Financial crisis, liquidity and dynamic linkages between large and small stocks: Evidence from the Athens Stock Exchange

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Abstract

This paper investigates return and volatility spillovers among Large, Medium and Small size stock portfolios in Athens Stock Exchange by employing an augmented univariate and multivariate VAR-EGARCH model. As a robustness test, a Monte Carlo simulation is undertaken in order to disentangle the impact of non-synchronous trading. We find that the transmission mechanism in ASE is less asymmetric after the recent financial crisis. In addition, there are spillovers among Large, Medium and Small size stocks, with a feedback effect revealed as well. The simulation results suggest that non-synchronous trading accounts for spillover effects in volatility in the post-crisis period. Our results entail implications for investors, listed companies and policy makers.

Keywords: return, volatility, spillovers, asymmetric response, non-synchronous trading

JEL Classification: G00;G01;G12;G14;C5

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1. Introduction

Understanding the transmission mechanisms between the returns and volatilities of stock investments remains central in our perception of market efficiency and market microstructure. In an efficient market, predicting the returns of a stock by using the return history of another stock would be impossible to achieve. Identification of the channels through which shocks are spreading from one stock (sector) to another has direct impact on passive and active investment strategies, portfolio diversification, and rebalancing. Moreover, evidence of volatility spillover effects might be relevant for various applications in finance that use estimates of conditional volatility as input, such as option pricing, portfolio optimization, value at risk and hedging.

Literature on dynamic linkages between assets maps itself into two distinct paths. On the one hand, there are studies that examine the interdependence between financial markets motivated mainly by the US stock market crash of October 1987 (Kotkatvuori-Örnberg et al. 2013, Aloui et al., 2011, Bhar and Nikolova, 2009, Forbes and Rigobon, 2002, Liu and Pan, 1997, Errunza and Losq 1985, Eun and Shim 1989, Von Fustenberg and Jeon 1989, Malliaris and Urrutia 1992, Theodossiou and Lee 1993, Arshanapalli and Doukas 1993 among others).

On the other hand, a number of studies have examined the spillover effects within a region or among different sectors within a country, documenting that market integration decreases with physical distance (Humavindu 2006, Gebka and Serwa 2007, Johansson and Ljungwall 2009, Hammoudeh et al. 2009). These studies document significant spillover effects for emerging stock markets in Eastern Europe, South America and South/East Asia and Greater China region and among Service, Banking, and Insurance sectors within Kuwait, Qatar, Saudi Arabia and UAE markets. However, investigating the temporal dynamics between stock returns of different size namely Large, Medium and Small size portfolios has not received much attention (Lo and McKinlay 1990a, 1990b, Conrad et al. 1991, McQueen et al. 1996, Reyes 2001). The main finding of these sparse studies is the existence of an asymmetric return and volatility spillover from Large stocks to Small stocks, but not vice versa.

A number of different explanations have been put forward for the reasons that Large and Small stocks might be correlated, and why only Larger stocks affect the Smaller. This may be due to (a) the negative quality of information induced by larger firms, (b) the quantity of information which causes a lead-lag relation from Larger to Smaller stocks and (c) the existence of non-synchronous trading effect. All the above constitute evidence for asymmetric volatility transmission and are tested in the context of the leverage effect and the volatility feedback effect theories. The leverage effect theory (Black, 1976) hypothesizes that a negative return causes the volatility of the equity to rise, while the feedback effect theory (Sentana and Wadwani 1992) asserts that an increase in volatility will raise the return on equity leading to a stock price decline. Below, we analyze how these three fundamental concepts are incorporated into our spillovers' study. We will also explain the impact of volume on volatility after the arrival of new information. Our empirical analysis will be based on the above three explanations and the two theories shedding light on the transmission mechanism in ASE.

Based on the above discussion, a number of studies have empirically examined the relationship of stock price returns and stock price volatilities (market risk) among different stock markets (Hamao *et al.* (1990) Ng *et al.* (1991), Theodossiou and Lee (1993), Susmel and Engle (1994), Liu and Pan (1997), Hammoudeh and Li (2008), Wang and Moore (2009)). They all used GARCH models confirming the presence of significant return and volatility spillovers across different national stock markets. They examined the markets of USA, UK, Japan, the Pacific Basin, Europe, and Asia, providing evidence that volatility persistence decreased and spillover effects increased after a sudden shift.

The above empirical studies shared the view that volatility increases more following negative returns than it does following positive returns and that the relationship between returns and volatility is negative. The importance of these two findings is that while the leverage effect explains why negative news is superior to good news the feedback effect justifies this negative relationship, namely the fact that volatility will raise the return on equity, producing a stock price decline. Black (1976) and Christie (1982) concluded that the common link between return and volatility is the financial leverage, without, of course, underestimating the explanatory power of the feedback effect. In particular, the second effect explains what remains unexplained by the first one. Thus, the two explanations of these two theories are indistinguishable.

The purpose of this paper is to shed light on the temporal dynamics between portfolios of Large, Medium and Small size stocks in Athens Stock Exchange (ASE hereafter) by employing an augmented univariate and multivariate VAR-EGARCH model originally proposed by Nelson (1991). We employ this asymmetric model as it accounts for both sign and size of innovations and in this way we can negate the common attitude that volatility spillovers from Large to Small stock portfolios are attributed to model misspecification.

In light of the recent global financial crisis and the ensuing sovereign debt crisis with their repercussions that severely hit the Greek stock market, it is challenging to explore whether shocks originating from one index (comprising Small, Medium or Large 'blue chip' stocks) can affect return and volatility of another index in an asymmetric way. Given prior experience, such as 1987 US crash, when volatility rose dramatically during the recession and returned to normal levels unusually quickly (see Schwert, 1990), it would be interesting to examine whether a similar effect is encountered in the Greek market. This might be a plausible explanation for asymmetric relation between volatility and returns, as negative returns lead to larger increases in volatility than positive returns do.

Greece is an interesting case to examine for various reasons. Amid the debt crisis and escalating fears of Eurozone exit, the Greek stock prices lost 91% of their value in the period from October 2007 through early June 2012. Since then, ASE has entered a new era as a result of the country's progressing fiscal consolidation and the restoration of investors' confidence. Thus, as of early November 2013, the ASE marked a 245% increase from its lowest value and ranked among the ten stock markets with the highest annual return for 2013.

Moreover, Greek stock market is a small, peripheral, and downgraded to emerging market status European stock market that is a member of the Eurozone. However, Greek stock market has lately been in the epicenter of large investment funds and this is exactly what the official data confirm. As of May 2014, almost 73%

of the reported trading value in ASE was performed by foreign investors and 43% of the total value of listed companies was held by international investors. Finally, recorded capital outflows from foreign investors have been outpaced by inflows in ASE for nineteen consecutive months.

Our study enhances and compliments a series of studies that explore the characteristics and the efficiency of Greek stock market. Apergis and Eleptheriou (2001), for the 1990–1999 period, provided evidence in favor of inefficiency of the Athens Stock Exchange. Siourounis (2002), employing a series of GARCH type models for a period during which ASE was listed as an emerging market found that the efficiency hypothesis of ASE is questionable. On the contrary, evidence in favor of weak-form efficiency of ASE was provided by Laopodis (2004). Recently, Dicle & Levendis (2011) attempted to shed light on the reasons why Greek stock market has failed to become a developed market and they attributed the underdevelopment of ASE mainly to market inefficiencies and especially to its strong integration with international markets. Overall, as Dicle & Levendis (2011) point out, relevant literature is summarized in the following three findings with respect to ASE: (1) there exist anomalies such as the DOW effect, (2) there is serial correlation in returns that gives rise to profitable trading strategies and (3) there is a close relation with European and US markets.

This paper's contributions to the literature are as follows. On methodological grounds, we propose an augmented VAR-EGARCH model, which is superior to the quadratic GARCH model proposed by Engle (1990) and the GJR-GARCH model, because the former tends to underpredict volatility associated with negative innovations (Engle and Ng, 1993) and the latter does not distinguish between positive and negative innovations as the EGARCH model does(Nelson, 1991). We provide up to date evidence for the ongoing debate on first and second moment interdependencies in the pre- and post-crisis periods among Large, Medium and Small indices. We examine the market efficiency of the Athens stock exchange through volatility spillovers. In addition, these two periods are influenced by the trading volume. We examine this influence in order to determine whether the market efficiency is more asymmetric in the pre than in the post-crisis period. Moreover, our study extends the return and volatility spillover literature, unveiling a more dynamic interaction among three heterogeneous, different size portfolios with a unique augmented EGARCH model, extending Koutmos (1996) approach. Finally, we consider the impact of both quantity (e.g. magnitude) and quality (e.g. positive and negative) of new information on the integration process of the Athens stock exchange to examine whether the magnitude or the sign of spillovers is different in the pre and post-crisis periods.

Finally, we investigate, through the augmented univariate EGARCH model, the impact of liquidity effects on stock price volatility, and, through the augmented multivariate EGARCH model, the liquidity effects on volatility spillovers. With respect to liquidity issues, Clark (1973) was the first one to use the Mixture of Distributions Hypothesis (MDH) theory which links trading volume and volatility, focusing on the information flow to the market by means of a mixture of conditional distributions with different degrees of efficiency in returns. This 'mixture variable', which was the trading volume, quantifies the arrival of new information in the market being able to explain the GARCH effects for daily price movements, as developed by Lamoureux and Lastrapes (1990). At this point, it is worth mentioning that Greek stock market is rather concentrated, with a significant number of stocks not regularly traded (thinly traded). A reliable measure of stock market concentration is the share in total trading value of the top 10 most traded domestic companies. Thus, according to the Federation of International Stock Exchanges, the relevant figure for 2012 was 83% in ASE, whereas in developed European stock markets, such as Euronext and Deutsche Borse, the percentages were 31% and 51% respectively.

