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Analysis of Stock Market Indices and Regimes on Commodity Markets

Doctoral Thesis

Author: Ing. Elena Kuchina

Supervisor: Doc. Ing. Tomáš Cahlík, CSc.

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Declaration

I declare that I carried out this doctoral thesis independently and cited all used sources and literature.

In Prague July, 25, 2017

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Signature

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Abstract

The thesis focuses on the identification of the typical scenarios of the mutual relations among the stock markets considering different regimes on the commodity markets. For the identified scenarios the investment recommendations have been suggested. Considering different regimes the commodity markets go through and the mutual linkage among the stock markets during different situations on the commodity markets, six scenarios of the stock markets' mutual relations have been analyzed. It was shown that during most unstable period, when highly volatile regime prevails simultaneously on the energy, precious metals and non-energy commodity markets, the whole economy becomes to be more tied: the stock market indices demonstrate stronger interdependence, and as a consequence the benefits of diversification begin to fail. During the simultaneous presence of low volatility on all three analyzed commodity markets the agreement between occurrences of highly volatile state of most stock markets, besides the indices within the European region (DAX, CAC 40, IBEX 35), is rather weak. Similarly the correlation within regions and with other regions is weaker comparing with other situations on the commodity markets, so the standard investment strategy can be kept. It was also shown that the interdependence among the stock markets during the period of high volatility on the energy market differs depending on the source underlying the oil price shocks causing higher volatility. The regimes prevailing on the commodity and stock markets during different time periods have been detected by applying *Hidden Markov Model* methodology. To examine the similarity between the stock market indices in terms of highly volatile regimes' occurrences, *Jaccard's similarity coefficient* is employed. The correlation among the stock markets was computed by *Spearman correlation coefficient*. The final part of research is devoted to the model-based approach used to analyze the dependence of the movement direction of SSEC index on other stock market indices between two trading days during different situations on the commodity markets. The dependency analysis was performed by applying *Stochastic Gradient Boosting* methodology.

Keywords: commodity market, stock market index, hidden Markov model, Jaccard's similarity coefficient, Spearman correlation coefficient, Stochastic Gradient Boosting, AUC ROC, Information Value.

Abstrakt

Disertační práce se zaměřuje na identifikaci typických scénářů vzájemných vztahů mezi akciovými trhy s přihlednutím k různým režimům na komoditních trzích. Pro nalezené scénáře byly navrženy investiční doporučení. S ohledem na různé režimy, kterými komoditní trhy procházejí, a na vzájemnou provázanost mezi akciovými trhy během různých situací na komoditních trzích, bylo analyzováno šest scénářů vzájemných vztahů mezi akciovými trhy. Bylo ukázano, že v době nejvíce nestabilního období, kdy vysoce volatilní stav převládá současně na energetickém trhu, na trhu drahých kovů a na neenergetickém komoditním trhu, se celá ekonomika stává více svázaná se silnějšími vzájemnými závislostmi mezi indexy akciových trhů, a jako důsledek začínají selhávat přínosy diverzifikace. Při současné přítomnosti nízké volatility na všech třech sledovaných komoditních trzích je shoda mezi výskyty vysoce volatilních stavů většiny indexů, kromě indexů v rámci evropského trhu (DAX, CAC 40, IBEX 35), poměrně slabá. Podobně i korelace v rámci regionů a s ostatními regiony je slabší ve srovnání s jinými situacemi na komoditních trzích, takže standardní investiční strategie může být zachovována. Rovněž bylo ukázano, že provázanost mezi akciovými trhy během období vysoké volatility na energetickém trhu se liší v závislosti na zdroji ropného šoku, způsobujícím vyšší volatilitu. *Skrytý Markovův model* je použit k určení režimů, převládajících na různých komoditních a akciových trzích během různých časových období. K měření podobnosti akciových trhů z hlediska výskytu stavu s vysokou volatilitou na daném trhu je použit *Jaccardův koeficient podobnosti*. Korelace mezi akciovými trhy byla vypočtena pomocí *Spearmanova korelačního koeficientu*. Závěrečná část výzkumu je věnována modelovému přístupu používanému k analýze závislosti směru pohybu hodnoty SSEC indexu na ostatních analyzovaných akciových indexech mezi dvěma obchodními dny během různých situací na komoditních trzích. Analýza závislosti byla provedena pomocí *Stochastického Gradientního Boostingu*.

Klíčová slova: komoditní trh, index akciového trhu, skrytý Markovův model, Jaccardův koeficient podobnosti, Spearmanův korelační koeficient, Stochastický Gradientní Boosting, AUC ROC, Informační hodnota.

Contents

Introduction and Motivation

An investor, operating on the stock markets, often has to deal with the risk associated with the portfolio maintaining and take some actions to ensure the portfolio's stability. In this context making the asset allocation decisions and choosing the appropriate investing strategy often relates to the question of diversification. As it can be often expected that the stocks' behavior of the foreign markets more differ from the behavior among the domestic stocks, the international diversification may become especially interesting. The analysis of the linkage between the international stock market indices may enlighten this question.

By looking for the ensuring the investment stability on other markets do the benefits of diversification persist during all time periods, or are there periods when the diversification strategy begins to fail and stops being sufficient to smooth out the risk associated with the maintaining the portfolio? In attempt to answer this question it may be beneficial to turn to the commodity markets. There is no doubt that the commodity markets play a crucial role in the global market as well as in each national market. Through different time periods different commodity markets may go through different states, and during these states, prevailing on the commodity markets, the behavior of some major world stock markets can be similar but the behavior of others may be different, and as a consequence the diversification strategy may also vary for different situations on the commodity markets. For instance, there is a company operating on the energy market. What the investment strategy should this company choose to ensure the stability of its business when there is highly volatile period on the energy market? What are its actions when the volatility prevails on other markets? Does the diversification strategy help? The analysis of the mutual behavior of the stock markets during different situations on the commodity markets may help to answer these questions.

The main research purpose of the thesis consists in *identification of the typical scenarios of mutual relations among the stock markets considering different regimes on the commodity markets.* For the identified scenarios the investment recommendations are suggested. To achieve this purpose the research is composed of the following steps:

- ➢ *Determine the states, which the commodity markets go through.*
  - ✓ *What main commodity markets can be distinguished?*
  - ✓ *What are the states prevailing on the particular commodity markets?*
- ➢ *Investigate the linkage between the international stock markets during different situations on the commodity markets.*
  - ✓ *How similar is the behavior of the stock markets in terms of highly volatile regimes' occurrences during different situations on the commodity markets?*
  - ✓ *What is the correlation among the stock markets under different situations on the commodity markets?*

- *Determine the typical scenarios of mutual relations among the stock markets considering the situations on the commodity markets.*

- *Is there a major and little correlated stock market? How does the changes of this market index in time t+1 depend on the rest considered market indices in time t during different situations on the commodity markets?*

To identify the market state, due to its latent nature, the appropriate methods for its identification should be used. In (Pagan and Sossounov, 2003) and (Lunde and Timmermann, 2004) the bull and bear markets in equity prices were determined by rule-based algorithms, consisting of rules to detect the turning points in the business cycle. The approach in (Pagan and Sossounov, 2003) is based on rules incorporating the conditions on determining the initial turning points and requirements for the phase's and cycle's duration. Following (Lunde and Timmermann, 2004) the rules, defining the switch between the market states, are based on comparing the stock prices with previous peaks and troughs and with a certain threshold. Comparing to the rule-based approaches, in (Hamilton, 1989) the parametric method was used to model the regimes' changes, where the author applied the Markov regime-switching model by proposing the idea that unobserved regimes follow a Markov process. *Hidden Markov Model* methodology then began rather widely applied in finance and economic analysis. Under the current thesis the methodology of *Hidden Markov Model* was applied, due to its ability to consider the mean and volatility of the analyzed market index and taking into account covariates at transition probabilities' calculations.

In the world there is a large number of different commodities that can be traded on the commodities exchanges, most of these commodities can be integrated to some aggregated units based on the commodity's use and origin. Under the current research three commodity markets are analyzed: Energy, Precious Metals and Non-energy Commodity Markets. By assuming that two states can prevail on the commodity market: "calm" state with lower volatility and state with higher volatility, the following situations on the commodity markets have been considered: high volatility on the energy market; high volatility on the precious metals market; high volatility on the non-energy market; simultaneous high and simultaneous low volatility on all three considered commodity markets, whereas the case of high volatility on the energy market is divided into two periods based on the source underlying the oil price shocks causing higher volatility. In (Kilian, 2009) three components of the real price of crude oil have been introduced: "*crude oil supply shocks"*, "*shocks to the global demand for all industrial commodities*" and "*demand shocks that are specific to the crude oil market*", where the latter shocks are associated with uncertainty about the expected supply deficit due to expected demand and are also denoted as "*precautionary demand shock* ". Considering these oil price shocks' triggers the period of high volatility on the energy market is divided into two periods: the first period covers higher volatility caused by the demand shocks, and the second one relates to the volatile period caused by supply or precautionary demand shocks.

As the regimes prevailing on the analyzed commodity markets have been identified, the next step of the research investigates the linkage between the chosen stock market indices during different situations on the commodity markets defined in the first step. The question of mutual relations between the stock market indices is of great interest for many researches and has been already discovered in many works. Investigation the relationships between the stock markets during different time periods is the subject of research for many studies. By conducting such analysis the question of "defining" the appropriate time periods, resp. their dating should be solved as one of the first. In (Junior and Franca, 2011) the years of crisis were defined based on the quantity of the major markets' drops. By applying this method in the paper four crisis periods were considered. Following (Glick and Hutchison, 2013) the authors considered three periods: before the Global Financial Crisis dated from June, 2005 to June, 2008; the crisis period lasting from July, 2008 to May, 2010; the period after the crisis from June, 2010 to October, 2012. In (Hui and Chan, 2013) two periods were distinguished: pre-crisis period from July, 2005 to September, 2008 and the crisis period dated from September, 2008 to November, 2011, where the criterion of identifying the starting point of the crisis period was used the day of the bankruptcy of Lehman Brothers. In (Fry-McKibbin, Hsiao, Tang, 2014) the regime switching model was used for the crises' dating in the source market, where nine crises were identified. Comparing to these approaches the current thesis proposes to analyze the mutual behavior of the international stock market indices by considering different periods on the commodity markets. The present thesis suggests to model the period, during which the stock markets' relations can be analyzed, by considering different states on the commodity markets. In this step of research the linkage among the stock markets is discovered from two perspectives: similarity in terms of highly volatile regimes' occurrences in the stock market and from the correlation perspective.

The question of investigating the similarity between the stock market indices in terms of highly volatile regimes' occurrences can be attributed to the discussion on the stock market dependencies when there are large changes in the stock markets indices. The dependencies between European stock markets when returns are unusually large were analyzed in (Schich, 2002) by using the approach from multivariate extreme value theory. The question of the extreme correlation of international equity markets was analyzed in (Longin and Solnik, 2001), where the extreme returns were defined as returns beyond given thresholds. The question of extreme returns was raised in (Bae, Karolyi, Stulz, 2000), where for the definition of the extreme returns different sizes of the tails of the overall return distribution were used, EGARCH model was applied as well. In the current thesis *Hidden Markov Model* is employed to detect the occurrences of the regime with high volatility on the national stock markets. In the regime detection process in case of the stock market indices, three states prevailing on the markets are assumed: volatile and negative market reflecting the higher uncertainty while in this state, "calm" market with low stock market's volatility and a state with "medium" volatility. After the stock markets' regimes identification, the level of the agreement between highly volatile regimes' occurrences of the different stock market indices during various situations on the commodity markets is examined by using the instruments of the categorical analysis, where *Jaccard Similarity Measure* is employed. To discover the mutual linkage at the same time *t* between the logarithmic returns of the international stock market indices under different regimes, prevailing on the commodity markets, the correlation analysis is conducted.

After identification of the regimes, prevailing on the commodity markets, and investigation of the linkage among the stock markets during these regimes, in the third step the concrete scenarios, describing the mutual relations among the stock markets by considering different situations on the commodity markets, are summarized, and investment recommendations are suggested.

The rest part of the present research tries to find the answer, if there is a large stock market which is little correlated to other markets, and how the changes of this market index tomorrow depend on the rest considered markets indices today. To analyze such dependence between two trading days the model-based approach is employed. Comparing to similarity and correlation analysis, which discovers the bivariate linkage between the stock markets at the same time *t*, the model-based approach makes possible to investigate how the changes of the chosen stock market index in time *t*+1 simultaneously depend on other stock market indices in time *t*. The analysis is conducted by considering different situations on the commodity markets, determined in the first step of the research. In the current thesis fifteen stock markets are analyzed, and among these market indices due to size and low correlation with other indices the direction's movements of *Shanghai Composite Index (SSEC index)* in time *t*+1 was chosen as the outcome variable. *Stochastic Gradient Boosting* algorithm, originally derived by (Friedman, 2001), was applied. *Stochastic Gradient Boosting* belongs to the powerful machine learning technique. The choice of applying the machine learning technique instead of the traditional statistical methods relates to the specific behavior of the major stock markets, which can be comparable with the complex systems due to comprising of the different large companies' stocks; and as a consequence, it becomes rather hard to define the data model and corresponding parameters while modeling the dependence among the stock markets between two trading days. Before the model based step the variable screening step is performed, where the isolated contribution of the market indices in time *t* to the changes of *SSEC index* in time *t*+1 is measured. The analysis of the increase/decrease patterns of *SSEC index* in time *t*+1 is also extended by concerning the chosen daily commodity prices.

The current thesis through investigating the linkage between the stock market indices during different situations on the commodity markets proposes to determine the typical scenarios of the mutual relations among the stock markets, and as a consequence suggests the investment recommendations for the determined scenarios. The proposed research contributes to the risk management and might be especially helpful in making the asset allocation decisions and in choosing the appropriate investing strategy, as helps better understand when the benefits of the diversification hold and when begin to fail during different periods on the commodity markets. The conducted research also contributes to the discussion on the investigating the relations among the stock markets during different time periods; and on analyzing the linkage between the stock markets, when extreme returns occur; the study also relates to debate on investigating the dependence of stock market index changes on a particular day using the information about other stock market indices in the previous day.

Literature Review

There are many approaches, which have been proposed to analyze the relations between the international stock markets.

The dependency relations between the international stock market indices were analyzed in (Junior, Mullokandov, Kenett, 2015), where the correlation and the flow of information between 83 international market indices and their one-day lagged values were examined by the correlation and information based measures. To investigate the causal relations among the stock market indices the authors used Transfer Entropy and Total Influence approach. The daily closing values of 83 international stock market indices from January, 2003 to December, 2014 were analyzed.

Some part of the papers focuses on the investigation the relations among the stock markets, when there are large changes in the stock markets indices. The dependencies between European stock markets when returns are unusually large were analyzed in (Schich, 2002) by using the approach from multivariate extreme value theory. The analyzed data set covered daily close prices of the stock market indices of Germany, the United Kingdom, France, the Netherlands and Italy for the period dated from January, 1973 to July, 2001, which was divided into two sub-samples with equal length: from January, 1973 to April, 1987; from April, 1987 to July, 2001. It was found that in the situation of unusually large returns the linkage between markets increased during the second sub-sample (more recent period), and in case of the large negative returns the market links are higher than in case of large positive ones.

The latter finding is consistent with results obtained in (Longin and Solnik, 2001), where by applying the extreme value theory to analyze the extreme correlation of international equity markets, it was found that "*correlation increases in bear markets, but not in bull markets*". The dataset used in the paper covered monthly equity index returns of the United States, the United Kingdom, France, Germany and Japan, and was dated from 1959 to 1996. The authors in the paper defined the extreme returns as returns beyond given thresholds.

In (Bae, Karolyi, Stulz, 2000) only the mixed evidence was found for supporting the latter statement regarding the correlation in bear and bull markets. The authors instead of computing the correlation of large returns focused on measuring the counts of joint occurrences of large returns, where the extreme returns were defined as returns, laying in the tails of the overall return distribution, EGARCH model was applied as well. The analyzed dataset was represented by the daily returns of IFC[1] indices of 17 Asian and Latin American markets, S&P 500 index and Datastream International Europe index[2], and was dated from December 31, 1995 to May 14, 1999. To analyze the contagion in financial markets the multinomial logistic regression was applied.

There are also number of studies examining the mutual linkage between the stock markets during different time periods. The correlation of the international financial markets in times of crisis were analyzed in (Junior and Franca, 2011), where the Random Matrix theory was applied. In the paper the years of crisis were defined based on the quantity of the major

[1] IFC - International Finance Corporation, (Bae, Karolyi, Stulz, 2000, p. 5)
[2] (Bae, Karolyi, Stulz, 2000, p. 6)

markets' drops. The following crisis were considered: Black Monday (1987), Russian Crisis (1998), the Burst of Dot-com bubble (2001), September 11 (2001) and the USA mortgage crisis (2008). Under these time periods the analyzed number of indices varied: 23 indices were considered for 1987; for 1998 63 indices were examined; 79 indices were used for 2001 and for the analysis in 2008 92 indices were considered. The relationship between the international stock market indices were investigated by considering four years: 1987, 1998, 2001 and 2008, where for each year the eigenvalues of the correlation matrix of the considered indices were calculated with performing the subsequent analysis. For each of these four periods the correlation matrices in running windows were calculated with the subsequent comparison "*the average correlation between markets with the volatility and average volatility of the market mode*", where the market mode, was defined as a "*co-movement of all indices*" and was obtained by analyzing the eigenvector corresponding to the largest eigenvalues of the correlation matrix of the considered market indices. The authors showed that during the time periods of high volatility "*markets tend to behave similarly*".

In (Hui and Chan, 2013) the contagion across European real estate markets during the European sovereign debt crisis was examined. In the paper two periods were distinguished: pre-crisis period from July, 2005 to September, 2008 and crisis period dated from September, 2008 to November, 2011, where the criterion of identifying the starting point of the crisis period was used the day of the bankruptcy of Lehman Brothers.

The financial linkages between Chinese and Asian markets before, during and after the Global Financial Crisis is analyzed in (Glick and Hutchison, 2013). The authors found that during the crisis period the linkage between the Chinese and other Asian equity markets increased and persists high after the crisis. Daily equity prices of China, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, Thailand and India were used to investigate the equity markets' linkage with the help of correlation and regression analysis. Three periods were considered: before the Global Financial Crisis dated from June, 2005 to June, 2008; the crisis period lasting from July, 2008 to May, 2010; the period after the crisis from June, 2010 to October, 2012.

In (Fry-McKibbin et al., 2014) the regime switching model was used for the crises' dating in the source market, where nine crises were identified: Asian crisis (1997-1998); Russian crisis (1998); the US (LTCM crisis) crisis (1998); the Brazilian crisis (1999); Dot-com crisis (2000); the Argentine crisis (2001-2002); the US sub-prime crisis (2007-2008); the Great Recession (2008-2009) and European debt crisis (2010-2013). After determining each crisis's dating, contagion is analyzed by using four tests for contagion. The sample consisted of the daily equity price indices of 27 equity markets.

With the advent of the growing computer power and technology the data mining techniques, using in the stock market analysis, become to be widely applied. In (Huang, Nakamori, Wang, 2005) the stock market movement direction was forecasted by applying the support vector machine (SVM), in (Qiu and Song, 2016) the direction of the stock market index movement was predicted by using the artificial neural network (ANN) model optimized by using the genetic algorithms, Adaboost algorithm was applied in (Rodríguez and Sosvilla-Rivero, 2006) to find direction-of-change patterns for S&P 500 index.

Following the literature review mentioned above, different time periods, during which the relations among the stock markets were analyzed, have been determined by several ways:

using some event happening in the global economy, which can be considered as one of the triggers of the global market shocks; expertly; or by "dealing with" the chosen stock markets by analyzing the major market's drops or the crisis source market. The present research proposes to determine the time periods to discover the stock markets' linkage by identifying the regimes on the commodity markets. The approach of analyzing the dependencies between the stock markets, when there are large changes in the stock market indices, applied in the thesis also differs from the methodology proposed in the literature described above. In the current thesis the extreme changes in the stock market indices are suggested to capture by applying *Hidden Markov Model* methodology and subsequently, the instruments of the categorical analysis. The model based approach by applying *Stochastic Gradient Boosting* technique originally derived by (Friedman, 2001), is used to investigate the dependence of the changes of the chosen stock market on the other stock markets between two trading days.

Outline of the Thesis

The thesis is structured into five main chapters. The first chapter describes the methodology applied in the thesis and provides the brief theoretical background of main steps solved in the current research. At the beginning of the chapter *Hidden Markov Model* approach is briefly introduced, then the brief description of similarity and correlation measures is followed, last two sub-chapters are devoted to the description of the variable explanatory analysis covering the Information Values and the area under the ROC curve, and to introduction of *Stochastic Gradient Boosting* Methodology.

Chapter 2 focuses on introduction and description of the analyzed commodity markets. There are three sub-chapters dealing with each considered commodity market: Energy, Precious Metals and Non-energy commodity markets.

Chapter 3 discusses the input data used in the analysis.

Chapter 4 summarizes the results and discussion of empirical applications, where the first sub-chapter focuses on the identifying the states on the commodity markets. Similarly to the commodity markets, the regimes of the stock markets are detected in the second sub-chapter. As the states prevailing on the commodity and stock markets are identified, the mutual linkage among the stock markets during different situations on the commodity markets is examined in next two sub-chapters: in the first of these sub-chapters the similarity among the stock markets in terms of highly volatile regime's occurrence in this market during different situations on the commodity markets is investigated, and the next sub-chapter focuses on the correlation analysis. The last sub-chapter is devoted to the summarization of the identified typical scenarios of mutual relations among the stock markets considering the situations on the commodity markets.

Chapter 5 deals with the model-based approach, where the dependence of increase/decrease patterns of SSEC index on other stock market indices between two trading days by applying *Stochastic Gradient Boosting* approach during different situations on the commodity markets, is performed. Before applying Stochastic Gradient Boosting approach the variable screening step, covering the computation of Information Values and the area under individual ROC curves, is made.

The thesis is finalized my main conclusions.

1 Methodology and Theoretical Background

1.1 Applied Methodology

As a first step, the regimes prevailing on the analyzed commodity markets during the particular time period should be determined. Three commodity markets are considered: Energy, Precious Metals and Non-energy Commodity Markets. It is assumed that two states can prevail on the commodity market: "calm" state with lower volatility and state with higher volatility. Due to the latent nature of the market state variable, the appropriate methods for its identification should be used. Under the current thesis the methodology of *Hidden Markov Model*, which can capture the hidden states through the sequence of the observed values of the market index, has been applied. Firstly, the parameters of the HMM have been calibrated by applying the *Expectation-Maximization* (*EM*) algorithm (Dempster et al., 1977). Then by using the obtained adjusted parameters of the model the most probable sequence of states associated with the given observation sequence has been determined by applying *Viterbi* algorithm (Viterbi, 1967), (Forney, 1973). The approach is applied to logarithmic changes of the monthly commodity market indices. After the regimes' detection the following situations, prevailing on the commodity markets, have been considered: high volatility on the energy market; high volatility on the precious metals market; high volatility on the non-energy market; simultaneous high and simultaneous low volatility on all three considered commodity markets, whereas the case of high volatility on the energy market is divided into two periods based on the source underlying the oil price shocks causing higher volatility.

As the regimes prevailing on the analyzed commodity markets have been identified, the linkage between the chosen stock market indices during different situations on the commodity markets is investigated. To answer the question of similarity between the stock markets in terms of of highly volatile regimes' occurrences, the states, through which the stock markets go during different time periods, should be determined. Similarly to the commodity markets' regime detection, the states of the market indices can be identified by applying *Hidden Markov Model* methodology, where the latent market states are determined through the sequence of the observed stock market index values. In case of the analyzed indices the approach has been applied to the logarithmic returns of the daily close prices. In the regime detection process, three states prevailing on the stock market have been distinguished: volatile and negative market reflecting the higher uncertainty while in this state, "calm" market with low stock market volatility and a state with "medium" volatility. To look how similarly individual stock market indices behave regards to bear market regime occurrences, the instruments of the categorical analysis can be used. The variable indicating the detected regime for each market index can be transformed to a binary variable, which takes a value 1 during the highly volatile and negative market (bear market), otherwise the value is equal to 0. By performing this transformation the similarity matrix between the binary variables can be computed. To measure the similarity between binary variables *Jaccard Similarity Measure* is used, which is suitable for asymmetric binary variables. The similarity between the stock market indices in terms of the highly volatile regime's occurrence is measured for different situations on the commodity markets, determined by regime's detection on the commodity markets.

As the agreement between the stock markets in terms of highly volatile regimes' appearance is examined, the correlation among the market indices during different situations on the commodity markets is analyzed by *Spearman correlation coefficient*.

To investigate the dependence of the particular market index changes in time t+1 on the rest considered markets indices in time t under different situations on the commodity markets the model-based approach is employed. In the current thesis the movement direction of *Shanghai Composite Index (SSEC index)* in time t+1 was chosen as the outcome variable, and *Stochastic Gradient Boosting* algorithm, originally derived by (Friedman, 2001), was applied. The model based step focuses on the analysis of the impact of the different stock market indices on the increase / decrease patterns of SSEC index value between two trading days. The direction's changes in the value of SSEC index, which is the outcome variable, can be captured by a binary dependent variable, which for each row in the final data set refers to the time point t, takes the value 1 when the index value goes up in time t+1 comparing with the value in time t, and takes 0 otherwise. The analysis of increase/decrease patterns of SSEC index in time t+1 is also extended by concerning the chosen commodity prices introduced in the *Data description* chapter. Due to the interest in changes of indices' values and their impact on the change of SSEC index all explanatory variables in the final data set are transformed to the logarithmic returns.

Due to the binary nature of the outcome variable the classification model can be applied. Before the modeling step, the isolated impact of one explanatory variable on the increase/ decrease patterns of SSEC index is examined by calculating the area under the individual *ROC* curves and by applying the *Information Value* approach. This variable screening step enables better understanding of the independent contribution of each considered variable to the outcome, and also can be helpful in the variable selection step in case of significant correlation among variables. Comparing to the use of AUC as a way to measure the classifier performance, where the predicted probability is an input of AUC computation, in case of AUC used to measure the predictors' importance the numeric predictor itself is used to compute the area under the ROC curve. As all predictors are numerical and the Information Value (IV) can be influenced by the way of binning, the Information Values are computed for explanatory variables binning into 5-12 equal width bins. Then for each way of binning the variables are ranked in descending order, and the final IV's rank has been determined based on the simple average of the IV's ranks computed for each way of binning.

After variables explanatory analysis the predictors' correlation is measured by Spearman correlation coefficient. In case of highly correlated predictors the information from the variable screening step is used. As the problem of highly correlated predictors is eliminated, the dependence of SSEC index movements on other indices and commodity prices is explored by *Stochastic Gradient Boosting* approach. Similarly to the previous step the analysis is conducted separately for the different situations on the commodity markets.

1.2 Introduction to Hidden Markov Model

Following (Rabiner and Juang, 1986, p. 5) "*HMM is a doubly stochastic process with an underlying stochastic process that is not observable, but can only be observed through another set of stochastic processes that produce the sequence of observed symbols*".

The description of the main elements of an HMM can be found in (Rabiner and Juang, 1986), (Rabiner, 1989):

1. N - finite number of hidden states in the model. Possible values of the individual states are $\boldsymbol{S} = \{S_1, S_2, ..., S_N\}$, q_t is the state at time t.
2. M is a number of distinct observation symbols per state. The set of the individual symbols is $\boldsymbol{V} = \{v_1, v_2, ..., v_M\}$.
3. $\boldsymbol{A} = \{a_{ij}\}$ - the state transition probability matrix, where $a_{ij} = P(q_{t+1} = S_j|q_t = S_i)$, $1 \leq i, j \leq N$.
4. $\boldsymbol{B} = \{b_j(k)\}$ - the observation symbol probability matrix, where $b_j(k) = P(v_k \text{ at } t|q_t = S_j)$, $1 \leq j \leq N$, $1 \leq k \leq M$.
5. $\boldsymbol{\pi} = \{\pi_i\}$ - the initial state probability distribution, where $\pi_i = P(q_1 = S_i)$, $1 \leq i \leq \mathrm{N}$.

The observation sequence $\boldsymbol{O} = O_1\ O_2\ ...\ O_T$ can be generated by using the HMM with the given appropriate values N, M, $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{\pi}$, where each observation O_t is one of the symbol from $\boldsymbol{V}$ and T is a number of observations in the sequence. An HMM can be represented by the compact notation $\lambda = \{A, B, \pi\}$.

There are three main problems of HMM: *Evaluation*, *Decoding* and *Learning*. Following (Rabiner, 1989) for HMMs these three fundamental problems are:

1. Problem 1: Given an HMM $\lambda = \{A, B, \pi\}$ and the observation sequence $\boldsymbol{O} = O_1\ O_2\ ...\ O_T$, determine the likelihood $P(O|\lambda)$, i.e. the probability of the observation sequence.
2. Problem 2: Given the model $\lambda = \{A, B, \pi\}$ and the observation sequence $\boldsymbol{O} = O_1\ O_2\ ...\ O_T$, discover the best [3] corresponding state sequence $Q = q_1\ q_2\ ...\ q_T$.
3. Problem 3: Given the observation sequence $\boldsymbol{O} = O_1\ O_2\ ...\ O_T$ and the set of states in the HMM, adjust the model parameters $\lambda = \{A, B, \pi\}$ to maximize $P(O|\lambda)$.

Problem 1 (*Evaluation*) consists in the computing the likelihood of the particular observation sequence. Comparing to a Markov Chain in a Hidden Markov Model the state sequence is hidden, so the question is how $P(O|\lambda)$ can be calculated efficiently. The procedure

[3] In (Rabiner L.R., 1989, p. 261) "*best explains the observations*"

that can be used to solve this problem is called the *Forward-Backward Algorithm* (Baum and Eagon, 1967), (Baum and Sell, 1968). The algorithm uses the principle of dynamic programming. Following (Rabiner, 1989) the forward variable $\alpha_t(i)$ is the probability of the partial observation sequence until time t is $O_1\ O_2 \ldots O_t$ and the state of the given model λ at time t is S_i, mathematically it can be defined as

$$\alpha_t(i) = P(O_1 O_2 \ \ldots\ O_t,\ q_t = S_i \mid \lambda). \tag{1}$$

The *Forward Algorithm* can be described as (Rabiner, 1989):

1. Initialization: $\alpha_1(i) = \pi_i b_i(O_1),\ 1 \le i \le N.$ (2)
2. Induction: $\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}),\ 1 \le t \le T-1,\ 1 \le j \le N.$ (3)
3. Termination: $P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i).$ (4)

This algorithm involves the computation in the order of N^2T. In a similar way the *Backward Algorithm* can be described. This algorithm calculates the probability $\beta_t(i)$ (backward variable), which can be defined as

$$\beta_t(i) = P(O_{t+1} O_{t+2}\ \ldots\ O_T,\ q_t = S_i \mid \lambda). \tag{5}$$

The probability $\beta_t(i)$ is the probability of the partial observation sequence from time t+1 to the end, given the model λ and state S_i at time t. The algorithm involves 2 steps:

1. Initialization: $\beta_T(i) = 1,\ 1 \le i \le N.$ (6)
2. Induction: $\beta_t(i) = \sum_{j=1}^{N} a_{ij} b_j(O_{t+1}) \beta_{t+1}(j),\ t = T-1,\ T-2,\ \ldots,1,\ 1 \le i \le N.$ (7)

As in case of the Forward Algorithm, the Backward Algorithms requires computations in the order of N^2T. The Backward Algorithm is not required to solve Problem 1, as the Evaluation problem can be solved by the Forward Procedure, but the Backward part of the *Forward-Backward Algorithm* will be used to solve Problem 3.

Problem 2 (*Decoding*) determines the most probable sequence of states associated with the given observation sequence. The *decoding* problem can be solved by *Viterbi Algorithm* (Viterbi, 1967), (Forney, 1973). Similarly to the Forward Algorithm, Viterbi Algorithm is based on the dynamic programming, and the goal is to find the single best state sequence. Following (Rabiner, 1989) the maximum probability along a single path, which ends up at time t in state S_i and accounts for the observed sequence $O_1\ O_2 \ldots O_t$, can be defined as

$$\delta_t(i) = \max_{q_1, q_2, \ldots, q_{t-1}} P[q_1 q_2\ \ldots\ q_t = i,\ O_1 O_2\ \ldots\ O_t \mid \lambda], \tag{8}$$

so by induction there is

$$\delta_{t+1}(j) = (\max_i \delta_t(i)a_{ij}) \cdot b_j(O_{t+1}). \tag{9}$$

The algorithm to find the best state sequence can be defined as (Rabiner, 1989):

1. Initialization: $\delta_1(i) = \pi_i b_i(O_1),\ 1 \le i \le N,$ (10)

   $\psi_1(i) = 0.$ (11)

2. Recursion: $\delta_t(j) = \max_{1\le i\le N}(\delta_{t-1}(i)a_{ij})b_j(O_t),\ 2 \le t \le T,\ 1 \le j \le N,$ (12)

   $\psi_t(j) = \arg\max_{1\le i\le N}(\delta_{t-1}(i)a_{ij}),\ 2 \le t \le T,\ 1 \le j \le N.$ (13)

3. Termination: $P^* = \max_{1\le i\le N}(\delta_T(i)),$ (14)

   $q_T^* = \arg\max_{1\le i\le N}(\delta_T(i)).$ (15)

4. State sequence backtracking:

   $q_t^* = \psi_{t+1}(q_{t+1}^*),\ t = T-1,\ T-2,\ ...,\ 1.$ (16)

Problem 3 (*Learning*) determines the model's parameters. The goal is to train the transition probabilities *A* and the emission probabilities *B* of the HMM. This problem can be solved by *Baum-Welch* algorithm (Baum et. al., 1970) or *Expectation-Maximization* (EM) algorithm (Dempster et al., 1977), *Baum-Welch* algorithm is a special case of EM algorithm. In both algorithms, which are iterative, $P(O|\lambda)$ is only locally maximized.

1.3 Similarity and Correlation Analysis

There are a large number of coefficients to measure the similarity between variables. The choice of the appropriate similarity measure is based on the type of the analyzed data. The summary of the different measures of similarity and dissimilarity can be found in (Řezanková, et al., 2009) and (Řezanková, 2005).

In the current thesis *Jaccard Similarity Measure* is used, which is suitable for asymmetric binary variables and can be computed according to the formula (Řezanková et al., 2009)

$$S_J = \frac{a}{a+b+c}, \tag{17}$$

where *a* is a number occurrences of the analyzed category in both variables. *b* refers to the number of presence 1 in a variable y_i and 0 in y_j. The number of variables being 0 in y_i and 1 in y_j is denoted by *c*.

To measure the strength and direction of the dependence between two quantitative variables the correlation coefficients can be computed. There are two basic measures, which are widely used in the correlation analysis: *Pearson correlation* and *Spearman rank* *correlation*. Pearson correlation coefficient between the variable k and l can be calculated as (Řezanková, Húsek, Snášel, 2009):

$$r_{kl} = \frac{\sum_{i=1}^{n}(x_{ik}-\overline{x}_k)(x_{il}-\overline{x}_l)}{\sqrt{\sum_{i=1}^{n}(x_{ik}-\overline{x}_k)^2 \sum_{i=1}^{n}(x_{il}-\overline{x}_l)^2}}\,. \tag{18}$$

Spearman rank correlation coefficient between two variable x and y can be computed as (Hindls et al., 2007)

$$r_{i_x i_y} = 1 - \frac{6\sum(i_x - i_y)^2}{n(n^2-1)}\,, \tag{19}$$

where i_x and i_y are the ranks of the corresponding values of x and y.

For the Pearson correlation both variables should be normally distributed (Chen and Popovich, 2002), which is not required in case of Spearman correlation coefficient's computation.

1.4 Variable Explanatory Analysis

1.4.1 Information Value

The *Information Value* (IV) and *Weight of Evidenc*e (*WOE*) is a widely used technique for binary classification problem especially in the credit risk modeling. *WOE* enables to analyze the relationship between the predictive variable and a binary target outcome, and *IV* evaluates the overall predictive power of the considered variable (Larsen, 2015)[4], (Lin, 2013)[5]. Considering the variable X_j divided into $B_1, \ldots, B_k$ bins, *WOE* for variable X_j for bin i can be calculated as (Larsen, 2015)[6]

$$WOE_{ij} = \log\frac{P(X_j \in B_i \mid Y=1)}{P(X_j \in B_i \mid Y=0)}\,, \tag{20}$$

and *Information Value*, which is the weighted sum of WOE of the variable's categories (resp. bins) can be gained as

$$IV_j = \sum_{i=1}^{k}(P(X_j \in B_i \mid Y=1) - P(X_j \in B_i \mid Y=0)) \times WOE_{ij}\,. \tag{21}$$

[4] Larsen K. (2015). Data Exploration with Weight of Evidence and Information Value in R. [Retrieved March 17, 2017]. http://multithreaded.stitchfix.com/blog/2015/08/13/weight-of-evidence/.

[5] Lin, Alec Zhixiao. (2013). Variable Reduction in SAS by Using Information Value and Weight of Evidence. SAS Global Forum 2013. Data Mining and Text Analytics. [Retrieved March 17, 2017]. http://support.sas.com/resources/papers/proceedings13/095-2013.pdf

[6] *viz*. note 4.

In *IV* computation the sum of *WOE* is weighted by the difference between the proportion of being $Y = 1$ and the proportion of outcome variable equal to 0 ($Y = 0$).

In case of the increase/decrease analysis of the stock market index behavior when the outcome variable takes 1 in case of increase in time t+1 comparing to time t and is equal to 0 in case of decrease the formula for computation *WOE* and *IV* can be rewritten as

$$WOE_{ij} = \log \frac{\%Increase_i}{\%Decrease_i}, \tag{22}$$

$$IV_j = \sum_{i=1}^{k} (\%Increase_i - \%Decrease_i) \times WOE_{ij}. \tag{23}$$

By analyzing the variables based on *IV* in (Siddiqi, 2006) the following rule of thumb has been proposed:

- IV < 0,02 : unproductive
- 0,02 ≤ IV ≤ 0,1: weak
- 0,1 ≤ IV ≤ 0,3: medium
- 0,3+ : strong.

Siddiqi in (Siddiqi, 2006) suggested that variables with IV greater than 0.5 cause suspision and "*should be checked for overpredicting"* (Siddiqi, 2006, p. 82).

1.4.2 Area under the ROC curve

Receiver operating characteristic curve (*ROC* curve) is a graph that enables visualizing the performance of classifiers. In a binary classification model, producing the probability of the class membership, the final instance's class assignment can be predicted by set the threshold. Considering the binary classification problem there are four possible outcomes (Fawcett, 2006): if the actual value of outcome is positive and it is classified as positive, then it is call a *true positive* (*TP*); if it is classified as negative, then it is counted as *false negative* (*FN*); when the actual outcome is negative and it is classified as negative, it is called as *true negative* (*TN*), and in case of classifying as positive, it is counted as *false positive* (*FP*). After introducing the possible outcomes from a binary classifier the *ROC* curve can be defined as a two-dimensional graph, plotting *true positive rate* on the *Y* axis and *false positive rat*e on *X* axis at varied threshold settings, where (Fawcett, 2006), (Bradley, 1997):

$$true\ positive\ rate = \frac{true\ positive}{total\ \ positives} \tag{24}$$

and

$$false\ positive\ rate = \frac{false\ positive}{total\ \ negatives}. \tag{25}$$

A common method to measure the classifier performance based on the ROC curve is the area under the *ROC* curve (*AUC*), which represents the probability that a randomly chosen positive example will be ranked by the classifier higher than a randomly chosen negative example (Fawcett, 2006). The value of AUC can be between 0 and 1. In case of a random classifier the ROC curve produces the points lying on the diagonal line between (0,0) and (1,1) with *AUC* equal to 0.5. The *AUC* value equal to 1 denotes the best classifier.

More details regarding the *ROC* curve and *AUC* can be found in (Fawcett, 2006), and investigation of the use of the area under the *ROC* curve as a performance measure for machine learning algorithms can be found in (Bradley, 1997).

1.5 Stochastic Gradient Boosting

Boosting is powerful machine learning technique for classification and regression problems. The algorithms of Gradient Boosting and Stochastic Gradient Boosting can be found in (Friedman, 1999) and (Friedman, 2001).

Following (Friedman, 1999) let y is a response variable and $\mathbf{x} = \{x_1,...,x_n\}$ is vector of explanatory variables. $\{y_i,\mathbf{x}_i\}_1^N$ is training sample of known (y, $\mathbf{x}$) values. The aim is to find a function $F^*(\mathbf{x})$ that maps $\mathbf{x}$ to y, so that over the join distribution of all (y, $\mathbf{x}$) values, the expected value of some specified loss function $\Psi(y, F(\mathbf{x}))$ is minimized (Friedman, 1999)

$$F^*(\mathbf{x}) = \arg\min_{F(\mathbf{x})} E_{y,\mathbf{x}} \Psi(y, F(\mathbf{x})). \tag{26}$$

Boosting approximates $F^*(\mathbf{x})$ by the "additive" expansion of the form

$$F(\mathbf{x}) = \sum_{m=0}^{M} \beta_m h(\mathbf{x};\mathbf{a}_m), \tag{27}$$

where the functions $h(x;a)$ ("base learner") are usually chosen to be simple function of x with parameters $\boldsymbol{a}$. For m = 1, 2, …,M

$$(\beta_m, \mathbf{a}_m) = \arg\min_{\beta,\mathbf{a}} \sum_{i=1}^{N} \Psi(y_i, F_{m-1}(\mathbf{x}_i) + \beta h(\mathbf{x}_i, \mathbf{a})) \tag{28}$$

and

$$F_m(\mathbf{x}) = F_{m-1}(\mathbf{x}) + \beta_m h(\mathbf{x};\mathbf{a}_m). \tag{29}$$

The function $h(\boldsymbol{x};\boldsymbol{a})$ is fit by least-squares

$$\mathbf{a}_m = \arg\min_{\mathbf{a},\rho} \sum_{i=1}^{N} [\tilde{y}_{im} - \rho h(\mathbf{x}_i;\mathbf{a})]^2 \tag{30}$$

to the current "pseudo" - residuals

$$\tilde{y}_{im} = -\left[\frac{\partial \boldsymbol{\Psi}(y_i, F(\mathbf{x}_i))}{\partial F(\mathbf{x}_i)}\right]_{F(\mathbf{x})=F_{m-1}(\mathbf{x}).} \tag{31}$$

Given $h(\boldsymbol{x};\boldsymbol{a}_m)$, the optimal value of the coefficient β_m is determined (Friedman, 1999)

$$\beta_m = \arg\min_{\beta} \sum_{i=1}^{N} \boldsymbol{\Psi}(y_i, F_{m-1}(\mathbf{x}_i) + \beta h(\mathbf{x}_i;\mathbf{a}_m)). \tag{32}$$

In (Friedman, 1999) it was shown that incorporating randomization into this procedure can improve the approximation accuracy and speed of gradient boosting. Following (Friedman, 1999) "*at each iteration a subsample of the training data is drawn at random from the full training data set*", which is then used "*to fit the base learner and compute the model update for the current iteration*".

The specification of the loss function depends on the distribution of the response variable. The loss-functions can be classified based on the type of the response variable. Following (Natekin and Knoll, 2013) the most frequently used loss-functions for continues response: Gaussian L_2 loss function, Laplace L_1 loss function, Huber loss function δ specified, Quantile loss function α specified; for the categorical response: Binominal loss function and Adaboost loss function; there are also loss functions for other families of response variable: loss functions for survival models, loss functions counts data, custom loss functions.

Boosting has the following tuning parameters (James et al., 2013), (Natekin and Knoll, 2013):

- *n.trees* - the number of trees
- λ - the shrinkage parameter
- *interaction depth* - the number of splits at each tree
- *n.minobsinnode* - the number of observations in leaves - the minimum number of observations in trees' terminal nodes.

In many practical applications it is useful to identify the variable importance. More details of determining the relative importance of input variables can be found in (Friedman, 2001).

Considering that the tree has L splits, the influence of the variable j in a single tree T can be defined as (Natekin and Knoll, 2013)

$$Influence_j(T) = \sum_{i=1}^{L-1} I_i^2 1(S_i = j). \tag{33}$$

S_i is a current splitting variable, and it is the same as a queried variable j. I^2_i - empirical squared improvement assigned to the model as result of the split. The overall influence of the variable j in the ensemble can be calculated as (Natekin and Knoll, 2013)

$$Influence_j = \frac{1}{M}\sum_{i=1}^{M} Influence_j(T_i). \qquad (34)$$

The fitted function in gradient boosting can be visualized by using partial dependence functions, showing the effect of a variable on the outcome after the average effects of all other variables in model are taken into account (Elith, Leathwick, Hastie, 2008). More information about *partial dependence plots* can be found in (Friedman, 2001).

For a given subset $\mathbf{x}_s$ of a predictor variable index by $s \subset \{1,2, ..., n\}$, the partial dependence of a function $F(\mathbf{x})$ on $\mathbf{x}_s$ is defined as (Friedman and Popescu, 2008)

$$F_s(\mathbf{x}_s) = E_{\mathbf{x}\backslash s}[F(\mathbf{x}_s, \mathbf{x}_{\backslash s})], \qquad (35)$$

where $\mathbf{x}_s$ is a prescribed set of joint values for the variables in the subset, the expected value is over the marginal (joint) distribution of all variables $\mathbf{x}_{\backslash s}$ not represented in $\mathbf{x}_s$. The entire variable set is $\mathbf{x} = (\mathbf{x}_s, \mathbf{x}_{\backslash s})$.

Partial dependence plots enable better understanding the value of the chosen variable influence on the response variable after averaging the influence of all other variables.

2 Commodity Markets

Following the *Commodity Market Outlook, October 2016*[7], there are five main commodity markets: Energy, Agriculture, Fertilizers, Metals and Minerals, Precious Metals. Under the current thesis three main commodity markets are examined: Energy, Precious Metals and Non-Energy market covering Agriculture, Fertilizers, Metals & Minerals. Firstly, the analyzed commodity markets will be briefly overviewed, then in the empirical part the regimes, prevailing on the particular market during different time periods, will be identified. The markets' regimes identification process will be conducted considering the assumption that for each market two main states can be distinguished: more "calm" and more volatile state.

2.1 Energy market

Energy commodity market refers to the main energy sources: crude oil, coal and natural gas. In recent years there can be noticed the movement to the renewable energy sources, e.g. wind, solar, different types of biomass, hydropower and etc., these types of energy sources are not the subject of the present thesis. According to *World Oil Outlook, 2016* [8] these days 81% of the energy mix is formed by fossil fuels, mainly, oil, gas and coal. Fig 1, Fig 2 and Fig 3 show the course of the crude oil, natural gas and coal monthly prices, which are dated from January, 1982 to November, 2016. In case of crude oil prices three crude oil price benchmarks are shown: crude oil, Brent; crude oil, Dubai; crude oil, WTI (West Texas Intermediate). It can be seen that the course of these three benchmarks behaves in a similar way, the visible difference can be noticed mainly between 2011 and 2014. The natural gas price is presented by prices of: natural gas, US; natural gas, Europe; Liquefied natural gas, Japan. The price of coal commodity is described by coal price, Australian. The graphs are created in R Studio with the help of *ggplot2* package (Wickham, 2009).

