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SKEWNESS AND COSKEWNESS DYNAMICS FOR THE ROMANIAN STOCK MARKET

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Abstract:

We are using a conditional skewness and coskewness model for the log-returns on the most liquid Romanian stocks in order to identify the individual and common asymmetries for the period between January 2010 and September 2015. A Markov switching analysis for all the series revealed the moments when the coskewness coefficient for the theoretical portfolio changed regimes and also the moments when the individual skewness coefficients switched their levels simultaneously. We provide a comment on these changes and their possible implications for risk management and direction of change.

Keywords: ***skewness, coskewness, Markov switching***

Introduction

The classical CAPM structure starts from the assumption that financial returns follow a normal distribution. In spite of this, empirical findings that for the vast majority of financial assets, this assumption has to be rejected. Given this property of non-normality, investors should consider higher moments in their risk assessment frameworks.

The higher order moments are considered important elements in the characterization of the dynamics of stock market returns. Several streams of literature reveal their importance for asset pricing and for risk management.

If the negative skewness is usually considered a stylized fact for most of the log-returns computed for the equity indices of developed markets, the coskewness coefficients are not so largely covered by the literature, especially in the case of emerging and frontier markets.

A pioneering theoretical formulation of the higher moments CAPM was introduced by Rubinstein (1973) and the topic was then refined in studies such as: Ingersoll (1975), Kraus and Litzenberger (1976), Barone-Adesi (1985), Fang and Lai (1997), Harvey (2000), Jurcenzko and Maillet (2001), Berényi (2002), Dittmar (2002), Galagedera, Henry and Silvapulle (2002), Chung, Johnson, and Schill (2006) and more recently in Back (2014) or Christoffersen et al (2015).

This paper contributes to this literature and aims to determine the individual and common asymmetries exhibited by the Romanian stock market. We are using log returns of the most liquid Romanian stocks for the January 2010 – September 2015 period and a Markov switching approach in order to observe regime changes for both skewness and coskewness coefficients.

The remainder of this paper is organized in the following manner. Section II deals with a short review of the related literature. Section III covers the data and the methodology used in this analysis. Section IV describes all the types of results that are obtained, and section V concludes.

Literature review

As previously shown, a large part of the coskewness literature consists of asset pricing models that include higher moments. Coskewness and cokurtosis are tractable solutions in such applications as they manifest the fact that in equilibrium, market participants will not be indemnified for diversifiable skewness or kurtosis.

Kraus and Litzenberger (1976) offer an early formulation of a three-moment pricing model and incorporate coskewness and covariance in order to characterize the dynamics of returns.

Fang and Lai (1997) focus on US stock and employ a four moment CAPM and demonstrate the fact that there is a link between cokurtosis and abnormal returns. In an approach that also focuses in a similar way to this study on emerging markets, Hwang and Satchell (1999) do not observe connections between returns and coskewness and cokurtosis, though they are successful in pointing out the fact that models incorporating higher moments outperform the classical CAPM.

In an extensive approach, Harvey (2000) studies a battery of 18 risk measures for 47 financial markets focusing on coskewness. The author concludes that world beta and coskewness are successful in explaining cross-sectional returns. Harvey and Siddique (2000) start from the idea that if assets are characterized by coskewness, investors should expect returns that reflect this risk and compensate it. The authors construct an asset pricing framework based on this logic and notice that conditional skewness is relevant in explaining the dynamics of expected returns. Moreover, Harvey and Siddique (2000) argue on the relevance of coskewness, reporting that it generates a risk premium situated around 3.6% per year.

Christie-David and Chaudry (2001) consider the way in which the third and the forth moments describe the formation of returns and try to characterize this phenomena through the use of a four moment model and a sample of 28 international future contracts. The study concludes that future returns are explained by both the third and fourth moments.

Barone-Adesi et all (2004) employ a quadratic model that characterizes the return formation process in order to observe portfolio coskewness. The authors show a correlation between the size of the firm and coskewnes, as small firms have negative coskewness and the other way around.

Other similar contributions can be traced to: Chung, Johnson and Schill (2006), Galagedera and Brooks (2007) or Nguyen and Puri (2009).

