**Feedback trading and short-term return dynamics in Athens Stock Exchange. Novel evidence and the role of size**

**Dimitrios Kyrkilis**
**Department of Balkan, Slavic and Oriental Studies**
**University of Macedonia, Thessaloniki, Greece**
**Athanasios Koulakiotis**
**University of Macedonia, Thessaloniki, Greece**
**Vassilios Babalos**
**Department of Accounting and Finance**
**Technological Educational Institute of Peloponnese, Kalamata, Greece**
**Maria Kyriakou**
**Hellenic Open University, Patra, Greece**

**Abstract**

**Purpose:** This study attempts to examine the hypothesis of feedback trading along with the short-term return dynamics of three size-based stock portfolios of Athens Stock Exchange (ASE) during the Greek debt crisis period.

**Design/Methodology/approach**:To this end, we employ for the first time in the literature two well-known models while the variance equation is modeled by means of a multivariate EGARCH specification. As a robustness test an innovative nested-EGARCH model is also employed.

**Findings:** Our assumption that positive feedback trading is an important component of the short-term return movements across the three stock portfolios receives significant support. Moreover, the volatility interdependence, both in magnitude and sign, is almost similar across the three models. Finally, bad news originating from the portfolio of small stock appears to have a higher impact on the volatility of large and medium size stock returns than good news during the Greek debt crisis period.

**Originality/value**: Our methodology is innovative and we test for the first time the feedback trading hypothesis across different size stocks. We believe that our results might entail significant policy implications for investors and market regulators.

**Keywords**: Feedback trading; multivariate EGARCH; Short-term dynamics; size portfolios
**JEL Classification:** G15

## 1. Introduction

It has long been recognized that financial indices and markets conform either to the LeBaron (1992) or to the Sentana and Wadhwani (1992) feedback model with significant interplay between them (Koutmos et al. 2006, Bohl and Siklos, 2008). In the majority of the studies that use these two models, the short-term dynamics and interdependence of stock returns are examined separately using non-linear models. Considering the above two models the first one captures the serial correlation of assets in different trading days while the second associates the buy and sell-off of assets in different equities for investors. In addition, different size of equities trade asymmetrically and bad news play more important role than good news during the Greek debt crisis period.

In this paper, however, we investigate these different approaches for the mean and variance equation following the research of Koutmos (1996) and Koutmos et al. (2006) who examined the interdependence of four major European stock exchanges and the short-term dynamics of the Cyprus stock exchange, respectively employing three non-linear equations for the conditional mean. These include: (i) the LeBaron (1992) exponential autoregressive model, (ii) the Sentana and Wadhwani (1992) positive feedback trading model, and (iii) a model that nests both (i) and (ii). Koutmos et al. (2006) modeled the conditional variance as a univariate EGARCH process and linked the variance of the second equation with the first equation of mean. Theodossiou and Lee (1993) followed a similar approach in order to examine the relationship between the variance and returns using a univariate GARCH-M model. Further analysis assumes that the financial integration is considered essential for the market turbulences (Rejeb and Arfaoni, 2016) and the interdependence between assets is important for risk management. Thus, investing in low correlated small, medium or large assets reduces the investment losses from diversification (Mensah and Alagidede, 2017).

With respect to short-term dynamics of stock returns in mean equation, Koutmos (1997a and 1997b) examined the pattern of autocorrelation of stock returns in several developed and emerging stock markets. He found that investors follow a positive feedback trading strategy and that emerging stock markets behave remarkably similar to those of mature stock markets. LeBaron (1992) and Sentana and Wadhwani (1992) examined the relationship of serial correlation and volatility and found evidence of interaction between these two measures. More specifically, Sentana and Wadhwani (1992) concluded that this interlink is due to feedback trading while LeBaron (1992) claimed that serial correlation varies over time but it is always related to stock price volatility.

In conjunction with the interdependence of stock exchanges, Hamao et al. (1990) used a univariate GARCH model to examine the interdependencies (first and second moment) between three stock exchanges (New York, Tokyo, and London) and found strong interplay among them. Kanas (2000) studied the volatility spillovers between stock returns and exchange rates for six countries (i.e. US, the UK, Japan, Germany, France and Canada). He found evidence of asymmetric volatility spillovers for five out of six countries. Germany was the only exception. In particular, he indicated that the volatility spillover emanating from the stock returns to exchange rates. Yang and Doong (2004) examined the transmission mechanism of stock prices and exchange rates for the G-7 countries. Their empirical evidence supported the view that the asymmetric volatility spillover originated from the stock prices and affected the future exchange rate dynamics. Also, Harris and Pisedtasalasai (2006) confirmed that volatility spillovers are likely to be asymmetric, in the sense that negative innovations in one market produce greater volatility spillover in another (compared to positive innovations of equal magnitude). Wang (2014) and Wu et al. (2013) examined the integration and causality of interdependencies for Asian stock markets considering their interaction with the USA during the recent global financial crisis. They found that there are interactions between Asian and the US markets however Asian markets are less responsive to US shocks after the crisis.

It is clear from the above that market interdependencies remain the focus of numerous studies. The majority of these studies examine the cross-border interdependence among national stock markets employing a variety of econometric tools and providing contradictory results. However, the existence of interdependencies within the stock market is an issue that has attracted little if no evidence at all in the extant literature. Therefore, in the context of the present study we attempt to measure both the short-term dynamics and interdependencies of three size-sorted stock portfolios of the Athens stock exchange (ASE, thereafter), that is the FTSE-ASE 20 (Large-size stocks), the FTSE-MID 40 (Medium-size stocks) and the FTSE-SMALL CAP 80 (Small-size stocks) employing three multivariate EGARCH models.

The motivation of this study stems from the potential of the three non-linear proposed models to capture the dynamic nature of the three ASE size portfolios during the Greek debt crisis and provide useful information to regulators and investors. In particular, regulators are concerned with the existence of speculative and volatility trading in the Greek stock market. On the other hand, feedback trading might lead to price destabilizing and excessive risk exposure for investors engaging in trading during the turbulent time of the Greek sovereign debt crisis. For that reason, the current study introduces and tests an innovative approach during the Greek debt crisis, which intends to assist regulators in taking the appropriate policies through the useful models that are used for the benefit of the market and investors alike.

This topic is of interest as it provides the basis for assessing the risk exposure of investors trading large, medium or small size stocks in the Athens Stock Exchange during a period of excessive uncertainty as the Greek debt crisis unfolds. Our aim is to shed light on the distinction of two theories (autocorrelation and feedback trading) and highlight the benefits and risks that may arise for investors when the one of the two theories is in place and how regulators should protect investors when they exposed to risk. Thus, this paper is a methodological one, as it uses two theories which affect investors' trading in the Athens stock exchange. It is worth mentioning that, the interdependencies between different sized stocks might be asymmetric while the fact that serial correlation or feedback trading might contribute to investors' risk exposure should not be overlooked.

Apart from the interest surrounding feedback trading behavior in stock markets, there is an additional aspect that has been scantly studied, namely the degree of feedback trading across different size stocks. Evidence from institutional investors' trading patterns reveal the existence of a positive-feedback trading of mutual funds in the middle size quintiles, with weak results in both the smallest and largest size quintiles (Jones et al. 1999). In the same vein, Lakonishok et al. (1992) found that for pension funds the tendency to positive-feedback trade is apparent only in small firms.

Against this background this paper's contributions to the literature are as follows. On methodological grounds, we propose to combine and extend the work of Koutmos (1996) and Koutmos et al. (2006). Therefore, in contrast to Koutmos et al. (2006), Theodossiou and Lee (1993) and Yavas and Dedi (2016) we set the non-linear mean equation of stock price returns to be governed by a multivariate conditional variance which takes into consideration the interdependence of stock price volatilities. Koutmos et al. (2006) found that the Cyprus stock exchange is adequately explained by the positive feedback trading model. This means that there is a reverse relationship between volatility and autocorrelation implying that periods of high volatility are associated with low autocorrelations. By augmenting Koutmos et al. (2006) model we set off to test the hypothesis of feedback trading in the Athens Stock Exchange accounting for differences across stocks' size. When it comes to modeling, the Nested-EGARCH model is supposed to be superior to the LeBaron-EGARCH model and the Feedback-EGARCH model since it combines both the LeBaron and the Feedback interactions in the mean equation of the EGARCH model. Moreover, to ensure that all our results are robust, we calculate the asymmetric response of volatility to good and bad news.