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[7] World Bank Group. 2016. *Commodity Markets Outlook, October*. World Bank, Washington, DC. [Retrieved December 12, 2016]. http://pubdocs.worldbank.org/en/143081476804664222/CMO-October-2016-Full-Report.pdf.

[8] Organization of the Petroleum Exporting Countries. *2016 OPEC World Oil Outlook*. October 2016. [Retrieved December 12, 2016] http://www.opec.org.

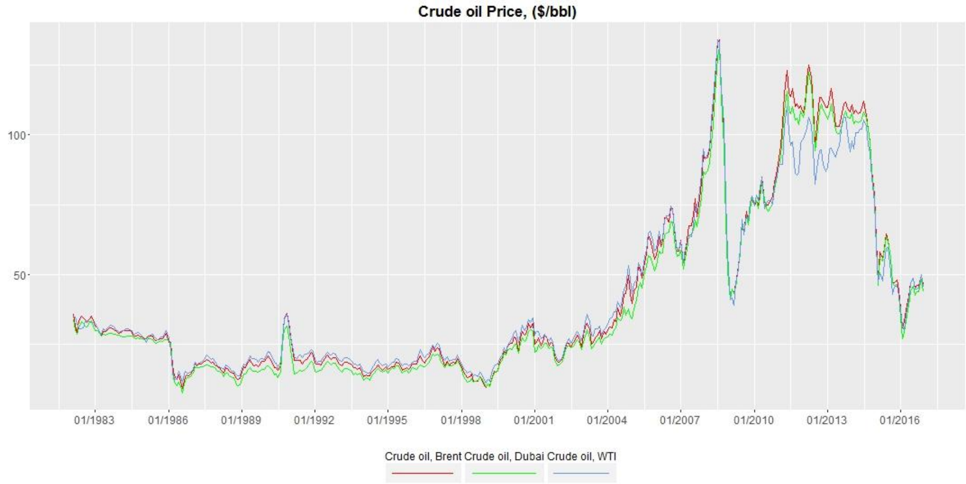


Fig 1 Crude oil prices, ($/bbl). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.* Own calculation in R Studio, *ggplot2* package.

Fig 2 Natural gas prices, ($/mmbtu). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2* package.

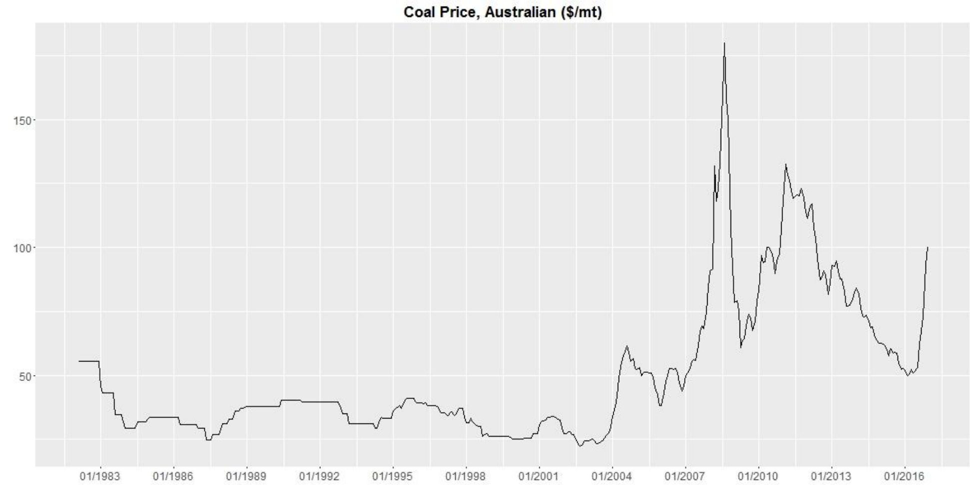


Fig 3 Coal price, Australian ($/mt). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.* Own calculation in R Studio, *ggplot2* package.

Following the *World Energy Balances, 2016* [9] oil, natural gas and coal accounted for 81% of the total primary energy supply in 2014, where oil forms 31%, natural gas covers 21% and the coal share is 29%. According to *Commodity Markets Outlook, January 2017* [10] the largest oil producers in 2015 were the United States, Saudi Arabia and the Russian Federation, together accounting for about 40% of the world oil production. The largest share of the world oil consumption in 2015 belonged to the United States (20%) and China (13%). Fig 4 and Fig 5 show the world oil production's and consumption's shares of the chosen countries during 2012 -2015.

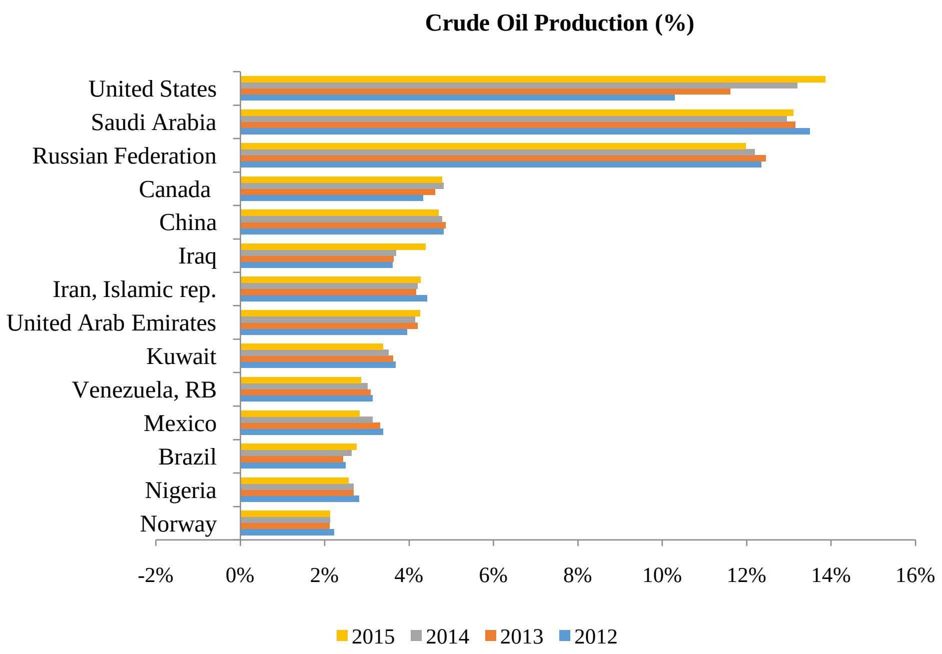


Fig 4 The World Oil Production's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January*. Own calculation in Excel.

[9] OECD (2016), *World Energy Balances 2016*, OECD Publishing, Paris.

[10] World Bank Group. 2017. *Commodity Markets Outlook*, *January*.World Bank, Washington, DC. [Retrieved February 12, 2017]. http://pubdocs.worldbank.org/en/820161485188875433/CMO-January-2017-Full-Report.pdf.

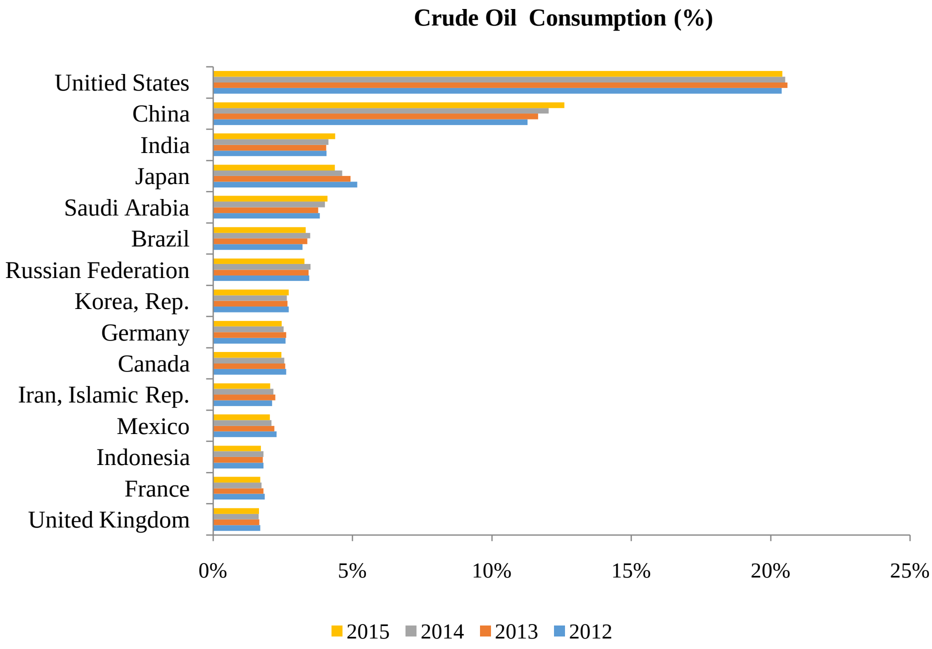


Fig 5 The World Oil Consumption's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook, January.* Own calculation in Excel.

Comparing the distribution of the world oil production and consumption illustrated on Fig 4 and Fig 5, it can be observed that the United States and China have larger share in the oil consumption' distribution than in oil production. The United States accounted in 2015 for more than 20% of the world oil consumption and for about 14% of the world oil production; China covered 14% of oil consumption share and 5% of the world oil production. Oppositely, the contribution of Saudi Arabia, the Russian Federation and Canada to the world oil production is more than their proportion in the oil consumption and reached in 2015: 13%, 12% and 5% correspondingly, whereas their share in the world oil consumption in the same year were: 4%, 3% and 2% correspondingly. According to *Key World Energy Statistics, 2016*[11] Saudi Arabia, the Russian Federation, the United Arab Emirates, Nigeria, Canada, Kuwait, Venezuela, Angola, Kazakhstan are net exporters, and net importers are: the United States, the People's Republic of China, India, Japan, Korea, Germany, Spain, Italy, France and the Netherlands.

Following *Key World Energy Statistics, 2016* the largest natural gas producers are: the United States, the Russian Federation, the Islamic Republic of Iran, Qatar, Canada, the People's Republic of China, Norway, Saudi Arabia, Turkmenistan and Algeria. The Russian Federation, Qatar, Norway, Canada, Turkmenistan, Algeria, Indonesia, Australia, Malaysia and Nigeria belong to net exporters, and natural gas net importers are Japan, Germany, Italy, the People's Republic of China, Turkey, Korea, France, Mexico, the United Kingdom and Spain. The distribution of the natural gas production and consumption among the chosen countries for the period from 2012 to 2015 is illustrated on Fig 6 and Fig 7.

[11] IEA (2016), *Key World Energy Statistics 2016*, IEA, Paris.

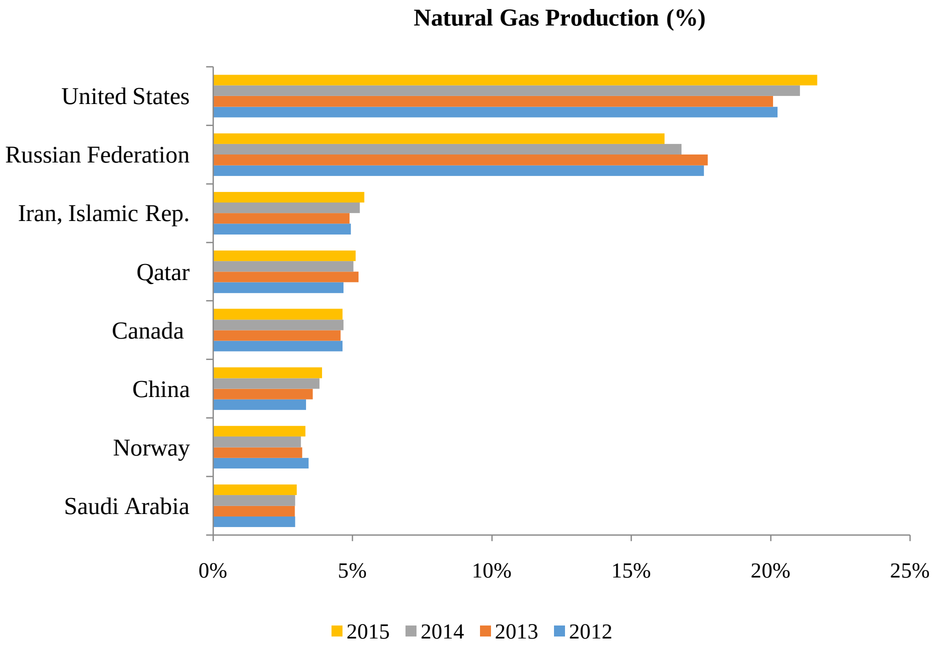


Fig 6 The World Natural Gas Production's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook, January*. Own calculation in Excel.

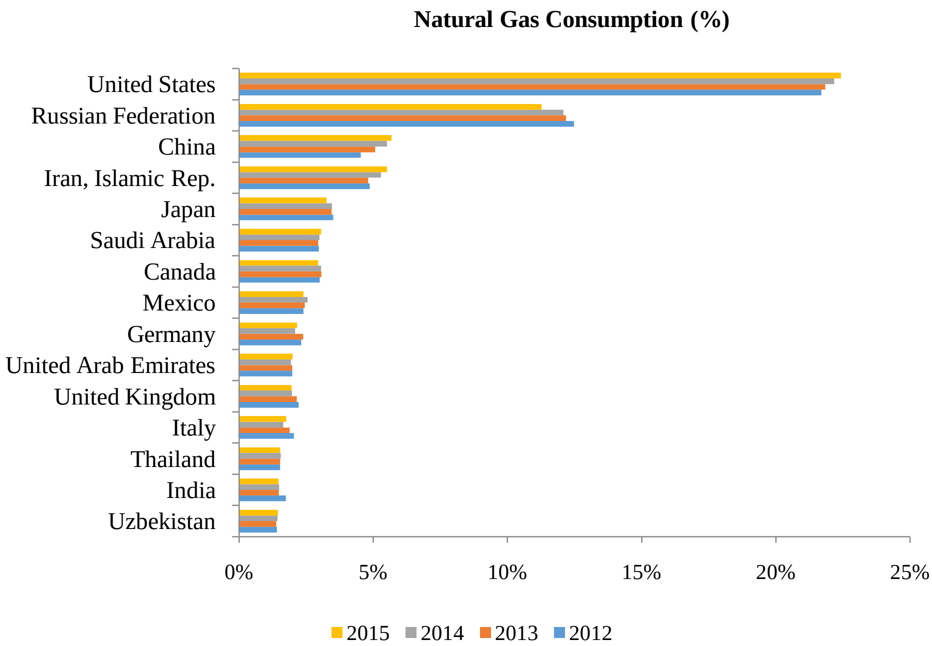


Fig 7 The World Natural Gas Consumption's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook, January*. Own calculation in Excel.

The world coal production's and consumption's distribution of the chosen countries can be found in Fig 8 and Fig 9. The China's share of the world coal production during 2012-2015 was more than 45% and in 2015 reached almost 48%. The United States, India, Australia, Indonesia, the Russian Federation and South Africa together accounted for 41% of the world coal production in 2015. In case of the coal consumption the China's share even slightly higher than in case of the production distribution and amounted to 50% in 2015. India, the United States, Japan, the Russian Federation, South Africa, the Republic of Korea, Indonesia and Germany covered for almost 35% of the world coal consumption in 2015.

Following *Key World Energy Statistics, 2016*[12] the net coal exporters are: Australia, Indonesia, the Russian Federation, Columbia, South Africa, the United States, Kazakhstan, Canada, the Republic of Korea and Mongolia. India, the People's Republic of China, Japan, Korea, Germany, Turkey, the United Kingdom, Malaysia, and Thailand belong to the net coal importers.

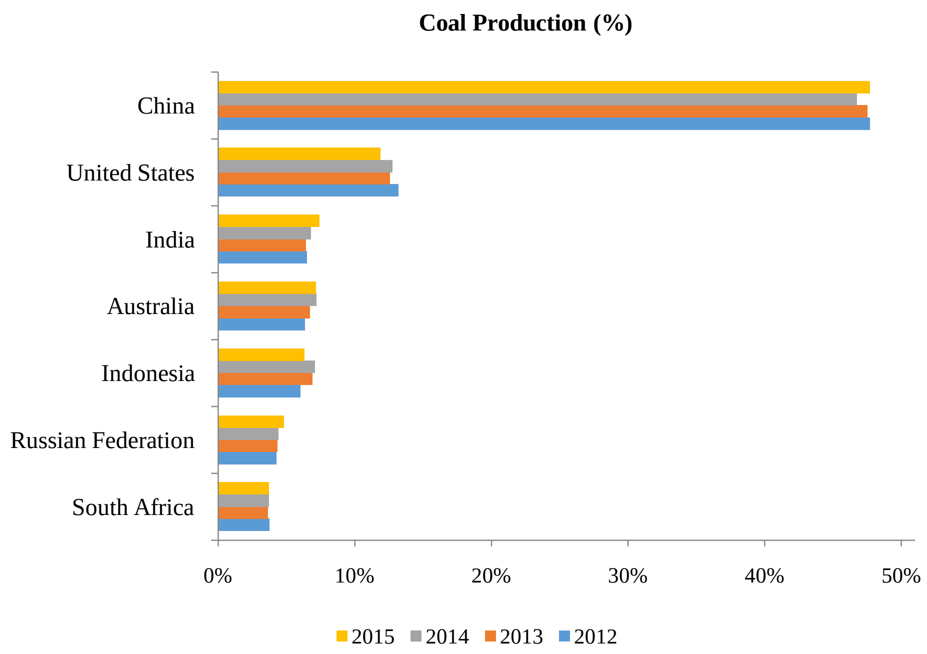


Fig 8 The World Coal Production's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January*. Own calculation in Excel.

[12] IEA (2016), *Key World Energy Statistics 2016*, IEA, Paris. (2015 provisional data)

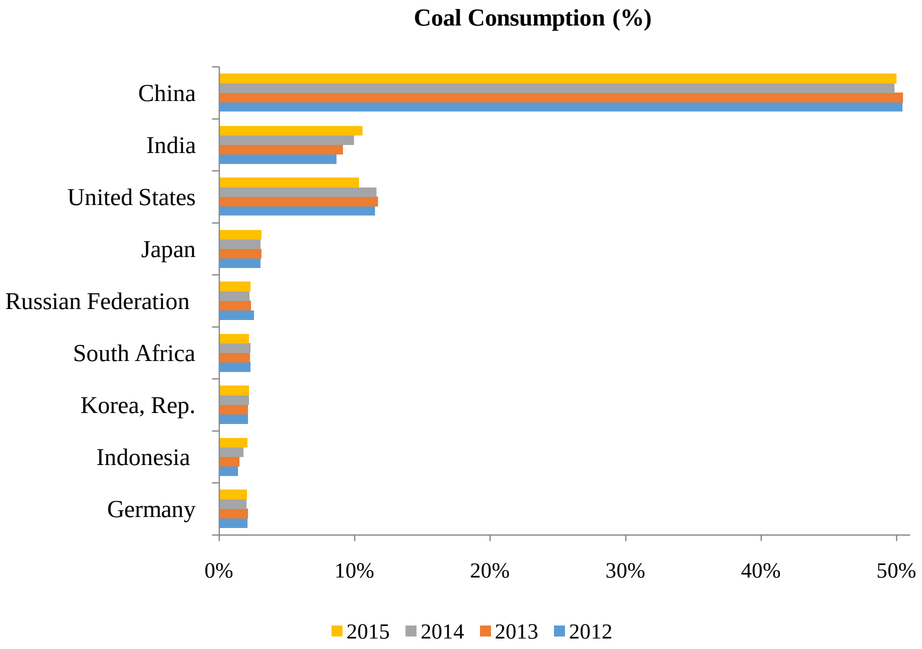


Fig 9 The World Coal Consumption's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January.* Own calculation in Excel.

2.2 Precious Metals Market

Precious metals commodity market covers mainly gold, silver and platinum. Monthly prices[13] dated from January, 1982 to November, 2016 can be found in Fig 10 (gold and platinum prices) and in Fig 11 (silver prices). Based on these figures similar patterns in the behavior of the precious metals' prices can be observed. Gold as the oil and other precious metals nowadays can be used not only as input commodity in manufacturing industry but are also demanded for investment purposes. The platinum and silver relations to the gold price may be partly explained by considering both these metals as alternative for gold during the uncertainty on the gold market. Following the *Commodity Markets Outlook, January 2017*[14] during the period from 2010 to 2015 the largest gold producer was China, accounting for more than 14% of the total world gold production in 2015. In case of the gold fabrication's distribution during 2010-2015 excepting the year 2013 the leading position belonged to India, accounting for 29% of the world gold fabrication in 2015. Then China follows with almost 24% of the total gold fabrication. Fig 12 and Fig 13 show the world gold production's and fabrication' shares of the chosen countries during 2010 -2015.

[13] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1

[14] World Bank Group. 2017. *Commodity Markets Outlook*, *January*.World Bank, Washington, DC. [Retrieved February 12, 2017] http://pubdocs.worldbank.org/en/820161485188875433/CMO-January-2017-Full-Report.pdf

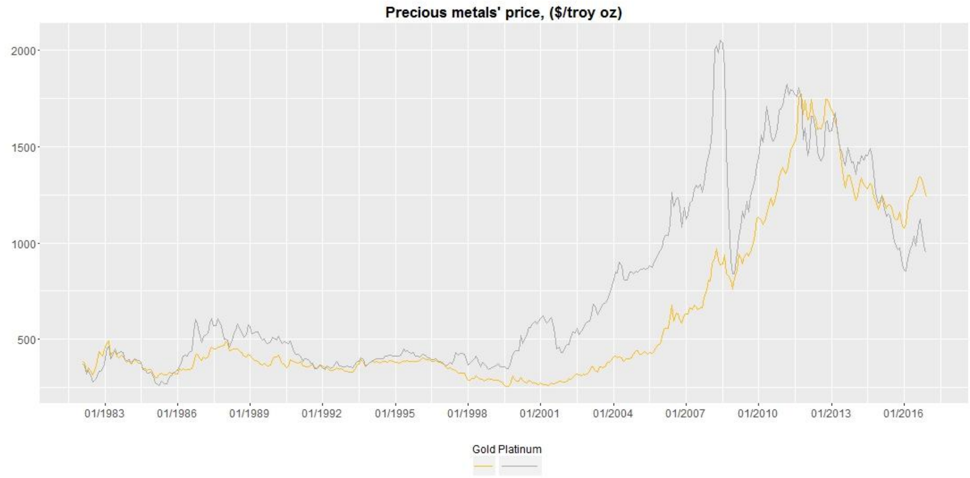


Fig 10 Gold and platinum monthly prices, ($/troy oz). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.* Own calculation in R Studio, *ggplot2* package.

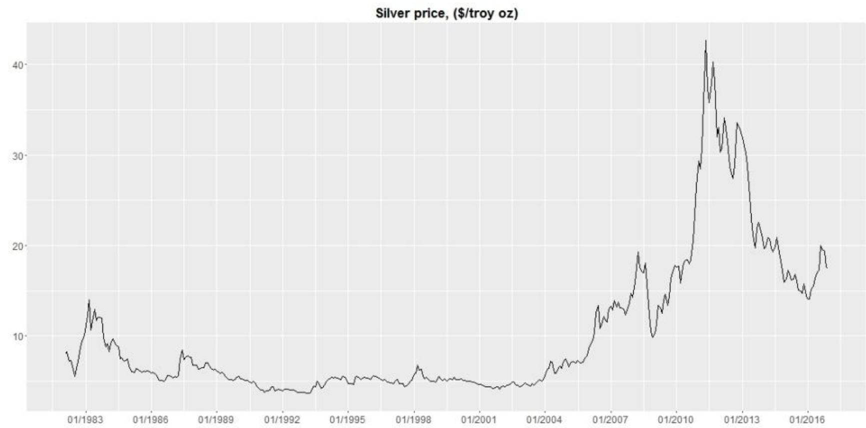


Fig 11 Silver monthly prices ($/troy oz). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.* Own calculation in R Studio, *ggplot2* package.

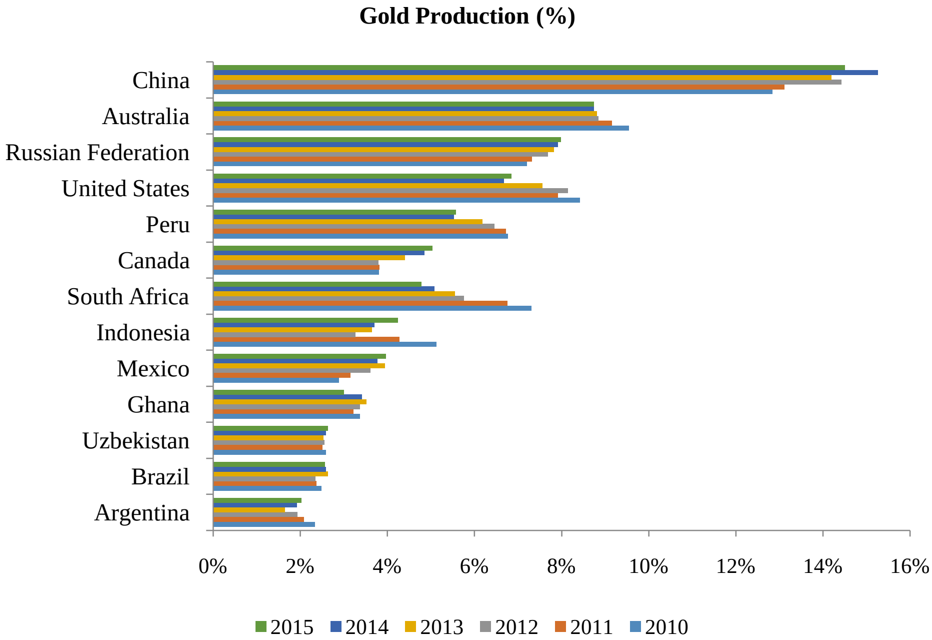


Fig 12 The World Gold Production's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January*. Own calculation in Excel.

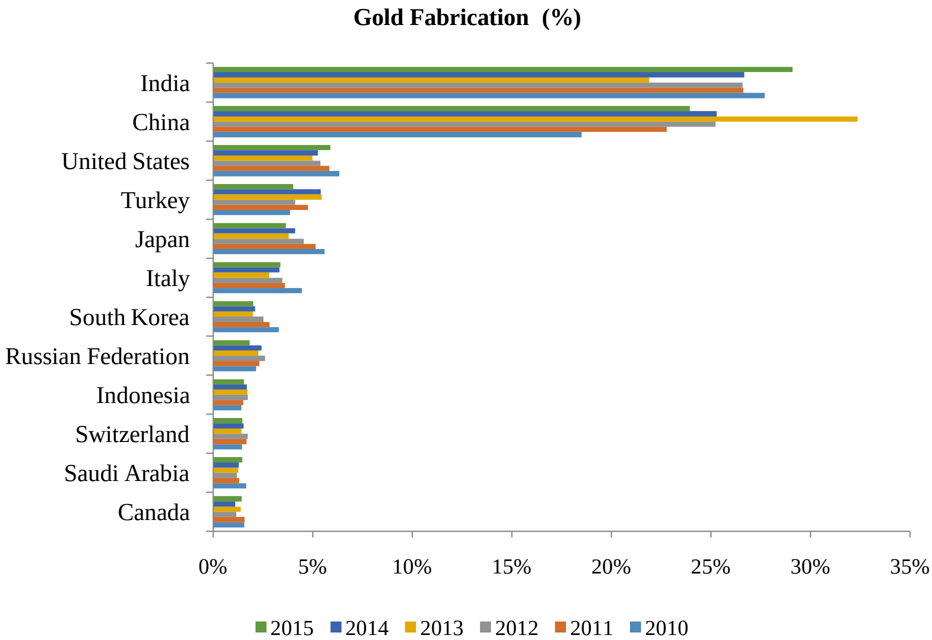


Fig 13 The World Gold Fabrication's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January*. Own calculation in Excel.

The highest share of the world silver production in 2015 belonged to Mexico (21%), then Peru (15%) and China (12%) followed; other countries with significant share in the silver production in 2015 were: the Russian Federation (6%), Australia (6%), Chile (5%), Bolivia (5%), Poland (5%), the United States (4%) and Argentina (4%) [15]. Fig 14 and Fig 15 show the world silver production's and fabrication' shares of the chosen countries during 2010-2015.

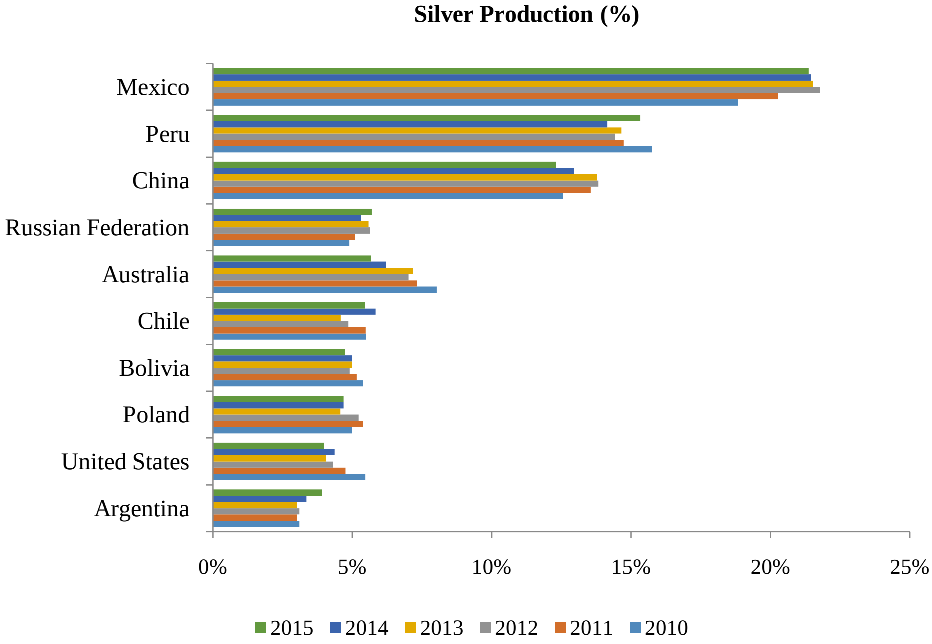


Fig 14 The World Silver Production's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook*, *January*. Own calculation in Excel.

[15] Calculations are made based on data retrived from *World Bank Commodity Markets Outlook, January 2017*. World Bank Group. 2017. *Commodity Markets Outlook*, *January*.World Bank, Washington, DC. [Retrieved February 12, 2017] http://pubdocs.worldbank.org/en/820161485188875433/CMO-January-2017-Full-Report.pdf

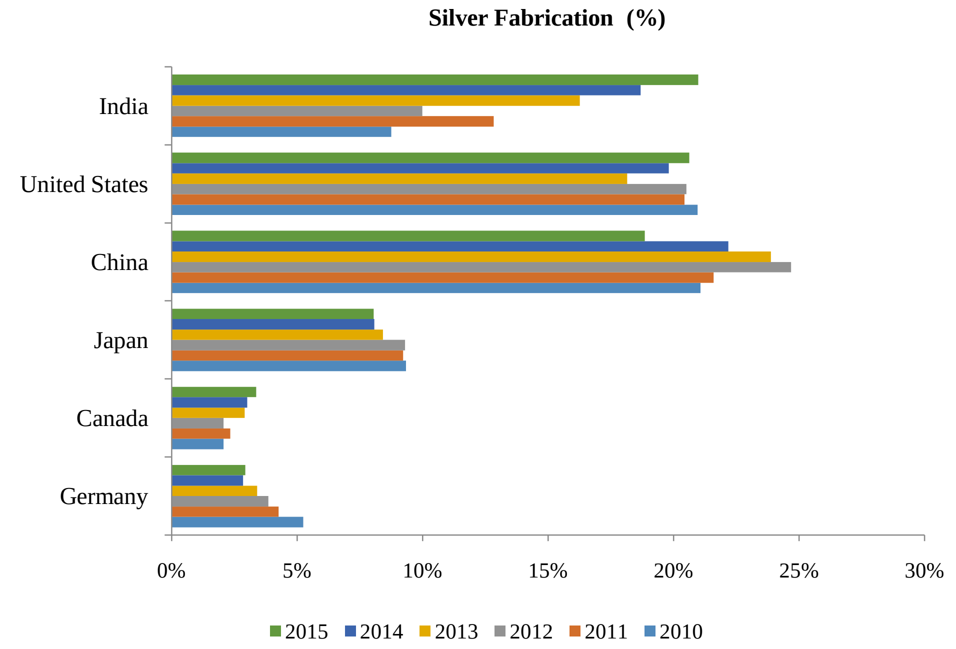


Fig 15 The World Silver Fabrication's share of the chosen countries. Data source: World Bank Group. 2017. *Commodity Markets Outlook, January.* Own calculation in Excel.

Based on the distribution of the world silver production and fabrication illustrated on Fig 14 and Fig 15, it can be observed that in 2015 the United States and India's shares in the fabrication were almost equal, whereas in 2010, 2012 the India's representation was almost twice smaller than the share of USA in the corresponding years and than itself representation in 2014 and 2015.

Following the *Commodity Markets Outlook, January 2017*[16] the leading position in platinum mine production during 2010-2015 bolonged to South Africa with more than 73% share on the total; the Russian Federation accounted for almost 12% of the total platinum mine production; Zimbabwe (6.5%), Canada (3.9%) and the United States (2.0%) in 2015 accounted together for more than 12% of the total platinum mine production.

2.3 Non-energy Market

Non-energy market covers such markets as: Agriculture, Fertilizers and Metals[17]. Fig 16 illustrates the course of Agriculture, Metals & Minerals and Fertilizers Monthly Indices for the period from February, 1982 to November, 2016. Comparing to the previous two markets, each of which was described by one monthly index covering several commodities, the diversity in case of non-energy market in terms of number of components is higher, as covering three monthly indices.

[16] World Bank Group. 2017. *Commodity Markets Outlook, January*.World Bank, Washington, DC. [Retrieved February 12, 2017] http://pubdocs.worldbank.org/en/820161485188875433/CMO-January-2017-Full-Report.pdf

[17] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

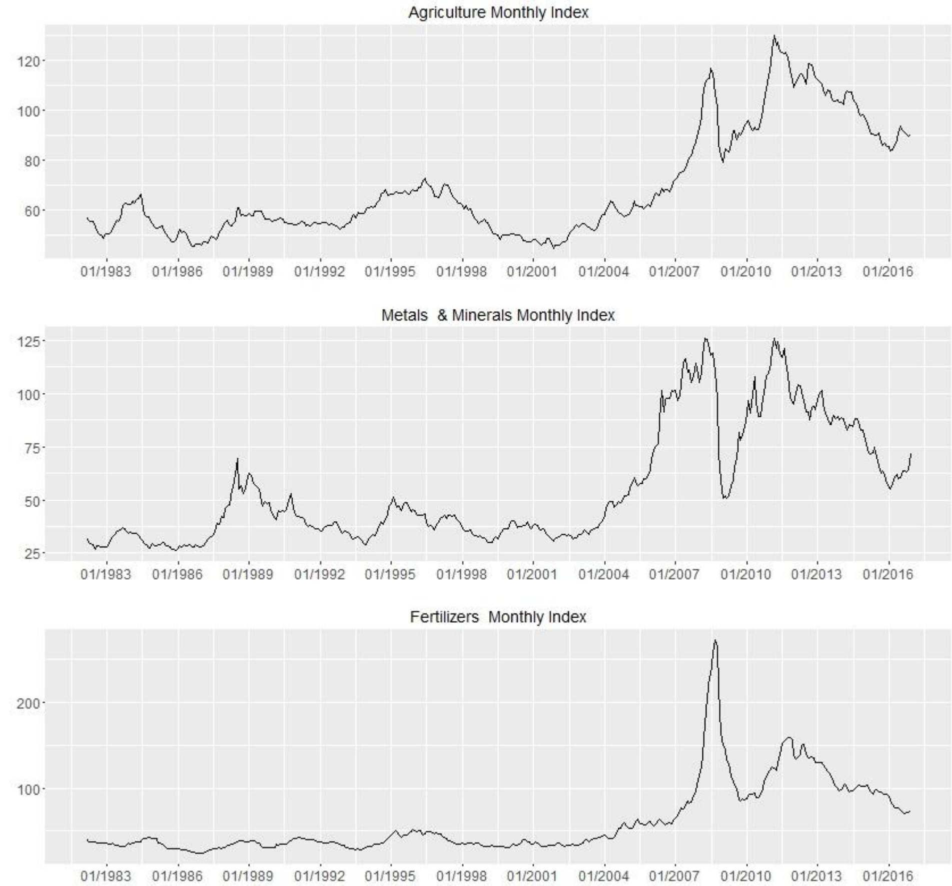


Fig 16 Agriculture, Metals & Minerals and Fertilizers Monthly Indices. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, ggplot2 package

Following the *Commodity Markets Outlook, January 2017*[18] during the period from 2012 to 2015 the largest aluminium bauxite producer was Australia, accounting for 28% of the total world aluminium bauxite production in 2015, the second position belonged to China with 23% share. In case of aluminium refined production and consumption China was an absolute leader with share exceeding 50% of the world production and consumption in 2015. The similar leading position in 2015 belonged to China in refined production and consumption of copper, lead, nickel. In case of lead the first position belonged to China in 2015 and in mine production by being equal to 46% of the total lead mine production. In case of copper mine production the main mine producer in 2015 was Chile, accounting for 30% of the world copper production, and in case of nickel mine production Philippines stood at the first position with 17% share on the total world nickel mine production. Australia was the leading iron ore producer in 2015 accounting for 40% of the world production, and in crude steel production 50% share of the world production belonged to China in 2015. In cotton production the leading position belonged to India and China with 26% and 20% share of the world production correspondingly in 2016/2017. In rice production, stocks and imports China had the leading position in 2016/2017. In soybeans production the first place belonged to the United States in 2016/2017. In the fertilizers-nitrogen production and consumption the

[18] *viz*. note 16

leading position belonged to China and India in 2014. In fertilizers-phosphate China had the largest share in the world production and consumption.

3 Data description

This section discusses the input data used in the analysis. To describe the commodity markets the monthly World Bank Commodity Price Indices[19] are used: Energy Price Index, Precious Metals Price Index and Non-energy Price Index dated from February, 1982 to November, 2016.

To investigate the relations among the stock markets the daily prices of the following stock market indices are chosen:

- S&P 500 (USA)
- Shanghai Composite Index (China)
- Hang Seng Index (China)
- Nikkei 225 (Japan)
- DAX (Germany)
- CAC 40 (France)
- IBEX 35 (Spain)
- Bovespa Index (Brazil)
- BSE 30 Sensitivity Index (India)
- S&P TSX Composite Index (Canada)
- All Ordinaries Index (Australia)
- IPC Index (Mexico)
- KOSPI Composite Index (South Korea)
- Jakarta Composite Index (Indonesia)
- MERVAL Index (Argentina).

All time series data have been retrieved from *Quandl*: Nikkei 225 index from *Nikkei database*, Bovespa index from *Central Bank of Brazil Statistical Database* and all other indices from *YFinace database* with the help of *Quandl* package (McTaggart, Daroczi, Leung, 2016) in R Studio.

Due to the differences in holidays between countries the observations for all indices are not available at some dates for the analyzed period. In the thesis the approach proposed in (Junior and Franca, 2011) has been applied, where the days were removed from the data if the

[19] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

number of closed markets was more than 30% at those days, and if this number was below 30% then the last computed index was repeated[20]. By applying this rule 101 rows have been removed.

The daily prices of the chosen commodities will be also included in the model based step of the current research:

- Europe Brent Spot Price FOB (Dollars per Barrel) [21] - daily data
- Henry Hub Natural Gas Spot Price (Dollars per Million Btu) [22] - daily data
- Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market, based in U.S. Dollars©, U.S. Dollars per Troy Ounce [23]
- Platinum Price (U.S. Dollars per Troy Ounce) - daily data [24]
- Wheat Futures, daily futures prices (Cents per bushel) [25]
- Soybean Futures, daily futures prices (Cents per bushel)[26]
- Rough Rice Futures, daily futures prices, quoted in Cents per hundredweight [27]
- Sugar Futures, daily futures prices (1/100 cent/lb) [28]
- Cotton Futures, daily futures prices (/100 of a cent (one point) per pound) [29]

In case of wheat, soybean, rough rice, sugar and cotton features, the continuous contracts from *Quandl CHRIS* database have been used, where contracts are rolled on their last trading day and prices are not adjusted.[30]

After merging the commodity prices with the stock market indices data set, the missed values of the commodity prices have been replaced with the last known value from the previous day.

[20] To replace the missing index value with the most recent known value *zoo* R package (Zeileis and Grothendieck , 2005) was used.

[21] U.S. Energy Information Administration. *Europe Brent Spot Price FOB*. [Retrieved January 14, 2017]. http://tonto.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=D

[22] U.S. Energy Information Administration. *Henry Hub Natural Gas Spot Price*. [Retrieved January 15, 2017]. http://tonto.eia.gov/dnav/ng/hist/rngwhhdd.htm

[23] ICE Benchmark Administration Limited (IBA), Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market, based in U.S. Dollars© [GOLDAMGBD228NLBM], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GOLDAMGBD228NLBM, January 14, 2017

[24] Quandl, *Johnson Matthey database*, *Platinum Prices*.[Retrieved February 16, 2017]. https://www.quandl.com/data/JOHNMATT/PLAT-Platinum-Prices

[25] Quandl, *Wiki Continuous Futures*, *Wheat Futures, Continuous Contract #1 (W1) (Front Month).*[Retrieved February 16, 2017]. https://www.quandl.com/data/CHRIS/CME_W1-Wheat-Futures-Continuous-Contract-1-W1-Front-Month

[26] Quandl, *Wiki Continuous Futures*, *Soybean Futures, Continuous Contract #1 (S1) (Front Month).*[Retrieved February 16, 2017]. https://www.quandl.com/data/CHRIS/CME_S1-Soybean-Futures-Continuous-Contract-1-S1-Front-Month

[27] Quandl, *Wiki Continuous Futures*, *Rough Rice Futures, Continuous Contract #1 (PR1) (Front Month).*[Retrieved February 16, 2017]. https://www.quandl.com/data/CHRIS/CME_RR1-Rough-Rice-Futures-Continuous-Contract-1-RR1-Front-Month

[28] Quandl, *Wiki Continuous Futures*, *Sugar No. 11 Futures, Continuous Contract #1 (SB1) (Front Month).*[Retrieved February 16, 2017]. https://www.quandl.com/data/CHRIS/ICE_SB1-Sugar-No-11-Futures-Continuous-Contract-1-SB1-Front-Month

[29] Quandl, *Wiki Continuous Futures*, *Cotton No. 2 Futures, Continuous Contract #1 (CT1) (Front Month).*[Retrieved February 16, 2017]. https://www.quandl.com/data/CHRIS/ICE_CT1-Cotton-No-2-Futures-Continuous-Contract-1-CT1-Front-Month

[30] Quandl. *Features* [Retrieved February 17, 2017]. https://www.quandl.com/collections/futures.

The stock market indices and commodity prices are transformed to the logarithmic returns for $k = \{1, 2\}$:

$$r_t = \log \frac{P_t}{P_{t-k}}, \tag{36}$$

where the value of a parameter k indicates the delay in days against the value in time t and will be $k = \{1, 2\}$.

For further text the abbreviation *t_t1* is used in case of logarithmic returns for $k = 1$ and *t_t2* for $k = 2$. In case of the identification of the regimes prevailing on the commodity and stock markets, as well as, in case of the mutual relations' investigation among the stock markets (Chapter 4) the logarithmic returns with first order delay (k=1) are used. In the model-based approach (Chapter 5) the delays of the first (k=1) and second order (k=2) are computed.

The whole data set used to investigate the stock markets' relations is dated from 04.07.1997 to 29.11.2016 and contains 4 955 observations.

4 Empirical Application

4.1 Identifying the States on the Commodity Markets

4.1.1 Identifying the states on the Energy Commodity Market

The regime detection was executed by applying Hidden Markov Model methodology that can capture the hidden states through the sequence of the observed index values. Firstly, the parameters of the HMM have been calibrated by applying the *Expectation-Maximization* (*EM*) algorithm (Dempster et al., 1977). Then by using the obtained adjusted parameters of the model $\lambda = \{A, B, \pi\}$ the most probable sequence of states associated with the given observation sequence is determined by applying *Viterbi* algorithm (Viterbi, 1967), (Forney, 1973).

For regime detection the historical data of logarithmic changes of the Energy Price Index[31] dated from February, 1982 to November, 2016 have been used. According to the *World Bank* calculation (*World Bank Commodity Price Data*, *Monthly prices*) the representation of the individual Energy Index's components are the following: crude oil - 84.6; natural gas - 10.8; coal - 4.7. The course of the historical prices of the Energy Index and its logarithmic returns are shown in Fig 17 and Fig 18.

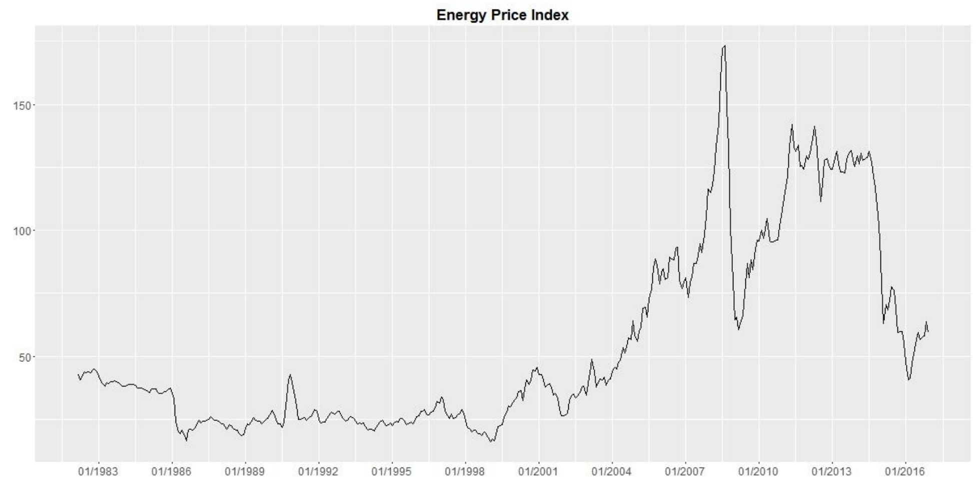


Fig 17 Energy Price Index, Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*.. Own calculation in R Studio, *ggplot2* package.