Previewing our results, we document some heterogeneous return and volatility transmission mechanisms between Small, Medium and Large size stocks in ASE. Consistent with the results obtained by Harris and Pisedtasalasai (2006) for the UK market, we find that both the return and volatility spillovers are significant, with some degree of asymmetry. The return and volatility spillover results from the augmented multivariate modelare consistent with the results obtained from the augmented univariate VAR(1)-EGARCH(1,1) model, with liquidity effects to play an explanatory role and being at most positive in both models, especially in the post-crisis period. The latter is in line with Hasan and Francis (1998) who claimed that the model retains its dynamic explanatory power when state variables are included in the conditional variance equation. It would be challenging to examine empirically if the new information which is captured through a state variable (e.g. volume) will produce high volatility and correlation or noise. Finally, we examine the utmost asymmetric feature, which is the effect of non-synchronous trading, on our results from the two VAR-EGARCH models, undertaking a Monte Carlo simulation with 1000 replications for the series of Large, Medium and Small portfolios. The simulation results suggest that, in the post-crisis period and in some cases, the spillover effects in volatility are significant under non-synchronous trading but turn to insignificant under synchronous trading. Compared to the literature, our results contradict those of Harris and Pisedtasalasai (2006) who reported that return spillovers are significant in the presence of non-synchronous trading while volatility spillovers are not. In particular, we empirically establish that volatility spillovers originating from Large to Small size and from Medium to Small size portfolios are significant in the post-crisis period in the presence of non-synchronous trading. In the case of synchronous trading in the post-crisis period, these results are no longer valid.

Overall, considering an extended univariate and multivariate model and a simulation study as well, our results reveal that the Greek stock market transmission process is moreintegrated after the crisis than before. This is in line with the literature findings, when financial crises are considered (Jeon and Seo, 2003, Kan and O'Callaghan, 2007, Lim et al., 2008). We are based on both models, univariate and multivariate EGARCH ones, to show that, when they are considered with accuracy and without mistreatments, they are indifferent on the effectiveness of the results they produce. In addition, a result, uncovered in our study through the Monte-Carlo simulation process and not mentioned in the literature, is that non-synchronous trading leads to non-negligible volatility spillovers, especially after the financial crisis. Furthermore, trading volume has a greater explanatory power to integration process in the post crisis than in the pre-crisis period. Also, our findings, based on the two main methodologies, indicate that asymmetric effects are mitigated in the post-crisis period.

The layout of the rest of the paper is as follows: Section 2 provides a description of the employed data and methodology. Section 3 presents a preliminary analysis of the asymmetry effect. Section 4 discusses the empirical findings. Section 5 investigates the impact of non-synchronous trading on spillovers and section 6 concludes the paper.

2. Data and methodology

2.1. Data Description

Our study is based on a sample of daily closing prices and aggregate trading volume (expressed in €) of the three FTSE/ASE size indices of the Athens Stock Exchange (ASE hereafter) for the period 05/06/2001 to 31/12/2012, yielding 2742 observations in total. The first member of the FTSE index family is the FTSE/ASE-20 index that consists of the 20 most liquid and largest in capitalization stocks, 'blue chips', whereas FTSE/ASE 40 includes medium size stocks and FTSE/ASE 80 comprises small cap stocks. Data are sourced from Bloomberg. Since we are interested in capturing the effects of the global financial crisis, we analyze spillover effects in mean and volatility for two sub-periods. The first sub-period runs from 5/6/2001 to 31/12/2008, while the second sub-period is from 1/1/2009 to 31/12/2012[3].

Table 1 reports summary statistics for the returns of the three indices. In particular, we provide information on the mean, standard deviation, skewness and kurtosis, as well as the Kolmogorov-Smirnov statistic which tests whether returns are normally distributed. All three series are negatively skewed and strongly leptokurtic. Thus, as expected, the Kolmogorov-Smirnov statistic rejects the null hypothesis of normal distribution for the three return series.

Table 1 also reports the Ljung–Box portmanteau statistic up to 12 lags providing evidence on the existence of any autocorrelation patterns in the series. The results suggest that returns are serially correlated and ARCH effects are strong for all series of returns. In addition, we provide the pair-wise unconditional correlations from which we infer that there is strong correlation between the three series of returns. This finding might be of relevance to investors who wish to form efficient portfolios.

Insert Table 1 here

2.2. Methodology

2.2.1. The Augmented Multivariate VAR(1)-EGARCH(1,1) model

GARCH models are generally used to explore the stochastic behavior of several financial time series and, in particular, to track the behavior of volatility over time (Theodossiou and Lee, 1993). Following Koutmos (1996), we employ the VAR-EGARCH model which allows for the estimation of volatility interactions in one-step ahead while, at the same time, incorporates the impact of any of asymmetric news on volatility spillovers.

The trivariate VAR-EGARCH model can be written as:

$$\text{Mean: } R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t} \;\; \text{for i, j} = 1,2,3\,3 \tag{1}$$

$$\text{Variance:: } \sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) + \varphi_i TV\} \;\text{for i, j} = 1,2,3 \tag{2}$$

$$f_j(z_{j,t-1}) = (|\, z_{j,t-1} \,| - E(|\, z_{j,t-1} \,| + \delta_j z_{j,t-1}) \;\text{for j} = 1,2,3 \tag{3}$$

$$\text{Covariance: } \sigma_{i,j,t} = \rho_{i,j} \sigma_{i,t} \sigma_{j,t} \;\; \text{for i, j} = 1,2,3 \text{ and i} \neq \text{j.} \tag{4}$$

Where,, $R_{i,t}$ is the percentage return at time t for market i, e.g. i=1,2,3 (1 = Large, 2 = Medium, 3 = Small), Ω_{t-1} is the σ-field generated by all the information available at

[3] Our sample ends in 2012 because the FTSE/ASE 80 stock index ceased to trade after 2012.

time t-1, $\sigma_{i,t}^{2}$ is the conditional variance, $\sigma_{i,j,t}$ is the conditional covariance between markets i and j, $\varepsilon_{i,t}$ is the innovation at time ($\varepsilon_{i,t} = R_{i,t} - \mu_{i,t}$), where $\mu_{i,t}$ is the conditional mean, $z_{i,t}$ is the standardized innovation $(i.e., z_{i,t} = (\varepsilon_{i,t} - \mu_{i,t}) / \sigma_{i,t}$, and φ^{i} is the actual value of number of traders.

Equation (1) formulates the returns of the three stock indices of the ASE in the context of a Vector Autoregressive model (VAR), where the conditional mean for each stock index is a function of its past own returns as well as of cross-index past returns. Lead and lag effects among ASE stock indices can be also captured by coefficients β_{ij} for i$\neq j$. A significant β_{ij} coefficient conveys that stock index j leads stock index i or current returns of stock price index j can be used to predict future returns of index i.

Equation (2) describes the conditional variance of returns for every stock index. In particular, it takes the form of an exponential function of past own as well as cross-index standardized innovations. The functional form of the standardized residuals is given in equation (3) and it is described by $f_j(z_{j,t-1})$. This function is asymmetric and for $z_{j,t-1} < 0$ the slope of f (.) function is equal to -1+δ_j, whereas for $z_{j,t-1} > 0$ the slope of f (.) becomes 1+δ_j. Therefore, equation (3) allows standardized innovations (own and cross-index) to affect the conditional variance of stock indices asymmetrically. The term $(| z_{j,t-1} | - E(| z_{j,t-1} |)$ measures the magnitude effect, while term $\delta_j z_{j,t-1}$ measures the sign effect. Assuming α_{ij} is positive, the impact of z $_{j,t-1}$ on $\sigma_{i,t}^{2}$ will be positive (negative) if the magnitude of $z_{j,t-1}$ is greater (Smaller) than its expected value $E| z_{j,t-1}|$. The sign effect may enhance or offset the magnitude effect. In particular, if δ_j is negative, decreases in stock price index j ($z_{j,t-1}$<0) will be followed by higher volatility than stock index increments. Such a response is consistent with the leverage effect, which is measured by the ratio |-1+δ_j|/(1+δ_j). Volatility spillovers across stock price indices are captured by $\alpha_{i,j}$ for i, j =1,2,3 and $i \neq j$. The asymmetric volatility transmission mechanism is interpreted as follows: A significantly positive $\alpha_{i,j}$ with a negative δ_j suggests that negative innovations in the stock price index j have a higher influence on the stock price index i than positive innovations have.

The persistence of volatility is measured by γ_i (equation 2). If γ_i is less than 1 the unconditional variance is finite, while if γ_i=1 then the unconditional variance follows an integrated process of order 1 (see Nelson, 1991). The conditional covariance specification (equation 4) captures the contemporaneous relationship amongst stock price returns of the three stock indices along with the impact of trading volume, if any, through the coefficient φ_i. Thus, following Hasan and Francis (1998), equation (2) introduces a multivariate asymmetric variance model allowing for state variables, such as the trading volume, which enhance our understanding of the transmission mechanism among different size portfolios. In addition, the correlation of stock index returns is constant and, as a result, the covariance between these three stock indices is proportional only to the cross-product of their standard deviations.

