The Buying and Selling Behavior of Institutional, Individual and Foreign Investors in the Korean Stock Exchange.

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Abstract

This study examines the impact of institutional and individual investors' buy and sell trades on stock market volatility. Our dataset also allows to investigate the trading behavior of six different institutional investors, namely the insurance companies, mutual funds, investment banks, commercial banks, savings banks and other companies. Insurance companies', mutual funds' and investment banks' trades have an asymmetric effect on volatility, with buy orders having a stabilizing effect and sell orders a destabilizing one up to the period of the Asian financial crisis. Commercial banks', savings banks' and other companies' buy and sell trades have a positive effect on volatility for all samples considered. The aggregated non-member institutional and individual investors' buy and sell trades affect volatility positively across all subsamples. The buy and sell trades of individual investors exacerbate volatility, supporting the argument that their buy and sell decisions carry little information and are possibly affected by psychological biases and market trends/momentum (Barber and Odean, 2011). Finally, foreign buy (sell) trades have a negative (positive) effect on volatility in the pre-crisis period while in the post crisis one both buy and sell trades affect volatility positively. Overall, buy orders are more informative and value motivated while sell orders are less informative and possibly more market phase (or momentum) driven.

Keywords: trading volume, volatility, institutional investors, individual investors.

JEL classification: G12, G15, G23

1 Introduction

Much of the empirical research in finance views individuals and institutions differently. In particular, while institutions are viewed as informed investors, individuals are believed to have psychological biases and are often characterized as noise traders (Black, 1986). Institutional investors consistently dedicate more resources to acquiring and analyzing information while their trading motives determine their investment styles (active or passive) and order placement strategies (market or limit orders) when they buy or sell stocks in the securities markets. Actively managed funds buy and sell stocks based on valuation beliefs but, for some institutions, trades are affected by pre-determined investment 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, based on short-lived information, it is likely to increase short-run volatility. DeLong et al.(1990) argue that in the presence of positive feedback traders, rational speculation (or trading by institutional investors) can be destabilizing. On the other hand, passive institutional traders who use limit orders and engage in more contrarian trades or value-motivated trades are likely to reduce volatility in the short-run. Avramov et al. (2006) decompose sell trades into contrarian and herding trades and they find that contrarian trades decrease volatility while herding trades increase volatility. They demonstrate that when the stock price declines, herding (sell) trades govern the increase in the next period volatility and when the stock price rises, contrarian trades lead to a decrease in the next period volatility.

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. Three factors contribute almost equally to the shortfall: perverse stock selection ability, commissions, and the transaction tax, with a somewhat smaller role being played by poor market timing choices. Behavioral biases such as overconfidence can possibly explain why retail investors trade so much and self-manage their portfolios (Daniel et al., 1998). Moreover, individual investors tend to hold on to losing common stock positions and sell their winners, buy stocks that catch their attention (or which they are familiar with), and under-diversify in their stock portfolios. 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 with increased levels of informed trading by institutional investors.

This study contributes to the literature about the impact of institutional and individual investors' buy and sell trades on stock market volatility. More importantly, our dataset allows us to investigate the trading behavior of six different institutional investors, namely the insurance companies, mutual funds, investment banks, commercial banks, savings banks, and other companies. Moreover, we examine the effect of member vs non-member as well the effect of domestic vs foreign investors' buy and sell trading on index price volatility. In line with the arguments of Daigler and Wiley (1999), we examine the effect of total trading volume on stock market volatility by trader type. Daigler and Wiley (1999) find empirical evidence indicating that the positive volume-volatility relation is driven by the (uninformed) general public whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility. We estimate the two main parameters driving the degree of persistence in volatility and its uncertainty using a univariate Generalized ARCH (GARCH) model that is Fractionally Integrated (FI) in both the Autoregressive (AR) mean and variance specifications. We refer to this model as the ARFI-FIGARCH. This provides a general and flexible framework with which to study complicated processes like volume and volatility. In order to be able to examine the volume-volatility relationship, we estimate the dual long memory model with lagged values of the trading volume included in the mean equation of volatility.

Insurance companies', mutual funds' and investment banks' trades have an asymmetric effect on volatility, with buy orders having a stabilizing effect and sell orders a destabilizing one up to the period of the Asian financial crisis. This is consistent with value-motivated purchase decisions such as using long-term fundamental information with limit orders and engaging in contrarian strategies. In the post crisis period, both buy and sell trades have the same destabilizing effect on volatility, indicating that trade decisions were less informative and more motivated by market momentum or excess liquidity. Commercial banks', savings banks' and other companies' buy and sell trades have a positive effect on volatility for the whole sample as well as for the subsamples examined. This result is contrary to the hypothesis that passive institutional traders use limit orders and engage in more contrarian trades (based on longer term information) which reduce the short-run volatility. Their effect is more in agreement with trades which contain less fundamental information and traders who engage in herding and positive feedback trades based on short-lived information.

We find that the aggregated non-member institutional and the individual investors' buy and sell trades affect volatility positively across all subsamples. Both types of investor are regarded here as less informed. The buy and sell trades of individual investors exacerbate volatility and this result is consistent with buy and sell decisions that carry little information and they are possibly affected by psychological biases and market trends (Barber and Odean, 2011). Securities companies, which are better informed among the domestic investors, show a negative impact on volatility through their purchases and sales in the pre-crisis period. Avramov et al. (2006) find that contrarian trades decrease volatility while herding trades increase volatility. Here, the buy and sell trades of member institutional investors decrease index price volatility, signaling either the contrarian nature of their trades or the continuous underreaction to new information. This result is reversed in the after crisis period, where both buy and sell trades affect volatility positively.

As regards the foreign buy (sell) trades we observe a negative (positive) effect on volatility in the period up to the Asian financial crisis while in the post crisis period both buy and sell trades affect volatility positively. It seems that foreign purchases are more value motivated while foreign sales are market phase or momentum driven. These findings are in accordance with Wang (2007), where it is found that foreign purchases tend to stabilize stock markets-by increasing the investor base and liquidity. As regards the aggregate domestic investors trading behavior, we observe that both buy and sell trades exacerbate volatility over the whole period and the subsamples examined. Finally, if we only use total buy and sell orders in our study we find that purchases decrease volatility in subsample A and increase volatility in subsample B. As far as sales are concerned, they increase volatility in both subsamples. Overall, buy orders are been more informative and value motivated while sell orders are been less informative and possibly more market phase driven.

Section 2 of this paper reviews the trading behavior of different institutional, individual and foreign investors and provides some empirical evidence. Section 3 summarizes the data, while Section 4 outlines the econometric model and estimation procedure that is used here. Section 5 provides the empirical results for different institutional (member/non-member), individual and foreign investors. Finally, section 6 presents the conclusion of this paper.

2 Theoretical background

2.1 The trading behavior of institutional investors

Institutional investors have different investment styles (active or passive, value or growth), order-placement strategies (market or limit orders) when they buy or sell stocks in the securities markets. Keim and Madhavan (1995) find considerable heterogeneity in investment style (buy-sell decision and past excess returns) across institutions. Surprisingly, the motivation for the trade decision is often not symmetric for buys versus sells. For example, some institutions that buy stocks after they fall in price do not follow the same trading rule when they sell. Additionally, institutional traders tend to spread buy orders over longer periods than equivalent sell orders. We also find significant differences in the choice of order type across institutional styles. Gompers and Metrick (2001) find that institutions invest in stocks that are larger, more liquid, and have had relatively low returns during the previous year.

