Herd behavior towards the market index: evidence from Romanian stock exchange

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HERD BEHAVIOR TOWARDS THE MARKET INDEX: EVIDENCE FROM ROMANIAN STOCK EXCHANGE[1]

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ABSTRACT

This paper uses the cross-sectional variance of the betas from the CAPM model to study herd behavior towards market index in Romania. For time-varying beta determination, three different modeling techniques are employed: two bivariate GARCH models (DCC and FIDCC GARCH), two Kalman filter based approaches and two bivariate stochastic volatility models. A comparison of the different models' in-sample performance indicates that the mean reverting process in connection with the Kalman filter and the stochastic volatility model with a t distribution for the excess return shocks are the preferred models to describe the time-varying behavior of stocks betas. Through the estimated values, the evolution of the herding measure, especially the pattern around the beginning of the subprime crisis is examined. Herding towards the market shows significant movements and persistence independently from and given market conditions and macro factors. Contrary to the common belief, the subprime crisis reduces herding and is clearly identified as a turning point in herding behavior.

Key words: Herd Behavior, CAPM, GARCH Models, Stochastic Volatility Models, Kalman Filter

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1. Introduction

In financial markets, herding is usually defined as the behavior of an investor to imitate the observed actions of others or the movements of market instead of following his own beliefs and information. The implications of the herd behavior for stock market efficiency are well documented in the financial literature. According to Chang, Cheng and Khorana (2000), when investing in a financial market where herding is present, a larger number of securities are needed to achieve the same level of diversification than in an otherwise normal market. Moreover, herding effect on stock price movements can lead to mispricing of securities since rational decision making is disturbed through the use of biased views of expected return and risk (Tan et al. (2008), Hwang and Salmon (2004)). Finally, the results about the existence of herd behavior are very useful for modeling stock behavior and provide information to the policymakers about whether or not they should be concerned about potential destabilizing effects of it (Demirer and Kutan (2006)).

Despite the number of studies that have been carried out on the stock markets, quite a rare have analyzed the tendency of herd behavior of European countries in general and of emerging European countries in particular. The emphasis is traditionally put on Asian countries and the United States. This study is relevant on two levels since, first, it focuses on an emerging European country, and second, it aims to verify the existence or non existence of the herding phenomena according to the method elaborated by Hwang and Salmon (2004, 2008).

In order to test for the existence of herding on the Romanian stock exchange, the concept of "***beta herding***" is used, as define by Hwang and Salmon (2008): "*Beta herding measures the behavior of investors who follow the performance of specific factors such as the market index or portfolio itself or particular sectors, styles, or macroeconomic signals and hence buy or sell individual assets at the same time disregarding the underlying risk-return relationship*". Although this measure can be easily applied to specific factors, say herding towards Fama-French HML or SMB factor for stock markets, the focus here is on beta herding towards the market portfolio.

One merit of the seminal paper of Hwang and Salmon (2004) is that they separate the real herding from "spurious herding", i.e. common movements in asset returns induced by movement in fundamentals (Bihkchandani and Sharma (2001)). They propose an approach based on the movements in the cross-sectional dispersion of the CAPM betas which leads to a measure that can empirically capture the extent of herding in the market, viewed as a latent and unobservable process.

In order to determine the time varying betas, Hwang and Salmon (2004, 2008), as well as Khan, Hassairi and Viviani (2011) in a similar study, use the standard OLS technique. Wang (2008) adopts a rolling robust regression approach. In this paper a comparison between three different modeling techniques is employed:

- GARCH conditional betas;
- stochastic volatility conditional betas;
- two Kalman Filter based approaches.

To determine the performance of the models in generating the best measure of time-varying systematic risk, the different techniques are formally ranked based on their in-sample performance.

Empirical studies of herding in advanced and emerging markets have found mixed evidence regarding herding during crises. Contrary to common belief, a crisis appears to stimulate a return towards efficiency rather than an increased level of herding. This hypothesis is tested using weekly data for the period 2003-2012 which was characterized by the beginning of the subprime crisis.

The rest of the paper is organized as follows: section 2 reviews the most important studies that appeared in the field of herd behavior, section 3 describes the concept of beta herding, as well as the competing modeling techniques used to investigate the time-varying behavior of systematic risk, section 4 presents the data, section 5 raises some problems regarding the estimation techniques employed and discusses the results, while section 6 concludes.

2. Literature review

In recent years there has been much interest in herd behavior in financial markets. In the middle of the current worldwide financial crisis, herd behavior seems a plausible explanation for the misalignment of prices and fundamentals. This part of the paper provides an overview of the main theoretical and empirical research on this topic.

2.1 Motives and determinants – theoretical models of herd behavior

The phenomenon of herding was first studied in psychology. For instance, Asch (1952) observed that individuals often abandon their own private signal to rely predominantly on group opinion. Seminal articles by Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992) and Welch (1992), among others, introduced herding models into the finance literature and highlighted its possible consequences for the overall functioning of financial markets and information processing by individuals. The main drawback of these seminal papers is the fact that they assume a perfectly elastic supply (investment opportunity is available to all individuals at the same price). This may be reasonable in some cases - for instance, Bikhchandani et al. (1992) refer to the choice of adoption of a new technology whose cost is fixed. However, this assumption makes them unsuitable to analyze stock market, where asset prices are certainly flexible.

The assumption of fixed prices is relaxed in Avery and Zemsky (1998). The presence of a price mechanism makes it more difficult for herding to arise. Nevertheless, there are cases in which it occurs[3].

There are three main reasons identified in literature for rational herd behavior in financial markets[4]: imperfect information, concern for reputation and compensation structures. The articles mentioned above are part of the ***information-based herding*** literature. Other relevant models are the ones of Chari and Kehoe (1999) and Calvo and Mendoza (1998). Seminal works for ***reputation-based herding*** include Scharsfstein and Stein (1990) and Graham (1999). Maug and Naik (1996) provide a single risky-asset model to explain how the ***compensation-based herding*** can occur. Admati and Pfleiderer (1997) extent the research to a multiple risky-assets model of delegated portfolio management.

2.2 Herding measures in empirical research

There is a lack of a direct link between the theoretical discussion of herd behavior and the empirical specifications used to test for herding. On one hand, theoretical research has tried to identify the reasons and mechanism through which herd can arise; the models proposed are

[3] The case considered in Avery and Zemsky (1998) is when there is uncertainty about the average accuracy of trader information (for example uncertainty about the occurrence of an information event or about the model parameters).

[4] Not rational herd behavior is beyond the scope of this paper. According to Devenov and Welch (1996), the irrational view focuses on investor psychology where an investor follows other blindly. Momentum-investment strategies are a well known example of this type of herd behavior.

abstract and cannot easily be brought to data. On the other hand, the empirical studies usually does not test a particular model of herd behavior described in the theoretical literature[5]; instead, they gauge whether clustering of decisions, in purely statistical sense, is taking place in financial markets or within certain investors groups. The empirical herding literature, therefore, besides some special contexts or experimental settings – Cipriani and Guarino (2005, 2008), uses herding as a synonym for systematic or clustered trading.

Two streams of empirical literature have been developed to investigate the existence of herding in financial markets.

The first stream analyzes the tendency of individuals or certain groups of investors to follow each other and trade an asset at the same time. The statistical measures proposed to assess for herd behavior include LSV measure, proposed by Lakonishok, Shleifer and Vishny (1992) and PCM (portfolio-change measure) proposed by Wermers (1995). The first measure uses only the number of investors on the two sides of market and their tendency to buy and sell the same set of stocks. The second measure of correlated trading takes into account also the amount of stock the investors buy or sell, measuring herding by the extent to which portfolio-weights assigned to the various stocks by different money managers move in the same direction. Neither one of the 2 measure make possible to determine if the correlation trades results from imitation or merely reflects that traders use the same information.

The second stream focuses on the market-wide herding, i.e. the collective behavior of all participants towards the market views. Two well known measures from this stream of the literature were developed by Christie and Huang (1995) and Huang and Salmon (2004, 2008).

Christie and Huang (1995) propose a method of detecting herding behavior using stock return data. They regress the cross-sectional (market wide) standard deviation of individual security returns on a constant and two dummy variables designed to capture extreme positive and negative market returns. They argue that during periods of market stress, rational asset pricing would imply positive coefficients on these dummy variables, while herding would suggest negative coefficients (during periods of extreme market movements, individuals tend to suppress their own beliefs, and their investment decisions are more likely based on the collective actions in the market; individual stock returns under these conditions should tend to cluster around the overall market return). There are several drawbacks with this measure of herding. First, there

[5] Exceptions include Wermers (1999), Graham (1999) and Cipriani & Guarino (2010).

isn't a fixed definition for "extreme"; in practice, investors may differ in their opinion as to what constitutes an extreme return. Second, this method captures herding only during periods of extreme returns. In addition, it does not control for movements in fundamentals, so it is hard to tell whether the negative coefficient, if there is any, is herding or just a sign of independent adjustment to fundamentals that is taking place.

Chang, Cheng and Khorana (2000) extend the work of Christie and Huang (1995) by using a non-linear regression specification for examining the relation between the level of equity return dispersions (as measured by the cross-sectional absolute deviation of returns) and the overall market return. They find no evidence of herding in developed markets, such as the U.S., Japan and Hong Kong. However, they do find evidence of herding in the emerging markets of South Korea and Taiwan.

Hwang and Salmon (2004) develop a new measure. They use the cross-sectional dispersion of the factor sensitivity of assets to detect herding towards the market index. More specifically, they offer a behavioral interpretation for the considerable empirical evidence that the CAPM betas for individual assets are biased away from their equilibrium values: significant changes in betas reflect changes in market sentiment rather than a time varying equilibrium, unless there are changes in fundamentals. When investors' beliefs shift so as to follow the performance of the overall market more than they should in equilibrium, they disregard the equilibrium relationship and move towards matching the return on individual assets with that of the market. So, herding towards the market takes place. When considering this type of herding, the underlying movements in the market itself are taken as given, so the proposed measure capture adjustments in the structure of the market due to herding rather than adjustments in the market due to what Bikhchandani and Sharma (2001) refer to as "spurious" or unintentional herding. Nevertheless, they use variables such as the dividend-price ratio, the Treasury bill rate, the term spread, and the default spread to check the robustness of the results in regards to fundamentals changes.

Hwang and Salmon (2004) apply their approach to the US, UK and South Korean stock markets and find that herding towards the market shows significant movements and persistence independently from and given market conditions as expressed in return volatility and the level of the mean return. Macro factors de not explain the herd behavior. In a similar research carried out for 21 markets divided into three groups (developed markets, emerging Latin American countries and emerging Asian countries)[6], Wang (2008) finds a higher level of herding in emerging markets then in developed markets. Additionally, the herding measure, like some macroeconomics aggregate variables, follows a pattern of cycles. Khan, Hassairi and Viviani (2011), using the same measure, find evidence of herding behavior occurring in countries classified as high-tech European markets (France, Germany, Italy and UK) in the period from 2003 to 2008 which was characterized by two important events: the dotcom bubble and the beginning of the crisis (subprime).

This empirical research on herding is important as it sheds light on the behavior of financial market participants and in particular whether they act in a coordinated fashion. Policy makers often express concerns that herding by financial market participants destabilizes markets and increases the fragility of the financial system. As specified in a recent research conducted by IMF (2011)[7], one of the key lessons that can be drawn regarding systemic crises is that pure contagion and herd behavior could propagate shocks beyond those related to trade and financial linkages.

3. The methodology

3.1 Risk-Return Equilibrium with the Existence of Herding towards the Market

The CAPM (Sharpe (1964)) is widely used in defining the risk-return equilibrium relationship of equities. The framework proposed is as follows: risk determines the asset return. However, Hirshleifer (2001) argues that expected return of an asset is not only compensated by its fundamental risk, but also related to the investor misevaluation caused by cognitive imperfection of investors and social dynamics such as herding.

The use of cross sectional distribution of stock returns as an indication of herding was first introduced by Christie and Huang (1995) in the form of the cross sectional standard deviation of individual stock returns during large price changes. Hwang and Salmon (2004, 2008) build on this idea but instead advocate the use of a standardized standard deviation of factor loadings to measure the degree of herding. Their measure has the advantage of capturing

[6] Included in the developed markets are France, Germany, Hong Kong, Japan, United Kingdom and the United States; included in the Latin American group are Argentina, Brazil, Chile, Colombia, Peru, Mexico and Venezuela; and included in the Asian group are China, India, Indonesia, Korea, Malaysia, Philippines and Thailand.