If normality holds, the log-likelihood for the trivariate VAR-EGARCH model can be written as:

$$L(\Theta) = -0.5(NT)\ln(2\pi) - 0.5\sum_{t=1}^{T}(\ln|S_t| + \varepsilon_t^{'} S_t^{-1}\varepsilon_t), \quad (5)$$

where, N is the number of equations, T is the number of observations, Θ is the parameter vector to be estimated, $\varepsilon_t^{'}$ is the vector of innovations at time t, S_t is the varying conditional variance-covariance matrix. The log-likelihood function is highly nonlinear in Θ and in such cases numerical maximization techniques are essential.

2.2.2. The Augmented Univariate VAR(1)-EGARCH(1,1) model

Following Hamao *et al.* (1990) and Hasan and Francis (1998), the variance equation of a VAR(1)-EGARCH(1,1) model is augmented with three error spillover terms and the daily trading volume measure. Thus, under this framework we can investigate both, the impact of: (1) the liquidity effects for the indices under examination and (2) the impact of the three (e.g. Large, Medium or Small) error spillovers on the respective stock market index's conditional asymmetric variance.

The VAR(1)-EGARCH(1,1) model proposed by Nelson (1991) takes the following form:

Mean: $R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{L,t-1} + \beta_{i,2}R_{M,t-1} + \beta_{i,3}R_{S,t-1} + e_{i,t}$ for i =1,2,3 (6)

The conditional variance of $e_{i,t}$ is given as:

Variance: $\sigma_{i,t}^2 = \exp(\alpha_0 + \alpha_{i,1}(|z_{t-1}| - E|z_{t-1}|) + \delta_i z_{t-1} + \gamma_i \ln(\sigma_{t-1}^2) + \sum_{\mu=1}^{3} \lambda_\mu \mathbf{e}_{i,t-1}^2 + \varphi_{i,1}\mathrm{TV})$**,**

for λ_1 = Large, λ_2 = Medium, and λ_3 = Small and i =1,2,3. (7)

where, $R_{i,t}$ is the stock price return of the series $i = 1,2,3$, $R_{L,t-1}$ is the stock price return of the Large stock index at time $t-1$, $R_{M,t-1}$ is the stock price return of the Medium stock index, $R_{S,t-1}$ is the stock price return of the Small stock index at $t-1$, $e_{i,t}$ is the error term for $i = 1,2,3$ at time. t

$\sigma_{i,t}^2$ is the conditional volatility at time t for $i = 1,2,3$, z_{t-1} is the standardized residuals at time $t-1$, TV denotes the actual number of trading volume term.

The VAR(1)-EGARCH(1,1) model for each stock index is estimated and the lagged squared error for stock market index j is introduced as an exogenous variable in the conditional asymmetric volatility equation of stock market index i. Also, the explanatory variable of Trading Volume is introduced into the conditional asymmetric volatility equation of stock equity index i.

The conditional variance follows an exponential generalized autoregressive conditionally heteroskedastic process of orders p=1 and q=1 (EGARCH (1,1). The original EGARCH model, suggested by Nelson (1991), has two advantages over Bollerslev's (1986) GARCH model. Firstly, the log function ensures positive variances, and secondly, volatility at time t depends on both the size and the sign of past normalized errors. The log-likelihood function takes the same form as in equation

(5). The EGARCH model is augmented here in order to accommodate for trading volume and error spillovers as explained earlier in equation (7).

3. Preliminary Analysis

3.1. Asymmetric tests for the full sample

Table 2 reports asymmetric statistics (sign bias, negative size, positive size and joint test) as developed by Engle and Ng (1993). We have included these tests due to prior allegations of superiority in detecting misspecification related to asymmetric effects. The asymmetric tests confirm that an asymmetric model might fit the data very well. Only the sign bias test for the Small stock index fails the asymmetric development of data at the 10% significance level.

Insert table 2 here

3.2. Cross-Correlations of returns and residuals for the pre – and post- crisis periods

Following Conrad et al. (1991) the asymmetric cross-correlations of returns and residuals for the three stock indices in the pre and post crisis periods are computed.
In particular, in Table 3, panel A reports the first-order lagged return correlations between the three value-weighted indices for the pre-crisis period. The results highlight the existence of a mild asymmetry. Specifically, the numbers below the diagonal of the matrix are smaller than those above the diagonal. The first-order lagged correlation between previous returns on Large stocks (Large_{t-1}) and next day return on Small stocks (Small_{t}) is 6.8%, whereas the cross-correlation between lagged Small_{t-1} and next day Large_{t} index is 5.6%. This asymmetry is important because fluctuations on stock price returns may have different asymmetric effects on the correlation between Large and Small equity indices. Panel B presents cross-correlation of residuals with a VAR (1) model for each index. A reduction is observed in the asymmetry of residuals for Large and Small indices. Similar results are revealed for the cross-correlations between Medium and Small equities. These results are in contrast to Conrad et al.(1991) findings regarding the asymmetric predictability of returns and residuals for different weighted stock indices.

Table 4, panel A presents return correlations between the three weighted indices for the post-crisis period. The numbers above the diagonal are larger than the numbers below the diagonal. This reflects a small degree of asymmetry being obvious in the series. More specifically, the lagged Large_{t-1} index is correlated with the next day returns of Small index and this is equal to 12.2 %, whereas the cross-correlation between lagged Small_{t-1} index and Large next day returns is equal to 1.9% with low persistence. In Panel B, the asymmetry of residuals for the three stock indices has been reduced dramatically for all the portfolios' series. These findings for the cross-correlation of returns and residuals contradict Conrad et al. (1991) findings.

Comparing the results during pre-crisis and post-crisis period, we may say that asymmetry is weaker in the cross-correlations of returns in the post-crisis period. This asymmetric effect is dramatically reduced in the cross-correlation of residuals for the same period. Autocorrelation is important in both, residuals and squared residuals with 12 lags in the pre-crisis period. However, in the post-crisis period, we observe significant serial correlation only in the squared residuals of the three series with 12 lags.

Insert Tables 3 and 4 here

4. Empirical Results

4.1. Multivariate VAR (1)-EGARCH (1,1) results

In the pre-crisis period (see Table 5), return spillovers are significant (range from 0.08 to 0.15) within the same index for all the three equity indices. In addition, there are linkages between Large and Medium equity indices ($\beta_{2,1}$), between Large and Small equity indices ($\beta_{3,1}$) and between Medium and Small equity indices ($\beta_{3,2}$). Asymmetry is substantial for the three conditional volatility indices as reflected in δ coefficient. Thus, news that runs from one index to the other is asymmetric, meaning that bad news has a bigger impact on volatility than good news of the same size. This finding supports the Leverage effect theory. However, the only significant volatility spillover ($\alpha_{2,1}$) is from Large to Medium equity index. All the other volatility spillover coefficients are statistically insignificant. In Table 6, return spillovers are statistically significant for all the equity indices within the same index. However, across the indices, spillovers are found to be significant only from Large to Small size index ($\beta_{3,1}$=-0.012).

Trading volume carries a positive sign when it is introduced in the variance equation, due to the arrival of new public information in ASE (see Admati and Pfleiderer (1988) for a discussion on traders' heterogeneity), and its asymmetry has been mitigated, agreement found consistent with MDH theory. Only δ_3 coefficient is significant, which means that volatility spillovers that run from Small size index generate a Larger impact of bad news than good news on the conditional volatility of Medium or Large size indices. This finding contradicts Lo and McKinlay's (1990a, 1990b) findings, but it is consistent with Harris and Pisedtasalasai's (2006) results who found feedback effects to play a significant role in the UK market. In particular, the results indicate a significant transmission channel running from Small to Medium size index with a value of 0.108, while the impact on Large stock index is insignificant.

Insert Tables 5 and 6 here

As for the post crisis period (see Table 7), surprisingly, return spillovers within the same stock index are statistically insignificant. However, spillovers across indices are dynamic and substantially significant. In particular, we observe that there are linkages between Large and Medium equities ($\beta_{2,1}$=0.094), Large and Small equities ($\beta_{3,1}$=0.099) and also between Small and Medium equities ($\beta_{2,3}$=-0.106).

Asymmetry in variance equation is significant only for the Medium stock index, as it is reflected in δ_2. This is a sign of the different impact of bad and good news on conditional volatility. Unfortunately, the results of volatility spillovers indicate that only the impact from Small to Medium index ($\alpha_{2,3}$) is statistically important, without other noticeable effects .

In Table 8, spillovers within the same stock index are insignificant. Linkages across the stock indices appear to be significant between Small and Medium stock equities.

