stock market.

The case of Korea is particularly interesting since this country considerably improved its economic performance and attracted much greater capital inflows in the period from 1996 to 2015. In particular, Korean GDP grew by 6.5 percent (on average per year) from 1996 to 2005 and by 3.5 percent from 2006 to 2015, and net capital flows were positive and averaged almost two billion dollars over the whole period considered. The Asian financial crisis in 1997 also brought changes to the Korean financial system such as abolishing the foreign ownership ceiling in the stock market, allowing free movement of investment profit, and providing transparent financial reports. Moreover, the Korean Derivatives Market opened in 1996 by introducing the KOSPI200 Index Futures. Since then, it has developed into an international exchange following the establishment of the KOSPI200 Options Market in 1997 and the Korea Treasury Bond Futures and the US Dollar Derivatives Market in 1999. As a result of the rapid growth of options/futures trading in the KOSPI 200, the KRX Derivatives Market overtook the main American, European, and other international exchanges to become a world leader in terms of annual trading volume. Specifically, the ratio of KOSPI200 futures cash trading value increased from 0.3 in 1997 to 2.5 in 2015.[6] These developments together with the two financial crises (the Asian and Global financial ones) the Korean Stock Exchange went through raise interesting research questions about their impact on investors'trading behaviour and stock market volatility over the last twenty years.

The Korean stock market has attracted the interest of various researchers (Choe et al., 1999, 2005, Jeon and Moffett, 2010, Umutlu and Shackleton, 2015) due to the unique dataset on the different trader types provided by the Korean Stock Exchange. It is undoubtedly one of the fastest growing stock markets (Bae et al., 2011) after it experienced a radical liberal reform of its financial system by the International Monetary Fund (IMF) following the AFC, which led to dramatic capital inflows from foreign institutional investors (Kim et al., 2005). However, nowadays, South Korea still remains at the frontier between emerging and developed markets. MSCI considers the Korean market in the emerging Asia-Pacific area[7] while FTSE has classified Korea in the developed markets since 2009,[8] which suggests that it shares characteristics of both market categories, developed (MSCI: Hong Kong, Singapore, and Japan) and emerging (MSCI: China, Indonesia, Malaysia, Thailand, etc.) Asian markets. For example, according to

[6] Source: Korean Stock Exchange Fact Book 2014-15.

[7] Source: MSCI Global Market Accessibility Review, June 2019.

[8] Source: Classifying South Korea as a Developed Market, January 2013, White Paper Report FTSE Publications by Woods, C.

the MSCI Accessibility Review, in terms of openness to foreign ownership, South Korea's qualitative level of openness can be compared to similar levels of emerging markets like China, Malaysia, and Philippines and the developed markets of Hong Kong and Singapore. Ease of capital flows, market infrastructure, and regulation measures are also comparable, exhibiting significant similarities among the Asian stock exchanges. By contrast, institutional framework standards in the emerging Asian markets remain behind the developed economies. Korea faces issues concerning its foreign exchange market liberalization, which represents an obstacle to its being classified as an MSCI developed market. Finally, Yang et al. (2017) focus on Korean investor sentiment, considering the Korean Stock Exchange as a representative emerging market characterized by significant information asymmetry with respect to investor types, high market sentiment, prevalent investor psychology, unique investor participation rates, and the various trading purposes of market participants. In conclusion, the KOSPI 200 index is widely regarded as a leading emerging financial market index in East Asia, which is worthy of closer investigation with important implications for the whole region.

3.1 Price Volatility

Using data on the daily high, low, opening, and closing prices in the index we generate a daily measure of price volatility. We can choose from among several alternative measures, each of which uses different information from the available daily price data. To avoid the microstructure biases introduced by high-frequency data, and on the basis of the conclusion of Chen et al. (2006) that 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 (VL_t) as follows

$$VL_t = \frac{1}{2}u^2 - (2\ln 2 - 1)c^2; \quad t \in N;$$

where u and c are the differences in the natural logarithms of the high and low, and of the closing and opening prices respectively. Figure 1 plots the Garman-Klass (GK) volatility from 1995 to 2005.

