**Asset allocation and regime switching on Croatian financial market**

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**Abstract**

It has been known for quite some time now that financial markets exhibit changes in regimes over time. Majority of the literature agrees that financial markets go through regimes of bull and bear markets. Therefore, this characteristic should be modeled in a proper way. Investors are always interested in beating the market: either by achieving better returns than others, or by minimizing their portfolio risks. There exist many mathematical and statistical models which are used as tools to achieve mentioned goals. Introducing the regime switching methodology in existing models has been found to be helpful to achieve those goals. This is why this study is going to utilize regime switching methodology on Croatian financial markets in order to find out whether it can be useful for Croatian investors. By using daily data from January 2nd 2007 to December 31st 2015 multivariate regime switching and non switching models have been estimated. It is assumed that investor is interested in the stock and bond market. The results from MGARCH and regime switching MGARCH models are compared in order to give answers whether it is useful to apply such methodology to the Croatian market and how investors can benefit from it. The majority of the results suggest incorporating this methodology into financial modeling in Croatia. This is a first research applying regime switching MGARCH methodology in Croatia (and the Balkan region as well) so we hope to contribute to the existing literature.

# Keywords: *MGARCH, regime switching, portfolio, Croatian financial market, nonlinear models*

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**1. Introduction**

Investors’ questions regarding risks, returns and portfolio management on financial markets have been known for quite some time now. Many different mathematical, statistical and econometric models and methods have been developed (and are still developing) in order to answer some of those questions. In the last 30 years there has been an explosion of research in the field of time series analysis, especially in the field of financial econometrics. Some of the reasons include the enhancement of software support; time series have extended. Furthermore, many different financial assets have been developed; investors’ interests in portfolio management have been deepened, etc. Initial models in finance and quantitative fields have been very simple with assumptions such as linearity of the relationship between variables. However, practice has noticed that relationships between economic and financial variables are not linear. That is why empirical estimations based upon wrong assumptions result with distorted outcomes. Portfolio management seeks to have valid estimations and forecasts in order to make quality decisions. Poor decisions, on the other hand, can affect not only individual portfolios (capital loss) but can affect whole markets.

Thus, the problem which economic theory and practice face today is the inability of linear models to successfully capture the reality. Some of the problems include: structural changes such as oil price shocks [21], sticky prices and exchange rate bands [34], output and unemployment asymmetry behavior over time [16], specific characteristics of financial markets and time series[[2]](#footnote-2) [17], changing correlations [2], financial crises [3], etc. Maybe the most popular characteristic is that financial markets exhibit regime switching behavior. This means that markets undergo phases of bull and bear markets, i.e. greater and smaller volatility, return and correlations. If this is true, investors should seek to exploit such behavior in order to achieve best results possible (in terms of return and/or risk). Many financial markets in the world have been proven to have aforementioned characteristics in empirical research. It is also natural to think that economies and markets undergo different regimes of better and worse performance [3]. Until the late 1980s, the standard procedure in financial modeling was to use univariate GARCH models, when MGARCH[[3]](#footnote-3) models have been introduced. They have been the most popular approach in financial modeling until today. However, there has been a rise in research which provides evidence that even (M)GARCH methodology cannot fully explain behavior of financial markets and assets. Not all asymmetry can be explained by standard models (see [6]); standard models predict greater volatility persistency than they actually should [15]; they cannot capture structure breaks very well [13, 24]; they carry false assumption that higher moments of return distributions do not change over time [1], etc. Croatian financial market has been experiencing the mentioned phenomena as well. Since this market is not sufficiently yet explored, there exist many possibilities to do so. Thus, directing the research towards this way can considerably help to increase the quality of investment decisions. Moreover, it can help in the recovery of the stagnating market which is still recuperating from the crisis in 2008. The main issue this paper will address is that standard models used in finance and econometrics cannot capture the reality as good as nonlinear models. On the other hand, we argue that nonlinear models are more successful. They can be used to form optimal portfolio which can result with desirable earnings, maximizing utility and/or managing risk. Specifically, we focus on the regime switching methodology as a superior tool in portfolio management. There exist only several papers which consider Croatian market within this methodology, but they only look at simpler questions without considering using the results in portfolio management. That is why we hope to contribute to the existing literature. The structure of this paper is as follows. Second section deals with results from previous research on this topic. Methodology used in this study is explained in the third section, whilst the results from empirical research are provided in the fourth section. The final, fifth section concludes the paper.