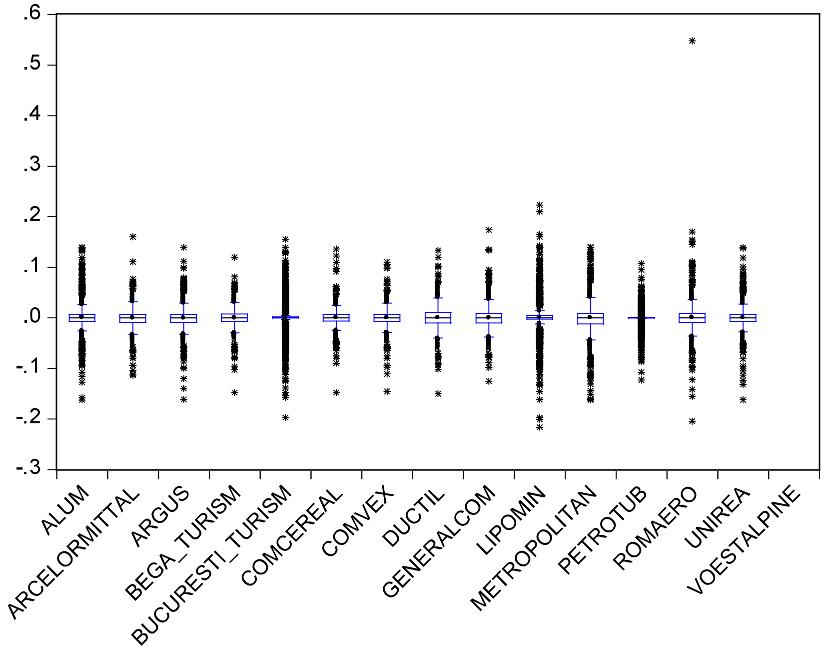
More recently, Dechant (2012) explores the influence of coskewness on real estate retuns. The study reports that modeling coskewness does not lead to an upgrade in the explanatory efficiency in comparison to the Fama-French model. However, the author remarks that coskewness is a key factor in the formation of conditional and unconditional returns for stocks belonging to EU real estate companies.

Christoffersen et al (2015) put forward an approach that studies the price of coskewness and cokurtosis. The authors consider that the price of coskewness risk relates to the spread of the physical and risk-neutral second moment. Using series of data for the 1996-2012 interval, Cristoffersen et al (2015) determine that the price of coskewness risk is negative in the vast majority of investigated cases.

Data and Methodology

Our data consists in daily prices for 14 most liquid stocks on the Romanian market for the period covering January 2010 until September 2015. A brief presentation of our data is provided in the chart below.

Figure 1 – A boxplot of log-returns for the most liquid Romanian stocks



Source: Datastream, authors' computations

We notice that the assets under analysis follow approximately the same type of empirical distribution, with similar shapes of the tails and approximately the same levels of mean and standard deviations.

Our analysis relies on the computation of the variance, skewness and coskewness coefficients for each time interval and relies on a methodology developed in Lupu (2014) based on the previous proposal of Gabrielsen (2012), by maximizing a Gram-Charlier likelihood function for a specification along the lines of the simple GARCH(1,1) model. Therefore, the dynamics for the variance and the skewness of the daily log-returns will be governed by the following relations:

$$R_t = \mu + \epsilon_t, \epsilon_t = \eta_t \sigma_t, \eta_t \sim i.i.d.(f(\eta_t))$$

$$\sigma_{t+1}^2 = \alpha_0 \sigma_t^2 + \theta_0 \epsilon_t^2 + \beta_0$$

$$sk_{t+1} = \alpha_1 \gamma_{1,t} + \theta_1 \eta_t^3 + \beta_1$$

considering R_t as the log-return at day *t*, σ_t^2 the variance and sk_t the skewness at the same moment *t* and $[f(\eta]_t)$ is a non-normal distribution dependent on the higher moments.

In order to estimate the coefficients that drive the dynamics of these log-returns we use the Cornish-Fisher relation for the standardized returns. Both the skewness and the kurtosis coefficients are inferred from this relation.

$$CF^{-1}(p) = \Phi^{-1} + \frac{\gamma_1}{6}\left((\Phi_p^{-1})^2 - 1\right) + \frac{\gamma_2}{24}\left((\Phi_p^{-1})^3 - 3\Phi_p^{-1}\right) - \frac{\gamma_1^2}{36}\left(2(\Phi_p^{-1})^3 - 5\Phi_p^{-1}\right)$$

This relation can be rewritten in terms of R_t, the standardized log-return, as a third degree equation in ϵ_t:

$$R_t = \epsilon_t + \frac{\gamma_1}{6}(\epsilon_t^2 - 1) + \frac{\gamma_2}{24}(\epsilon_t^3 - 3\epsilon_t) - \frac{\gamma_1^2}{36(2\epsilon_t^3 - 5\epsilon_t)}$$

The parameters α_1, β_1 and θ_1 are obtained by maximizing the standard normal log-likelihood function

$$L = \max_{\alpha_1,\theta_1,\beta_1} \sum_{t=1}^{T} [L_1 + L_2 + L_3]$$

$$L = \max_{\alpha_1,\beta_1} \sum_{t=1}^{T} \left(-\frac{1}{2}\right)[(\ln 2\pi + x_{1,t}^2) + (\ln[2\pi + x_{2t}^2) + (\ln[2\pi + x_{3,t}^2)]]]$$

in which we denote by $x_{1.t}, x_{2.t}$ and $x_{3.t}$ the real roots of the Cornish-Fisher equation at day t . L_1, L_2 and L_3 correspond to the log-likelihoods for each root of the equation that is a real number.