We opt to investigate the Greek stock market, which features striking differences compared to other markets, for three reasons. First, the Greek stock market is a relatively less regulated than the more mature capital markets where earnings management and high ownership concentration blur the information transmission mechanism. Second, the ASE has experienced tremendous volatility periods during the last decade where the main stock index (the general stock index) reached bottom and peak values in short period of time. During that period, there was a remarkable capital inflow from foreign investors who until the burst of the global credit crunch stood to hold more than half of the market capitalization of the Greek listed firms. At the same time, the ASE has attracted the attention of many small individual domestic investors who put their savings in Greek stocks. However, the high volatile periods of the ASE lowered the ongoing investing interest. Third, the ASE, as a regional stock market of the EU, is vulnerable to stock market shocks from other sizeable stock exchanges (Dicle & Levendis (2011)). At the same time, the ASE is the leading stock market in the South Eastern Europe (SEE) in terms of listed firms and market capitalization. Many Greek listed firms keep majority stockholdings in a number of listed firms around the SEE. Therefore, it is expected that market interdependencies in the ASE should *ex ante* affect the stock market behaviour of the SEE markets. Moreover, as Koulakiotis et al. (2016) point out '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.'

Moreover, our period of study spans a series of important events stemming from the Greek debt crisis and exerts significant effect on the Athens stock exchange. We refer mainly to the three bailout plans which have been undertaken by troika (European Central Bank, IMF and European Commission) in order to restore Greek public financial situation and decide on the implementation of a long-term schedule of debt relief. Our period of analysis is characterized by a highly unstable economic and political situation resulting in substantial risk undertaken by investors in Athens stock market. The Greek Government was unwilling to adopt heavy austerity measures in the first place and this brought anxiety and speculation in the Athens market due to the fact that the Greek Government showed reluctance to comply with the directions of troika. As a result, Greek economy was found on the verge of bankruptcy which in turn pushed market volatility to unseen levels (Kosmidou et al., 2015). In the context of the present study, we cover the period from 2003 to 2012, incorporating the year 2009 (when the socialists took power) to 2012 (when the EU and IMF agreed on the third Greek bailout). Our study relies on three non-linear return models linked with an asymmetric volatility model aiming to capture the above events. It is our belief that these events might influence the volatility process in Athens Stock Exchange.

Previewing our results we can infer that the behavior of the three size portfolios of the ASE is consistent with that documented in the relevant literature for other markets. In particular, there is scant evidence that the non-linear mean equation follows the positive feedback model and some evidence that volatility spillovers are asymmetric. This result confirms that investors who put their money in small stocks listed in the ASE buy after price increases and sell after price decreases. In particular, there are few significant asymmetric volatility spillovers from the portfolios of small size stocks to large stocks and from the portfolios of small size stocks to medium size stocks. This means that bad news (negative innovations) in the stock index of small size stock returns have a higher impact on the volatility of stock index of large and medium size stock returns than good news (positive innovations) for the three models under consideration. This shows that investors should take into consideration the shocks that arrive in the ASE amongst stocks of different size since profits may arise from the trading of different size within the market.

Against this background the remainder of the paper is organized as follows: Section 2 presents the multivariate models, the employed data and the preliminary findings of the asymmetric tests. Section 3 outlines the main results while Section 4 concludes.

## 2. Methodology and data

To assess the short term dynamics and interdependencies in the ASE we employ the multivariate EGARCH volatility process with the following non linear specifications for the conditional mean: (i) the non-linear LeBaron's (1992) exponential autoregressive model, (ii) the non-linear Sentana and Wadhwani's (1992) positive feedback trading model, and (iii) a model that nests both (i) and (ii).

### *2.1 Exponential autoregressive model*

The exponential autoregressive model assumes that stock returns ($r_t$) are related to past returns in the following non-linear model as suggested by LeBaron (1992):

$$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3 \exp\{-\sigma_t^2\})r_{t-1} + \varepsilon_t \qquad (2)$$

the parameter $\beta_0$ is the constant, the parameter $\beta_1$ is an EGARCH-M effect that links volatility and return series in a linear function. The parameters $\beta_2$ and $\beta_3$ represent the autocorrelation of returns led by an exponential function of the conditional variance of the multivariate EGARCH model which can be high during periods of low volatility and low during periods of high volatility. The autoregression tends to $\beta_2$ when the conditional variance of the multivariate EGARCH model tends to infinity and to zero when it tends to $\beta_2 + \beta_3$. This model is different from previous models because the negative function of exponential volatility of the EGARCH model is driven by the variance of the multivariate EGARCH model. Also, the coefficients of $\beta_2$ and $\beta_3$ show that lower autocorrelation, especially for the coefficient $\beta_3$ is related to higher volatility.

***2.2 Positive feedback trading model***

The positive feedback model proposed by Sentana and Wadhwani (1992) differs from that of LeBaron (1992) model as it is not exponential for the volatility term of coefficient $\beta_3\sigma_t^2$ and takes the following form:

$$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2)r_{t-1} + \varepsilon_t \qquad (3)$$

where $\beta_2$ captures the possibility to be present constant autocorrelation in the above model. The presence of positive feedback trading implies that the coefficient of $\beta_3$ is both negative and statistically significant. This could be the case because the term of $\beta_1\sigma_t^2$, which actually is equal to the term of - $\beta_3\sigma_t^2$, implies that the presence of positive feedback trading will lead to negative autocorrelation in returns, and consequently the higher the volatility of the multivariate EGARCH model the more negative would be the autocorrelations. This model has the advantage that it can capture the feedback strategies that investors might follow and also the degree of asymmetry for the relationship between volatility and serial correlation of stock returns.

***2.3 Nested model***

The conditional mean of the stock returns could nest the above two models in one, (i.e. the exponential autoregressive and the positive feedback trading models) as following:

$$r_t = \beta_0 + \beta_1\sigma_t^2 + (\beta_2 + \beta_3\sigma_t^2 + \beta_4 \exp\{-\sigma_t^2\})r_{t-1} + \varepsilon_t \tag{4}$$

The above model implies that volatility might approach zero as the return autocorrelation approaches $\beta_2 + \beta_4$ and for high volatility values autocorrelation becomes $\beta_2 + \beta_3\sigma_t^2$. Finally, if $\beta_4 = 0$ and $\beta_3 < 0$ then positive feedback trading can drive the time-varying autocorrelation of stock returns.

***2.4 The Multivariate EGARCH volatility process***

The multivariate EGARCH model can be written as follows:

$$\text{Variance: } \sigma_{i,t}^2 = \exp\{\alpha_{i,0} + \sum_{j=1}^{3}\alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln(\sigma_{i,t-1}^2)\} \text{ for i, j} = 1,2,3 \tag{5}$$

$$f_j(z_{j,t-1}) = (|z_{j,t-1}| - E(|z_{j,t-1}| + \delta_j z_{j,t-1}) \text{ for j} = 1,2,3 \tag{6}$$

$$\text{Covariance: } \sigma_{i,j,t} = \rho_{i,j}\sigma_{i,t}\sigma_{j,t} \text{ for i, j} = 1,2,3 \text{ and i} \neq \text{j.} \tag{7}$$

where: $\sigma_{i,t}^2$ is the conditional variance, $\sigma_{i,j,t}$ is the conditional covariance between markets i and j, $\varepsilon_{i,t}$ the innovation at time t(i.e. $\varepsilon_{i,t} = r_{i,t} - \mu_{i,t}$), where $\mu_{i,t}$ is the conditional mean, $z_{i,t}$ is the standardized innovation (i.e., $z_{i,t} = (\varepsilon_{i,t} - \mu_{i,t}) / \sigma_{i,t}$).