[7] Analytics of Systemic Crises and the Role of Global Financial Safety Nets.

"intentional" herding towards a given factor, such as the market (the approach considered in this paper), rather than "spurious" herding during market crises. They find that, in the case of US and South Korea, herding towards the market happens especially during quiet periods for the market, rather than when the market is under stress.

In essence, Hwang and Salmon (2004, 2008) measure herding on observed deviations from the equilibrium beliefs expressed in the CAPM. In a market with rational investors, the CAPM in equilibrium can be expressed as:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt}) \tag{1}$$

where r_{it} and r_{mt} are the excess returns on asset *i* and the market at time *t*; β_{imt} is the systematic risk measure, E(·) is the conditional expectation at time *t*.

The assumption of Hwang-Salmon is that investors form firstly the common market-wide view, $E_t(r_{mt})$, and their behavior is then conditional on it. When herding towards the market occurs, the investors shift their beliefs to follow the performance of the overall market more than they should in the CAPM: they buy the asset with a beta less than 1, since it appears to be relatively cheap compared to the market, and sell an asset with a beta more than 1, since the asset appears to be relatively expensive compared with the market. In other words, they ignore the equilibrium relationship in the CAPM and move towards matching the return on individual assets with that of the market. So, instead of the above equilibrium relationship, the following relationship it's assumed to hold in the presence of herding towards the market:

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1) \tag{2}$$

where $E_t^b(r_{it})$ and β_{imt}^b are the market's biased short run conditional expectation on the excess returns of asset *i* and its beta at time *t*, and h_{mt} is a latent herding parameter that changes over time, $h_{mt} \leq 1$.

- When h_{mt} = 0, there is no herding and the equilibrium CAPM holds.
- When h_{mt} = 1, there is perfect herding towards the market portfolio and all the individual assets move in the direction and with same magnitude as the market portfolio.
- In general, when 0 < h_{mt}< 1, beta herding exists in the market and the degree of herding depends on the magnitude of h_{mt}. In this situation we have $\beta_{imt} > \beta_{imt}^b > 1$ for an equity with $\beta_{imt} > 1$ and $\beta_{imt} < \beta_{imt}^b < 1$ for an equity with $\beta_{imt} < 1$. The individual betas are biased towards 1.

- When h_{mt} < 0, there is reversed herding and high betas (betas larger than 1) become higher and low betas (betas less than 1) become lower. This represents means reversion towards the long term equilibriumβ_{imt}, an adjustment back towards the equilibrium CAPM from mispricing both above and below equilibrium.

So when there is beta herding in the market, betas less than 1 tend to increase while betas larger than 1 tend to decrease. Using the relation described in Eq. 2, this tendency can be measured by calculating cross-sectional variance of (biased) betas:

$$Std_c\left(\beta_{mt}^b\right) = Std_c(\beta_{mt})(1 - h_{mt}) \tag{3}$$

where $Std_c(\cdot)$ represents the cross standard deviation.

The existence of herding makes the cross-sectional dispersion of the betas smaller than it would be in equilibrium. The impact of idiosyncratic changes in β_{imt} is minimized by calculating $Std_c(\beta_{mt})$ for all the assets in the market. So $Std_c(\beta_{mt})$ is not expected to change significantly unless the structure of companies within the market changed dramatically (and this is not the case for a short time scale). The assumption of constant $Std_c(\beta_{mt})$, although may appear strong, it is then justified. With this assumption, changes in $Std_c\left(\beta_{mt}^b\right)$ over a short time interval can be attributed to changes in h_{mt}.

Taking logarithms of Eq.3 on both sides, it is obtained:

$$\log\left[Std_c\left(\beta_{mt}^b\right)\right] = log\left[Std_c(\beta_{mt})\right] + \log(1 - h_{mt}) \tag{4}$$

Using the assumption on $Std_c(\beta_{mt})$, it can be written:

$$\log\left[Std_c(\beta_{mt})\right] = \mu_m + \upsilon_{mt} \tag{5}$$

where $\mu_m = E(log\left[Std_c(\beta_{mt})\right])$ and $\upsilon_{mt} \sim iid(0, \sigma_{m\upsilon}^2)$, and then:

$$\log\left[Std_c\left(\beta_{mt}^b\right)\right] = \mu_m + H_{mt} + \upsilon_{mt} \tag{6}$$

where $H_{mt} = log(1 - h_{mt})$.

Moving forward, H_{mt} is assumed to follow a mean zero AR(1) process:

$$H_{mt} = \phi_m H_{mt-1} + \eta_{mt} \tag{7}$$

where $\eta_{mt} \sim iid(0, \sigma_{m\eta}^2)$.

This is now a standard state space model with Eq.6 as the measurement equation and Eq.7 as the transition equation. It can be estimated with the Kalman filter.

3.2 The determination of time varying betas

The difficult part in applying the methodology described above is the determination of time-varying betas.

Beta represents one of the most widely used concepts in finance: it is used to estimate a stock's sensitivity to the overall market, to identify mispricing of a stock, to calculate the cost of capital etc. In the context of capital asset pricing model (Sharpe (1964)), beta is assumed to be constant over time and is estimated via ordinary least squares (OLS). However, there now exists widespread evidence across many markets that beta risk is unstable over time (Brooks, Faff and Lee (1994), Fabozzi and Francis (1978) etc.). Based on this evidence, it is appropriate to specify beta as a conditional time-varying series.

Several different econometrical methods have been applied in the recent literature to estimate time-varying betas of different countries and firms (see for example Choudhrya and Wu (2007), Brooks, Faff and McKenzie (2002) etc.). Given the different methods, the empirical question to answer is which econometrical method offers the best results in terms of in-the-sample and out-of-the-sample forecasting accuracy.

This paper investigates the time-varying behavior of systematic risk for 65 stocks listed on Romania stock exchange. Using weekly data over the period January 2003 - March 2012, three different modeling techniques are employed:

- GARCH conditional betas;
- stochastic volatility conditional betas;
- two Kalman Filter based approaches.

The results are compared only in terms of in-sample forecasting accuracy, as for determining the herd behavior parameter there is no interest in evaluating the forecast performances out-of-sample.

3.2.1 GARCH Conditional Betas

While in the traditional CAPM returns are assumed to be IID, it is well established in the empirical finance literature that this is not the case for returns in many financial markets. Signs of autocorrelation and volatility clusters contradict the assumption of independence and identical return distribution over time. In this case the variance-covariance matrix of a stock and market excess returns is time-dependent and a non-constant beta can be defined as:

$$\hat{\beta}_{it}^{GARCH} = \frac{Cov(r_{it}, r_{mt})}{Var(r_{mt})}$$

where the conditional beta is based on the calculation of the time-varying conditional covariance between a stock and the overall market and the time-varying conditional market variance.

There are numerous studies in finance literature on the estimation of conditional beta with bivariate GARCH models, including Choudhry and Wu (2007) and others. There is also a vast literature on multivariate models with a number of different specifications for the volatility processes (Bauwens, Laurent and Rombouts (2006) survey the most important developments in multivariate ARCH-type modeling).

In this paper the **Dynamic Conditional Correlation (DCC) multivariate GARCH model** is employed. In the initial form proposed by Engle and Sheppard (2001), a univariate GARCH model is considered for each return series. As the estimated GARCH model parameters sum very close to one, indicating a high degree of volatility persistence to a shock, an alternative statistical specification for the DCC GARCH model is also tested by replacing the univariate GARCH model with the Fractionally Integrated GARCH model (Baillie, Bollerslev and Mikkelsen (1996)). The fractionally integrated version of the DCC (**FIDCC**) GARCH model is quite new to the literature: Halbleib and Voev (2010) use FIDCC GARCH model for dynamic modelling and forecasting of realized covariance matrices for six highly liquid stocks from NYSE, while Butler, Gerken and Okada (2011) use the same model to test for long memory in the conditional correlation between assets.

The multivariate DCC GARCH model of Engle and Sheppard (2001) can be formulated as the following statistical specification:

Model 1 (DCC GARCH)

$$r_t \,/\, \Omega_{t-1} \sim N(0, H_t) \qquad (1)$$

$$H_t = D_t R_t D_t \qquad (2)$$

$$D_t = diag\{h_{i,t}^{1/2}\} \qquad (3)$$

$$h_{i,t} = \omega_i + \sum_{q=1}^{Q_i} \alpha_{i,q} u_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{i,p} h_{i,t-p} \qquad (4)$$

$$\varepsilon_t = D_t^{-1} u_t \qquad (5)$$

$$Q_t = (1 - \sum_{n=1}^{N} \alpha_n - \sum_{m=1}^{M} \beta_m)\, \bar{Q} + \sum_{n=1}^{N} \alpha_n (\varepsilon_{t-n} \varepsilon_{t-n}') + \sum_{m=1}^{M} \beta_m Q_{t-m} \qquad (6)$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}\,. \qquad (7)$$

The conditional variance-covariance matrix $D_t R_t D_t$ is composed of diagonal D_t matrix of time-varying standard variation from univariate GARCH-processes (Eq. 4) and a correlation matrix R_t containing time-varying conditional correlation coefficients. The conditional correlation is also the conditional covariance between the standardized disturbances (determined in Eq. 5). The symbols ω_i, α_i, and β_i stand for constants and coefficients associated with ARCH and GARCH terms, respectively.

The proposed dynamic correlation structure is presented in Eq. 6. $\bar{Q}$ is the unconditional covariance of the standardized disturbances:

$$\bar{Q} = \mathrm{Cov}\,(\varepsilon_t \varepsilon_t') = \mathrm{E}\,[\varepsilon_t \varepsilon_t'].$$

As H_t has to be positive definite as it is a covariance matrix, it follows that R_t has to be positive definite. Furthermore, by the definition of the conditional correlation matrix, all the R_t elements have to be between -1 and 1. Eq. 7 guarantees that both these requirements are met. Q_t^{*-1} rescales the elements in Q_t to ensure $|q_{ij}|\leq 1$. In other words Q_t^{*-1} is simply the inverted diagonal matrix with the square root of the diagonal elements of Q_t:

$$Q_t^{*-1} = \begin{pmatrix} 1/\sqrt{q_{11t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1/\sqrt{q_{kkt}} \end{pmatrix}.$$

The typical element of R_t is of the form $\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{ii} q_{jj}}}$.

The specification of the univariate GARCH models is not limited to the standard GARCH(P,Q), but can include any GARCH process with normally distributed errors that satisfies appropriate stationarity conditions and non-negativity constraints[8]. As mentioned before, an alternative approach taken in this paper is to model the volatilities as FIGARCH(P,d,Q) processes:

$$\phi\,(L)\,(1-L)^d\,u_t^2 = \omega + [1-\beta(L)]v_t,$$

where $v_t = u_t^2 - h_t$ can be viewed as an unexpected volatility variation, $\phi(L) = 1 - \sum_{j=1}^{J-1} \varphi_j L^j$ and $\beta(L) = \sum_{p=1}^{P} \beta_p L^p$ are polynomials in L of order J-1 and P, J=max{P, Q}. It is the fractional differencing operator $(1-L)^d$ that allows volatility to have the long memory

[8] Engle and Sheppard (2001) present the sufficient, not necessary, restrictions on parameters to guarantee positive definiteness for H_t. Exact conditions are much more complicated and can be found in Nelson and Cao (1992).

property. The fractional differencing operator is in fact a notation for the following infinite polynomial:

$$(1-L)^d = \sum_{j=0}^{\infty} \frac{\Gamma(j-d)}{\Gamma(j+1)\Gamma(-d)} L^j, \text{ where } \Gamma(\cdot) \text{ is the standard gamma function.}$$

To ensure stability of the process, it is assumed that all the roots of $\phi(L)$ and $[1-\beta(L)]$ lie outside the unit circle and that d is a fraction number between 0 and 1. Furthermore, the parameters of the FIGARCH model must be subject to additional restrictions to ensure that the resulting conditional variances are all non-negative[9].