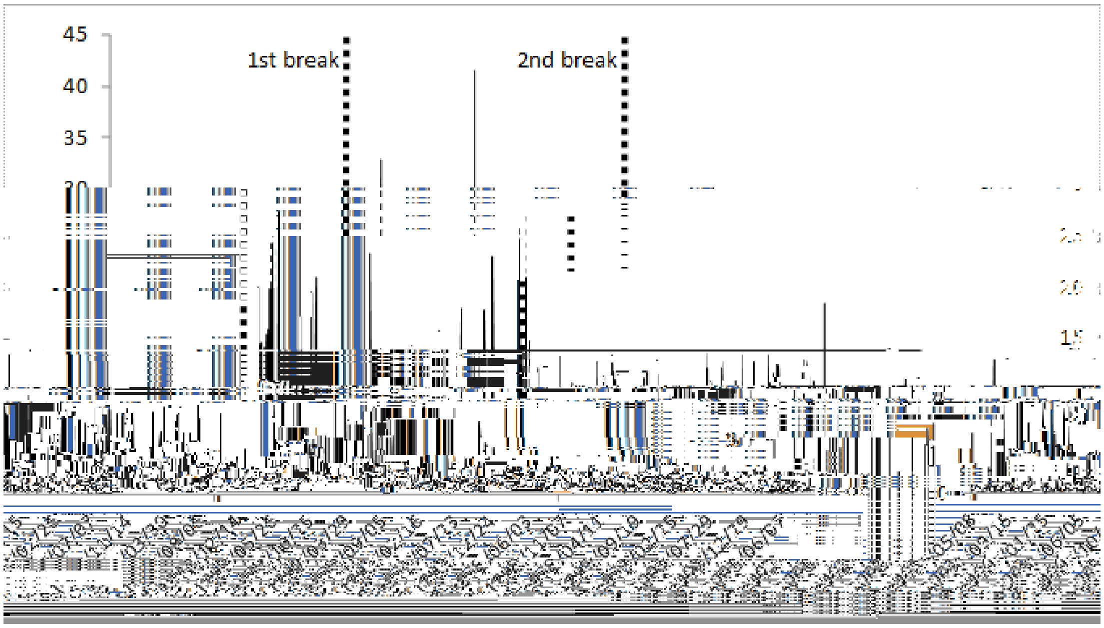

Figure 1. Garman-Klass Volatility (AFC period)

Various measures of GK volatility have been employed by, among others, Daigler and Wiley (1999), Kawaller et al. (2001), Wang (2002), Chen and Daigler (2008) and Chen et al. (2006). Chou (2005) proposes a Conditional Autoregressive Range (CARR) model for the range, defined as the difference between the high and low prices. In line with previous research, in what follows we model GK volatility as an autoregressive process taking into account the feedback from volume to volatility, dual long-memory characteristics and GARCH effects.

3.2 Trading Activity

We use the daily trading volume of foreign investors and eight different domestic investors, that is individual investors, securities companies, insurance companies, mutual funds, investment banks, commercial banks, savings banks, and other companies. Trading volume is also aggregated into four categories based on investor type (institutional, individual) and access to the trading system (member, non-member). Specifically, the four aggregate categories used here are member institutional (securities companies), non-member institutional (insurance companies, mutual funds, investment banks, commercial banks, savings banks, other companies), non-member individual and non-member foreign investors. We analyse each volume series from its buy and sell side, as well as its total ([buy+sell]/2). Further, we use the buy and sell volume series for the turnover and include this as a measure of buy and sell trades in our model. This is computed as the ratio of the value of shares bought or sold to the value of shares outstanding (see

Campbell et al., 1993; Bollerlsev and Jubinski, 1999). Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (see Lobato and Velasco, 2000). We form a trend-stationary (DTR_t) time series of log-turnover (TR_t) by incorporating the procedure used by Campbell et al. (1993), who use a 100-day backward moving average as follows:

$$DTR_t = \frac{TR_t}{\frac{1}{100}\sum_{i=1}^{100} TR_{t-i}}.$$

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.[8] Figure 2 plots the total ending in 1997. There is a fourfold increase in the average trading volume from 1998 to 2000 and it reaches the staggering amount of 3,607 trillion Won towards the end of 2003. This increase in trading volume across the years is not shared evenly among the di¤erent types of traders. Individual investors are the major players in the Korean Stock Exchange. From 1995 to 2000 nearly 75% of all buy and sell trades involve individual investors, while from 2000 onwards this percentage falls to near 50%. The presence of foreign investors in the cash market increases signi…cantly from 2001 to 2003, with the buy side reaching 37.9% of the total buy volume compared to an average of 7% from 1995 to 2000. The sell trades also increased during the same period, but not as much as the buy ones.