Equation (5) shows the conditional variance of stock returns in each of the stock price index and it is an exponential function of past own as well as cross-index standardized innovations. The way of modeling the standardized residuals are given in Equation (6) and are given by $f_j(z_{j,t-1})$.This way of describing the standardized residuals is asymmetric and for $z_{j,t-1} < 0$ the slope of f (.) function becomes -1+$\delta_j$ whereas, for $z_{j,t-1} > 0$ the slope is equal to 1+$\delta_j$. Thus, Equation (6) allows standardized innovations (own and cross-index) to affect the conditional variance of the stock indices asymmetrically. The term $(|z_{j,t-1}| - E(|z_{j,t-1}|)$ refers to the magnitude effect while the term $\delta_j z_{j,t-1}$ refers to the sign effect. Assuming $\alpha_{ij}$ is positive, the impact of $z_{j,t-1}$ on $\sigma_{i,t}^2$ will be positive or negative if the size of $z_{j,t-1}$ is greater or smaller than its expected value $E|z_{j,t-1}|$. The sign effect may be reinforcing or it may offset the size effect. More specifically, if $\delta_j$ is negative, stock price index declines in stock price index j ($z_{j,t-1}$<0) will be led by higher volatility than stock index advances. Such a response is consistent with the leverage effect, which is measured by the ratio $|-1+\delta_j|/(1+\delta_j)$. Volatility spillovers (second moments) across stock price indices are measured by $\alpha_{i,j}$ coefficient for i,j=1,2,3 and $i \neq j$. The asymmetric volatility transmission mechanism is interpreted as follows: A significant positive $\alpha_{i,j}$ with a negative $\delta_j$ means that negative innovations in the stock price index of j have a higher influence on the stock price index of i than positive innovations. The persistence of volatility is measured by $\gamma_i$ (equation 5). If $\gamma_i$ takes a value less than 1 the unconditional variance will be finite, while if $\gamma_i$ is equal to 1 then the unconditional variance will follow an integrated process of order 1 (Nelson, 1991).

The conditional covariance specification (Equation 7) captures the contemporaneous relationship between the returns of the three stock portfolios. This case means that the correlation of the returns of the stock portfolios is constant or the covariance is proportional to the product of the standard deviations.

Assuming normality, the log-likelihood for the multivariate EGARCH model can be written as:

$$L(\Theta) = -0.5(NT)\ln(2\pi) - 0.5\sum_{t=1}^{T}(\ln|S_t| + \varepsilon_t^{'} S_t^{-1}\varepsilon_t), \tag{8}$$

where N is the number of equations, T is the number of observations, $\Theta$ 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 significantly nonlinear in $\Theta$ and numerical maximization techniques should be used.

### *2.5 Data*

Daily closing prices of the three size-sorted stock portfolios of the Athens Stock Exchange are employed. In particular, we employ the closing prices of FTSE-ASE 20 (the first 20 stocks in market capitalization), the FTSE-ASE 40 (the next 40 stocks in market capitalization) and the FTSE Small Cap 80 (the next 80 stocks in market capitalization). Daily percentage returns are calculated as 100*log ($\frac{P_t}{P_{t-1}}$) where, $P_t$ is the closing price of the index at day t. Our dataset runs from January 2003 through December 2012. [3]

The descriptive statistics for the return series of the three size portfolios as well as tests for normality, skewness, kurtosis, independence and ARCH (autoregressive conditional heteroskedastic) effects are reported in Table 1. The mean values for the three stock portfolios are 0.1002 for the FTSE-ASE 20, 0.1003 for the FTSE-MID 40 and 0.0596 for the FTSE-SMALL CAP 80. The standard deviation varies from 1.1468 (FTSE-ASE 20) to 1.5221 (FTSE-SMALL CAP 80). With respect to skewness and kurtosis it can be seen that the return series are negatively skewed and leptokurtic in terms of normal distribution. The Ljung-Box (12) measure for returns and squared returns reveals the existence of linear and non-linear dependencies, respectively. The test of ARCH effects indicates that, in general, ARCH type models can describe to a large degree the data set of stock returns. Non-linear dependencies may be due to the existence of ARCH effects as has been noted by Nelson (1991) and Booth et al. (1992). The unconditional correlation coefficients vary from 0.6771 for the FTSE MID 40 and FTSE SMALL CAP 80, to 0.9082 for FTSE-ASE 20 and FTSE SMALL CAP 80.

**Insert Table 1 around here**

In Table 2, we report the asymmetric test statistics (sign bias, negative size, positive size and joint tests) which have been developed by Engle and Ng (1993). These tests offer valuable insight for potential sources of model misspecification related to asymmetric effects. From a quick review of the results it is evident that an asymmetric model might fit the data quite well. Only the sign bias of FTSE-MID 40 and the positive size bias tests of FTSE-ASE 20 and FTSE-MID 40 fail the asymmetric test at the 10% level of significance. From the above we can infer that only for these cases the asymmetric model performs worse. In general, the results of the asymmetric tests offer solid grounds for the use of EGARCH methodology.

**Insert Table 2 around here**

[3] Our sample ends at 2012 since the Small size stock index ceased to trade after that year.

## 3. Empirical Findings

The multivariate EGARCH model which was developed by Koutmos (1996) is similar to that developed by Bollerslev (1990) with the exception that the conditional variances follow the EGARCH, rather than the GARCH process. This is further augmented in order to compare the LeBaron-EGARCH and Feedback-EGARCH models with theNested-EGARCH model. Our first task is to examine the nature of price spillovers and the short-term dynamics of the conditional mean of the two non-linear models as compared to the nested model. Then, we compare the volatility interdependence of the above two models with the Nested model.

Tables 3 to 5 contain the parameter estimates and diagnostic tests for the three models of the mean and variance equations. Focusing on the mean equation of the three models, it can be inferred that the LeBaron model shows that the coefficients $\beta_{1,3}, \beta_{2,3},$ and $\beta_{3,3}$ are positive and statistically significant. Therefore, the daily stock returns of FTSE-ASE 20, FTSE-MID 40, and FTSE-SMALL CAP 80 are linked to the past returns in a non-linear fashion. These results are in line with those of Koutmos et al. (2006) for the Cyprus stock exchange and of LeBaron (1992) for the USA market. During low volatility periods the first-order autocorrelation approaches $\beta_{i,2} + \beta_{i,3}$(0.538 for FTSE-ASE 20, 0.472 for FTSE-MID 40, and 0.5624 for FTSE-SMALL CAP 80) and during high volatility periods, autocorrelation approaches $\beta_{i,2}$ (-0.0519 for FTSE-ASE 20, 0.0032 for FTSE-MID 40, and -0.0360 for FTSE-SMALL CAP 80).

The positive feedback trading model shows that $\beta_{i,3}$ is negative and statistically significant, as predicted by the model. It seems that the assumption that positive feedback trading is an important component of the short-term return movements in the stock indices of FTSE-ASE 20, FTSE-MID 40, and FTSE-SMALL CAP 80 receives significant support. This finding is consistent with the findings of Koutmos et al. (2006) for the Cyprus stock exchange and Sentana and Wadhwani (1992) for the US stock market. As the two models are not nested, we are not able to decide which of the two is superior. This task is achieved by employing the Nested-EGARCH model which nests both the LeBaron and the Positive Feedback Trading model. The feedback parameter ($\beta_{1,3}, \beta_{2,3}, and \beta_{3,3}$) of the three stock indices is negative and statistically significant only for the case of FTSE-SMALL CAP 80 stock index (0,0227), whereas the LeBaron parameter ($\beta_{1,4}, \beta_{2,4}, and \beta_{3,4}$) is positive for the stock indices of FTSE-MID 40 and FTSE-SMALL CAP 80, however, statistically insignificant in all cases. The reverse relation between volatility and autocorrelation due to the positive feedback trading pursued by some investors is present in the stock index of FTSE-SMALL CAP 80.