[31] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

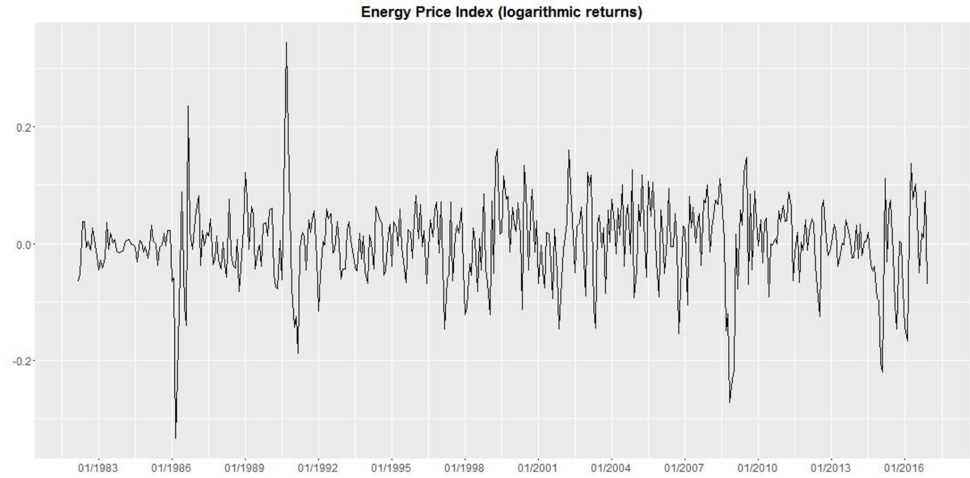


Fig 18 Energy Price Index (logarithmic returns). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2* package.

The results of the 2-*state* HMM are shown in Fig 19. The market states' identification has been made in statistical software *R-Studio* with the help of *depmixS4* package (Visser and Speekenbrink, 2010). The relative likelihood criterion was used as a convergence criterion, where the convergence on iteration *i* is achieved when

$$\frac{\log L(i) - \log L(i-1)}{\log L(i-1)} < tol \,,$$

where *tol* is set equal to 10^{-8}.[32]

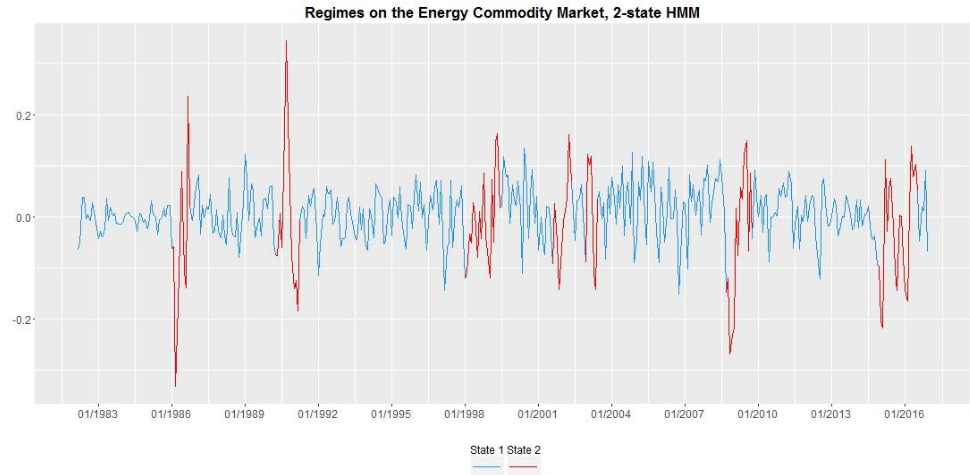


Fig 19 Regimes on the Energy Commodity Market by applying 2-state HMM to the Energy index logarithmic returns. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2*, *depmixS4* packages.

The values of the transition matrix can be found in Table 1, the Information criterions' values are in Table 2 and the response parameters' estimation is presented in Table 3.

[32] *viz.* depmixS4 package documentation. https://cran.r-project.org/web/packages/depmixS4/depmixS4.pdf

Table 1 Transition Matrix, 2-state HMM, Energy Price Index

States	*to State 1*	*to State 2*
from State 1	0.947	0.053
from State 2	0.146	0.854

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*.

Table 2 Information Criterion and Log likelihood values, 2-state HMM, Energy Price Index

Information Criterion	*Value*
AIC	-1111.379
BIC	-1083.130
LL	562.689

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*.

Table 3 Response parameters' estimation, 2-state HMM, Energy Price Index

Market States	*Re1.(Intercept)*	*Re1.sd*
State 1	0.008	0.045
State 2	-0.019	0.112

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.*

Based on the values of transition probabilities (Table 1) and response parameters' estimation (Table 3) and with being graphically illustrated in Fig 19 it can be inferred that *State 1* refers to more stable period on the market with rather high probability (0.95) of remaining in *State 1* and lower volatility comparing to *State 2*, which is characterized by lower probability of remaining in the state and by higher volatility on the energy market, most part of which can be explained by the oil price crises. The first detected period with higher volatility since 1982 is from 1985M12 to 1986M8 which is related to 1980s oil glut. According to *World Bank Commodity Price Data, Monthly Prices*[33] the Brent oil price fell down in July, 1987 to 9.45 $/bbl. OPEC Embargo (1973 - 1974), Iranian revolution (1978 - 1979) and Iran-Iraq War precede these oil price collapse in 1980s related to the oil glut (Hamilton, 2011). In 1973 - 1974 the price of crude oil more than tripled[34], after minor dropping in 1975 - 1978, the price more than doubled[35] in 1979-1980 due to downturn in the oil production caused by Iranian revolution and Iran-Iraq War. Following (Hamilton , 2011) the long term demand response to the supply shocks reflected to decrease in petroleum consumption, and then between 1981- 1985 Saudi Arabia voluntarily dropped its production by 3/4. This was not enough, and to regain the market share Saudi Arabia increased the

[33] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1

[34] Crude Oil, Dubai. World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

[35] v*iz.* note 34

production, as a consequence the oil price collapsed in 1986. The second detected period of *State 2* (higher volatility, 1990M3-1991M2) since 1982 is related to First Persian Gulf War (Hamilton, 2011), and as a consequence the oil price spiked at the end of 1990. The next detected period (1997M12-1999M4) identified with higher volatility is associated with East Asian Crisis in 1997-1998. In 1999 the oil price began to recover, as the Asian region was back to its growth and the world petroleum consumption increased (Hamilton, 2011). The periods of 2001M7-2002M3 and 2002M11-2003M4 have been identified as *State 2* (state with higher volatility). This detection refers mainly to 9/11 terrorist attack in 2001, Invasion of Iraq and the oil workers strike in Venezuela (Hamilton, 2011). The next period of *State 2* is associated with the Global Financial Crisis, when Brent oil price was at its maximum in July, 2008 (daily spot price according to *EIA*[36] was above 140 $/bbl), but due to the Financial Crisis and as a consequence recession and falling in the petroleum demand, the oil price began to decline and in December, 2008 dropped down to below 40 $/bbl[37]. Other period associated with the significant decrease in the oil price related to the period 2014-2016 (the period from 2014M10 to 2016M5 was detected as *State 2*). The volatility during this period can be explained by the excess capacity. The mean and the standard deviation of both states in different time periods are summarized in Table 4. It can be seen that the characteristics of the analyzed dataset vary through time. The greatest standard deviation relates to the 1980s oil glut and then to the Global Financial Crisis.

Table 4 Mean and standard deviation value for State 1 and State 2 for the corresponding time period

Number	Period	State	Mean	Standard deviation
1	*1982M2-1985M11*	*State 1*	-0.004	0.023
2	***1985M12-1986M8***	***State 2***	**-0.067**	**0.160**
3	*1986M9-1990M2*	*State 1*	0.006	0.045
4	***1990M3-1991M2***	***State 2***	**-0.006**	**0.152**
5	*1991M3-1997M11*	*State1*	0.001	0.046
6	***1997M12-1999M4***	***State 2***	**-0.013**	**0.087**
7	*1999M5-2001M6*	*State 1*	0.021	0.061
8	***2001M7-2002M3***	***State 2***	**-0.017**	**0.091**
9	*2002M4-2002M10*	*State 1*	0.026	0.043
10	***2002M11-2003M4***	***State 2***	**-0.001**	**0.126**
11	*2003M5-2008M7*	*State 1*	0.024	0.059
12	***2008M8-2009M8***	***State 2***	**-0.052**	**0.140**
13	*2009M9-2014M9*	*State 1*	0.005	0.043
14	***2014M10-2016M5***	***State 2***	**-0.036**	**0.109**
15	*2016M6-2016M11*	*State 1*	0.007	0.055

Source: Own calculation in R Studio, *depmixS4* package, Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*

[36] U.S. Energy Information Administration. *Europe Brent Spot Price FOB*. [Retrieved January 14, 2017]. http://tonto.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=D
[37] *viz.* note 36

Regardless of the similarity in the volatility trends it is important to distinguish the source, underlying the oil price shocks in the energy commodity market. In (Kilian, 2009) the demand and supply shocks in the global crude oil market were identified. The structural decomposition of the real price of crude oil has been proposed. Three components have been introduced: "*crude oil supply shocks*", "*shocks to the global demand for all industrial commodities*", "*demand shocks that are specific to the crude oil market*". The latter shocks are also denoted as precautionary demand shocks associated with uncertainty about the expected supply deficit due to expected demand. Following (Economou, 2016, Table 1, p. 4) *Asian Financial Crisis* and *Global Financial Crisis,* which stand behind the higher volatility on the energy commodity market, are associated with demand shocks. Venezuelan crisis and Iraq War is identified as supply shocks (Economou, 2016, Table 1, p.4). According to (Economou, 2016, Table 1, p.4) the oil price shock associated with excess capacity can be classified as precautionary demand shock, with strong supply and stagnant demand.

4.1.2 Identifying the states on the Precious Metals Commodity Market

To capture the fluctuations on this market the *Precious Metals Price Index*[38] dated from February, 1982 to November, 2016 can be used. According the World Bank Commodity Markets, Monthly Prices [39] the gold price accounts for the major part of this index - 77.8, the second is the silver price - 18.9 and the rest is covered by the platinum price - 3.3. The *Precious Metals Index* values and its logarithmic returns during the analyzed period can be found in Fig 20 and Fig 21.

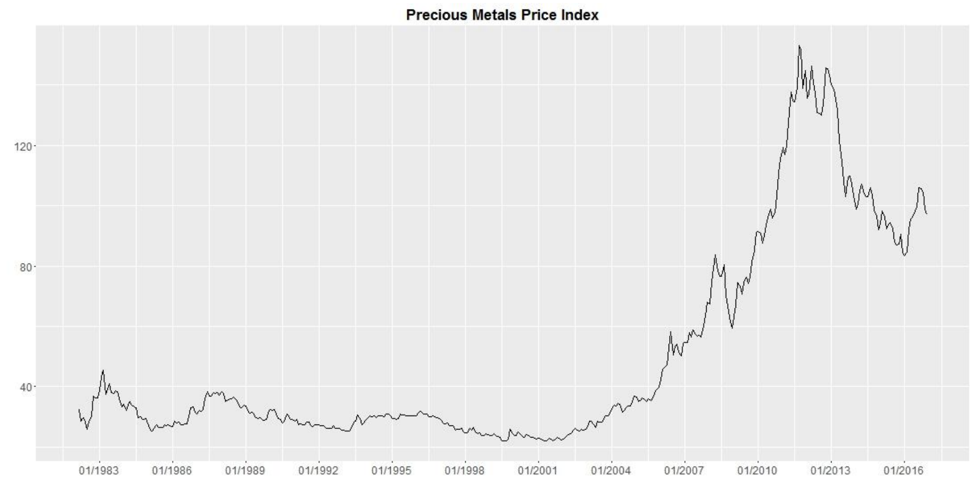


Fig 20 Precious Metals Index. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2* package.

[38] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

[39] *viz*. note 38

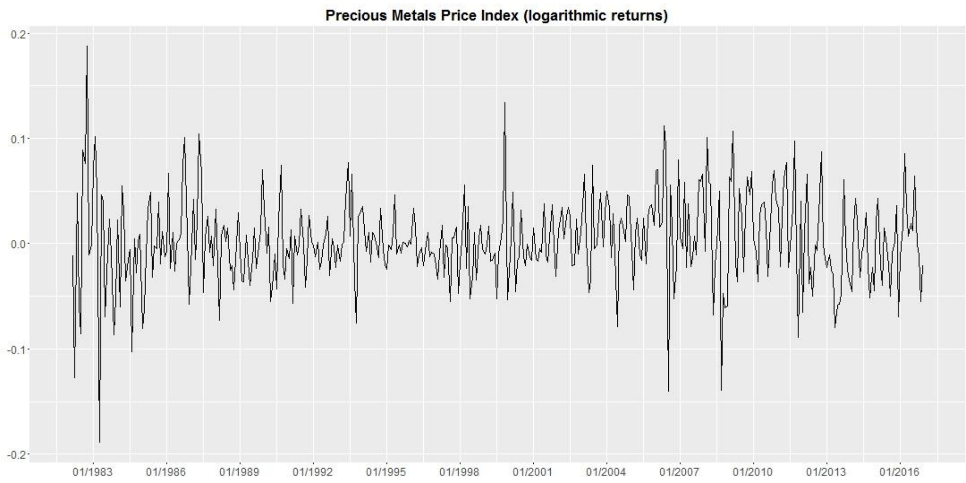
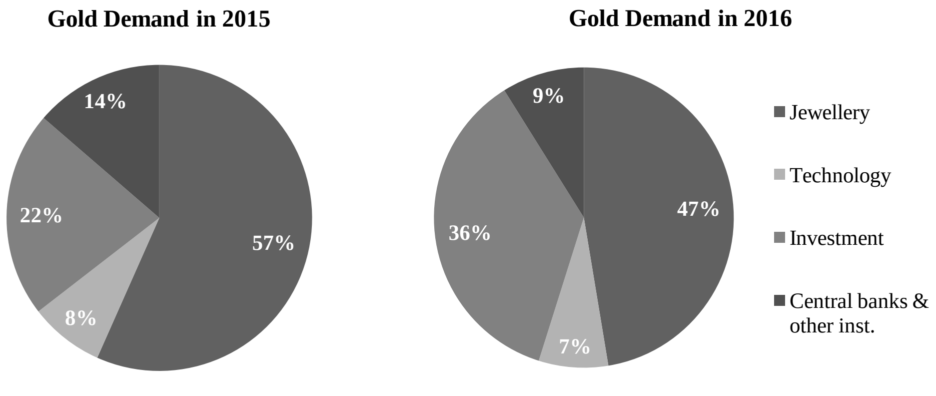


Fig 21 Precious Metals Price Index (logarithmic returns). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2* package.

Major part of fluctuations in the *Precious Metal Index* corresponds to the gold prices' variations with respect to the largest representation in the index calculation. There are several factors which can drive the gold prices. The basic theory of supply and demand may help in attempt to explain the gold price fluctuations. According to the *World Gold Council* [40], the demand for gold is formed by using gold in jewellery and technology, by central banks and investors. Gold supply covers mine production, net producer hedging and recycled gold. The structure of gold demand and supply can be found in Fig 22.

In (Levin and Wright, 2006) the short-run and long-run determinants of the gold price are analyzed. The results of this research correspond to the existence of the long-term relationship between the gold price and the general price level in the USA. The main findings of this paper are consistent with the belief that gold is a long-term hedge against inflation. Following (Levin and Wright, 2006) by analyzing the short-run demand for gold, two components can be identified: "use" and "asset" demand, where the "use" component of the short-run demand refers to demand for jewellery and other kinds or gold use in the industrial purposes, the "asset" demand relates to gold, which is sought after for investment purposes.



[40] World Gold Council. *Gold data & Statistics, Supply and demand Data*. [Retrieved March 5, 2017] http://www.gold.org

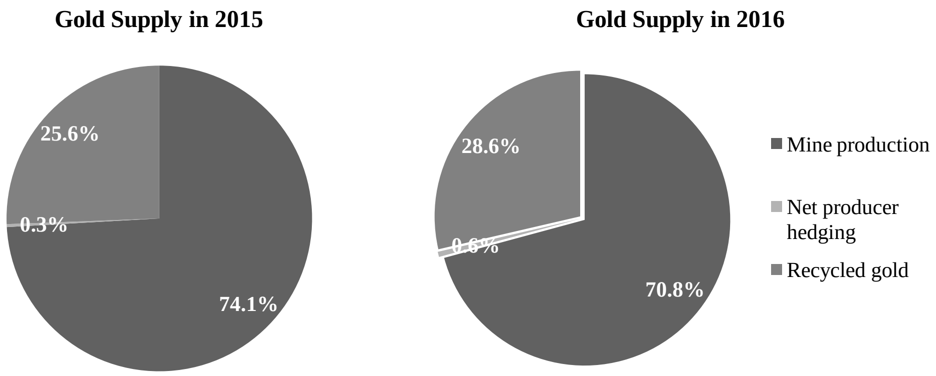


Fig 22 Gold Demand and Supply. Data source: World Gold Council, Gold Data & Statistics, Supply and demand Data. Own calculation in Excel.

Concerning this evidence in the regime detection step, executing by applying Hidden Markov Model methodology, the Consumer Price Index, USA [41] is included as a covariate in the transition probabilities.

As in case of the energy commodity market's regime detection, the parameters of the HMM $\lambda = \{A, B, \pi\}$ are determined by *EM* algorithm (Dempster et al., 1977), then the best state sequence is obtained by applying *Viterbi Algorithm* (Viterbi, 1967), (Forney, 1973). The results of 2-*state* HMM with including CPI, USA as a covariate in the transition probabilities are shown in Fig 23. The values of information criterions and log likelihood of 2-*state* HMM with and without a covariate are summarized in Table 5.

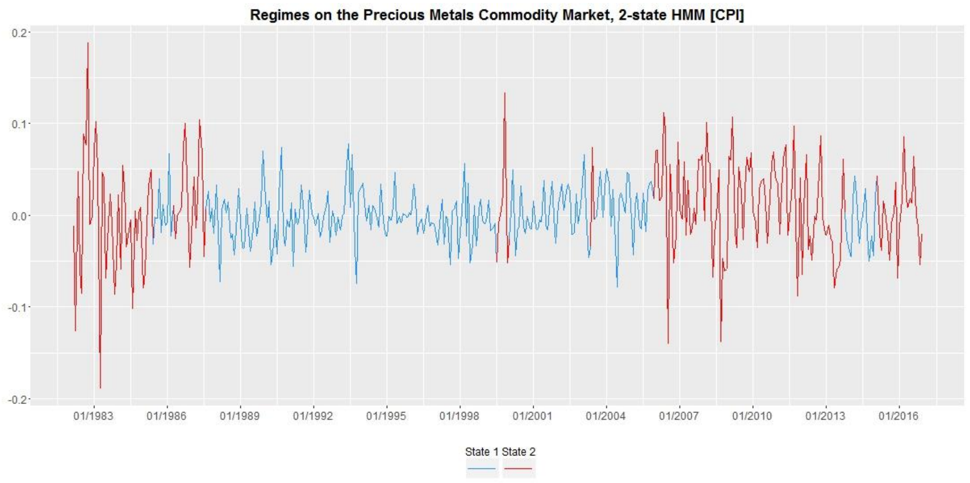


Fig 23 Regimes on the Precious Metals Commodity Market by applying 2-*state* HMM to the Precious metals index logarithmic returns. CPI as a covariant included in the transition probabilities. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices; U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis*. Own calculation in R Studio, *ggplot2*, *depmixS4* packages.

[41] U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/CPIAUCSL, December 25, 2016., Consumer Price Index for All Urban Consumers: All Items, Index 1982-1984=100, Monthly, Seasonally Adjusted

Table 5 Information Criterion and Log Likelihood Values, 2-*state* and 2-*state* HMM with a covariate, Precious Metals Index

Information Criterion	*2-state HMM*	*2-state HMM [CPI]*
AIC	-1523.831	-1524.486
BIC	-1495.582	-1488.166
LL	768.9153	771.2429

Source: Own calculation in R Studio, *depmixS4* package, Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*; *U.S. Bureau of Labor Statistics, Consumer Price Index for All Urban Consumers: All Items [CPIAUCSL], retrieved from FRED, Federal Reserve Bank of St. Louis*.

Based on the results in Table 5 it can be noticed that in case of 2-*state* HMM with a covariate the value of AIC is lower and the log likelihood value is higher than in case of 2-*state* HMM without CPI as a covariate. It can be inferred that 2-*state* HMM including CPI as a covariate in transition probabilities fit data better, and is chosen as more preferable choice of possible segregation on the Precious Metals Commodity Market. Based on the response parameters' estimation in Table 6 and graphical illustration in Fig 23 it can be noticed that *State 2* refers to more volatile period on the Precious Metals Market, oppositely *State 1* marks more "calm" periods on the market during the analyzed period.

Table 6 Response parameters' estimation, 2-state HMM with a covariate, Precious Metals Index

Market States	*Re1.(Intercept)*	*Re1.sd*
State 1	-0.003	0.027
State 2	0.010	0.055

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.*

The states, which have been identified as states with higher volatility, are: *1982M2-1985M4, 1986M3-1987M6, 1999M6-1999M11, 2003M4-2003M5, 2005M11-2013M8, 2015M1-2016M11*. The volatile period during the 1980s can be attributed to the world currency exchange rates' fluctuations, growing U.S. private and Third World debt and worries about U.S. budget and trade deficits [42, 43]. Greater volatility on the precious metals commodity market in 1999 can be related to the *Central Bank Gold Agreement*, which was signed in 1999 by major European central banks and limits the amount of gold that signatories can collectively sell[44]. Then the following *Central Bank Gold Agreements* were signed in 2004, 2009 and 2014.[45] Higher volatility in 2003 can be related to Invasion of Iraq. The most part of the subsequent higher volatile period on the precious metals commodity market can be related to the Global Financial Crisis, and the volatility during the latest period can be attributed to

[42] Amey, E. B. Gold. U.S. Bureau of Mines Minerals. [Retrieved June 22, 2017]. https://minerals.usgs.gov/minerals/pubs/commodity/gold/300798.pdf
[43] George M. W. (2010). Gold, *in* Metal Prices in the United States Through 2010: U.S. Bureau of Mines Minerals. [Retrieved June 22, 2017]. https://pubs.usgs.gov/sir/2012/5188/sir2012-5188.pdf#Gold
[44] World Gold Council. *Central Bank Gold Agreements.* [Retrieved June 16, 2017] http://www.gold.org
[45] *viz*. note 44

the expectation about the interest rate raising by U.S. Federal Reserve System[46] and the United Kingdom's referendum vote to leave the European Union[47].

4.1.3 Identifying the states on the Non-energy Commodity Market

The regime detection is executed by applying the HMM methodology to *Non-energy Price Index*, where *Agriculture* market accounts for the major part of this index - 64.9; the weight of *Metals* market is 31.6 and *Fertilizers* market takes the rest index weight - 3.6.[48] The index is dated from February, 1982 to November, 2016. The values of the *Non-energy Index* and its logarithmic returns are shown in Fig 24 and Fig 25.

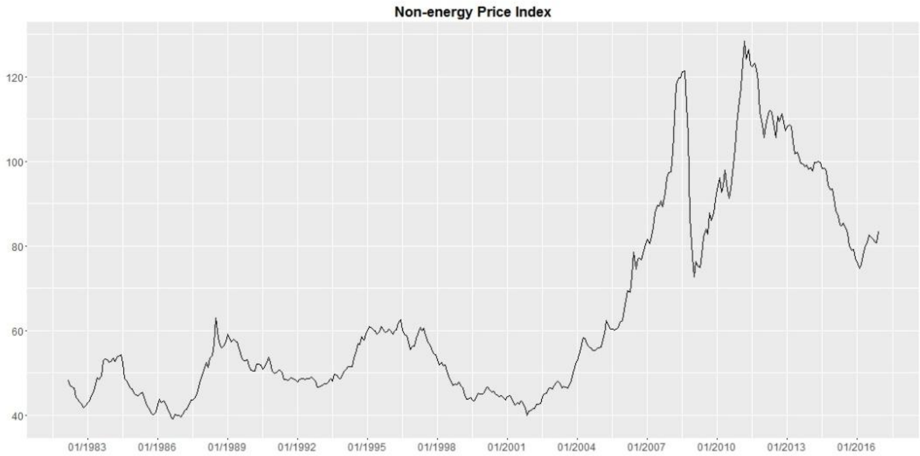


Fig 24 Non-energy Index. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, ggplot2 package.

[46] U.S. Geological Survey, 2016, Mineral commodity summaries 2016: U.S. Geological Survey, 202 p., [Retrieved June 16, 2017]. https://minerals.usgs.gov/minerals/pubs/mcs/2016/mcs2016.pdf.

[47] U.S. Geological Survey, 2017, Mineral commodity summaries 2017: U.S. Geological Survey, 202 p., [Retrieved June 16, 2017]. https://minerals.usgs.gov/minerals/pubs/mcs/2017/mcs2017.pdf.

[48] World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. World Bank, Washington, DC. [Retrieved December 21, 2016]. http://www.worldbank.org/en/research/commodity-markets#1.

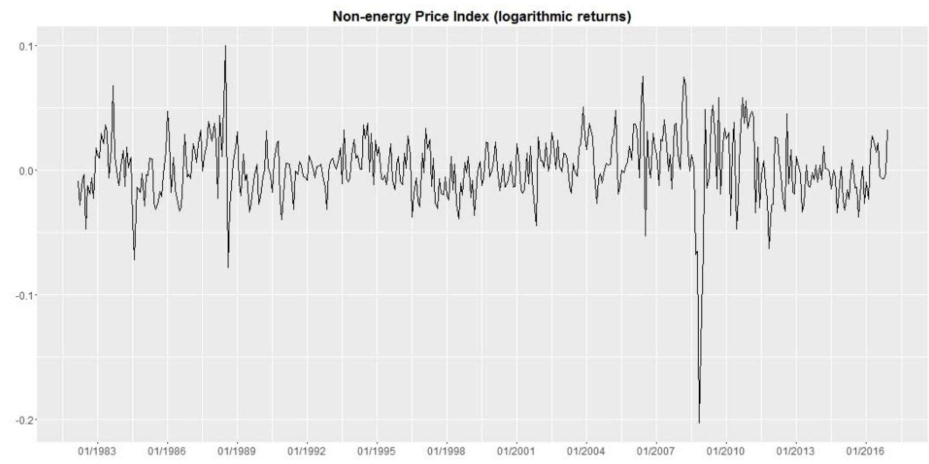


Fig 25 Non-energy Index (logarithmic returns). Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, ggplot2 package.

Similarly to the previous steps when the market regimes have been identified, in case of the non-energy commodity market, the parameters of the HMM $\lambda = \{A, B, \pi\}$ are determined by *EM* algorithm (Dempster et al., 1977), then the most probable sequence of states associated with the given observation sequence is obtained by applying *Viterbi Algorithm* (Viterbi, 1967), (Forney, 1973). The results of the 2-*state* HMM applying to the non-energy market can be found in Fig 26.

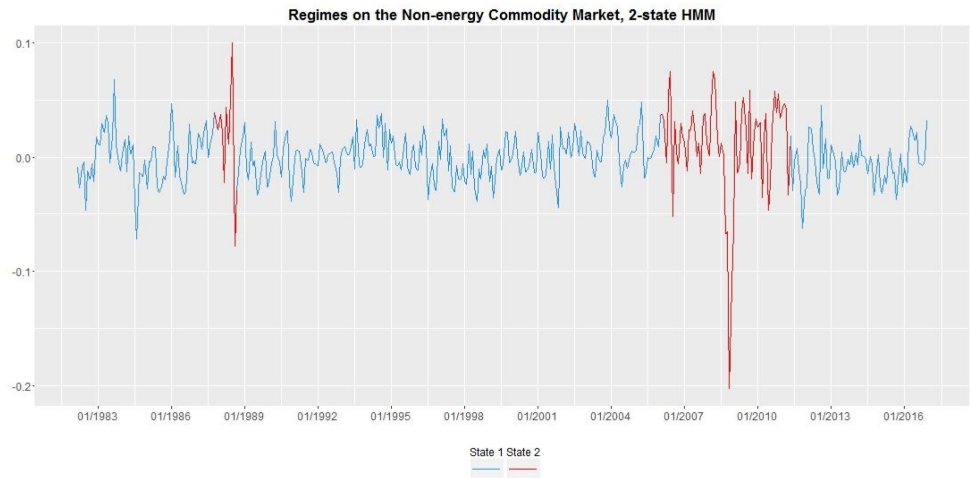


Fig 26 Regimes on the Non-energy Commodity Market by applying 2-*state* HMM to the Non-energy index logarithmic Returns. Data source World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, ggplot2, depmixS4 packages.

The values of the transition matrix are illustrated in Table 7, the Information criterions's values are in Table 8 and response parameters' estimation is presented in Table 9.

Table 7 Transition Matrix, 2-state HMM, Non-energy Price Index

States	*to State 1*	*to State 2*
from State 1	0.986	0.014
from State 2	0.062	0.938

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*.

Table 8 Information Criterion and Log likelihood values, 2-state HMM, Non-energy Price Index

Information Criterion	*Value*
AIC	-1940.824
BIC	-1912.575
LL	977.412

Source: Own calculation in R Studio, *depmixS4* package. Data source: *World* World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*.

Table 9 Response parameters' estimation, 2-state HMM, Non-energy Price Index

Market States	*Re1.(Intercept)*	*Re1.sd*
State 1	-0.001	0.019
State 2	0.010	0.046

Source: Own calculation in R Studio, *depmixS4* package. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices.*

Based on the values in the transition matrix (Table 7) both states are rather stable with the probability of remaining in each of the state is more than 0.9 but in case of *State 1* this probability is higher. Following the values of the response parameters' estimation (Table 9) it can be inferred that *State 1* refers to more calm period on the market with lower volatility comparing to *State 2*, which is identified as a regime with a higher volatility and covers the periods: 1987M9 -1988M7 and 2005M12-2011M3.

The combination of the detected regimes on the Energy, Precious Metals and Non-energy commodity markets applied to the corresponding indices: Energy Index, Precious Metals Index and Non-energy Index can be found in Fig 27, Fig 28 and Fig 29 correspondingly. It can be noticed that during the Global Financial Crisis more volatile regime prevailed on all analyzed commodity markets.

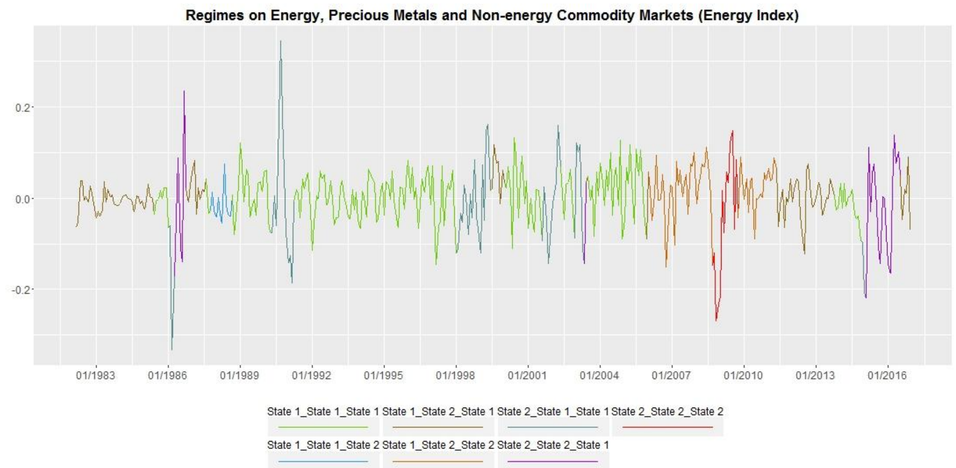


Fig 27 Regimes on Energy, Precious Metals and Non-energy Commodity Markets applied to Energy Index logarithmic Returns. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2, depmixS4* packages.

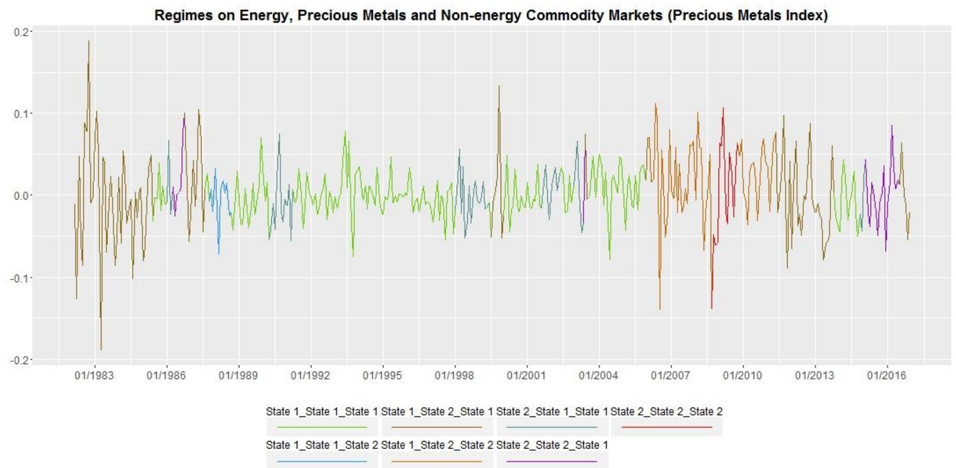


Fig 28 Regimes on Energy, Precious Metals and Non-energy Commodity Markets applied to Precious Metals Index logarithmic Returns. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2, depmixS4* packages.

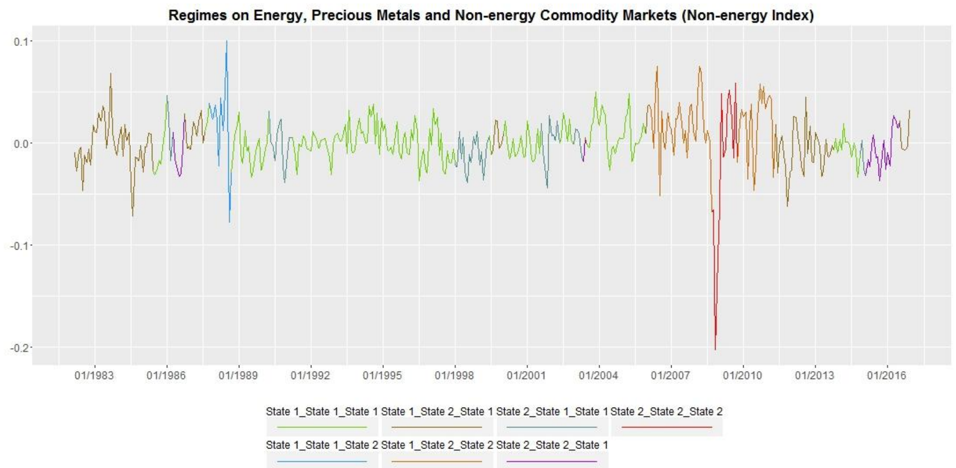


Fig 29 Regimes on Energy, Precious Metals and Non-energy Commodity Markets applied to Non-energy Index logarithmic Returns. Data source: World Bank Group. 2016. *World Bank Commodity Price Data, Monthly Prices*. Own calculation in R Studio, *ggplot2, depmixS4* package.

4.2 Stock Markets

4.2.1 Identification the states on the Stock Markets

Similarly to the commodity markets' regime detection, the states of the stock market indices are determined by applying Hidden Markov Model methodology, assuming that in case of the stock markets there are three states: state with high, low and medium volatility. Following the estimation of the mean and the standard deviation corresponding to each state of the analyzed indices in Table 10, it can be derived that *State 1* refers to volatile and negative market reflecting the higher uncertainty while in this state; oppositely *State 3* refers to "calm" market with low stock market's volatility; *State 2* can be diagnosed as a state with "medium" volatility. In case of SSEC, Bovespa and MERVAL indices only two states have been identified. The detected regimes for each analyzed market index for the period from July, 1997 to November, 2016 can be found in Fig 30 (North America), Fig 31 (Europe), Fig 32 (South America), Fig 33 and Fig 34 (Asia Pacific).

Table 10 Response parameters' estimation based on HMM

	Re1.(Intercept)	**Re1.sd**	**Re1.(Intercept)**	**Re1.sd**
	S&P 500		**DAX**	
State 1	-0.001	0.027	-0.002	0.029
State 2	0.000	0.012	0.000	0.014
State 3	0.001	0.006	0.001	0.008
	S&P TSX		**CAC 40**	
State 1	-0.002	0.024	-0.002	0.029
State 2	0.000	0.010	0.000	0.014
State 3	0.001	0.006	0.001	0.007
	IPC		**IBEX 35**	
State 1	-0.001	0.025	-0.002	0.028
State 2	0.001	0.012	0.000	0.014
State 3	0.001	0.007	0.001	0.007
	HSI		**Nikkei 225**	
State 1	-0.001	0.027	-0.002	0.028
State 2	0.001	0.012	0.000	0.013
State 3	0.000	0.002	0.000	0.001
	KOSPI		**JKSE**	
State 1	-0.001	0.027	-0.003	0.032
State 2	0.000	0.012	0.001	0.013
State 3	0.001	0.004	0.001	0.007
	BSE Sensex		**AORD**	
State 1	-0.003	0.032	-0.002	0.019
State 2	0.000	0.015	0.000	0.009
State 3	0.001	0.008	0.001	0.005
	SSEC		**BOVESPA**	
State 1	-0.001	0.027	-0.002	0.039
State 2	0.000	0.010	0.001	0.015
	MERVAL			
State 1	-0.001	0.034		
State 2	0.001	0.014		

Source: Own calculation in R Studio, *depmixS4, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl*.

North America

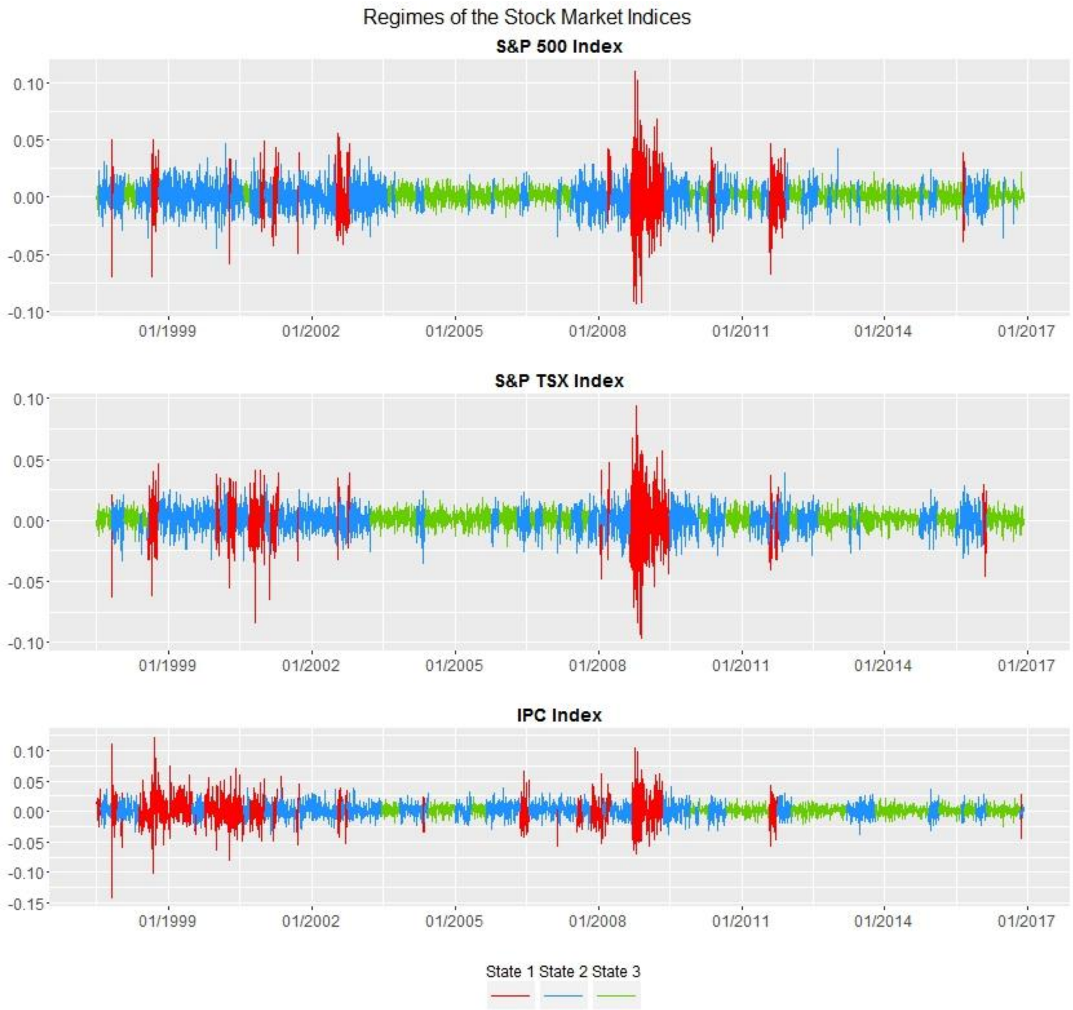


Fig 30 Regimes of the Stock Market Indices. North America. 3-*state* HMM. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Europe

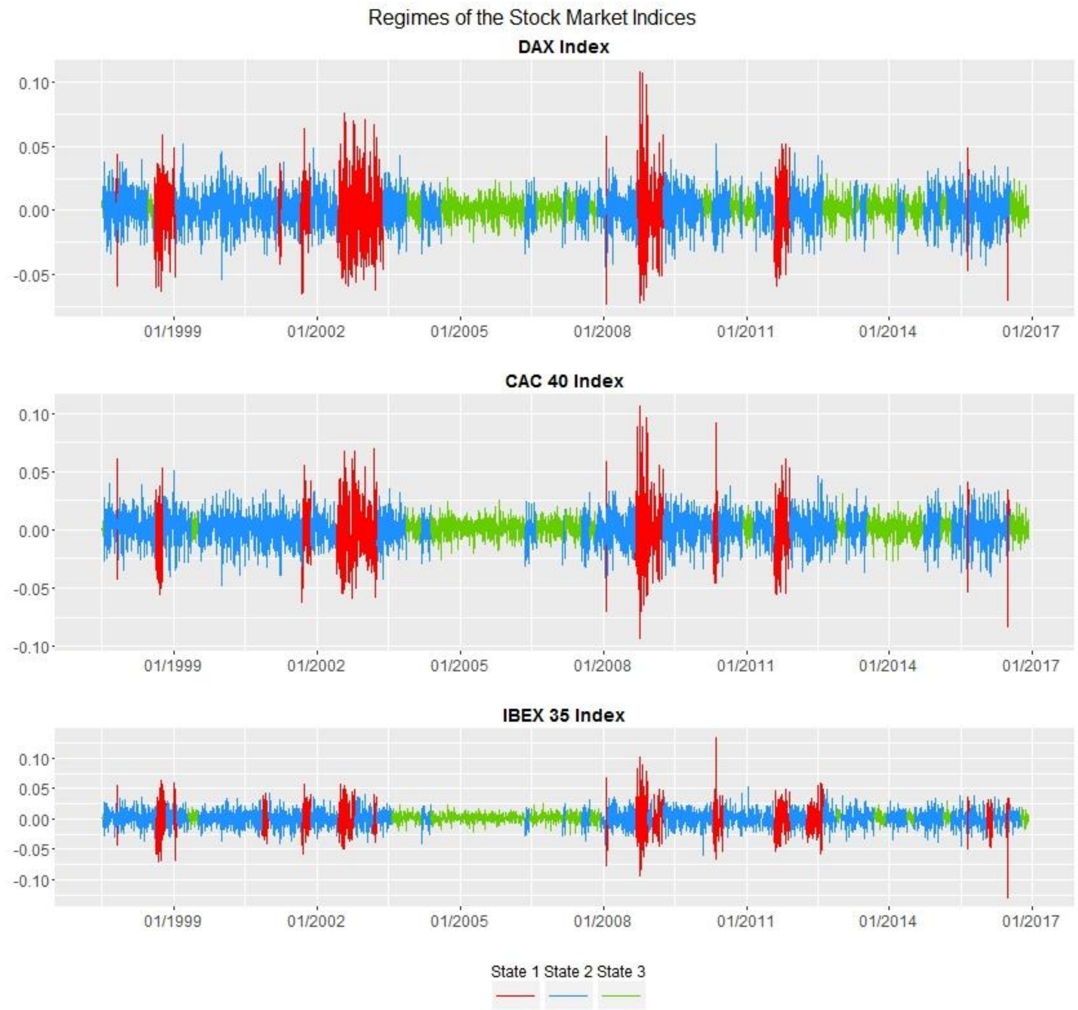


Fig 31 Regimes of the Stock Market Indices. Europe. 3-*state* HMM. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

South America

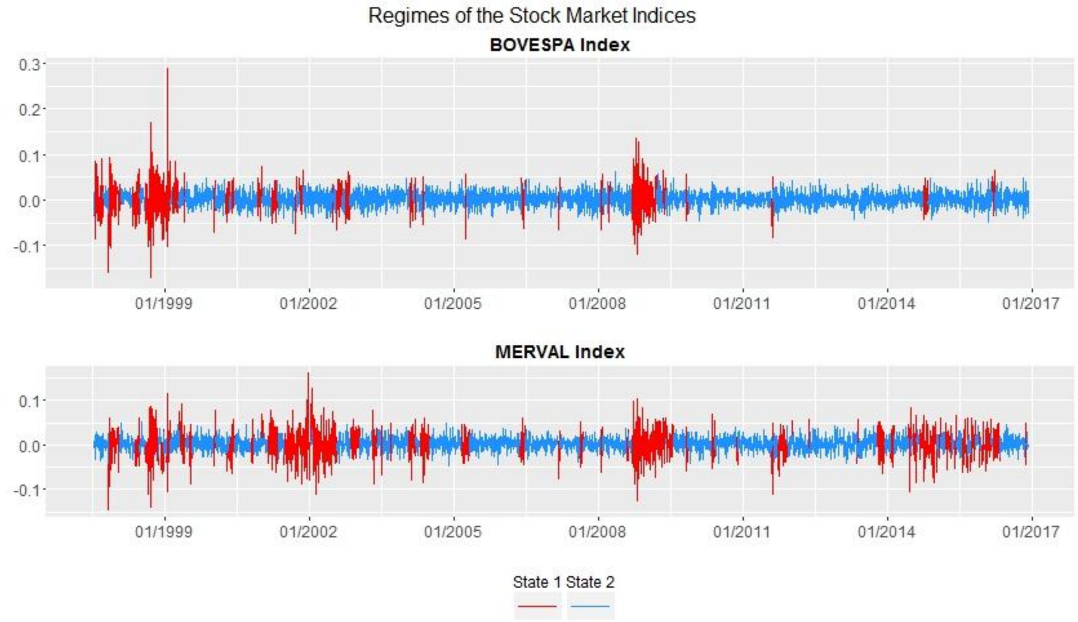


Fig 32 Regimes of the Stock Market Indices. South America. 2-*state* HMM. Data source: the time series data have been retrieved from *Quandl YFinace*, *Central Bank of Brazil Statistical Database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Asia Pacific

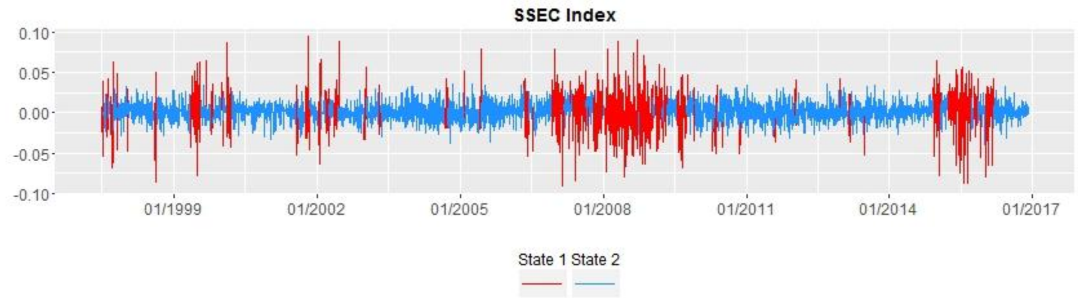


Fig 33 Regimes of the Stock Market Indices. Asia Pacific (SSEC Index). 2-*state* HMM. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

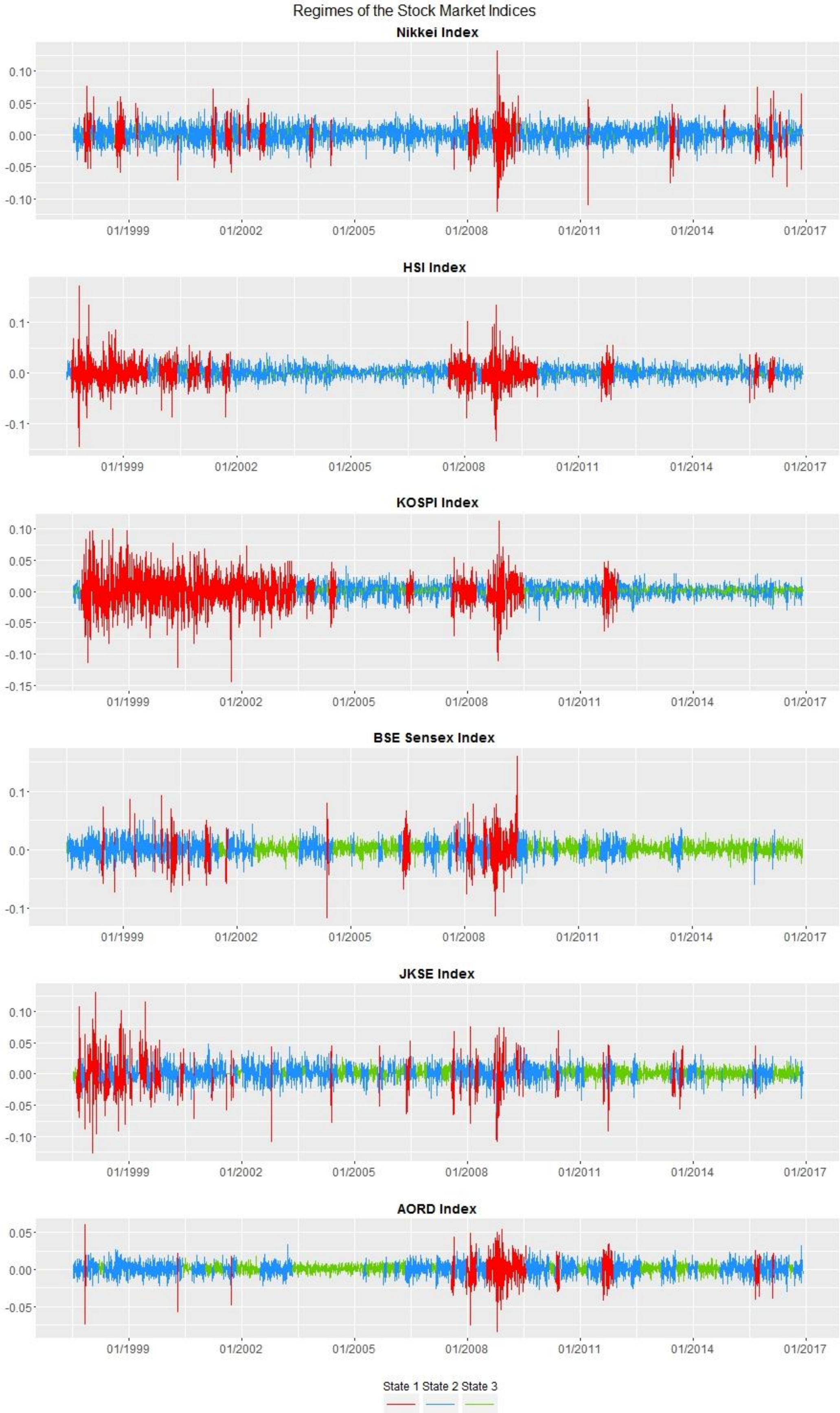


Fig 34 Regimes of the Stock Market Indices. Asia Pacific. 3-*state* HMM. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2, depmixS4, Quandl* packages.