Member institutional investors' average percentage of buy trades was only 5.1% for the three years

Table 1. Trading Volume by trader type (AFC period)

Our results (not reported) indicate two breaks for volatility. The …rst is detected in October 1997 and the second in November 2000. Accordingly, we split the sample into three sub-periods. The …rst is

5 Empirical Analysis

5.1 Model Characteristics

Within the framework of the ARFI-FIGARCH model, we analyze the dynamic adjustments of both the conditional mean and variance of volatility for all three AFC subsample periods and the entire sample, as well as the implications of these dynamics for the direction of causality from volume to volatility. The estimates of the various formulations were obtained by quasi maximum likelihood estimation (QMLE) as implemented by James Davidson (2017) 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 (see equation (1)) is chosen according to the minimum value of the information criteria. For the conditional mean of volatility (VL_t), we choose an ARFI($3; d_m$) process for the pre-crisis period and an ARFI($1; d_m$) for the other two subsamples and the entire period. That is, $(L) = 1 \quad {}_3L^3$ and $(L) = 1 \quad {}_1L$, respectively. We also calculate Ljung–Box Q statistics at 12 lags for the levels and squares of the standardized residuals for the estimated dual long-memory models. The test results show that the time-series models for the conditional mean and the conditional variance adequately capture the distribution of the disturbances. Autoregressive coefficients and test statistics are not reported for space considerations.

Moreover, we employ the diagnostic tests proposed by Engle and Ng (1993), which focus on the asymmetry of the conditional variance to news. According to the joint test of the size and sign bias, for the entire sample period, the sign and the negative size bias test statistics (not reported) for asymmetries in the conditional variance of volatility are significant. For the pre-crisis period (subsample A) there is no indication of asymmetry in the conditional variance. By contrast, for the post-crisis period (subsample B) the results from the diagnostic tests point to the presence of a leverage effect in the conditional variance.[10]

Finally, the application of a bivariate extension of the dual long-memory model does not have an impact on the empirical findings produced by the univariate one.

5.2 Fractional Mean Parameters

Estimates of the fractional mean parameters are shown in Table 2. In all cases, the estimated value of d_m is robust to the measures of volume used[11]. In other words, all ARFI models for the subsamples

[10] To check the sensitivity of our results to different error distributions, we re-estimate our dual long-memory GARCH models using the skewed-t density with asymmetries. The results of the volume-volatility link are identical to those reported for the normal distribution (these results are available upon request).

[11] In addition, we test the hypothesis of long-memory following Robinson's (1995) semiparametric bivariate approach and the results are consistent with the parametric ones.

generated very similar estimates of d_m. For example, in the total sample, the twelve long-memory mean parameters are between 0:40 and 0:44. For the post-crisis period (subsample B) the estimated values of d_m (0:38 0:42) are similar to the total sample's estimates but higher than the corresponding values for the pre-crisis period (subsample A): 0:23 0:27. Overall, we …nd that the apparent long-memory in volatility is quite robust to mean shifts.

Table 2. Mean Equations: Fractional parameters d_m (AFC period)

Panel A. Non-Member Institutional Domestic Investors

	Insurance Companies	Mutual Funds	Investment Banks	Commercial Banks	Savings Banks	Other Companies
Total Sample	0:43 (0:06)	0:43 (0:05)	0:42 (0:05)	0:40 (0:11)	0:44 (0:05)	0:42 (0:05)
Subsample A	0:24 (0:06)	0:25 (0:07)	0:27 (0:08)	0:24 (0:06)	0:25 (0:08)	0:23 (0:08)
Subsample B	0:41 (0:03)	0:42 (0:04)	0:41 (0:04)	0:38 (0:04)	0:42 (0:04)	0:42 (0:04)