Actively managed equity mutual funds buy and sell stocks based on valuation beliefs. The structure of open-end funds also leads them to trade for liquidity, tax and window-dressing purposes. Alexander et al. (2007) relate the performance of mutual fund trades to their motivation. They find that managers making purely valuation-motivated purchases substantially beat the market but are unable to do so when compelled to invest excess cash from investor inflows (liquidity-motivated trading results in significant trading losses).[1] A similar, but weaker, pattern is found for stocks that are sold. Grinblatt and Keloharju (2000) using buy and sell trades of individuals and institutions in the Finnish stock market find evidence that investors are reluctant to realize losses (disposition effect), they engage in tax-loss selling activity, and they conclude that past returns and historical price patterns, such as being at a monthly high or low, affect trading behavior. 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, dealers, foreigners, and mutual funds) gain from trade.

Herding and feedback trading have the potential to explain destabilizing stock prices or excess volatility. However, they have also been used to explain momentum and reversals in stock prices depending on who trades and on what type of information. Griffin et al. (2003) find that the 5-minute intervals with the largest institutional buying (selling) activity are preceded by large positive (negative) abnormal stock returns in the previous 30-minute period. 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. DeLong et al. (1990) argue that in the presence of positive feedback traders, rational speculation (or trading by institutional investors) can be destabilizing. The opposite view is that positive feedback trading will bring prices closer to fundamentals if stocks underreact to news. Finally, institutional traders use different portfolio strategies (herding, positive or negative feedback) which by and large offset each other (resulting in zero excess demand). For example, trading does not destabilize asset prices if there are enough negative-feedback traders to offset the positive-feedback traders.

2.2 The trading behavior of individual investors

Empirical evidence indicates that the average individual investor underperforms the market (see Barber and Odean, 2011). Part of the poor performance borne by individual investors can be attributed to transaction costs (e.g. commissions and bid–ask spread). However, individual investors also seem to lose money on their trades before costs. Barber and Odean (2000) find that households significantly

[1] For example, a fund manager who buys stocks when there are heavy investor outflows is likely to be motivated by the belief that the stocks are significantly undervalued. In contrast, when there are heavy inflows, the manager is likely to be motivated to work off excess liquidity by buying stocks.

underperform a value-weighted market index, after a reasonable accounting for transaction costs. After accounting for the fact that the average household tilts its common stock investments toward small value stocks with high market risk, the underperformance is even worse. Interestingly, the average household turns over approximately 75 percent of its common stock portfolio annually. The poor performance of the average household can be traced to the costs associated with this high level of trading.

Behavioral motivations (or biases) can possibly explain why retail investors trade so much and self-manage their portfolios. Overconfidence can explain the relatively high turnover rates (increased trading) and poor performance of individual investors (see Daniel et al., 1998; Gervais and Odean, 2001; Odean, 1998; Kelley and Tetlock, 2013). Attention can also affect the trading behavior of individual investors (Barber and Odean, 2008). Barber and Odean (2008) also find that individual investors underperform standard benchmarks (e.g., a low cost index fund) and sell winning investments while holding losing investments (the "disposition effect"). They also engage in naïve reinforcement learning by repeating past behaviors that coincided with pleasure while avoiding past behaviors that generated pain. 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 likely contribute to the correlated trading of individuals, which leads investors to systematically buy stocks with strong recent performance, to refrain from selling stocks held for a loss, and to be net buyers of stocks with unusually high trading volume. Kaniel et al. (2008) provide evidence that individuals tend to buy stocks following declines in the previous month and sell following price increases. The patterns are consistent with the notion that risk-averse individuals provide liquidity (through their contrarian trades) to institutions that require immediacy. Several authors characterize the trading behavior of individual investors as contrarian (Choe et al., 1999; Griffin et al., 2003; Barber and Odean, 2002; Grinblatt and Keloharju, 2000, 2001). Shapira and Venezia (2001) show that both professional and independent investors exhibit the disposition effect[2], although the effect is stronger for independent investors. They demonstrate that professionally managed accounts were more diversified and that round trips were both less correlated with the market and slightly more profitable than those of independent accounts. Yao and Li (2013) model a market in which investors with prospect theory preferences interact with investors with constant relative

[2]Individual investors have a strong preference for selling winner stocks too early and hold on to loser stocks for too long (Shefrin and Statman, 1985).

risk aversion (CRRA) and find that this interaction commonly generates a negative-feedback trading tendency, which favors the disposition effect and contrarian behavior, for prospect theory investors.

2.3 The trading behavior of foreign investors

Brennan and Cao (1997) present a theoretical model and empirical evidence that supports the view that foreign investors must pursue momentum strategies and achieve inferior performance because they are less informed than domestic investors. Froot et al. (2001) and Choe et al. (1999) find that foreign investors tend to be momentum investors. Choe et al. (1999) also 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. Wang (2007) documents a strong contemporaneous relationship between foreign equity trading and market volatility in Indonesia and Thailand.[3] Bae et al. (2006) find that foreign investors consistently generate gains from trade due to good market timing, although their average sell price is lower than the average purchase price. Specifically, foreign investors extract significant portions of their gains by trading against Japanese institutional investors when Japanese investors trade before their fiscal-year end. Barber et al. (2009) find that foreigners earn nearly half of all institutional profits when profits are tracked over six months (and one-quarter at shorter horizons). The profits of foreigners represent an unambiguous wealth transfer from Taiwanese individual investors to foreigners. Grinblatt and Keloharju (2001) also find that foreign investors, often professionally managed funds or investment banking houses, pursue momentum strategies and achieve superior performance. After removing momentum investing's contribution to performance, they find that the momentum-adjusted performance of foreigners is still highly significant.

2.4 Informed vs Uninformed Investors/Trades

In most theoretical models, trading arises because of new information signals. Institutional or large block trades are more informative than small trades and more likely to cause permanent price changes (Easley and O'Hara, 1987, Easley et al., 1997a).[4] However, any relation between information effects and the size of the block is attenuated if informed traders make numerous smaller trades and information is gradually

[3] 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 group, investors are relatively homogeneous in terms of capital endowments and information. Moreover, in Thailand foreign net purchase is negatively associated with market volatility, therefore foreign purchase 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.

[4] Easley et al. (1997a) also find that uninformed trades are highly positively correlated while sequences and reversals of trades provide differing information, with the latter being particularly informative.

incorporated into prices (Kyle, 1985).[5] Easley et al. (2008) find that it is the presence of information, rather than variation in the intensity of uninformed trade that determines the arrival rate of informed traders. 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 actually be considered as informed compared to trades initiated by individuals. This result is consistent with the argument that institutional investors are better informed and the fact that institutional investors can gain many more profits than individuals. Kelley and Tetlock (2013) show that overconfidence (not hedging) explains nearly all uninformed trading, while rational informed speculation accounts for most overall trading.

Avramov et al. (2006) decompose sell trades into contrarian and herding trades and conjecture that herding trades are uninformed and contrarian trades are informed using serial correlation tests. They find that contrarian trades decrease volatility while herding trades increase volatility. They demonstrate that when the stock price declines, herding (sell) trades govern the increase in next period volatility and when the stock price rises, contrarian trades lead to a decrease in next period volatility. Hence, the trading activity of contrarian and herding investors seems to explain the relation between daily volatility and lagged returns. Daigler and Wiley (1999) find empirical evidence indicating that the positive volume-volatility relation is driven by the (uninformed) general public whereas the activity of informed traders such as clearing members and floor traders is often inversely related to volatility.