**2. Previous research**

This section provides results from previous research which has incorporated regime switching methodology in MGARCH models. The majority of papers focus on developed markets, which is not surprising. Moreover, since this methodology is still developing, many of these papers are neither strictly theoretical nor empirical. Majority of them develop a certain model and test it afterwards. Initial research dates from late 1990s. Ramchand and Susmel [30] have observed 18 developed stock markets. They estimated univariate regime switching models for individual volatilities. Afterwards, they estimate bivariate VAR(1) models between selected pairs of countries with the assumption that there exist two regimes: high and low volatility which affects return correlations. The methodology is a basic form of Bollerslev model [10]. They showed that there exists a need for two regimes which can be exploited by investors, although they did not check all of the needed diagnostics. In 2001, Edwards and Susmel [14] use the same methodology in order to explore several developing markets. They look at stock markets again and estimate returns as ARMA and VAR(1) models without regimes. Risks are modeled with the assumption of regime switching. Results are similar as three years before. Next, they focused on interest rates [15] in the same set of developing markets. Here they modeled three regimes because tests have shown that there exists such a need.

After these initial papers, more complex research has emerged. Cappiello and Fearnley [11] estimated ICAPM model (International CAPM) as a regime switching BEKK. However, they did not consider the whole theoretical part of it. Their interest was focused on three developed capital markets (American, Japanese and European). Several explanatory variables were included in the model. The regime switching models were superior in forecasting compared to non switching ones. Billio and Pelizzon [8,9] estimated Value at Risk for Italian stocks and volatility transmission between selected European markets. Several regime switching specifications were applied: univariate models, beta model, factor and multivariate switching. Not surprisingly, they were superior to non switching models. Thus, they recommended incorporating switching methodology in existing models.

A more complete theoretical methodology of multivariate regime switching was done in Pelletier [29]. In his model, he assumes that correlations are constant within the regime. It is a transition from CCC (constant conditional correlation) to DCC (dynamic) model. The empirical part of the paper focused on interest rates. He showed that his model was superior in forecasting compared to the DCC model. Billio and Caporin [7] extended that model with the assumption that correlations change within the regime and successfully test it on several developed capital markets. Baele [6] takes a step further and introduces some diagnostic tests. He focused on the integration of West Europe capital markets. The regimes were shown to be economically and statistically significant. Lee and Yoder [25,26] were the first who developed regime switching BEKK model, but they considered only a bivariate case. Hedging opportunities were better in the switching model. Nomikos, Alizadeh and Pouliasis [27] showed that regime switching BEKK was suitable for futures markets (USA data).

Significant contribution was provided in Haas and Mittnik [19]. They fully defined a multivariate generalization of regime switching GARCH model. It is a diagonal VEC model. In that way they assured that the variance-covariance matrix is positive definite. However, they assume that the same latent variable is governing regimes of different variables. The application of the model was provided on American, British and German stock returns. Statistical diagnostics showed that their model was better compared to other models they used in the study. In the following year Chen [12] developed his model. He focuses on the CCC model. Moreover, he elaborates that in Haas and Mittnik [19] model it is difficult to estimate the correlation. The reason lies in the fact that when correlation changes, it is not known how much does the change in the variance of one return or the other affect it. He solves that problem. Furthermore, he assumes that each return series has its own latent variable which governs the regime switching behavior. Since this paper solves many issues from previous research, in this paper we use the Chen [12] model in the empirical part of this paper. In recent couple of years there have been emerging several more papers which focus on specific markets. Some studies include Sheu and Lee [31], Otranto [28], Haas and Liu [18], Sheu, Lee and Lai [32], etc. All of the mentioned research emphasizes the importance of incorporating regime switching methodology when modeling risk and return on financial markets.