When trading volume is included in the variance equation, it sheds light on the process of asymmetry and it shows that asymmetry is valid only for the Medium stock index and this was also confirmed in Table 7. This means that trading volume carries a Small influence on the asymmetric sign or size of volatility spillovers. In particular, we find that symmetric volatility spillovers are dynamic in Table 8 without asymmetry playing an important role. In particular, only one asymmetric volatility spillover effect exists, which runs from the Large size index to the Small size, and is equal to -0.203, with good news having a larger impact than bad news of the same size. While, there is no other asymmetric news effect, we document some symmetric effects which highlight the dynamic impact of trading volume on both symmetric and asymmetric spillovers. The fact that positive news is larger than negative news supports both theories namely the feedback trading and the leverage effect. The value of volume is negative for the Small equity index due to less noise and the possible existence of private information (see He and Wang, 1995). Thus, informed traders with private information will be interested in the speculative trading activity which might arise and thus will affect negatively the stock market's liquidity in ASE (e.g. volume, becomes more negative in the Small equity index). In general, the spillovers run from the Small size to the Large ($\alpha_{1,3}$=-0.224) and Medium size ($\alpha_{2,3}$=0.100) index with a bilateral response from the Medium size index to the Small ($\alpha_{3,2}$=0.176).

The dynamic nature of volatility spillovers is further confirmed by the different responses of impulses methodologies that are carried out in this investigation. In particular, the robustness of our results is examined by a comparison of CCC-EGARCH model's with the CCC-GJR-GARCH model's responses in the pre-crisis period and with a DCC-GJR-GARCH model in the post-crisis period. Overall, the impulse response patterns between our methodology and the other two methodologies show similar results which confirm the importance of our results, which were captured by the initial CCC-EGARCH model. The robustness check of DCC-GJR-GARCH model in the post-crisis period is based on the methodology of Cappiello, Engle and Sheppard (2006).

Insert Tables 7 and 8 here

4.2. Univariate VAR(1)-EGARCH(1,1) results

In the pre-crisis period, for the Large and Medium equity indices, there are no linkages between these and the Small stock index. For the Small equity index model, return spillovers are statistically significant for all three equity indices. In particular, the lagged Large and Medium equity indices are linked with the next day Small equity index and remain unresponsive when trading volume is included in the variance equation.

When trading volume is included in the variance equation of the univariate EGARCH model (see Table 9) the GARCH effects are weakened. In particular, both the impact of bad and good news (in terms of size and sign) on conditional volatility is reduced in the three stock indices, without, however, bad news ($\delta - \alpha_1$) losing its dominance over good news ($\delta + \alpha_1$). In addition, λ measures the impact of spillovers (with one lag) for the three indices from each one to another index. Only in the Medium stock index model is there a significant spillover effect from the other two indices. There are also two spillover effects within the same market for the Large and Medium stock indices, as indicated by λ_1 and λ_2 in the third model of the Medium stock index case. We observe that trading volume carries a positive sign without affecting the dynamic nature of spillovers, but it has an impact on the GARCH effects (see Clark, 1973 and Lamoureux and Lastrapes, 1990 for a discussion about MDH theory and the impact of volume on GARCH effects).

Insert Table 9 here

Considering the post crisis period (see Table 10), for the Large equity index model, there are no return spillovers within this stock index and with respect to the other two. For Medium stock index model, we observe that the Small equity index is linked with the Medium size regardless of the inclusion of trading volume. In this model there are return spillovers within the Medium index in the three cases out of four: (a) in the simple model, (b) with spillovers model, and (c) with both spillovers and volume effects model. Last, for the Small stock index model, there are significant linkages between the lagged Large (or Medium) equity index and the next day Small stock index. In particular, the lagged Large stock index and the next day Small stock index (see Lo and McKinlay, 1990a, 1990b who reached a similar result) are linked together and a similar effect exists between the next day Small stock index and the previous day Medium stock index. There is also a link between the lagged Large and the next day Small index in the cases where volume is included or not, and when volume and spillovers are considered in the variance equation. There are similar linkages between the lagged Small size index and the next day Small size index.
The inclusion of trading volume in the variance equation decreases the volatility persistence in a way and amplifies the impact of bad ($\delta - \alpha_1$) and good ($\delta + \alpha_1$) news on conditional volatility from Large to (Medium and Small) size indices. These results are partly consistent with the findings of Conrad et al. (1991) for the US market. While the impact of bad and good news is obvious, there is an increase in their magnitude, however, the statistical tests indicate that this is not substantial. This means that the effects among the stock indices are symmetric as the information which flows into the Athens Stock Exchange is less speculative and more efficient. Thus, in absolute terms, for the coefficients of bad and good news, the t-test indicates that their mean difference with respect to the asymmetric impact of news has decreased dramatically. Moreover, trading volume is insignificant for most of the cases. This means that the impact of noise and speculation has decreased, as volume is not statistically significant, however it has a positive sign (see Girard and Biswas, 2007). Nevertheless, when volume is included in the models, we observe slight changes in the significance of spillovers and important effects on the new direction of spillovers. This is obvious in the third and fourth specifications of Table 10 for the

Large size index model, where the spillover from the lagged Large stock index to itself (λ_1=0.121) is significant in the absence of volume. When volume is included in the variance equation, then the situation is drastically different (see Fama and French 1988, 1989 who documented a predictable variation in returns). In particular, the spillover runs from the Small equity index (λ_3=-0.037) to the Large equity index. Our results reveal that available information is first integrated into the large stocks prices volatility before being absorbed into the small stocks prices volatility. The same pattern is observed in the third and fourth model of Medium stock index, where different λ coefficients are significant when volume is incorporated in the model (see Hasan and Francis (1998) for the impact of different state variables on variance). Finally, λ_3 the coefficient of Small spillover for the Small stock index model became insignificant, when trading volume is included in the last case. The other two coefficients of λ remain unchanged.As a robustness test, the volatility spillover analysis was repeated in the context of international stock markets in the presence of trading volume and without it. The results indicate that the Athens stock exchange is not case sensitive but it is well integrated in the international financial system and, in total, remains more efficient after the crisis. The magnitude of volatility spillover responses among Large, Medium and Small indices vary in size, however without the nature of importance being lost in the transmission mechanism. In summary, the stock markets of Madrid, Frankfurt and London exhibit strong similarities with the Athens stock market as far as the patterns and the direction of spillovers are concerned.

Insert Table 10 here

5. The impact of Non-synchronous trading on return and volatility spillovers

Lo and McKinlay (1990a, 1990b) found that non-synchronous trading can generate asymmetry in the transmission mechanism of returns among different size portfolios. To this end, we employ a modified simulation version with 1000 replications which was originally used by Harris and Pisedtasalasai (2006)[4] as an attempt to investigate the effects of non-synchronous trading in our series.

Next, we proceed to introduce non-synchronous trading into the simulation model. Firstly, we have to create the observed returns, (R_i^0). If a stock did not trade in period t but it traded in period t+1, then the observed return at t+1 is calculated, taking into account the sum of all returns which did not trade till period t+1. The observed return takes the formula:

$$R_{i,t}^0 = \sum_{k=0}^{\infty} X_{i,t}(k) R_{i,t-k}\text{, i=1,...N} \tag{8}$$

Where, $X_{i,t}(k)$ is a variable that equals 1 when a security i trades at time t and it has not been traded previously until period k, and 0 otherwise.

We estimate the non-synchronous trading frequencies from the historical distribution of stocks non-trading record and we calculate an observed return for each stock. The daily returns constitute the three portfolios of Large, Medium and Small size portfolios and, as a reference point, we set the non-synchronous trading probabilities

[4] They based their experiment on a non-synchronous trading model developed by Lo and McKinlay (1990a)

of the three series to zero in order to compare the results of return and volatility spillovers between non-synchronous and synchronous trading.

The simulated return transmission model for the three portfolios takes the form:

$$R^0_{i,t} = \xi_{i,0} + \xi_{i,1}R^0_{L,t-1} + \xi_{i,2}R^0{}_{M,t-1} + \xi_{i,3}R^0_{S,t-1} + \mathrm{u}_{\mathrm{i,t}} \quad \text{for i=1,2,3} \tag{9}$$

Where $\xi_{i,0}$ is a constant, and $\xi_{i,1}$, $\xi_{i,2}$, and $\xi_{i,3}$ are the coefficients of Large, Medium and Small stock indices with one lag, respectively.

Harris and Pisedtasalasai (2006) employed an extended univariate GJR-GARCH (1,1) model with spillovers in order to investigate the impact of non-synchronous trading on volatility spillovers. Their model accounted only for bad news. On the contrary, we employ an augmented univariate EGARCH (1,1) model which accounts for the different impact of bad and good news on conditional volatility. Our empirical model takes the following form for examining volatility spillovers among Large, Medium and Small portfolios:

$$u^2_{i,t} = \exp\left(c_{i,0} + c_{i,1}(|u_{i,t-1}| - E|u_{i,t-1}|) + c_{i,2}u_{i,t-1} + c_{i,3}u^2_{1,t-1} + c_{i,4}u^2_{2,t-1} + c_{i,5}u^2_{3,t-1} + v_{i,t}\right),$$

for c_3 = Large, c_4 = Medium, c_5 = Small and i =1,2,3 (10)

where, $c_{i,0}$ is a constant, and $c_{i,1}$, and $c_{i,2}$ are the lagged coefficients for asymmetry and persistence, respectively, $c_{i,3}$, $c_{i,4}$ and $c_{i,5}$ are the coefficients of the lagged squared return shocks of the Large, Medium and Small stock indices, respectively.

The equations above are analogous to the multivariate and univariate VAR(1)-EGARCH(1,1) models that are also used in the empirical analysis.