The parameters ($\alpha_{i,j}$) of the three models (i.e. LeBaron-EGARCH, Feedback-EGARCH, and Nested-EGARCH) indicate the lead/lag relationships that exist between the three stock indices (i.e. FTSE-ASE 20, FTSE-MID 40, and FTSE-SMALL CAP 80). Looking at the volatility spillovers of the LeBaron-EGARCH model of Table 3, it is clear that there are volatility spillovers from the FTSE-SMALL CAP 80 to the FTSE-ASE 20 (0.1026) and from the FTSE-SMALL CAP 80 to the FTSE-MID 40 (0.1958). The spillover mechanism is asymmetric only for the innovations originating from the FTSE-SMALL CAP 80 stock index. However, the asymmetric coefficient of the FTSE-SMALL CAP 80 is not statistically significant in the Feedback-EGARCH model. In particular, the spillover from the FTSE-SMALL CAP 80 to the FTSE-ASE 20 is equal to 0.1246, from the FTSE-SMALL CAP 80 to the FTSE-MID 40 is equal to 0.2095 and from the FTSE-MID 40 to the FTSE-SMALL CAP 80 is equal to -0.0733. Finally, the results from the Nested-EGARCH model indicate that volatility spillovers emanate from the FTSE-SMALL CAP 80 to the FTSE-ASE 20 (0.1194), and from the FTSE-SMALL CAP 80 to the FTSE-MID 40 (0.2046).

The degree and direction of volatility spillovers for the LeBaron, and Feedback models are quite similar with the Nested model with respect to the magnitude and the sign of volatility spillovers. Thus, we observe that the magnitude remains at a high level and the sign is similar for the volatility spillovers amongst the three models. Despite the fact that there are some trivial differences in magnitude and sign of volatility spillovers among the three models, the results overall indicate a quite strong interdependent Greek stock market for the three stock indices.

The degree of asymmetry (coefficient $\delta_i$) is significant only for the FTSE-SMALL CAP 80 for the case of the LeBaron model (-0.0759). Volatility persistence, measured by $\gamma_i$ appears high and close to unity in all cases. The estimates of the conditional correlation for the two out of the three cases are smaller than the unconditional correlation estimates reported in Table 1. In particular, for the LeBaron-EGARCH model, the returns correlation between FTSE-ASE 20 and FTSE-SMALL CAP 80 and FTSEMID40 and FTSE-ASE 20 has dropped from 0.8963 to 0.7835 and from 0.9082 to 0.6875. In the Feedback-EGARCH model, we observe that there is a downward shift in the returns correlation. More specifically, the correlation between FTSE-ASE 20 and FTSE-SMALL CAP 80 dropped from 0.8936 to 0.7830 and between FTSE-MID 40 and FTSE-ASE 20 from 0.9082 to 0.6908. Looking at the correlations of returns between FTSE-ASE 20 and FTSE-SMALL CAP 80 and between FTSE-MID 40 and FTSE-ASE 20, we observe a drop in the first case from 0.8936 to 0.7842 and from 0.9082 to 0.6912 in the latter case. In addition, in all the above three models it is shown that there is an increase in correlation of returns between FTSE-MID 40 and FTSE-SMALL CAP 80 from the Table 1 to Tables 3-5 which contain the correlations amongst the three stock portfolios.

The diagnostic tests are based on standardized residuals and indicate that the mean and square mean is zero for both cases. The Ljung-Box test (12) shows that there exists some degree of dependence in the standardized residuals of the ASE stock portfolios. The Kolmogorov-Smirnov statistic also rejects the hypothesis that returns are normally distributed.

**Insert Table 3, 4 and 5 around here**

Panel A of Table 6 reports the coefficients of the volatility spillovers of the three models under consideration indicating that the results are very similar between the LeBaron and the Nested model. The results show that the spillovers between the above three non-linear models are similar. Looking at the magnitude and the sign of spillovers we can say that the three models display similar patterns (Figure 1). This means that the three models have predicted a well-integrated Greek stock market without differences in the magnitude and the sign of spillovers, a result that lends support for the importance of the three non-linear models with respect to the similarities which have been identified amongst these models.

**Insert Table 6 and Figure 1 around here**

Following Yang and Doong (2004), we investigate the volatility persistence (measured by $\gamma_i$) among the FTSE-ASE 20, FTSE-MID 40 and FTSE-SMALL CAP 80 indices (Panel A of Table 7). Using the LeBaron-EGARCH model, the volatility shocks persist 11, 7 and 14 days respectively, for the Feedback-EGARCH 10, 7 and 16 and for the Nested-EGARCH model 10, 7 and 16 days, respectively.

In Panel B of Table 8, the asymmetric impact of positive and negative innovations is shown for the three models. Since $\delta_j$ is not significant for the FTSE-ASE 20 and FTSE-MID 40 for all the EGARCH models, there is no difference between negative and positive innovations for these respective portfolios. Asymmetric effects exist only for innovations for the FTSE-SMALL CAP 80 index and for the one of the three EGARCH models. In particular, a negative innovation of the FTSE-SMALL CAP 80 index has an impact on conditional volatility of the other stock indices 1.16 times larger than positive innovations estimated from the LeBaron model. This means that the impact of negative innovation from the FTSE-SMALL CAP 80 stock index on the volatility of the other two stock indices is similar to the positive innovation for the LeBaron model as the negative impact found to be just above 1 times larger than positive innovations. The same holds for the rest of the results when we examine the impact of negative and positive innovations. Overall, the asymmetric impact of the one stock index on the other one is found to be similar between the three non-linear models.

**Insert Table 7 around here**

Based on the estimations of the three multivariate EGARCH models, we perform a simulation on the different impact of good and bad news on cross-market volatility within a stock market and across them, as in Yang and Doong (2004). The results are presented in Table 8. The total impact of spillover effects from market j to market i is measured by $\alpha_{i,j}(1+\delta_j)$ for a 1% positive innovation and $\alpha_{i,j}\,|-1+\delta_j\,|$ for a 1% negative innovation. For example, a 1% (-1%) innovation in the FTSE-ASE 20 decreases volatilities by 0.0359 (0.0298) in the FTSE-MID 40. The same size of innovation in the FTSE-SMALL CAP 80 index decreases volatility by 0.0530 (0.0448) in the FTSE-ASE 20 and 0.0439 (0.0366) in the FTSE-MID 40. Also, a 1% (-1%) innovation in the FTSE-ASE 20 increases volatility by 0.0948 (0.1103) in the FTSE-SMALL CAP 80, in the FTSE-MID 40 decreases volatility by 0.0099 (0.0068) in the FTSE-ASE 20, and increases by 0.1809 (0.2106) in the FTSE-SMALL CAP 80. With a similar way, we can interpret the results of the impact of positive and negative innovations from a stock index to others within a specific model based on the other two non-linear models which are presented in Table 8.

More specifically, the results that have been presented right above (Table 8, Panel A) with the results of the other two models (Table 8, Panels B-C) we can say that the positive and negative innovations of +1%(or -1%) that begin at time t-1 from the FTSE-ASE 20 and impact on the FTSE-ASE 20 at time t are similar and equal to around 0.12 (0.08) for the three models. In contrast, there is a different sign's impact for the innovations from the FTSE-MID 40 at time t-1 to the FTSE-ASE 20 at time t with big differences in the estimation of magnitude of shocks for the three models. The same does not hold for the impact of +1% (-1%) change of innovations from the FTSE-SMALL CAP 80 at t-1 on the FTSE-ASE 20 at time t with the difference in magnitude of shocks not to be important. In particular, it was found to be equal to around -0.05 (-0.04) for the other two models. With respect to the impact of innovations from the FTSE-ASE 20 at time t-1 to the FTSE-MID 40 at time t, we could observe that the prediction is around -0.05 (-0.04) for the LeBaron, and the Feedback models with the Nested one as well.