Panel B. Member/Non-Member - Domestic/Foreign Investors

	Institutional Menbers	Institutional Non-members	Individual	Total	Domestic	Foreign
Total Sample	0:42 (0:05)	0:41 (0:05)	0:41 (0:05)	0:43 (0:05)	0:41 (0:05)	0:42 (0:08)
Subsample A	0:25 (0:06)	0:23 (0:06)	0:24 (0:06)	0:25 (0:06)	0:24 (0:06)	0:25 (0:06)
Subsample B	0:41 (0:04)	0:41 (0:04)	0:42 (0:04)	0:41 (0:04)	0:42 (0:04)	0:40 (0:04)

Notes: The table reports the fractional parameter estimates of the long memory in the mean equations. d_m is de…ned in equation (1). The estimates are reported only for the case when total volume is added as a regressor. Estimates with buy/sell volume as regressors are very similar to total volume. The estimates for subsample B1 are not reported for space reasons.

*** denotes signi…cance at the 0:01 level. The numbers in parentheses are standard errors.

5.3 FIGARCH Speci…cations

Table 3 presents the estimates of the fractional parameter of the FIGARCH model. The parameter d_v governs the long-run dynamics of the conditional heteroskedasticity of volatility and is robust to the measures of volume used. In other words, all FIGARCH models for the various subsamples generated very similar fractional variance parameters. In the post-crisis period, these (0:55 0:59) are higher than the corresponding parameters for the total sample (0:40 0:43); in the case of commercial banks' turnover the estimate of d_v for the total sample (0:49) is also higher than the corresponding one (0:46) lower for subsample B. In the pre-crisis period the estimates of d_v are close to and not signi…cantly di¤erent from

used to find the causal effect, we tested for the significance of up to the twentieth lag. The first two lags show an immediate causal effect of volume on volatility, lag order five indicates a one-week effect and so on. The twentieth lag points to a one-month in advance effect of the trading turnover volume on

Table 4. Mean Equations - Cross effects of Institutional Non-members (AFC period)

Panel A. Active Institutional Non-member Domestic Investors

	Insurance Companies			Mutual Funds			Investment Banks		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	0:06	0:08	0:06	0:03	0:06	0:02	0:08	0:11	0:07
	(0:03)	(0:03)	(0:03)	(0:01)	(0:03)	(0:01)	(0:03)	(0:05)	(0:03)
	[8]	[8]	[6]	[7]	[2]	[6]	[2]	[2]	[5]
Subsample A	0:08	0:08	0:05	0:05	0:08	0:02	0:14	0:11	0:09
	(0:03)	(0:04)	(0:02)	(0:03)	(0:05)	(0:01)	(0:07)	(0:05)	(0:04)
	[8]	[8]	[6]	[8]	[8]	[6]	[1]	[1]	[6]
Subsample B	0:34	0:22	0:29	0:03	0:23	0:02	0:53	0:34	0:38
	(0:18)	(0:14)	(0:18)	(0:02)	(0:15)	(0:01)	(0:25)	(0:18)	(0:19)
	[1]	[7]	[1]	[6]	[1]	[6]	[1]	[1]	[1]

Panel B. Passive Institutional Non-member Domestic Investors

	Commercial Banks			Savings Banks			Other Companies		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	0:10	0:07	0:15	0:03	0:04	0:05	0:04	0:06	0:05
	(0:05)	(0:04)	(0:07)	(0:01)	(0:03)	(0:03)	(0:03)	(0:04)	(0:02)
	[4]	[6]	[4]	[3]	[6]	[4]	[6]	[6]	[5]
Subsample A	0:13	0:10	0:12	0:03	0:04	0:08	0:16	0:06	0:06
	(0:06)	(0:05)	(0:06)	(0:02)	(0:02)	(0:05)	(0:08)	(0:04)	(0:04)
	[5]	[5]	[5]	[3]	[3]	[4]	[6]	[1]	[5]
Subsample B	0:07	0:15	0:20	0:07	0:05	0:07	0:04	0:10	0:10
	(0:04)	(0:08)	(0:11)	(0:05)	(0:02)	(0:02)	(0:03)	(0:07)	(0:06)
	[4]	[1]	[1]	[1]	[10]	[11]	[17]	[12]	[12]

Notes: The table reports parameter estimates of the cross effects φ_s in the mean equations (as defined in (1)). The estimates of subsample B1 are not reported for space reasons. *** , ** , * , denote significance at the $0.01; 0.05; 0.10; 0.15$ level respectively. The numbers in parentheses are standard errors. The numbers in brackets are the lag order s of the regressor.