Table 11 reports the results for the return transmissions in the pre-and post- crisis periods. Panel A shows asymmetric spillovers in the pre-crisis period from the previous day Large returns to the next day Large portfolio, when non-synchronous trading is allowed. The same holds for the Small size portfolio. This asymmetry in return spillover effects is consistent with the empirical results reported in Tables 5 and 9. However, the estimated parameters in the simulation process are partly lower than those observed in Tables 5 and 9. When we allow for synchronous trading, these spillovers are still present. Similarly, in the post-crisis period, when non-synchronous trading is introduced, there are some return spillovers from lagged Large portfolio to itself for the next day and from lagged Large portfolio to Medium and Small portfolio for the next day.

The results when non-synchronous trading is present do not cater any additional explanation for the asymmetric return spillover effects among Large, Medium and Small portfolios between the pre and post crisis periods in comparison to synchronous trading. Thus, in these two periods return spillovers are similar under synchronous and non-synchronous trading.

With respect to the direction of spillovers, Lo and McKinlay (1990a, 1990b) and Harris and Pisedtasalasai (2006) found that in the presence of non-synchronous trading return spillovers are sufficient to describe the spillovers effects between Large and Small portfolios and among Large, Medium and Small portfolios, respectively. However, these authors were unable to explain the magnitude of lagged cross-correlations for stocks that traded in USA and UK. In contrast to the above authors,

we were unable to account for the significant difference of return spillovers among Large, Medium and Small portfolios in the presence of non-synchronous trading.
Table 12, panel A, suggests that in the pre-crisis period non-synchronous trading offers no additional explanation for the observed volatility spillovers among Large, Medium and Small size portfolios. However, non-synchronous trading accounts for a small asymmetric pattern of volatility spillovers observed in the post-crisis period. In particular, there is a spillover effect running from previous period return of Large portfolio to next day Large portfolio (0.147), from previous day Small portfolio to next day Large portfolio (-0.814) with low persistence and from previous day Small portfolio to next day Medium portfolio (0.256). The latter spillover effect does not vary substantially in magnitude from that captured by the multivariate model. This spillover effect is equal to 0.176 when we include volume as explanatory variable. These results are in line with those reported by Lo and McKinlay (1990a, 1990b) and Harris and Pisedtasalasai (2006) who found that the magnitude of spillovers cannot be accurately justified under the simulation process allowing for non-synchronous trading. Moreover, we documented that these volatility spillovers disappear when synchronous trading is taken into account. This result contradicts that of Harris and Pisedtasalasai (2006) who found that non-synchronous trading is unlikely to account for asymmetry in volatility spillovers. It is worth mentioning that their simulation analysis for volatility spillovers was based on an extended GJR-GARCH(1,1) model incorporating only the effect of bad news, while we employed an augmented EGARCH(1,1) model which accounts both for bad and good news.

Insert Tables 11 and 12 here

6. Conclusion

In this paper we examine return and volatility spillovers among Large, Medium and Small size portfolios in Athens Stock Exchange employing two models: (i) an augmented univariate and (ii) an augmented multivariate VAR-EGARCH model. Our period of analysis extends from 05/06/2001 to 31/12/2012. In order to isolate the impact of the global financial crisis, our sample is divided into two non-equal length subperiods with the first sub-period from 5/6/2001 to 31/12/2008 while the second sub-period runs from 1/1/2009 to 31/12/2012.
The unique characteristics of Athens Stock Exchange, coupled with the events that unfolded during the European sovereign debt crisis, render Greek stock market an interesting market to examine. We find that in the post-crisis period, return and volatility spillovers of Large and Medium size portfolios run to the Small size portfolio (Ross,1989, Lo and McKinlay,1990a, 1990b, Mech,1990, and Conrad et al.,1991) with some feedback occurring (see Harris and Pisedtasalasai ,2006 for the UK) and that trading volume accounts only for a part of the volatility spillovers (Hasan and Francis (1998)).
Our contribution to the literature of 'volatility spillovers' is reinforced by the results of the different impact of trading volume (e.g. liquidity) on the market efficiency of the Athens stock exchange, in the pre and post-crisis periods, through volatility transmission. Transmission of volatility plays a more significant role in the post crisis

period. To begin with, there is a larger mitigating influence of trading volume on spillovers in this period than in the pre crisis period (e.g. Lamoureux and Lastrapes (1990)). In addition, volatility asymmetry was found to be lower in the post-crisis period than in the pre crisis period. Therefore, consistent with the results for international markets (e.g. Karpoff (1987), Jeon and Seo (2003), Lim *et al. (*2008), Huyghebaert and Wang (2010)), market efficiency appears stronger in the post-crisis period than in the pre-crisis period. Furthermore, contrary to literature (e.g. Lo and McKinlay (1990), Harris and Pisedtsalasai (2006)), simulations in non-synchronous trading play a significant role in volatility spillovers.

From the above it follows naturally that the innovative simulated univariate and multivariate VAR-EGARCH models successfully captured the different effects on volatility transmission, either in the presence of non-synchronous trading or not. Overall, our results reveal that available information is firstly incorporated into the large size stocks and then absorbed by the small size stocks.

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APPENDIX

Table 1. Sample statistics of daily stock return series for the full sample

Descriptive Statistics			
Basic Statistics	**Large**	**Medium**	**Small**
Mean	-0.082	-0.069	-0.066
Standard deviation	1.977	1.647	1.712
Skewness	0.157	-0.335	-0.330
Kurtosis	4.833	5.925	4.810
Klomogorv-Smirnov	0.077*	0.082*	0.070*
LB(12) for R $_t$	38.416*	71.817*	49.940*
ARCH (4)	397155.219*	605459.018*	333470.861*
Correlation matrix			
	Large	**Medium**	**Small**
Large	1	0.840	0.767
Medium		1	0.855
Small			1

Notes: LB(k) is the Ljung-Box Q statistic for k order serial correlation, which distributes as a chi-square variate with k degree of freedom. Kolmogorov-Smirnov tests for normality (5% critical value is 1.36/ $\sqrt{T}$ where, T number of observations). (*) denotes significance at the (0.01) level

Table 2. Asymmetric tests for the returns of the full sample

(i)Sign bias test: $z_t^2 = a + bI_t^- + e_t$

(ii)Negative size bias test: $z_t^2 = a + bI_t^- E_{t-1} + e_t$

(iii)Positive size bias test: $z_t^2 = a + b(1 - I_t^-)E_{t-1} + e_t$

(iv)Joint test: $z_t^2 = a + b_1 I_t^- + b_2 I_t^- E_{t-1} + b_3(1 - I_t^-)E_{t-1} + e_t$

Table 2 Asymmetric statistics for the stock indexes

Stock indexes	Sign bias (t-test)	Negative size bias (t-test)	Positive size bias test (t-test)	Joint test (F-test)
Large	2.591*	-8.228*	3.983*	39.593*
Medium	2.262**	-7.094*	3.029*	27.797*
Small	1.070	-5.928*	2.823*	20.604*

Notes: z_t is the normalized residual from an AR (p) filter using constant variance. I_t^- is unity if E_{t-1} is negative and zero otherwise. The t-statistics for the sign bias, negative size bias and positive size bias tests are those of coefficient b in regression (i), (ii) and (iii), respectively. The F-statistic is based on regression (iv). (*) (**) (***) denotes significance at the (0.01), (0.05) and (0.10) level, respectively.

Table 3. Cross-Correlations of Returns and Residuals from a mean VAR (1) return approach in the pre crisis period

$$R_{i,t} = \beta_{i,0} + \beta_{i,1} R_{L,t-1} + \beta_{i,2} R_{M,t-1} + \beta_{i,3} R_{S,t-1} + \varepsilon_{i,t}, \; i = \text{Large, Medium and Small}$$

Pre-crisis period			
Panel A: Return cross-correlations			
	Large $_t$	**Medium** $_t$	**Small** $_t$
Large $_{t-1}$	0.083	0.111	0.068
Medium $_{t-1}$	0.085	0.138	0.107
Small $_{t-1}$	0.056	0.103	0.092
Panel B: Residual Cross-Correlations			
	Large $_t$	**Medium** $_t$	**Small** $_t$
Large $_{t-1}$	0.002	-0.004	-0.005
Medium $_{t-1}$	0.003	-0.006	-0.008
Small $_{t-1}$	0.002	-0.004	-0.006
Panel C: Residual Autocorrelations			
	Large	**Medium**	**Small**
LB(12)	25.692**	39.113*	41.496*
LB^2 **(12)**	1494.673*	763.840*	709.486*

Notes: (*)(**)(***) denote significance at the (0.01)(0.05)(0.10) level, respectively. R $_L$ stands for the Large stock index returns, R $_M$ stands for the Medium stock index returns, R $_S$ stands for the Small stock index returns.