Similarly, the effects of innovations from the FTSE-MID 40 at time t-1 to the FTSE-MID 40 at time t are quite close for the three non-linear models having the same sign in all three models. When examining the impact of +1% (-1%) innovations from the FTSE-SMALL CAP 80 at time t-1 to the FTSE-MID 40 at time t stock index, we find that exists a high impact with a negative effect being around 0.04 (0.04) for the LeBaron model, 0.08 (0.06) for the Positive Feedback model and 0.06 (0.05) for the Nested model. Here, we observe that the three non-linear models 'estimate' a different sign for the impact of innovations from the FTSE-SMALL CAP 80 at time t-1 to the FTSE-MID 40 at time t. This means that the three non-linear models assume a decrease.

Comparing the results of the three non-linear models with respect to the impact of +1% (-1%) innovations from the FTSE-ASE 20 and the FTSE-MID 40 at time t-1 to the FTSE-SMALL CAP 80 at time t, we observe a very large 'estimation' for the three non-linear models. While this prediction for the three models was between 0.09 and 0.11 (0.11 to 0.13) for the first case with a positive sign and between 0.18 and 0.19 (0.21 to 0.22) for the latter case with a positive sign as well. Finally, the impact of +1%(-1%) innovation from the FTSE-SMALL CAP 80 at time t-1 to the FTSE-SMALL CAP 80 at time t is around 0.25 or 0.26 (0.30) for the three models under consideration.

In general, the results show that the three non-linear models mainly differ slightly in most cases where shocks from one stock index to the other are considered for +1% (-1%) change. However, exception is the case of the impact of innovations of +1% (-1%) from the FTSE-ASE 20 at time t-1 to the FTSE-ASE 20 at time t, and from the FTSE-SMALL CAP 80 at time t-1 to the FTSE-SMALL CAP 80 at time t. For these cases, we found that the impact of shocks within the stock market index in the Athens stock exchange is similar in magnitude and sign between the three non-linear models (LeBaron, Feedback and Nested). There is also a similarity of innovations from the FTSE-MID 40 at time t-1 to the FTSE-MID 40 at time t in sign effect but not in magnitude effect among the three models.

**Insert Table 9 around here**

To test the joint significance of the second moment interactions among the three indices we use the likelihood ratio statistic: LR = 2*[L($\Theta_1$)-L($\Theta_2$)], where L($\Theta_1$) and L($\Theta_2$) are the maximum log likelihood values obtained by the three non-linear models. The estimated value is [-884.9765-(-889.1825)] =4.206 for Nested and the LeBaron models, and [-884.9765-(-886.9354)] =1.959 for the Feedback and Nested models. This is asymptotically chi-squared distributed with degrees of freedom equal to the parameters of the benchmark model, which is equal to 30 (chi-squared (30) = 14.953 critical value) and suggest that there is no a superior model in comparison to the Nested one at the 1% significance level.

**4. Summary and Concluding Remarks**

This paper proposes to combine the approaches of Koutmos (1996) and Koutmos et al. (2006) in order to investigate both the short-term return dynamics and return and volatility interdependence of three size-sorted stock portfolios, namely the FTSE-ASE 20, FTSE-MID 40 and FTSE-SMALL CAP 80 during the Greek debt crisis. In particular, the short-term dynamics are investigated using three non-linear models (1) the LeBaron, (2) the Positive Feedback and (3) the Nested model. With respect to the mean equation, the results show that the Positive-Feedback model can capture quite well the behavior of the FTSE-SMALL CAP 80 stock index and the volatility interdependence for this case is similar to the other three models. With respect to the volatility interdependencies between the three stock indices, these are linked through the three non-linear models in mean equation. In particular, the statistically significant results are similar in magnitude and sign for the three models: (i) LeBaron, (ii) Positive-Feedback and (iii) Nested models.

This means that the three EGARCH models could describe quite well the interplay in the second moment of returns between the three stock indices in the ASE. However, the exception is the asymmetric mechanism which is found to be not significant in the case of Positive-Feedback and Nested models. In addition, we find that the innovation from the FTSE-ASE 20 at time t-1 to the FTSE-SMALL CAP 80 at time t is positive in the three models (LeBaron, Positive-Feedback and Nested). There are many examples of ‘over-estimation’ or ‘under-estimation’ within the performance of the simulation process of bad and good news on the volatility of the three non-linear models There are also similarities among the estimation process of the three non-linear models as indicates the simulation process of bad and good news on the volatility of the three stock indices.

Overall, the number of 'over-estimations' and 'under-estimations' is higher than the similarities of the simulation process showing that this process indicates a difference on the modeling ability of the three non-linear models. Furthermore, the importance of the Positive-Feedback trading is confirmed from the mean equation through the Nested model where the FTSE-SMALL CAP 80 stock index is found to be the stock index which conforms to the feedback process. The results for the rest of the stock indices are not statistically significant. The implication of these results is the preference of investors to small stocks which are preferred by buyers after price increases and sold after price decreases during the Greek debt crisis. The empirical results of the current study entail significant implications for regulators regarding the threats arising from speculative trading and for investors for risk exposure.

## References

Bohl, MT, Siklos P.L., (2008), Empirical evidence on feedback trading in mature and emerging stock markets. Applied Financial Economics, 18,pp. 1379-1389.

Bollerslev, T., (1990). Modelling the coherence in short run nominal exchange rates: A multivariate generalized ARCH approach. Review of Economics and Statistics Vol. 72: 498-505.

Booth, C.G., Hatem, J., Vitranen, I., Yli-Olli, P., (1992). Stochastic modeling of security returns: Evidence from the Helsinki stock exchange. European Journal of Operational Research, 56, 98-106.

Cheung, L., L. Fung, and C-S Tam, (2008), Measuring financial market interdependence and assessing possible contagion risk in the EMEAP region, Honk Kong Monetary Authority, working paper series.

Dicle, M.F., Levendis, J., (2011). Greek market efficiency and its international integration. Journal of International Financial Markets, Institutions & Money 21, 229–246.

Engle, R.F. and V. K. Ng, (1993), Measuring and testing the impact of news on volatility, *The Journal of Finance* 48 (5), pp. 1749-1778.

Hamao, Y., R.W. Masulis, and V. Ng, (1990), Correlations in price changes and volatility across international stock markets, *The Review of Financial Studies* 3 (2), 281-307.

Harris, R.D.F. and A. Pisedtasalasai, (2006), Return and volatility spillovers between Large and Small stocks in the UK, *Journal of Business, Finance and Accounting* 33 (9) & (10), 1556-1571.

Jones, S.L., Lee, D., and Weis, E. (1999). Herding and Feedback Trading by Different Types of Institutions and the Effects on Stock Prices. Working Paper.

Kanas, A., (2000), Volatility spillovers between stock returns and exchange rate changes: international evidence, Journal of Business, Finance, and Accounting 27, 447-467.

Kosmidou, V.K. ,Kousenidis, V.D., Negkakis, I.C.,(2015),The impact of the EU/ECB/IMF bailout programs on the financial and real sectors of the ASE during the Greek sovereign crisis*, Journal of Banking and Finance,*50,440-454

Koulakiotis, A., Babalos, V., Papasyriopoulos, N. (2016). Financial crisis, liquidity and dynamic linkages between large and small stocks: Evidence from the Athens Stock Exchange, Journal of International Financial Markets, Institutions & Money, 40, 46-62.

Koutmos, G., (1997a), Feedback trading and the autocorrelation pattern of stock returns: further evidence, *Journal of International Money and Finance* 16 (4), pp. 625-636.

Koutmos, G., (1997b), Do emerging and developed stock markets behave alike? Evidence from six pacific basin stock markets, *Journal of International Financial markets* 7, pp. 221-234.