4.3 Stock and Commodity Markets

4.3.1 Stock Markets' Similarity and Regimes on the Commodity Markets

Based on the figures above it can be inferred that some stock markets have similar patterns in behavior regards to the volatility's regimes, e.g. DAX and CAC 40 or S&P 500 and S&P TSX; some indices behave differently than others, e.g. in case of KOSPI index the longstanding higher volatile regime has been identified between 1997 and 2003, which differed from other analyzed indices; it can be noticed that for North America, Europe and South America behavior within its region is more similar than in case of Asia Pacific region. At the same time it can be noticed that the similarity of the stock markets' behavior with respect to the prevailing market regime can differ within different time periods. To look how similarly individual stock market indices behave regards to the identified regimes, the instruments of the categorical analysis can be used. The variable indicating the detected regime for each market index can be transformed to a binary variable, which takes a value one during the highly volatile market (*State* 1), otherwise the value is equal to zero. By performing this transformation the similarity matrix between the binary variables can be computed. To measure the similarity between binary variables *Jaccard Similarity Measure* is used (Chapter 1.3). The results can be found in Table 11.

Table 11 Proximity Matrix between Stock Market Indices, Jaccard similarity measure

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.47	0.29	0.21	0.30	0.47	0.53	0.48	0.32	0.24	0.21	0.31	0.22	0.43	0.13
S&P TSX	0.47	1.00	0.37	0.24	0.32	0.28	0.28	0.29	0.30	0.33	0.25	0.40	0.23	0.35	0.14
IPC	0.29	0.37	1.00	0.24	0.39	0.26	0.19	0.22	0.26	0.50	0.48	0.33	0.31	0.23	0.19
MERVAL	0.21	0.24	0.24	1.00	0.28	0.26	0.23	0.21	0.28	0.31	0.38	0.19	0.23	0.21	0.23
BOVESPA	0.30	0.32	0.39	0.28	1.00	0.31	0.25	0.24	0.33	0.33	0.27	0.25	0.34	0.17	0.13
DAX	0.47	0.28	0.26	0.26	0.31	1.00	0.75	0.49	0.29	0.23	0.31	0.18	0.18	0.25	0.12
CAC 40	0.53	0.28	0.19	0.23	0.25	0.75	1.00	0.56	0.26	0.18	0.25	0.19	0.16	0.31	0.13
IBEX 35	0.48	0.29	0.22	0.21	0.24	0.49	0.56	1.00	0.26	0.22	0.21	0.15	0.17	0.28	0.12
Nikkei 225	0.32	0.30	0.26	0.28	0.33	0.29	0.26	0.26	1.00	0.28	0.24	0.28	0.25	0.29	0.17
HSI	0.24	0.33	0.50	0.31	0.33	0.23	0.18	0.22	0.28	1.00	0.54	0.26	0.33	0.31	0.29
KOSPI	0.21	0.25	0.48	0.38	0.27	0.31	0.25	0.21	0.24	0.54	1.00	0.23	0.26	0.20	0.20
BSE Sensex	0.31	0.40	0.33	0.19	0.25	0.18	0.19	0.15	0.28	0.26	0.23	1.00	0.21	0.34	0.20
JKSE	0.22	0.23	0.31	0.23	0.34	0.18	0.16	0.17	0.25	0.33	0.26	0.21	1.00	0.19	0.16
AORD	0.43	0.35	0.23	0.21	0.17	0.25	0.31	0.28	0.29	0.31	0.20	0.34	0.19	1.00	0.24
SSEC	0.13	0.14	0.19	0.23	0.13	0.12	0.13	0.12	0.17	0.29	0.20	0.20	0.16	0.24	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

To find more similar groups of the market indices with regards to highly volatile states' occurrence, the hierarchical cluster algorithm might be helpful, where *Between - Group linkage* method with *Jaccard similarity* measure is used. By applying *Between - Group linkage* method, the distance between two clusters is calculated as the average distance of all pairs of the data points, where one member belongs to the first cluster and another to the second. More details can be found in (Řezanková et al., 2009). The *agglomerative* clustering approach was applied where each observation creates its own cluster and then these clusters are merged moving up the hierarchy. The market indices' assignment to different clusters depending on the chosen number of groups can be found in Table 12. Analyzing the proximity matrix between the individual market indices the greatest similarity between the highly volatile market regime's occurrence can be observed among indices within European region: particularly between DAX and CAC 40, and less between CAC 40 and IBEX 35, DAX and IBEX 35. Looking at Table 12 these three indices are assigned to one cluster till dividing into 12 clusters. The percentage of agreement of S&P 500 index with S&P TSX, DAX, CAC 40, IBEX 35 indices moves about the midpoint. Within Asia Pacific region the similarity exceeds the midpoint in case of HSI and KOSPI indices; between HSI and IPC indices the similarity is close to the midpoint. The lowest similarity to all analyzed indices can be observed in case of SSEC index. *Jaccard's similarity coefficient*, computed between SSEC index and all other analyzed indices does not exceed 0.3 at any cases. The highest value of similarity in terms of higher volatile regime's occurrence of SSEC index is in relation to HSI index. In case of splitting the indices into two clusters all 14 analyzed market indices except SSEC are assigned to one cluster and SSEC is to another, in fact SSEC index in case of dividing into 2-14 clusters always creates its own cluster.

Table 12 Stock Market Indices' clusters

Stock Market Index/ Number of clusters	14	13	12	11	10	9	8	7	6	5	4	3	2
S&P 500	1	1	1	1	1	1	1	1	1	1	1	1	1
S&P TSX	2	2	2	2	2	2	2	2	2	2	2	1	1
IPC	3	3	3	3	3	3	3	3	3	3	3	2	1
MERVAL	4	4	4	4	4	4	4	4	4	4	3	2	1
BOVESPA	5	5	5	5	5	5	5	5	3	3	3	2	1
DAX	6	6	6	1	1	1	1	1	1	1	1	1	1
CAC 40	6	6	6	1	1	1	1	1	1	1	1	1	1
IBEX 35	7	7	6	1	1	1	1	1	1	1	1	1	1
Nikkei 225	8	8	7	6	6	6	6	6	5	2	2	1	1
HSI	9	9	8	7	3	3	3	3	3	3	3	2	1
KOSPI	10	9	8	7	3	3	3	3	3	3	3	2	1
BSE Sensex	11	10	9	8	7	2	2	2	2	2	2	1	1
JKSE	12	11	10	9	8	7	7	5	3	3	3	2	1
AORD	13	12	11	10	9	8	2	2	2	2	2	1	1
SSEC	14	13	12	11	10	9	8	7	6	5	4	3	2

Source: Own calculation in SPSS 16. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Due to the global market interconnection it is fair to suppose that behavior of the stock markets may differ depending on different situations on the commodity markets. In Chapter 4.1 the regime detection on the Energy, Precious Metals and Non-energy commodity markets has been executed by applying the *Hidden Markov Model* methodology to the logarithmic changes of the aggregated price indices. Two states have been identified: *State 1* referring to more "calm" period and *State 2* characterizing by higher volatility. The behavior of the logarithmic returns of the stock market indices under different regimes on the commodity markets can be found in Fig 35 (North America), Fig 36 (South America), Fig 37 (Europe) and Fig 38, Fig 39 (Asia Pacific), where different colors correspond to the different identified combinations of regimes prevailing on the commodity markets, the meaning of the used labels is the following:

- "*State1_State1_State1*" - simultaneous low volatility on the energy, precious metals and non-energy commodity markets;
- "*State1_State2_State1*" - low volatility on the energy and non-energy markets and high volatility on the precious metals commodity market;
- "*State1_State2_State2*" - low volatility on the energy market and high volatility on the precious metals and non-energy commodity markets;
- "*State2_State1_State1*" - high volatility on the energy market and low volatility on the precious metals and non-energy commodity markets;
- "*State2_State2_State1*" - high volatility on the energy and precious metals markets and low volatility on the non-energy commodity market;
- "*State2_State2_State2*" - simultaneous high volatility on the energy, precious metals and non-energy commodity markets.

The behavior of the close prices of the stock market indices under different regimes on the commodity markets can be found in Appendix 1. By looking at the behavior of the logarithmic returns of the market indices under different regimes' combination on the commodity markets, it can be inferred that the situation with higher volatility (State 2) on all three analyzed commodity markets simultaneously refers mostly to the *Global Financial Crisis* and for most indices it corresponds to the highly volatile state in that particular stock market index, most in case of regions of North America, South America and Europe. In case of SSEC index this situation on the commodity markets captures highly volatile states of the index just partly, visible part of the volatile state corresponds to the combination of low volatility on the energy market and high on the precious metals and non-energy markets or high volatility on the energy and precious metals markets and low on the non-energy market. More "calm" situation on the commodity markets, characterized by simultaneous low volatility (State 1) on the energy, precious metals and non-energy markets, for the period from June, 2003 to October, 2005 in case of the analyzed indices of North America and European region corresponds to states with low or medium volatility of the particular stock market index. For Asia Pacific region such behavior during "calm" period on the commodity markets is valid for HSI and AORD indices.

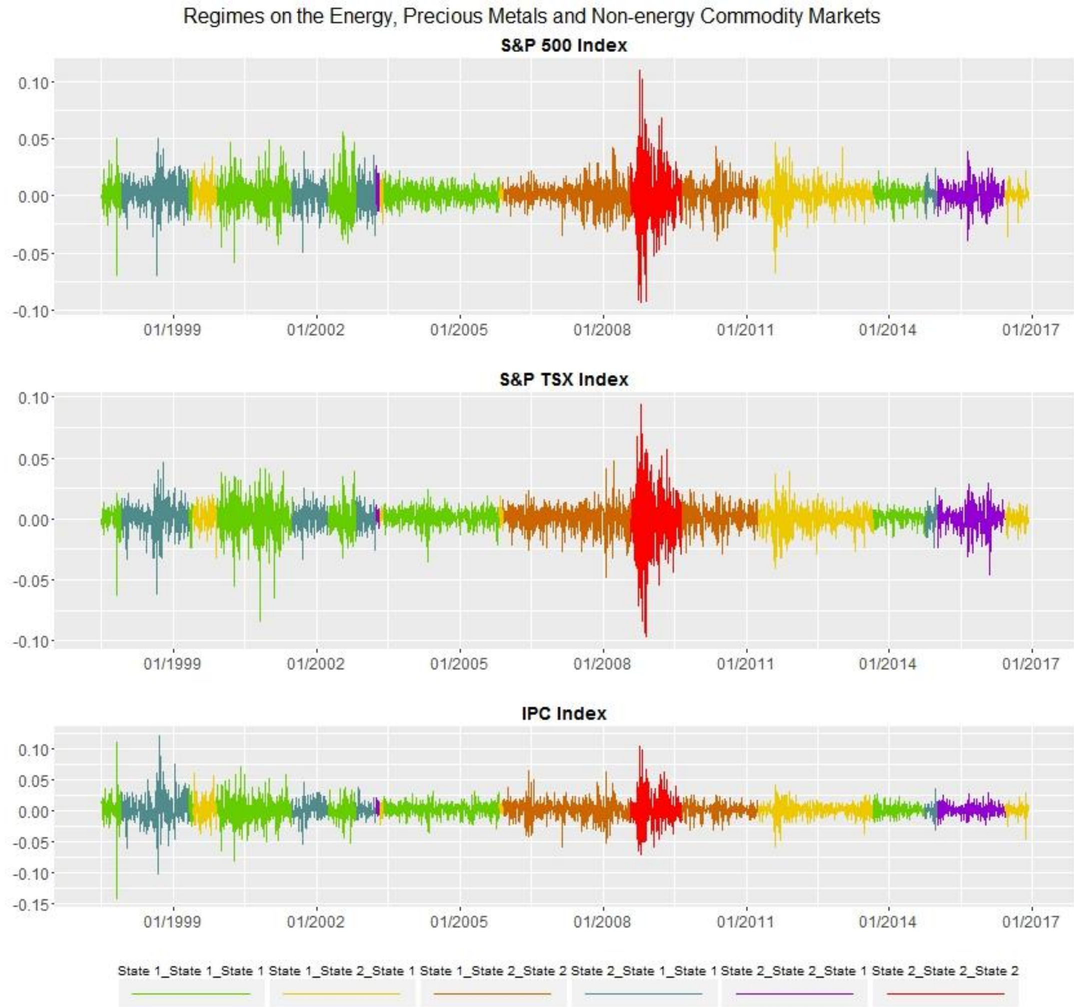


Fig 35 Stock Market Indices' logarithmic returns under different regimes on the commodity markets. North America. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

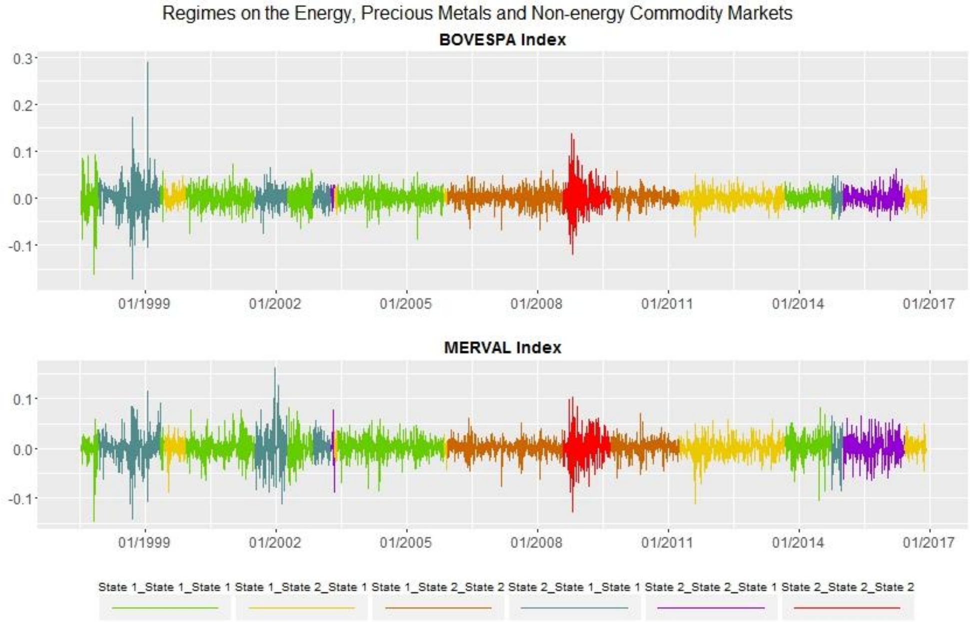


Fig 36 Stock Market Indices' logarithmic returns under different regimes on the commodity markets. South America. Data source: the time series data have been retrieved from *Quandl YFinace, Central Bank of Brazil Statistical Database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4, Quandl* packages.

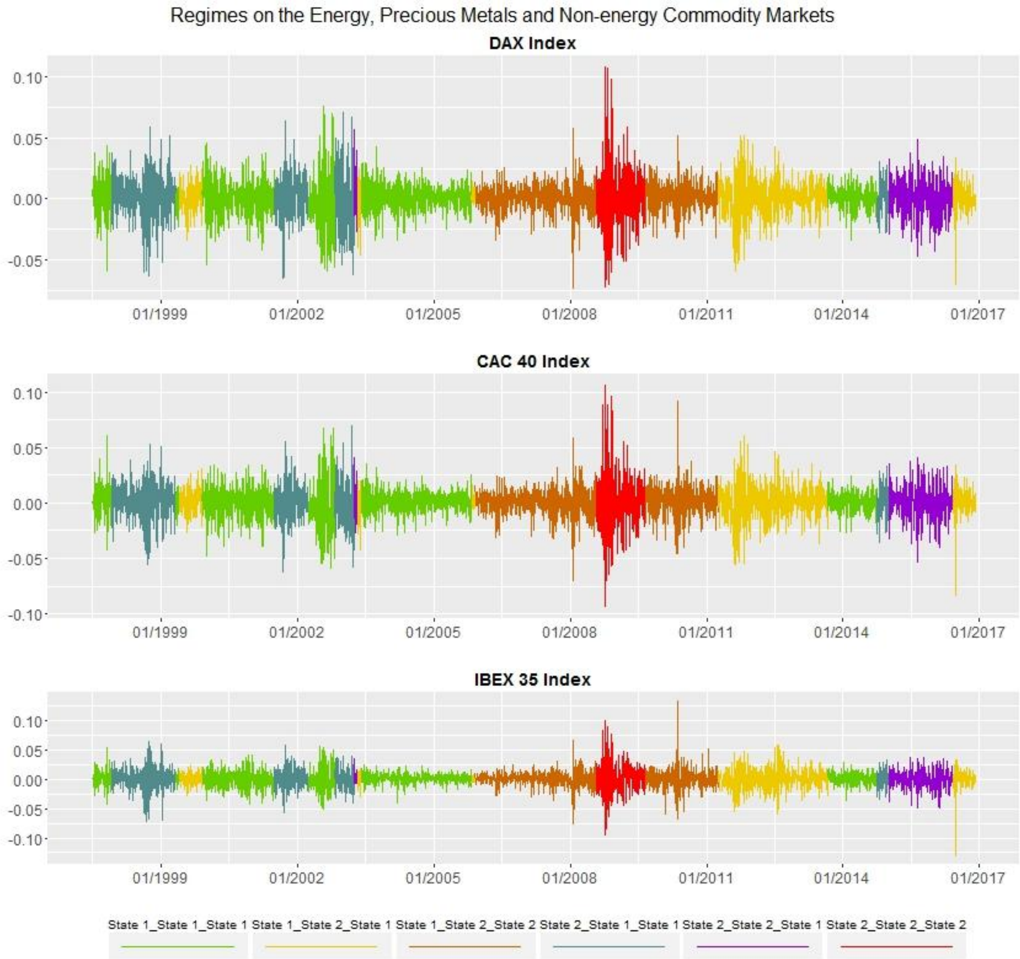


Fig 37 Stock Market Indices' logarithmic returns under different regimes on the commodity markets. Europe. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

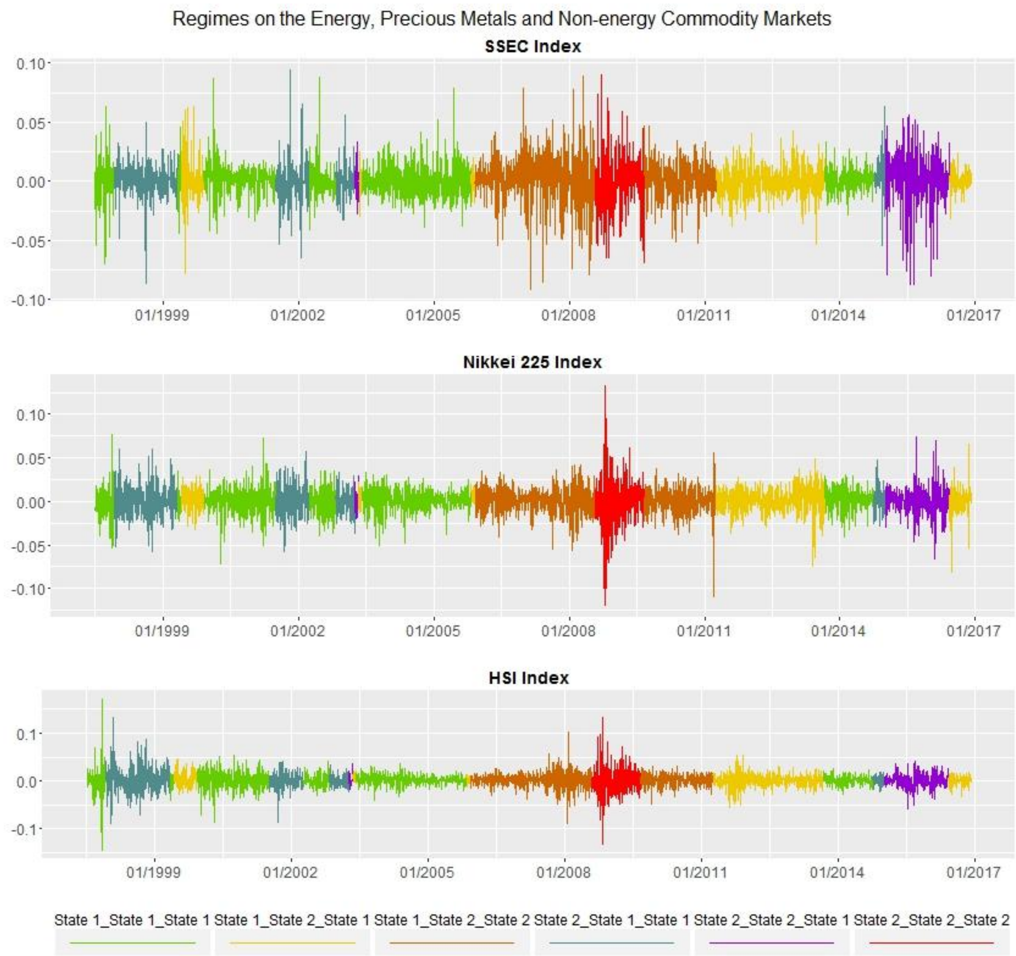


Fig 38 Stock Market Indices' logarithmic returns under different regimes on the commodity markets. Asia Pacific. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

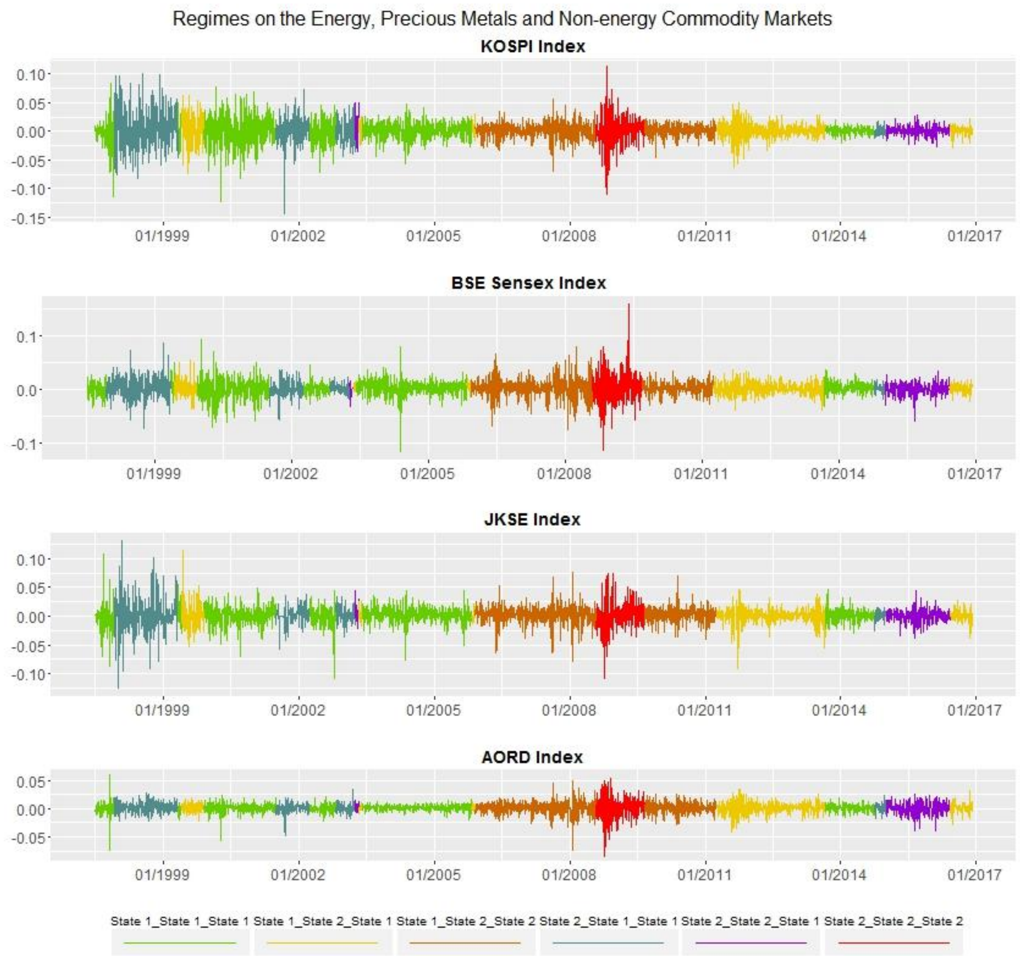


Fig 39 Stock Market Indices' logarithmic returns under different regimes on the commodity markets. Asia Pacific. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Based on the figures above it is obviously to expect that market indices are more similar regards to the occurrences of the highly volatile regimes of the particular stock market index during most unstable period, when highly volatile regimes prevail on the energy, precious metals and non-energy commodity markets simultaneously. The computed proximity matrix between the stock markets in terms of higher volatile regime's occurrence by using *Jaccard Similarity* during the highly volatile states' prevailing on all three analyzed commodity markets can be found in Table 13. The values of this proximity matrix indicate rather high similarity between the stock market indices in terms of bear market regime's occurrence during the presence of the increased volatility on all three commodity markets simultaneously. It can be also noticed that during this combination of the simultaneous volatile regimes on the commodity markets SSEC index, which was the least similar to other markets during the whole period (Table 11), has the agreements with most markets above the midpoint. The occurrences of the regime with higher volatility are the least similar to others in case of JKSE index. During the opposite situation, when states with lower volatility (State 1) prevail on all analyzed commodity markets, the percentage of agreement between occurrences of the highly volatile states of most stock market indices is lower (Table 14) comparing to the previous case (Table 13), but still there is rather high similarity between indices within the Europe region, between HSI and S&P TSX, HSI and IPC, the percentage of agreement between S&P 500 and European indices are close to the midpoint. The results of computing *Jaccard similarity* in case of other situations on the commodity markets can be found in Table 15 - Table 19. For the energy commodity market the proximity matrix has been computed for whole higher volatile regime on the energy market (Table 15), then separately for higher volatility caused by the demand shocks (Table 16) and by supply or precautionary demand shocks (Table 17) (*viz*. Chapter 4.1).

Table 13 Jaccard similarity matrix, Energy, Non-energy and Precious Metals Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.86	0.93	0.82	0.80	0.77	0.83	0.70	0.88	0.64	0.77	0.98	0.48	0.73	0.61
S&P TSX	0.86	1.00	0.79	0.86	0.68	0.66	0.72	0.60	0.78	0.75	0.90	0.86	0.47	0.85	0.55
IPC	0.93	0.79	1.00	0.76	0.72	0.83	0.81	0.68	0.81	0.59	0.72	0.91	0.41	0.67	0.59
MERVAL	0.82	0.86	0.76	1.00	0.65	0.63	0.67	0.57	0.72	0.79	0.84	0.80	0.43	0.89	0.56
BOVESPA	0.80	0.68	0.72	0.65	1.00	0.75	0.82	0.68	0.82	0.51	0.62	0.78	0.46	0.58	0.50
DAX	0.77	0.66	0.83	0.63	0.75	1.00	0.92	0.77	0.82	0.49	0.59	0.75	0.29	0.56	0.52
CAC 40	0.83	0.72	0.81	0.67	0.82	0.92	1.00	0.84	0.90	0.54	0.65	0.82	0.36	0.61	0.57
IBEX 35	0.70	0.60	0.68	0.57	0.68	0.77	0.84	1.00	0.75	0.45	0.54	0.69	0.36	0.51	0.46
Nikkei 225	0.88	0.78	0.81	0.72	0.82	0.82	0.90	0.75	1.00	0.60	0.72	0.90	0.39	0.68	0.56
HSI	0.64	0.75	0.59	0.79	0.51	0.49	0.54	0.45	0.60	1.00	0.83	0.66	0.35	0.88	0.71
KOSPI	0.77	0.90	0.72	0.84	0.62	0.59	0.65	0.54	0.72	0.83	1.00	0.79	0.42	0.94	0.64
BSE Sensex	0.98	0.86	0.91	0.80	0.78	0.75	0.82	0.69	0.90	0.66	0.79	1.00	0.48	0.74	0.63
JKSE	0.48	0.47	0.41	0.43	0.46	0.29	0.36	0.36	0.39	0.35	0.42	0.48	1.00	0.40	0.38
AORD	0.73	0.85	0.67	0.89	0.58	0.56	0.61	0.51	0.68	0.88	0.94	0.74	0.40	1.00	0.60
SSEC	0.61	0.55	0.59	0.56	0.50	0.52	0.57	0.46	0.56	0.71	0.64	0.63	0.38	0.60	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 14 Jaccard similarity matrix, Energy, Non-energy and Precious Metals Commodity market (State 1)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.27	0.21	0.09	0.32	0.58	0.45	0.52	0.30	0.16	0.19	0.16	0.09	0.06	0.01
S&P TSX	0.27	1.00	0.43	0.16	0.26	0.12	0.06	0.16	0.12	0.52	0.29	0.39	0.12	0.03	0.03
IPC	0.21	0.43	1.00	0.17	0.31	0.12	0.08	0.15	0.16	0.60	0.48	0.24	0.19	0.04	0.13
MERVAL	0.09	0.16	0.17	1.00	0.19	0.10	0.08	0.06	0.18	0.19	0.30	0.17	0.16	0.03	0.08
BOVESPA	0.32	0.26	0.31	0.19	1.00	0.23	0.20	0.21	0.24	0.31	0.21	0.19	0.28	0.06	0.10
DAX	0.58	0.12	0.12	0.10	0.23	1.00	0.78	0.61	0.37	0.06	0.17	0.08	0.07	0.04	0.02
CAC 40	0.45	0.06	0.08	0.08	0.20	0.78	1.00	0.66	0.25	0.01	0.16	0.00	0.04	0.05	0.03
IBEX 35	0.52	0.16	0.15	0.06	0.21	0.61	0.66	1.00	0.23	0.08	0.17	0.00	0.03	0.04	0.02
Nikkei 225	0.30	0.12	0.16	0.18	0.24	0.37	0.25	0.23	1.00	0.15	0.19	0.16	0.19	0.09	0.02
HSI	0.16	0.52	0.60	0.19	0.31	0.06	0.01	0.08	0.15	1.00	0.40	0.30	0.27	0.05	0.17
KOSPI	0.19	0.29	0.48	0.30	0.21	0.17	0.16	0.17	0.19	0.40	1.00	0.18	0.12	0.02	0.10
BSE Sensex	0.16	0.39	0.24	0.17	0.19	0.08	0.00	0.00	0.16	0.30	0.18	1.00	0.17	0.02	0.09
JKSE	0.09	0.12	0.19	0.16	0.28	0.07	0.04	0.03	0.19	0.27	0.12	0.17	1.00	0.07	0.13
AORD	0.06	0.03	0.04	0.03	0.06	0.04	0.05	0.04	0.09	0.05	0.02	0.02	0.07	1.00	0.02
SSEC	0.01	0.03	0.13	0.08	0.10	0.02	0.03	0.02	0.02	0.17	0.10	0.09	0.13	0.02	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 15 Jaccard similarity matrix, Energy Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.74	0.46	0.26	0.37	0.39	0.50	0.49	0.47	0.30	0.24	0.70	0.31	0.58	0.26
S&P TSX	0.74	1.00	0.47	0.32	0.38	0.37	0.45	0.50	0.48	0.37	0.29	0.60	0.34	0.62	0.28
IPC	0.46	0.47	1.00	0.32	0.60	0.44	0.33	0.38	0.41	0.55	0.47	0.46	0.40	0.32	0.19
MERVAL	0.26	0.32	0.32	1.00	0.36	0.34	0.30	0.30	0.41	0.43	0.51	0.24	0.28	0.28	0.36
BOVESPA	0.37	0.38	0.60	0.36	1.00	0.41	0.32	0.37	0.44	0.49	0.43	0.32	0.45	0.25	0.18
DAX	0.39	0.37	0.44	0.34	0.41	1.00	0.76	0.52	0.36	0.32	0.47	0.31	0.27	0.26	0.22
CAC 40	0.50	0.45	0.33	0.30	0.32	0.76	1.00	0.57	0.35	0.25	0.38	0.40	0.23	0.34	0.25
IBEX 35	0.49	0.50	0.38	0.30	0.37	0.52	0.57	1.00	0.42	0.32	0.28	0.38	0.31	0.34	0.25
Nikkei 225	0.47	0.48	0.41	0.41	0.44	0.36	0.35	0.42	1.00	0.41	0.36	0.37	0.31	0.39	0.26
HSI	0.30	0.37	0.55	0.43	0.49	0.32	0.25	0.32	0.41	1.00	0.62	0.30	0.45	0.39	0.29
KOSPI	0.24	0.29	0.47	0.51	0.43	0.47	0.38	0.28	0.36	0.62	1.00	0.25	0.37	0.25	0.22
BSE Sensex	0.70	0.60	0.46	0.24	0.32	0.31	0.40	0.38	0.37	0.30	0.25	1.00	0.26	0.57	0.25
JKSE	0.31	0.34	0.40	0.28	0.45	0.27	0.23	0.31	0.31	0.45	0.37	0.26	1.00	0.21	0.13
AORD	0.58	0.62	0.32	0.28	0.25	0.26	0.34	0.34	0.39	0.39	0.25	0.57	0.21	1.00	0.33
SSEC	0.26	0.28	0.19	0.36	0.18	0.22	0.25	0.25	0.26	0.29	0.22	0.25	0.13	0.33	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 16 Jaccard similarity matrix, Energy Commodity market (State 2 - I)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.82	0.47	0.56	0.43	0.60	0.81	0.65	0.67	0.34	0.36	0.74	0.31	0.63	0.50
S&P TSX	0.82	1.00	0.48	0.63	0.44	0.58	0.72	0.58	0.64	0.41	0.44	0.63	0.35	0.70	0.49
IPC	0.47	0.48	1.00	0.61	0.67	0.60	0.43	0.45	0.52	0.64	0.70	0.46	0.40	0.34	0.31
MERVAL	0.56	0.63	0.61	1.00	0.63	0.53	0.49	0.49	0.57	0.60	0.61	0.50	0.51	0.53	0.37
BOVESPA	0.43	0.44	0.67	0.63	1.00	0.58	0.43	0.44	0.60	0.60	0.65	0.36	0.52	0.29	0.27
DAX	0.60	0.58	0.60	0.53	0.58	1.00	0.68	0.66	0.66	0.39	0.42	0.44	0.32	0.38	0.37
CAC 40	0.81	0.72	0.43	0.49	0.43	0.68	1.00	0.74	0.68	0.30	0.32	0.61	0.26	0.52	0.48
IBEX 35	0.65	0.58	0.45	0.49	0.44	0.66	0.74	1.00	0.61	0.30	0.33	0.46	0.33	0.40	0.35
Nikkei 225	0.67	0.64	0.52	0.57	0.60	0.66	0.68	0.61	1.00	0.43	0.47	0.53	0.40	0.47	0.39
HSI	0.34	0.41	0.64	0.60	0.60	0.39	0.30	0.30	0.43	1.00	0.93	0.34	0.50	0.38	0.33
KOSPI	0.36	0.44	0.70	0.61	0.65	0.42	0.32	0.33	0.47	0.93	1.00	0.36	0.54	0.38	0.29
BSE Sensex	0.74	0.63	0.46	0.50	0.36	0.44	0.61	0.46	0.53	0.34	0.36	1.00	0.25	0.66	0.52
JKSE	0.31	0.35	0.40	0.51	0.52	0.32	0.26	0.33	0.40	0.50	0.54	0.25	1.00	0.21	0.21
AORD	0.63	0.70	0.34	0.53	0.29	0.38	0.52	0.40	0.47	0.38	0.38	0.66	0.21	1.00	0.57
SSEC	0.50	0.49	0.31	0.37	0.27	0.37	0.48	0.35	0.39	0.33	0.29	0.52	0.21	0.57	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 17 Jaccard similarity matrix, Energy Commodity market (State 2 - II)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.17	0.27	0.03	0.01	0.06	0.07	0.11	0.09	0.12	0.02	0.26	0.37	0.28	0.03
S&P TSX	0.17	1.00	0.27	0.05	0.04	0.04	0.05	0.27	0.15	0.20	0.02	0.26	0.19	0.26	0.06
IPC	0.27	0.27	1.00	0.03	0.08	0.07	0.06	0.12	0.07	0.09	0.04	0.56	0.32	0.14	0.00
MERVAL	0.03	0.05	0.03	1.00	0.10	0.20	0.17	0.15	0.27	0.21	0.41	0.03	0.05	0.08	0.35
BOVESPA	0.01	0.04	0.08	0.10	1.00	0.10	0.10	0.16	0.10	0.09	0.06	0.06	0.05	0.04	0.06
DAX	0.06	0.04	0.07	0.20	0.10	1.00	0.87	0.35	0.07	0.16	0.55	0.07	0.13	0.07	0.11
CAC 40	0.07	0.05	0.06	0.17	0.10	0.87	1.00	0.36	0.04	0.14	0.48	0.08	0.15	0.07	0.10
IBEX 35	0.11	0.27	0.12	0.15	0.16	0.35	0.36	1.00	0.16	0.39	0.20	0.13	0.25	0.18	0.16
Nikkei 225	0.09	0.15	0.07	0.27	0.10	0.07	0.04	0.16	1.00	0.34	0.20	0.05	0.09	0.22	0.14
HSI	0.12	0.20	0.09	0.21	0.09	0.16	0.14	0.39	0.34	1.00	0.13	0.10	0.18	0.39	0.23
KOSPI	0.02	0.02	0.04	0.41	0.06	0.55	0.48	0.20	0.20	0.13	1.00	0.04	0.06	0.02	0.15
BSE Sensex	0.26	0.26	0.56	0.03	0.06	0.07	0.08	0.13	0.05	0.10	0.04	1.00	0.52	0.14	0.00
JKSE	0.37	0.19	0.32	0.05	0.05	0.13	0.15	0.25	0.09	0.18	0.06	0.52	1.00	0.20	0.02
AORD	0.28	0.26	0.14	0.08	0.04	0.07	0.07	0.18	0.22	0.39	0.02	0.14	0.20	1.00	0.10
SSEC	0.03	0.06	0.00	0.35	0.06	0.11	0.10	0.16	0.14	0.23	0.15	0.00	0.02	0.10	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 18 Jaccard similarity matrix, Precious Metals Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.58	0.41	0.38	0.42	0.65	0.76	0.51	0.37	0.35	0.35	0.42	0.30	0.56	0.18
S&P TSX	0.58	1.00	0.39	0.39	0.50	0.45	0.48	0.34	0.45	0.34	0.33	0.48	0.29	0.51	0.19
IPC	0.41	0.39	1.00	0.28	0.35	0.34	0.35	0.25	0.33	0.38	0.56	0.48	0.34	0.42	0.28
MERVAL	0.38	0.39	0.28	1.00	0.30	0.34	0.35	0.30	0.30	0.36	0.34	0.29	0.24	0.43	0.31
BOVESPA	0.42	0.50	0.35	0.30	1.00	0.38	0.41	0.24	0.37	0.20	0.23	0.47	0.26	0.30	0.16
DAX	0.65	0.45	0.34	0.34	0.38	1.00	0.78	0.46	0.31	0.28	0.35	0.31	0.17	0.41	0.13
CAC 40	0.76	0.48	0.35	0.35	0.41	0.78	1.00	0.58	0.34	0.29	0.32	0.34	0.23	0.47	0.15
IBEX 35	0.51	0.34	0.25	0.30	0.24	0.46	0.58	1.00	0.28	0.27	0.24	0.23	0.18	0.38	0.14
Nikkei 225	0.37	0.45	0.33	0.30	0.37	0.31	0.34	0.28	1.00	0.33	0.26	0.45	0.24	0.42	0.24
HSI	0.35	0.34	0.38	0.36	0.20	0.28	0.29	0.27	0.33	1.00	0.58	0.32	0.23	0.57	0.43
KOSPI	0.35	0.33	0.56	0.34	0.23	0.35	0.32	0.24	0.26	0.58	1.00	0.42	0.31	0.50	0.31
BSE Sensex	0.42	0.48	0.48	0.29	0.47	0.31	0.34	0.23	0.45	0.32	0.42	1.00	0.27	0.43	0.26
JKSE	0.30	0.29	0.34	0.24	0.26	0.17	0.23	0.18	0.24	0.23	0.31	0.27	1.00	0.28	0.20
AORD	0.56	0.51	0.42	0.43	0.30	0.41	0.47	0.38	0.42	0.57	0.50	0.43	0.28	1.00	0.29
SSEC	0.18	0.19	0.28	0.31	0.16	0.13	0.15	0.14	0.24	0.43	0.31	0.26	0.20	0.29	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl*

Table 19 Jaccard similarity matrix, Non-energy Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	BOVESPA	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.73	0.49	0.60	0.57	0.61	0.72	0.60	0.59	0.32	0.37	0.54	0.42	0.54	0.27
S&P TSX	0.73	1.00	0.49	0.63	0.60	0.62	0.61	0.44	0.61	0.40	0.48	0.55	0.36	0.59	0.24
IPC	0.49	0.49	1.00	0.51	0.46	0.44	0.41	0.34	0.52	0.44	0.66	0.61	0.38	0.50	0.37
MERVAL	0.60	0.63	0.51	1.00	0.57	0.46	0.55	0.42	0.46	0.40	0.49	0.50	0.45	0.61	0.31
BOVESPA	0.57	0.60	0.46	0.57	1.00	0.62	0.61	0.43	0.54	0.27	0.36	0.50	0.38	0.38	0.23
DAX	0.61	0.62	0.44	0.46	0.62	1.00	0.80	0.56	0.57	0.25	0.30	0.44	0.20	0.37	0.19
CAC 40	0.72	0.61	0.41	0.55	0.61	0.80	1.00	0.71	0.56	0.26	0.31	0.44	0.30	0.44	0.23
IBEX 35	0.60	0.44	0.34	0.42	0.43	0.56	0.71	1.00	0.45	0.22	0.26	0.37	0.27	0.40	0.20
Nikkei 225	0.59	0.61	0.52	0.46	0.54	0.57	0.56	0.45	1.00	0.42	0.46	0.60	0.33	0.56	0.31
HSI	0.32	0.40	0.44	0.40	0.27	0.25	0.26	0.22	0.42	1.00	0.68	0.44	0.25	0.60	0.52
KOSPI	0.37	0.48	0.66	0.49	0.36	0.30	0.31	0.26	0.46	0.68	1.00	0.66	0.33	0.66	0.45
BSE Sensex	0.54	0.55	0.61	0.50	0.50	0.44	0.44	0.37	0.60	0.44	0.66	1.00	0.37	0.55	0.38
JKSE	0.42	0.36	0.38	0.45	0.38	0.20	0.30	0.27	0.33	0.25	0.33	0.37	1.00	0.37	0.27
AORD	0.54	0.59	0.50	0.61	0.38	0.37	0.44	0.40	0.56	0.60	0.66	0.55	0.37	1.00	0.39
SSEC	0.27	0.24	0.37	0.31	0.23	0.19	0.23	0.20	0.31	0.52	0.45	0.38	0.27	0.39	1.00

Source: Own calculation in SPSS 16 and Excel. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

It can be noticed that the similarity between the stock market indices in terms of highly volatile regimes' occurrences differs and is stronger for the period of high volatility presence on the energy market caused by the demand shocks in the oil price and is weaker for the volatile period caused by supply or precautionary demand shocks. For the latter period the weak similarity between the occurrences of states with high volatility can be comparable with the situation of simultaneous low volatility on all three commodity markets. This difference in the stock markets' relations during different volatile periods on the energy market, depending on the source of the oil price shock, can support the thought that the demand oil shocks, causing the increase volatility on the energy market, turn out more globally, whereas the supply shocks impact the occurrence of high volatility on the stock markets more selectively. The interconnection among the stock market indices within region (North America, South America, Europe and Asia Pacific) in terms of high volatile state’s appearance is stronger for the presence of high volatility on the non-energy market comparing with volatile regime on the precious metals market. The similarity in behavior between DAX and CAC 40 regards of the volatile state's appearing is rather high for all considered situations on the commodity markets. Considering the whole period the least agreement between the bear regime's occurrences in the stock markets is in case of SSEC index. Analyzing different situations on the commodity markets the results can differ: during the period of high volatility on all three commodity markets the lowest similarity was observed in case of JKSE index and then in case of SSEC index; during the simultaneous presence of low volatility the least agreement of bear regime' occurrences can be noticed in case of AORD index and then in case of SSEC index.