Table 4. Cross-Correlations of Returns and Residuals from a mean VAR (1) return approach in the post crisis period

$R_{i,t} = \beta_{i,0} + \beta_{i,1}R_{L,t-1} + \beta_{i,2}R_{M,t-1} + \beta_{i,3}R_{S,t-1} + \varepsilon_{i,t}$, $i =$ Large, Medium and Small

Post-crisis period			
Panel A: Return cross-correlations			
	Large $_t$	**Medium** $_t$	**Small** $_t$
Large $_{t-1}$	0.020	0.079	0.122
Medium $_{t-1}$	-0.009	0.058	0.099
Small $_{t-1}$	-0.019	0.015	0.056
Panel B: Residual Cross-Correlations			
	Large $_t$	**Medium** $_t$	**Small** $_t$
Large $_{t-1}$	-0.003	-0.001	-0.003
Medium $_{t-1}$	0.000	0.001	-0.000
Small $_{t-1}$	0.006	0.003	0.003
Panel C: Residual Autocorrelations			
	Large	**Medium**	**Small**
LB(12)	17.451	14.921	13.513
LB^2 **(12)**	70.290*	50.791*	36.469*

Notes: (*)(**)(***) denote significance at the (0.01), (0.05) and (0.10) level, respectively. R $_L$ stands for the Large stock index returns, R $_M$ stands for the Medium stock index returns, R $_S$ stands for the Small stock index returns.

Table 5. Maximum likelihood estimates of the multivariate VAR(1)-EGARCH (1,1) approach in the pre-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}$ for i, j = 1,2,3

Variance: $\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\}$ for i, j = 1,2,3

Covariance: $\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}$ for i, j = 1,2,3 and i ≠ j.

	Large (1)		Medium (2)		Small (3)
$\beta_{1,0}$	-0.016 (0.016)	$\beta_{,2,0}$	-0.019 (0.015)	$\beta_{3,0}$	-0.051 (0.018)*
$\beta_{1,1}$	0.152 (0.030)*	$\beta_{2,1}$	0.047 (0.029)***	$\beta_{3,1}$	-0.052 (0.028)***
$\beta_{1,2}$	-0.039 (0.030)	$\beta_{2,2}$	0.083 (0.032)*	$\beta_{3,2}$	0.064 (0.034)***
$\beta_{,13}$	-0.007 (0.025)	$\beta_{2,3}$	0.017 (0.025)	$\beta_{3,3}$	0.098 (0.030)*
$\alpha_{1,0}$	0.025 (0.004)*	$\alpha_{2,0}$	0.029 (0.004)*	$\alpha_{3,0}$	0.048 (0.006)*
$\alpha_{1,1}$	0.152 (0.022)*	$\alpha_{2,1}$	0.067 (0.022)*	$\alpha_{3,1}$	-0.012 (0.024)
$\alpha_{1,2}$	0.029 (0.026)	$\alpha_{2,2}$	0.101 (0.025)*	$\alpha_{3,2}$	-0.032 (0.028)
$\alpha_{1,3}$	-0.016 (0.023)	$\alpha_{2,3}$	0.024 (0.020)	$\alpha_{3,3}$	0.250 (0.025)*
δ_1	-0.174 (0.055)*	δ_2	-0.125 (0.056)**	δ_3	-0.099 (0.041)**
γ_1	0.966 (0.005)*	γ_2	0.953 (0.006)*	γ_3	0.938 (0.008)*
R^2	0.009		0.020		0.013

Correlation Matrix

	Large	Medium	Small
Large	1	0.820 (0.005)*	0.747 (0.008)*
Medium		1	0.848 (0.004)*
Small			1

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. (*)(**)(***) denotes significance at the (0.01), (0.05) and (0.10) level, respectively.

Table 6. Maximum likelihood estimates of the multivariate VAR(1)-EGARCH (1,1) approach with liquidity effects in the pre-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}$ for i, j = 1,2,3

Variance: $\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) + \varphi_i TV\}$ for i, j = 1,2,3

Covariance: $\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}$ for i, j = 1,2,3 and i ≠ j.

Large(1)		Medium(2)		Small(3)	
$\beta_{1,0}$	-0.004 (0.019)	$\beta_{2,0}$	-0.006 (0.017)	$\beta_{3,0}$	-0.042 (0.019)**
$\beta_{1,1}$	0.131 (0.033)*	$\beta_{2,1}$	0.004 (0.030)	$\beta_{3,1}$	-0.012 (0.033)*
$\beta_{1,2}$	0.018 (0.046)	$\beta_{2,2}$	0.157 (0.045)*	$\beta_{3,2}$	0.115 (0.050)**
$\beta_{,13}$	-0.033 (0.031)	$\beta_{2,3}$	-0.013 (0.031)	$\beta_{3,3}$	0.094 (0.033)*
$\alpha_{1,0}$	0.016 (0.009)***	$\alpha_{2,0}$	0.005 (0.011)	$\alpha_{3,0}$	-0.011 (0.012)
$\alpha_{1,1}$	0.136 (0.029)*	$\alpha_{2,1}$	0.029 (0.029)	$\alpha_{3,1}$	-0.0178 (0.030)
$\alpha_{1,2}$	-0.008 (0.040)	$\alpha_{2,2}$	0.088 (0.038)**	$\alpha_{3,2}$	-0.081 (0.042)***
$\alpha_{1,3}$	0.049 (0.036)	$\alpha_{2,3}$	0.108 (0.039)*	$\alpha_{3,3}$	0.270 (0.041)*
φ_1	0.001 (0.001)*	φ_2	0.001 (0.001)*	φ_3	0.001 (0.001)*
δ_1	-0.104 (0.085)	δ_2	-0.087 (0.090)	δ_3	-0.193 (0.060)*
γ_1	0.907 (0.019)*	γ_2	0.875 (0.016)*	γ_3	0.900 (0.016)*
R^2	0.009		0.020		0.013

Correlation Matrix

	Large	Medium	Small
Large	1	0.822 (0.007)*	0.752 (0.009)*
Medium		1	0.866 (0.006)
Small			1

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. (*)(**)(***) denotes significance at the (0.01), (0.05), and (0.10) level, respectively. TV stands for the actual trading volume term.

Table 7. Maximum likelihood estimates of the multivariate VAR(1)-EGARCH (1,1) approach in the post-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}$ for i, j = 1,2,3

Variance: $\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\}$ for i, j = 1,2,3

Covariance: $\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}$ for i, j = 1,2,3 and i ≠ j.

Large(1)		**Medium(2)**		**Small(3)**	
$\beta_{1,0}$	-0.145 (0.083)***	$\beta_{2,0}$	-0.118 (0.059)**	$\beta_{3,0}$	-0.090 (0.058)
$\beta_{1,1}$	0.091 (0.067)	$\beta_{2,1}$	0.094 (0.047)**	$\beta_{3,1}$	0.099 (0.045)**
$\beta_{1,2}$	-0.060 (0.099)	$\beta_{2,2}$	0.037 (0.073)	$\beta_{3,2}$	0.037 (0.070)
$\beta_{,13}$	-0.064 (0.079)	$\beta_{2,3}$	-0.106 (0.058)***	$\beta_{3,3}$	-0.075 (0.059)
$\alpha_{1,0}$	0.189 (0.126)	$\alpha_{2,0}$	2.252 (0.220)*	$\alpha_{3,0}$	0.494 (0.192)*
$\alpha_{1,1}$	0.045 (0.039)	$\alpha_{2,1}$	-0.039 (0.072)	$\alpha_{3,1}$	-0.278 (0.086)*
$\alpha_{1,2}$	0.022 (0.027)	$\alpha_{2,2}$	0.122 (0.067)***	$\alpha_{3,2}$	0.099 (0.068)
$\alpha_{1,3}$	0.006 (0.039)	$\alpha_{2,3}$	0.101 (0.044)**	$\alpha_{3,3}$	0.207 (0.065)*
δ_1	0.133 (0.197)	δ_2	-0.746 (0.351)**	δ_3	0.337 (0.391)
γ_1	0.904 (0.063)*	γ_2	-0.631 (0.153)*	γ_3	0.627 (0.144)*
R^2	0.013		0.023		0.024

Correlation Matrix

	Large	**Medium**	**Small**
Large	1	0.854 (0.009)*	0.821 (0.011)*
Medium		1	0.836 (0.010)*
Small			1

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. (*)(**)(***) denotes significance at the (0.01), (0.05) and (0.10) level, respectively.

Table 8. Maximum likelihood estimates of the multivariate VAR(1)-EGARCH (1,1) approach with liquidity effects in the post-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j} R_{j,t-1} + \varepsilon_{i,t}$ for i, j = 1,2,3

Variance: $\sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2) + \varphi_i TV\}$ for i, j = 1,2,3

Covariance: $\sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t}$ for i, j = 1,2,3 and i ≠ j.

	Large(1)		**Medium(2)**		**Small(3)**
$\beta_{1,0}$	-0.359 (0.054)*	$\beta_{2,0}$	-0.243 (0.042)*	$\beta_{3,0}$	-0.179 (0.024)*
$\beta_{1,1}$	-0.004 (0.075)	$\beta_{2,1}$	0.063 (0.053)	$\beta_{3,1}$	0.072 (0.053)
$\beta_{1,2}$	-0.040 (0.096)	$\beta_{2,2}$	0.070 (0.072)	$\beta_{3,2}$	0.045 (0.069)
$\beta_{,13}$	0.010 (0.066)	$\beta_{2,3}$	-0.093 (0.056)***	$\beta_{3,3}$	-0.060 (0.053)
$\alpha_{1,0}$	1.441 (0.030)*	$\alpha_{2,0}$	0.096 (0.025)*	$\alpha_{3,0}$	0.082 (0.026)*
$\alpha_{1,1}$	0.071 (0.068)	$\alpha_{2,1}$	-0.137 (0.039)*	$\alpha_{3,1}$	-0.203 (0.048)*
$\alpha_{1,2}$	0.027 (0.061)	$\alpha_{2,2}$	0.141 (0.033)*	$\alpha_{3,2}$	0.176 (0.038)*
$\alpha_{1,3}$	-0.224 (0.076)*	$\alpha_{2,3}$	0.100 (0.047)**	$\alpha_{3,3}$	0.030 (0.042)
φ_1	0.001 (0.001)*	φ_2	0.001 (0.001)	φ_3	-0.001 (0.001)
δ_1	0.474 (0.171)*	δ_2	0.319 (0.190)***	δ_3	0.068 (0.106)
γ_1	-0.176 (0.058)*	γ_2	0.933 (0.018)*	γ_3	0.946 (0.019)*
R^2	0.013		0.023		0.024

Correlation Matrix

	Large	**Medium**	**Small**
Large	1	0.839 (0.014)*	0.813 (0.016)*
Medium		1	0.828 (0.010)*
Small			1

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. (*)(**)(***) denotes significance at the (0.01), (0.05), and (0.10) level, respectively. TV stands for the actual trading volume term.