The corresponding conditional variance h_t can be expressed more explicitly as:

$$[1-\beta(L)]h_t = \omega + [1-\beta(L)-\phi(L)(1-L)^d]u_t^2.$$

Using the FIGARCH model described above, the second statistical specification for the DCC GARCH model considered in this paper is:

Model 2 (FIDCC GARCH)

$$r_t / \Omega_{t-1} \sim N(0, H_t) \tag{1}$$

$$H_t = D_t R_t D_t \tag{2}$$

$$D_t = diag\{h_{i,t}^{1/2}\} \tag{3}$$

$$[1-\beta(L)]h_{i,t} = \omega + [1-\beta(L)-\phi(L)(1-L)^d]u_{i,t}^2 \tag{4}$$

$$\varepsilon_t = D_t^{-1} u_t \tag{5}$$

$$Q_t = \left(1 - \sum_{n=1}^{N} \alpha_n - \sum_{m=1}^{M} \beta_m\right) \bar{Q} + \sum_{n=1}^{N} \alpha_n (\varepsilon_{t-n}\varepsilon'_{t-n}) + \sum_{m=1}^{M} \beta_m Q_{t-m} \tag{6}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}. \tag{7}$$

The assumption of normality in the first equation (Model 1 and Model 2) gives rise to a likelihood function:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log(|H_t|) + r'_t H_t^{-1} r_t)$$

Without this assumption, the estimator will still have the Quasi-Maximum Likelihood (QML) interpretation.

[9] Two different sets of sufficient conditions, valid for the FIGARCH (P, d, Q), P≤1, Q≤1, are available: Baillie, Bollerslev and Mikkelsen, (1996) and Chung (2001). Higher order models don't make the subject of this paper. The sufficient conditions imposed in estimation are presented in the results' section.

The estimation takes place in two stages. In the first stage univariate GARCH models are estimated for each series by replacing R with I (the identity matrix). The second stage is estimated using the correctly specified likelihood, conditioning on the parameters estimated in the first stage likelihood. Peters (2008) discussed in details the DCC(1, 1) model employed in this paper.

3.2.2 Stochastic Volatility Conditional Betas

The stochastic volatility (SV) models (Taylor (1982)) are considered as a successful alternative to the class of Autoregressive Conditionally Heteroscedastic (ARCH) models introduced by Engle (1982) and generalized by Bollerslev (1986) and others.

The basic SV model is commonly found in the literature under the following form:

$$\begin{cases} y_t = \sigma_t \cdot u_t = exp(h_t/2) \cdot u_t \\ h_{t+1} = \mu + \varphi \cdot (h_t - \mu) + \eta \cdot v_t \end{cases}$$

where $\{y_t\}$ is a sequence of financial returns (or excess returns), $\{h_t\}$ is a sequence of the log-variances of the returns, φ is the persistence parameter, η is the standard deviation of the log-variance process, and $\{u_t\}$ and $\{v_t\}$ are Gaussian white noises sequences with mean 0 and variance 1. In the basic model corr(u_t, v_t) = 0. The model allows for a leptokurtic unconditional distribution as is often seen on financial time series (Andersen, Chung and Sorensen (1999)).

Due to the inclusion of an unobservable shock to the return variance, the variance becomes a latent process which cannot be characterized explicitly with respect to observable past information. As a consequence, the parameters of the SV model cannot be estimated by a direct application of standard maximum likelihood techniques. This is the reason why there is a quite a large list of alternative methods to estimate SV models:

- Generalized Method of Moments (Melino and Turnbull (1990));
- Quasi – Maximum Likelihood (Harvey et al. (1994));
- A Bayesian approach employing a Monte Carlo Markov Chain (MCMC) technique as proposed by Jacquier et al. (1994) etc.

The SV model considered in this paper for time-varying beta estimation is the one developed by Johansson (2009). He proposes a combination of two existing approaches: causal volatility and dynamic correlation (Yu and Meyer (2006)). The model is defined as follows:

Model 3 (SV model with a normal distribution for the excess return shocks)

$$y_t/h_t = diag\left(exp\left(\frac{h_t}{2}\right)\right) \cdot \varepsilon_t, \varepsilon_t \sim iid\ N\left(0, \Sigma_{\varepsilon,t}\right)$$
$$\Sigma_{\varepsilon,t} = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}$$
$$h_{t+1} = \gamma_0 + \Gamma \cdot (h_t - \gamma_0) + \eta_t, \eta_t \sim iid\ N\left(0, diag\left(\sigma_{\eta_1,t}, \sigma_{\eta_2,t}\right)\right) with\ h_0 = \gamma_0$$
$$z_{t+1} = \delta_0 + \delta_1 \cdot (z_t - \delta_0) + \sigma_p \cdot v_t, v_t \sim N(0,1), \rho_t = \frac{exp(z_t) - 1}{exp(z_t) + 1}\ with\ z_0 = \delta_0.$$

The second equation shows that the correlation between the variables is time-varying. The correlation process is based on an AR(1) process. However, ρ_t needs to be bounded and for this a Fischer transformation is used. The Fischer transformation clearly bounds ρ_t by -1 and 1.

For the particular case discussed in this paper (time varying beta estimation), the model described above allows to see the correlation between a specific stock and the market index as evolutionary, while, at the same time, allows for volatility spillover. Γ is thus a 2X2 matrix with parameters for persistence in volatility and volatility spillover.

As an excess kurtosis is a common feature in asset return distributions, a second specification for the SV model is also considered, i.e. a Student distribution for the return shock. Hence excess kurtosis is allowed.

Model 4 ***(SV model with a t distribution for the excess return shocks)***

$$y_t/h_t = diag\left(exp\left(\frac{h_t}{2}\right)\right) \cdot \varepsilon_t, \varepsilon_t \sim iid\ t\left(0, \Sigma_{\varepsilon,t}, v\right)$$
$$\Sigma_{\varepsilon,t} = \begin{pmatrix} 1 & \rho_t \\ \rho_t & 1 \end{pmatrix}$$
$$h_{t+1} = \gamma_0 + \Gamma \cdot (h_t - \gamma_0) + \eta_t, \eta_t \sim iid\ N\left(0, diag\left(\sigma_{\eta_1,t}, \sigma_{\eta_1,t}\right)\right) with\ h_0 = \gamma_0$$
$$z_{t+1} = \delta_0 + \delta_1 \cdot (z_t - \delta_0) + \sigma_p \cdot v_t, v_t \sim N(0,1), \rho_t = \frac{exp(z_t) - 1}{exp(z_t) + 1}\ with\ z_0 = \delta_0.$$

The 2 SV models are estimated using a MCMC technique as the comparative studies in the literature are in favor of this approach (see for example Andersen, Chung and Sorensen (1999)).

The method is based on the Bayesian approach to modeling. The Bayesian approach involves the specification of the full probability model, that is the specification of the *likelihood*, p(y|θ), and the *prior distribution* for the parameters, p(θ). The likelihood represents the probability of the data, y, given the parameters, θ, and the prior distribution represents the prior knowledge about the parameter distribution. The posterior distribution (what we are looking for) is related to priors through **Bayes' rule**:

$$p(\Theta/y) = \frac{p(y/\theta)\cdot p(\theta)}{p(y)}.$$

Furthermore, since the left-hand side is a density for Θ, the observation y can be seen as a constant. The density p(y) can thus also be seen as a constant and the above expression may be generalized into:

$$p(\Theta/y) \propto p(y/\theta) \cdot p(\theta)$$

The prior for the parameters has to be specified independently from the data sample and here very common distributions from the empirical literature are used (Chang, Qian and Jian (2012), Sima (2007), Meyer and Yu (2006), Meyer and Yu (2000)):

$\gamma_1 \sim N(0, 25)$
$\gamma_2 \sim N(0, 25)$
$\gamma_{11}^* \sim beta(20, 1.5), \quad \gamma_{11}^* = (\gamma_{11} + 1)/2$
$\gamma_{22}^* \sim beta(20, 1.5), \quad \gamma_{22}^* = (\gamma_{22} + 1)/2$
$\gamma_{12} \sim N(0, 10)$
$\gamma_{21} \sim N(0, 10)$
$\sigma_{\eta 1}^2 \sim Igamma(2.5, 0.025)$
$\sigma_{\eta 2}^2 \sim Igamma(2.5, 0.025)$
$\delta_0 \sim N(0.7, 10)$
$\delta_1^* \sim beta(20, 1.5), \quad \delta_1^* = (\delta_1 + 1)/2$
$\sigma_\rho^2 \sim Igamma(2.5, 0.025)$
$v^* \sim \chi^2_{(4)}, \quad v^* = v/2$

They imply very general prior information of the different parameters. The means and standard deviations of these prior distributions are reported in *Appendix 3*.

The estimation is carried out in **WinBUGS** (Bayesian Analysis Using Gibbs Sampling for Windows). Although this limits the construction of Markov chains from the required distribution (the posterior distribution in this case) to the Gibbs algorithm, there are several advantages that stood at the base of this choice. First, WinBUGS includes an expert system that can choose the best algorithms for sampling from full conditional posterior distribution without any needs for the user to specify the sampling method[10]. Second, WinBUGS contains a deviance information criterion (DIC) module, which can be used to assess and compare different models for the same data according to both model goodness-of-fit and complexity. Third, WinBUGS is free and user-friendly. Meyer & Yu (2003) illustrate the convenience and ease of estimating univariate SV model within WinBUGS, and Meyer and Yu (2006) compare nine multivariate SV specifications by use of it again. Chang, Qian and Jian (2012) extend Meyer and Yu's work by showing that Bayesian estimation and comparison of multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) and multivariate stochastic volatility (MSV) models with MCMC methods could be straightforwardly and successfully conducted in WinBUGS package.

The comparison between the two proposed specifications of the SV model (Model 3 and Model 4) is realized through deviance information criteria (**DIC**), automatically implemented in WinBUGS as mentioned above. The deviance is the difference between the fitted and the "perfect" model for the data. It was proposed by Spiegelhalter, Best, Carlin and Linde (2002) and is defined as:

$\boldsymbol{DIC = \bar{D} + p_d}$, where:

1. $D(\Theta) = -2 \cdot \log(p(y/\theta))$ the posterior distribution of the loglikelihood or the deviance
   $\bar{D}$ = E [D(Θ)] the posterior mean of the deviance
2. $\bar{\theta}$ = E [Θ]
   D($\bar{\theta}$) the deviance of the posterior mean
   p_d= $\bar{D}$ – D($\bar{\theta}$) the effective number of parameters.

Θ represents the model parameters, y the data and p(y|θ) the likelihood function.

So, DIC combines a Bayesian measure of fit (the larger the $\bar{D}$ is, the worse the fit) with a measure of complexity (p_d represents a penalty for increasing the model complexity). When computing the DIC, a smaller value of the criterion indicates a better-fitting model. Meyer and Yu (2006) demonstrate its usefulness in the model selection process for the family of stochastic volatility models.

Once the conditional variance series of the stock i and the market, have been obtained, the time-varying beta for stock *i* is constructed as:

[10] Lunn, Thomas, Best and Spiegelhalter (2000) present the sampling methods used in WinBUGS.

$$\hat{\beta}_{it}^{SV} = \frac{\rho_t^i \cdot (\exp(h_{stock\, i,t}))^{1/2}}{(\exp(h_{market,t}))^{1/2}}.$$

3.2.3 Kalman Filter Based Approaches

In contrast to the volatility-based techniques where the conditional beta series can be constructed only after the conditional variances of the market and stock *i* have been obtained, the state space approach allows to model and to estimate the time-varying structure of beta directly.

Among the different algorithms for estimating the state space, the Kalman filter is in the center. It is a recursive procedure for computing the optimal estimator for the state vector at time t, based on the information available at time t. The derivation of the Kalman filter rests on the assumption that the disturbances and the initial state vector are normally distributed. When the normality assumption is dropped, there is no longer any guarantee that the Kalman filter will give the conditional mean of the state vector. However, it is still an optimal estimator in the sense that it minimizes the MSE within the class of all linear estimators.