If we observe research which deals with Croatian market within this methodology, it can be seen that there only exist several papers. All of them are much simpler compared to methodology in the foreign research. For example, Arnerić and Erjavec [4] were the first ones to use regime switching on Croatian data. They estimated univariate model for the Croatian capital market. Regime switching model was superior in context of diagnostics. Kunovac [23] considered asymmetry in the behavior of risk and return on Zagreb Stock Exchange and several European markets. Again, he looks at univariate cases. However, he did some post-estimation analysis, something which is not provided in [4]. Some basic portfolio management was simulated. Regime switching portfolios had greater returns compared to other portfolios, but the author did not analyze risks. Visković, Arnerić and Rozga [36] estimated several univariate switching models for 6 European countries. They recommend using this methodology to solve problems of structural breaks in data. Škrinjarić [33] considered regime switching CAPM model for 21 stocks on Croatian market. It was found that this model was better compared to the original linear model and beta could be used as a measure of risk after all. Arnerić and Škrabić [5] made a similar research as [36] for similar countries. As it can be seen, existing research is scarce, simple and does not provide a post-estimation analysis which could be useful for portfolio management and investors. That is why this paper has a purpose to fulfill that gap. The next section provides information on the methodology used in the empirical research.

**3. Methodology**

As mentioned in the previous section, the main model we follow is Chen [12]. Reasons lie in facts that this model corrected some of the pitfalls of models which were developed earlier. It is more realistic to assume that each financial asset has its own latent variable which governs the regime switching dynamics. If all of the financial markets were behaving exactly the same, there would not be any diversification possibilities. Moreover, this model is slightly simpler to estimate compared to previous ones. The CCC model of Bollerslev [10] is the base of the modeling. Individual volatilities follow their own regime switching behavior. Covariance is modeled as a three component process. It depends on individual volatilities, as well as the correlation between them. Chen [12] observed stock and bond market interactions. In a similar way, we observe those two markets in Croatia as well. Denote with  the volatility of *i*-th return in state *s*(*t*) in time *t*, , , ,  return vector,  conditional mean vector and  residual vector. The main model is defined as:

  (1)

with  and

 . (2)

Individual volatilities are modeled as a GARCH(1,1) processes in each regime  and it is assumed that, , . This setup allows doing a two-stage estimation (using maximum likelihood method). First of all, return series are filtered by an adequate ARMA(*p*,*q*) model. Then the two-step procedure is as follows. In the first step, univariate regime switching models are estimated and the coefficients are obtained. These coefficients are fixed in the second step in which rest of the parameters in the model are estimated. Details on maximum likelihood estimation of this model are given in Chen [12:26-27]. We state the stationary condition for the each regime switching process, while details are given in Chen [12:27-28] and Haas, Mittnik and Paollela [20:500-501]. Consider the matrix

 , (3)

 where ,  , and  is a *k*1 unit vector, . The model is stationary if the largest eigenvalue of ***M***, eig(***M***), is less than one. Ang and Bekaert (2000) defined a regime classification measure which shows how good does the chosen regime switching model classify observations of a process: ,where *pi*,*t* is the smoothed regime probability. It is a normalized measure (ranging from 0 to 100); with the lower values of it meaning that the model is more successful in regime classification. This measure will be used in this study.

**4. Empirical results**

For the purpose of empirical research, daily data on stock index CROBEX and bond index CROBIS was collected for the period January 2nd 2007 to December 31st 2015 from ZSE [36]. All of the estimation was performed in Time Series Modelling 4 software. Returns on stock and bond market were calculated as compound returns. The purpose is to estimate a regime switching MGARCH model described in the previous section and its non switching counterpart. Furthermore, a comparison of these models will be done in terms of diagnostics and portfolio optimization possibilities. Both return series were found to be stationary on usual levels of significance. Firstly, appropriate ARMA(*p*,*q*) models have been used on raw return data in order to filter it. CROBEX was modeled as an ARMA(1,1) and CROBIS as an AR(1) process[[4]](#footnote-4). Then, filtered data was used to estimate univariate regime switching GARCH(1,1) models, where it is assumed that there exist two regimes. This assumption is based upon previous empirical research on Croatian financial market in which all of the existing studies agree that there are two regimes. Estimation results are given in table 1. It can be seen that both returns are greater in regime 1 compared to the regime 2. Moreover, reactions of individual volatilities to market shocks and volatility persistence are greater in regime 2. That is why we call regime 1 bull market and regime 2 bear market. Duration of regime 1 for CROBEX is equal to 22.72 days and for CROBIS 3.16 (duration = 1/(1−*p*11)). However, stock market resulted with losses on average in both regimes. Stationarity condition is fulfilled for both assets. Matrices ***M****ij* and ***M*** for both assets and the corresponding eigenvalues were calculated next. As it can be seen, stationarity conditions are met[[5]](#footnote-5). In the second step, we fix the parameters from upper part of table 1 and estimate the rest of the model. Results are shown in lower part of table 1. It can be seen that in regime 1 the correlation is smaller compared to regime 2. It is not statistically significant. This is in favor of diversification purposes for investors. The result that correlation is greater in the bear market is not surprising. It is in accordance with previous literature. Moreover, the duration of the regime 1 with such correlation is greater than regime 2 (4.5 days vs. 1.3 days), which could provide more portfolio management benefits. Finally, the RCM measure was calculated in order to see how accurate does this model classify the regimes. Value of 30.7 was the final result, which means that this model is moderately good.