Table 9: Univariate VAR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers in the pre-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \beta_{i,1} R_{L,t-1} + \beta_{i,2} R_{M,t-1} + \beta_{i,3} R_{S,t-1} + e_{i,t}$ for i =Large, Medium, Small

Variance: $\sigma^2_{i,t}$ = exp ($\alpha_0 + \alpha_{i,1}(|z_{t-1}| - E|z_{t-1}|) + \delta_i z_{t-1} + \gamma_i \ln(\sigma^2_{t-1}) + \sum_{\mu=1}^{3} \lambda_\mu e^2_{i,t-1} + \varphi_{i,1}$ **TV), for** λ_1 **= Large,** λ_2 **= Medium,** λ_3 **= Small and** i **=1,2,3**

Dependent Variable	β_0	β_1	β_2	β_3	α_0	**δ**	**γ**	α_1	λ_1	λ_2	λ_3	φ_1
(1) L_S	0.025	0.105	0.003	-0.007	0.016	-0.074	0.978	0.187				
	(0.019)	(0.030)*	(0.040)	(0.031)	(0.004)*	(0.011)*	(0.005)*	(0.022)*				
(2) L_V	0.028	0.125	-0.011	-0.001	0.010	-0.089	0.954	0.184				0.001
	(0.027)	(0.042)*	(0.052)	(0.035)	(0.009)	(0.017)*	(0.012)*	(0.028)*				(0.001)
(3) L_T	0.026	0.105	0.003	-0.007	0.015	-0.077	0.971	0.172	0.004	-0.003	0.001	
	(0.023)	(0.031)*	(0.046)	(0.031)	(0.005)*	(0.012)*	(0.009)*	(0.024)*	(0.002)***	(0.004)	(0.002)	
(4) L_{VT}	0.024	0.130	-0.002	-0.006	-0.001	-0.095	0.930	0.136	0.013	-0.009	0.006	0.001
	(0.021)	(0.034)*	(0.050)	(0.036)	(0.011)	(0.017)*	(0.020)*	(0.035)*	(0.008)	(0.007)	(0.004)	(0.001)
(1) M_S	0.028	-0.004	0.145	0.016	0.024	-0.096	0.959	0.263				
	(0.024)	(0.021)	(0.030)*	(0.025)	(0.005)*	(0.014)*	(0.006)*	(0.022)*				
(2) M_V	0.036	-0.005	0.154	0.018	-0.004	-0.113	0.947	0.253				0.001
	(0.003)*	(0.038)	(0.052)*	(0.031)	(0.012)	(0.017)*	(0.009)*	(0.025)*				(0.001)**
(3) M_T	0.024	-0.016	0.159	0.011	0.020	-0.098	0.953	0.266	0.008	-0.017	0.009	
	(0.022)	(0.030)	(0.043)*	(0.031)	(0.006)*	(0.013)*	(0.008)*	(0.027)*	(0.002)*	(0.005)*	(0.003)*	
(4) M_{VT}	0.032	-0.005	0.162	0.014	-0.016	-0.120	0.936	0.231	0.018	-0.025	0.013	0.001
	(0.023)	(0.033)	(0.047)*	(0.034)	(0.013)	(0.017)*	(0.013)*	(0.036)*	(0.006)*	(0.008)*	(0.004)*	(0.001)**
(1) S_S	-0.024	-0.111	0.119	0.104	0.036	-0.084	0.959	0.306				
	(0.023)	(0.030)*	(0.046)*	(0.038)*	(0.006)*	(0.013)*	(0.007)*	(0.023)*				
(2) S_V	-0.005	-0.171	0.110	0.148	-0.029	-0.109	0.955	0.249				0.001
	(0.025)	(0.037)*	(0.053)**	(0.038)*	(0.012)**	(0.016)*	(0.008)*	(0.027)*				(0.001)*
(3) S_T	-0.024	-0.111	0.119	0.101	0.039	-0.085	0.966	0.319	0.001	-0.004	-0.001	
	(0.024)	(0.026)*	(0.041)*	(0.036)*	(0.007)*	(0.013)*	(0.009)*	(0.030)*	(0.002)	(0.005)	(0.004)	
(4) S_{VT}	-0.007	-0.171	0.112	0.145	-0.025	-0.114	0.963	0.268	0.006	-0.007	-0.001	0.001
	(0.030)	(0.030)*	(0.053)**	(0.037)*	(0.015)***	(0.017)*	(0.011)*	(0.036)*	(0.006)	(0.008)	(0.005)	(0.001)*

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. Trading volume is the actual number of people trading on the stock price indexes of Large, Medium and Small equities. (*)(**)(***) denotes significance at the (0.01), (0.05) and (0.10) level, respectively. R $_L$ stands for the Large stock price index returns, R $_M$ stands for the Medium stock index returns, and R $_S$ stands for the Small stock index returns. TV stands for the actual trading volume term. L $_S$ refers to the simple Large equity index model without the impact of trading volume or spillovers, L_V refers to the Large equity index model with the impact of trading volume, L_T refers to the impact of Large equity index model from spillovers of itself and the other two indexes, L_{VT} refers to the impact of Large equity index from both spillovers form itself and the other two indexes as well its trading volume, M_S refers to the simple Medium stock index model without the impact of trading volume and spillovers, M_V refers to the Medium equity index model with the impact of trading volume, M_T refers to the Medium stock index model with the impact of spillovers, M_{VT} refers to the Medium stock index model with the impact of both trading volume and spillovers, S_S refers to the simple Small stock index model without the impact of trading volume and spillovers, S_V refers to the Small equity index model with the impact of trading volume, S_T refers to the Small stock index model with the impact of spillovers, S_{VT} refers to the Small stock index model with the impact of both trading volume and spillovers.

Table 10: Univariate VAR(1)-EGARCH(1,1) results with or without liquidity effects and spillovers in the post-crisis period

Mean: $R_{i,t} = \beta_{i,0} + \beta_{i,1} R_{L,t-1} + \beta_{i,2} R_{M,t-1} + \beta_{i,3} R_{S,t-1} + e_{i,t}$ for i =Large, Medium, Small

Variance: $\sigma^2_{i,t} = \exp\left(\alpha_0 + \alpha_{i,1}(|z_{t-1}| - E|z_{t-1}|) + \delta_i z_{t-1} + \gamma_i \ln(\sigma^2_{t-1}) + \sum_{\mu=1}^{3} \lambda_\mu e^2_{i,t-1} + \varphi_{i,1}\,\mathbf{TV}\right)$, **for** λ_1 **= Large,** λ_2 **= Medium,** λ_3 **= Small and** i **=1,2,3**