4.3.2 Stcok Markets' Correlation Analysis and Regimes on the Commodity Markets

In the previous step by computing *Jaccard Index* between two market indices the similarity has been measured only between the occurrences of the highly volatile states on the stock markets, where the presence of regimes with low or medium volatility on both markets simultaneously have been not considered. By measuring the relationship between the binary variables, only the question of the level of agreement between the highly volatile regimes' occurrence can be answered. To look how the stock market indices are correlated, *Spearman correlation coefficient* is computed. Table 20 contains the correlation coefficients' values between the logarithmic returns of the stock market indices for the whole period regardless of the situation on the commodity market.

Table 20 Spearman correlation

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.67	0.59	0.44	0.52	0.52	0.50	0.45	0.12	0.16	0.13	0.14	0.07	0.11	0.03
S&P TSX	0.67	1.00	0.51	0.43	0.48	0.49	0.50	0.45	0.17	0.24	0.18	0.19	0.13	0.20	0.06
IPC	0.59	0.51	1.00	0.43	0.54	0.43	0.44	0.41	0.16	0.24	0.18	0.20	0.15	0.18	0.06
MERVAL	0.44	0.43	0.43	1.00	0.49	0.33	0.33	0.34	0.11	0.18	0.13	0.14	0.11	0.13	0.05
Bovespa	0.52	0.48	0.54	0.49	1.00	0.37	0.38	0.36	0.13	0.20	0.17	0.17	0.13	0.14	0.05
DAX	0.52	0.49	0.43	0.33	0.37	1.00	0.87	0.78	0.23	0.31	0.24	0.26	0.19	0.24	0.06
CAC 40	0.50	0.50	0.44	0.33	0.38	0.87	1.00	0.83	0.25	0.33	0.24	0.28	0.20	0.27	0.06
IBEX 35	0.45	0.45	0.41	0.34	0.36	0.78	0.83	1.00	0.23	0.29	0.22	0.26	0.18	0.24	0.05
Nikkei 225	0.12	0.17	0.16	0.11	0.13	0.23	0.25	0.23	1.00	0.47	0.47	0.25	0.30	0.50	0.15
HSI	0.16	0.24	0.24	0.18	0.20	0.31	0.33	0.29	0.47	1.00	0.49	0.37	0.39	0.51	0.28
KOSPI	0.13	0.18	0.18	0.13	0.17	0.24	0.24	0.22	0.47	0.49	1.00	0.30	0.32	0.44	0.16
BSE Sensex	0.14	0.19	0.20	0.14	0.17	0.26	0.28	0.26	0.25	0.37	0.30	1.00	0.28	0.28	0.13
JKSE	0.07	0.13	0.15	0.11	0.13	0.19	0.20	0.18	0.30	0.39	0.32	0.28	1.00	0.33	0.12
AORD	0.11	0.20	0.18	0.13	0.14	0.24	0.27	0.24	0.50	0.51	0.44	0.28	0.33	1.00	0.16
SSEC	0.03	0.06	0.06	0.05	0.05	0.06	0.06	0.05	0.15	0.28	0.16	0.13	0.12	0.16	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

It can be seen that the correlation between the indices within European region is high, actually the highest correlation is between DAX and CAC 40 then the pair IBEX 35 and DAX follows. There is also rather strong correlation between the indices within the North America and is not inconsiderable between the indices of the North America and European region. There is also pretty notable correlation between North and South America's market indices. The correlation between the Mexican IPC and Brazilian Bovespa exceeds 0.5. The indices within the Asia Pacific region are weaker correlated to other indices expecially to the indices of Europe, North and South America. The correlation coefficient slightly exceeds 0.5 between HSI and AORD, and is close to 0.5 in case of HSI and Nikkei 225, HSI and KOSPI, Nikkei 225 and KOSPI, Nikkei 225 and AORD. The lowest correlation to other indices is in case of SSEC index. The highest value of the correlation coeffient is only toward HSI index and is equal to 0.28. According to the matrix of the corresponding *p*-values, which can be found in Appendix 2, the null hypothesis about the absence of the monotonic association between the pairs of indices can be rejected on the 5% level of significant for all indices excepting the pair SSEC and S&P 500 index where the null hypotheisis can be rejected on the 10% level of significance. The tables below illustrate Spearman correlation coefficients under different situation on the comodity markets. Table 21 contains the correlation coefficients for higher volatility on the energy market as a whole, then it is divided into higher volatility on the energy market caused by demand shocks (Table 22), and by supply or precautionary demand shocks (Table 23). The correlation coeffecients' computation for the regimes with higher volatility on the precious metals and non-energy markets are presented in Table 24 and Table 25 correspondingly. The correlation matrices for the most volatile situation, where all analyzed commodity markets are at State 2 (high volatility), and for the most "calm" situations on the commodity markets, where all are at State 1, are presented in Table 26 and Table 27. The strongest correlation for most indices measured by Spearman coefficient between the logarithmic returns of the market indices is in case of the situation, where highly volatile regimes prevail on the energy, precious metals and non-energy markets simulatniously. In case of DAX and CAC 40 indices the value of the correlation coefficient exceeds 0.9; SSEC index is more correlated to other indices than during other situations on the commodity markets, although the correlation with European indices is still weak but higher than under other analyzed situations on the comodity markets, and in case of HSI index the correlation coefficient value is more than 0.5. Following the corresponding *p*-values (Appendix 2) the null hypothesis can be rejected for all indices on the 5% level of significance, excepting the pair of SSEC and S&P 500 indices, where the null hypotheisis can be rejected on the 10% level of significance, and in case of Nikkei 225 and S&P 500 indices, where the null hypothesis about the absence of the monotonic association between the pairs of indices cannot be rejected either on 5% or 10% level of significance. During the opposite situation on the commodity markets referring to the most "calm" situation with State 1 prevailing on all analyzed commodity markets, the correlation between most indices are lower. The SSEC index correlation to others is very weak and for the null hypothesis of absence of monotonic association between SSEC index and others cannot be rejected either on 5% or on 10% level of significance for all indices besides HSI and KOSPI (*viz.* Appendix 2). There is strong, weaker than in the previous case, but still high and statistically significant correlation between the indices within the European region and moderatly strong and statistical significant correlation within North America Region.

Table 21 Spearman Correlation, Energy Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.69	0.58	0.45	0.53	0.54	0.52	0.48	0.15	0.19	0.15	0.20	0.09	0.13	0.04
S&P TSX	0.69	1.00	0.53	0.45	0.50	0.51	0.52	0.49	0.16	0.27	0.17	0.25	0.16	0.21	0.04
IPC	0.58	0.53	1.00	0.46	0.55	0.46	0.46	0.47	0.21	0.28	0.18	0.23	0.20	0.22	0.06
MERVAL	0.45	0.45	0.46	1.00	0.54	0.32	0.32	0.33	0.13	0.19	0.12	0.14	0.16	0.15	0.03
Bovespa	0.53	0.50	0.55	0.54	1.00	0.38	0.40	0.39	0.18	0.23	0.18	0.20	0.18	0.16	0.05
DAX	0.54	0.51	0.46	0.32	0.38	1.00	0.87	0.79	0.24	0.35	0.22	0.29	0.23	0.23	0.07
CAC 40	0.52	0.52	0.46	0.32	0.40	0.87	1.00	0.85	0.27	0.35	0.22	0.32	0.23	0.27	0.08
IBEX 35	0.48	0.49	0.47	0.33	0.39	0.79	0.85	1.00	0.26	0.34	0.22	0.32	0.22	0.28	0.07
Nikkei 225	0.15	0.16	0.21	0.13	0.18	0.24	0.27	0.26	1.00	0.46	0.41	0.24	0.29	0.47	0.15
HSI	0.19	0.27	0.28	0.19	0.23	0.35	0.35	0.34	0.46	1.00	0.43	0.38	0.39	0.51	0.29
KOSPI	0.15	0.17	0.18	0.12	0.18	0.22	0.22	0.22	0.41	0.43	1.00	0.28	0.31	0.39	0.14
BSE Sensex	0.20	0.25	0.23	0.14	0.20	0.29	0.32	0.32	0.24	0.38	0.28	1.00	0.28	0.30	0.15
JKSE	0.09	0.16	0.20	0.16	0.18	0.23	0.23	0.22	0.29	0.39	0.31	0.28	1.00	0.34	0.13
AORD	0.13	0.21	0.22	0.15	0.16	0.23	0.27	0.28	0.47	0.51	0.39	0.30	0.34	1.00	0.17
SSEC	0.04	0.04	0.06	0.03	0.05	0.07	0.08	0.07	0.15	0.29	0.14	0.15	0.13	0.17	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 22 Spearman Correlation, Energy Commodity market (State 2 - I)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.69	0.61	0.57	0.62	0.50	0.52	0.48	0.11	0.19	0.14	0.21	0.10	0.14	0.02
S&P TSX	0.69	1.00	0.56	0.55	0.55	0.51	0.53	0.50	0.18	0.29	0.14	0.24	0.18	0.23	0.05
IPC	0.61	0.56	1.00	0.59	0.66	0.45	0.46	0.47	0.21	0.31	0.15	0.25	0.22	0.24	0.08
MERVAL	0.57	0.55	0.59	1.00	0.67	0.43	0.43	0.43	0.18	0.28	0.14	0.16	0.23	0.22	0.06
Bovespa	0.62	0.55	0.66	0.67	1.00	0.41	0.45	0.42	0.19	0.26	0.19	0.19	0.21	0.21	0.08
DAX	0.50	0.51	0.45	0.43	0.41	1.00	0.85	0.78	0.25	0.39	0.24	0.30	0.29	0.32	0.09
CAC 40	0.52	0.53	0.46	0.43	0.45	0.85	1.00	0.82	0.29	0.37	0.22	0.33	0.28	0.34	0.09
IBEX 35	0.48	0.50	0.47	0.43	0.42	0.78	0.82	1.00	0.27	0.36	0.23	0.31	0.28	0.35	0.08
Nikkei 225	0.11	0.18	0.21	0.18	0.19	0.25	0.29	0.27	1.00	0.47	0.38	0.21	0.32	0.54	0.18
HSI	0.19	0.29	0.31	0.28	0.26	0.39	0.37	0.36	0.47	1.00	0.39	0.38	0.47	0.55	0.30
KOSPI	0.14	0.14	0.15	0.14	0.19	0.24	0.22	0.23	0.38	0.39	1.00	0.25	0.32	0.37	0.19
BSE Sensex	0.21	0.24	0.25	0.16	0.19	0.30	0.33	0.31	0.21	0.38	0.25	1.00	0.29	0.30	0.22
JKSE	0.10	0.18	0.22	0.23	0.21	0.29	0.28	0.28	0.32	0.47	0.32	0.29	1.00	0.37	0.15
AORD	0.14	0.23	0.24	0.22	0.21	0.32	0.34	0.35	0.54	0.55	0.37	0.30	0.37	1.00	0.18
SSEC	0.02	0.05	0.08	0.06	0.08	0.09	0.09	0.08	0.18	0.30	0.19	0.22	0.15	0.18	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 23 Spearman Correlation, Energy Commodity market (State 2 - II)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.71	0.58	0.33	0.42	0.58	0.54	0.49	0.19	0.20	0.18	0.21	0.08	0.12	0.07
S&P TSX	0.71	1.00	0.51	0.36	0.44	0.52	0.52	0.50	0.16	0.24	0.24	0.28	0.12	0.18	0.03
IPC	0.58	0.51	1.00	0.35	0.41	0.49	0.49	0.48	0.21	0.26	0.27	0.22	0.19	0.21	0.05
MERVAL	0.33	0.36	0.35	1.00	0.42	0.22	0.22	0.24	0.08	0.10	0.12	0.13	0.08	0.07	0.01
Bovespa	0.42	0.44	0.41	0.42	1.00	0.36	0.35	0.36	0.17	0.21	0.20	0.22	0.14	0.10	0.03
DAX	0.58	0.52	0.49	0.22	0.36	1.00	0.89	0.80	0.24	0.32	0.21	0.30	0.16	0.13	0.05
CAC 40	0.54	0.52	0.49	0.22	0.35	0.89	1.00	0.87	0.26	0.33	0.24	0.32	0.18	0.20	0.07
IBEX 35	0.49	0.50	0.48	0.24	0.36	0.80	0.87	1.00	0.26	0.32	0.23	0.33	0.17	0.20	0.06
Nikkei 225	0.19	0.16	0.21	0.08	0.17	0.24	0.26	0.26	1.00	0.47	0.45	0.30	0.27	0.40	0.13
HSI	0.20	0.24	0.26	0.10	0.21	0.32	0.33	0.32	0.47	1.00	0.52	0.42	0.28	0.48	0.30
KOSPI	0.18	0.24	0.27	0.12	0.20	0.21	0.24	0.23	0.45	0.52	1.00	0.34	0.31	0.43	0.08
BSE Sensex	0.21	0.28	0.22	0.13	0.22	0.30	0.32	0.33	0.30	0.42	0.34	1.00	0.28	0.32	0.08
JKSE	0.08	0.12	0.19	0.08	0.14	0.16	0.18	0.17	0.27	0.28	0.31	0.28	1.00	0.32	0.08
AORD	0.12	0.18	0.21	0.07	0.10	0.13	0.20	0.20	0.40	0.48	0.43	0.32	0.32	1.00	0.16
SSEC	0.07	0.03	0.05	0.01	0.03	0.05	0.07	0.06	0.13	0.30	0.08	0.08	0.08	0.16	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 24 Spearman Correlation, Precious Metals Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.69	0.63	0.53	0.59	0.56	0.57	0.50	0.10	0.18	0.17	0.21	0.13	0.13	0.07
S&P TSX	0.69	1.00	0.57	0.54	0.58	0.51	0.53	0.47	0.16	0.26	0.23	0.25	0.18	0.20	0.12
IPC	0.63	0.57	1.00	0.50	0.60	0.49	0.51	0.46	0.17	0.26	0.24	0.26	0.22	0.20	0.11
MERVAL	0.53	0.54	0.50	1.00	0.58	0.42	0.44	0.41	0.13	0.21	0.18	0.23	0.18	0.16	0.11
Bovespa	0.59	0.58	0.60	0.58	1.00	0.43	0.46	0.42	0.12	0.25	0.23	0.25	0.19	0.16	0.12
DAX	0.56	0.51	0.49	0.42	0.43	1.00	0.92	0.81	0.25	0.33	0.28	0.37	0.25	0.27	0.12
CAC 40	0.57	0.53	0.51	0.44	0.46	0.92	1.00	0.86	0.27	0.35	0.27	0.38	0.26	0.28	0.12
IBEX 35	0.50	0.47	0.46	0.41	0.42	0.81	0.86	1.00	0.24	0.32	0.25	0.35	0.24	0.26	0.10
Nikkei 225	0.10	0.16	0.17	0.13	0.12	0.25	0.27	0.24	1.00	0.53	0.56	0.32	0.39	0.57	0.23
HSI	0.18	0.26	0.26	0.21	0.25	0.33	0.35	0.32	0.53	1.00	0.58	0.48	0.51	0.58	0.40
KOSPI	0.17	0.23	0.24	0.18	0.23	0.28	0.27	0.25	0.56	0.58	1.00	0.38	0.44	0.54	0.26
BSE Sensex	0.21	0.25	0.26	0.23	0.25	0.37	0.38	0.35	0.32	0.48	0.38	1.00	0.38	0.36	0.21
JKSE	0.13	0.18	0.22	0.18	0.19	0.25	0.26	0.24	0.39	0.51	0.44	0.38	1.00	0.42	0.20
AORD	0.13	0.20	0.20	0.16	0.16	0.27	0.28	0.26	0.57	0.58	0.54	0.36	0.42	1.00	0.23
SSEC	0.07	0.12	0.11	0.11	0.12	0.12	0.12	0.10	0.23	0.40	0.26	0.21	0.20	0.23	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 25 Spearman Correlation, Non-energy Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.68	0.66	0.58	0.66	0.54	0.55	0.49	0.09	0.17	0.17	0.21	0.12	0.10	0.06
S&P TSX	0.68	1.00	0.59	0.59	0.65	0.48	0.50	0.44	0.15	0.23	0.22	0.25	0.17	0.17	0.10
IPC	0.66	0.59	1.00	0.56	0.68	0.51	0.53	0.49	0.17	0.27	0.24	0.27	0.24	0.20	0.13
MERVAL	0.58	0.59	0.56	1.00	0.63	0.47	0.48	0.44	0.12	0.24	0.20	0.26	0.21	0.19	0.12
Bovespa	0.66	0.65	0.68	0.63	1.00	0.46	0.49	0.43	0.13	0.25	0.23	0.26	0.21	0.15	0.14
DAX	0.54	0.48	0.51	0.47	0.46	1.00	0.93	0.83	0.27	0.33	0.29	0.39	0.28	0.29	0.13
CAC 40	0.55	0.50	0.53	0.48	0.49	0.93	1.00	0.87	0.30	0.35	0.29	0.41	0.30	0.31	0.13
IBEX 35	0.49	0.44	0.49	0.44	0.43	0.83	0.87	1.00	0.25	0.32	0.26	0.37	0.28	0.29	0.11
Nikkei 225	0.09	0.15	0.17	0.12	0.13	0.27	0.30	0.25	1.00	0.57	0.64	0.35	0.42	0.63	0.25
HSI	0.17	0.23	0.27	0.24	0.25	0.33	0.35	0.32	0.57	1.00	0.61	0.52	0.56	0.60	0.39
KOSPI	0.17	0.22	0.24	0.20	0.23	0.29	0.29	0.26	0.64	0.61	1.00	0.41	0.47	0.58	0.27
BSE Sensex	0.21	0.25	0.27	0.26	0.26	0.39	0.41	0.37	0.35	0.52	0.41	1.00	0.44	0.40	0.23
JKSE	0.12	0.17	0.24	0.21	0.21	0.28	0.30	0.28	0.42	0.56	0.47	0.44	1.00	0.44	0.20
AORD	0.10	0.17	0.20	0.19	0.15	0.29	0.31	0.29	0.63	0.60	0.58	0.40	0.44	1.00	0.24
SSEC	0.06	0.10	0.13	0.12	0.14	0.13	0.13	0.11	0.25	0.39	0.27	0.23	0.20	0.24	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 26 Spearman Correlation, Energy, Non-energy and Precious Metals Commodity market (State 2)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.74	0.76	0.63	0.75	0.61	0.60	0.57	0.06	0.23	0.23	0.37	0.20	0.15	0.10
S&P TSX	0.74	1.00	0.69	0.65	0.74	0.56	0.58	0.55	0.19	0.29	0.25	0.36	0.24	0.22	0.13
IPC	0.76	0.69	1.00	0.64	0.77	0.66	0.64	0.64	0.21	0.39	0.33	0.44	0.35	0.28	0.21
MERVAL	0.63	0.65	0.64	1.00	0.70	0.57	0.56	0.54	0.18	0.28	0.24	0.35	0.34	0.24	0.17
Bovespa	0.75	0.74	0.77	0.70	1.00	0.58	0.59	0.56	0.16	0.33	0.29	0.38	0.32	0.20	0.24
DAX	0.61	0.56	0.66	0.57	0.58	1.00	0.93	0.86	0.29	0.37	0.39	0.50	0.36	0.34	0.21
CAC 40	0.60	0.58	0.64	0.56	0.59	0.93	1.00	0.91	0.33	0.40	0.37	0.52	0.38	0.38	0.20
IBEX 35	0.57	0.55	0.64	0.54	0.56	0.86	0.91	1.00	0.36	0.44	0.40	0.52	0.42	0.43	0.20
Nikkei 225	0.06	0.19	0.21	0.18	0.16	0.29	0.33	0.36	1.00	0.59	0.64	0.35	0.46	0.69	0.33
HSI	0.23	0.29	0.39	0.28	0.33	0.37	0.40	0.44	0.59	1.00	0.63	0.60	0.62	0.61	0.54
KOSPI	0.23	0.25	0.33	0.24	0.29	0.39	0.37	0.40	0.64	0.63	1.00	0.44	0.49	0.56	0.39
BSE Sensex	0.37	0.36	0.44	0.35	0.38	0.50	0.52	0.52	0.35	0.60	0.44	1.00	0.46	0.42	0.34
JKSE	0.20	0.24	0.35	0.34	0.32	0.36	0.38	0.42	0.46	0.62	0.49	0.46	1.00	0.48	0.32
AORD	0.15	0.22	0.28	0.24	0.20	0.34	0.38	0.43	0.69	0.61	0.56	0.42	0.48	1.00	0.29
SSEC	0.10	0.13	0.21	0.17	0.24	0.21	0.20	0.20	0.33	0.54	0.39	0.34	0.32	0.29	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Table 27 Spearman Correlation, Energy, Non-energy and Precious Metals Commodity market (State 1)

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	1.00	0.64	0.58	0.33	0.46	0.46	0.40	0.36	0.09	0.10	0.08	0.05	0.01	0.07	-0.02
S&P TSX	0.64	1.00	0.47	0.31	0.38	0.46	0.44	0.39	0.16	0.20	0.15	0.10	0.06	0.18	0.01
IPC	0.58	0.47	1.00	0.35	0.50	0.39	0.37	0.36	0.13	0.20	0.15	0.14	0.05	0.16	0.01
MERVAL	0.33	0.31	0.35	1.00	0.38	0.24	0.23	0.27	0.09	0.15	0.09	0.07	0.01	0.09	0.00
Bovespa	0.46	0.38	0.50	0.38	1.00	0.31	0.27	0.29	0.11	0.16	0.13	0.09	0.06	0.13	0.02
DAX	0.46	0.46	0.39	0.24	0.31	1.00	0.83	0.75	0.22	0.26	0.22	0.14	0.10	0.21	-0.01
CAC 40	0.40	0.44	0.37	0.23	0.27	0.83	1.00	0.80	0.23	0.29	0.23	0.16	0.11	0.27	-0.02
IBEX 35	0.36	0.39	0.36	0.27	0.29	0.75	0.80	1.00	0.21	0.26	0.23	0.17	0.10	0.23	0.00
Nikkei 225	0.09	0.16	0.13	0.09	0.11	0.22	0.23	0.21	1.00	0.42	0.44	0.18	0.19	0.42	0.03
HSI	0.10	0.20	0.20	0.15	0.16	0.26	0.29	0.26	0.42	1.00	0.44	0.26	0.24	0.39	0.13
KOSPI	0.08	0.15	0.15	0.09	0.13	0.22	0.23	0.23	0.44	0.44	1.00	0.25	0.22	0.35	0.06
BSE Sensex	0.05	0.10	0.14	0.07	0.09	0.14	0.16	0.17	0.18	0.26	0.25	1.00	0.19	0.18	0.03
JKSE	0.01	0.06	0.05	0.01	0.06	0.10	0.11	0.10	0.19	0.24	0.22	0.19	1.00	0.19	0.03
AORD	0.07	0.18	0.16	0.09	0.13	0.21	0.27	0.23	0.42	0.39	0.35	0.18	0.19	1.00	0.03
SSEC	-0.02	0.01	0.01	0.00	0.02	-0.01	-0.02	0.00	0.03	0.13	0.06	0.03	0.03	0.03	1.00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Based on the analyzed values of Spearman correlation coefficients under different situations on the commodity markets, it can be concluded that between indices within European region the correlation is strong and statistically significant during all analyzed situations on the commodity markets, although the highest values are achieved when the highly volatile regimes prevail on all commodity markets, during other situations the values of the correlation coefficients' remain strong. Within North America region the correlation between the indices is less than in case of the European region but still strong and statistically significant under all analyzed situations on the commodity markets, where the highest values have been achieved during State 2 prevailing on all commodity markets. The most changeable results regards to the correlation coefficient's value and statistical significance under different situations on the commodity markets are in case of SSEC index.

Rolling Correlation between SSEC index and other stock market indices

To trace how the correlation between SSEC index and other indices is changing through time under different situations on the commodity markets, the rolling correlation can be helpful. The 30-day[49] rolling correlation by applying *Spearman correlation* coefficient between the logarithmic returns of SSEC index and all other analyzed indices can be found in Fig 40 (North America), Fig 41 (South America), Fig 42 (Europe) and Fig 43, Fig 44 (Asia Pacific Region) . The 60-day correlation between SSEC index and other indices is available in Appendix 3.

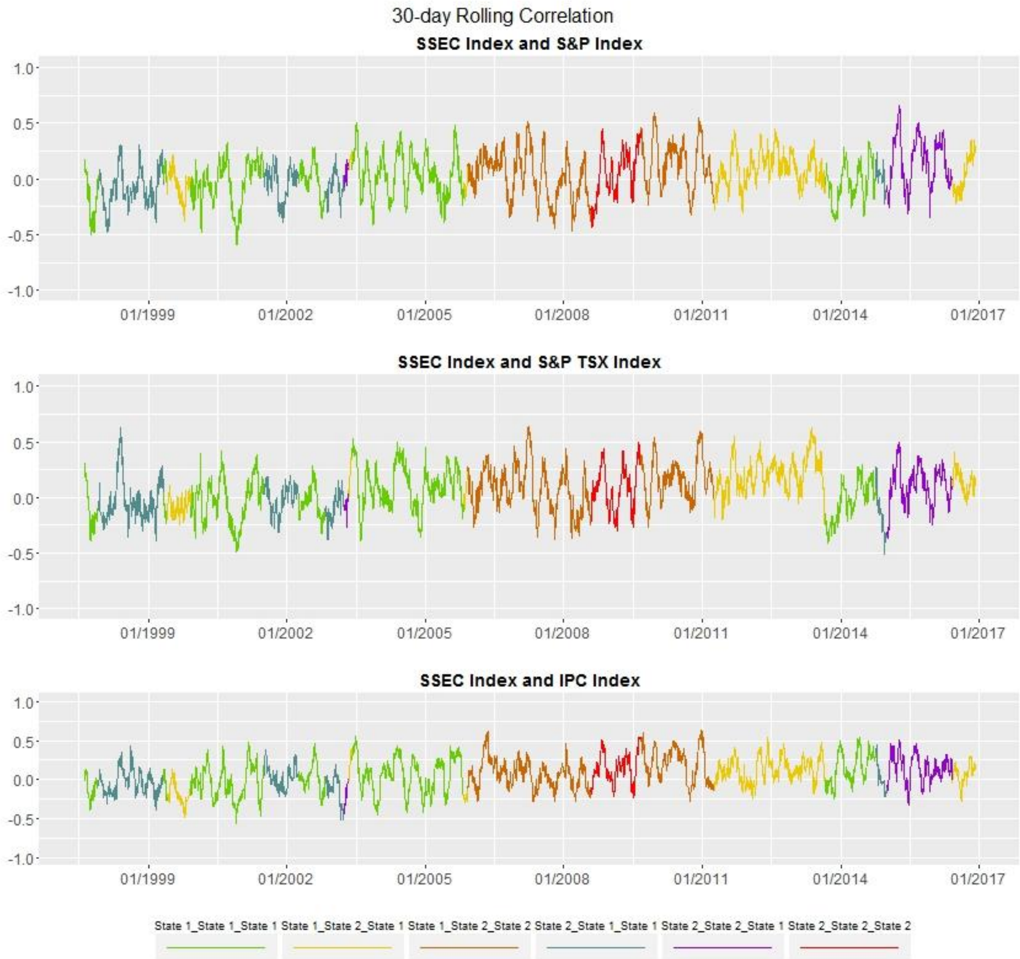


Fig 40 30-day rolling correlation beween logarithmic returns of SSEC and S&P 500, S&P TSX and IPC Indices under different regimes on the commodity markets. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

[49] *30-day* means 30 data points.

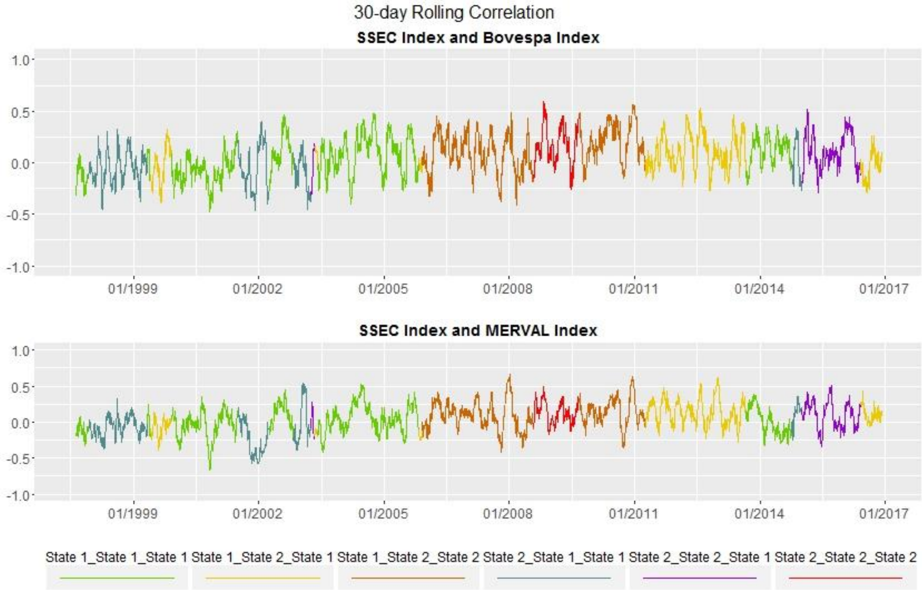


Fig 41 30-day rolling correlation beween logarithmic returns of SSEC and Bovespa, MERVAL Indices under different regimes on the commodity markets. Data source: the time series data have been retrieved from *Quandl YFinace*, *Central Bank of Brazil Statistical Database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

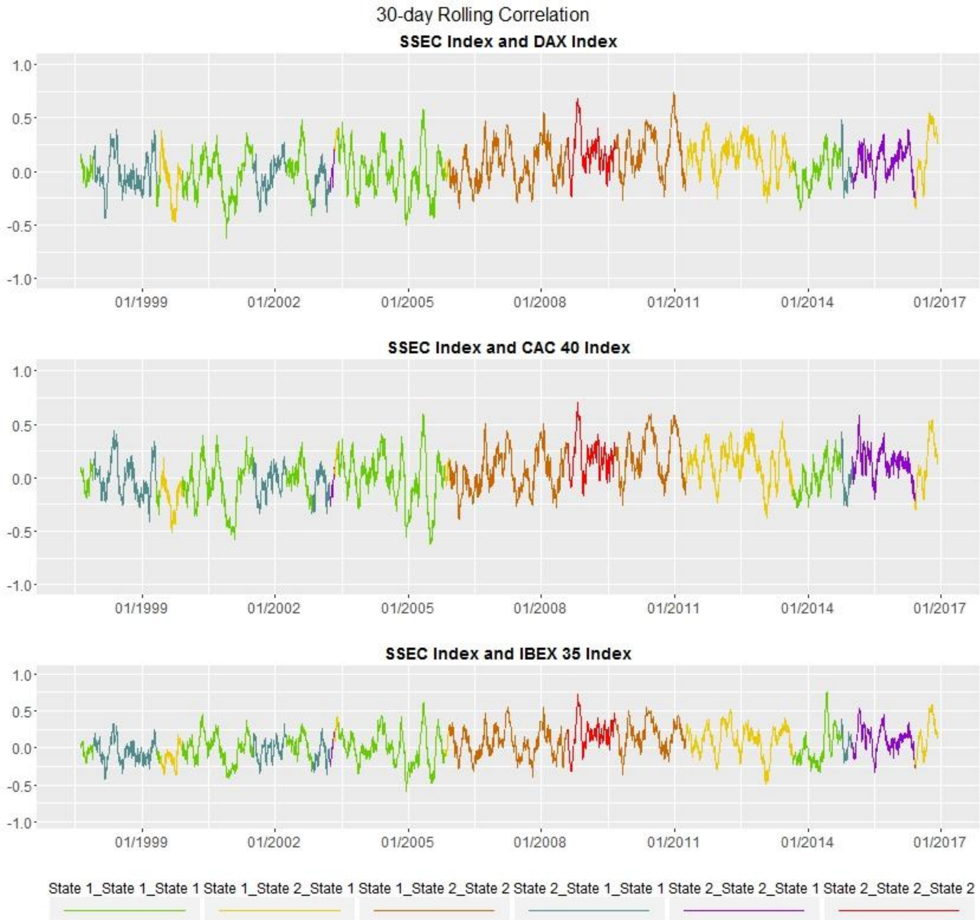


Fig 42 30-day rolling correlation beween logarithmic returns of SSEC and DAX, CAC 40 and IBEX 35 Indices under different regimes on the commodity markets. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

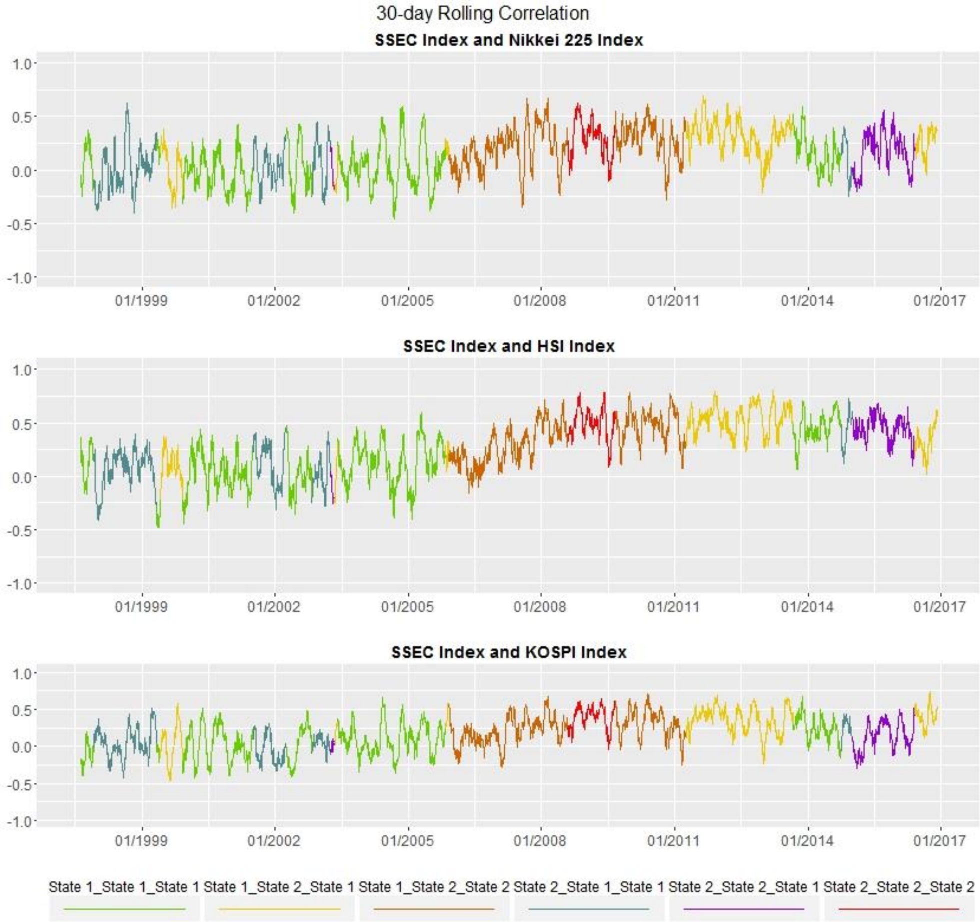


Fig 43 30-day rolling correlation beween logarithmic returns of SSEC and Nikkei 225, HSI and KOSPI Indices under different regimes on the commodity markets. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

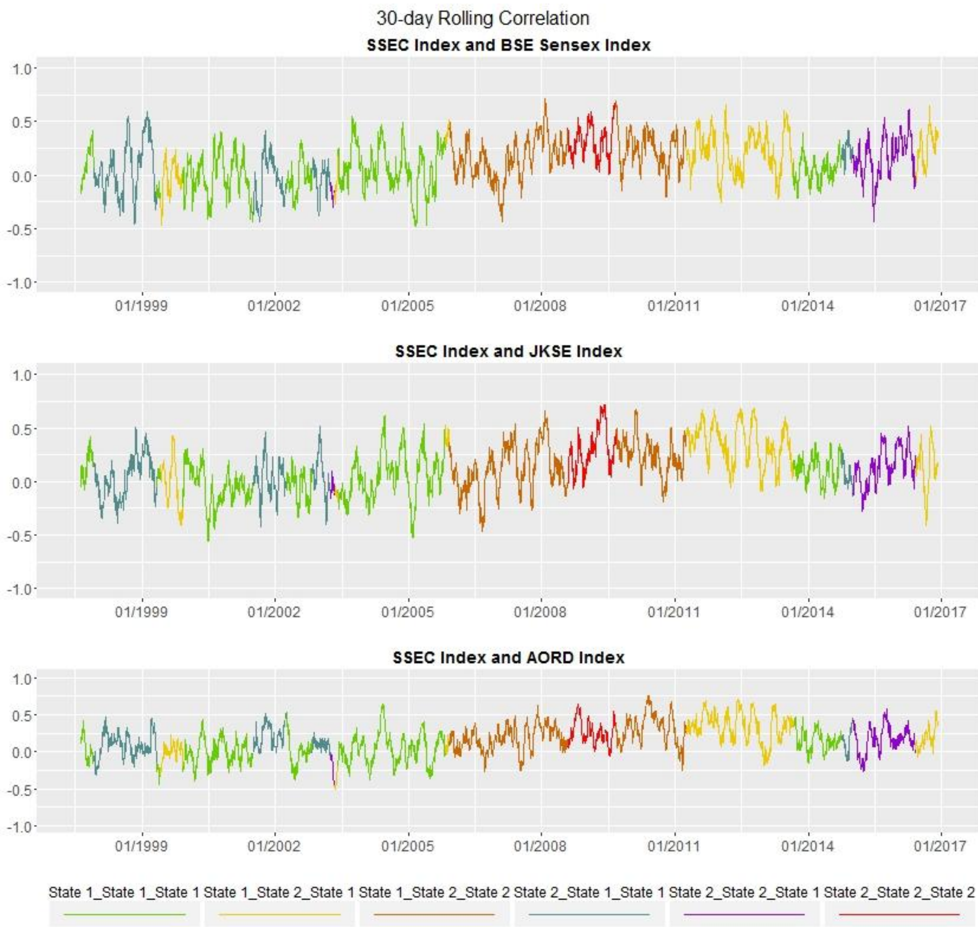


Fig 44 30-day rolling correlation beween logarithmic returns of SSEC and BSE sensex, JKSE and AORD Indices under different regimes on the commodity markets. Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Based on the figures above it can be seen that the value of 30-day correlation coefficients between SSEC index and the indices of European, North and South America very rare exceed the window from -0.5 to 0.5. The 30-day rolling correlation among SSEC index towards the Asia Pacific indices is higher comparing to other regions, where the increasing trend can be observed. This increasing trend can be also observed in case of 60-day rolling correlation (Appendix 3), especially between SSEC and HSI indices.

4.3.3 Scenarios of mutual relations among the Stock Markets

In the previous sub-chapters it was shown that during different situations on the commodity markets the mutual relations between the international stock market indices differ, and as a consequence the investment strategy can differ as well. Considering different regimes the commodity markets go through and the mutual linkage among the stock markets during different situations on the commodity markets, six scenarios of the stock markets' mutual relations are described considering the following situations on the commodity markets: high volatility on the energy market; high volatility on the precious metals market; high volatility on the non-energy market; simultaneous high and simultaneous low volatility on all three considered commodity markets, whereas the case of high volatility on the energy market is divided into two periods based on the source underlying the oil price shocks causing higher volatility.

During most unstable period, when highly volatile regime prevails simultaneously on the energy, precious metals and non-energy commodity markets, the whole economy becomes to be more tied: the stock market indices demonstrate stronger interdependence. Due to this stronger interconnection among the stock markets the benefits of diversification begin to fail, and the increasing risk associated with very limited opportunity to diversify may grow the cost of the investment decisions. This period refers mostly to the *Global Financial Crisis*, when the access to finance becomes to be tough, so when there are some evidences of the forthcoming period of high volatility on all commodity markets, it is important to secure funding in advance even for higher prices.

When the period of low volatility simultaneously prevails on all three analyzed commodity markets the agreement between occurrences of *bear* state of most stock markets, besides the indices within the European region (DAX, CAC 40, IBEX 35), is rather weak. Similarly the correlation within region and with other regions is weaker comparing with other situations on the commodity markets. Under this situation of weaker stock markets' interdependence the diversification strategy may be functional to smooth out the risk associated with the maintaining the portfolio and to ensure the investments' stability, so the standard investor's strategy can be kept.

The interconnection among the stock market indices within region in terms of highly volatile state appearance is stronger for the presence of high volatility on the non-energy market comparing with volatile regime on the precious metals market. During the highly volatile period prevailing on the non-energy market, the diversification strategy may become more functional by focusing on the international markets out of the particular region.

By considering the period of high volatility on the energy markets the similarity between the stock market indices in terms of highly volatile regimes' occurrences differs and is stronger for the period of highly volatility present on the energy market caused by the demand shocks in the oil price and is weaker for the volatile period caused by supply or precautionary demand shocks. For the latter period the weak similarity between the occurrences of states with high volatility can be comparable with the situation of simultaneous low volatility on all three commodity markets, which makes the latter period more attractive to apply the diversification strategy. During the volatile period on the energy market related to the demand oil price shocks when the opportunity of the international diversification stands on rather low level, the sectoral diversification may be one of the solution to smooth out the risk associated with operating on the energy market. When the main trigger of the volatility on the energy market relates to the supply or precautionary demand shocks the opportunities for diversification are higher and the standard investor's strategy can be kept. By computing the correlation coefficients for the highly volatile state on the energy market, the difference in influence of source, underlying the oil price shocks causing higher volatility, is not so apprent, as it was shown in case of measuring the agreement between the bear markets' occurrences on the stock markets.

5 Model Based Approach. Evidence from SSEC Index Analysis

In the previous chapter the mutual relationships between the stock market indices have been analyzed. Firstly, the stock market regimes have been identified with the subsequent analysis of the similarity between the high volatile states' occurrence, and then the correlation between the logarithmic returns of the stock market indices has been explored, concerning different regimes on the commodity markets determined in Chapter 4.1. One of the least similar behavior comparing to other market indices was in case of SSEC index, but in spite of this during the highly volatile states on the commodity markets the similarity amplified. This part of the thesis will be focused on analyzing the impact of the different stock market indices on the increase/decrease patterns of the SSEC index value between two trading days by applying model based approach.

5.1 Shanghai Composite Index

Shanghai Composite Index is a market index of stocks traded at the Shanghai Stock Exchange. The base day for SSEC index is December 19, 1990; the index is published from July 15, 1991.[50] Following the *Shanghai Stock Exchange Fact Book, 2016* [51] as at the end of 2015 on SSE there were 1 081 listed companies; the stocks on SSE are: Class A shares, which are limited to domestic investors and QFIIs, and Class B shares, which are available for domestic and foreign investors. As the end of 2015 top ten companies by market capitalizations are: *PETROCHINA*, *ICBC*, *AGRICULTURAL BANK OF CHINA*, *BANK OF CHINA*, *CHINA LIFE*, *SINOPEC CORP.*, *PING AN OF CHINA*, *CMB*, *SPD BANK*, *INDUSTRIAL BANK*.[52] The course of the daily close price values of the SSEC index from July, 1997 to November, 2016 can be found in Fig 45.

Fig 45 SSEC Index, daily close price. Data source: *Quandl, YFinace database*. Own calculation in R Studio, ggplot2 package.

[50] Shanghai Stock Exchange. *Indices & Statistics. SSE Indices*. [Retrieved February 16, 2017]. http://english.sse.com.cn/indices/indices/introduction/info/.
[51] Shanghai Stock Exchange. *FactBook 2016*. [Retrieved February 16, 2017]. http://english.sse.com.cn/indices/publications/factbook/c/4172526.pdf.
[52] *viz.* note 51

According to *World Bank GDP Ranking 2015*[53] China is the second largest economy in the world measured by GDP.

5.2 Model Building Details

The whole analyzed data set is dated from 04.07.1997 to 29.11.2016 and is closed to the balanced with respect to representation of both classes of the outcome variable: SSEC index value increased in 49.2% of cases during the analyzed period and decreased (or did not change) in 50.8%. The whole data set consists of 4 955 observations.

Similarly to the previous step the analysis will be conducted separately for the different situations on the commodity markets: higher volatility on the Energy, Precious Metals and Non-energy market separately; then for the period of higher volatility prevailing on three commodity markets simultaneously and then the situation of simultaneous "calm" commodity markets will be explored. As it was mentioned above, as a first step for each analyzed situation the variable screening procedure will be performed by computing the area under the ROC curve and Information Value.

As all predictors are numerical and the Information value can be influenced by the way of binning, the Information Values for the following steps have been computed for explanatory variable binning into 5-12 equal width bins. Then for each way of binning the variables have been ranked in descending order, and the final IV's rank has been determined based on the simple average of the Information Values' ranks computed for each way of binning.

After variables' explanatory analysis the predictors' correlation is measured by Spearman correlation coefficient. In case of highly correlated predictors the information from the variable screening step has been used. As the problem of highly correlated predictors is eliminated, the model building step can be performed by applying the *Stochastic Gradient Boosting* approach.

By applying the *Stochastic Gradient Boosting* approach to ensure the reproducible structure and avoiding the over-fitting the resample techniques are used: 5 repeats of 10 cross-validation have been applied and tuning parameter grid is specified as:

- *n.trees* from 50 to 500, step is 50
- *interaction depth* - {1, 2, 3, 4, 5}
- *shrinkage* (λ) - {0.01, 0.001}
- *n.minobsinnode* was set equal to 10.

[53] World Bank. *GDP Ranking 2015*. [Retrieved February 16, 2016]. http://data.worldbank.org/data-catalog/GDP-ranking-table

The optimal model has been chosen based on the value of the area under the *ROC* curve *(AUC).*

All calculations were done in R Studio. The area under the *ROC* curve and *Stochastic Gradient Boosting* approach was performed by using *caret* (Kuhn et al., 2016) and *gbm* (Ridgeway et al., 2015) packages. To evaluate the models performance based on AUC value under the ROC curve *pROC* (Robin et al., 2011) package is used. The *Information* package (Larsen, 2016) has been used for Information values' calculation.

As the initial step, preceding the variable screening and modeling, the stratified random split of the data was performed, where for all models 75% of data were allocated to the training set and the rest 25% creates the testing set.