2.5 Hypothesis

In our study we associate the trading of institutional and individual investors with those of informed and uninformed traders respectively. We assume that active institutional traders use market orders to assure rapid execution (at the cost of large price impacts) and engage in herding and positive feedback trades (based on shortlived information) which exacerbate short-run volatility. We also assume that passive institutional traders use limit orders and engage in more contrarian trades (based on longer term information) which reduce short-run volatility. Although for some institutions the buy-sell decision has no association with prior excess returns[6], for other institutions there is a significant relation between trades and past excess returns. However, the overall effect of these strategies may be offsetting, because some traders pursue contrarian strategies while others follow trends. As regards individual investors, recent studies find that their trading patterns are significantly affected by psychological biases, which lead to increased levels of trading, systematic behavior and high trading costs. For example, individual investors

[5] Easley et al. (1997b) find that, on days on which information events occur, the trade size provides no information content beyond that contained in the underlying transaction.

[6] For some institutions, trades are determined primarily by pre-determined investment objectives (index tracking, value, growth), liquidity needs and tax-management purposes.

tend to hold on to losing common stock positions and sell their winners (disposition effect rather than contrarian trades), buy stocks that catch their attention or they are familiar with, and under-diversify in their stock portfolios. As a result, the buy and sell decisions of individual traders are likely to take place within a broader range of prices unless the extra liquidity provided by individual traders is accompanied by increased levels of informed trading by institutional investors.

Finally, we examine whether trading by member and non-member investors of the Korean stock exchange destabilizes/stabilizes the market. If investors have an information advantage (informed) due to access to market economic data this is likely to form homogeneous expectations about market movements and the fundamental characteristics of an asset. If this is true informed traders, proxied by members here, are expected to buy and sell within a small range of prices around the fair value of the asset. On the other hand, for investors with no access to order flow data (less informed) we expect them to form heterogeneous beliefs as they cannot differentiate short term liquidity demand from changes in overall fundamental supply and demand. As a result, less informed traders, proxied by non-members, are expected to buy and sell within a large range of prices around the fair value of the asset. Thus, we expect member investor trading to be associated with less volatility in the Korean stock exchange while trading by non-members will destabilize stock market prices overall.

3 Data description and sub-periods

The data set used in this study comprises 2850 daily trading volumes 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 Price volatility

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

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

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 GK volatility from 1995 to 2005.

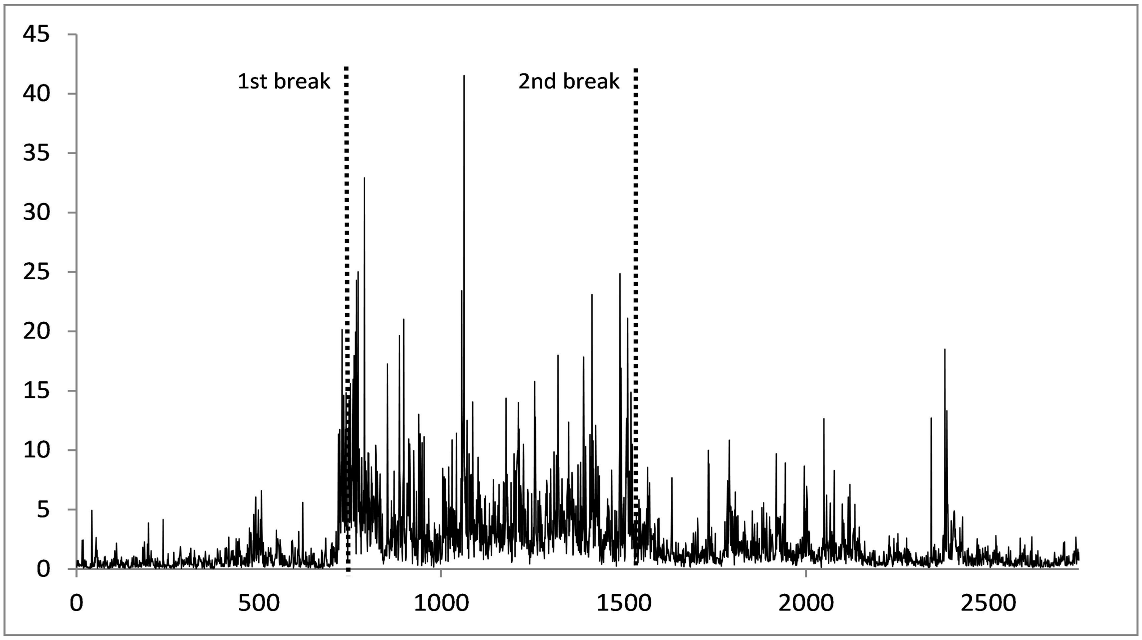

Figure 1. Garman-Klass Volatility

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).[7]

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. The eight domestic investors are added to construct the domestic volume. We study each volume series from its buy and sell side as well as its total *(=(buy+sell)/2)*. We use the volume series to form the turnover and include it as a measure of volume in our model. This is the ratio of the value of shares traded to the value of shares outstanding (see Campbell et al., 1993; Bollerlsev and Jubinski, 1999). Because trading volume is nonstationary several detrending procedures for the volume data have been considered in the empirical finance literature (see, for details, Lobato and Velasco, 2000). We form a trend-stationary time series of turnover (TV_t) by incorporating the procedure used by

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

Campbell et al. (1993) that uses a 100-day backward moving average $TV_t = \frac{VLM_t}{\frac{1}{100}\sum_{i=1}^{100} VLM_{t-i}}$ 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[8]. Figure 2 plots the total turnover volume from January 1995 to October 2005.