5.4.2 Institutional and Individual (Domestic) Investors

trading system. This gives an information advantage to this type of investors, as they have minute information about the supply and demand orders of the cash market. In the case of these companies, which are the most informed among domestic investors (and among the main liquidity providers), there is a negative impact on volatility through their purchases and sales in the pre-crisis period (in line with H2b). However, this result is reversed when we consider the post-crisis period, where both buy and sell trades affect volatility positively. Overall, the evidence for the whole sample suggests that for institutional investors who are members the causal negative effect from total volume to volatility reflects the causal relation between buy trades and volatility in the pre-crisis period. It is now interesting to compare

AFC to positive in the post-crisis period. It seems that foreign purchases are more informative than foreign sales. That is, foreign purchases are more value motivated, while foreign sales are market phase or momentum-driven. These …ndings are in accordance with those of Wang (2007), who reported that foreign purchases tend to stabilize stock markets - by increasing the investor base in emerging markets -

A positive link is the prevailing result for the domestic investors' trading activity when all domestic investor groups are aggregated. On the other hand, foreign investors stabilize the market with their total and buy orders, which is also reflected in the total volume (total and buy side) of all investors trading on the KOSPI 200 index for the entire 10-year period around the AFC and the pre-crisis subsample. This result confirms the findings in Wang (2007) for Indonesia and Thailand.

It is important to highlight here again that, overall, buy orders appear to be more informative and value-based, while sell orders are less informative and more market phase driven. Additionally, the

Table 6. The Volume - Volatility link (AFC period)									
Panel A. Active Institutional Non-member Domestic Investors									
	Insurance Companies			Mutual Funds			Investment Banks		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample			+			+			+
Subsample A			+			+			+
Subsample B/B1	+	+	+	+	+	+	+	+	+
Panel B. Passive Institutional Non-member Domestic Investors									
	Commercial Banks			Savings Banks			Other Companies		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	+	+	+	+	+	+	+	+	+
Subsample A	+	+	+	+	+	+	+	+	+
Subsample B/B1	+	+	+	+	+	+	+	+	+
Panel C. Institutional and Individual Domestic Investors									
	Institutional (M)			Institutional (NM)			Individual		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample			+	+	+	+	+	+	+
Subsample A				+	+	+	+	+	+
Subsample B/B1	+	+	+	+	+	+	+	+	+
Panel D. Total, Domestic and Foreign Investors									
	Total			Domestic			Foreign		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample			+	+	+	+			+
Subsample A			+	+	+	+			+
Subsample B/B1	+	+	+	+	+	+	+	+	+

6 The GFC Period

Following the empirical analysis of the volume e¤ect on volatility around the Asian turmoil, we extend our investigation to the 2008 global …nancial crisis in order to compare the two crises in terms of the trader-type e¤ects on the Korean stock market volatility. Our GFC sample spans from the 26th of May 2006 to the 30th of December 2014 (2133 observations). We calculate the detrended turnover volumes for the di¤erent investor categories and the Garman-Klass volatility, similarly to the AFC period data. By

which is a result of the negative volume link for all six non-member categories buy side. This is also re‡ected in the fact that domestic investors’purchases activity lowers volatility in the pre-crisis period, a

Table 7. The Volume - Volatility link (GFC period)

Panel A. Active Institutional Non-member Domestic Investors

	Insurance Companies			Mutual Funds			Investment Banks		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	+		+	+		+	+		+
Subsample A			+	+		+	+		+
Subsample B/B1/B2	+	+	+	+	+	+	+	+	+