|  |  |  |
| --- | --- | --- |
| **Estimated parameters****Univariate models** | **CROBEX** | **CROBIS** |
| **Regime 1** |
|  | -0.00021 (0.143) | 0.00002 (0.601) |
|  | 0.00271 (0.000) | 0.00065 (0.000) |
|  | 0.076 (0.000) | 0.047 (0.007) |
|  | 0.896 (0.000) | 0.496 (0.000) |
| **Regime 2** |
|  | -0.0022 (0.684) | -0.00003 (0.76) |
|  | 0.011 (0.000) | 0.0001 (0.000) |
|  | 0.921 (0.354) | 0.192 (0.001) |
|  | 0.824 (0.000) | 0.926 (0.000) |
|  |
| *p*11 | 0.956 | 0.684 |
| *p*22 | 0.010 | 0.351 |
| Log L | 7494.93 | 11459.2 |
| *eig*(***M***) | 0.99 | 0.99 |
|  |
| **Multivariate model:** |
|  | Regime 1 | Regime 2 |
| Correlation coefficient | 0.016 (0.488) | 0.108 (0.037) |
|  |
| *p*11 | 0.780 |
| *p*22 | 0.235 |
| Log L | 20809.8 |
| Roots of MA System | 0.896; 0.496 |

Table 1: Estimation results from univariate and multivariate regime switching models

Note: *p*-values are given in brackets. Log L stands for log likelihood. eig(*M*) stands for the largest eigenvalue of matrix *M*.

Next, a CCC model without regimes was estimated, in order to compare the two. In that way we can see if there truly exists a need for regimes. Results are given in table 3. The value of log likelihood function is lower compared to the regime switching model. This is a first sign of a need for including this assumption into the analysis. Stock return alpha is greater than bonds return, as it is in the regime switching model. However, the correlation coefficient is an average of the two regimes (being 0.058 compared to 0.016 and 0.108), which could be misleading.

|  |  |  |
| --- | --- | --- |
| Estimated parameters | CROBEX | CROBIS |
|  | -0.0002 (0.181) | 0.000004 (0.901) |
|  | 0.000001 (0.000) | 4.7∙10-8 (0.000) |
|  | 0.108 (0.000) | 0.076 (0.000) |
|  | 0.890 (0.000) | 0.916 (0.000) |
| Correlation coefficient | 0.058 (0.002) |
| Log L | 18541.09 |

Table 3: Estimation results from multivariate CCC model without regimes

Since this methodology can be used in portfolio management, some applications have been made. Kroner and Ng [22] derived optimal portfolio weights for two assets with the expression: , where  denotes optimal portfolio weight for the first asset,  first asset variance,  second asset variance and  the covariance in time *t*. Conditional variances and covariances have been estimated for each day in both models, and optimal portfolio weights have been calculated. Figure 1 shows the differences in optimal weight of CROBEX. The non switching model constantly includes more stocks in the portfolio over time. Both models however, show that fewer stocks should have been included in the portfolio in crisis period. In the last few years, the stock weight has increased, because the market is getting more stabilized and stocks provide greater returns.



Figure 1: Optimal portfolio weight for CROBEX, non switching model (black line) and regime switching model (gray line)

Test for differences in average portfolio weights has been made, and on usual levels of statistical significance, the two differ (*z*-test value is equal to 29.86 with *p*-value 0.000). Thus, the expected returns and risks of two portfolios from these models could differ as well. Before we compare them, efficient frontiers from Markowitz portfolio theory have been constructed for both models. As it can be seen in figure 2, the differences are substantial. With the assumption of no regimes, it is not possible to achieve positive returns. However, this changes if the investor takes advantage of the two regime model. When regime 1 occurs, he could achieve positive returns. When regime 2 occurs, he could invest on other markets (exchange rate, metals, etc.) in order to avoid loses.