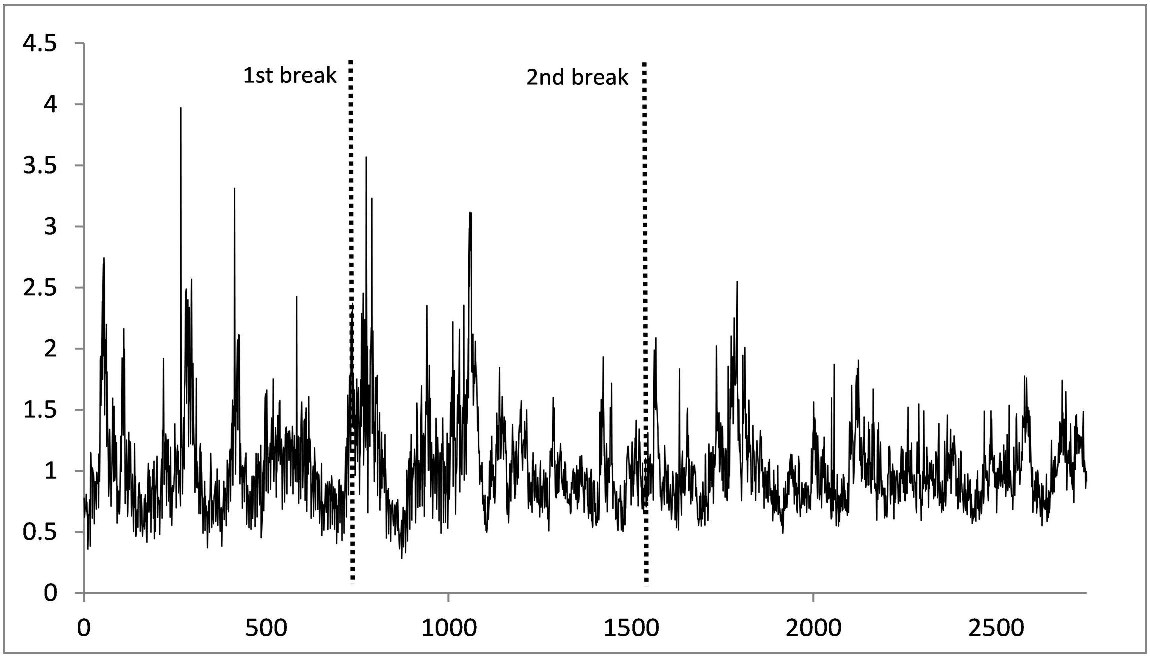

Figure 2. Turnover volume

Table 1 reports the descriptive statistics regarding the percentage breakdown of the total buy and sell volume into four trader categories. Average (daily) total trading volume is 510 trillion Korean won for the three years ending in 1997. There is a fourfold increase in the average trading volume from 1998 to 2000 and it reaches the staggering 3,607 trillion won for the three years ending in 2003. Towards the end of the sample, average daily trading volume is around 2,507 trillion won. This increase in trading volume across the years is not shared evenly among the different 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%. Member institutional investors' average percentage of buy trades was only 5.1% for the three years ending in 1997

[8] We needed (in order to reach any result) to use an outlier reduced series for Savings banks Sell Turnover and Other companies Sell Turnover: the variance of the detrended data is estimated, and any value outside four standard deviations is replaced by four standard deviations. Chebyshev's inequality is used as it i) gives a bound of what percentage ($1/k^2$) of the data falls outside of k standard deviations from the mean, ii) holds no assumption about the distribution of the data, and iii) provides a good description of the closeness to the mean,especially when the data are known to be unimodal as in our case.

and, thereafter, decreases to 2.1% for the two years ending in 2005. The sell side figures for the same investors are not different. The presence of foreign investors in the cash market increases tremendously 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. Finally, non-member institutional investors' trading is relatively stable at levels slightly above 10% until the end of 2003, reaching a maximum of 17.1% by the end of 2005. Their sell trades are close to 15% of total sell volume across all subperiods examined.

Table 1. Trading Volume by trader type
This table presents daily average buy and sell volume statistics for four categories of investors. The categories are: Member Institutional Investors (MFI), Non-member Institutional (NMFI), Non-member Individual Investors (NMI) and Non-member Foreign Investors (NMF). Panel A (B) shows the breakdown in percent of buy (sell) volume by category and the total daily volume (in trillion Korean won). Percentages sum to 100 over each period.

Panel A: Average Buy Volume as a Percentage of Total Buy Volume					
Investor Type	MFI	NMFI	NMI	NMF	Total
Period					
1995-97	5.1%	12.1%	76.9%	5.9%	510
1998-00	3.1%	13.2%	75.5%	8.2%	2157
2001-03	2.3%	10%	49.8%	37.9%	3607
2004-05	2.1%	17.1%	58.1%	22.7%	2520
Panel A: Average Sell Volume as a Percentage of Total Sell Volume					
Investor Type	MFI	NMFI	NMI	NMF	Total
Period					
1995-97	6.1%	17.6%	70.9%	5.4%	510
1998-00	3.5%	14.2%	75.4%	6.9%	2157
2001-03	3.4%	14.1%	70.1%	12.4%	3607
2004-05	2.2%	16.3%	59.4%	22.1%	2520

3.3 Structural Breaks

We also examine whether there are any structural breaks in volatility. We test for structural breaks by employing the methodology in Bai and Perron (1998, 2003a,b), who address the problem of testing for multiple structural changes in a least squares context and under very general conditions on the data and the errors. In addition to testing for the presence of breaks, these statistics identify the number and location of multiple breaks. Bai and Perron (1998, 2003a,b) form confidence intervals for the break dates under various hypotheses about the structure of the data and the errors across segments. This allows us to estimate models for different break dates within the 95 percent confidence interval and also evaluate whether our inferences are robust to these alternative break dates. Our results (not reported) seem to be invariant to break dates around the one which minimizes the sum of squared residuals.

The overall picture dates two change points for volatility. The first is detected in October 1997 and the next one is in November 2000. Accordingly, we break our entire sample into three sub-periods. 1st period (the pre-crisis period, subsample A hereafter): 3rd January 1995 - 15th October 1997; 2nd: 16th October 1997 - 26th October 2005 (the post-crisis period including the in-crisis period and the economic recovery of Korea, subsample B hereafter); the 3rd period: 7th November 2000 - 26th October 2005 (the post-crisis period characterized by the world recession period, which starts with the second change-point in volatility, subsample B1 hereafter).

The first change point in volatility is associated with the financial crisis in 1997. As mentioned earlier on, we break our entire sample into three 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, the 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 Asian Financial Crisis. The Thai crisis sent repercussions throughout the region. 2nd) 16th October 1997- 26th October 2005: the post-crisis period including the in-crisis period and the economic recovery. 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 labour 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. In 1999-2000 the Korean economy achieved an early and strong recovery from the severe recession. 3rd) 7th November 2000 - 26th October 2005: the world recession period. After the end of 2000 the Korean economy faced many challenges, economically and politically, compounded by a global economic slowdown with hesitant recovery, terrorist attacks, regional wars, avian flu outbreaks in Asia, and domestic and global uncertainty ahead. A 2005 World Bank research paper on Korea concluded that "the national economy is now suffering from weak investment, slow growth and slow job creation and rising unemployment"(Crotty and Lee, 2006).

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

4 Estimation procedures

4.1 Estimation methodology

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

Furthermore, in many applications the sum of the estimated variance parameters is often close to one, which implies integrated GARCH (IGARCH) behavior. For example, Chen and Daigler (2008) emphasize that in most cases both variables possess substantial persistence in their conditional variances. In particular, the sum of the variance parameters was at least 0.950. Most importantly, Baillie et al. (1996), using Monte Carlo simulations, show that data generated from a process exhibiting FIGARCH effects may be easily mistaken for IGARCH behavior. Therefore we focus our attention on the topic of long-memory and persistence in terms of the second moments of volatility. Consequently, we utilize a univariate ARFI-FIGARCH model to test for the causal effect of volume on volatility.

4.2 Dual long-memory

Along these lines we discuss the dual long-memory time series model for volatility.

Let us first define the two variables. In the expression below the equation represents the GK volatility (VL_t), where turnover volume (TV_t) is added as regressor. The ARFI$(1, d_m)$ model for the conditional mean of volatility is given by

$$(1-L)^{d_m}\phi(L)(VL_t - \varphi_s L^s TV_t - \mu) = \varepsilon_t, \quad (1)$$

where L is the lag operator, $\phi(L) = 1 - \sum_{i=1}^{p} \phi_i L^i$ is the AR polynomial, and $0 \leq d_m \leq 1$. The φ_s coefficient captures the effect from volume on volatility. We assume $\boldsymbol{\varepsilon}_t$ is conditionally normal with mean 0 and variance h_t.

Further, the FIGARCH$(1, d_v, 1)$ process for the conditional variance of volatility is defined by

$$(1 - \beta L)h_t = \omega + [(1 - \beta L) - (1 - cL)(1 - L)^{d_v}]\varepsilon_t^2, \tag{2}$$

where $\omega \in (0, \infty)$ and $0 \leq d_v \leq 1$.[9] 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 and Conrad, 2010).[10] When $d_v = 0$ the model reduces to the GARCH(1, 1) model: $(1 - \beta L)h_t = \omega + \alpha L\varepsilon_t^2$, where $\alpha = c - \beta$.