The estimation of the coskewness coefficient for the whole portfolio relies on the same specification to which we add one more equation:

$$cosk_{t+1} - \alpha_3 cosk_t + \theta_3 cosk(\eta_{t,i,j,k}) + \beta_3$$

and we consider that the factor $cosk(\eta_{t,i,j,k})$ is governed by the following relation:

$$cosk(\eta_{t,i,j,k}) = \sum_{i=1}^{3}\sum_{j=1}^{3}\sum_{k=1}^{3} R_{t,i}R_{t,j}R_{t,k} - (R_{t,i}^3 + R_{t,j}^3 + R_{t,k}^3)$$

Under this specification, the estimation of the coskewness coefficients becomes possible at each moment in time. We will compute these statistics for the portfolio consisting in all the returns taken into account in our analysis.

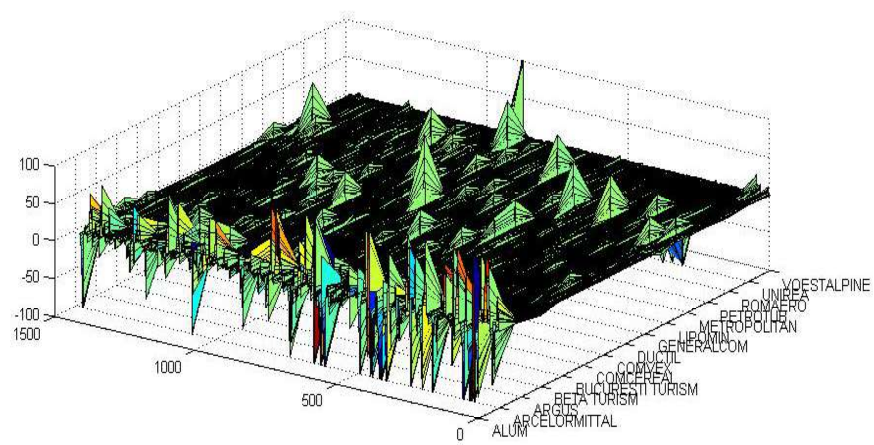
The series of individual skewness coefficients for each moment in time were also analysed under the framework of a Markov regime switching model, in which we allowed for the existence of two possible states. The moments when the transition probabilities from one state to another were larger than 0.9 were considered as indications for the shifts in the states of the dynamics of these individual skewness coefficients. This perspective allowed us to inquire the extent to which these regime switches were realized simultaneously across the whole sample of log-returns in our portfolio along the lines of Lupu (2015). An indication of this simultaneous

shifts will signal the existence of the contagion phenomenon in the national stock market dynamics.
The same regime switching model was used for the series of coskewness coefficients computed for the whole portfolio.

Results

Figure 2 presents the skewness coefficients for each return series involved in this study. We notice that besides the first series of returns (which corresponds to the Alum financial assets), the others exhibit normal values for the coefficients. We observe only few significant changes in the return distribution of the financial assets at the same time and also few situations in which we can spot the existence of simultaneous jumps.

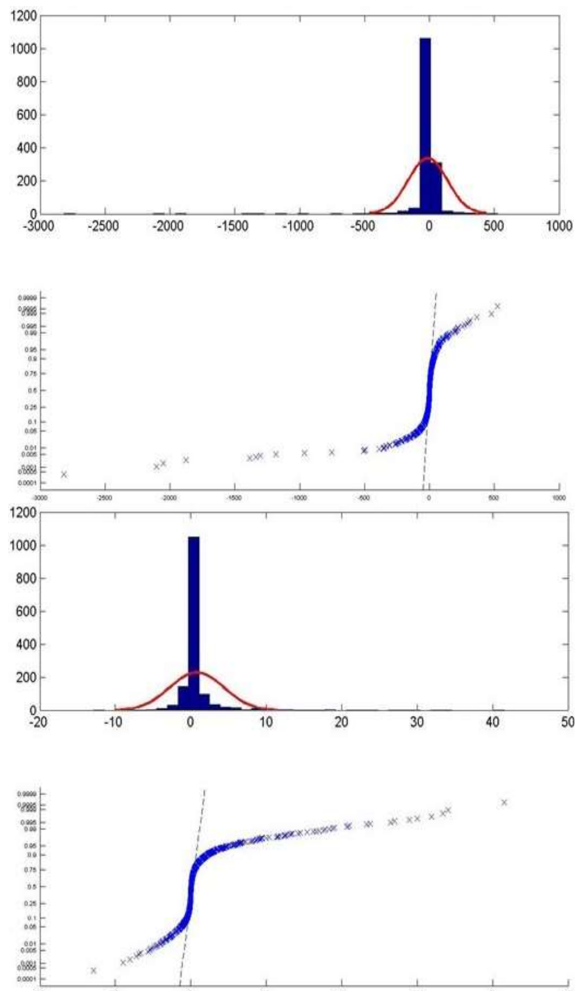
Figure 2. The dynamics of skewness coefficients for each series of returns