The Kalman filter is based on the representation of the dynamic system with a state space regression, modeling the beta dynamics through an autoregressive process:

$$\begin{cases} r_{it} = \beta_{it} r_{mt} + \varepsilon_{it} \\ \beta_{it} = \phi_i \beta_{i,t-1} + \eta_{it}, \end{cases}$$

with ϕ_i denoting the constant transition parameter. The observation error ε_{it} and the state equation error η_{it} are assumed to be Gaussian:

$$\mathrm{E}(\varepsilon_{it}\varepsilon_{it}') = \begin{cases} \sigma_i^2, for\ t = T \\ 0, otherwise \end{cases}$$

$$\mathrm{E}(\eta_{it}\eta_{it}') = \begin{cases} \sigma_{\eta i}^2, for\ t = T \\ 0, otherwise \end{cases}$$

and to be uncorrelated at all lags:

$$E(\varepsilon_{it}\eta_{it}') = 0) \text{ for all t and T.}$$

In this paper, two state space specifications of the evolution of time-varying beta are considered:

Model 5 (beta coefficient develops as a random walk)

$$\begin{cases} r_{it} = \beta_{it}^{K\,RW} r_{mt} + \varepsilon_{it} \\ \beta_{it}^{K\,RW} = \beta_{i,t-1}^{K\,RW} + \eta_{it} \end{cases}$$

Model 6 (beta coefficient develops as a mean-reverting process)

$$\begin{cases} r_{it} = \beta_{it}^{K\,MR} r_{mt} + \varepsilon_{it} \\ \beta_{it}^{K\,MR} = \bar{\beta}_i + \phi_i\,(\beta_{i,t-1}^{K\,MR} - \bar{\beta}_i) + \eta_{it} \end{cases}$$

4. Data

Empirical studies of herding have found mixed evidence regarding herding during crisis. Using the framework developed above, the issue is addresses here for an emerging European country (Romania) using weekly excess returns of market index BET-C[11] and weekly excess returns of stocks listed on Bucharest Stock Exchange, covering the period from January 2003 to March 2012 (65 stocks). The de-listed companies (either as a cause of bankruptcy or by own choice) are not excluded from the study, trying to avoid in this way selection bias. The newly listed stocks during the considered period are included in the analysis from the time they entered the market. The only condition for a stock to be kept in the study is to have at least 1 year of trading history.

Weekly excess returns between period *t* and *t-1* for stock *i* are computed as:

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) - r_t^f,$$

where $P_{i,t}$ is the average closing price in week t, ln is the natural logarithm and r_t^f is the risk-free interest rate (deposit facility interest rate).

In the *second appendix* some statistical properties of the stocks returns are reported. For the sample period, all the stocks returns are leptokurtic and thus non-gaussian.

5. EMPIRICAL RESULTS

5.1 Modeling Conditional Betas

In this section empirical results as long with some estimations problems, for the 3 techniques presented earlier, are discussed:

[11] Reflects the evolution of all listed stocks, with the exception of Investment Funds.

5.1.1 GARCH Conditional Betas

A DCC(1, 1) – bivariate GARCH model[12] is employed. The univariate GARCH(P, Q) models estimated for conditional variances (*Model 1*) are selected by finding the minimum of the Akaike information criterion (AIC), allowing for $P \leq 2$ and $Q \leq 2$. In the fractionally integrated version of the DCC (FIDCC) GARCH, the variances are modeled as FIGARCH(P, d, Q) processes (*Model 2*), allowing for $P \leq 1$ and $Q \leq 1$. Like in the previous case, the specification with the minimum AIC value is chosen. The reason why the analysis is restricted to short and relatively few lag specification is simply to keep the burden of estimation of all the models at a manageable size. It is reasonable to expect that the models with more lag will not result in more accurate forecasts than more parsimonious models. So, limiting the attention to the models with short lags should not affect the analysis.

The estimation is carried out in Matlab, using the MFE and UCSD GARCH Toolboxes provided by Kevin Sheppard. In order to ensure the stationarity and a positive definite variance-covariance matrix the following conditions are imposed:

- *GARCH(P,Q)* - the following constrains are used (they are right for the (1,1) case or any ARCH case):
  - (1) $\omega > 0$
  - (2) $\alpha_i >= 0$ for i = 1,2,...Q
  - (3) $\beta_i >= 0$ for i = 1,2,...P
  - (4) sum($\alpha_i + \beta_j$) < 1 for i = 1,2,...Q and j = 1,2,...P
- *FIGARCH(P,d,Q)* - the following constraints are used:
  - (1) $\omega > 0$
  - (2) $0 <= d <= 1$
  - (3) $0 <= \Phi <= (1-d)/2$
  - (3) $0 <= \beta <= d + \Phi$

The notations are the same with the ones used in section 3.2.1.

For each of the chosen specification, Engle and Sheppard's (2001) test for constant correlation is also considered. More information about this test are provided in *Appendix 1*. The test is implemented in the present study using 5 lags.

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[12] Engle and Sheppard (2001) shows that the DCC(1,1) - MVGARCH model demonstrates very strong performance especially considering the ease of implementation of the estimator.

For *Model 1* the popular GARCH(1,1) and GARCH(2,1) specifications are chosen in more than 75% of the cases.

For *Model 2* with only one exception, UAM stock, FIGARCH(1, d, 0) model is selected for modeling the conditional variances. For UAM stock FIGARCH (1, d, 1) is chosen.

The selected GARCH model specification for modeling conditional variances for each of the stocks is reported in *Table 1* from *Appendix 4*. The results of Engle and Sheppard's (2001) test for constant correlation are also provided (*Table 2* from *Appendix 4)*. The null of constant correlation, is rejected by the test in favor of a time varying correlation matrix for all the chosen specifications at the 10% significant level.

A possible explanation for the poor results provided by FIDCC model may be related to the initial conditions required to start up the recursions for the conditional variance function when estimating the FIGARCH model. More specifically, unlike the finite-lag representation for the classical GARCH(P,Q), the approximate maximum likelihood technique (QMLE) for FIGARCH(P,d,Q) necessitates the truncation of the infinite distributed lags. Since the fractional differencing parameter is designed to capture the long-memory features, truncating at too low a lag may destroy important long-run dependencies, as shown in Baillie, Bollerslev and Mikkelsen (1996) who fix the truncation lag at 1,000 after performing Monte Carlo simulations. The estimation considered here was conducted using weekly data, and not daily data as in Baillie, Bollerslev a Mikkelsen (1996) and other papers that raise the problem of the truncation lag (Caporin (2003), Chung (2001)) and the maximum number of available observations for each security is 472. So fixing the truncation lag at 1,000 is not possible and anyway is not a suitable choice since the data is weekly and not daily. The lag length was set using all available past data.

The descriptive statistics (mean and standard deviation) of the betas determined using the most suitable GARCH specification are provided in *Table 5* from *Appendix 4*.

5.1.2 Stochastic Volatility Conditional Betas

Stochastic volatility models represent the second technique from the class of volatility models used in this study to model time-varying betas.

Estimation for Model 3 and Model 4 is carried out in WinBUGS. The reasons for choosing this program have been already exposed in the section 3.2.2 of the paper. However, one drawback with this program is the fact that, due to the single move Gibbs sampler, convergence can be slow. Therefore, to achieve a satisfactory precision for parameter estimates, a large number of iterations are needed, increasing the computational cost.

The term *convergence* of an MCMC algorithm is referring to situations where the algorithm has reached its equilibrium and generates values from the desired target distribution. Generally it is unclear how much we must run an algorithm to obtain samples from the correct target distributions. However, a suitable large sample (e.g. 10,000 iterations) is considered to be an accurate approach (Gamerman and Lopes (2006)). Furthermore, there are several ways in WinBUGS to monitor the convergence of the algorithm (Ntzoufras (2009)):

- The simplest way is to monitor the *Monte Carlo error* since small values of this error will indicate that the quantity of interest was calculated with precision. The Monte Carlo error measures the variability of each estimate due to the simulation.
- Monitoring autocorrelations is also very useful since low or high values indicate fast or slow convergence, respectively.
- Another way is to monitor the plot of iterations: if all values are within a zone without strong periodicities and (especially) tendencies, then we can assume convergence.
- Another tactic is to run multiple chains with different starting points. When the lines of different chains mix or cross in trace then convergence is ensured.
- Finally, several statistical tests have been developed and used as convergence diagnostics. CODA and BOA software programs have been developed in order to implement such diagnostics to the output of BUGS and WinBUGS software.

In this paper, the first 3 ways of monitoring convergences are considered. In determining time-varying beta estimates, a number of 310,000 iterations for each stock are employed. To minimize the dependence of the choice of starting values, a burn-in-sample of 10,000 iterations that are discarded from the final sample is used. Then, every 30^{th} iteration of the following 300,000 iterations are stored (in order to control for autocorrelation). So, a number of approximately 10,000 values are used for determining the posterior summary estimates of the MCMC output: mean, standard deviation, Monte Carlo (MC) error, histograms etc.

For the two stochastic volatility models (Model 3 and Model 4), the value of deviance information criteria (DIC) is determined in order to establish which one of the two models fits better the data (*Table 3* from *Appendix 4*). As shown in section 3.2.2 of the paper, a smaller value of the criterion indicates a better-fitting model. With no exception, the second model (the return shocks modeled by a Student distribution) is chosen.

The conditional correlation parameters indicate persistent correlation patterns between the stocks and the market, with a posterior mean larger than 0.5 in all cases. The significance of the parameters in the correlation process indicates the importance of allowing for a dynamic correlation structure in the model specification.

The descriptive statistics (mean and standard deviation) of the betas determined using the 2 SV models are provided in *Table 5* from *Appendix 4*.

5.1.3 Kalman Filter based approaches

The Kalman Filter has been applied to the two proposed specifications according to which the state vector β_{it} is either modeled as a random walk (*Model 5*) or as a mean-reverting process (*Model 6*). Even though the mean-reverting model requires the estimation of two additional parameters, the AIC is generally smaller than for the simpler random walk specification. So, for most of the stocks the second Kalman Filter specification is preferred (Model 6).

Although according to Faff et al. (2000) the random walk gives the best characterization of the conditional beta with highest convergence rates and shortest time to converge, seven firms (CBC, COTR, EPT, SNO, SPCU, UAM, UZT) fail to converge to a unique solution when the random walk is chosen as the form of transition equation. This is indicative of a misspecification in the transition equation.

The parameter estimates are presented in *Table 4* from *Appendix 4*, along with the AIC value. In the mean-reverting model, the estimates for the speed can be clustered into three groups:

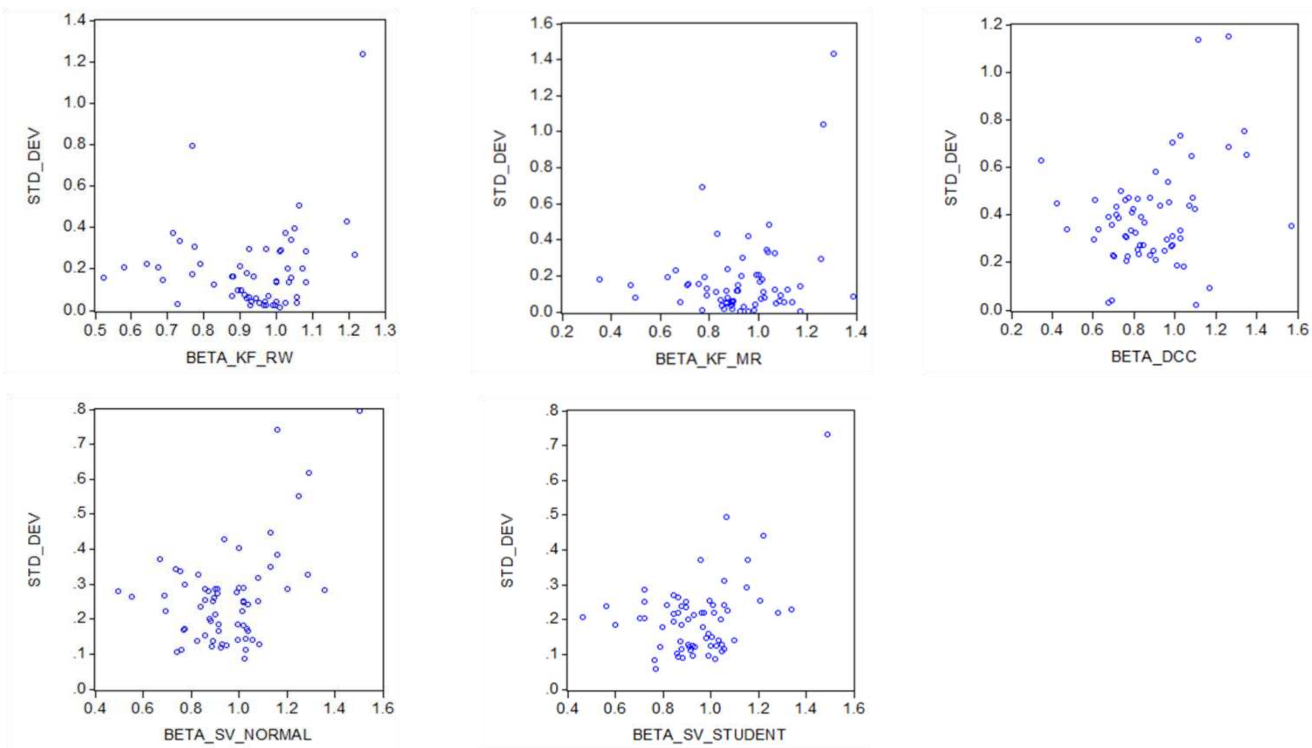
- Φ_i is close to unity: the resulting series of conditional betas become similar to the random walk series;
- Φ_i is around 0.5: the conditional betas return faster to their individual means;
- Φ_i is not statistically different from 0: the resulting beta series follow a random coefficient model.