5.2.1 SSEC Index and Energy Commodity Market

As it was stated in chapter 4.1, where the regimes prevailing on the commodity markets have been identified, the higher volatile regime on the Energy Market (State 2) relates to the oil price shocks. The source underlying these shocks may vary in the different periods. The following shocks have been distinguished: crude oil supply shocks, demand shocks and precautionary demand shocks (Kilian, 2009).

Due to the difference in the oil price shocks' triggers the analysis of the increase/decrease patterns of SSEC index dependence is performed separately for *State 2* covering the periods: 1997M12-1999M4 and 2008M8-2009M8 referring to the demand shock; *State 2* combining the periods: 2001M7-2002M3, 2002M11-2003M4 and 2014M10-2016M5. Although the latter period relates to precautionary demand shock, it is analyzed together with supply shocks as the reason lying behind it does not refer to the financial crises.

I. <u>Higher volatility on the Energy Commodity Market (State 2 - I)</u>

Highly volatile regime on the Energy Commodity Market, referring to the Asian and Global financial crisis covers the period: 1997M12-1999M4 and 2008M8-2009M8 (demand shocks). The data set corresponding to the analyzed period contains 635 observations. The increased patterns appear in 47.4% of cases and the decrease or did not change patterns can be observed in 52.6% of the analyzed data points. As the stratified random data splitting has been executed: training set consist of 477 observations (75%) and in the testing data set there are 158 data rows (25%).

As a first step, the independent contribution of the logarithmic returns of the stock market indices to the binary outcome is examined by calculating the area under the ROC curve and Information Value for each predictor separately independently on others. The variables' screening results applying to the training data set by computing the AUC and IV values with corresponding ranking in descending order can be found in Table 28, the IV's ranks for each way of binning are summarized in Appendix 5.

Table 28 AUC and IV values, SSEC Index, Energy Commodity Market (State2 - I)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
S&P 500 t_t2	0.60	0.15	0.14	0.14	0.14	0.20	0.18	0.31	0.18	1	2
S&P 500 t_t1	0.59	0.11	0.20	0.15	0.15	0.20	0.14	0.19	0.27	2	3
S&P TSX t_t1	0.58	0.10	0.11	0.18	0.19	0.23	0.25	0.26	0.21	3	1
MERVAL t_t2	0.58	0.12	0.11	0.15	0.14	0.13	0.17	0.21	0.20	4	5
DAX t_t1	0.58	0.08	0.17	0.17	0.16	0.16	0.18	0.15	0.21	5	6
S&P TSX t_t2	0.58	0.11	0.07	0.15	0.12	0.13	0.19	0.17	0.25	6	7
Bovespa t_t1	0.57	0.09	0.08	0.15	0.09	0.09	0.10	0.10	0.13	7	12
MERVAL t_t1	0.57	0.06	0.07	0.07	0.11	0.11	0.08	0.13	0.08	8	14
IBEX 35 t_t2	0.57	0.08	0.09	0.11	0.09	0.10	0.13	0.15	0.16	9	10
Bovespa t_t2	0.57	0.07	0.06	0.07	0.08	0.09	0.07	0.09	0.09	10	17
IBEX 35 t_t1	0.56	0.06	0.07	0.08	0.08	0.08	0.08	0.11	0.13	11	16
IPC t_t1	0.56	0.11	0.12	0.12	0.21	0.18	0.19	0.21	0.21	12	4
DAX t_t2	0.55	0.05	0.04	0.05	0.07	0.08	0.12	0.08	0.07	13	21
IPC t_t2	0.55	0.04	0.06	0.08	0.06	0.07	0.09	0.19	0.08	14	17
BSE Sensex t_t1	0.55	0.08	0.08	0.13	0.10	0.14	0.13	0.11	0.14	15	11
CAC 40 t_t1	0.55	0.05	0.04	0.06	0.07	0.06	0.09	0.15	0.07	16	23
CAC 40 t_t2	0.55	0.06	0.07	0.08	0.06	0.07	0.18	0.09	0.15	17	15
JKSE t_t1	0.53	0.11	0.10	0.13	0.12	0.13	0.14	0.19	0.16	18	9
KOSPI t_t2	0.53	0.08	0.09	0.08	0.07	0.18	0.16	0.12	0.16	19	13
KOSPI t_t1	0.53	0.02	0.04	0.04	0.04	0.07	0.06	0.05	0.09	20	25
HSI t_t1	0.53	0.04	0.05	0.06	0.10	0.08	0.08	0.10	0.15	21	19
JKSE t_t2	0.52	0.10	0.09	0.19	0.20	0.13	0.13	0.17	0.20	22	8
BSE Sensex t_t2	0.52	0.04	0.03	0.04	0.09	0.09	0.10	0.13	0.10	23	21
HSI t_t2	0.52	0.07	0.04	0.07	0.10	0.06	0.11	0.15	0.06	24	20
AORD t_t1	0.51	0.05	0.03	0.03	0.13	0.09	0.07	0.08	0.10	25	24
AORD t_t2	0.50	0.02	0.04	0.02	0.05	0.01	0.04	0.02	0.05	26	27
Nikkei 225 t_t1	0.50	0.02	0.01	0.02	0.02	0.02	0.03	0.06	0.04	27	28
Nikkei 225 t_t2	0.49	0.03	0.01	0.03	0.02	0.06	0.09	0.06	0.11	28	26

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

It can be noticed that ranks based on AUC and IV metrics do not have to coincide, e.g. the strongest variable in relation to the isolated contribution to the dependent variable based on AUC value is S&P 500 index logarithmic returns (k=2), by using the IV average rank the first position belongs to S&P TSX index (k=1). It can be also observed that the way of binning may influence the variable's rank regards of IV. S&P 500 index (k=2) computing as strongest predictor based on AUC, was twice ranked at the first position in case of binning into 5 or 11 intervals and for k=1 was twice ranked at the first position in case of binning into 6 or 12 intervals. By analyzing the AUC and IV values, it can be noticed that all predictors except Nikkei 225 have AUC greater than 0.5. Following the rule of thumb suggested in (Siddiqi, 2006) only Nikkei 225 and AORD (k=2) with IV less than 0.02 in some ways of binning (Nikkei 225 *t_t1* - splitting into 5, 6, 7 bins; Nikkei 225 *t_t2* - 6, 8 bins; AORD *t_t2* - 7,9 bins) and can be evaluated as unpredictive for the corresponding way of binning. The rest predictors have the Information Value above 0.02. The predictors with medium predictive power (IV is above 0.1) in case of all considered ways of binning are: S&P 500 (k=1 and k=2), MERVAL (k=2), IPC (k=1) and JKSE (k=1). The predictors with IV above 0.1 at least for 7 ways of binning (from 8 computing): S&P TSX (k=1 and k=2) and DAX (k=1). Summarizing the individual contribution of each predictor separately to the increase/decrease patterns of SSEC index in t+1, it can be concluded that in absolute terms any of the analyzed stock market indices has the strong impact on the direction's movements of SSEC index, but relatively to each other S&P 500, S&P TSX, MERVAL, IPC, DAX, JKSE indices have greater contribution to the binary outcome variable than other analyzed indices.

Before conducting the model building step, the correlation matrix by computing Spearman correlation coefficients is analyzed. The correlation matrices computed in Chapter 4 (for *k*=1) cannot be used in the current step, as were computed for all observations, whereas in the model building step the computation should be performed only using the data from the training set, as the testing date set is used to evaluate the model performance. The matrices of the computed Spearman correlation coefficients and corresponding *p*-values can be found in Appendix 4, where the values greater than 0.6 are in grey color. Based on the correlation matrix, it can be noticed that for all indices there is a correlation between the logarithmic returns within a given index for *k*=1 and *k*=2. Similarly as in Chapter 4 the indices of Europe, North and South America are more correlated than the analyzed indices of the Asia Pacific region.

By using the information of correlation matrix and from the variable screening step the following variables have been chosen as input variables in the model building step: S&P TSX (*k*=1), MERVAL (*k*=2), DAX (*k*=1), IPC (*k*=1), BSE Sensex (*k*=1), JKSE (*k*=1), KOSPI (*k*=1), HSI (*k*=1), AORD (*k*=1), Nikkei 225 (*k*=1).

After determining the input variables the dependence of the SSEC index's movements on other indices can be explored by *Stochastic Gradient Boosting*. The tuning parameters' values of the final model determined by using the ROC metric and the AUC value based on the test set can be found in Table 29.

Table 29 AUC and Tuning Parameters's values - SSEC Index, Energy Commodity Market (State2 - I)

Tuning Parameters	*Value*
n.trees	450
interaction depth	4
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.5671

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Fig 46 shows the relative influence of the variables based on the stochastic gradient boosting model's results applied to Shanghai Composite Index.

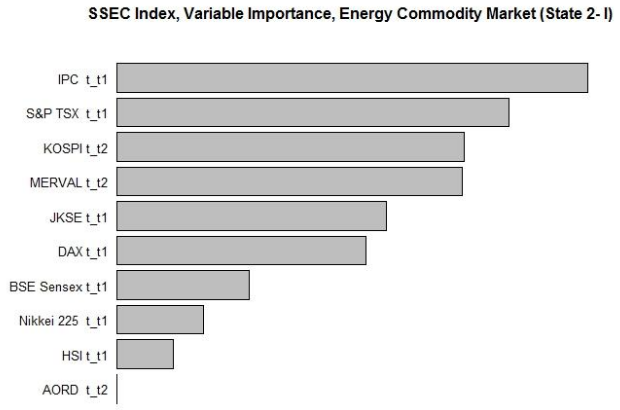


Fig 46 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Energy Commodity Market (State2 - I) Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Based on Table 29 it can be seen that the AUC computed for the test set is above 0.5 but still has rather low value, so it is important to emphasize that the purpose of the current analysis does not consist in the construction of the best prediction model of the Shanghai Composite Index direction's movements but in analyzing the dependence of such movements in time *t*+1 on other international stock market indices, and then extending by commodity prices. Other words the aim is to examine the impact of other indices on the increase/decrease patterns of SSEC index in time *t*+1 under different situations regards to the volatility on the commodity markets. In case of building the appropriate prediction model, it is fare to expect the strong market index dependence on the changes in the main issues, which the index is comprised of.

To gain sense about the effect of the particular stock market index on the direction's movements of SSEC index after accounting for the average effect of all other market indices, entering the model as input variables, the partial dependence plots may be helpful. Fig 47 shows the partial dependence plots for 6 most influential variables based on the results of the stochastic gradient boosting. Looking at these partial dependence plots which can be used as a tool of the fitted function's visualization, it can be inferred that the predicted probability is higher for lower negative values of the logarithmic returns of IPC, S&P TSX, DAX (*k*=1) and KOSPI (*k*=2). In case of IPC index the predicted probability begins to slightly drop as the logarithmic return begin to be more than about -0.04, and declines noticeably when the value of logarithmic returns exceeds -0.03. In case of S&P TSX index the predicted probability is higher for logarithmic returns less than about -0.03; for DAX index when the logarithmic returns do not exceed -0.02; and for KOSPI index less than about -0.05.

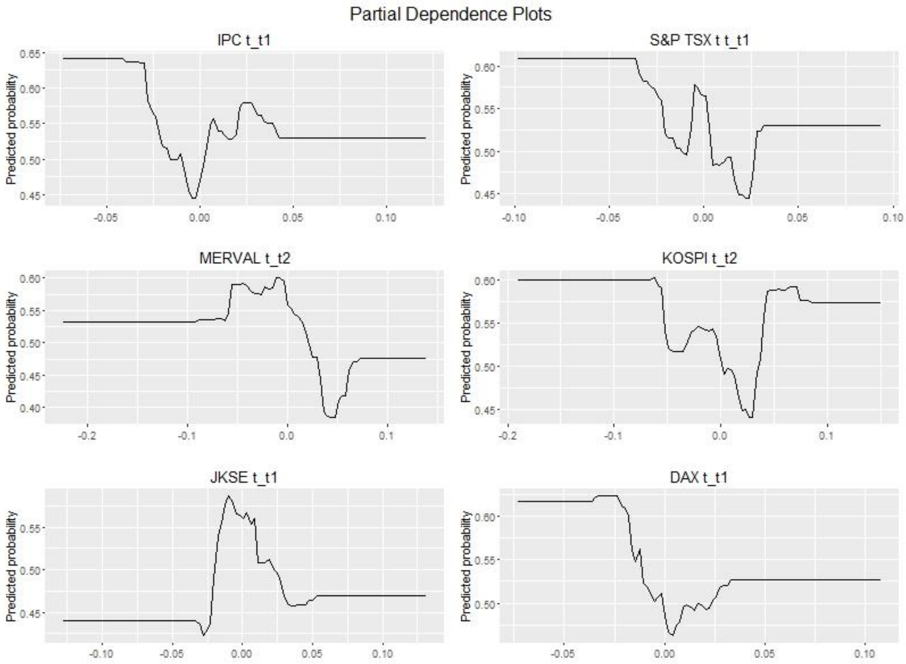


Fig 47 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Energy Commodity Market (State2 - I) Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

II. <u>Higher volatility on the Energy Commodity Market (State 2 - II)</u>

Higher volatility on the Energy Commodity Market relates to the period: 2001M7-2002M3, 2002M11-2003M4 and 2014M10-2016M5 (supply and precautionary demand shocks). The data set corresponding to the analyzed period contains 733 observations. The increased patterns appear in 49.1% of cases and the decrease or did not change patterns can be observed in 50.9% of the analyzed data points. By executing the stratified random data splitting training set consists of 550 observations (75%) and in the testing data set there are 183 data rows (25%). In Table 30 the AUC and IV values with corresponding ranking are summarized. The IV's ranks for different ways of bining can be found in Appendix 5.

Table 30 AUC and IV values, SSEC Index, Energy Commodity Market (State2 - II)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
IBEX 35 t_t1	0.56	0.05	0.03	0.07	0.07	0.08	0.09	0.09	0.09	1	10
KOSPI t_t1	0.55	0.04	0.04	0.05	0.05	0.10	0.06	0.11	0.09	2	11
S&P TSX t_t1	0.55	0.06	0.04	0.07	0.09	0.12	0.10	0.13	0.12	3	4
IBEX 35 t_t2	0.55	0.04	0.06	0.10	0.08	0.07	0.14	0.14	0.14	4	5
HSI t_t1	0.54	0.04	0.07	0.06	0.05	0.09	0.09	0.09	0.09	5	9
AORD t_t2	0.53	0.05	0.16	0.10	0.14	0.11	0.23	0.14	0.19	6	2
S&P TSX t_t2	0.53	0.02	0.03	0.04	0.03	0.04	0.04	0.06	0.08	7	24
KOSPI t_t2	0.53	0.02	0.02	0.03	0.05	0.07	0.04	0.06	0.08	8	20
IPC t_t1	0.53	0.06	0.05	0.08	0.04	0.10	0.10	0.11	0.11	9	6
DAX t_t1	0.53	0.02	0.04	0.03	0.05	0.05	0.08	0.08	0.07	10	18
CAC 40 t_t1	0.53	0.04	0.10	0.15	0.10	0.12	0.14	0.14	0.18	11	3
JKSE t_t1	0.53	0.03	0.03	0.05	0.06	0.05	0.09	0.04	0.05	12	17
DAX t_t2	0.53	0.03	0.02	0.02	0.03	0.05	0.06	0.06	0.07	13	23
S&P 500 t_t2	0.53	0.05	0.05	0.03	0.07	0.06	0.08	0.11	0.07	14	13
JKSE t_t2	0.52	0.02	0.02	0.05	0.04	0.04	0.04	0.06	0.06	15	25
HSI t_t2	0.52	0.10	0.08	0.12	0.09	0.13	0.13	0.17	0.18	16	1
IPC t_t2	0.52	0.04	0.03	0.07	0.09	0.11	0.09	0.10	0.12	17	7
Nikkei 225 t_t2	0.52	0.01	0.06	0.01	0.04	0.09	0.07	0.08	0.13	18	15
S&P 500 t_t1	0.52	0.04	0.05	0.05	0.05	0.08	0.06	0.05	0.06	19	16
AORD t_t1	0.52	0.04	0.02	0.12	0.05	0.09	0.09	0.09	0.11	20	12
CAC 40 t_t2	0.52	0.01	0.01	0.02	0.01	0.01	0.03	0.03	0.05	21	28
BSE Sensex t_t1	0.52	0.03	0.01	0.05	0.03	0.03	0.06	0.08	0.11	22	20
MERVAL t_t1	0.51	0.01	0.03	0.04	0.04	0.05	0.04	0.07	0.07	23	22
Nikkei 225 t_t1	0.51	0.04	0.06	0.05	0.05	0.08	0.09	0.13	0.10	24	8
BSE Sensex t_t2	0.51	0.00	0.03	0.03	0.02	0.03	0.03	0.02	0.05	25	27
Bovespa t_t2	0.50	0.02	0.02	0.05	0.02	0.06	0.04	0.10	0.07	26	19
MERVAL t_t2	0.49	0.02	0.05	0.05	0.05	0.08	0.06	0.12	0.07	27	14
Bovespa t_t1	0.49	0.02	0.02	0.02	0.02	0.04	0.05	0.06	0.04	28	26

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*

Based on the AUC and IV ranking, there is less than in the previous situation agreement between the variables' ranks assigned based on AUC value and IV. The highest value of AUC is less than in the previous step and achieved 0.56 in case of IBEX 35 (*k*=1), by using IV ranking the strongest variable is HSI index (*k*=2), which has the 16th position in case of AUC ranking. Comparing to the previous step there are more variables, which at least at one way of binning have IV less than 0.02: KOSPI (*k*=2 , 6 bins), DAX (*k*=1, 5 bins), JKSE (*k*=2, 5 and 6 bins), Nikkei 225 (*k*= 2, 5 and 7 bins), AORD (*k*=1, 6 bins), CAC 40 (k=2, 5-9 bins), BSE Sensex (*k*=1, 6 bins), MERVAl (*k*=1, 5 bins), BSE Sensex (*k*=2, 5 and 8 bins). There are no predictors, which fulfill the rule of thumb (Siddiqi, 2006) for medium predictive power (IV is between 0.1-0.3) for all considered ways of binning. The "maximum" fulfillment is achieved in case of HSI (*k*=2), CAC 40 (*k*=1) and AORD (*k*=2) indices, where IV is greater than 0.1 for 6 from 8 possible binning approaches.

Analyzing the correlations matrix, which with corresponding *p*-values can be found in Appendix 4, it can be noticed that comparing to the previous step, corresponding to the higher volatility on the Energy commodity market related to the Asian and Global Financial Crisis, there are less pairs of variables, between which the correlation coefficient exceeds 0.6. Comparing to the previous step there is first of all less correlation between IPC (Mexico) and Bovespa (Brazil) and other indices, especially with S&P 500 and S&P TSX. Brazil and Mexico belong to rather significant oil producers with average share on the world oil production for 2012-2015 about 3%.

By using the information of correlation matrix and from the variable screening step the following variables have been chosen as input variables in the model building step: IBEX 35, KOSPI, S&P TSX, IPC, JKSE, BSE Sensex, MERVAL, Nikkei 225 (for all of these variable *k*=1); AORD, S&P 500, HSI, Bovespa (*k*=2). Due to less correlation among variables the amount of input variables is higher and equal to 12 comparing with 10 in the previous step.

As the input variables have be determined, the dependence of the SSEC index's movements on other indices can be explored by *Stochastic Gradient Boosting*. The tuning parameters' values of the final model determining using the ROC metric and the AUC value based on the test set can be found in Table 31.

Table 31 AUC and Tuning Parameters's values - SSEC Index, Energy Commodity Market (State2 - II)

Tuning Parameters	*Value*
n.trees	500
interaction depth	5
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.537

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Fig 48 shows the relative influence of the variables based on the stochastic gradient boosting model's results applied to Shanghai Composite Index.

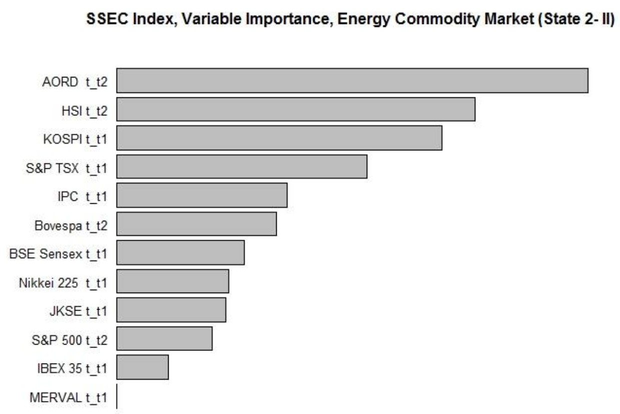


Fig 48 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Energy Commodity Market (State2 - II) Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

By evaluating the model performance based on computing the AUC value by applying the estimated model to the testing set, slightly lower value of AUC is observed. The marginal effect of 6 most influential variables based on the model' results to binary outcome variable by having "average out" the influence of other variables inputting the model can be found in Fig 49, where can be noticed that the predicted probability is higher for negative logarithmic returns of KOSPI and S&P TSX index, and in case of Bovespa index for oppositely positive logarithmic returns.

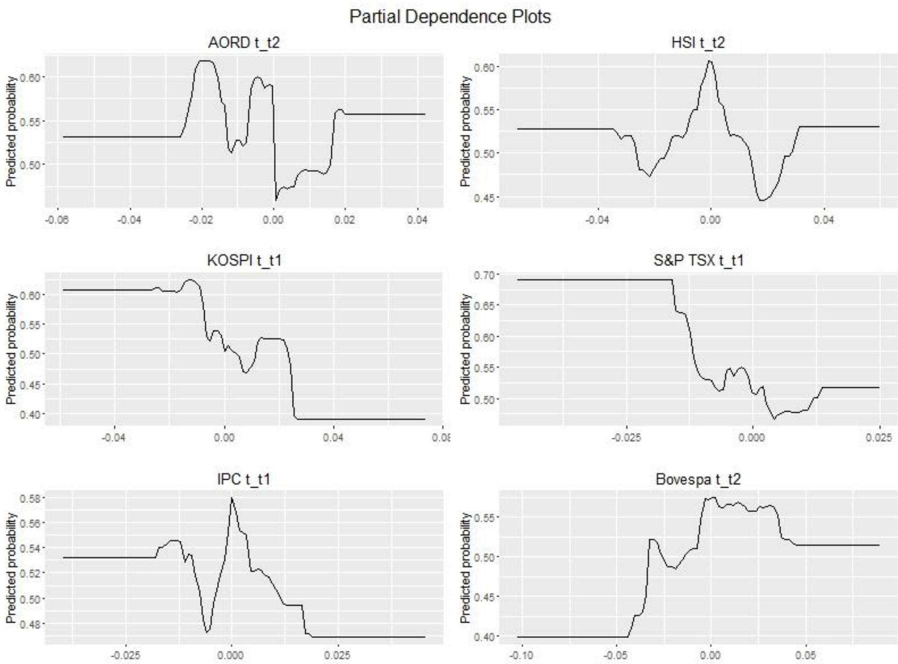


Fig 49 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Energy Commodity Market (State2 - II) Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

5.2.2 SSEC Index and Precious Metals Commodity Market

The regime with higher volatility on the Precious Commodity Market covers the period: 1999M6-1999M11, 2003M4-2003M5, 2005M11-2013M8, 2015M1-2016M11. The data set corresponding to the analyzed period contains 2 660 observations. The increased patterns appear in 51.3% of cases and the decrease or did not change patterns can be observed in 48.7% of the analyzed data points. By executing the stratified random data splitting training set consists of 1 995 observations (75%) and in the testing data set there are 665 data rows (25%). In Table 32 the AUC and IV values with corresponding ranking are summarized.

Table 32 AUC and IV values, SSEC Index, Precious Metals Commodity Market (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
S&P 500 t_t1	0.57	0.06	0.08	0.08	0.08	0.08	0.09	0.09	0.09	1	1
Bovespa t_t1	0.56	0.06	0.05	0.05	0.05	0.05	0.07	0.07	0.06	2	6
DAX t_t1	0.56	0.04	0.05	0.05	0.05	0.06	0.06	0.06	0.07	3	5
MERVAL t_t1	0.55	0.03	0.04	0.05	0.04	0.05	0.05	0.05	0.06	4	9
CAC 40 t_t1	0.55	0.06	0.04	0.06	0.08	0.07	0.09	0.11	0.10	5	2
IBEX 35 t_t1	0.55	0.06	0.05	0.05	0.06	0.06	0.07	0.06	0.07	6	4
S&P TSX t_t1	0.55	0.04	0.06	0.06	0.07	0.08	0.08	0.08	0.10	7	3
S&P 500 t_t2	0.55	0.05	0.05	0.07	0.06	0.05	0.07	0.05	0.08	8	7
IPC t_t1	0.55	0.03	0.04	0.04	0.04	0.05	0.05	0.05	0.05	9	8
S&P TSX t_t2	0.54	0.03	0.02	0.02	0.03	0.03	0.03	0.04	0.04	10	12
Bovespa t_t2	0.53	0.02	0.02	0.05	0.02	0.02	0.04	0.03	0.05	11	13
IBEX 35 t_t2	0.53	0.02	0.01	0.03	0.04	0.03	0.05	0.04	0.04	12	11
DAX t_t2	0.53	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.03	13	18
CAC 40 t_t2	0.53	0.01	0.02	0.02	0.01	0.03	0.02	0.02	0.02	14	15
BSE Sensex t_t1	0.52	0.02	0.01	0.02	0.03	0.04	0.06	0.04	0.03	15	14
HSI t_t1	0.52	0.01	0.01	0.00	0.01	0.01	0.02	0.01	0.01	16	26
JKSE t_t1	0.52	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	17	27
MERVAL t_t2	0.52	0.01	0.02	0.03	0.03	0.06	0.06	0.04	0.04	18	10
IPC t_t2	0.52	0.01	0.01	0.01	0.02	0.03	0.02	0.02	0.02	19	23
BSE Sensex t_t2	0.52	0.01	0.01	0.03	0.01	0.01	0.03	0.03	0.02	20	20
KOSPI t_t2	0.51	0.01	0.02	0.01	0.01	0.03	0.02	0.02	0.03	21	22
KOSPI t_t1	0.50	0.01	0.02	0.02	0.03	0.01	0.04	0.03	0.04	22	16
JKSE t_t2	0.50	0.01	0.00	0.01	0.01	0.01	0.02	0.02	0.01	23	25
HSI t_t2	0.50	0.01	0.03	0.01	0.02	0.03	0.03	0.02	0.04	24	18
Nikkei 225 t_t2	0.49	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.01	25	28
AORD t_t2	0.49	0.00	0.02	0.02	0.02	0.03	0.02	0.02	0.04	26	17
Nikkei 225 t_t1	0.49	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.03	27	21
AORD t_t1	0.49	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	28	24

Source: Own calculation in R Studio, *caret, Information*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

By analyzing the predictors' ranks based on the AUC and IV values in case of higher volatility on the Precious Metals commodity market, the decision about the strongest predictors in terms of the isolated contribution to the binary outcome variable measured by AUC and IV, is unequivocal, as the first position based on both criterions belongs to S&P 500 (k=1). Comparing to the volatile energy market, analyzed in the previous step, there are more than half predictors have IV less than 0.02 at least at one way of binning, and excepting CAC 40 (for k=1 and 11 bins), any of the predictors at any ways of binning (5-12) achieved IV greater than 0.1.

The values in the correlation matrix (*viz.* Appendix 4) are similar as in case of higher volatility on the Energy commodity market related to the Asian and Global Financial Crisis.

By choosing variables among predictors with correlation coefficient lower than 0.6 and by using the information from the variable screening step the following variables have been chosen as input variables in the model building step: S&P 500, CAC 40, MERVAL, BSE Sensex, JKSE, KOSPI, Nikkei 225 (for all of these variables k=1); S&P TSX and HSI (k=2).

By applying the *Stochastic Gradient Boosting* to the chosen variables the tuning parameters' values of the final model determining using the ROC metric and the AUC value based on the test set can be found in Table 33 and the relative influence of the variables based on the model's results applied to Shanghai Composite Index are shown in Fig 50.

Table 33 AUC and Tuning Parameters's values - SSEC Index, Precious Metals' Commodity Market (State2)

Tuning Parameters	*Value*
n.trees	350
interaction depth	1
shrinkage	0.001
n.minobsinnode	10
AUC *test set*	0.5913

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

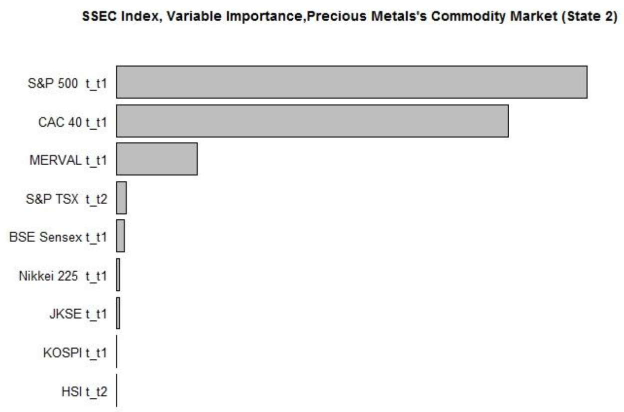


Fig 50 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Precious Metals' Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

The AUC value, computed for the testing set applying the estimated model, is greater than in case of higher volatility on the Energy Commodity Market, even though the isolated contribution of each stock market index to the SSEC index direction's movements measured in the variable screening step is lower than in two previous cases.

The gained results can be explained by China's being at the leading position of gold and silver world production (*viz.* Chapter 2). It can be also noticed that S&P 500 index (k=1) has the first position in the ranking by both metrics (AUC and IV) in the variable screening step, and by applying the stochastic gradient boosting model S&P 500 index has the highest relative influence to the binary outcome comparing to other indices. One of the explanation may be found in the existence of the long-term relationship between the gold price and the general price level in USA. The results of research conducted in (Levin et al., 2006) correspond to the existence of such relationship.

The partial dependence plots, visualizing the effect of 4 most influential stock market indices on the increase/decrease patterns of SSEC index after accounting for the average effect of all other market indices entering the model, can be found in Fig 51. Higher predicted probability can be seen for negative logarithmic returns in case of all four indices: in case of S&P index the probability begins to decline for logarithmic returns higher than -0.025; in case of CAC 40 index when the log returns exceed -0.018; for MERVAL and S&P TSX higher than -0.03 and -0.025 correspondingly.

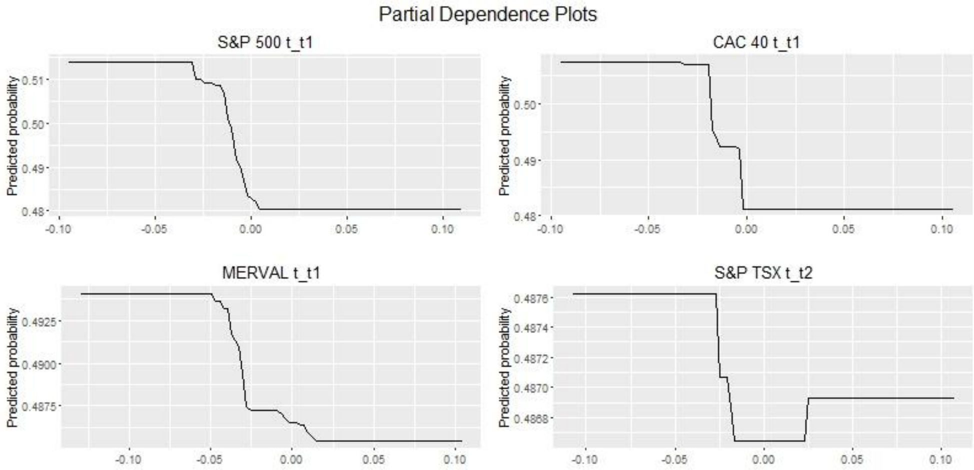


Fig 51 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Precious Metals' Commodity Market (State2). Own calculation in R Studio, *caret*, *gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

5.2.3 SSEC Index and Non-energy Commodity Market

Higher volatility on the Non-energy Commodity Market includes the period: 2005M12-2011M3. The data set corresponding to the analyzed period contains 1 360 observations. The increased patterns appear in 53.75% of cases and the decrease or did not change patterns can be observed in 46.25% of the analyzed data points. By executing the stratified random data splitting training set consists of 1 020 observations (75%) and in the testing data set there are 340 data rows (25%). In Table 34 the AUC and IV values with corresponding ranking are summarized.

Table 34 AUC and IV values, SSEC Index, Non-energy Commodity Market (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
IPC t_t1	0.58	0.09	0.08	0.10	0.10	0.11	0.10	0.13	0.10	1	5
Bovespa t_t1	0.57	0.07	0.09	0.10	0.12	0.11	0.10	0.10	0.13	2	4
S&P 500 t_t1	0.57	0.08	0.09	0.09	0.11	0.12	0.11	0.12	0.10	3	3
IBEX 35 t_t1	0.57	0.08	0.10	0.08	0.10	0.10	0.11	0.12	0.12	4	7
DAX t_t1	0.57	0.10	0.10	0.09	0.09	0.09	0.12	0.12	0.10	5	8
CAC 40 t_t1	0.57	0.07	0.09	0.10	0.11	0.11	0.10	0.14	0.14	6	1
S&P 500 t_t2	0.57	0.07	0.09	0.09	0.10	0.07	0.09	0.10	0.13	7	9
MERVAL t_t1	0.57	0.06	0.06	0.07	0.09	0.11	0.10	0.10	0.12	8	10
S&P TSX t_t1	0.56	0.08	0.08	0.10	0.11	0.13	0.13	0.12	0.14	9	2
S&P TSX t_t2	0.55	0.04	0.05	0.05	0.06	0.08	0.08	0.09	0.11	10	11
JKSE t_t1	0.55	0.05	0.05	0.07	0.05	0.04	0.06	0.06	0.07	11	14
MERVAL t_t2	0.55	0.03	0.05	0.08	0.03	0.06	0.07	0.11	0.10	12	13
Bovespa t_t2	0.54	0.04	0.09	0.10	0.06	0.13	0.12	0.11	0.17	13	6
HSI t_t1	0.54	0.03	0.02	0.03	0.04	0.05	0.04	0.04	0.07	14	19
BSE Sensex t_t1	0.54	0.01	0.02	0.04	0.04	0.03	0.04	0.03	0.05	15	23
IPC t_t2	0.54	0.02	0.03	0.04	0.04	0.07	0.03	0.05	0.06	16	18
IBEX 35 t_t2	0.53	0.03	0.04	0.04	0.05	0.06	0.05	0.06	0.06	17	16
DAX t_t2	0.53	0.03	0.03	0.04	0.04	0.07	0.05	0.05	0.09	18	15
CAC 40 t_t2	0.53	0.01	0.02	0.03	0.03	0.06	0.05	0.06	0.05	19	19
KOSPI t_t1	0.52	0.02	0.04	0.02	0.05	0.06	0.06	0.07	0.06	20	17
AORD t_t1	0.51	0.02	0.02	0.03	0.03	0.05	0.04	0.03	0.04	21	24
BSE Sensex t_t2	0.51	0.02	0.02	0.01	0.01	0.03	0.04	0.04	0.05	22	25
JKSE t_t2	0.50	0.01	0.02	0.01	0.01	0.03	0.02	0.02	0.04	23	26
Nikkei 225 t_t1	0.50	0.00	0.01	0.01	0.03	0.02	0.01	0.02	0.05	24	28
KOSPI t_t2	0.50	0.03	0.06	0.06	0.05	0.07	0.07	0.08	0.10	25	12
HSI t_t2	0.49	0.01	0.02	0.01	0.02	0.03	0.01	0.02	0.03	26	27
AORD t_t2	0.48	0.02	0.02	0.03	0.03	0.02	0.05	0.06	0.04	27	22
Nikkei 225 t_t2	0.48	0.03	0.02	0.03	0.03	0.03	0.06	0.05	0.06	28	21

Source: Own calculation in R Studio, *caret, Information*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

In case of higher volatility on the non-energy commodity market there are slightly higher values of AUC and IV; there are less variables with IV less than 0.02 at least in one way of binning (9 from 28); variables with IV under 0.02 at 4 and more way of binning are: BSE Sensex (*k*=2), JKSE (*k*=2), Nikkei 225 (*k*=1) and HSI (*k*=2). Comparing to higher volatility on the precious metals commodity market there are indices with medium predictor power, i.e. with IV higher than 0.1 according to the rule of thumb (Siddiqi, 2006). The IV greater than 0.1 occur only for binning starting with 7 and more intervals. The variables exceeding 0.1 in IV at least in 4 from 8 ways of binning are: IPC, S&P 500, IBEX 35, CAC 40, S&P TSX (*k*=1) and Bovespa (*k*=1 and *k*=2). The highest value of AUC belongs to IPC (*k*=1) and achieved 0.58, and the first position in terms of Information Value is taken by CAC 40 index (*k*=2). The correlation relationships (the correlation matrix with corresponding *p*-values can be found in Appendix 4) in case of European indices and indices of the North and South America look similar to the situations of higher volatility on the precious metals market and on the energy commodity market related to the Asia and Global Financial Crisis, but increase in case of some indices of Asia Pacific region: the correlation coefficient exceeds 0.6 for KOSPI and Nikkei 225 (for both *k*=1 and *k*=2), between KOSPI and S&P TSX (*k*=2), between Nikkei 225 and IPC (*k*=1 and k=2), for Nikkei 225 and AORD (*k*=1 and *k*=2), for Nikkei 225 and HSI (*k*=2) , HSI and KOSPI (*k*=1 and *k*=2) and between HSI and AORD (*k*=2). In case of higher volatility on the whole energy market (considering both first models) KOSPI and Nikkei 225 indices are correlated with exceeding the value of correlation coefficient 0.6 only within the same index for *k*=1 and *k*=2.

Taking into account the values of correlation coefficients and ranking based on AUC and IV in the variable screening step, the variables used in the follow-up models as input predictors are: S&P 500, IBEX 35, JKSE, HSI, BSE Sensex (*k*=1) and KOSPI, Bovespa (*k*=2).

The tuning parameters' values of the final model determined by using the ROC metric and the AUC value based on the test set can be found in Table 35 and the relative influence of the variables based on the model's results applied to SSEC index are shown in Fig 52.

Table 35 AUC and Tuning Parameters's values - SSEC Index, Non-energy Commodity Market (State2)

Tuning Parameters	*Value*
n.trees	450
interaction depth	4
shrinkage	0.001
n.minobsinnode	10
AUC *test set*	0.5683

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

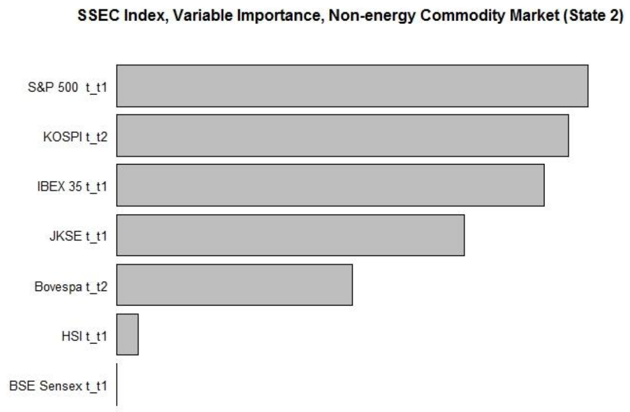


Fig 52 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Non-energy Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

The AUC value is similar to the first model's results in case of higher volatility on the energy market covers the periods related to the Asian and Global Financial Crisis, lower than the second model's result corresponding to another part of higher volatility on the energy market and lower than in case of higher volatility prevailing on the precious metals commodity market. The partial dependence plots, visualizing the effect of 6 most influential stock market indices on the increase/decrease patterns of SSEC index are shown in Fig 53.

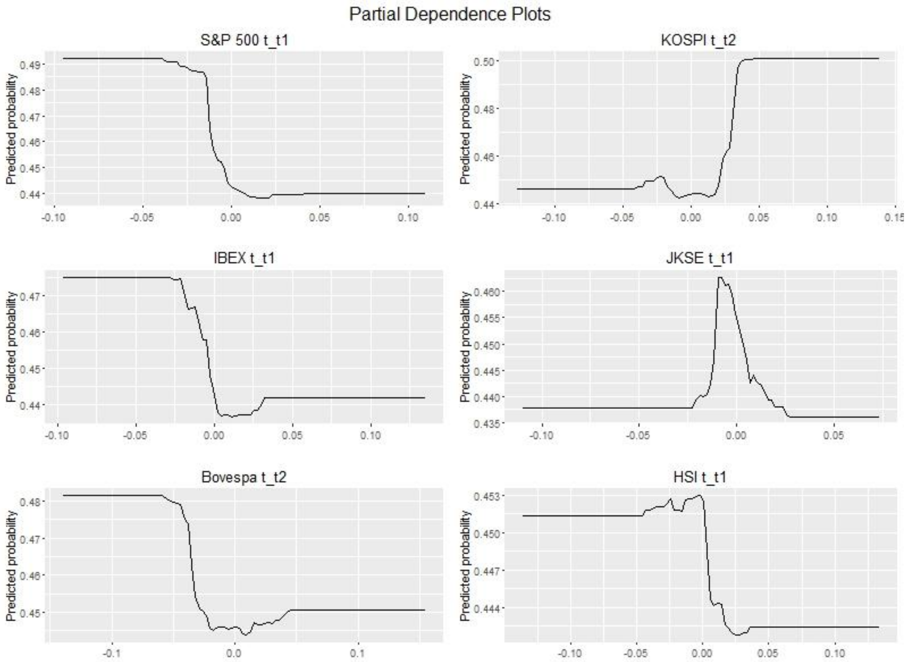


Fig 53 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Non-energy Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

5.2.4 SSEC Index and high volatility on the Energy, Precious Metals and Non-energy Markets

Higher volatility on the Energy, Precious Metals and Non-energy commodity markets simultaneously covers the period 2008M8-2009M8, which refers mainly to the *Global Financial Crisis*. The data set corresponding to the analyzed period contains 276 observations. The increased patterns appear in 50.7% of cases and the decrease or did not change patterns can be observed in 49.3% of the analyzed data points. By executing the stratified random data splitting training set consists of 207 observations (75%) and in the testing data set there are 69 data rows (25%). In Table 36 the AUC and IV values with corresponding ranking are summarized.

Table 36 AUC and IV values, SSEC Index, Energy, Precious Metals and Non-energy Commodity Markets (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
IPC t_t1	0.65	0.42	0.45	0.45	0.42	0.46	0.59	0.62	0.57	1	1
S&P 500 t_t1	0.64	0.29	0.26	0.36	0.36	0.35	0.36	0.39	0.49	2	5
MERVAL t_t1	0.63	0.36	0.38	0.49	0.42	0.49	0.55	0.41	0.53	3	2
MERVAL t_t2	0.62	0.21	0.27	0.29	0.29	0.25	0.37	0.44	0.40	4	8
S&P 500 t_t2	0.61	0.21	0.26	0.21	0.29	0.26	0.33	0.31	0.40	5	9
IBEX 35 t_t1	0.61	0.43	0.38	0.38	0.43	0.45	0.48	0.40	0.46	6	3
Bovespa t_t1	0.61	0.29	0.25	0.33	0.35	0.52	0.35	0.40	0.35	7	6
S&P TSX t_t1	0.61	0.30	0.23	0.38	0.32	0.33	0.39	0.56	0.42	8	4
DAX t_t1	0.61	0.25	0.29	0.36	0.27	0.31	0.34	0.41	0.34	9	7
CAC 40 t_t1	0.60	0.18	0.22	0.30	0.23	0.22	0.27	0.25	0.30	10	13
S&P TSX t_t2	0.58	0.09	0.26	0.18	0.23	0.27	0.23	0.32	0.35	11	11
IPC t_t2	0.57	0.08	0.12	0.19	0.16	0.23	0.30	0.30	0.18	12	17
Bovespa t_t2	0.57	0.15	0.23	0.34	0.38	0.27	0.25	0.31	0.38	13	10
JKSE t_t1	0.56	0.12	0.14	0.16	0.17	0.19	0.19	0.31	0.19	14	18
BSE Sensex t_t1	0.56	0.24	0.13	0.08	0.27	0.13	0.32	0.33	0.24	15	15
IBEX 35 t_t2	0.56	0.05	0.24	0.17	0.25	0.21	0.26	0.32	0.32	16	14
DAX t_t2	0.55	0.14	0.22	0.10	0.23	0.27	0.23	0.23	0.34	17	16
CAC 40 t_t2	0.55	0.07	0.07	0.06	0.14	0.09	0.15	0.12	0.18	18	26
HSI t_t1	0.52	0.23	0.18	0.22	0.20	0.26	0.39	0.22	0.32	19	12
KOSPI t_t1	0.52	0.09	0.08	0.20	0.18	0.17	0.16	0.18	0.21	20	20
JKSE t_t2	0.50	0.06	0.04	0.05	0.15	0.10	0.07	0.18	0.24	21	25
Nikkei 225 t_t1	0.50	0.04	0.09	0.07	0.11	0.17	0.08	0.15	0.16	22	27
KOSPI t_t2	0.49	0.08	0.09	0.12	0.13	0.08	0.23	0.29	0.25	23	21
AORD t_t1	0.49	0.07	0.01	0.16	0.09	0.13	0.18	0.28	0.14	24	23
BSE Sensex t_t2	0.48	0.05	0.09	0.15	0.07	0.12	0.16	0.15	0.17	25	24
Nikkei 225 t_t2	0.48	0.03	0.04	0.06	0.04	0.05	0.09	0.07	0.21	26	28
AORD t_t2	0.46	0.04	0.17	0.10	0.14	0.18	0.19	0.19	0.26	27	22
HSI t_t2	0.45	0.16	0.13	0.12	0.11	0.18	0.23	0.37	0.16	28	19

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

In chapter 3 the greatest similarity, valuated by Jaccard similarity measure in terms of the higher volatility states' occurrence on the particular stock markets, has been appeared in case of the simultaneous presence of the higher volatile regimes on the Energy, Precious Metals and Non-energy markets. Based on the results of the model based step similar conclusion regarding the intensity of the indices' mutual relationships can be inferred. The AUC value in the variable screening process exceeds 0.6 for 10 variables (from 28) and achieved 0.65 in case of IPC index (k=1), which has the first position in the both ranking: based on AUC and IV. Looking at the IV for the different ways of binning there is only one case when IV is less than 0.02: AORD index (k=1), splitting into 6 bins. The minority of variables have IV less than 0.1. For several variables IV for all ways of binning exceeds 0.3: IPC, MERVAL and IBEX 35, for all variables k =1. Indices with IV greater than 0.3 at least for 5 from 8 ways of binning are: S&P 500, S&P TSX, BOVESPA and DAX, for all of them k=1.

Based on the correlation matrix (Appendix 4), the variables are most correlated compared to the higher volatility on the commodity markets separately. Due to higher correlation, more indices have similar information gain to the outcome variable, and as a consequence less variables enter the model based step. Using the information about the correlation coefficients' values and the achieved AUC and IV, the following input variables have been chosen: IPC, HSI, JKSE (k=1); KOSPI, MERVAL (k=2).

In Table 37 there are tuning parameters' values of the final model determined by using the ROC metric and the AUC value based on the test set. The relative influence of the variables based on the model's results applied to SSEC index is shown in Fig 54.