Dependent Variable	β_0	β_1	β_2	β_3	α_0	δ	γ	α_1	λ_1	λ_2	λ_3	φ_1
(1) L_S	-0.192 (0.089)**	0.084 (0.069)	0.006 (0.099)	-0.1007 (0.0865)	0.111 (0.045)**	-0.067 (0.023)*	0.944 (0.023)*	0.157 (0.038)*				
(2) L_V	-0.352 (0.072)*	-0.031 (0.061)	0.047 (0.086)	-0.049 (0.076)	0.415 (0.171)**	-0.071 (0.057)	-0.264 (0.056)*	-0.096 (0.083)				0.001 (0.001)*
(3) L_T	-0.240 (0.052)*	-0.047 (0.041)	-0.001 (0.060)	0.028 (0.052)	0.416 (0.082)*	0.005 (0.053)	-0.044 (0.066)	-0.083 (0.112)	0.121 (0.007)*	0.012 (0.011)	-0.011 (0.014)	
(4) L_{VT}	-0.364 (0.076)*	-0.028 (0.065)	0.030 (0.086)	-0.071 (0.063)	0.473 (0.191)**	-0.036 (0.057)	-0.297 (0.064)*	-0.105 (0.138)	0.013 (0.009)	0.005 (0.010)	-0.037 (0.009)*	0.001 (0.001)*
(1) M_S	-0.201 (0.065)*	0.085 (0.048)***	0.151 (0.072)**	-0.172 (0.060)*	0.081 (0.030)*	-0.045 (0.020)*	0.946 (0.021)*	0.169 (0.035)*				
(2) M_V	-0.166 (0.069)**	0.101 (0.047)**	0.061 (0.069)	-0.167 (0.062)*	1.835 (0.162)*	-0.104 (0.039)*	-0.561 (0.092)*	0.182 (0.060)*				0,001 (0.001)*
(3) M_T	-0.150 (0.038)*	0.001 (0.028)	0.104 (0.041)*	-0.059 (0.036)	-0.194 (0.062)*	-0.002 (0.052)	0.074 (0.051)	-0.009 (0.104)	-0.009 (0.007)	0.208 (0.008)*	-0.012 (0.012)	
(4) M_{VT}	-0.188 (0.064)*	0.074 (0.047)	0.163 (0.072)**	-0.135 (0.065)**	0.062 (0.025)**	-0.042 (0.021)**	0.926 (0.025)*	0.157 (0.050)*	0.001 (0.003)	-0.008 (0.006)	0.016 (0.005)*	0.001 (0.001)
(1) S_S	-0.146 (0.066)**	0.097 (0.049)**	0.115 (0.072)	-0.122 (0.065)***	0.110 (0.054)**	-0.075 (0.027)*	0.920 (0.040)*	0.185 (0.059)*				
(2) S_V	-0.147 (0.067)**	0.096 (0.047)**	0.114 (0.071)	-0.122 (0.064)***	0.131 (0.072)***	-0.087 (0.033)*	0.886 (0.066)*	0.218 (0.072)*				0.001 (0.001)
(3) S_T	-0.156 (0.044)*	0.031 (0.028)	0.021 (0.045)	-0.008 (0.036)	-0.162 (0.077)**	-0.056 (0.054)	0.002 (0.055)	-0.045 (0.108)	-0.011 (0.005)**	0.015 (0.009)***	0.211 (0.013)*	
(4) S_{VT}	-0.143 (0.059)**	0.092 (0.041)**	0.120 (0.065)***	-0.124 (0.057)**	0.185 (0.100)***	-0.080 (0.035)**	0.855 (0.097)*	0.217 (0.101)**	-0.010 (0.005)***	0.016 (0.009)***	-0.001 (0.011)	0.001 (0.001)

Notes: Numbers in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. Trading volume is the actual number of people trading on the stock price indexes of Large, Medium and Small equities. (*)(**)(***) denotes significance at the (0.01), (0.05), and (0.10) level, respectively. R_L stands for the Large stock price index returns, R_M stands for the Medium stock index returns, and R_S stands for the Small stock index returns. TV stands for the actual trading volume term. L_S refers to the simple Large equity index model without the impact of trading volume or spillovers, L_V refers to the Large equity index model with the impact of trading volume, L_T refers to the impact of Large equity index model from spillovers of itself and the other two indexes, L_{VT} refers to the impact of Large equity index from both spillovers form itself and the other two indexes as well its trading volume, M_S refers to the simple Medium stock index model without the impact of trading volume and spillovers, M_V refers to the Medium equity index model with the impact of trading volume, M_T refers to the Medium stock index model with the impact of spillovers, M_{VT} refers to the Medium stock index model with the impact of both trading volume and spillovers, S_S refers to the simple Small stock index model without the impact of trading volume and spillovers, S_V refers to the Small equity index model with the impact of trading volume, S_T refers to the Small stock index model with the impact of spillovers, S_{VT} refers to the Small stock index model with the impact of both trading volume and spillovers.

Table 11: Simulation Results for non-synchronous and synchronous trading of returns in the pre and post crisis period

$R^0{}_{i,t} = \xi_{i,0} + \xi_{i,1} R^0{}_{L,t-1} + \xi_{i,2} R^0{}_{M,t-1} + \xi_{i,3} R^0{}_{S,t-1} + u_{i,t}$ for i = Large, Medium, and Small

Pre-crisis period			
Panel A: Non-synchronous Trading			
	$R^0_{L,t}$	$R^0_{M,t}$	$R^0_{S,t}$
$R^0_{L,t-1}$	0.143	0.125	0.071
	(0.046)*	(0.082)	(0.095)
$R^0_{M,t-1}$	-0.012	0.001	-0.040
	(0.032)	(0.057)	(0.066)
$R^0_{S,t-1}$	-0.004	0.042	0.113
	(0.022)	(0.039)	(0.045)**
Panel B: Synchronous-Trading			
	$R^0_{L,t}$	$R^0_{M,t}$	$R^0_{S,t}$
$R^0_{L,t-1}$	0.165	0.095	0.001
	(0.050)*	(0.061)	(0.056)
$R^0_{M,t-1}$	-0.033	0.001	-0.009
	(0.051)	(0.062)	(0.056)
$R^0_{S,t-1}$	-0.018	0.047	0.122
	(0.042)	(0.051)	(0.047)*
Post-crisis period			
Panel A: Non-synchronous Trading			
	$R^0_{L,t}$	$R^0_{M,t}$	$R^0_{S,t}$
$R^0_{L,t-1}$	0.184	0.381	0.620
	(0.069)*	(0.143)*	(0.210)*
$R^0_{M,t-1}$	-0.044	-0.083	-0.074
	(0.037)	(0.076)	(0.112)
$R^0_{S,t-1}$	-0.024	-0.044	-0.068
	(0.015)	(0.031)	(0.045)
Panel B: Synchronous-Trading			
	$R^0_{L,t}$	$R^0_{M,t}$	$R^0_{S,t}$
$R^0_{L,t-1}$	0.188	0.191	0.133
	(0.081)**	(0.079)**	(0.047)*
$R^0_{M,t-1}$	-0.085	-0.079	-0.023
	(0.095)	(0.092)	(0.054)
$R^0_{S,t-1}$	-0.144	-0.131	-0.120
	(0.0919)	(0.089)	(0.052)**

Notes: This table reports the coefficients, and standard errors in parentheses of the VAR model for the observed returns of the three portfolios; Large, Medium and Small equities. R^0_L, R^0_M and R^0_S symbolize the returns of the Large, Medium and Small stock indexes, respectively. For the non-synchronous-trading case, the observed returns have been calculating taking into account the non-trading frequencies, instead of the non-trading probabilities, for each equity separately. For the synchronous-trading case, the non-trading frequencies are set equal to zero. The simulation is based on 1000 replications. (*)(**)(***) denote statistical significance at the (0.01) (0.05) and (0.10) percent level, respectively.

Table 12: Simulation Results for non-synchronous and synchronous trading of volatility in the pre and post crisis period

Var: $u_{i,t}^2$ **= exp (** $c_0 + c_1(|u_{i,t-1}| - E|u_{i,t-1}|) + c_2 u_{i,t-1} + c_3\ u_{1,t-1}^2 + c_4\ u_{2,t-1}^2 + c_{5,t-1}\ u_{3,t-1}^2 + v_{i,t}$ **),**

for c_3 = Large, c_4 = Medium, c_5 = Small and i = Large, Medium, and Small

Pre-crisis period			
Panel A: Non-synchronous Trading			
	$u_{1,t}^2$	$u_{2,t}^2$	$u_{3,t}^2$
$u_{1,t-1}^2$	-0.281 (0.059)*	-0.934 (0.170)*	-0.973 (0.197)*
$u_{2,t-1}^2$	0.195 (0.021)*	0.602 (0.060)*	0.497 (0.070)*
$u_{3,t-1}^2$	-0.085 (0.013)*	-0.183 (0.037)*	-0.120 (0.0437)*
Panel B: Synchronous-Trading			
	$u_{1,t}^2$	$u_{2,t}^2$	$u_{3,t}^2$
$u_{1,t-1}^2$	-0.252 (0.061)*	-0.449 (0.082)*	-0.283 (0.059)*
$u_{2,t-1}^2$	0.427 (0.048)*	0.629 (0.064)*	0.309 (0.046)*
$u_{3,t-1}^2$	-0.308 (0.047)*	-0.283 (0.063)*	-0.097 (0.045)**
Post-crisis period			
Panel A: Non-synchronous Trading			
	$u_{1,t}^2$	$u_{2,t}^2$	$u_{3,t}^2$
$u_{1,t-1}^2$	0.147 (0.079)***	0.119 (0.273)	-0.874 (0.585)
$u_{2,t-1}^2$	-0.010 (0.019)	0.026 (0.068)	0.271 (0.145)***
$u_{3,t-1}^2$	0.001 (0.005)	0.022 (0.019)	0.077 (0.041)***
Panel B: Synchronous-Trading			
	$u_{1,t}^2$	$u_{2,t}^2$	$u_{3,t}^2$
$u_{1,t-1}^2$	0.131 (0.089)	0.033 (0.070)	-0.018 (0.024)
$u_{2,t-1}^2$	-0.100 (0.113)	-0.004 (0.089)	0.025 (0.031)
$u_{3,t-1}^2$	0.119 (0.176)	0.175 (0.138)	0.091 (0.048)***

Notes: This table reports the coefficients, and standard errors in parentheses of the univariate EGARCH model for the observed volatility of the three portfolios; Large, Medium and Small equities. u_1^2, u_2^2 and u_3^2 symbolize the observed volatility of the Large, Medium and Small portfolios of equities, respectively. These volatilities have been initially taken from a VAR model. For the non-synchronous-trading case, the observed volatility have been calculating taking into account the non-trading frequencies, instead of the non-trading probabilities, for each equity separately. For the synchronous-trading case, the non-trading frequencies are set equal to zero. The simulation is based on 1000 replications. (*)(**)(***) denote statistical significance at the (0.01) (0.05) and (0.10) percent level, respectively.