Source: Authors' computation

In order to conduct a thorough analysis of those coefficients and be capable of characterising the conditional distribution of returns towards the third central moment we will present a set of results that explain the distribution of skewness coefficients for each financial asset. Figures 3 to 7 show the normal distribution calibrated on the skewness coefficients histogram and the quantile in comparison with the normal distribution for each financial asset included in the study.

Figure 3: Aerostar Bacău and Albalact

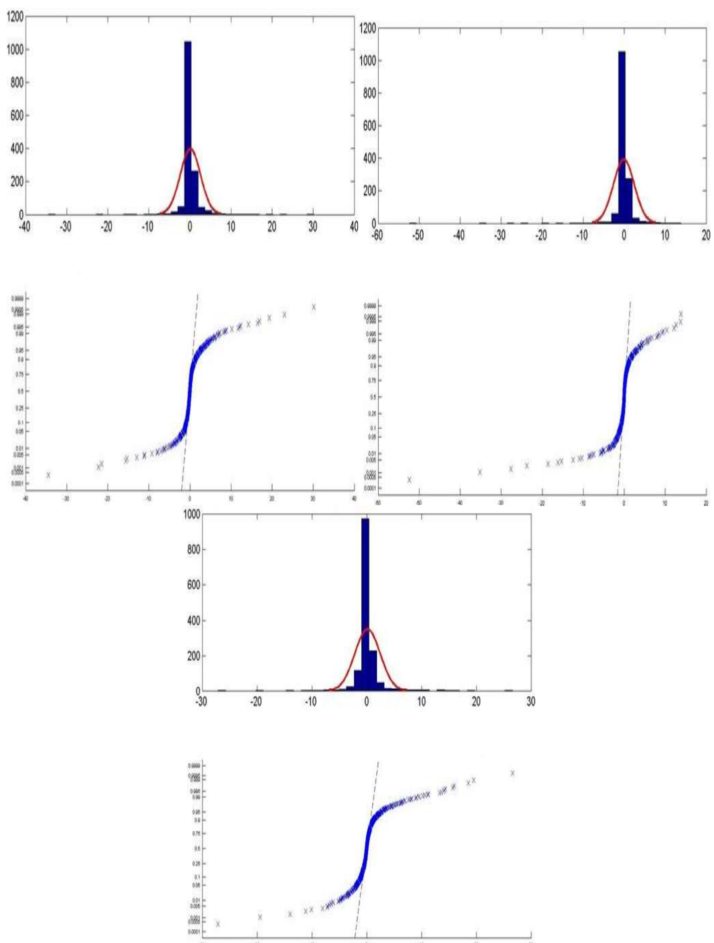


Source: Authors' computation

The dynamics of skewness coefficients for the returns of Aerostar Bacău shows cases with very low values and a concentration around zero. The second part of the figure shows that the distribution of skewness coefficients deviates significantly from the normal distribution given the fact that in the area of the distribution tails the coefficients are far from the line of the Gaussian function.

In the case of Albalact we observe skewness coefficients that deviate to the right, having very high values. This situation is visible in both graphs that characterize Albalact, the mean being placed in the right side of the computed graphs. An analysis that focuses on previous periods can confirm the positive evolution of this company and whether it can be included in an investment portfolio.