Table 37 AUC and Tuning Parameters's values - SSEC Index, Energy, Precious Metals' and Non-energy Commodity Markets (State2)

Tuning Parameters	*Value*
n.trees	350
interaction depth	4
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.6454

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

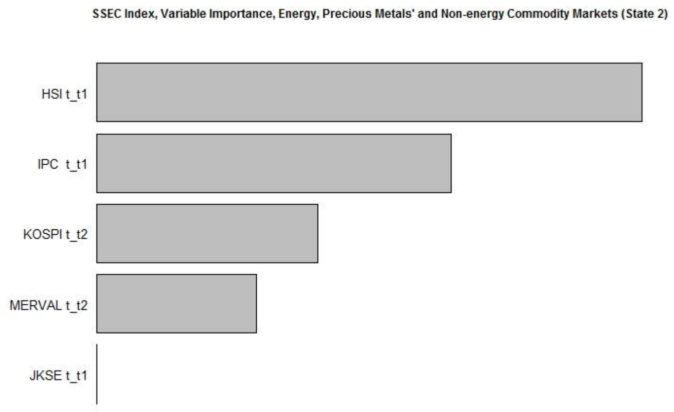


Fig 54 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Energy, Precious Metals'and Non-energy Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Based on the model results, the AUC value stated for the test set is about 0.65, what by itself is not high value, indicating about strong model performance, but is the highest comparing to all models analyzed in the previous steps, where higher volatile regimes on the commodity markets have been analyzed separately.

The partial dependence plots, visualizing the effect of 4 most influential stock market indices on the increase/decrease patterns of SSEC index, are shown in Fig 55. It can be noticed that the top values of the predicted probabilities (*y* axis) are higher than in the previous steps. For IPC index the predicted probability is higher for logarithmic returns less than -0.03 and in case of MERVAL index less than -0.04; for KOSPI index conversely the predicted probability is at higher values for logarithmic returns achieved 0.04 and more. In case for HSI index the predicted probability has the highest values for the logarithmic returns slightly under and above zero.

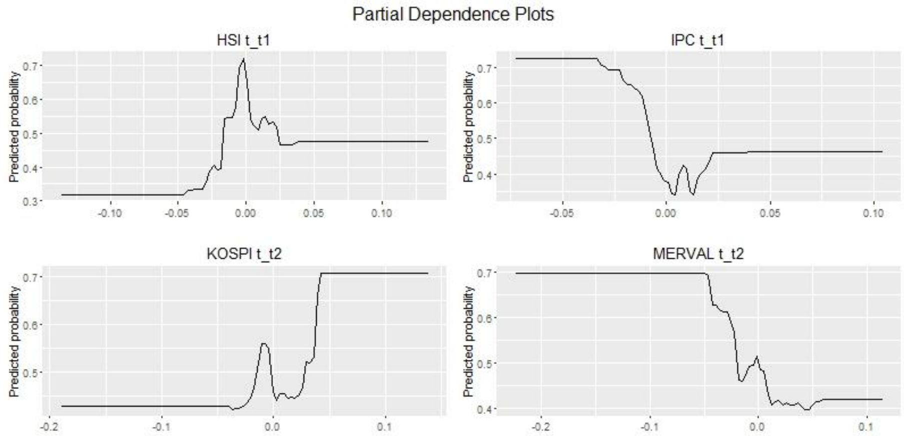


Fig 55 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Energy, Precious Metals'and Non-energy Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

In the next step the opposite situation will be considered, when less volatile regimes simultaniously prevail on all analyzed commodity markets.

5.2.5 SSEC Index and low volatility on the Energy, Precious Metals and Non-energy Markets

More "calm" regime on the Energy, Precious Metals and Non-energy commodity markets simultaneously covers the periods: 1997M7-1997M11, 1995M5, 1999M12-2001M6, 2002M4-2002M10, 2003M6-2005M10, 2013M9-2014M9. The data set corresponding to the analyzed period contains 1 581 observations. The increased patterns appear in 47.7% of cases and the decrease or did not change patterns can be observed in 52.3% of the analyzed data points. By executing the stratified random data splitting training set consists of 1 186 observations (75%) and in the testing data set there are 395 data rows (25%). In Table 38 the AUC and IV values with corresponding ranking are summarized.

Table 38 AUC and IV values, SSEC Index, Energy, Precious Metals and Non-energy Commodity Markets (State1)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	AUC_rank	IV_rank
MERVAL t_t1	0.52	0.01	0.01	0.03	0.03	0.04	0.07	0.08	0.04	1	7
S&P TSX t_t2	0.52	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02	2	27
MERVAL t_t2	0.52	0.00	0.01	0.02	0.02	0.02	0.03	0.03	0.03	3	17
Bovespa t_t2	0.51	0.01	0.02	0.02	0.02	0.04	0.03	0.03	0.04	4	13
S&P TSX t_t1	0.51	0.00	0.01	0.02	0.01	0.02	0.02	0.01	0.02	5	26
S&P 500 t_t1	0.51	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.01	6	28
HSI t_t1	0.51	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	7	2
Bovespa t_t1	0.51	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.03	8	25
S&P 500 t_t2	0.51	0.02	0.02	0.01	0.02	0.04	0.02	0.04	0.04	9	14
CAC 40 t_t2	0.51	0.00	0.01	0.01	0.01	0.02	0.03	0.03	0.03	10	22
AORD t_t1	0.50	0.00	0.02	0.02	0.02	0.02	0.01	0.04	0.04	11	16
IPC t_t2	0.50	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.03	12	15
IPC t_t1	0.50	0.04	0.03	0.03	0.03	0.04	0.04	0.04	0.06	13	5
CAC 40 t_t1	0.50	0.00	0.02	0.01	0.02	0.02	0.02	0.04	0.02	14	17
KOSPI t_t1	0.50	0.03	0.02	0.02	0.06	0.05	0.05	0.05	0.05	15	6
DAX t_t2	0.50	0.01	0.03	0.05	0.04	0.06	0.05	0.07	0.09	16	4
IBEX 35 t_t1	0.49	0.00	0.02	0.02	0.01	0.02	0.01	0.04	0.03	17	19
IBEX 35 t_t2	0.49	0.01	0.01	0.01	0.03	0.02	0.02	0.02	0.02	18	24
Nikkei 225 t_t1	0.49	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.05	19	8
BSE Sensex t_t2	0.49	0.01	0.03	0.03	0.02	0.02	0.02	0.04	0.05	20	12
AORD t_t2	0.49	0.02	0.02	0.04	0.03	0.04	0.02	0.05	0.05	21	9
DAX t_t1	0.49	0.02	0.01	0.01	0.01	0.03	0.03	0.01	0.03	22	20
HSI t_t2	0.49	0.04	0.04	0.07	0.06	0.06	0.09	0.08	0.08	23	1
BSE Sensex t_t1	0.48	0.01	0.04	0.06	0.05	0.03	0.04	0.03	0.04	24	10
JKSE t_t2	0.48	0.01	0.01	0.01	0.02	0.02	0.03	0.02	0.03	25	20
KOSPI t_t2	0.47	0.01	0.01	0.01	0.01	0.02	0.01	0.04	0.03	26	23
Nikkei 225 t_t2	0.47	0.02	0.04	0.02	0.03	0.02	0.03	0.03	0.04	27	11
JKSE t_t1	0.46	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.07	28	3

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Analyzing the isolated contribution of the analyzed stock market indices to the SSEC index direction's movements under the situation of "calm" commodity markets, it can be inferred that this contribution is lower comparing to all previous steps of volatile commodity markets. The maximum AUC is equal to 0.52, and for 12 predictors from 28 is even less than 0.5. In terms of IV for most variables there is at least one way of binning with IV less than 0.02 excepting HSI, IPC, JKSE (k=1) and HSI, Nikkei (k=2). For the cases when IV is greater than 0.02, it does not exceed 0.1 for any variable at any way of binning.

Analyzing the correlation coefficients (*viz.* Appendix 4) the similar inferences can be followed. For most indices there are values of correlation coefficient above 0.6 only within the same index for k= 1 and k=2; there are correlation coefficients with values exceeding 0.6 for the European region but the values are less than in the previous steps; Spearman correlation coefficient also exceeds 0.6 between S&P 500 and S&P TSX (k=1 and k=2), and for S&P 500 and DAX (k=2).

Considering the information regarding the correlation and the variables' individual contribution to the binary outcome the following variables will enter the follow-up model based step: HSI, JKSE, MERVAL, IPC, BSE Sensex, KOSPI, AORD, Nikkei 225, DAX, S&P TSX (k=1); S&P 500, Bovespa, IBEX 35 (k=2).

In Table 39 there are tuning parameters' values of the final model determined by using the ROC metric and the AUC value based on the test set. The relative influence of the variables based on the model's results applied to SSEC index is shown in Fig 56.

Table 39 AUC and Tuning Parameters's values - SSEC Index, Energy, Precious Metals' and Non-energy Commodity Markets (State1)

Tuning Parameters	*Value*
n.trees	450
interaction depth	5
shrinkage	0.001
n.minobsinnode	10
AUC *test set*	0.5099

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

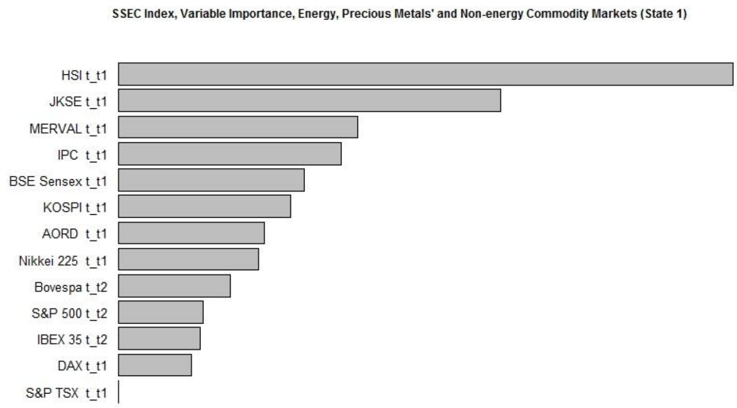


Fig 56 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index, Energy, Precious Metals'and Non-energy Commodity Market (State1). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

The AUC ROC (Table 39) computed by applying the estimated model to the test set is very low and just slightly above 0.5. Based on the variable screening analysis and then applying the model based approach, it can be inferred that under the "calm" situations on the commodity markets there is very small individual contribution to the direction's movements of SSEC index, and the dependence of increase/decrease patterns of SSEC index on other market indices is also very close to the random classifier. The partial dependence plots of the first 6 variables ordering by their relative influence based on the models results can be found in Fig 57.

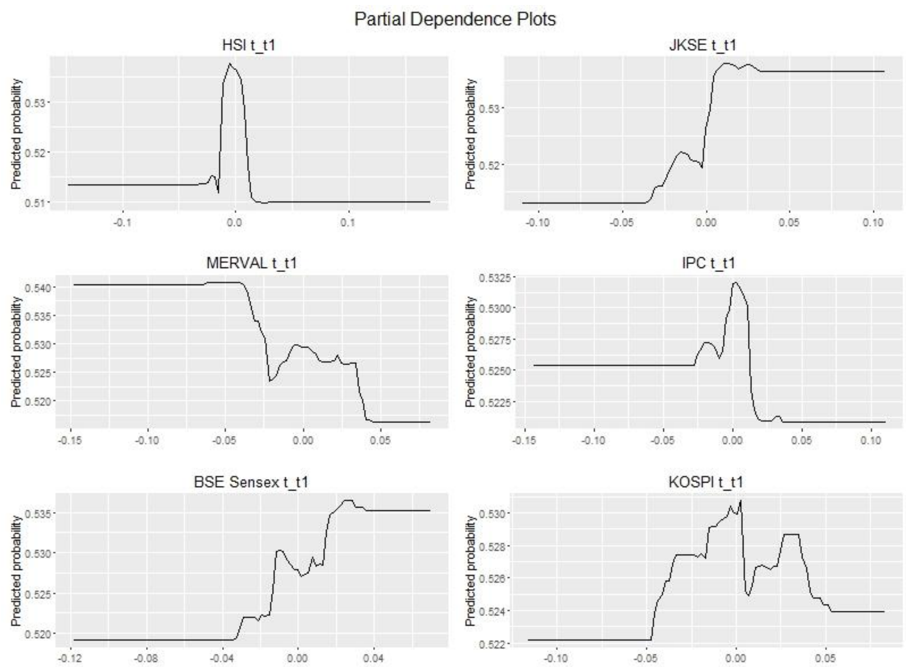


Fig 57 Partial dependence plots based on the Stochastic Gradient Boosting model - SSEC Index, Energy, Precious Metals'and Non-energy Commodity Market (State 1). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

5.2.6 SSEC Index and Commodity prices

By applying the similar methodology as in the previous steps to analyze the dependence of increase/decrease patterns in SSEC index on the daily logarithmic changes (for k=1 and k=2) of the chosen commodities defined in the data description subchapter, the following conclusions can be made:

- in the variable screening step when the isolated contribution of each variable to the binary outcome variable has been measured by computing area under the ROC curve for each predictor and Information Values for different ways of binning: from 5 to 12 intervals, the highest AUC values and IV were achieved in case of simultaneous presence the highly volatile regime on the Energy, Precious Metals and Non-energy commodity markets.
- the correlation measured by *Spearman correlation* coefficients exceeds the value 0.6 for all analyzed situations only within the same index for k=1 and k=2, excepting the situations of high volatility on the precious metals and non-energy markets and high volatility on all considered markets simultaneously, where Spearman correlation coefficient exceeds 0.6 between gold and platinum logarithmic returns.
- in the model based step where the stochastic gradient boosting approach has been applied the highest value of the area under the ROC curve, computed by applying the gained model to the test set, was achieved in case of simultaneous prevailing higher volatile regimes on the Energy, Precious Metals and Non-energy commodity markets, and is equal to 0.59. In Table 40 there are tuning parameters' values of the final model

determined by using the ROC metric and the AUC value based on the test set. The relative influence of the variables is shown in Fig 58. All results of variable screening and model based steps can be found in Appendix 6.

Table 40 AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Energy, Precious Metals' and Non-energy Commodity Markets (State2)

Tuning Parameters	*Value*
n.trees	150
interaction depth	1
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.5908

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

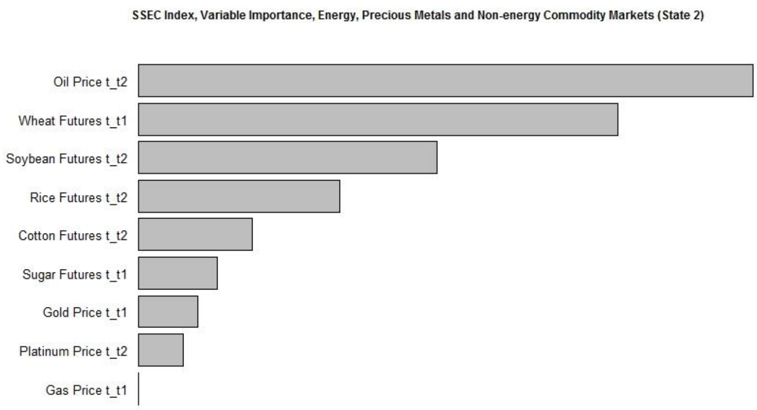


Fig 58 Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Energy, Precious Metals and Non-energy Commodity Market (State2). Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Conclusion

The purpose of the current thesis consists in identification of the typical scenarios of mutual relations among the stock markets considering different regimes on the commodity markets, as a consequence for the identified scenarios the investment recommendations are suggested. To achieve this research purpose, the following steps have been done: firstly, the regimes on the commodity markets have been detected; secondly, the mutual linkage among the stock markets during different situations on the commodity markets have been examined; then the typical scenarios with the suggestion of the investment recommendation have been summarized; and finally, the model-based approach, investigating the dependence of direction's movements of *Shanghai Composite Index* in time t+1 on the rest analyzed stock market indices in time t during different situations on the commodity markets, is examined.

Three commodity markets have been analyzed: Energy, Precious Metals and Non-energy Commodity Markets, where the Non-energy market covers Agriculture, Metals & Minerals and Fertilizers markets. It was assumed that on each commodity market two main regimes can be identified: more "calm" regime and the state with higher volatility. The commodity markets' regimes were identified by applying *Hidden Markov Model* methodology. Firstly, the parameters of the HMM have been calibrated by applying the *Expectation-Maximization* algorithm (Dempster et al., 1977). Then by using the obtained adjusted parameters of the model the most probable sequence of states associated with the given observation sequence was determined by applying *Viterbi* algorithm (Viterbi, 1967), (Forney, 1973). On the Precious Metals commodity market the Consumer Price Index, USA was included as a covariate in the transition probabilities due to existence of the long-term relationship between the gold price and the general price level in USA (Levin and Wright, 2006).

As the regimes, prevailing on the commodity markets, were identified, the analysis of the relations between the stock market indices was conducted by considering the following situations: high volatility on the energy market; high volatility on the precious metals market; high volatility on the non-energy market; simultaneous high and simultaneous low volatility on all three considered commodity markets, whereas the case of high volatility on the energy market is divided into two periods based on the source underlying the oil price shocks causing higher volatility. The analysis was conducted to fifteen national market indices. The investigation of the linkage among the stock markets during these identified situations on the commodity markets was carried out from two perspectives: firstly, the similarity between the stock markets indices in terms of highly volatile regimes' occurrences was analyzed, and secondly, correlation analysis among the stock markets was conducted. For the first perspective the bear market (volatile and negative market regime) was identified with the help of *Hidden Markov Model* methodology similarly to the commodity market' regime detection, to examine the similarity between the stock market indices in terms of bear market regime's occurrences, *Jaccard Similarity Measure* was employed. To investigate the correlation, the *Spearman correlation coefficients* were computed. By discovering these two perspectives of investigation of the linkage among the stock markets, it was shown that during different situations on the commodity markets the mutual relations between the international stock market indices differ, and as a consequence the investment strategy can differ as well. The summarization of the identified scenarios of the mutual relations among the stock markets considering different regimes on the commodity markets are recapitulated in Table 41.

Table 41 Scenarios of mutual relations among the stock markets considering different regimes on the commodity markets

	Commodity Markets			Stock Markets
Description	Energy Market	Precious Metals Market	Non-energy Market	Stock markets' similarity
1. higher volatility on the energy market caused mainly by the demand price shocks	$\uparrow^{p}$	X	X	↑↑
2. higher volatility on the energy market caused mainly by supply and precautionary demand price shocks	$\uparrow^{s}$	X	X	↓↓
3. higher volatility on the precious metals market	X	↑	X	≈
4. higher volatility on the non-energy market	X	X	↑	↑
5. simultaneous low volatility on the Energy, Precious Metals and Non-energy commodity markets	↓	↓	↓	↓↓
6. simultaneous high volatility on the Energy, Precious Metals and Non-energy commodity markets	↑	↑	↑	↑↑

Source: Own calculation.

In Table 41 six scenarios of the stock markets' mutual relations are summarized. The first scenario describes the linkage among the stock markets during the volatile period on the energy market related to the demand price shocks, whereas the second scenario covers the period of high volatility on the energy markets associated with supply or precautionary demand shocks. It was shown that the similarity between the stock market indices in terms of highly volatile regimes' occurrences differs and is stronger for the period of highly volatility present on the energy market caused by the demand shocks in the oil price and is weaker for the volatile period caused by supply or precautionary demand shocks. For the latter period the weak similarity between the occurrences of states with high volatility can be comparable with the situation of simultaneous low volatility on all three commodity markets. The necessity to distinguish the source underlying the oil price shocks has been documented in (Kilian, 2009), where the author showed the different effect of the oil shocks depending on the shock's triggers on the real oil price and US macroeconomic aggregates. This difference in the stock markets' relations during different volatile periods on the energy market, differing by the source of the oil price shock, can support the thought that the demand oil shocks, causing the increase volatility on the energy market, turn out more globally, whereas the supply shocks impact the occurrence of high volatility on the stock markets more selectively, which makes the latter period more attractive to apply the diversification strategy. During the volatile period on the energy market related to the demand oil price shocks when the opportunity of the international diversification stands on rather low level, the sectoral diversification may be one of the solution to smooth out the risk associated with operating on the energy market. When the main trigger of the volatility on the energy market relates to the supply or precautionary demand shocks the opportunities for diversification are higher and the standard investor's strategy can be kept.

By computing the correlation coefficients for the highly volatile state on the energy market, the difference in influence of source, underlying the oil price shocks causing higher volatility, is not so apparent, as it was shown in case of measuring the agreement between the bear markets' occurrences on the stock markets.

The interconnection among the stock market indices within region in terms of highly volatile state appearance is stronger for the presence of high volatility on the non-energy market comparing with volatile regime on the precious metals market. During the highly volatile period prevailing on the non-energy market, the diversification strategy may become more functional by focusing on the international markets out of the particular region.

By examining the relations among the stock markets it was shown that during most unstable period, when highly volatile regime prevails simultaneously on the energy, precious metals and non-energy commodity markets the whole economy becomes to be more tied: the stock market indices demonstrate stronger interdependence. The results are similar to (Junior and Franca, 2011), where the authors concluded that the behavior of markets is similar during the time of high volatility. The results also correspond to the part of conclusion in (Glick and Hutchison, 2013) related to the statement that during the crisis period the linkage between the Chinese and other Asian equity markets increased. The approaches used in these works to determine the crisis period or time of high volatility differ from the approach applied in the current thesis, but the conclusion regarding the relations among the stock markets during highly volatile time periods are coincident. Due to stronger interconnection among the stock markets during the situation of simultaneous high volatility's presence on all three commodity markets, the benefits of diversification begin to fail, and the increasing risk associated with very limited opportunity to diversify may grow the cost of the investment decisions. The period of simultaneous high volatility on all three analyzed commodity markets refers to the Global Financial Crisis, when the access to finance becomes to be tough, so when there are some evidences of the forthcoming period of high volatility on all commodity markets, it is important to secure funding in advance even for higher prices.

During the simultaneous presence of low volatility on all three analyzed commodity markets the agreement between occurrences of *bear* state of most stock markets, besides the indices within the European region (DAX, CAC 40, IBEX 35) is rather weak. Similarly the correlation within region and with other regions is weaker comparing with other situations on the commodity markets. Under this situation of weaker stock markets' interdependence the diversification strategy may be functional to smooth out the risk associated with the maintaining the portfolio and to ensure the investments' stability, so the standard investor's strategy can be kept.

By turning back to the example of the company operating on the energy market given in the introduction part of the thesis, one of an example of the investment strategy when there is a volatility on the energy commodity market can be the following: firstly, the source underlying the oil price shocks should be determined, if the main trigger relates to the demand shocks then the company can think about sectoral diversification, when the main reason of the volatile period on the energy market is associated with the supply shocks then the standard investment company's strategy can be kept; when there are some evidences of the forthcoming increased volatility on all commodity markets, the company should ensure the self-financing of its business and stable credit line in advance, as during this period, when high volatility prevails on all three commodity markets, the benefits of diversification begin to fail.

The most similar behavior in terms of bear market regime's occurrences and in terms of mutual correlation during all situations on the commodity markets was observed between DAX (Germany) and CAC 40 (France) market indices.

Considering the whole period the least agreement between the bear regime's occurrences in the stock markets is in case of SSEC index. Analyzing different situations on the commodity markets the results can differ: during the period of high volatility on all three commodity markets the lowest similarity was observed in case of JKSE index and then in case of SSEC index; during the simultaneous presence of low volatility the least agreement of bear regime' occurrences can be noticed in case of AORD index and then in case of SSEC index. Due to this low similarity of SSEC index and its most changeable results regards to the correlation coefficient's value and statistical significance under different situations on the commodity markets comparing to other indices, and because China is one of the largest economy in the world, the rest part of the present research investigated the dependence of the increase/decrease pattern of SSEC index in time t+1 on other stock market indices in time t during different regimes on the commodity markets. To discover such dependence, firstly the variable screening step was conducted, when the information about the isolated contribution of each index to the direction's movements of SSEC index was examined by computation the area under individual ROC curves and Information Value. Then the dependence of the increase/decrease patterns of SSEC index on other indices was examined by Stochastic Gradient Boosting approach. In the model based step the dependence of increase/decrease patterns of SSEC index in time t+1 on other international stock market indices in time t was rather weak in absolute term for all considered situations on the commodity markets, but in relative term the obtained results support the findings in the previous steps, where the strongest dependence appears during the volatile regime's presence simultaneously on the energy, precious metals and non-energy commodity markets. The stronger dependence measured by individual AUC and IV values in the variable screening step and model AUC value was also in case of the highly volatile period on the energy market caused by demand oil shocks than in case of supply or precautionary demand shocks. The least dependence was obtained during the period of low volatility on all three commodity markets. The analysis of the increase/decrease patterns of SSEC index in time t+1 is also extended by concerning the chosen daily commodity prices, where as in the previous steps the strongest dependence was achieved in case of simultaneous prevailing higher volatile regimes on the Energy, Precious Metals and Non-energy commodity markets.

As a direction of the possible continuation of the conducted research the following topics can be suggested: definition of the scenarios by analyzing the short- and long-run relations among the stock and commodity prices; investigation the links between the stock and commodity markets by considering different industries of the stock markets; discover the predictability of the stock markets by using the information about other stock markets, commodity markets, macroeconomic factors and main issues, which the market index is comprised of during different time periods.

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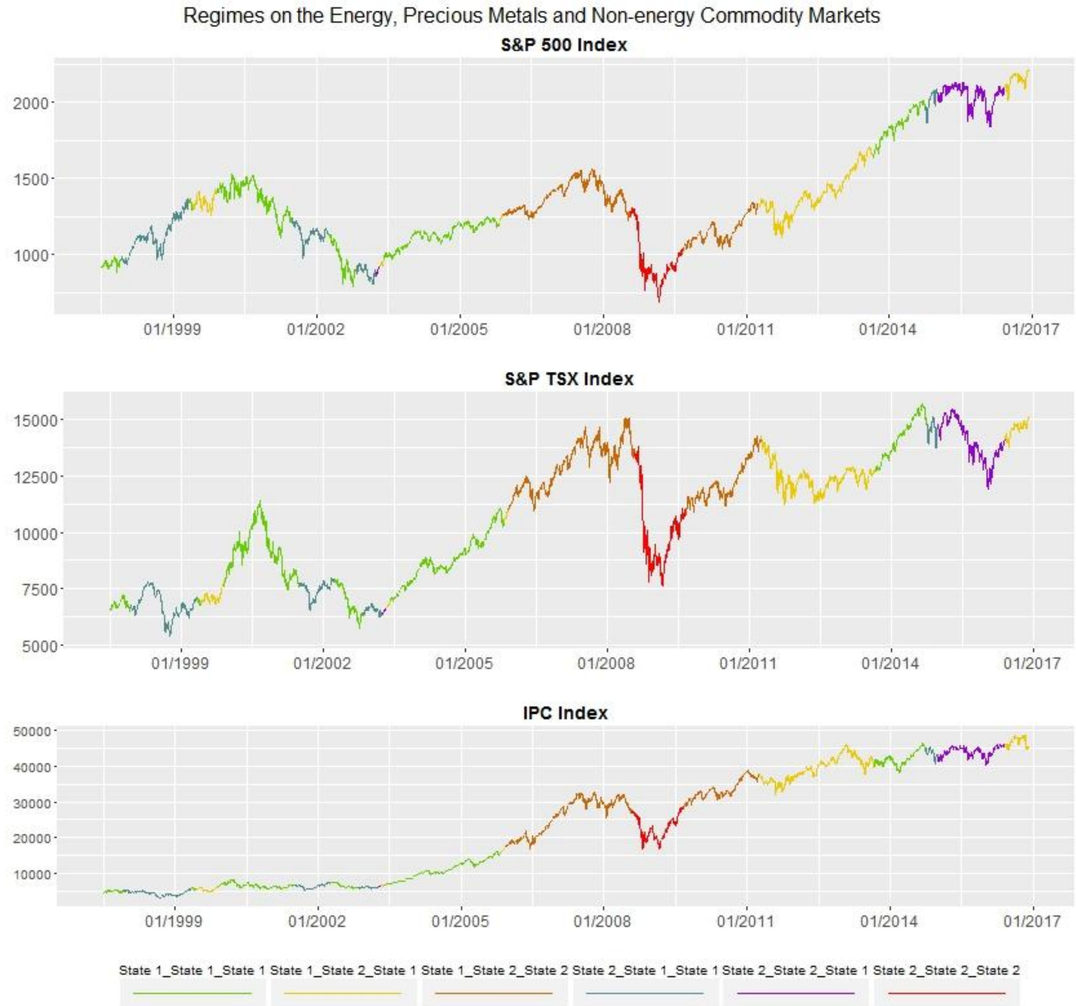
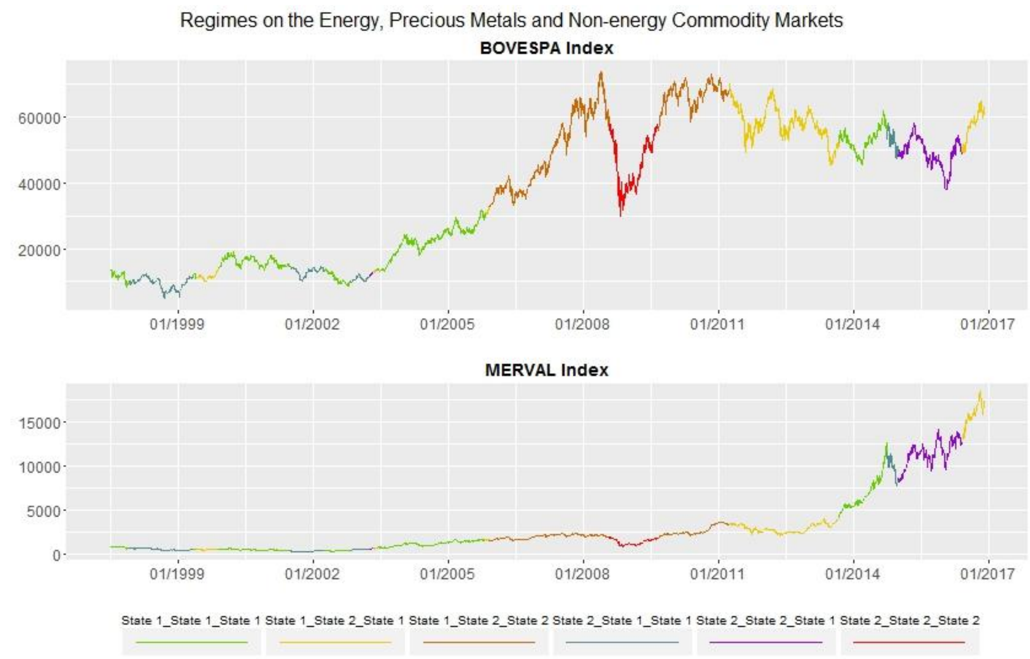
Appendix

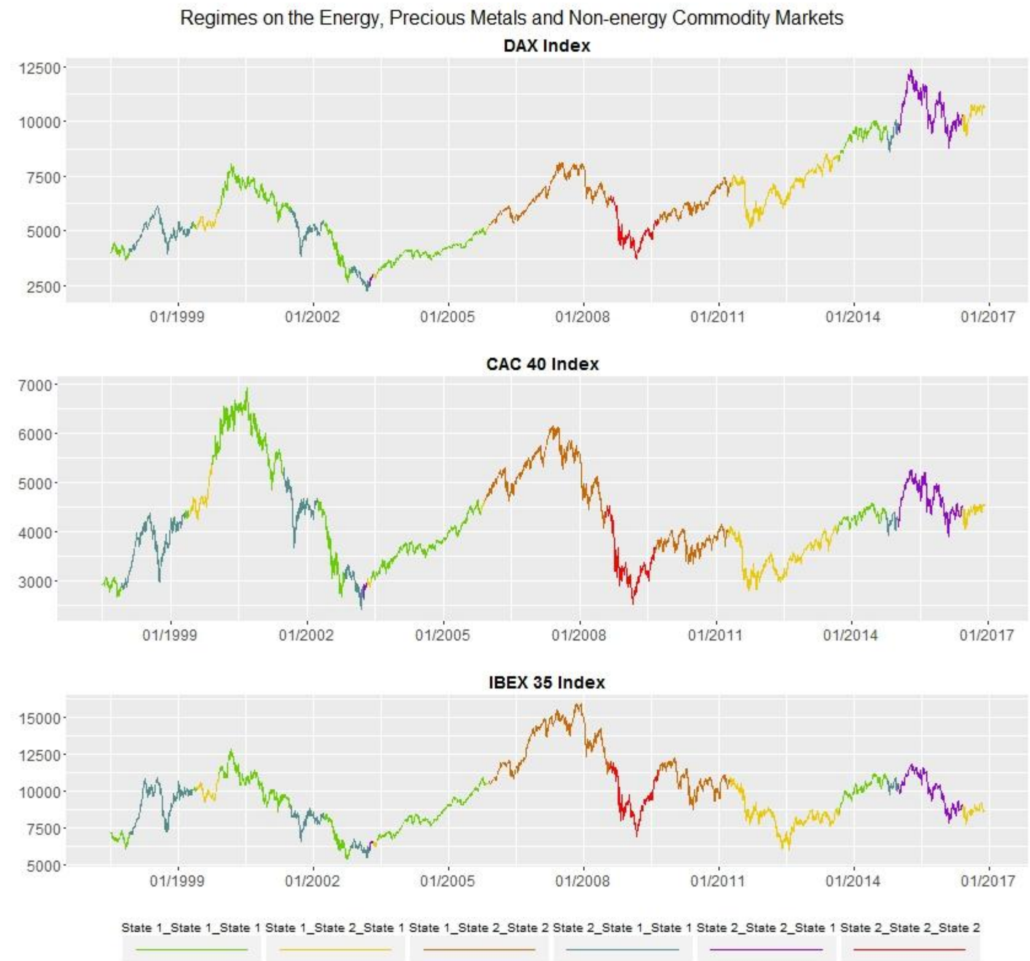
Appendix 1



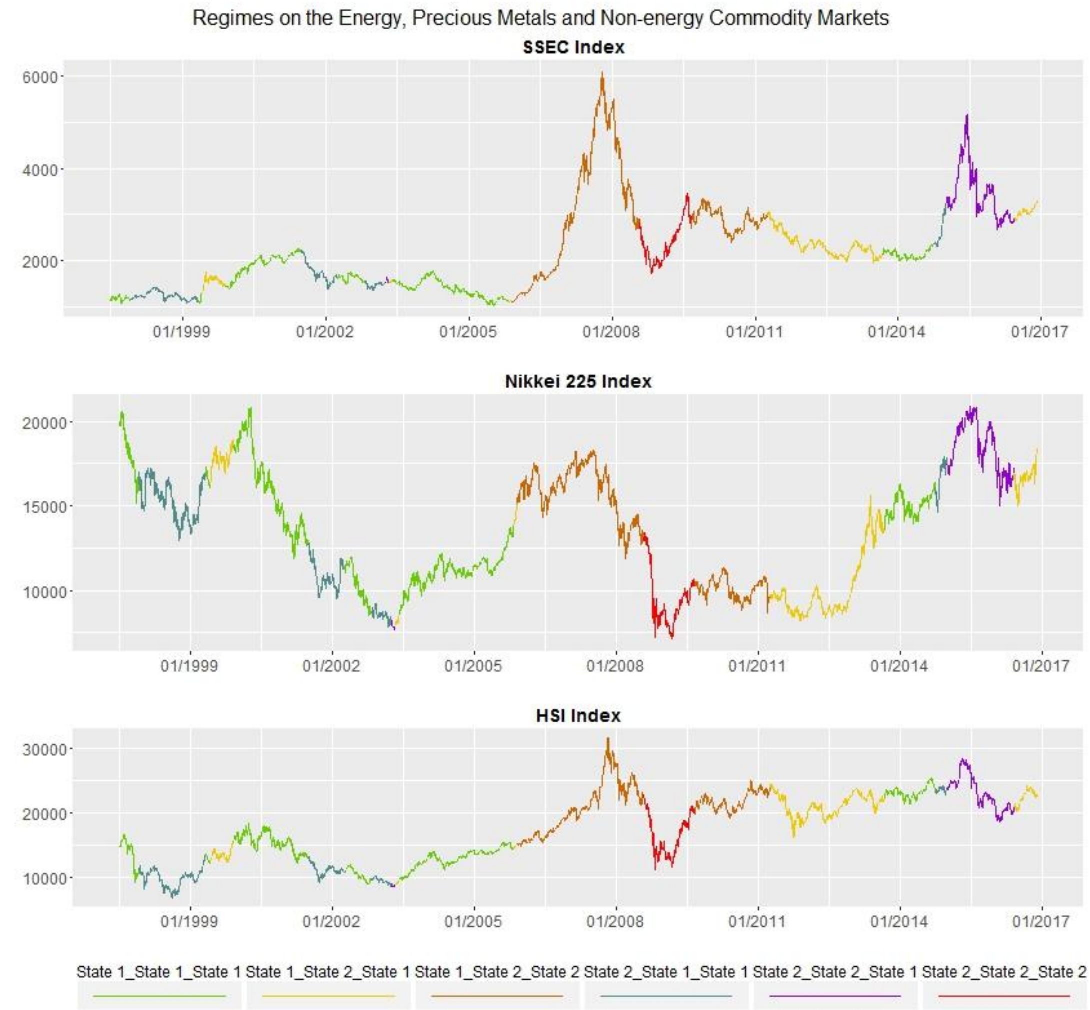
Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace*, *Central Bank of Brazil Statistical Database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace*, *Nikkei database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Appendix 2

Spearman correlation , *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Energy Commodity market (State 2), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,12
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,29
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,02
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,12	0,13	0,02	0,29	0,07	0,01	0,00	0,02	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Energy Commodity market (State 2 - I), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,63
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,18
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,17
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,06
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,04
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,63	0,18	0,04	0,17	0,06	0,02	0,02	0,04	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Energy Commodity market (State 2 - II), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,06
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,41
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,15
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,03	0,01	0,00	0,00	0,03	0,06	0,84
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,39
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,18
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,13
Nikkei 225	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,02
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,03
JKSE	0,03	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,03
AORD	0,00	0,00	0,00	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,06	0,41	0,15	0,84	0,39	0,18	0,07	0,13	0,00	0,00	0,02	0,03	0,03	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Precious Metals Commodity market (State 2), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Non-energy Commodity market (State 2), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, Energy, Non-energy and Precious Metals Commodity market (State 2), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,34	0,00	0,00	0,00	0,00	0,02	0,10
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225	0,34	0,00	0,00	0,00	0,01	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
BSE Sensex	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
JKSE	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
AORD	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
SSEC	0,10	0,03	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

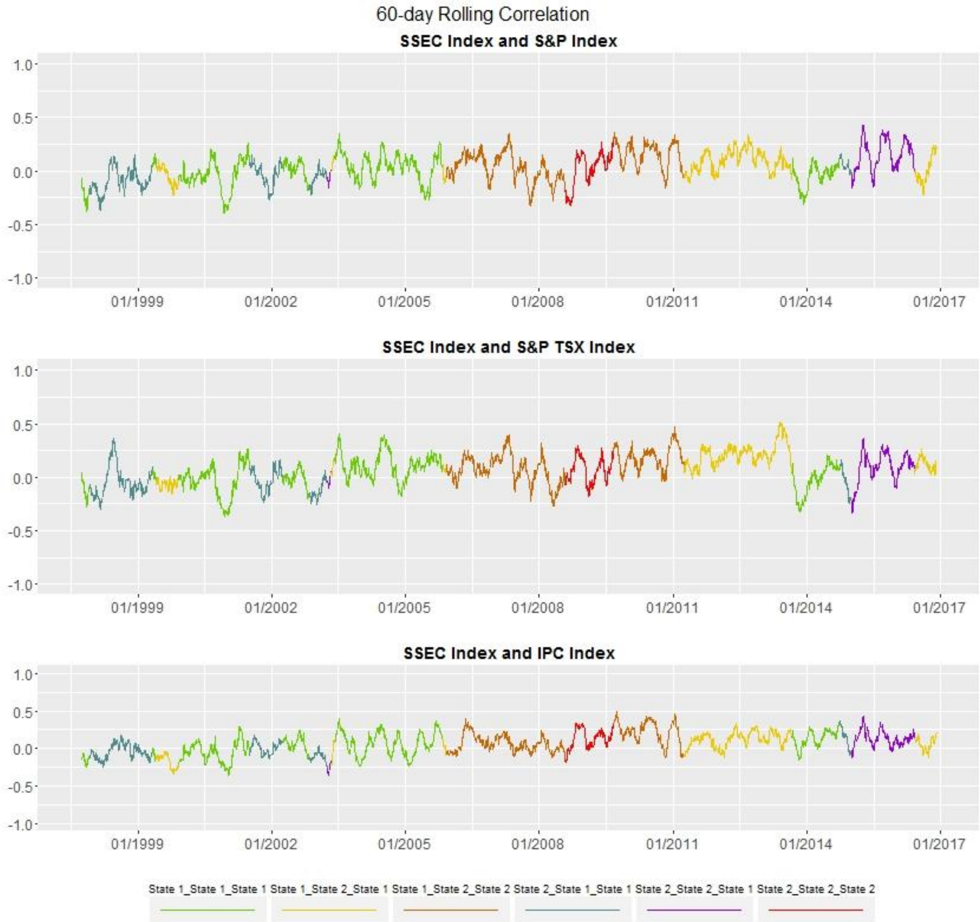
Spearman Correlation, Energy, Non-energy and Precious Metals Commodity market (State 1), *p*-values

	S&P 500	S&P TSX	IPC	MERVAL	Bovespa	DAX	CAC 40	IBEX 35	Nikkei 225	HSI	KOSPI	BSE Sensex	JKSE	AORD	SSEC
S&P 500	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,80	0,01	0,37
S&P TSX	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,66
IPC	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,00	0,57
MERVAL	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,59	0,00	0,96
Bovespa	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,48
DAX	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,55
CAC 40	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,52
IBEX 35	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,99
Nikkei 225	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,18
HSI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
KOSPI	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,02
BSE Sensex	0,07	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,32
JKSE	0,80	0,03	0,07	0,59	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,26
AORD	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,31
SSEC	0,37	0,66	0,57	0,96	0,48	0,55	0,52	0,99	0,18	0,00	0,02	0,32	0,26	0,31	NA

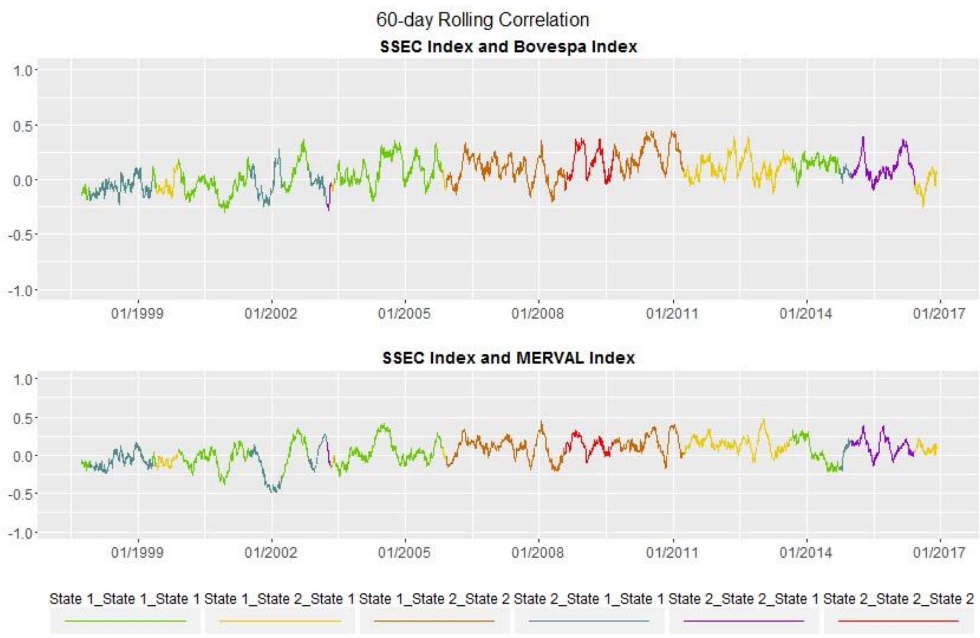
Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Appendix 3

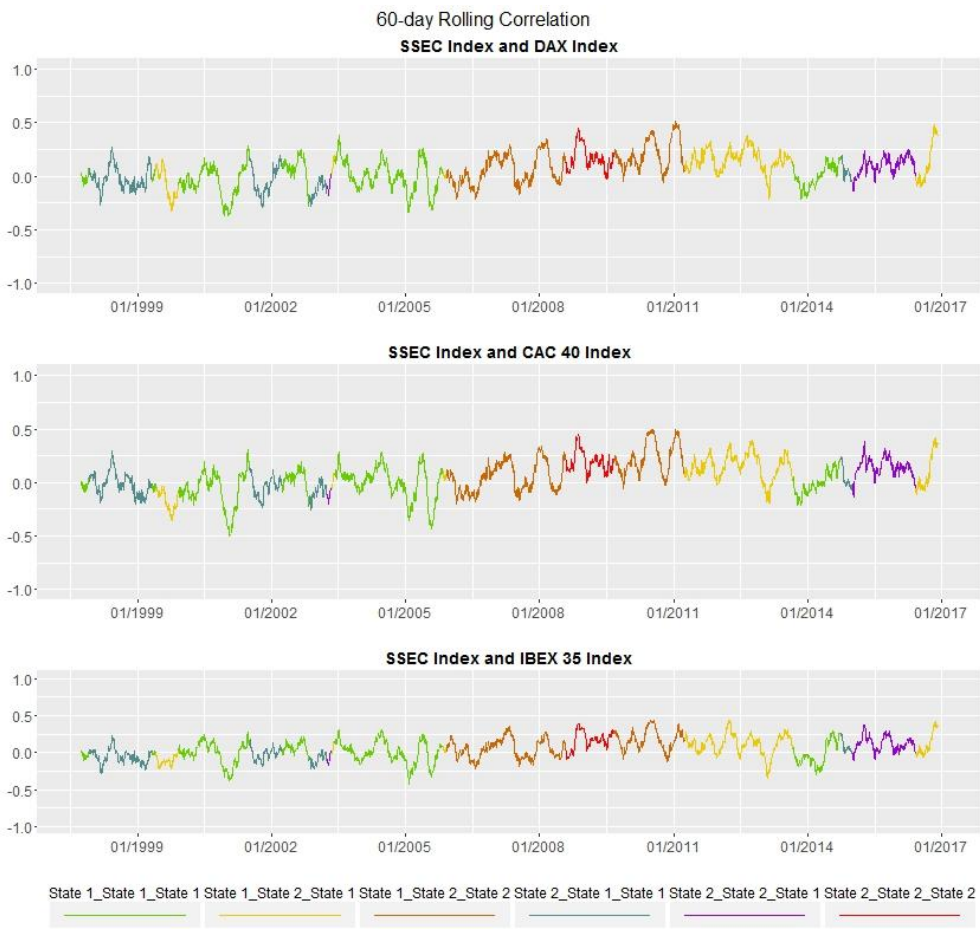
60-day Rolling correlation between logarithmic returns of SSEC and other indices by computing *Spearman correlation coefficient*.