The estimation is carried out in Eviews.

5.2 Comparison of Conditional Betas Estimates

All conditional betas series are summarized by their respective mean and standard deviation in *Table 5* from the *Appendix 4*. The GARCH based technique display the greatest variation, while the Kalman Filter based techniques the lowest one:

Figure 1: *The mean and the standard deviation of time-varying beta*



To determine which approach generates the relatively best measure of time-varying systematic risk, the different techniques are formally ranked based on their in-sample performance. Having forecast $\hat{r}_{it}$ using each of the conditional beta series (the excess return forecasts for security i is calculated as the product of conditional beta series estimated over the entire sample and the series of excess market return which is assumed to be known in advance), one may assess their accuracy using a measure of forecast error which compares the forecasts with the actual data. As is very possible that a large error will have a significant impact on the measure of herd behavior, the chosen measure for determining the in-sample performance is the root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(r_{it} - \hat{r}_{it})^2}{n}}$$

Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors, placing a heavier penalty on outliers than other measures (for example the mean absolute error).

The resulting RMSE for the different modeling techniques are reported in *Table 6* from *Appendix 4*. The RMSE is calculated only after the best specification for each of 3 different modeling techniques is determined based on information criteria: Akaike for Kalman Filter approaches and DCC GARCH models, DIC for SV models, respectively.

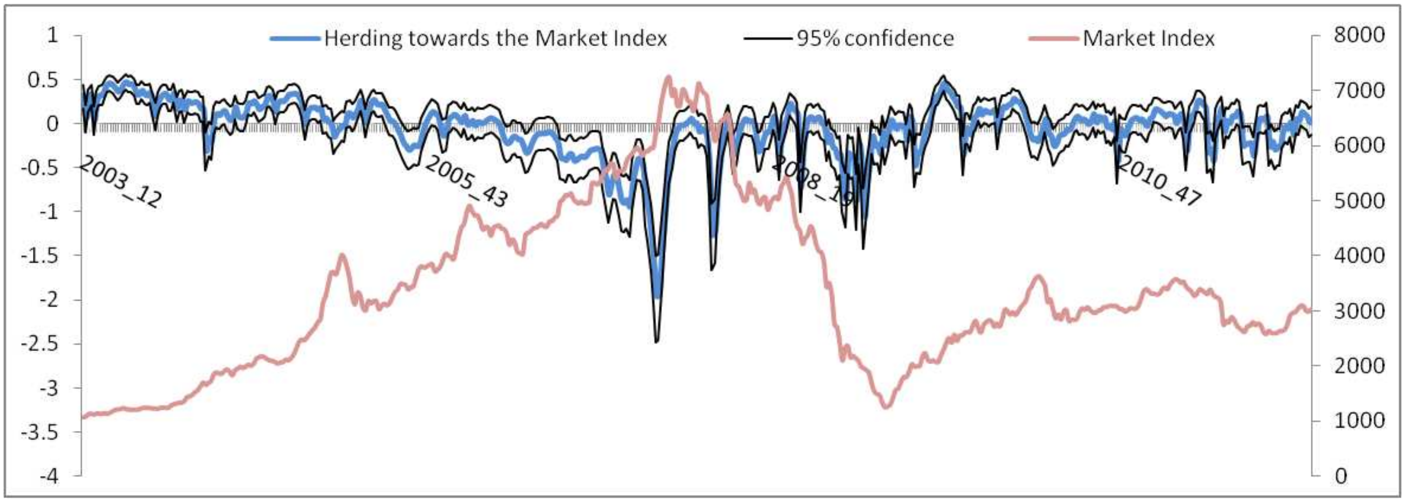
Within the class of volatility models, the SV approach with a t-student distribution clearly outperforms the GARCH model. Only in one case (RPH stock), the DCC GARCH model with a GARCH(0,1) specification for modeling conditional variances performs better in terms of RMSE. Kalman Filter technique also performs well in terms of RMSE, and in almost half of the cases considered ranks first, outperforming the SV model.

5.3 Results for the herding measure

As a final step, the Kalman filter is employed to estimate the herding indicator (H_{mt}) using Eq. 6 and Eq. 7 from section 3.1. The main results are reported in the first column of *Table 7* from *Appendix 4*. H_{mt} is highly persistent with ϕ_m large and significant. More important the estimate of σ_{mn} (the standard deviation of η_{mn}) is highly significant and thus we can conclude that there is herding towards the market portfolio.

The below figure shows the evolution of the herding measure $h_{mt} = 1 - \exp(H_{mt})$ along with the 95% confidence interval (primary axis). For a more comprehensive view, the evolution of the market index BETC is also plotted (secondary axis).

Figure 2: *The evolution of the herding measure (h_{mt})*



The largest value of h_{mt} is far less than one which indicates that there was never an extreme degree of herding towards the market portfolio during the sample period considered. The figure shows several cycles of herding and adverse herding towards the market portfolio as h_{mt} has moved around its long term average of zero over the last 9 years since 2003:

- The Romanian market was on an upward trend during the first part of the analysis (years 2003 and 2004). In this period the herding measure is significantly different from zero within a 95% confidence interval. As shown by Wang (2008), investors in newly established or emerging markets, with very little experience regarding stock exchange transactions, find it difficult or expensive to gather information in order to conduct fundamental analysis. Instead, observing and imitating other investors' decision or the market index is relative cheap and easy.
- In 2005 and 2006 the BET-C evolution is quite similar. The upward trend continued, but there was two suddenly falls in the index value, both in the first quarter of the year. The two periods coincide with a small decline in herd behavior, but only the second fall convinced the investors to stop herding.
- Starting with the second quarter of 2006 the market shows an adverse herding behavior. This is in place with the findings of Hwang and Salmon (2004) for the US and South Korea markets: herding behavior turned before the market itself turned. However what is interesting in the Romania case is the fact that the herd behavior turned with more than 1

year before the market.[13] As shown in section 3.1 adverse herding must exist if herding exists since there must be some systematic adjustments back towards the equilibrium CAPM relation from mispricing both above and below equilibrium. However there are 2 periods with extreme adverse herd behavior: July 2007 and November 2007. The first period coincides with is considered to be the beginning of the worldwide financial crisis: Bear Stearns liquidates two hedge funds that invested in various types of mortgage-backed securities. The second one is a result of a period of high volatility of the market index, with November being the month from which a downward trend began.

- From 2007 the market doesn't show important movements in herding. During market stress investors turn to fundamentals rather than overall market movements. However there are some periods of interest. The first one is the 4th quarter of 2008 – 1st quarter of 2009: before the BET-C index reached its minimum value[14], the market experienced once again a period of adverse herding, with betas moving away from their long run average levels. The next ones are June-July 2009 and December 2009 when herding behavior is again significantly different from zero within a 95% confidence interval. However, this is only for a short period of time; the important correction suffered by the index in 2008 and the beginning of 2009 made the investors more risk-adverse and less willing to follow the market movements.

5.4 Robustness of the herding measure

The main assumption done for detecting and measuring herding is regarding $Std_c(\beta_{mt}^b)$ that is expected to change over time in response to the level of herding in the market. However, as shown by Hwang and Salmon (2004, 2008), an important question remains as to whether the herd behavior extracted from $Std_c(\beta_{mt}^b)$ is robust in the presence of variables reflecting the state of the market, in particular the degree of market volatility or the market returns, as well as potentially variables reflecting macroeconomic fundamentals.

To check if changes in $Std_c(\beta_{mt}^b)$ could be explained by changes in these fundamentals rather than herding the following two alternatives models are considered:

[13] According to Hwang and Salmon (2004), in the US case, herding started to fall with 4 months before the Asian crisis of 1997 and Russian crisis of 1998. This same pattern is repeated for the market fall in September 2000, except that herding started to fall some 9 months beforehand in this case.
[14] On the 02/25/2009 BET-C reached its minimum value: 1,887.14 points.

Alternative model 1

$$\begin{cases} \log\left[Std_c\left(\beta_{mt}^b\right)\right] = \mu_m + H_{mt} + c_{m1}log\sigma_{mt} + c_{m2}r_{mt} + \upsilon_{mt}\,,\ \upsilon_{mt} \sim iid(0,\sigma_{m\upsilon}^2) \\ H_{mt} = \phi_m H_{mt-1} + \eta_{mt},\ \eta_{mt} \sim iid(0,\sigma_{m\eta}^2) \end{cases}$$

Alternative model 2

$$\begin{cases} \log\left[Std_c\left(\beta_{imt}^b\right)\right] = \mu_m + H_{mt} + c_{m1}log\sigma_{mt} + c_{m2}r_{mt} + c_{m3}DR_t + c_{m4}Div_t + \upsilon_{mt}\,,\ \upsilon_{mt} \sim iid(0,\sigma_{m\upsilon}^2) \\ H_{mt} = \phi_m H_{mt-1} + \eta_{mt},\ \eta_{mt} \sim iid(0,\sigma_{m\eta}^2) \end{cases}$$

where $log\sigma_{mt}$ = market log-volatility[15]

r_{mt} = market return

DR_t = average deposit interest rate for population

Div_t = average dividend ratio.

The results of the estimation are reported in the second and third column of *Table 7* from *Appendix 4*. Only the market return (Alternative model 1) and the market return and the dividend ratio (Alternative model 2) are found to be significant. $\sigma_{m\eta}$ is still significantly different from zero in both the alternatives models, although the degree of persistence is lower.

So with or without these independent variables, we find highly persistent herd behavior in the market.

6. Conclusions

Herding is widely believed to be an important element of behavior in financial markets and particularly when the market is in stress, such as during the current worldwide financial crisis. The study of the herd behavior is important due to its implications for stock market efficiency.

In this paper the approach of Hwang and Salmon (2004, 2008) is proposed for measuring and testing herding. This measure conditions automatically on fundamentals and also accounts for the influence of time series volatility.

In order to determine the measure of beta herding, explicit modeling of time-varying systematic risk for all the assets in the market is needed. The present paper has realized a

[15] Determined as in Schwert (1989).

comparison between three different modeling techniques: two bivariate GARCH models (DCC and FIDCC GARCH), two Kalman filter based approaches (beta develops as a random walk process and beta develops as a mean-reverting process, respectively) and two bivariate stochastic volatility models (with a normal and a Student distribution, respectively, for the stock return shocks). Within the class of volatility models, the stochastic volatility approach with a t-student distribution clearly outperforms the GARCH model in terms of in-sample forecasting accuracy. Only in one case (RPH stock), the DCC GARCH model performs better in terms of RMSE. Kalman Filter technique also performs well in terms of RMSE, and in almost half of the cases considered ranks first, outperforming the stochastic volatility models.