Figure 2: Efficient frontiers, non switching model (dashed line) and regime switching (black line – regime 1, gray line – regime 2)

|  |  |  |  |
| --- | --- | --- | --- |
| Descriptive statistics | Expected return | Portfolio risk | Standardized return |
| No regime | 2 Regimes | No regime | 2 Regimes | No regime | 2 Regimes |
|  Mean | **-2.22∙10-6** | -7.33∙10-6 |  4.14∙10-6 |  **3.52∙10-6** | -13.18961 |  **17.94320** |
|  Median |  **1.18∙10-5** |  1.09∙10-5 |  2.23∙10-6 | **1.07∙10-6** |  4.418038 |  **5.170249** |
|  Maximum | **0.017704** |  0.017317 |  5.92∙10-5 |  **0.000142** |  3577.093 |  **2992.546** |
|  Minimum | **-0.013664** | -0.014355 |  7.44∙10-7 |  **4.74∙10-7** | -4971.165 | **-2773.165** |

Table 4: Descriptive statistics for multivariate models without and with 2 regimes

Note: bolded numbers denote better portfolio performance.

Based upon figure 1, expected returns and risks for both portfolios have been calculated for the observed period. It can be seen in table 4 that on average, no regime portfolio performs better in terms of expected return. This is not surprising due to the greater weight of stocks (see figure 1) in portfolio. However, investors are interested in risks as well, even more often than returns. The regime switching model is better in terms of risk minimization. Moreover, it is better when we observe both return and risk together (standardized return). Finally, a simulation of portfolio rebalancing was made in the observed period. We invested into CROBEX and CROBIS according to figure 1 each trading day. Cumulative returns[[6]](#footnote-6) have been calculated and compared on figure 3. Majority of the time the regime switching model is superior to the non switching one. Even if the investor invested only in CROBEX or CROBIS (a passive strategy) alone, he would still not achieve results as with the regime switching model (results are not shown but are available upon request).



Figure 3: Cumulative returns, non switching model (gray line) and regime switching (black line)

**5. Conclusion**

This paper had several purposes. One was to familiarize readers with problems in quantitative finance and existing models. Their inability to capture the reality has stimulated the development of regime switching models. Existing research is relatively scarce if we focus on multivariate models. Main reason lies upon facts that it is technically difficult to estimate them. However, the empirical research which applies this methodology has shown its superiority compared to other models. This study focused on the Croatian financial market due to lack of similar studies. The regime switching model assumes 2 regimes: a bull and a bear market. Estimations were in accordance with foreign literature which distinguishes the two states. More importantly, this model was superior to its non switching counterpart. This means that regime switching methodology can improve portfolio performance and reduce overall risks. Given information can be very important and useful to (potential) investors. Some of the pitfalls of the study were: the absence of transaction costs, focus only on daily data and two assets, focus on basic calculations, etc. That is why future research is going to eliminate the mentioned pitfalls. Moreover, we are going to compare other models and different trading strategies, as well as try to answer some other questions investors are interested in. They include important topics such as what drives the regimes on financial market in Croatia, can we find better models to achieve even better results and so on. However, this is a first research applying regime switching MGARCH methodology in Croatia (and the Balkan region as well) so we hope to contribute to the existing literature.

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1. Corresponding author [↑](#footnote-ref-1)
2. Such as asymmetric behavior, outliers, volatility clustering, etc. [↑](#footnote-ref-2)
3. Multivariate Generalized Autoregressive Conditional Heteroskedasticity. [↑](#footnote-ref-3)
4. Results from stationarity tests and ARMA modeling have been omitted due to lack of space but are available upon request. Appropriate ARMA model was chosen based upon BIC, AIC and HQ information criteria, as well as on statistical significance of estimated parameters. [↑](#footnote-ref-4)
5. We omit the full details, but they are available upon request. [↑](#footnote-ref-5)
6. The returns are standardized in order to take into consideration both risk and return. [↑](#footnote-ref-6)