5 Empirical analysis

5.1 Dual long-memory model characteristics

Within the framework of the ARFI-FIGARCH model we will analyze the dynamic adjustments of both the conditional mean and variance of volatility for all four subsample periods, 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 (2009) 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 (not reported here). 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 three subsamples. That is, $\phi(L) = 1 - \phi_3 L^3$ and $\phi(L) = 1 - \phi_1 L$, respectively. We do not report the estimated AR coefficients because of 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 and squares of the standardized residuals for the estimated dual long-memory GARCH models. The results (not reported) show that the time-series models for the conditional mean and the conditional variance adequately capture the distribution of the disturbances.

Finally, we employ the diagnostic tests proposed by Engle and Ng (1993), which emphasize the

[9] 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 ARFI-FIGARCH process.

[10] 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 (2007).

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. In sharp 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. To check the sensitivity of our results to the possible presence of skewness in the conditional variance of volatility in Section *6.1* we reestimate our models using the skewed-t density without asymmetries.

5.2 Buy and sell trade links with stock market volatility

To recapitulate, we employ the univariate ARFI-FIGARCH model with lagged values of volume included in the mean equation of volatility to test for causality. The estimated coefficients φ_s, defined in equation (1), which capture the possible feedback between the two variables, are reported inTable 2. We also tested the contemporaneous effect of volume on volatility adding the volume series in the volatility equation (1) with lag order $s = 0$. The estimated value of φ_0 (not reported) was always positive and significant, indicating a positive contemporaneous effect of volume on volatility. Regarding the lags used to find the causal effect, we tried to test the first ten lags for significance and in case of reaching no significant lag we extended our search 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 can mean a one-month in advance effect of the trading turnover volume on the market's volatility, which we count as a weaker relationship between the two variables (ie. other companies' total volume in subsample B and securities companies-members' purchases in subsample B). In most cases, we used up to eight lags to detect the causal effect. The likelihood ratio tests and the information criteria (not reported) choose the specification for the feedback from volume to volatility.

5.2.1 Non member institutional (domestic) investors

Panels A and B of Table 2 give the results of the volume-volatility link from 6 different domestic investor groups that are regarded as non-members of the market. Insurance companies', mutual funds' and investment banks' trades have an asymmetric (feedback) effect on volatility, with buy orders having a stabilizing effect and sell orders a destabilizing one up to the period of the Asian financial crisis. As regards the period after the Asian financial crisis, we observe that buy and sell trades have the same destabilizing effect on volatility. Insurance companies, mutual funds and investment banks are investors oriented towards trading and investing in stock markets and more likely to spend extra resources to acquire and analyze important company fundamental and market wide information (despite not holding a seat on the stock exchange). It seems that the buy decisions of this group of investors are more informative in terms of value, resulting in less price volatility for subsample A. This is consistent with institutional investors trading less frequently at the beginning, using limit orders and engaging in more contrarian trades (based on longer term information) which can reduce volatility in the short-run. The same trading behavior is not evident, though, for subsample B, where buy trades are associated with more volatility, possibly pointing towards momentum and positive feedback trading activities by this group of investors. Interestingly, the sell trades are destabilizing for the whole period, indicating that they contain less information, possibly being affected by the market's trend or momentum. Overall, the evidence for the whole sample suggests that, for the insurance companies, mutual funds and investment banks, the causal negative effect from total volume to volatility reflects the causal relation between buy trades and volatility in the pre crisis period.

Commercial banks', savings banks' and other companies' buy and sell trades have a positive (feedback) effect on volatility for the whole sample as well as for the subsamples examined. This group of investors participate in the markets as a residual portfolio activity rather than as a core business operation, like acceptance of deposits and loan supply. This result is contrary to the hypothesis that passive institutional traders use limit orders and engage in more contrarian trades (based on longer term information) which reduce short-run volatility. The positive buy and sell feedback effect on volatility by commercial and savings banks is more consistent with trades which contain less fundamental information and traders who engage in herding and positive feedback trades based on short lived information. We restrain from reaching strong conclusions about the impact of each non-member institutional investor as their trading, individually, is much less compared with the trading of member institutional and non-member individual investors. It is now worth looking at the aggregate buy and sell trading behavior of member and non-member investors as well as that of individual investors.

Table 2. Mean Equations - Cross effects									
Panel A. Non-member Institutional 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. Non-member Institutional 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.

5.2.2 Institutional and individual (domestic) investors

In Panel A of Table 3, non-member institutionals' buy and sell trades are aggregated and presented with the other two domestic investors, namely the member institutional (securities companies) and the individual investors. The aggregated non-member institutional and individual investors buy and sell trades affect volatility positively across all subsamples. Both types of investors are regarded here as less informed because they do not hold a seat at the Korean Stock Exchange and as a result they receive information about the order flow on a second hand basis. Non-member institutional and individual traders are also less likely to have access to temporary private information such as trader risk aversion, trading constraints and the supply and distribution of the underlying assets which affect prices in these markets. More importantly, the literature on individual trader behavior highlights their tendency to hold on to losing common stock positions and sell their winners (disposition effect rather than contrarian trades), buy stocks that catch their attention or which they are familiar with, and under-diversify their stock portfolios. The buy and sell trades of individual investors in this study increase stock market volatility. This result is consistent with buy and sell trades that are affected by psychological biases and carry less information (Barber and Odean, 2011).

Securities companies are members of the Korean Stock Exchange and they have direct access to the trading system. This gives an information advantage to this type of investor as they have up to the minute information about the supply and demand orders of the cash market. The securities companies, which are the most informed among the domestic investors (and among the main liquidity providers), show a negative impact on volatility through their purchases and sales in the pre-crisis period. Moreover, Avramov et al. (2006) find that contrarian trades decrease volatility while herding trades increase volatility. They demonstrate that when the stock price falls, herding (sell) trades govern the increase in next period volatility and when the stock price rises, contrarian trades lead to a decrease in the next period volatility. Here, the buy and sell trades of member institutional investors decrease index price volatility, either signaling the contrarian nature of their trades or the continuous underreaction to new information (such that even momentum trades push prices closer to fundamentals). This result is reversed when we consider the after crisis period, where both buy and sell trades affect volatility positively. Recall here the argument of DeLong et al. (1990) that in the presence of positive feedback traders, rational speculation (or trading by institutional investors) can destabilize asset prices. It is now interesting to compare differences in the trading behavior of domestic and foreign investors overall. Overall, the evidence for the whole sample suggests that for institutional investors who are members (securities companies) the causal negative effect from total volume to volatility reflects the causal relation between buy trades and volatility in the pre crisis period.

5.2.3 Domestic and foreign investors

Panel B of Table 3 shows the effect of the total, domestic and foreign buy and sell trades on volatility. The foreign buy (sell) trades have a negative (positive) effect on volatility in the period up to the Asian financial crisis while after the crisis both buy and sell trades affect volatility positively. It seems that foreign purchases are more informative than foreign sales. In other words foreign purchases are more value motivated while foreign sales are market phase or momentum driven. These findings are in accordance with Wang (2007), where it is found 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. On the other hand, when we consider subsample B, both buy and sell trades from foreign investors increase volatility, indicating that their information and trading strategies are not any different from the other non-member investors (institutional and individuals).