Through the estimated values obtained from a state space model, the evolution of the herding measure is examined, especially the pattern around the beginning of the subprime crisis. Herding towards the market shows significant movements and persistence independently from and given market conditions (the market volatility and the market return – Alternative model 1) and macro factors (average deposit interest rate for population and average dividend ratio – Alternative model 2). Contrary to the common belief, the crisis has contributed to a reduction in herding and is clearly identified as a turning point in herding behavior.

This study has focused entirely on one emerging European country (Romania). An extension of the research to other emerging European countries (Poland, Czech Republic, Hungary) can contribute to a better understanding of the phenomenon. Also, this paper does not take into account the herding behavior towards other factors like size and book to market value (Fama-French factors). It would be interesting to incorporate these in the econometric formulation to study the behavior of agents in the markets.

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APPENDIX

Appendix 1: *Engle and Sheppard's (2001) test for constant correlation*

Given the equations of the DCC GARCH model (section 3.2.1), Engle and Sheppard (2001) propose the following test:

$$H_0: R_t = \bar{R} \ \forall \ \mathrm{t} \in \mathrm{T}$$

against

$$H_1: vech^u(R_t) = vech^u(\bar{R}) + \beta_1 vech^u(R_{t-1}) + \beta_2 vech^u(R_{t-2}) + \ldots + \beta_p vech^u(R_{t-s}),$$

where $vech^u$ is a modified $vech$ which only selects elements above the diagonal.

The standardized residuals from the estimation of the first stage $(\varepsilon_t = D_t^{-1} u_t)$ are used. These residuals are standardized again by the symmetric square root decomposition of the constant correlation $\bar{R}$:

$$v_t = \varepsilon_t' \bar{R}^{-1/2}.$$

Let $Y_t = vech^u[v_t v_t' - I_k]$. Under the null of constant correlation, the residuals v_t should be i.i.d., and the constant and the lagged parameters in the vector autoregression $Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_s Y_{t-s} + \eta_t$ should be zero. The test statistic is thus given by:

$$\frac{\hat{\delta} X' X \hat{\delta}'}{\hat{\delta}^2} \sim \chi^2 \ (s+1)$$

where $\hat{\delta}$ are the estimated regression parameters and X is a matrix consisting of the regressors.

Appendix 2: *The data* (*Statistical properties of the weekly stock returns)*

	Mean	Std. Dev.	Skewness	Kurtosis	Jargue-Bera
ALR	-0.0035	0.0665	-0.6330	8.6171	355.0380
ALT	-0.0048	0.0646	0.3332	9.2261	480.3121
ALU	-0.0079	0.0672	-0.8309	9.8184	523.3005
AMO	-0.0003	0.0824	0.6049	8.1301	546.3757
APC	0.0044	0.0588	1.2343	8.5367	575.7493
ARS	0.0068	0.0512	0.7684	4.7888	59.0895
ARTE	0.0035	0.0712	0.7581	8.5717	655.7389
ART	0.0012	0.0693	0.1245	8.6725	441.9518
ATB	0.0032	0.0479	-1.0084	12.3131	1,785.7360
AZO	0.0073	0.0879	1.0917	12.5392	1,209.0130
ARM	-0.0011	0.0599	0.5821	7.4184	255.7476
BIO	0.0004	0.0686	-0.0527	8.5389	343.9900
BCC	-0.0028	0.0492	-0.2422	14.2254	1,967.3090
BRD	-0.0003	0.0495	-0.7785	8.1673	415.0264
BRK	-0.0074	0.0923	-0.3471	4.9850	23.4019
BRM	-0.0005	0.0589	-0.0138	6.7567	209.3489
CBC	0.0086	0.0763	0.8509	8.0325	316.3198
CEON	-0.0113	0.0667	-0.2118	10.9441	495.7968
CGC	-0.0141	0.0905	-2.1093	11.1084	428.1591
CMF	0.0074	0.0573	2.1043	12.4436	766.0748
CMP	0.0032	0.0699	-0.7577	14.2747	2,545.1800
COFI	-0.0063	0.1231	0.2449	10.8717	677.4001
COMI	-0.0060	0.0870	0.1873	8.2711	281.5789
COTR	-0.0002	0.0940	1.0386	9.9931	558.7952
DAFR	-0.0107	0.0973	-2.4569	23.2908	4,885.2810
ECT	0.0003	0.0602	0.9307	7.8526	509.8606
EFO	0.0011	0.0679	2.1691	16.8792	3,365.6080
ELGS	0.0135	0.0883	0.8724	10.1999	384.1743
ELMA	0.0012	0.0709	1.3541	14.5446	1,224.5030
ENP	-0.0052	0.0782	0.9357	6.5495	67.0905
EPT	-0.0012	0.0871	2.1861	21.2554	6,390.0250
EXC	0.0075	0.0534	1.9641	14.7339	1,020.7720
FLA	-0.0136	0.0650	-0.6508	15.0125	1,374.7780
IMP	0.0064	0.0829	0.2242	16.7550	2,359.6230
MEF	-0.0016	0.0638	0.6090	3.8345	23.4338
MJM	0.0075	0.0616	1.0934	8.4229	183.7729
MPN	-0.0007	0.0602	0.9714	8.4319	293.9791
OIL	0.0019	0.0629	0.7198	13.0976	2,045.9810
OLT	0.0161	0.0706	1.2204	6.3439	74.9847

PCL	0.0069	0.0539	0.1832	5.8955	107.1880
PEI	-0.0011	0.0617	1.0128	9.1069	814.1324
PPL	0.0119	0.0697	2.3576	13.7029	815.0143
PREH	-0.0008	0.0964	1.7694	15.6717	2,048.2960
PTR	0.0075	0.0702	1.5938	16.6975	3,889.7000
RMAH	0.0006	0.1242	-4.6789	62.6578	3,657.0500
ROCE	-0.0096	0.0589	-0.9627	9.5735	471.1408
RPH	0.0144	0.0851	7.0012	70.7887	2,946.7800
RRC	-0.0005	0.0606	1.0212	10.0365	914.8586
RTRA	0.0032	0.0492	0.3181	5.4374	39.6620
SCD	0.0027	0.0471	0.4093	12.9919	1,976.6570
SNO	-0.0017	0.0597	0.8755	9.9088	609.5729
SNP	0.0026	0.0467	-0.4455	7.4414	403.5552
SOCP	0.0007	0.0556	1.0178	9.1029	563.9257
SPCU	0.0039	0.0880	1.4043	10.2112	776.0631
SRT	-0.0068	0.0535	0.1252	9.1370	507.7194
STZ	0.0055	0.0756	0.5549	8.6505	449.0428
TBM	-0.0093	0.0609	0.3101	6.9597	201.4675
TEL	-0.0013	0.0459	-0.2410	5.3302	67.7116
TLV	0.0074	0.0449	3.7090	25.7996	6,922.1190
TUFE	-0.0082	0.0560	-0.8505	7.5219	251.8906
UAM	0.0043	0.0725	0.9075	6.5114	201.1596
UZT	0.0021	0.0923	-1.0325	10.1936	282.3920
VESY	-0.0027	0.0649	0.3716	8.2218	381.3693
VNC	-0.0017	0.0482	-0.0275	5.9273	123.2204
ZIM	0.0055	0.0583	0.6617	4.8807	59.5841

Source: www.bvb.ro
www.kmarket.ro
www.tranzactiibursiere.ro

Appendix 3: ***Means and standard deviations of the prior distributions for the parameters in the SV models***

	γ_1	γ_2	γ_{11}	γ_{12}	γ_{21}	γ_{22}	$\sigma_{\eta 1}$	$\sigma_{\eta 2}$	δ_0	δ_1	σ_p	v
Prior mean	0	0	0.86	0	0	0.86	0.12	0.12	0.7	0.86	0.12	8
Prior SD	5	5	0.11	3.3	3.3	0.11	0.05	0.05	3.3	0.11	0.05	4

Appendix 4: *Estimation results*

Table 1: *GARCH specification chosen by the AIC for modeling conditional variances in DCC(1,1) GARCH model*

For every asset, the second series considered in the bivariate DCC GARCH specification is the excess return of the market index BET-C.

Specification	Stock
GARCH(1,0)	RTRA, BRK, COMI, ELGS, IMP, SOCP, STZ, TLV
GARCH(2,0)	-
GARCH(0,1)	ART, CBC, CGC, RMAH, RPH
GARCH(1,1)	ALR, ALU, ARTE, ARM, BRD, CEON, CMF, EFO, FLA, MEF, MJM, MPN, OLT, PEI, PPL, RRC, SNO, SRT, TBM, VESY, VNC, ZIM
GARCH(2,1)	AMO, APC, ARS, ATB, AZO, BIO, BCC, BRM, CMP, COFI, DAFR, ECT, EPT, EXC, OIL, PCL, PREH, ROCE, SCD, SNP, SPCU, TEL, TUFE, UAM
GARCH(0,2)	ELMA, ENP
GARCH(1,2)	ALT, COTR, PTR
GARCH(2,2)	-
FIGARCH(0,d,1)	-
FIGARCH(1,d,0)	-
FIGARCH(1,d,1)	-

Table 2: *Results for Engle and Sheppard's test for constant correlation*

For every asset, the second series considered in the bivariate DCC GARCH specification is the excess return of the market index BET-C. The GARCH specification used to model the conditional variances was chosen using the AIC and it is specified in Tabel 1.

Symbol	p-value	Symbol	p-value	Symbol	p-value	Symbol	p-value
ALR	0.015	CEON	0.0132	IMP	0.0009	SCD	0.0004
ALT	0.0512	CGC	0.0345	MEF	0.0163	SNO	0.0001
ALU	0.0072	CMF	0.0812	MJM	0.0001	SNP	0.0003
AMO	0.0021	CMP	0.0010	MPN	0.0033	SOCP	0.0000
APC	0.0056	COFI	0.0100	OIL	0.0003	SPCU	0.0001
ARS	0.0502	COMI	0.0005	OLT	0.0004	SRT	0.0004
ARTE	0.0007	COTR	0.0387	PCL	0.1165	STZ	0.0040
ART	0.0026	DAFR	0.0227	PEI	0.0002	TBM	0.0102
ATB	0.0012	ECT	0.0017	PPL	0.0015	TEL	0.0023
AZO	0.0582	EFO	0.0309	PREH	0.0162	TLV	0.0106
ARM	0.0137	ELGS	0.0008	PTR	0.0423	TUFE	0.0058
BIO	0.0281	ELMA	0.0061	RMAH	0.0399	UAM	0.0041
BCC	0.0246	ENP	0.1024	ROCE	0.0001	UZT	0.0561

BRD	0.0065	EPT	0.0193	RPH	0.096	VESY	0.0042
BRK	0.0009	EXC	0.0952	RRC	0.0044	VNC	0.0174
BRM	0.0007	FLA	0.0363	RTRA	0.0285	ZIM	0.0723
CBC	0.0076						

Table 3: *The values of deviance information criteria (DIC) for the 2 stochastic volatilities models (Model 3 and Model 4)*