Koutmos, G., A. Pericli and L. Trigeorgis, (2006), Short-term dynamics in the Cyprus Stock Exchange, *European Journal of Finance* 12 (3), pp. 205-216.

Koutmos, G., (1996), Modeling the dynamic interdependence of major European stock markets, *Journal of Business Finance and Accounting* 23 (7), 975-988.

Lakonishok, J, Shleifer, A. and Vishny, R. (1992), The impact of institutional trading on stock prices, Journal of Financial Economics 32, 23-43.

LeBaron, B., (1992), Some relations between volatility and serial correlations in stock market returns, Journal of Business 65, pp. 199-219.

Mensah, J.O., and Alagidede, P., (2017), How are Africa's emerging stock markets related to advanced markets? Evidence from copulas, *Economic Modelling*, 60,1-10

Nelson, D., (1991), Conditional heteroskedasticity in asset returns: A new approach, *Econometrica,* 59, 347-370.

Rejeb, A.B., and Arfaoni, M.,(2016) Financial market interdependencies: a quantile regression analysis of volatility spillover, *Research in International Business and Finance* ,36, 140–157.

Sentana, E. and S. Wadwani, (1992), Feedback traders and stock return correlations: Evidence from a century of daily data, *The Economic Journal* 102, pp. 415-425.

Theodossiou, P. and U. Lee, (1993), Mean and volatility spillovers across major national stock markets: Further empirical evidence, *The Journal of Financial Research* 16 (4), 337-350.

Wang, L., (2014), Who moves East Asian stock markets? The role of the 2007-2009global financial crisis, *Journal of International Financial Markets, Institutions and Money*, 28,182-203

Wu, L., Meng, Q, Xu, K.,(2013), Slow-burn spillover and fast furious contagion: a study of international stock markets, Working Paper, Dalhousie University.

Yang, S-Y, and S-C. Doong, (2004), Price and volatility spillovers between stock prices and exchange rates: Empirical evidence from the G-7 countries, *International Journal of Business and Economics* 3 (2), 139-153.

Yavas, B.F., Dedi, L.,(2016), An investigation of return and volatility linkages among equity markets: a study of selected European and emerging countries, *Research in International Business and Finance*, 37, 583–596. http://dx.doi.org/10.1016/j.ribaf.2016.01.025.

APPENDIX

Table 1. Sample statistics on daily stock return series

| Statistics | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| $\mu$ | 0.1002 | 0.1003 | 0.0596 |
| $\sigma$ | 1.1468 | 1.2019 | 1.5221 |
| S | -0.0556 | -0.5071* | -0.5920* |
| K | 1.8411* | 3.7930* | 5.2208* |
| D | 0.046* | 0.064* | 0.080* |
| LB(12) for $R_t$ | 17.7069 | 37.6338* | 38.2373* |
| LB(12) for $R_t^2$ | 151.4468* | 293.3253* | 187.1531* |
| ARCH(4) | 15.1584* | 40.6675* | 20.8388* |
| | | Correlation Matrix | |
| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |

| | | | |
|---|---|---|---|
| FTSE-ASE 20 | 1 | 0.8936 | 0.9082 |
| FTSE-MID 40 | | 1 | 0.6771 |
| FTSE-SMALL CAP 80 | | | 1 |

Notes: (*) denotes significance at the 1% level.

Table 2. Volatility specification tests for returns

| Market Index | Sign bias(t-test) | Negative size bias (t-test) | Positive size bias test (t-test) | Joint test (F-test) |
|---|---|---|---|---|
| FTSE-ASE 20 | 2.7723* | -3.71242* | -1.1167 | 4.8777* |
| FTSE-MID 40 | 0.0771 | -2.91847* | 0.9282 | 4.6215* |
| FTSE-SMALL CAP 80 | -1.3267 | -2.2310* | 2.4049* | 3.7982* |

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

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

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

Joint test:

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

Notes: (*) (**) (***) denotes significance at the (1%) (5%) (10%) level. $z_t$ is the normalized residual from an AR (p) filter using constant variance. $S_t^-$ 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).

Table 3. Maximum Likelihood Estimates of the LeBaron -EGARCHMean:
$r_{i,t} = \beta_{i,0} + \beta_{i1}\sigma_{i,t}^2 + (\beta_{i2} + \beta_{i3}\exp\{-\sigma_{i,t}^2\})r_{i,t-1} + \varepsilon_{i,t}$, for i = 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.

| FTSE 20 (1) | | FTSE-MID 40 (2) | | FTSE-SMALL CAP 80 (3) | |
|---|---|---|---|---|---|
| $\beta_{1,0}$ | 0.0459<br>(0.0835) | $\beta_{2,0}$ | -0.0265<br>(0.0563) | $\beta_{3,0}$ | -0.1148<br>(0.0531)** |
| $\beta_{1,1}$ | 0.0322<br>(0.0700) | $\beta_{2,1}$ | 0.0831<br>(0.0477)*** | $\beta_{3,1}$ | 0.0834<br>(0.0325)* |

| | | | | | |
|---|---|---|---|---|---|
| $\beta_{1,2}$ | -0.0519 (0.0650) | $\beta_{2,2}$ | 0.0032 (0.0477) | $\beta_{3,2}$ | -0.0360 (0.0358) |
| $\beta_{1,3}$ | 0.5899 (0.2124)* | $\beta_{2,3}$ | 0.4688 (0.1478)* | $\beta_{3,3}$ | 0.5984 (0.1411)* |
| $\alpha_{1,0}$ | 0.0151 (0.0006)** | $\alpha_{2,0}$ | 0.0260 (0.0083)* | $\alpha_{3,0}$ | 0.0341 (0.0081)* |
| $\alpha_{1,1}$ | 0.1014 (0.0288)* | $\alpha_{2,1}$ | -0.0084 (0.0342) | $\alpha_{3,1}$ | -0.0448 (0.0310) |
| $\alpha_{1,2}$ | -0.0329 (0.0359) | $\alpha_{2,2}$ | 0.1112 (0.0392)* | $\alpha_{3,2}$ | -0.0403 (0.0370) |
| $\alpha_{1,3}$ | 0.1026 (0.0385)* | $\alpha_{2,3}$ | 0.1958 (0.0352)* | $\alpha_{3,3}$ | 0.2772 (0.0306)* |
| $\delta_1$ | 0.1841 (0.1264) | $\delta_2$ | 0.0913 (0.0996) | $\delta_3$ | -0.0759 (0.0434)*** |
| $\gamma_1$ | 0.9387 (0.0151)* | $\gamma_2$ | 0.9032 (0.0153)* | $\gamma_3$ | 0.9509 (0.0090)* |

Correlation Matrix

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| FTSE 20 | 1 | 0.7835 (0.0123)* | 0.6875 (0.0161)* |
| FTSE-MID 40 | | 1 | 0.8117 (0.0105)* |
| FTSE-SMALL CAP 80 | | | 1 |

Model Diagnostics

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| E$(z_{i,t})$ | -0.0255 | -0.0392 | -0.0429 |
| E$(z_{i,t}^2)$ | 0.4290 | 0.4183 | 0.4445 |
| LB(12); $z_{i,t}$ | 8.3024 | 29.3200* | 17.4473** |
| LB(12); $z_{i,t}^2$ | 23.6230* | 16.2628** | 15.9714** |
| D | 0.119* | 0.121* | 0.129* |

LB(12) for cross product of standardized Residuals

LB($z_{1,2}$)= 31.6108* , LB($z_{1,3}$)=32.0039*, LB($z_{2,3}$)=22.7086*

Notes: Number in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. . D=Kolmogorov-Smirnov testing for normality (5% critical value is 1.36/$\sqrt{T}$ where, T number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as $x^2$ with n degrees of freedom). $z_{i,t}$ is the standardized residual for market i. (*)(**)(***) denotes significance at the 1%(5%)(10%) level. $z_{ij}$ is the cross product of the standardized residuals.