As regards domestic investors' trading behavior, we observe that both buy and sell trades exacerbate volatility over the whole period and the subsamples examined. Interestingly, we see that when we construct the aggregate of all domestic investors we fail to recognize the negative effect of the purchase orders on volatility for member institutional and non-member insurance companies, mutual funds and investment banks, especially for subsample A. Considering subsample B, the results (buy and sell orders affect volatility positively) for domestic investors are in agreement with all decompositions of traders to members/non-members and to non-member insurance companies, mutual funds, investment banks, commercial banks, savings banks and other companies. In other words, domestic investors (member or non-member, institutional or individual) destabilize the stock market with their buy and sell orders across subsample B. This result is more likely to be generated by herding or positive feedback trading rather than informed or value motivated trading over time.

Finally, if we only use total buy and sell orders in our study we find that purchases decrease volatility in subsample A and increase volatility in subsample B. As regards sales, they increase volatility in both subsamples. It is important to note here, that, overall, buy orders have been more informative and value based while sell orders have been less informative and more market phase driven. Additionally, the results suggest that the causal effect from volume on volatility is sensitive to structural changes. We find a uniform positive and significant link between buy/sell orders and volatility in the post-crisis period (subsample B) across all types of investors. However, in the pre-crisis period (subsample A) buy (and some sell) orders affect volatility negatively for various types of investors.

Overall, the evidence for the whole sample suggests that the causal negative effect from total volume to volatility reflects the causal relation between foreign buy trades and volatility in the pre crisis period.

Table 3. Mean Equations - Cross effects									
Panel A. Institutional and Individual (Domestic) Investors									
	Members			Non-members			Individual Investors		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	-0.06^{*}	-0.05^{*}	0.04^{*}	0.07^{*}	0.15^{***}	0.07^{**}	0.12^{*}	0.23^{***}	0.12^{**}
	(0.04)	(0.03)	(0.03)	(0.05)	(0.07)	(0.05)	(0.07)	(0.10)	(0.07)
	[2]	[2]	[5]	[5]	[6]	[4]	[1]	[6]	[5]
Subsample A	-0.09^{****}	-0.07^{**}	-0.08^{***}	0.12^{**}	0.13^{**}	0.09^{**}	0.14^{**}	0.13^{**}	0.12^{**}
	(0.03)	(0.04)	(0.04)	(0.07)	(0.07)	(0.05)	(0.08)	(0.08)	(0.07)
	[8]	[8]	[8]	[5]	[5]	[5]	[5]	[5]	[5]
Subsample B	0.25^{****}	0.15^{*}	0.20^{****}	0.34^{***}	0.26^{**}	0.33^{***}	0.63^{****}	0.71^{****}	0.50^{****}
	(0.10)	(0.10)	(0.08)	(0.17)	(0.14)	(0.16)	(0.21)	(0.23)	(0.20)
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]
Panel B. Domestic and Foreign Investors									
	Total			Domestic			Foreign		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
Total Sample	-0.16^{****}	-0.16^{****}	0.11^{*}	0.13^{**}	0.16^{**}	0.12^{***}	-0.03^{***}	-0.02^{****}	0.12^{****}
	(0.05)	(0.05)	(0.07)	(0.08)	(0.09)	(0.06)	(0.01)	(0.01)	(0.04)
	[8]	[8]	[5]	[5]	[1]	[5]	[2]	[2]	[6]
Subsample A	-0.15^{****}	-0.15^{****}	0.12^{**}	0.15^{***}	0.17^{***}	0.13^{**}	-0.02^{****}	-0.01^{***}	0.08^{***}
	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.01)	(0.00)	(0.04)
	[8]	[8]	[5]	[5]	[5]	[5]	[2]	[2]	[6]
Subsample B	0.79^{****}	0.79^{****}	0.79^{****}	0.78^{****}	0.84^{****}	0.71^{****}	0.37^{**}	0.22^{*}	0.35^{**}
	(0.29)	(0.28)	(0.28)	(0.26)	(0.27)	(0.26)	(0.21)	(0.15)	(0.21)
	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]	[1]

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.

5.3 Discussion

Tables 2 and 3 also give an overview of the volume-volatility link over the entire sample period and the three different subsamples considered. Panel A of Table 2 gives the results of the volume-volatility link from the 6 different domestic investor groups that are regarded as non-members of the market. Commercial banks', savings banks' and other companies' turnover volume has a positive effect on volatility across all subsamples. Insurance companies, mutual funds and investment banks affect the market's volatility negatively in the pre-crisis period. This finding is explained by the fact that the latter three investors are more informed than the former three, as they participate in the stock markets more actively and are more keen on spending resources to acquire value related information. Additionally, insurance companies, mutual funds and investment banks are investors who trade and invest more frequently in stock markets. On the other hand, commercial and savings banks participate in markets as a residual portfolio activity rather than as a core business operation. So, insurance companies, mutual funds and investment banks are specialized in trading and, therefore, more informed to stabilize the markets than the other non-member institutional investors.

In Panel B of Table 2 non-members' volumes are aggregated and presented with the member institutional (securities companies) and the individual investors. The aggregated non-member institutional and individual investors affect volatility positively across all samples. In sharp contrast, the securities companies, which are the most informed among the domestic investors, show a negative impact on volatility in the pre-crisis period.[11] Panel B of Table 3 shows the effect of the total, domestic and foreign trading volumes on volatility. The total and foreign volume have a negative effect on volatility in the total sample, while the domestic volume affects it positively. This volume-volatility link is in line with the results in Karanasos and Kartsaklas (2009), who find that the negative effect from total volume to volatility is similar to the causal relation between foreign volume and volatility. Regarding the structural breaks considered, the results suggest that the causal effect from volume on volatility is sensitive to structural changes. We always find a positive and significant link between the two variables in the post-crisis sample periods B and B1 for all volume series. In the pre-crisis period (subsample A) total/foreign (domestic) volume affects volatility negatively (positively).

Foreign investors' purchases show a negative link to volatility in the pre-crisis period. In sharp contrast, all investors' sales have a positive impact on volatility. It is noteworthy here 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 claims 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).

Table 4 presents a summary of the results. Our main findings are drawn on the chart below and refer to the sign of the volume effect on volatility with focus on the total trading volume and its buy side regarding the total sample and the pre-crisis period (subsample A). We focus on these aspects as the sell side of the trading activity and the post-crisis samples (B, B1) in all volumes always result in a positive sign. Domestic non-members affect the market's volatility positively, while the more informed ones among them show a negative effect, which is overridden by the less informed investors' positive impact. Domestic members have a negative effect on volatility in contrast to individuals that show a positive impact, the same as the non-members. The 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 affect volatility negatively, which is reflected also in the total volume, when all investors are included together.

[11] This result is consistent with the views that (i) the activity of informed traders is often inversely related to volatility, and (ii) a marketplace with a larger population of liquidity providers will be less volatile than one with a smaller population.