Symbol	Model 3 (Normal distribution)	Model 4 (Student distribution)	Symbol	Model 3 (Normal distribution)	Model 4 (Student distribution)	Symbol	Model 3 (Normal distribution)	Model 4 (Student distribution)	Symbol	Model 3 (Normal distribution)	Model 4 (Student distribution)
ALR	-1,797.50	-2,074.34	CEON	-1,220.46	-1,429.59	IMP	-2,114.47	-2,406.52	SCD	-3,626.79	-4,131.01
ALT	-2,052.00	-2,369.47	CGC	-766.58	-909.44	MEF	-1,668.30	-1,943.28	SNO	-1,963.72	-2,284.48
ALU	-1,839.28	-2,108.06	CMF	-1,245.93	-1,431.28	MJM	-813.99	-955.05	SNP	-3,852.14	-4,370.05
AMO	-3,105.48	-3,603.23	CMP	-3,365.53	-3,869.65	MPN	-1,336.34	-1,569.34	SOCP	-2,288.72	-2,893.50
APC	-2,509.12	-2,940.91	COFI	-1,535.08	-1,813.15	OIL	-3,360.49	-3,855.27	SPCU	-1,997.00	-2,344.99
ARS	-1,801.95	-2,082.56	COMI	-1,557.52	-1,799.38	OLT	-1,960.33	-2,307.48	SRT	-2,186.10	-2,547.69
ARTE	-3,114.70	-3,641.35	COTR	-1,476.80	-1,741.29	PCL	-2,052.18	-2,383.30	STZ	-2,059.67	-2,400.89
ART	-2,264.74	-2,619.25	DAFR	-1,847.57	-2,117.55	PEI	-3,230.58	-3,753.95	TBM	-2,174.84	-2,500.93
ATB	-3,925.14	-4,158.81	ECT	-3,014.26	-3,509.79	PPL	-1,061.14	-1,214.07	TEL	-2,224.24	-2,552.87
AZO	-2,058.29	-2,359.86	EFO	-2,580.56	-2,979.36	PREH	-1,678.64	-1,960.45	TLV	-2,411.92	-2,688.00
ARM	-1,979.04	-2,286.89	ELGS	-991.21	-1,176.16	PTR	-3,347.09	-3,842.65	TUFE	-1,814.91	-2,094.29
BIO	-2,021.62	-2,297.57	ELMA	-1,542.99	-1,775.89	RMAH	-1,648.94	-1,909.84	UAM	-1,979.43	-2,306.83
BCC	-2,861.53	-3,247.79	ENP	-567.17	-663.15	ROCE	-1,521.05	-1,792.47	UZT	-721.47	-850.69
BRD	-2,928.66	-3,294.26	EPT	-3,084.32	-3,610.89	RPH	-1,082.48	-1,215.73	VESY	-2,140.03	-2,514.43
BRK	-1,203.24	-1,381.70	EXC	-1,254.37	-1,413.47	RRC	-2,968.09	-3,414.96	VNC	-2,609.43	-2,988.17
BRM	-2,467.41	-2,851.99	FLA	-1,607.89	-1,842.64	RTRA	-1,056.79	-1,237.69	ZIM	-1,808.26	-2,097.62
CBC	-1,652.30	-1,970.60									

Table 4*: Parameters' estimates for Kalman Filter based models*

This table reports the estimated parameters for the two Kalman-Filter based models, along with the value for AIC.
* means that the estimated parameter is not significant at the 10% level.

	RW			MR				
	σ	σ_η	AIC	σ	σ_η	$\bar{\beta}$	ϕ	AIC
ALR	0.0022	0.0269	-3.0957	0.0017	0.2413	1.0317	0.6036	-3.1827
ALT	0.0025	0.0026	-3.1070	0.0023	0.0661	1.0389	0.5084*	-3.1290
ALU	0.0020	0.0613	-3.1120	0.0011	0.6024	1.0449	0.0658	-3.3110
APC	0.0030	0.0002	-2.3825	0.0029	0.0123	0.8485	0.8467	-2.3767
ARS	0.0026	0.0015	-2.9435	0.0022	0.1648	0.8886	0.0110*	-2.9468
ARTE	0.0043	0.0005	-2.5777	0.0044	0.0000*	1.0951	0.9965	-2.5705
ART	0.0037	0.0016	-2.7328	0.0025	0.5179	1.0380	0.1598*	-2.8187

ATB	0.0011	0.0072	-3.8605	0.0010	0.0546*	0.9197	0.5923	-3.9176
AZO	0.0043	0.2341	-2.2989	0.0032	1.0117	0.7665	0.5282	-2.4225
ARM	0.0033	0.0000	-2.8684	0.0024	0.3007	0.8747	0.0677*	-2.9144
BIO	0.0020	0.0010	-3.3233	0.0018	0.0556	1.0911	0.5454	-3.3392
BCC	0.0014	0.0211	-3.5564	0.0012	0.1533	0.9340	0.4488	-3.6532
BRD	0.0005	0.0095	-4.5786	0.0004	0.0540	1.0676	0.4964	-4.6458
BRK	0.0045	0.0010	-2.5763	0.0042	0.0000*	1.4589	0.9675	-2.5874
BRM	0.0029	0.0002	-2.9853	0.0025	0.1500	0.8691	0.0410*	-3.0027
CBC	FTC^a	FTC^a	FTC^a	-2.3463	0.0105*	0.7958	0.9265	-2.3407
CEON	0.0030	0.0308	-2.7913	0.0028	0.1208	0.9930	0.6722	-2.8318
CGC	0.0065	0.0268	-2.0885	0.0070	0.0000*	1.1706	-0.6388*	-2.0551
CMP	0.0028	0.0078	-2.9734	0.0024	0.2271	1.0184	0.1869*	-3.0233
COFI	0.0118	0.0126	-1.5354	0.0110	0.1807	1.2658	0.7970	-1.5483
COMI	0.0037	0.0288	-2.6112	0.0034	0.1430	1.0645	0.7782	-2.6413
COTR	FTC^a	FTC^a	FTC^a	0.0077	0.0000*	0.9848	-0.8573*	-1.9909
DAFR	0.0059	0.0093	-2.2200	0.0031	0.6627	1.3085	-0.9111	-2.3884
ECT	0.0031	0.0000	-2.9217	0.0030	0.0268	0.8952	-0.6773*	-2.9244
EFO	0.0042	0.0000	-2.6281	0.0042	0.0000*	2.9143	1.0004	-2.6231
ELGS	0.0131	0.0004	-1.4679	0.0130	0.0000*	-0.0080*	0.9956	-1.4545
ELMA	0.0046	0.0000	-2.7864	0.0035	0.0000*	0.9271	-0.8880*	-2.7759
ENP	0.0055	0.0002	-2.3156	0.0053	0.0141*	0.8908	0.7210	-2.2914
EPT	1.0000	1.0000	-2.2598	0.0058	0.0623*	1.1368	0.4338	-2.2606
EXC	0.0028	0.0018	-2.9986	0.0028	0.0000*	0.3097*	0.9780	-3.0075
FLA	0.0036	0.0288	-2.6509	0.0024	0.6436	0.9600	0.1097*	-2.7375
MEF	0.0040	0.0000*	-2.6702	0.0040	0.0000*	2.2701	1.0009	-2.6605
MPN	0.0037	0.0013	-2.7150	0.0037	0.0012	0.6666	0.9510	-2.7110
OIL	0.0026	0.0000	-3.1062	0.0024	0.0865	1.0272	0.0230*	-3.1146
OLT	0.0037	0.0000	-1.9631	0.0037	0.0000*	1.5292	0.9948	-1.9547
PEI	0.0034	0.0001	-2.8312	0.0034	0.0000*	2.3926	1.0003	-2.8271
PPL	0.0040	0.0001*	-2.6469	0.0037	0.1059	0.9966	0.7679	-2.6307
PTR	0.0035	0.0136	-2.7282	0.0027	0.3743	0.9385	0.4041	-2.8049
RMAH	0.0110	0.1938	-1.4682	0.0078	1.9095	1.3012	0.5992	-1.5333
ROCE	0.0030	0.0002	-2.9369	0.0028	0.0384	0.8714	0.4355	-2.9509
RRC	0.0024	0.0029	-3.1402	0.0022	0.0596	1.0134	0.7772	-3.1484
RTRA	0.0010	0.0016	-3.9809	0.0009	0.0563	0.5011	0.2562*	-4.0128
SCD	0.0014	0.0058	-3.6641	0.0013	0.0155	0.7786	0.9264	-3.6742
SNO	FTC^a	FTC^a	FTC^a	0.0028	0.0015*	0.8924	0.9467	-3.0169
SNP	0.0007	0.0032	-4.3440	0.0006	0.0502	1.0235	0.5038	-4.4112
SOCP	0.0027	0.0001	-3.0714	0.0026	0.0130*	0.8503	0.7369	-3.0723
SPCU	FTC^a	FTC^a	FTC^a	0.0080	0.0000*	0.8444	-0.7923*	-2.2494
SRT	0.0025	0.0011	-3.1308	0.0025	0.0005*	0.8954	0.9342	-3.1124
STZ	0.0049	0.0000	-2.4605	0.0043	0.1590	0.9165	0.4413	-2.4730
TBM	0.0022	0.0000	-3.2512	0.0019	0.1193	1.1196	0.3048*	-3.2691

TEL	0.0009	0.0000*	-4.1450	0.0009	0.0020*	0.9614	-0.5478*	-4.1405
TLV	0.0018	0.0003	-3.4436	0.0017	0.0406	0.8266	0.7180	-3.4513
TUFE	0.0019	0.0017	-3.3901	0.0018	0.0112	1.0124	0.8426	-3.3966
UAM	FTC^a	FTC^a	FTC^a	0.0043	0.0000*	0.8699	0.9863	-2.5788
VESY	0.0041	0.0001	-2.6358	0.0041	0.0000*	0.7672	0.8994	-2.6392
VNC	0.0015	0.0000*	-3.6319	0.0013	0.1090	0.9155	0.2150*	-3.6668
ZIM	0.0032	0.0008	-2.8637	0.0032	0.0000*	3.7446	1.0010	-2.8671

[a] Failed to converge

Table 5: *Properties of the time-varying beta estimates*

The mean of the time-varying beta estimates is presented for each security. In the brackets the standard deviation is shown.

For the DCC Garch model, only the results obtained through the most suitable GARCH specification for the conditional variances (chosen using AIC) are shown because of the space limitation (11 specifications were tested).

Observation: First two months' data for each security were deleted in order to eliminate the effect of IPO (Initial Public Offerings) underpricing.

Symbol	KF RW	KF MR	DCC GARCH	SV normal distribution	SV t-student distribution
ALR	1.0422	1.0345	0.9904	1.0367	0.9990
	(0.3397)	(0.3468)	(0.3089)	(0.1651)	(0.1249)
ALT	1.0303	0.8327	0.8327	1.0380	1.0434
	(0.2008)	(0.4308)	(0.39)	(0.2432)	(0.2013)
ALU	1.0494	1.0431	1.0254	1.0168	1.0064
	(0.3936)	(0.4818)	(0.3)	(0.1824)	(0.1497)
AMO	1.0015	1.0861	0.8199	0.9379	0.9579
	(0.1341)	(0.0624)	(0.4679)	(0.43)	(0.3721)
APC	0.9027	0.8468	0.7926	0.8814	0.8737
	(0.0973)	(0.0673)	(0.4114)	(0.194)	(0.1375)
ARS	0.9193	0.8624	0.7641	0.8989	0.9295
	(0.0581)	(0.0151)	(0.3081)	(0.2142)	(0.2135)
ARTE	0.8821	0.9867	0.7379	0.8731	0.8617
	(0.1655)	(0.041)	(0.4992)	(0.2797)	(0.2639)
ART	1.0405	1.0379	1.0698	1.0789	1.0698
	(0.1554)	(0.3343)	(0.4367)	(0.2504)	(0.226)
ATB	0.8997	0.9189	0.8761	0.8865	0.8840
	(0.2103)	(0.1185)	(0.2298)	(0.1214)	(0.0894)
AZO	0.7670	0.7723	0.7584	0.9110	0.9056
	(0.7931)	(0.6906)	(0.4628)	(0.2851)	(0.2004)
ARM	0.7273	0.8734	0.7606	0.8276	0.8608
	(0.0287)	(0.2342)	(0.2086)	(0.1377)	(0.1029)
BIO	1.0812	1.0921	0.9739	1.0180	1.0142
	(0.1337)	(0.0944)	(0.4549)	(0.2486)	(0.2204)