Panel B. Passive Institutional Non-member Domestic Investors

	Commercial Banks			Savings Banks			Other Companies		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample				+		+			+
Subsample A				+		+			+
Subsample B/B1/B2	+	+	+	+	+	+	+	+	+

Panel C. Institutional and Individual Domestic Investors

	Institutional (M)			Institutional (NM)			Individual		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	+	+	+	+		+	+	+	+
Subsample A		+		+		+	+	+	+
Subsample B/B1/B2	+	+	+	+	+	+	+	+	+

Panel D. Total, Domestic and Foreign Investors

	Total			Domestic			Foreign		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	+	+	+	+	+	+	+	+	+
Subsample A				+		+			
Subsample B/B1/B2	+	+	+	+	+	+	+	+	+

7 Conclusions

This paper has examined the long-run dynamics of stock market volatility using a dual long-memory model and it has investigated the effects of buy and sell trades by trader type in the Korean Stock Exchange during two crisis periods, the Asian one and the Global crash. It has investigated whether these effects are robust to the financial crisis structural breaks.

Sales have been shown to exhibit a destabilizing effect on the market in most cases for both crises, confirming the result in Avramov et al. (2006) that sell herding trades increase volatility, whereas purchases seem to be more informative. During the post-crisis periods, the trading volume has been shown to increase volatility across all investor groups.

In the AFC domestic individual trades exacerbate volatility, a result which is consistent with the finding in Foucault et al. (2011) that noise trading leads to excess volatility. Domestic institutional investors are split into non-members, whose behaviour also has a destabilizing effect, and members with a stabilizing trading impact. This negative influence is consistent with the results in Umutlu and Shackleton (2015), who find that in Korea trading by informed domestic institutional investors reduces volatility. Inside the institutional non-members group, we observe that passive investors increase volatility, whereas the stabilizers are the active ones. Domestic investors' aggregate trading has a positive impact on volatility, reflecting the less informative trading of individuals and institutional non-members.

Foreign investors' buy orders have a stabilizing effect on volatility in the AFC, which is in accordance with value-motivated purchase decisions. These findings are in line with Wang (2007), who finds that 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 negative impact of total trading on volatility is determined by the foreign investors' purchases. Interestingly, in the GFC both buy and sell trades from foreign investors, and, as a result, total volume as well, affect volatility positively. This destabilizing impact is consistent with the results in Choe et al. (1999), Froot et al. (2001), and Che (2018), who find that foreign investors are momentum traders. They also confirm the results for the Korean market by Choe et al. (2005), who find that foreign investors are less informed, and by Jeon and Moffet (2010), who find that foreign investors in Korea are involved in hedging and positive feedback strategies.

Another major difference between the two crises is that in the global crash, all six active and passive

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A APPENDIX

Table A1. Variance Equations: GARCH coe¢ cients (AFC period)

Panel A. Active Institutional Non-member Domestic Investors

	Insurance Companies		Mutual Funds		Investment Banks	
Total Sample	0:16	0:59	0:16	0:59	0:16	0:59
	(0:15)	(0:22)	(0:15)	(0:23)	(0:15)	(0:23)
Subsample A	0:15	0:72	0:14	0:73	0:23	0:61
	(0:16)	(0:22)	(0:22)	(0:32)	(0:28)	(0:33)
Subsample B	0:29	0:70	0:26	0:74	0.9738(Tf-9000 0:ms70-22228(F)-24mms	
	(0:17)	(0:16)	(0:16)			

Table A2. Variance Equations: GARCH coe¢ cients (AFC period)						
Panel A. Institutional and Individual Domestic Investors						
	Institutional (M)		Institutional (NM)		Individual	
Total Sample	0:16 (0:15)	0:59 (0:24)	0:16 (0:15)	0:60 (0:21)	0:16 (0:15)	0:

Table A3. The Impact of Volume on Volatility: A Summary of Papers				
Investor Categories	Authors	Countries	Impact	Hypothesis
Institutional	Daigler and Wiley (1999)			
	Li and Wang (2010)			
	Cai et al. (2010)			
	Umutlu and Shackleton (2015)			
	Yang et al. (2017)			
	Che (2018)			
	Basak and Pavlova (2013)			