Figure 4: Alro Slatina, Antibiotice and Artrom Slatina

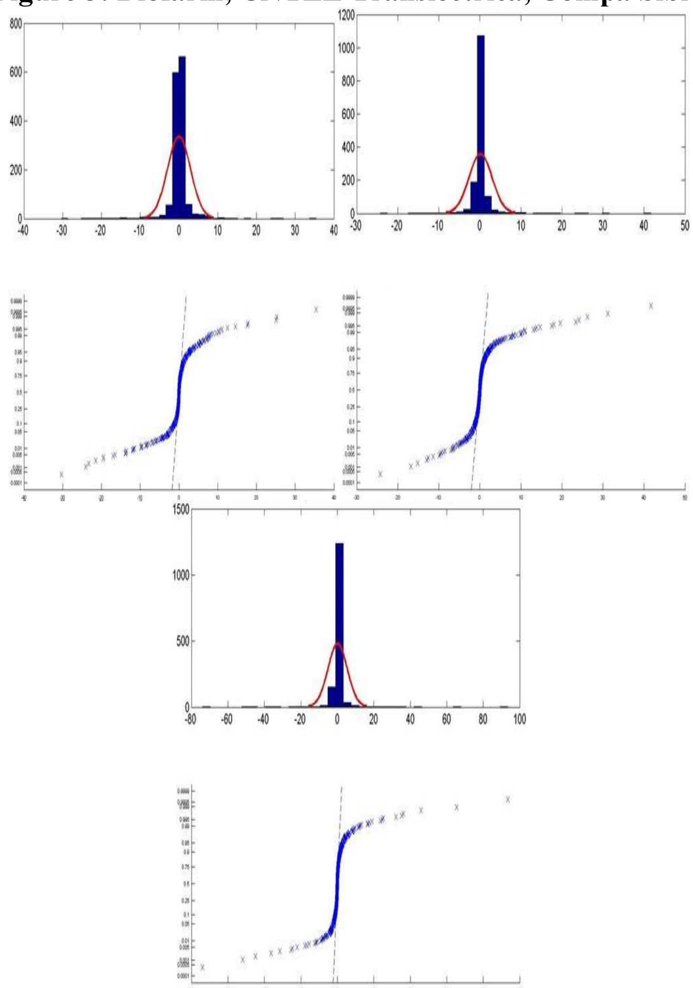


Source: Authors' computation

For the Alro Company, the results show a distribution of the skewness coefficients that is almost symmetrical, showing only a mild deviation to the left and a slight tendency to have negative returns that are higher than the positive ones.

Antibiotice is one of the cases in which the distribution is oriented towards the left, with negative skewness coefficients higher than the positive ones. This evolution can be attributed to the frequent regime changes of the first period, as it will be shown in the dedicated section.

Figure 5: Biofarm, CNTEE Translectrica, Compa Sibiu

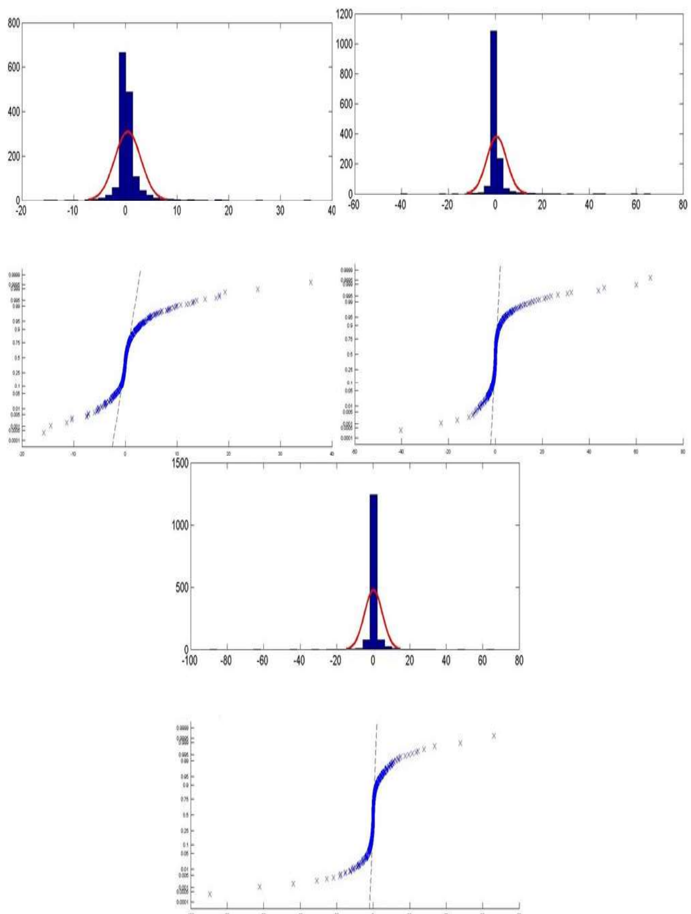


Source: Authors' computation

Artrom Slatina and Biofarm have distributions that are almost symmetrical, with the same type of deviation from the normal distribution for the distribution tails – which motives the investigation of the dynamics of the forth central moment of the conditional distribution, meaning the dynamics of the kurtosis.

Transelectrica exhibits positive skewness coefficients that are greater than the negative ones which position the company as an interesting candidate for inclusion in a portfolio tradable at the Bucharest Stock Exchange.

Figure 6: Electromagnetica, IAR and Impact Developer & Contr.