Table 4. The Volume - Volatility link					
Panel A. The effect of Non members' trading volume on volatility					
Sample:		Total	A	B	B1
Insurance Companies	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	positive	positive	positive
Mutual Funds	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	positive	positive	positive
Investment Banks	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	positive	positive	positive
Commercial Banks	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Savings Banks	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Other Companies	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Panel B. The effect of Domestic Investors' trading volume on volatility					
Sample:		Total	A	B	B1
Members (Securities Companies)	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	negative	positive	positive
Non-members	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Individual Investors	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Panel C. The effect of Total trading volume on volatility					
Sample:		Total	A	B	B1
Total	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	positive	positive	positive
Domestic	total	positive	positive	positive	positive
	buy	positive	positive	positive	positive
	sell	positive	positive	positive	positive
Foreign	total	**negative**	**negative**	positive	positive
	buy	**negative**	**negative**	positive	positive
	sell	positive	positive	positive	positive

5.4 Fractional mean parameters

Estimates of the fractional mean parameters are shown in Table 5. Several findings emerge from this Table. In all cases the estimated value of d_m is robust to the measures of volume used.[12] In other words, all ARFI models across each subsample period 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): $0.23 - 0.27$. Generally speaking, we find that the apparent long-memory in volatility is quite resistant to mean shifts.

Table 5. Mean Equations: Fractional parameters (d_m)

Panel A. Non-member domestic investors

v	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. Total trading volume - Domestic investors

v	Total	Domestic	Foreign	Members	Non-members	Individual
Total Sample	0.43**** (0.05)	0.41**** (0.05)	0.42**** (0.08)	0.42**** (0.05)	0.41**** (0.05)	0.41**** (0.05)
Subsample A	0.25**** (0.06)	0.24**** (0.06)	0.25**** (0.06)	0.25**** (0.06)	0.23**** (0.06)	0.24**** (0.06)
Subsample B	0.41**** (0.04)	0.42**** (0.04)	0.40**** (0.04)	0.41**** (0.04)	0.41**** (0.04)	0.42**** (0.04)

Notes: The table reports the fractional parameter estimates of the long-memory in the mean equations. d_m is defined in equation (1). The estimates are reported only for the case when total TV_t is added as regressor and not the buy - sell side of each series. The estimates for subsample B1 are not reported for space reasons. **** denotes significance at the 0.01 level. The numbers in parentheses are standard errors.

5.5 FIGARCH specifications

Table 6 presents estimates of the d_v of the FIGARCH model.[13] d_v's govern the long-run dynamics of the conditional heteroskedasticity of volatility. The fractional parameter d_v is robust to the measures of volume used. In other words, all FIGARCH models across each subsample period generated very similar fractional variance parameters. For example, in the post-crisis period the fractional variance parameters $(0.55 - 0.59)$ are higher than the corresponding parameters of the total sample: $0.40 - 0.43$, except for the case when the commercial banks' turnover volume is added, where d_v is 0.46 in subsample B, lower than the 0.49 of the total sample. In the pre-crisis period d_v's are close to and not significantly different from zero. In other words, the conditional variances are characterized by a GARCH behaviour. Overall, when allowing for 'structural breaks' the order of integration of the variance series decreases considerably, as

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

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

in the pre-crisis period the long-memory in variance disappears.

Finally, the estimated values of the GARCH coefficients in the conditional variance are robust to the different volumes added as regressors (see the Appendix). Note that in all cases the necessary and sufficient conditions for the non-negativity of the conditional variances are satisfied (see Conrad and Haag, 2006).

Table 6. Variance Equations: Fractional parameters (d_v)

Panel A. Non-member domestic investors						
v	Insurance Companies	Mutual Funds	Investment Banks	Commercial Banks	Savings Banks	Other Companies
Total Sample	0.42**** (0.16)	0.42**** (0.16)	0.42**** (0.16)	0.49**** (0.10)	0.40**** (0.14)	0.42**** (0.15)
Subsample A	–	–	–	–	–	–
Subsample B	0.59**** (0.17)	0.57**** (0.18)	0.56**** (0.16)	0.46**** (0.08)	0.57**** (0.18)	0.55**** (0.17)
Panel B. Total trading volume - Domestic investors						
v	Total	Domestic	Foreign	Members	Non-members	Individual
Total Sample	0.42**** (0.16)	0.43**** (0.16)	0.43**** (0.17)	0.42**** (0.16)	0.42**** (0.15)	0.43**** (0.16)
Subsample A	–	–	–	–	–	–
Subsample B	0.56**** (0.17)	0.56**** (0.17)	0.58**** (0.18)	0.57**** (0.19)	0.56**** (0.17)	0.57**** (0.17)

Notes: The table reports the fractional parameter estimates of the long-memory in the variance equations. d_v is defined in equation (2). The estimates are reported only for the case when total TV_t is added as regressor and not for the buy and sell side of each series, due to space reasons. The estimates of the subsample B1 are not reported for space reasons. **** denotes significance at the 0.01 level.The numbers in parentheses are standard errors

6 Sensitivity analysis

6.1 Distributional assumptions

To check the sensitivity of our results to different error distributions we reestimate the ARFI-FIGARCH models using the skewed-t density without asymmetries. We do not report the estimated results because of space considerations.

A comparison of the results with those obtained when the normal distribution is used reveals that the results are qualitatively very similar. The sign of the volume effect on volatility remains the same in most cases. This similarity disappears in the case of securities companies' trading activity, which is positively related to volatility as a total and in its buy side in the total sample, contrary to the link found with the QMLE, which is negative. Moreover, a major difference between the two distributional assumptions is detected in the foreign volume: that is the foreign investors' total turnover has a positive impact on volatility using the skewed-t density, contrary to the QMLE case, where the respective link is negative. However, foreign purchases are robust to the distributional choice and remain negative in both cases, confirming the view that foreign purchases tend to stabilize emerging stock markets. Finally, in the entire sample period the total turnover and its buy side have a positive effect on volatility in the skewed-t density, whereas in the normal distribution the link is negative. In the former case, the total purchases seem to reflect the domestic investors' activity most, in contrast with the latter case, where the total purchases' link to volatility is determined by the negative link of the foreign investors' purchases.

Comparing the quantitative measures, we observe that the same specifications are chosen in the AR lags of the mean equations and the FIGARCH coefficients of the variance equations. In particular, the ARCH and GARCH coefficients $[\alpha(= c - \beta), \beta]$ are higher in the normal distribution than in the skewed -t in most cases. The estimated values of the fractional variance parameters (d_v) are lower in the skewed-t density than in the normal case and remain constant across the different volume series added in the mean equations. The same conclusion can be derived comparing the fractional mean parameters (d_m). Finally, we observe that the further lag order s chosen for the turnover series added as regressors in the volatility mean equation in the skewed-t density is slightly lower in comparison with the QMLE case. Overall the results appear very robust and are generally insensitive to the presence of skewness.

6.2 Structural dynamics

Furthermore, we check the robustness of our results given by the specification in equation (1) , where the lagged values of TV_t exhibit 'error dynamics', since a transformation allows it to be rewritten with only the error terms entering in the infinite moving average representation. So, we also estimate a model where the lagged values of TV_t exhibit 'structural dynamics', since they have a distributed lag representation. Overall the new results (not reported) are in broad agreement with those presented above.

7 Conclusion

This paper has investigated the issue of temporal ordering of the range-based volatility and turnover volume in the Korean market for the period 1995–2005. We examined the long-run dynamics of volatility and its uncertainty using a dual long-memory model. We also studied the nature of the volume-volatility link, focusing on the one-side effect of trading volume on volatility, by adding the volume as regressor to the volatility model. The volume effect was examined separately for the purchases and the sales of each investor, including eight different domestic investor groups as well as the foreign investors. We further distinguished volume trading before the Asian financial crisis from trading after the crisis, taking into account the structural breaks in volatility.