BCC	0.9253	0.9340	0.8478	0.9156	0.9090
	(0.2943)	(0.2003)	(0.2704)	(0.1662)	(0.1226)
BRD	1.0739	1.0681	1.0444	1.0543	1.0465
	(0.2017)	(0.1209)	(0.1832)	(0.1405)	(0.1267)
BRK	1.0562	1.3886	1.5718	1.3561	1.3376
	(0.0354)	(0.0874)	(0.3543)	(0.2836)	(0.2298)
BRM	0.9129	0.8686	0.6755	0.7680	0.7905
	(0.076)	(0.1152)	(0.3922)	(0.1694)	(0.1223)
CBC	FTC[a]	0.7916	0.6908	0.7563	0.7232
		(0.091)	(0.3586)	(0.3382)	(0.2036)
CEON	1.0264	1.0009	0.8297	1.0292	1.0455
	(0.3744)	(0.206)	(0.2742)	(0.1449)	(0.1086)
CGC	1.0815	1.1706	1.2624	1.1334	1.0227
	(0.2874)	(0.0003)	(0.6846)	(0.3487)	(0.1243)
CMF	0.6737	0.7159	(0.4216)	0.5550	0.5604
	(0.2085)	(0.157)	(0.4471)	(0.2646)	(0.2386)
CMP	1.0106	1.0183	0.9700	1.0023	0.9962
	(0.2874)	(0.183)	(0.4506)	(0.2878)	(0.2545)
COFI	1.1951	1.2586	1.2615	1.5054	1.4908
	(0.4275)	(0.2947)	(1.1517)	(0.7939)	(0.7325)
COMI	1.0617	1.0694	1.1008	1.1581	1.1527
	(0.5067)	(0.3243)	(0.0205)	(0.3849)	(0.2922)
COTR	FTC[a]	0.9850	0.7861	1.0166	0.9682
		(0.011)	(0.3362)	(0.2523)	(0.1779)
DAFR	1.2170	1.3071	1.3384	1.2885	1.2829
	(0.2671)	1.4303	0.7522	(0.3273)	(0.2212)
ECT	0.9431	0.8952	0.7677	0.8579	0.8766
	(0.0586)	(0.0549)	(0.225)	(0.153)	(0.1154)
EFO	0.9526	0.8935	0.7120	0.8596	0.8449
	(0.0344)	(0.06)	(0.4023)	(0.2561)	(0.2155)
ELGS	0.9798	0.7115	1.1003	1.1333	1.0559
	(0.0676)	(0.1475)	(0.4235)	(0.448)	(0.312)
ELMA	0.9721	0.9270	0.9038	0.8779	0.8652
	(0.0244)	(0.0052)	(0.5787)	(0.2019)	(0.0941)
ENP	1.0010	0.8907	0.8795	0.9952	0.9887
	(0.0415)	(0.0372)	(0.4697)	(0.1392)	(0.0971)
EPT	FTC[a]	1.1366	1.0824	1.2508	1.2202
		(0.051)	(0.6467)	(0.5506)	(0.4423)
EXC	0.6442	(0.4785)	(0.4743)	(0.4945)	(0.4635)
	(0.2228)	(0.1509)	(0.3398)	(0.2784)	(0.2066)
FLA	0.7158	0.9617	0.6061	0.6944	0.7055
	(0.3749)	(0.4188)	(0.2962)	(0.2243)	(0.2048)
IMP	0.7760	1.1699	1.1712	0.8316	0.8799
	(0.3053)	(0.1422)	(0.0903)	(0.3271)	(0.2373)

MEF	0.9958	0.8773	0.7266	0.9248	0.9343
	(0.0276)	(0.0771)	(0.3863)	(0.1174)	(0.123)
MJM	0.9380	0.7908	0.7753	0.8410	0.8457
	(0.161)	(0.128)	(0.471)	(0.2343)	(0.1934)
MPN	0.7678	0.6845	0.6997	0.8588	0.8466
	(0.1716)	(0.0559)	(0.2268)	(0.2856)	(0.2688)
OIL	1.0092	1.0267	0.9666	1.0132	0.9829
	(0.0142)	(0.0762)	(0.5363)	(0.2243)	(0.1486)
OLT	1.0236	1.1096	1.1096	1.2094	1.1814
	(0.0220)	(0.0607)	(0.0607)	(0.3989)	(0.3365)
PCL	0.8793	0.7580	0.7593	0.7734	0.7999
	(0.1633)	(0.1571)	(0.3127)	(0.1728)	(0.1794)
PEI	0.9318	0.8989	0.7154	0.9174	0.9134
	(0.0388)	(0.0572)	(0.4325)	(0.1837)	(0.1138)
PPL	1.0256	0.9924	1.0287	0.9998	0.9640
	(0.0371)	(0.2037)	(0.7329)	(0.4037)	(0.2182)
PREH	1.0084	0.9416	0.9416	1.1224	1.1231
	(0.0137)	(0.0318)	(0.0318)	(0.3252)	(0.2370)
PTR	0.9732	0.9380	1.0289	1.0211	1.0076
	(0.2946)	(0.3016)	(0.3363)	(0.2886)	(0.2431)
RMAH	1.2391	1.2645	1.1119	1.1602	1.0664
	(1.2346)	(1.0396)	(1.1364)	(0.7416)	(0.4963)
ROCE	0.9242	0.8715	0.8950	0.9490	0.9261
	(0.0647)	(0.0507)	(0.2498)	(0.1256)	(0.0958)
RPH	0.5807	0.6286	(0.3477)	0.6724	0.5989
	(0.2075)	(0.1929)	(0.6286)	(0.3706)	(0.1843)
RRC	1.0116	1.0092	0.9590	1.0793	1.0557
	(0.2899)	(0.1674)	(0.2943)	(0.3179)	(0.242)
RTRA	0.5223	(0.4981)	0.6730	0.7609	0.7686
	(0.1589)	(0.0805)	(0.0316)	(0.1138)	(0.0591)
SCD	0.7345	0.7828	0.6260	0.7371	0.7219
	(0.3359)	(0.1899)	(0.3398)	(0.3438)	(0.2847)
SNO	FTC[a]	0.8925	0.9476	1.0335	1.0343
		(0.0399)	(0.2479)	(0.1729)	(0.1407)
SNP	1.0337	1.0228	1.0118	1.0244	1.0206
	(0.136)	(0.1101)	(0.187)	(0.0856)	(0.0854)
SOCP	0.8948	0.8499	0.6933	0.9895	0.9728
	(0.0947)	(0.0372)	(0.0382)	(0.2761)	(0.2207)
SPCU	FTC[a]	1.0720	1.0867	1.2013	1.2055
		(0.0451)	(0.473)	(0.2848)	(0.2541)
SRT	0.9189	0.8953	0.8511	0.8994	0.8980
	(0.1804)	(0.0156)	(0.3684)	(0.2846)	(0.2502)
STZ	0.9664	0.9173	0.7976	0.8966	0.8620
	(0.0264)	(0.1456)	(0.4235)	(0.2601)	(0.2188)

TBM	1.0583	1.1200	0.9881	1.0825	1.0975
	(0.0629)	(0.126)	(0.2747)	(0.1295)	(0.1407)
TEL	0.9907	0.9614	0.9068	0.9296	0.9260
	(0.0263)	(0.0061)	(0.2109)	(0.1267)	(0.1258)
TLV	0.8264	0.8276	0.8217	0.9106	0.8777
	(0.1224)	(0.108)	(0.2351)	(0.2744)	(0.1849)
TUFE	0.9991	1.0119	0.9844	0.9934	0.9892
	(0.1384)	(0.0706)	(0.2658)	(0.1836)	(0.161)
UAM	FTC[a]	0.8697	0.8045	0.8910	0.8949
		(0.0454)	(0.3244)	(0.2503)	(0.235)
UZT	FTC[a]	0.9428	1.3501	1.2921	1.1564
		(0.0287)	(0.6506)	0.6185	(0.3727)
VESY	0.8781	0.7699	0.6074	0.7755	0.8185
	(0.0676)	(0.0111)	(0.4644)	(0.2974)	(0.2414)
VNC	0.9676	0.9125	0.8153	0.8900	0.9082
	(0.0418)	(0.1183)	(0.2529)	(0.1364)	(0.129)
ZIM	0.7917	0.6652	0.6993	0.6882	0.7221
	(0.2228)	(0.2336)	(0.232)	(0.2676)	(0.2511)

[a] Failed to converge

Table 6: *In sample root mean squared errors*

This table reports the estimated in-sample RMSE for the 65 securities listed on Romanian Stock Exchange. The RMSE is calculated only after the best specification for each of 3 different modeling techniques is determined based on information criteria: AIC for Kalman Filter approach and DCC GARCH model, DIC for SV model, respectively.

Symbol	KF RW	KF MR	DCC GARCH	SV normal distribution	SV t-student distribution
ALR		**0.0351**	0.0523		0.0481
ALT		0.0530	0.0525		**0.0476**
ALU	**0.0388**		0.0536		0.0478
AMO	0.0731		0.0748		**0.0687**
APC		0.0527	0.0548		**0.0527**
ARS	0.0494		0.0501		**0.0480**
ARTE	0.0655		0.0681		**0.0633**
ART		**0.0455**	0.0626		0.0588
ATB		**0.0299**	0.0357		0.0336
AZO		**0.0489**	0.0783		0.0763
ARM		**0.0454**	0.0592		0.0560
BIO		**0.0417**	0.0473		0.0425
BCC		**0.0362**	0.0490		0.0464
BRD		**0.0192**	0.0251		0.0221
BRK		0.0430	0.0456		**0.0412**

BRM		**0.0470**	0.0538	0.0509
CBC		0.0730	0.0757	**0.0726**
CEON		**0.0502**	0.0639	0.0600
CGC	**0.0674**		0.0690	0.0717
CMF	0.0589		0.0624	**0.0580**
CMP		**0.0454**	0.0573	0.0509
COFI		**0.1019**	0.1071	0.1035
COMI		**0.0540**	0.0666	0.0628
COTR		0.0758	0.0786	**0.0746**
DAFR		**0.0392**	0.0571	0.0512
ECT		**0.0535**	0.0571	0.0543
EFO	0.0649		0.0664	**0.0638**
ELGS	0.1130		0.1146	**0.1120**
ELMA		0.0694	0.0706	**0.0683**
ENP		0.0450	0.0495	**0.0447**
EPT		0.0759	0.0796	**0.0717**
EXC		0.0522	0.0536	**0.0520**
FLA		**0.0434**	0.0656	0.0624
IMP	**0.0611**		0.0678	0.0650
MEF		0.0626	0.0640	**0.0616**
MJM	0.0586		0.0661	**0.0582**
MPN	0.0577		0.0590	**0.0573**
OIL		**0.0474**	0.0533	0.0494
OLT		0.0910	0.0915	**0.0885**
PCL		0.0498	0.0513	**0.0489**
PEI	0.0586		0.0617	**0.0573**
PPL	0.0591		0.0598	**0.0556**
PREH	0.0894		0.0923	**0.0876**
PTR		**0.0469**	0.0618	0.0561
RMAH		**0.0625**	0.1121	0.1022
ROCE		**0.0476**	0.0532	0.0496
RPH		0.0866	**0.0840**	0.0845
RRC		**0.0427**	0.0486	0.0445
RTRA		0.0462	0.0461	**0.0454**
SCD		**0.0351**	0.0391	0.0359
SNO		0.0476	0.0499	**0.0468**
SNP		**0.0222**	0.0282	0.0256
SOCP		0.0501	0.0517	**0.0492**
SPCU		0.0777	0.0791	**0.0756**
SRT	0.0493		0.0520	**0.0485**
STZ		**0.0638**	0.0713	0.0680

TBM		**0.0414**	0.0495	0.0456
TEL		0.0288	0.0300	**0.0278**
TLV		**0.0399**	0.0439	0.0411
TUFE		**0.0389**	0.0432	0.0394
UAM		0.0657	0.0678	**0.0635**
UZT		0.0900	0.0902	**0.0857**
VESY		0.0601	0.0621	**0.0585**
VNC		**0.0322**	0.0392	0.0369
ZIM	0.0560		0.0574	**0.0556**

Table 7: *Estimates of state-space models for herding in the Romanian Market*

	No exogenous variables (Basic model)	Excess market return and volatility (Alternative Model 1)	Excess market return and volatility, deposit interest rate, dividend rate (Alternative model 2)
μ_m	-1.4461	-1.4518	-1.3666
	(0.0000)	(0.0000)	(0.0000)
Φ_m	0.9052	0.9025	0.8489
	(0.0000)	(0.0000)	(0.0000)
σ_{mv}	0.1048	0.1028	0.0986
	(0.0000)	(0.0000)	(0.0000)
$\sigma_{m\eta}$	0.1228	0.1234	0.1284
	(0.0000)	(0.0000)	(0.0000)
c_{m1}		0.0008	0.0001
		(0.8715)*	(0.986)*
c_{m2}		-0.5734	-0.6141
		(0.0081)	(0.0052)
c_{m3}			0.2315
			(0.8526)*
c_{m4}			-1.1535
			(0.0000)

*The estimate is not significant at 5% level.