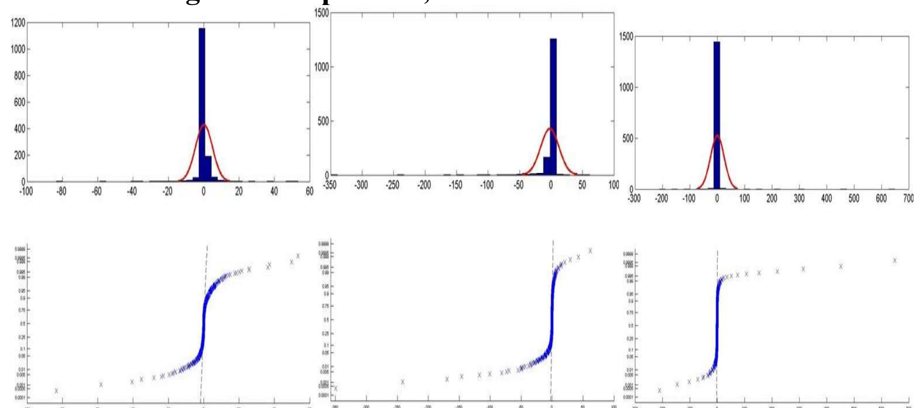
Source: Authors' computation

IAR Braşov and Impact have a dynamics of the skewness coefficients that determined almost symmetrical empirical distribution (in comparison to the other financial assets in our sample).
This symmetry has to be further examined in order to determine if these are correlated with the other assets on the Romanian market.

In the cases of Vrancart and Ropharma we also observe the tendency of higher negative returns in comparison to the positive ones, which again points to the need of further studying the correlations that this asset might have with the rest of the assets of a potential portfolio in order to observe if they are capable of inducing diversification effects.

Zentiva Company has an important deviation to the left, with high values of the coefficients situated in the right of the empirical distribution which positions the company as an interesting candidate for a portfolio located at the Bucharest Stock Exchange.

Figure 7: Ropharma, SC Vrancart and Zentiva

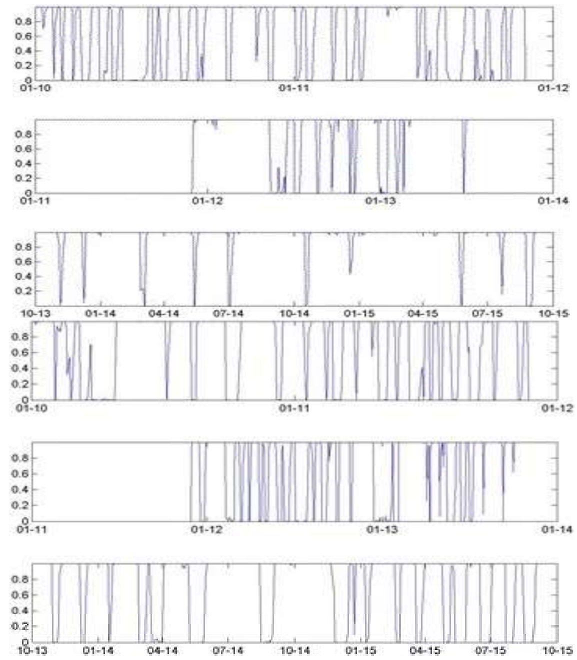


Source: Authors' computation

The following section is based on an analysis of the measure in which these financial assets present a dynamics that could show a contagion phenomenon. Our objective was to capture the existence of simultaneous movements of the distributions regimes, or in other words the simultaneity of regimes shifts. We consider that such an analysis allows us to measure if the studied returns are integrated in a financial market that is highly influenced by the same factors. The existence of differences in regime shifts of the skewness coefficients can be considered as an empirical evidence in support of the idea that the returns of the financial assets of the Bucharest Stock Exchange have evolutions that are highly dependent on idiosyncratic phenomena and less dependent on systemic factors, which means that the impact of these regime changes can be reduced through diversification.

In order to achieve this objective we used a Markov based methodology that identifies regimes shifts. The results for the Markov algorithm for each financial asset have been summarised in graphs like the following two examples presented in Figure 8.

Figure 8: Markov results for Aerostar Bacău and Albalact



Source: Authors' computation

For almost all of the analysed financial assets we observe that the most regime changes occurred in the first period considered (the top window of the graph). This was perceived in general as a period of important structural changes for the Romanian economy, but also for the evolution of the international business environment (especially for the European one as a consequence of the relevant events that took place on the US. market).

The dynamics of the regime for the skewness coefficients can be considered to be important for each industry represented by the financial assets traded at the Bucharest Stock Market. The pharmaceutical industry represented by Antibiotice follows approximately the same pattern of regime shifts. Besides this fact, unlike the other companies, the evolution of regime changes of the skewness coefficients demonstrate the fact that these switches are evenly frequent in the third period. Thus we can state that the 2014 – 2015 interval was perceived by investors as a period with equal volatility as 2010 - 2012 in which the Romanian economy was beginning to manifest the shocks deriving from the international environment.

The same pattern as in the case of Antibiotice is presented for Biofarm. The periods with constant regimes are scarce and we observe frequent episodes of regime switching.