Table 4. Maximum Likelihood Estimates of the Feedback -EGARCH

Mean: $r_{i,t} = \beta_{i,0} + \beta_{i,1}\sigma_{i,t}^2 + (\beta_{i,2} + \beta_{i,3}\sigma_{i,t}^2)r_{i,t-1} + \varepsilon_{i,t}$ for i=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.

| FTSE 20 (1) | | FTSE-MID 40 (2) | | FTSE-SMALL CAP 80 (3) | |
|---|---|---|---|---|---|
| $\beta_{1,0}$ | 0.0763 (0.0840) | $\beta_{2,0}$ | 0.0063 (0.0575) | $\beta_{3,0}$ | -0.0769 (0.0535) |
| $\beta_{1,1}$ | -0.0002 (0.0695) | $\beta_{2,1}$ | 0.0462 (0.0489) | $\beta_{3,1}$ | 0.0509 (0.0321) |

| | | | | | |
|---|---|---|---|---|---|
| $\beta_{1,2}$ | 0.3045<br>(0.0738)* | $\beta_{2,2}$ | 0.2371<br>(0.0434)* | $\beta_{3,2}$ | 0.2099<br>(0.0400)* |
| $\beta_{1,3}$ | -0.1301<br>(0.0535)** | $\beta_{2,3}$ | -0.0616<br>(0.0264)** | $\beta_{3,3}$ | -0.0486<br>(0.0146)* |
| $\alpha_{1,0}$ | 0.0167<br>(0.0072)** | $\alpha_{2,0}$ | 0.0250<br>(0.0078)* | $\alpha_{3,0}$ | 0.0292<br>(0.0075)* |
| $\alpha_{1,1}$ | 0.1056<br>(0.0294)* | $\alpha_{2,1}$ | -0.0046<br>(0.0333) | $\alpha_{3,1}$ | -0.0400<br>(0.0300) |
| $\alpha_{1,2}$ | -0.0499<br>(0.0362) | $\alpha_{2,2}$ | 0.0767<br>(0.0366)** | $\alpha_{3,2}$ | -0.0733<br>(0.0352)** |
| $\alpha_{1,3}$ | 0.1246<br>(0.0408)* | $\alpha_{2,3}$ | 0.2095<br>(0.0331)* | $\alpha_{3,3}$ | 0.2784<br>(0.0289)* |
| $\delta_1$ | 0.1911<br>(0.1275) | $\delta_2$ | 0.1289<br>(0.0994) | $\delta_3$ | -0.0489<br>(0.0450) |
| $\gamma_1$ | 0.9316<br>(0.0167)* | $\gamma_2$ | 0.9071<br>(0.0148)* | $\gamma_3$ | 0.9585<br>(0.0081)* |

Correlation Matrix

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| FTSE 20 | 1 | 0.7830<br>(0.0125)* | 0.6908<br>(0.0162)* |
| FTSE-MID 40 | | 1 | 0.8117<br>(0.0105)* |
| FTSE-SMALL CAP 80 | | | 1 |

Model Diagnostics

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| E$(z_{i,t})$ | -0.0244 | -0.0388 | -0.0439 |
| E$(z_{i,t}^2)$ | 0.4332 | 0.4239 | 0.4343 |
| LB(12); $z_{i,t}$ | 9.1914 | 30.0422* | 19.7640** |
| LB(12); $z_{i,t}^2$ | 26.8387* | 16.5073*** | 12.8091 |
| D | 0.120* | 0.122* | 0.126* |

LB(12) for cross product of standardized Residuals

LB(z $_{1,2}$ )=34.2657* , LB(z $_{1,3}$ )=37.4364* , LB(z $_{2,3}$ )=21.6205*

Notes: Number in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. D=Kolmogorov-Smirnov testing for normality (5% critical value is 1.36/ $\sqrt{T}$ where, T number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as $x^2$ with n degrees of freedom). z $_{i,t}$ is the standardized residual for market i. (*)(**)(***) denotes significance at the 1%(5%)(10%) level.z $_{ij}$ is the cross product of the standardized residuals.

## Table 5. Maximum Likelihood Estimates of the Nested -EGARCH

Mean: $r_{i,t} = \beta_{i,0} + \beta_{i,1}\sigma_{i,t}^2 + (\beta_{i,2} + \beta_{i,3}\sigma_t^2 + \beta_{i,4}\exp\{-\sigma_{i,t}^2\})r_{i,t-1} + \varepsilon_{i,t}$ for i=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 $\neq$ j.

| FTSE 20 (1) | | FTSE-MID 40 (2) | | FTSE-SMALL CAP 80 (3) | |
|---|---|---|---|---|---|
| $\beta_{1,0}$ | 0.0769<br>(0.0851) | $\beta_{2,0}$ | -0.0050<br>(0.0569) | $\beta_{3,0}$ | -0.0787<br>(0.0537) |
| $\beta_{1,1}$ | -0.0012<br>(0.0705) | $\beta_{2,1}$ | 0.0542<br>(0.0491) | $\beta_{3,1}$ | 0.0510<br>(0.0325) |
| $\beta_{1,2}$ | 0.3904<br>(0.3651) | $\beta_{2,2}$ | 0.0577<br>(0.1469) | $\beta_{3,2}$ | 0.1592<br>(0.0922)*** |

| | | | | | |
|---|---|---|---|---|---|
| $\beta_{1,3}$ | -0.1637<br>(0.1415) | $\beta_{2,3}$ | -0.0175<br>(0.0480) | $\beta_{3,3}$ | -0.0396<br>(0.0227)*** |
| $\beta_{1,4}$ | -0.1433<br>(0.6390) | $\beta_{2,4}$ | 0.4128<br>(0.2820) | $\beta_{3,4}$ | 0.1663<br>(0.2196) |
| $\alpha_{1,0}$ | 0.0169<br>(0.0071)** | $\alpha_{2,0}$ | 0.0266<br>(0.0083)* | $\alpha_{3,0}$ | 0.0310<br>(0.0077)* |
| $\alpha_{1,1}$ | 0.1006<br>(0.0287)* | $\alpha_{2,1}$ | -0.0145<br>(0.0337) | $\alpha_{3,1}$ | -0.0495<br>(0.0306) |
| $\alpha_{1,2}$ | -0.0418<br>(0.0367) | $\alpha_{2,2}$ | 0.1040<br>(0.0383)* | $\alpha_{3,2}$ | -0.0563<br>(0.0357) |
| $\alpha_{1,3}$ | 0.1194<br>(0.0410)* | $\alpha_{2,3}$ | 0.2046<br>(0.0346)* | $\alpha_{3,3}$ | 0.2751<br>(0.0297)* |
| $\delta_1$ | 0.1975<br>(0.1283) | $\delta_2$ | 0.1025<br>(0.0984) | $\delta_3$ | -0.0637<br>(0.0444) |
| $\gamma_1$ | 0.9317<br>(0.0165)* | $\gamma_2$ | 0.9021<br>(0.0155)* | $\gamma_3$ | 0.9564<br>(0.0084)* |

Correlation Matrix

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| FTSE 20 | 1 | 0.7842<br>(0.0124)* | 0.6912<br>(0.0162)* |
| FTSE-MID 40 | | 1 | 0.8124<br>(0.0104)* |
| FTSE-SMALL CAP 80 | | | 1 |

Model Diagnostics

| | FTSE-ASE 20 | FTSE-MID 40 | FTSE-SMALL CAP 80 |
|---|---|---|---|
| E$(z_{i,t})$ | -0.0243 | -0.0383 | -0.0449 |
| E$(z^2_{i,t})$ | 0.4358 | 0.4200 | 0.4375 |
| LB(12); $z_{i,t}$ | 9.2400 | 30.0544* | 20.2913** |
| LB(12); $z^2_{i,t}$ | 27.3863* | 16.3107*** | 13.0496 |
| D | 0.121* | 0.120* | 0.127* |

LB(12) for cross product of standardized Residuals

LB($z_{1,2}$)= 34.8268* , LB($z_{1,3}$)=36.6472* , LB($z_{2,3}$)=22.2706*

Notes: Number in parentheses are asymptotic errors. Stock returns are logarithmic percentage changes. D=Kolmogorov-Smirnov testing for normality (5% critical value is 1.36/$\sqrt{T}$ where, T number of observations); LB(n) is the Ljung-Box statistic for up to n lags (distributed as $x^2$ with n degrees of freedom). $z_{i,t}$ is the standardized residual for market i. (*)(**)(***) denotes significance at the 1%(5%)(10%) level.$z_{ij}$ is the cross product of the standardized residuals.