Insurance companies', mutual funds' and investment bank' trades have an asymmetric effect on volatility with buy orders having a stabilizing effect and sell orders a destabilizing one up to the period of the Asian financial crisis. This is consistent with value-motivated purchase decisions. In the post crisis period, both buy and sell trades have the same destabilizing effect on volatility, indicating that trade decisions are less informative and more motivated by the market's momentum or excess liquidity. Commercial banks', savings banks' and other companies' buy and sell trades have a positive effect on volatility for the whole sample as well as for the subsamples examined. This result is contrary to the hypothesis that passive institutional traders use limit orders and engage in more contrarian trades (based on longer term information) which reduce short-run volatility. The positive buy and sell feedback effect on volatility by commercial and savings banks is more consistent with trades which contain less fundamental information and traders who engage in herding and positive feedback trades based on short lived information.

The aggregated non-member institutional and the individual investors' buy and sell trades affect volatility positively across all subsamples. Both types of investors are regarded here as less informed because they do not hold a seat at the Korean Stock Exchange and as a result they receive information about the order flow on a second hand basis. The buy and sell trades of individual investors here exacerbate volatility and this result is consistent with buy and sell decisions that carry little information and are possibly affected by psychological biases and market trends (Barber and Odean, 2011). Securities companies, which are the most informed among the domestic investors, show a negative impact on volatility through their purchases and sales in the pre-crisis period. Avramov et al. (2006) find that contrarian trades decrease volatility while herding trades increase volatility. Here, the buy and sell trades of member institutional investors decrease index price volatility, either signaling the contrarian nature of their trades or the continuous underreaction to new information. This result is reversed when we consider the after crisis period, where both buy and sell trades affect volatility positively. This is in agreement with the argument of DeLong et al. (1990) that, in the presence of positive feedback traders, rational speculation (or trading by institutional investors) can be destabilizing. As regards the foreign buy (sell) trades we find a negative (positive) effect on volatility in the period up to the Asian financial crisis while in the post crisis period both buy and sell trades affect volatility positively. It seems that foreign purchases are more value motivated while foreign sales are market phase or momentum driven.[14] Post crisis, both buy and sell trades from foreign investors increase volatility, indicating that their information and trading

[14] These findings are in accordance with Wang (2007), where it is found 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.

strategies are not any different from the other non-member investors (institutionals and individuals). As regards the aggregate domestic investors' trading behavior, we observe that both buy and sell trades exacerbate volatility over the whole period and the subsamples considered.

Another interesting result of our study is that when we construct the aggregate of all domestic investors we fail to recognize the negative effect of the purchase orders on volatility for member institutional and non-member insurance companies, mutual funds and investment banks, especially for subsample A. Finally, using total buy and sell orders in our study we find that purchases decrease volatility in subsample A and increase volatility in subsample B. As regards sales, they increase volatility in both subsamples. Overall, buy orders are more informative and value motivated while sell orders are less informative and possibly more market phase (or momentum) driven.

The results of this study suggest that the buy and sell trades of institutional vs individual, member vs non-member, domestic vs foreign have a different effect on volatility over time. This is also true when we examine the aggregate volume-volatility relationship. Total domestic investors affect volatility positively across all subsamples, while the most informed 'market players' (securities companies, investment banks, mutual funds and insurance companies), when examined separately, are proved to have a negative impact on volatility in the pre-crisis period. This result is in line with the theoretical argument that the activity of informed traders tends to stabilize the market, while the positive impact of volume on volatility is driven by the uninformed general public (Daigler and Wiley, 1999). Regarding foreign investors' trading volume, in the pre-crisis period it affects volatility negatively, while in the post-crisis period this effect turns to positive.[15] Most of the effects found in our study are quite robust to the distributional assumptions concerning our model's error distribution, as the estimates from the normal and the skewed-t density gave similar results. Lastly, we find that the apparent long-memory in volatility is quite resistant to 'mean shifts'. However, when we take into account structural breaks the order of integration of the conditional variance series decreases considerably.

[15] This is consistent with the view that foreign purchases tend to lower volatility in emerging markets-especially when foreigners start buying into local markets-whereas foreign sales increase volatility. This behavior is reflected also in the total volume's respective effects.

A Appendix: Variance Equations GARCH coefficients

Variance Equations: GARCH coefficients						
Panel A. Non-member domestic investors						
	Insurance Companies		Mutual Funds		Investment Banks	
	α	β	α	β	α	β
Total Sample	-0.16 (0.15)	0.59^{****} (0.22)	-0.16 (0.15)	0.59^{****} (0.23)	-0.16 (0.15)	0.59^{****} (0.23)
Subsample A	0.15 (0.16)	0.72^{****} (0.22)	0.14 (0.22)	0.73^{***} (0.32)	0.23 (0.28)	0.61^{**} (0.33)
Subsample B	-0.29^{**} (0.17)	0.70^{****} (0.16)	-0.26^{**} (0.16)	0.71^{****} (0.21)	-0.25^{**} (0.14)	0.71^{****} (0.20)
Panel B. Non-member domestic investors						
	Commercial Banks		Savings Banks		Other Companies	
	α	β	α	β	α	β
Total Sample	-0.15 (0.14)	0.55^{****} (0.21)	-0.17 (0.14)	0.52^{**} (0.27)	-0.16 (0.15)	0.60^{****} (0.21)
Subsample A	0.16 (0.26)	0.73^{***} (0.35)	0.16 (0.25)	0.71^{***} (0.35)	0.17 (0.15)	0.74^{****} (0.18)
Subsample B	-0.11 (0.11)	0.59^{****} (0.16)	-0.27^{**} (0.16)	0.71^{****} (0.19)	-0.25^{**} (0.15)	0.69^{****} (0.23)

Notes: The table reports estimates of the ARCH (α) and GARCH (β) parameters in the variance equations. α, β are defined in equation (2). The estimates are reported only for the case when total TV_t is added as regressor and not for the buy-sell side of each series, The estimates of the 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.

Variance Equations: GARCH coefficients						
Panel C. Domestic investors						
	Members		Non-members		Individual Investors	
	α	β	α	β	α	β
Total Sample	-0.16 (0.15)	0.59^{***} (0.24)	-0.16 (0.15)	0.60^{****} (0.21)	-0.16 (0.15)	0.60^{****} (0.23)
Subsample A	0.13 (0.12)	0.76^{****} (0.18)	0.16 (0.28)	0.71^{**} (0.38)	0.14 (0.17)	0.75^{****} (0.26)
Subsample B	-0.26^{*} (0.16)	0.72^{****} (0.22)	-0.25^{**} (0.15)	0.72^{****} (0.20)	-0.26^{**} (0.15)	0.71^{****} (0.22)
Panel D. Total trading volume						
	Total		Domestic		Foreign	
	α	β	α	β	α	β
Total Sample	-0.16 (0.15)	0.60^{****} (0.21)	-0.16 (0.15)	0.61^{****} (0.22)	-0.16 (0.15)	0.61^{****} (0.24)
Subample A	0.14 (0.15)	0.74^{****} (0.22)	0.13 (0.16)	0.76^{****} (0.24)	0.11 (0.10)	0.78^{****} (0.16)
Subsample B	-0.25^{**} (0.15)	0.72^{****} (0.21)	-0.25^{**} (0.15)	0.71^{****} (0.22)	-0.25^{**} (0.16)	0.73^{****} (0.21)

Notes: The table reports estimates of the ARCH (α) and GARCH (β) parameters in the variance equations. α, β are defined in equation (2). The estimates are reported only for the case when total TV_t is added as regressor and not for the buy-sell side of each series. The estimates of the 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.

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