Compa Sibiu has the same type of dynamics for the regime shifts for which we observe a high density in the first investigation period followed by a reduction in frequency for the last two periods.

A similar situation is found for Electromagnetica where we find the same style of regime shift probabilities. These movements have been more frequent in the beginning of 2012 and followed a battery of high probability changes at the beginning of 2013. The shift were less frequent for 2014 and for the first half of 2015.

For IAR Braşov we observe only few regime shifts in the first period and a growth in shift density in 2012 and 2013. This is followed by a reduction of the number of regime changes in the third period, especially towards the end of 2014.

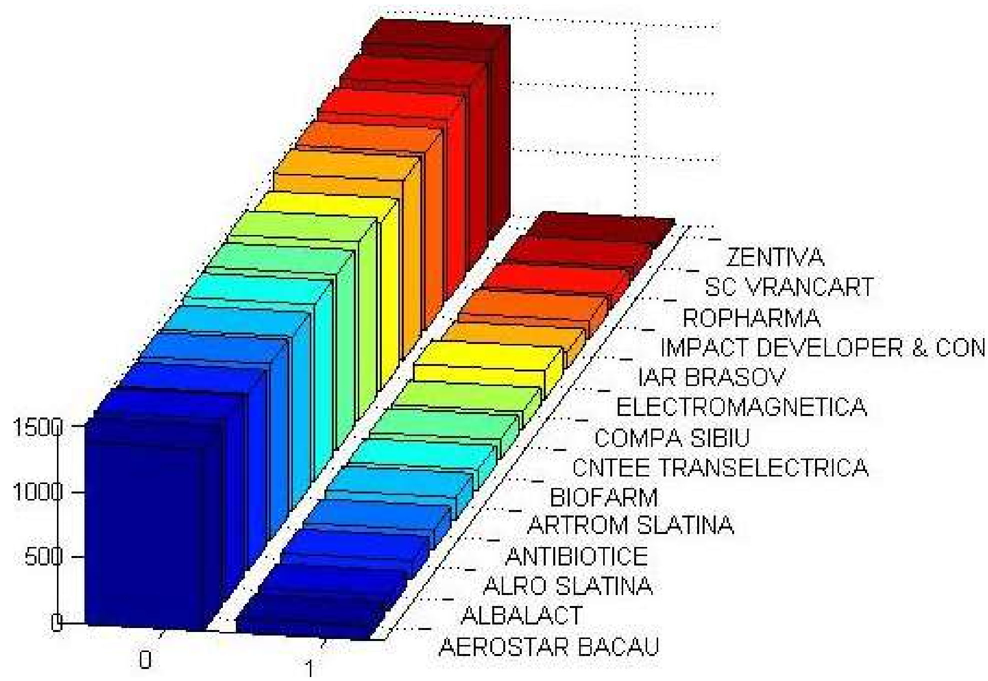
For Impact and Ropharma the results also show a period that is less dense in regime modifications in the first year (with only few modifications for Ropharma) and an intense period in 2012 and 2013. The last analysed interval does not contain significant regime changes and in 2015 we find for Impact a three month regime stagnation.

For the first third of the study period the skewness coefficients for Vrancart had a very low dynamics. However, the last third exhibits an important growth of the number of regime changes with little stagnation in the beginnings of 2014 and 2015.

Zentiva presents a high frequency of regime shifts especially in 2010. After this, the regime changes are less frequent compared to the other financial assets involved in this study and the most stable period is observed in 2014 and 2015.

A presentation of the regime changes for the skewness coefficients for each financial asset is shown in Figure 9. The zero values marks the frequency of the situation that did not exhibited regime changes while the value one is specific for the cases of regime shifts. We observe that the highest number of changes occurred for Elecromagnetica, while the lowest number is found for Zentiva.