Table 6: Comparison of volatility spillovers' coefficients amongst the three models

| | LeBaron | Feedback | Nested |
|---|---|---|---|
| $\alpha_{1,2}$ | -0.0329 | -0.0499 | -0.0418 |
| $\alpha_{1,3}$ | 0.1026 | 0.1246 | 0.1194 |
| $\alpha_{2,1}$ | -0.0084 | -0.0046 | -0.0145 |
| $\alpha_{2,3}$ | 0.1958 | 0.2095 | 0.2046 |
| $\alpha_{3,1}$ | -0.0448 | -0.0400 | -0.0495 |
| $\alpha_{3,2}$ | -0.0403 | -0.0733 | -0.0563 |

Notes: *(**) denotes significance at the 1% (5%) level based on the results of the four EGARCH models. The coefficients of the volatility spillovers are similar between the VAR and the LeBaron, Feedback models and Nested models. This is also apparent in the figure 1.

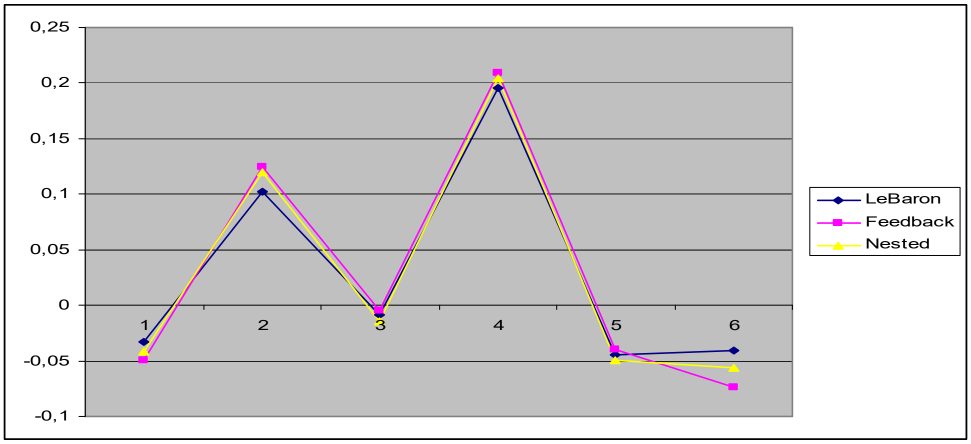


Figure 1: Comparison of volatility spillovers' coefficients for the three models

Table 7. Impact of Innovations on Volatility

| From the full LeBaron-EGACRH model | |
|---|---|
| Panel A: Degree of volatility persistence | |
| | Volatility Persistence |
| FTSE-ASE 20 | 10.9667 |
| FTSE-MID 40 | 6.8084 |
| FTSE-SMALL CAP 80 | 13.7793 |
| Panel B: Degree of volatility asymmetric impact of Negative and Positive innovations | |
| | Volatility Asymmetry |
| FTSE-ASE 20 | 0.6890 |
| FTSE-MID 40 | 0.8326 |
| FTSE-SMALL CAP 80 | 1.1642 |
| From the full Feedback-EGACRH model | |
| Panel A: Degree of volatility persistence | |
| | Volatility Persistence |

| | |
|---|---|
| FTSE-ASE 20 | 9.7895 |
| FTSE-MID 40 | 7.1087 |
| FTSE-SMALL CAP 80 | 16.3853 |
| Panel B: Degree of volatility asymmetric impact of Negative and Positive innovations | |
| | Volatility Asymmetry |
| FTSE-ASE 20 | 0.6791 |
| FTSE-MID 40 | 0.7716 |
| FTSE-SMALL CAP 80 | 1.1028 |
| From the full Nested-EGACRH model | |
| Panel A: Degree of volatility persistence | |
| | Volatility Persistence |
| FTSE-ASE 20 | 9.8033 |
| FTSE-MID 40 | 6.7291 |
| FTSE-SMALL CAP 80 | 15.5752 |
| Panel B: Degree of volatility asymmetric impact of Negative and Positive innovations | |
| | Volatility Asymmetry |
| FTSE-ASE 20 | 0.6701 |
| FTSE-MID 40 | 0.8140 |
| FTSE-SMALL CAP 80 | 1.1360 |

Notes: Entries in Panel A denote the degree of volatility persistence, based on the half-life of a shock (defined as $\ln(0.5)/\ln(\gamma_i)$). Entries in Panel B denote the number of times that negative innovations increase volatility more than that of positive innovations, which is defined as $|-1+\delta_j|/(1+\delta_j)$.

Table 8. Total impact of innovations on volatility from the full EGARCH models

| Panel A: Percentage change from the full LeBaron-EGARCH model | | | |
|---|---|---|---|
| Innovation at t-1 from: | FTSE-ASE 20 at t | FTSE-MID 40 at t | FTSE-SMALL CAP 80 at t |
| +1% FTSE-ASE 20 | 0.1200 | -0.0359 | 0.0948 |
| -1% FTSE-ASE 20 | 0.0827 | -0.0298 | 0.1103 |
| +1% FTSE-MID 40 | -0.0099 | 0.1213 | 0.1809 |
| -1% FTSE-MID 40 | -0.0068 | 0.1010 | 0.2106 |
| +1% FTSE-SMALL CAP 80 | -0.0530 | -0.0439 | 0.2561 |
| -1% FTSE-SMALL CAP 80 | -0.0448 | -0.0366 | 0.2982 |
| Panel B: Percentage change from the full Feedback-EGARCH model | | | |
| Innovation at t-1 from: | FTSE-ASE 20 at t | FTSE-MID 40 at t | FTSE-SMALL CAP 80 at t |
| +1% FTSE-ASE 20 | 0.1257 | -0.0563 | 0.1185 |
| -1% FTSE-ASE 20 | 0.0854 | -0.0434 | 0.1306 |
| +1% FTSE-MID 40 | -0.0054 | 0.0865 | 0.1992 |

| | | | |
|---|---|---|---|
| -1% FTSE-MID 40 | -0.0037 | 0.0668 | 0.2197 |
| +1% FTSE-SMALL CAP 80 | -0.0476 | -0.0827 | 0.2647 |
| -1% FTSE-SMALL CAP 80 | -0.0323 | -0.0638 | 0.2920 |
| Panel C: Percentage change from the full Nested-EGARCH model | | | |
| Innovation at t-1 from: | FTSE-ASE 20 at t | FTSE-MID 40 at t | FTSE-SMALL CAP 80 at t |
| +1% FTSE-ASE 20 | 0.1204 | -0.0460 | 0.1117 |
| -1% FTSE-ASE 20 | 0.0807 | -0.0375 | 0.1270 |
| +1% FTSE-MID 40 | -0.0173 | 0.1146 | 0.1915 |
| -1% FTSE-MID 40 | -0.0116 | 0.0933 | 0.2176 |
| +1% FTSE-SMALL CAP 80 | -0.0592 | -0.0620 | 0.2575 |
| -1% FTSE-SMALL CAP 80 | -0.0397 | -0.0505 | 0.2926 |

Notes: Entries represent the total impact of innovations of index j to index I, which is defined as $\alpha_{ij}(1+\delta_j)$ for a positive 1% innovation and $\alpha_{ij}\,|-1+\delta_j|$ for a negative 1% innovation.