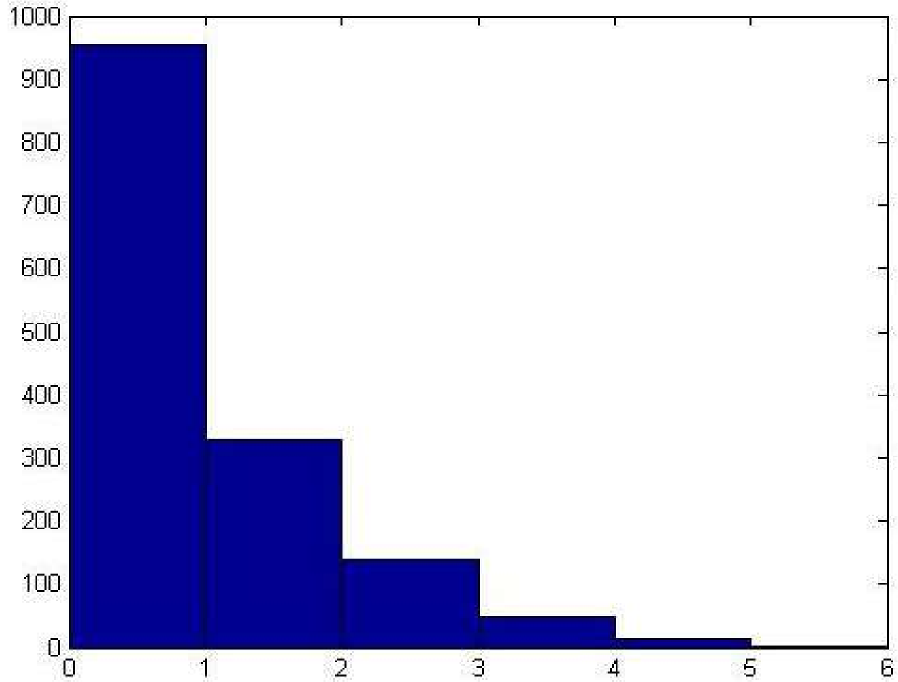
Figure 9 Histogram of the regime shifts for the skewness coefficients for each financial asset



Source: Authors' computation

Figure 10 shows the simultaneity of regime changes. We observe that the most situations of simultaneous changes occurred for 6 financial assets. The number of commune regime changes grows when the number of companies with simultaneous changes is reduced to 5,4,3,2,1.

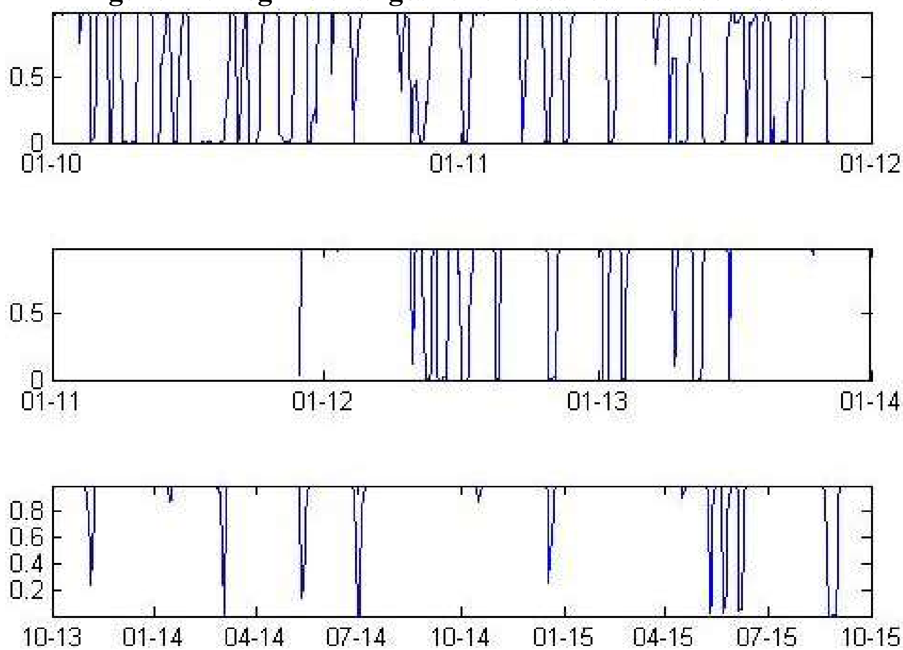
Figure 10 Histogram of the simultaneous regime changes for skewness coefficients for each financial asset



Source: Authors' computation

Figure 11 shows the regime shits for the coskewness coefficients for the sample of studied financial assets.

Figure 11: Regime changes for the coskewness coefficients



Source: Authors' computation

We can observe that the portfolio formed by the analysed financial assets suffered more regime changes in the 2010 – 2012 period (the first third of the studied interval). This was followed by a second third with a lower number of regime changes and a third only with sporadic modifications.

Conclusions

In this paper we focused on the study of skewness and coskewness for the log-returns of the most liquid stocks traded on the Bucharest Stock Exchange in order to identify individual and common asymmetries.

Our first set of results discusses the distribution of skewness coefficients for each financial asset included in the study. We explore the normal distribution calibrated on the histogram of the skewness coefficients and the quantile in comparison to the normal distribution of the financial assets.

After this point we employed the Markov methodology and observed regime shifts for almost the entire series of financial assets for the first investigation period. Besides this, on an aggregate level we noticed that the highest number of regime changes occurred for Electromagnetica, while lowest number was observed for Zentiva.

The results are similar for the case of coskewness. The results show the fact that the most numerous regime changes took place in the 2010 - 2012 period.

A direction in which this research can be expanded is to study if these coskewness coefficients exhibit regime changes in relation to events that are relevant for the Romanian stock market.

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