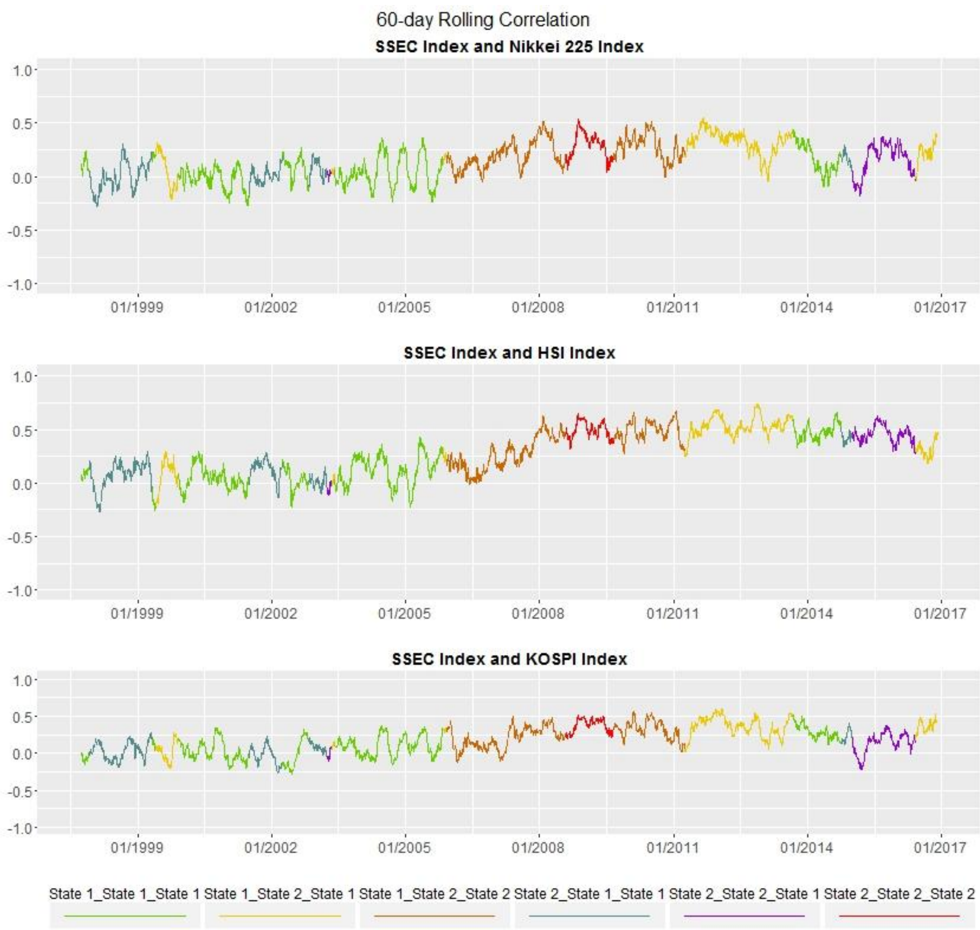
Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



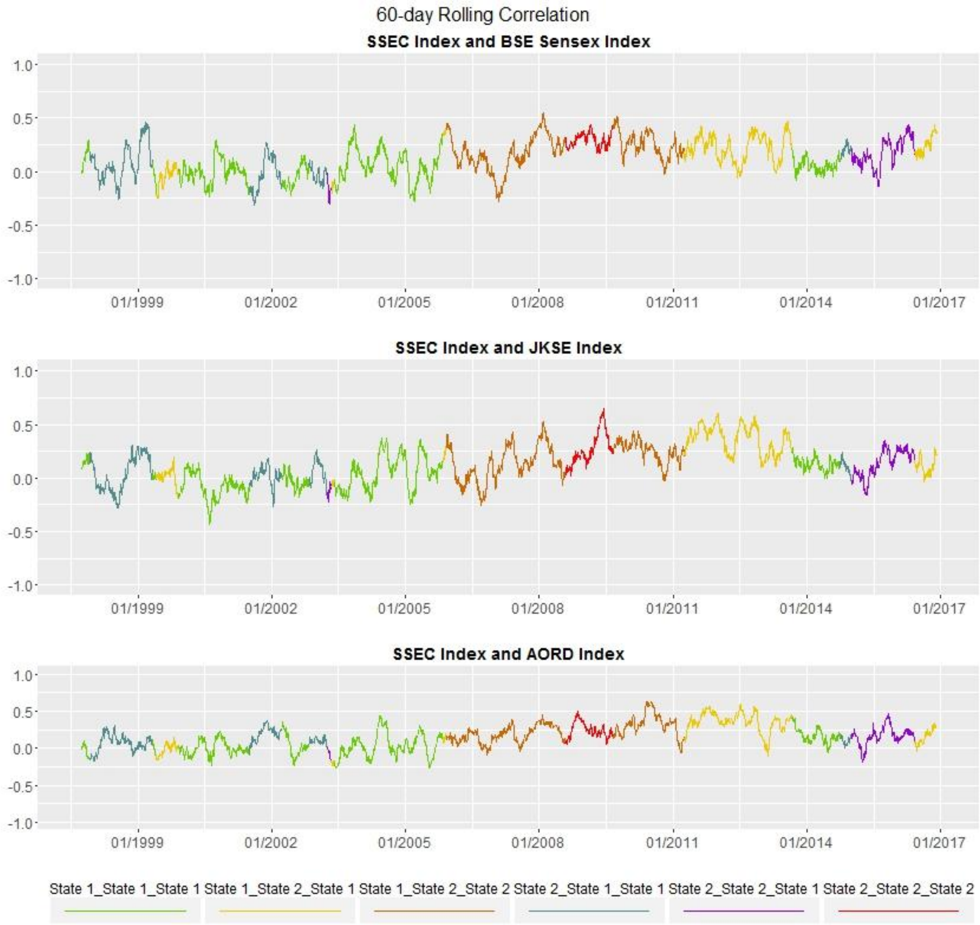
Data source: the time series data have been retrieved from *Quandl YFinace*, *Central Bank of Brazil Statistical Database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.



Data source: the time series data have been retrieved from *Quandl YFinace database* with the help of *Quandl*. Own calculation in R Studio, *ggplot2*, *depmixS4*, *Quandl* packages.

Appendix 4

Spearman Correlation Coefficients and *p*-values - Model Based step

Higher volatility on the Energy Commodity Market (State 2 - I)

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	1,00	0,61	0,51	0,35	0,49	0,34	0,47	0,33	0,58	0,34	0,08	0,07	0,08	0,09	0,62	0,40	0,10	0,04	0,70	0,39	0,20	0,09	0,64	0,41	0,08	0,09	0,15	0,12
S&P 500 t_t2	0,61	1,00	0,55	0,69	0,54	0,69	0,53	0,65	0,50	0,65	0,29	0,26	0,29	0,29	0,53	0,71	0,50	0,39	0,52	0,73	0,31	0,28	0,51	0,71	0,40	0,37	0,42	0,40
CAC 40 t_t1	0,51	0,55	1,00	0,69	0,84	0,59	0,82	0,57	0,44	0,35	0,27	0,19	0,18	0,11	0,47	0,41	0,30	0,19	0,54	0,46	0,35	0,21	0,47	0,42	0,24	0,15	0,35	0,24
CAC 40 t_t2	0,35	0,69	0,69	1,00	0,61	0,88	0,62	0,85	0,38	0,55	0,34	0,36	0,28	0,31	0,36	0,58	0,54	0,50	0,42	0,66	0,31	0,35	0,40	0,60	0,44	0,46	0,42	0,48
DAX t_t1	0,49	0,54	0,84	0,61	1,00	0,67	0,78	0,57	0,43	0,38	0,30	0,22	0,21	0,17	0,46	0,44	0,29	0,17	0,52	0,43	0,32	0,19	0,44	0,42	0,21	0,15	0,37	0,26
DAX t_t2	0,34	0,69	0,59	0,88	0,67	1,00	0,58	0,84	0,38	0,56	0,34	0,37	0,31	0,35	0,38	0,61	0,53	0,49	0,42	0,63	0,32	0,37	0,38	0,59	0,43	0,47	0,45	0,51
IBEX 35 t_t1	0,47	0,53	0,82	0,62	0,78	0,58	1,00	0,69	0,43	0,38	0,27	0,21	0,20	0,16	0,47	0,45	0,31	0,21	0,49	0,45	0,34	0,20	0,45	0,40	0,23	0,18	0,32	0,24
IBEX 35 t_t2	0,33	0,65	0,57	0,85	0,57	0,84	0,69	1,00	0,39	0,55	0,32	0,35	0,31	0,35	0,37	0,60	0,51	0,50	0,41	0,64	0,32	0,36	0,39	0,57	0,43	0,50	0,40	0,47
MERVAL t_t1	0,58	0,50	0,44	0,38	0,43	0,38	0,43	0,39	1,00	0,69	0,23	0,19	0,16	0,23	0,59	0,50	0,22	0,17	0,54	0,42	0,18	0,18	0,64	0,54	0,18	0,19	0,29	0,30
MERVAL t_t2	0,34	0,65	0,35	0,55	0,38	0,56	0,38	0,55	0,69	1,00	0,34	0,32	0,29	0,34	0,44	0,71	0,46	0,43	0,37	0,62	0,15	0,24	0,43	0,74	0,34	0,39	0,39	0,46
JKSE t_t1	0,08	0,29	0,27	0,34	0,30	0,34	0,27	0,32	0,23	0,34	1,00	0,69	0,34	0,35	0,20	0,34	0,36	0,27	0,18	0,34	0,31	0,27	0,21	0,36	0,32	0,26	0,47	0,34
JKSE t_t2	0,07	0,26	0,19	0,36	0,22	0,37	0,21	0,35	0,19	0,32	0,69	1,00	0,25	0,43	0,17	0,33	0,31	0,43	0,16	0,36	0,22	0,36	0,15	0,31	0,24	0,39	0,35	0,52
KOSPI t_t1	0,08	0,29	0,18	0,28	0,21	0,31	0,20	0,31	0,16	0,29	0,34	0,25	1,00	0,70	0,12	0,28	0,36	0,27	0,12	0,28	0,26	0,25	0,21	0,34	0,42	0,33	0,37	0,34
KOSPI t_t2	0,09	0,29	0,11	0,31	0,17	0,35	0,16	0,35	0,23	0,34	0,35	0,43	0,70	1,00	0,18	0,33	0,26	0,39	0,17	0,31	0,18	0,31	0,20	0,37	0,28	0,46	0,34	0,50
IPC t_t1	0,62	0,53	0,47	0,36	0,46	0,38	0,47	0,37	0,59	0,44	0,20	0,17	0,12	0,18	1,00	0,69	0,22	0,16	0,55	0,38	0,24	0,17	0,69	0,49	0,16	0,16	0,28	0,23
IPC t_t2	0,40	0,71	0,41	0,58	0,44	0,61	0,45	0,60	0,50	0,71	0,34	0,33	0,28	0,33	0,69	1,00	0,47	0,42	0,39	0,61	0,27	0,30	0,47	0,72	0,37	0,40	0,44	0,47
AORD t_t1	0,10	0,50	0,30	0,54	0,29	0,53	0,31	0,51	0,22	0,46	0,36	0,31	0,36	0,26	0,22	0,47	1,00	0,64	0,20	0,54	0,27	0,33	0,20	0,48	0,54	0,39	0,52	0,42
AORD t_t2	0,04	0,39	0,19	0,50	0,17	0,49	0,21	0,50	0,17	0,43	0,27	0,43	0,27	0,39	0,16	0,42	0,64	1,00	0,16	0,51	0,21	0,39	0,09	0,37	0,35	0,60	0,39	0,61
S&P TSX t_t1	0,70	0,52	0,54	0,42	0,52	0,42	0,49	0,41	0,54	0,37	0,18	0,16	0,12	0,17	0,55	0,39	0,20	0,16	1,00	0,64	0,23	0,16	0,56	0,41	0,17	0,21	0,30	0,25
S&P TSX t_t2	0,39	0,73	0,46	0,66	0,43	0,63	0,45	0,64	0,42	0,62	0,34	0,36	0,28	0,31	0,38	0,61	0,54	0,51	0,64	1,00	0,26	0,31	0,37	0,61	0,41	0,46	0,44	0,48
BSE Sensex t_t1	0,20	0,31	0,35	0,31	0,32	0,32	0,34	0,32	0,18	0,15	0,31	0,22	0,26	0,18	0,24	0,27	0,27	0,21	0,23	0,26	1,00	0,69	0,22	0,24	0,22	0,14	0,38	0,27
BSE Sensex t_t2	0,09	0,28	0,21	0,35	0,19	0,37	0,20	0,36	0,18	0,24	0,27	0,36	0,25	0,31	0,17	0,30	0,33	0,39	0,16	0,31	0,69	1,00	0,11	0,26	0,25	0,28	0,34	0,45
Bovespa t_t1	0,64	0,51	0,47	0,40	0,44	0,38	0,45	0,39	0,64	0,43	0,21	0,15	0,21	0,20	0,69	0,47	0,20	0,09	0,56	0,37	0,22	0,11	1,00	0,66	0,19	0,17	0,27	0,19
Bovespa t_t2	0,41	0,71	0,42	0,60	0,42	0,59	0,40	0,57	0,54	0,74	0,36	0,31	0,34	0,37	0,49	0,72	0,48	0,37	0,41	0,61	0,24	0,26	0,66	1,00	0,38	0,39	0,40	0,41
Nikkei 225 t_t1	0,08	0,40	0,24	0,44	0,21	0,43	0,23	0,43	0,18	0,34	0,32	0,24	0,42	0,28	0,16	0,37	0,54	0,35	0,17	0,41	0,22	0,25	0,19	0,38	1,00	0,63	0,46	0,34
Nikkei 225 t_t2	0,09	0,37	0,15	0,46	0,15	0,47	0,18	0,50	0,19	0,39	0,26	0,39	0,33	0,46	0,16	0,40	0,39	0,60	0,21	0,46	0,14	0,28	0,17	0,39	0,63	1,00	0,36	0,56
HSI t_t1	0,15	0,42	0,35	0,42	0,37	0,45	0,32	0,40	0,29	0,39	0,47	0,35	0,37	0,34	0,28	0,44	0,52	0,39	0,30	0,44	0,38	0,34	0,27	0,40	0,46	0,36	1,00	0,67
HSI t_t2	0,12	0,40	0,24	0,48	0,26	0,51	0,24	0,47	0,30	0,46	0,34	0,52	0,34	0,50	0,23	0,47	0,42	0,61	0,25	0,48	0,27	0,45	0,19	0,41	0,34	0,56	0,67	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,14	0,07	0,04	0,00	0,00	0,03	0,38	0,00	0,00	0,00	0,06	0,00	0,00	0,07	0,06	0,00	0,01
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t2	0,14	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,01	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,04	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,38	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,01	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	0,00	0,00	0,01	NA	0,00	0,00	0,00	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,06	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Higher volatility on the Energy Commodity Market (State 2 - II)

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2
S&P 500 t_t1	1,00	0,64	0,49	0,36	0,54	0,39	0,46	0,31	0,32	0,17	0,10	0,03	0,17	0,14
S&P 500 t_t2	0,64	1,00	0,52	0,68	0,48	0,69	0,50	0,63	0,22	0,30	0,26	0,20	0,36	0,38
CAC 40 t_t1	0,49	0,52	1,00	0,68	0,89	0,64	0,87	0,58	0,19	0,16	0,17	0,08	0,23	0,18
CAC 40 t_t2	0,36	0,68	0,68	1,00	0,59	0,92	0,62	0,88	0,17	0,25	0,23	0,23	0,39	0,43
DAX t_t1	0,54	0,48	0,89	0,59	1,00	0,65	0,80	0,52	0,20	0,14	0,16	0,08	0,19	0,15
DAX t_t2	0,39	0,69	0,64	0,92	0,65	1,00	0,61	0,84	0,18	0,24	0,24	0,24	0,38	0,42
IBEX 35 t_t1	0,46	0,50	0,87	0,62	0,80	0,61	1,00	0,68	0,22	0,21	0,18	0,08	0,22	0,17
IBEX 35 t_t2	0,31	0,63	0,58	0,88	0,52	0,84	0,68	1,00	0,19	0,31	0,24	0,23	0,36	0,41
MERVAL t_t1	0,32	0,22	0,19	0,17	0,20	0,18	0,22	0,19	1,00	0,66	0,09	0,09	0,11	0,16
MERVAL t_t2	0,17	0,30	0,16	0,25	0,14	0,24	0,21	0,31	0,66	1,00	0,13	0,17	0,11	0,19
JKSE t_t1	0,10	0,26	0,17	0,23	0,16	0,24	0,18	0,24	0,09	0,13	1,00	0,64	0,30	0,23
JKSE t_t2	0,03	0,20	0,08	0,23	0,08	0,24	0,08	0,23	0,09	0,17	0,64	1,00	0,17	0,28
KOSPI t_t1	0,17	0,36	0,23	0,39	0,19	0,38	0,22	0,36	0,11	0,11	0,30	0,17	1,00	0,68
KOSPI t_t2	0,14	0,38	0,18	0,43	0,15	0,42	0,17	0,41	0,16	0,19	0,23	0,28	0,68	1,00
IPC t_t1	0,58	0,51	0,49	0,42	0,48	0,42	0,48	0,39	0,34	0,22	0,23	0,10	0,28	0,25
IPC t_t2	0,37	0,64	0,40	0,59	0,36	0,57	0,39	0,55	0,25	0,36	0,30	0,28	0,34	0,40
AORD t_t1	0,09	0,43	0,21	0,44	0,13	0,41	0,20	0,41	0,05	0,17	0,32	0,19	0,43	0,33
AORD t_t2	0,12	0,43	0,18	0,47	0,14	0,42	0,20	0,46	0,12	0,24	0,21	0,30	0,30	0,44
S&P TSX t_t1	0,71	0,55	0,52	0,43	0,51	0,45	0,50	0,39	0,33	0,21	0,15	0,08	0,24	0,22
S&P TSX t_t2	0,47	0,74	0,47	0,64	0,42	0,63	0,47	0,62	0,25	0,34	0,24	0,24	0,34	0,43
BSE Sensex t_t1	0,22	0,31	0,33	0,38	0,33	0,37	0,35	0,36	0,11	0,15	0,27	0,14	0,34	0,28
BSE Sensex t_t2	0,16	0,34	0,23	0,44	0,21	0,41	0,26	0,44	0,07	0,20	0,24	0,30	0,28	0,41
Bovespa t_t1	0,42	0,36	0,35	0,26	0,36	0,28	0,36	0,27	0,42	0,28	0,17	0,06	0,17	0,13
Bovespa t_t2	0,31	0,50	0,32	0,42	0,29	0,41	0,35	0,44	0,31	0,43	0,19	0,15	0,26	0,29
Nikkei 225 t_t1	0,17	0,39	0,25	0,43	0,22	0,40	0,25	0,41	0,08	0,16	0,25	0,17	0,42	0,34
Nikkei 225 t_t2	0,08	0,35	0,17	0,43	0,15	0,40	0,17	0,42	0,10	0,18	0,11	0,24	0,31	0,51
HSI t_t1	0,22	0,46	0,35	0,46	0,32	0,44	0,32	0,44	0,11	0,17	0,23	0,13	0,52	0,39
HSI t_t2	0,16	0,45	0,25	0,51	0,21	0,47	0,25	0,49	0,16	0,23	0,14	0,23	0,38	0,56

	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	0,58	0,37	0,09	0,12	0,71	0,47	0,22	0,16	0,42	0,31	0,17	0,08	0,22	0,16
S&P 500 t_t2	0,51	0,64	0,43	0,43	0,55	0,74	0,31	0,34	0,36	0,50	0,39	0,35	0,46	0,45
CAC 40 t_t1	0,49	0,40	0,21	0,18	0,52	0,47	0,33	0,23	0,35	0,32	0,25	0,17	0,35	0,25
CAC 40 t_t2	0,42	0,59	0,44	0,47	0,43	0,64	0,38	0,44	0,26	0,42	0,43	0,43	0,46	0,51
DAX t_t1	0,48	0,36	0,13	0,14	0,51	0,42	0,33	0,21	0,36	0,29	0,22	0,15	0,32	0,21
DAX t_t2	0,42	0,57	0,41	0,42	0,45	0,63	0,37	0,41	0,28	0,41	0,40	0,40	0,44	0,47
IBEX 35 t_t1	0,48	0,39	0,20	0,20	0,50	0,47	0,35	0,26	0,36	0,35	0,25	0,17	0,32	0,25
IBEX 35 t_t2	0,39	0,55	0,41	0,46	0,39	0,62	0,36	0,44	0,27	0,44	0,41	0,42	0,44	0,49
MERVAL t_t1	0,34	0,25	0,05	0,12	0,33	0,25	0,11	0,07	0,42	0,31	0,08	0,10	0,11	0,16
MERVAL t_t2	0,22	0,36	0,17	0,24	0,21	0,34	0,15	0,20	0,28	0,43	0,16	0,18	0,17	0,23
JKSE t_t1	0,23	0,30	0,32	0,21	0,15	0,24	0,27	0,24	0,17	0,19	0,25	0,11	0,23	0,14
JKSE t_t2	0,10	0,28	0,19	0,30	0,08	0,24	0,14	0,30	0,06	0,15	0,17	0,24	0,13	0,23
KOSPI t_t1	0,28	0,34	0,43	0,30	0,24	0,34	0,34	0,28	0,17	0,26	0,42	0,31	0,52	0,38
KOSPI t_t2	0,25	0,40	0,33	0,44	0,22	0,43	0,28	0,41	0,13	0,29	0,34	0,51	0,39	0,56
IPC t_t1	1,00	0,72	0,22	0,20	0,51	0,45	0,26	0,21	0,43	0,37	0,22	0,14	0,29	0,24
IPC t_t2	0,72	1,00	0,36	0,42	0,39	0,59	0,27	0,32	0,31	0,48	0,30	0,32	0,36	0,41
AORD t_t1	0,22	0,36	1,00	0,69	0,17	0,40	0,31	0,30	0,07	0,24	0,38	0,28	0,50	0,39
AORD t_t2	0,20	0,42	0,69	1,00	0,19	0,47	0,29	0,44	0,10	0,28	0,32	0,45	0,39	0,57
S&P TSX t_t1	0,51	0,39	0,17	0,19	1,00	0,69	0,28	0,22	0,45	0,39	0,14	0,11	0,25	0,20
S&P TSX t_t2	0,45	0,59	0,40	0,47	0,69	1,00	0,33	0,40	0,32	0,50	0,32	0,35	0,40	0,45
BSE Sensex t_t1	0,26	0,27	0,31	0,29	0,28	0,33	1,00	0,69	0,21	0,23	0,31	0,23	0,41	0,31
BSE Sensex t_t2	0,21	0,32	0,30	0,44	0,22	0,40	0,69	1,00	0,15	0,27	0,32	0,42	0,34	0,46
Bovespa t_t1	0,43	0,31	0,07	0,10	0,45	0,32	0,21	0,15	1,00	0,69	0,17	0,07	0,20	0,14
Bovespa t_t2	0,37	0,48	0,24	0,28	0,39	0,50	0,23	0,27	0,69	1,00	0,23	0,21	0,31	0,33
Nikkei 225 t_t1	0,22	0,30	0,38	0,32	0,14	0,32	0,31	0,32	0,17	0,23	1,00	0,66	0,48	0,37
Nikkei 225 t_t2	0,14	0,32	0,28	0,45	0,11	0,35	0,23	0,42	0,07	0,21	0,66	1,00	0,35	0,55
HSI t_t1	0,29	0,36	0,50	0,39	0,25	0,40	0,41	0,34	0,20	0,31	0,48	0,35	1,00	0,69
HSI t_t2	0,24	0,41	0,39	0,57	0,20	0,45	0,31	0,46	0,14	0,33	0,37	0,55	0,69	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,42	0,00	0,00
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,05	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,04	0,04	0,01	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,01	0,00
JKSE t_t1	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,04	0,00	NA	0,00	0,00	0,00
JKSE t_t2	0,42	0,00	0,06	0,00	0,06	0,00	0,05	0,00	0,04	0,00	0,00	NA	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,01	0,00	0,00	NA	0,00
KOSPI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,28	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,18	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00	0,00	0,00
Nikkei 225 t_t2	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,01	0,00	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
HSI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00
S&P 500 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,28	0,01	0,00	0,00	0,01	0,09	0,00	0,00	0,06	0,02	0,01	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
JKSE t_t2	0,01	0,00	0,00	0,00	0,07	0,00	0,00	0,00	0,18	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,11	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,11	0,02	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,13	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,13	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

<u>Higher volatility on the Precious Metals Commodity Market (State 2)</u>

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	1,00	0,62	0,56	0,39	0,55	0,38	0,50	0,33	0,51	0,30	0,12	0,05	0,17	0,09	0,64	0,40	0,12	0,07	0,69	0,40	0,21	0,11	0,59	0,38	0,09	0,04	0,17	0,09
S&P 500 t_t2	0,62	1,00	0,57	0,73	0,56	0,71	0,51	0,63	0,43	0,57	0,36	0,30	0,39	0,36	0,53	0,71	0,49	0,42	0,54	0,73	0,34	0,34	0,46	0,67	0,44	0,36	0,44	0,40
CAC 40 t_t1	0,56	0,57	1,00	0,67	0,91	0,62	0,86	0,57	0,44	0,37	0,27	0,17	0,26	0,18	0,51	0,45	0,28	0,19	0,53	0,45	0,37	0,24	0,45	0,43	0,26	0,17	0,34	0,23
CAC 40 t_t2	0,39	0,73	0,67	1,00	0,63	0,92	0,59	0,85	0,35	0,53	0,36	0,39	0,43	0,45	0,39	0,63	0,52	0,53	0,40	0,64	0,37	0,45	0,36	0,59	0,49	0,49	0,48	0,53
DAX t_t1	0,55	0,56	0,91	0,63	1,00	0,68	0,80	0,54	0,41	0,36	0,26	0,19	0,28	0,21	0,49	0,44	0,26	0,20	0,51	0,43	0,37	0,25	0,42	0,41	0,25	0,17	0,33	0,24
DAX t_t2	0,38	0,71	0,62	0,92	0,68	1,00	0,55	0,80	0,34	0,52	0,35	0,38	0,42	0,46	0,38	0,61	0,50	0,51	0,39	0,62	0,37	0,46	0,34	0,57	0,46	0,47	0,46	0,51
IBEX 35 t_t1	0,50	0,51	0,86	0,59	0,80	0,55	1,00	0,68	0,41	0,35	0,25	0,15	0,25	0,16	0,45	0,41	0,26	0,17	0,47	0,40	0,34	0,22	0,42	0,39	0,23	0,13	0,32	0,20
IBEX 35 t_t2	0,33	0,63	0,57	0,85	0,54	0,80	0,68	1,00	0,32	0,49	0,30	0,32	0,38	0,39	0,33	0,55	0,46	0,47	0,35	0,57	0,33	0,41	0,33	0,53	0,43	0,42	0,43	0,47
MERVAL t_t1	0,51	0,43	0,44	0,35	0,41	0,34	0,41	0,32	1,00	0,67	0,17	0,14	0,17	0,18	0,47	0,37	0,16	0,15	0,54	0,41	0,22	0,17	0,57	0,44	0,13	0,12	0,20	0,18
MERVAL t_t2	0,30	0,57	0,37	0,53	0,36	0,52	0,35	0,49	0,67	1,00	0,30	0,31	0,30	0,35	0,33	0,53	0,38	0,39	0,39	0,60	0,27	0,32	0,36	0,61	0,34	0,33	0,35	0,38
JKSE t_t1	0,12	0,36	0,27	0,36	0,26	0,35	0,25	0,30	0,17	0,30	1,00	0,67	0,44	0,32	0,22	0,37	0,42	0,34	0,18	0,37	0,37	0,32	0,18	0,35	0,39	0,27	0,50	0,37
JKSE t_t2	0,05	0,30	0,17	0,39	0,19	0,38	0,15	0,32	0,14	0,31	0,67	1,00	0,33	0,49	0,16	0,37	0,33	0,50	0,10	0,34	0,30	0,45	0,11	0,35	0,31	0,45	0,35	0,56
KOSPI t_t1	0,17	0,39	0,26	0,43	0,28	0,42	0,25	0,38	0,17	0,30	0,44	0,33	1,00	0,65	0,23	0,37	0,53	0,39	0,21	0,38	0,38	0,35	0,21	0,38	0,56	0,36	0,57	0,42
KOSPI t_t2	0,09	0,36	0,18	0,45	0,21	0,46	0,16	0,39	0,18	0,35	0,32	0,49	0,65	1,00	0,15	0,36	0,38	0,59	0,15	0,39	0,31	0,48	0,17	0,40	0,38	0,58	0,39	0,62
IPC t_t1	0,64	0,53	0,51	0,39	0,49	0,38	0,45	0,33	0,47	0,33	0,22	0,16	0,23	0,15	1,00	0,68	0,20	0,14	0,57	0,40	0,26	0,17	0,59	0,44	0,16	0,10	0,25	0,17
IPC t_t2	0,40	0,71	0,45	0,63	0,44	0,61	0,41	0,55	0,37	0,53	0,37	0,37	0,37	0,36	0,68	1,00	0,44	0,42	0,41	0,61	0,34	0,36	0,41	0,64	0,37	0,34	0,42	0,42
AORD t_t1	0,12	0,49	0,28	0,52	0,26	0,50	0,26	0,46	0,16	0,38	0,42	0,33	0,53	0,38	0,20	0,44	1,00	0,67	0,20	0,48	0,35	0,36	0,15	0,43	0,58	0,39	0,57	0,42
AORD t_t2	0,07	0,42	0,19	0,53	0,20	0,51	0,17	0,47	0,15	0,39	0,34	0,50	0,39	0,59	0,14	0,42	0,67	1,00	0,15	0,48	0,30	0,48	0,13	0,41	0,42	0,62	0,43	0,65
S&P TSX t_t1	0,69	0,54	0,53	0,40	0,51	0,39	0,47	0,35	0,54	0,39	0,18	0,10	0,21	0,15	0,57	0,41	0,20	0,15	1,00	0,65	0,26	0,18	0,59	0,45	0,15	0,12	0,25	0,17
S&P TSX t_t2	0,40	0,73	0,45	0,64	0,43	0,62	0,40	0,57	0,41	0,60	0,37	0,34	0,38	0,39	0,40	0,61	0,48	0,48	0,65	1,00	0,33	0,37	0,41	0,66	0,41	0,41	0,42	0,44
BSE Sensex t_t1	0,21	0,34	0,37	0,37	0,37	0,37	0,34	0,33	0,22	0,27	0,37	0,30	0,38	0,31	0,26	0,34	0,35	0,30	0,26	0,33	1,00	0,70	0,24	0,32	0,32	0,25	0,46	0,35
BSE Sensex t_t2	0,11	0,34	0,24	0,45	0,25	0,46	0,22	0,41	0,17	0,32	0,32	0,45	0,35	0,48	0,17	0,36	0,36	0,48	0,18	0,37	0,70	1,00	0,17	0,37	0,32	0,42	0,39	0,55
Bovespa t_t1	0,59	0,46	0,45	0,36	0,42	0,34	0,42	0,33	0,57	0,36	0,18	0,11	0,21	0,17	0,59	0,41	0,15	0,13	0,59	0,41	0,24	0,17	1,00	0,66	0,12	0,09	0,23	0,18
Bovespa t_t2	0,38	0,67	0,43	0,59	0,41	0,57	0,39	0,53	0,44	0,61	0,35	0,35	0,38	0,40	0,44	0,64	0,43	0,41	0,45	0,66	0,32	0,37	0,66	1,00	0,35	0,33	0,43	0,46
Nikkei 225 t_t1	0,09	0,44	0,26	0,49	0,25	0,46	0,23	0,43	0,13	0,34	0,39	0,31	0,56	0,38	0,16	0,37	0,58	0,42	0,15	0,41	0,32	0,32	0,12	0,35	1,00	0,64	0,53	0,40
Nikkei 225 t_t2	0,04	0,36	0,17	0,49	0,17	0,47	0,13	0,42	0,12	0,33	0,27	0,45	0,36	0,58	0,10	0,34	0,39	0,62	0,12	0,41	0,25	0,42	0,09	0,33	0,64	1,00	0,35	0,60
HSI t_t1	0,17	0,44	0,34	0,48	0,33	0,46	0,32	0,43	0,20	0,35	0,50	0,35	0,57	0,39	0,25	0,42	0,57	0,43	0,25	0,42	0,46	0,39	0,23	0,43	0,53	0,35	1,00	0,65
HSI t_t2	0,09	0,40	0,23	0,53	0,24	0,51	0,20	0,47	0,18	0,38	0,37	0,56	0,42	0,62	0,17	0,42	0,42	0,65	0,17	0,44	0,35	0,55	0,18	0,46	0,40	0,60	0,65	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t2	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

<u>Higher volatility on the Non-energy Commodity Market (State 2)</u>

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	1,00	0,59	0,53	0,35	0,52	0,36	0,48	0,32	0,58	0,31	0,11	0,03	0,19	0,08	0,66	0,39	0,09	0,03	0,66	0,33	0,24	0,12	0,66	0,39	0,09	0,04	0,18	0,09
S&P 500 t_t2	0,59	1,00	0,56	0,74	0,54	0,73	0,51	0,66	0,48	0,63	0,34	0,27	0,40	0,38	0,57	0,74	0,49	0,41	0,49	0,69	0,38	0,36	0,49	0,71	0,45	0,35	0,46	0,42
CAC 40 t_t1	0,53	0,56	1,00	0,64	0,92	0,61	0,87	0,56	0,47	0,38	0,30	0,15	0,30	0,17	0,52	0,46	0,30	0,20	0,48	0,43	0,43	0,26	0,47	0,43	0,29	0,17	0,36	0,23
CAC 40 t_t2	0,35	0,74	0,64	1,00	0,60	0,93	0,59	0,87	0,35	0,57	0,37	0,37	0,43	0,47	0,38	0,65	0,54	0,56	0,34	0,62	0,40	0,47	0,33	0,60	0,53	0,52	0,49	0,54
DAX t_t1	0,52	0,54	0,92	0,60	1,00	0,64	0,82	0,52	0,45	0,37	0,28	0,15	0,29	0,18	0,50	0,44	0,28	0,19	0,46	0,41	0,41	0,26	0,44	0,41	0,26	0,16	0,34	0,22
DAX t_t2	0,36	0,73	0,61	0,93	0,64	1,00	0,55	0,83	0,35	0,57	0,34	0,35	0,41	0,46	0,38	0,64	0,52	0,53	0,35	0,61	0,38	0,47	0,32	0,58	0,49	0,49	0,47	0,52
IBEX 35 t_t1	0,48	0,51	0,87	0,59	0,82	0,55	1,00	0,67	0,44	0,35	0,28	0,15	0,26	0,13	0,49	0,44	0,30	0,18	0,43	0,39	0,38	0,24	0,42	0,39	0,24	0,13	0,35	0,22
IBEX 35 t_t2	0,32	0,66	0,56	0,87	0,52	0,83	0,67	1,00	0,34	0,52	0,32	0,33	0,39	0,39	0,36	0,60	0,50	0,51	0,32	0,56	0,33	0,43	0,30	0,54	0,46	0,44	0,45	0,49
MERVAL t_t1	0,58	0,48	0,47	0,35	0,45	0,35	0,44	0,34	1,00	0,66	0,20	0,13	0,20	0,16	0,56	0,43	0,18	0,12	0,59	0,46	0,27	0,18	0,63	0,49	0,11	0,08	0,25	0,19
MERVAL t_t2	0,31	0,63	0,38	0,57	0,37	0,57	0,35	0,52	0,66	1,00	0,36	0,35	0,35	0,38	0,41	0,62	0,46	0,43	0,39	0,67	0,31	0,35	0,38	0,68	0,35	0,31	0,42	0,45
JKSE t_t1	0,11	0,34	0,30	0,37	0,28	0,34	0,28	0,32	0,20	0,36	1,00	0,68	0,46	0,32	0,24	0,38	0,43	0,33	0,16	0,38	0,44	0,34	0,19	0,40	0,40	0,29	0,55	0,39
JKSE t_t2	0,03	0,27	0,15	0,37	0,15	0,35	0,15	0,33	0,13	0,35	0,68	1,00	0,33	0,51	0,17	0,37	0,32	0,51	0,09	0,35	0,31	0,49	0,08	0,36	0,31	0,47	0,36	0,60
KOSPI t_t1	0,19	0,40	0,30	0,43	0,29	0,41	0,26	0,39	0,20	0,35	0,46	0,33	1,00	0,64	0,25	0,38	0,57	0,40	0,23	0,37	0,40	0,35	0,24	0,41	0,63	0,39	0,60	0,42
KOSPI t_t2	0,08	0,38	0,17	0,47	0,18	0,46	0,13	0,39	0,16	0,38	0,32	0,51	0,64	1,00	0,15	0,37	0,40	0,64	0,15	0,40	0,30	0,49	0,13	0,40	0,41	0,65	0,38	0,64
IPC t_t1	0,66	0,57	0,52	0,38	0,50	0,38	0,49	0,36	0,56	0,41	0,24	0,17	0,25	0,15	1,00	0,70	0,19	0,11	0,58	0,41	0,29	0,17	0,69	0,52	0,16	0,09	0,28	0,18
IPC t_t2	0,39	0,74	0,46	0,65	0,44	0,64	0,44	0,60	0,43	0,62	0,38	0,37	0,38	0,37	0,70	1,00	0,45	0,42	0,39	0,62	0,36	0,37	0,45	0,72	0,39	0,35	0,46	0,45
AORD t_t1	0,09	0,49	0,30	0,54	0,28	0,52	0,30	0,50	0,18	0,46	0,43	0,32	0,57	0,40	0,19	0,45	1,00	0,63	0,17	0,52	0,38	0,36	0,14	0,47	0,61	0,41	0,60	0,43
AORD t_t2	0,03	0,41	0,20	0,56	0,19	0,53	0,18	0,51	0,12	0,43	0,33	0,51	0,40	0,64	0,11	0,42	0,63	1,00	0,12	0,49	0,30	0,49	0,07	0,39	0,43	0,68	0,42	0,68
S&P TSX t_t1	0,66	0,49	0,48	0,34	0,46	0,35	0,43	0,32	0,59	0,39	0,16	0,09	0,23	0,15	0,58	0,39	0,17	0,12	1,00	0,61	0,27	0,17	0,65	0,45	0,15	0,12	0,23	0,16
S&P TSX t_t2	0,33	0,69	0,43	0,62	0,41	0,61	0,39	0,56	0,46	0,67	0,38	0,35	0,37	0,40	0,41	0,62	0,52	0,49	0,61	1,00	0,34	0,37	0,41	0,69	0,42	0,42	0,43	0,45
BSE Sensex t_t1	0,24	0,38	0,43	0,40	0,41	0,38	0,38	0,33	0,27	0,31	0,44	0,31	0,40	0,30	0,29	0,36	0,38	0,30	0,27	0,34	1,00	0,69	0,27	0,35	0,33	0,25	0,50	0,37
BSE Sensex t_t2	0,12	0,36	0,26	0,47	0,26	0,47	0,24	0,43	0,18	0,35	0,34	0,49	0,35	0,49	0,17	0,37	0,36	0,49	0,17	0,37	0,69	1,00	0,16	0,38	0,32	0,44	0,39	0,59
Bovespa t_t1	0,66	0,49	0,47	0,33	0,44	0,32	0,42	0,30	0,63	0,38	0,19	0,08	0,24	0,13	0,69	0,45	0,14	0,07	0,65	0,41	0,27	0,16	1,00	0,64	0,13	0,08	0,25	0,16
Bovespa t_t2	0,39	0,71	0,43	0,60	0,41	0,58	0,39	0,54	0,49	0,68	0,40	0,36	0,41	0,40	0,52	0,72	0,47	0,39	0,45	0,69	0,35	0,38	0,64	1,00	0,38	0,34	0,46	0,48
Nikkei 225 t_t1	0,09	0,45	0,29	0,53	0,26	0,49	0,24	0,46	0,11	0,35	0,40	0,31	0,63	0,41	0,16	0,39	0,61	0,43	0,15	0,42	0,33	0,32	0,13	0,38	1,00	0,62	0,55	0,41
Nikkei 225 t_t2	0,04	0,35	0,17	0,52	0,16	0,49	0,13	0,44	0,08	0,31	0,29	0,47	0,39	0,65	0,09	0,35	0,41	0,68	0,12	0,42	0,25	0,44	0,08	0,34	0,62	1,00	0,34	0,62
HSI t_t1	0,18	0,46	0,36	0,49	0,34	0,47	0,35	0,45	0,25	0,42	0,55	0,36	0,60	0,38	0,28	0,46	0,60	0,42	0,23	0,43	0,50	0,39	0,25	0,46	0,55	0,34	1,00	0,62
HSI t_t2	0,09	0,42	0,23	0,54	0,22	0,52	0,22	0,49	0,19	0,45	0,39	0,60	0,42	0,64	0,18	0,45	0,43	0,68	0,16	0,45	0,37	0,59	0,16	0,48	0,41	0,62	0,62	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,37	0,00	0,01	0,00	0,00	0,00	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,24	0,00	0,00
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t2	0,37	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,32	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,02	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,24	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl*

Lower volatility on the Energy, Precious Metals and Non-energy Commodity Market (State 1)

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2
S&P 500 t_t1	1,00	0,66	0,41	0,29	0,48	0,33	0,37	0,25	0,32	0,21	0,00	0,00	0,10	0,08
S&P 500 t_t2	0,66	1,00	0,50	0,59	0,49	0,62	0,43	0,52	0,24	0,34	0,13	0,07	0,27	0,23
CAC 40 t_t1	0,41	0,50	1,00	0,66	0,82	0,58	0,80	0,54	0,23	0,23	0,11	0,04	0,24	0,14
CAC 40 t_t2	0,29	0,59	0,66	1,00	0,56	0,84	0,53	0,80	0,16	0,27	0,17	0,12	0,33	0,32
DAX t_t1	0,48	0,49	0,82	0,56	1,00	0,66	0,74	0,49	0,24	0,22	0,10	0,05	0,23	0,15
DAX t_t2	0,33	0,62	0,58	0,84	0,66	1,00	0,54	0,76	0,17	0,27	0,19	0,15	0,34	0,34
IBEX 35 t_t1	0,37	0,43	0,80	0,53	0,74	0,54	1,00	0,67	0,28	0,28	0,11	0,05	0,23	0,16
IBEX 35 t_t2	0,25	0,52	0,54	0,80	0,49	0,76	0,67	1,00	0,18	0,30	0,16	0,12	0,30	0,32
MERVAL t_t1	0,32	0,24	0,23	0,16	0,24	0,17	0,28	0,18	1,00	0,67	0,01	-0,02	0,08	0,04
MERVAL t_t2	0,21	0,34	0,23	0,27	0,22	0,27	0,28	0,30	0,67	1,00	0,07	0,02	0,15	0,13
JKSE t_t1	0,00	0,13	0,11	0,17	0,10	0,19	0,11	0,16	0,01	0,07	1,00	0,71	0,22	0,20
JKSE t_t2	0,00	0,07	0,04	0,12	0,05	0,15	0,05	0,12	-0,02	0,02	0,71	1,00	0,14	0,24
KOSPI t_t1	0,10	0,27	0,24	0,33	0,23	0,34	0,23	0,30	0,08	0,15	0,22	0,14	1,00	0,67
KOSPI t_t2	0,08	0,23	0,14	0,32	0,15	0,34	0,16	0,32	0,04	0,13	0,20	0,24	0,67	1,00
IPC t_t1	0,57	0,47	0,36	0,28	0,39	0,29	0,36	0,27	0,34	0,23	0,05	0,04	0,15	0,11
IPC t_t2	0,37	0,59	0,36	0,46	0,34	0,45	0,35	0,44	0,23	0,34	0,14	0,09	0,27	0,24
AORD t_t1	0,08	0,42	0,27	0,42	0,20	0,41	0,23	0,40	0,09	0,20	0,19	0,14	0,34	0,24
AORD t_t2	0,06	0,31	0,15	0,41	0,13	0,39	0,16	0,39	0,07	0,18	0,19	0,21	0,27	0,37
S&P TSX t_t1	0,64	0,54	0,44	0,33	0,48	0,34	0,40	0,29	0,30	0,22	0,05	0,01	0,17	0,10
S&P TSX t_t2	0,41	0,70	0,44	0,55	0,42	0,55	0,37	0,47	0,20	0,30	0,12	0,08	0,30	0,25
BSE Sensex t_t1	0,06	0,15	0,19	0,18	0,16	0,19	0,20	0,20	0,07	0,13	0,19	0,17	0,25	0,20
BSE Sensex t_t2	0,07	0,13	0,13	0,20	0,12	0,22	0,17	0,24	0,06	0,11	0,19	0,25	0,24	0,30
Bovespa t_t1	0,47	0,36	0,27	0,18	0,31	0,23	0,28	0,19	0,37	0,22	0,07	0,05	0,15	0,10
Bovespa t_t2	0,32	0,48	0,31	0,34	0,31	0,37	0,30	0,33	0,25	0,34	0,14	0,11	0,25	0,23
Nikkei 225 t_t1	0,11	0,37	0,24	0,38	0,22	0,38	0,22	0,34	0,11	0,18	0,18	0,12	0,44	0,32
Nikkei 225 t_t2	0,06	0,28	0,13	0,37	0,13	0,37	0,13	0,33	0,06	0,16	0,16	0,21	0,32	0,47
HSI t_t1	0,11	0,34	0,31	0,35	0,26	0,37	0,26	0,33	0,14	0,21	0,24	0,16	0,45	0,32
HSI t_t2	0,06	0,27	0,16	0,38	0,15	0,39	0,16	0,36	0,06	0,19	0,25	0,27	0,35	0,48

	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	0,57	0,37	0,08	0,06	0,64	0,41	0,06	0,07	0,47	0,32	0,11	0,06	0,11	0,06
S&P 500 t_t2	0,47	0,59	0,42	0,31	0,54	0,70	0,15	0,13	0,36	0,48	0,37	0,28	0,34	0,27
CAC 40 t_t1	0,36	0,36	0,27	0,15	0,44	0,44	0,19	0,13	0,27	0,31	0,24	0,13	0,31	0,16
CAC 40 t_t2	0,28	0,46	0,42	0,41	0,33	0,55	0,18	0,20	0,18	0,34	0,38	0,37	0,35	0,38
DAX t_t1	0,39	0,34	0,20	0,13	0,48	0,42	0,16	0,12	0,31	0,31	0,22	0,13	0,26	0,15
DAX t_t2	0,29	0,45	0,41	0,39	0,34	0,55	0,19	0,22	0,23	0,37	0,38	0,37	0,37	0,39
IBEX 35 t_t1	0,36	0,35	0,23	0,16	0,40	0,37	0,20	0,17	0,28	0,30	0,22	0,13	0,26	0,16
IBEX 35 t_t2	0,27	0,44	0,40	0,39	0,29	0,47	0,20	0,24	0,19	0,33	0,34	0,33	0,33	0,36
MERVAL t_t1	0,34	0,23	0,09	0,07	0,30	0,20	0,07	0,06	0,37	0,25	0,11	0,06	0,14	0,06
MERVAL t_t2	0,23	0,34	0,20	0,18	0,22	0,30	0,13	0,11	0,22	0,34	0,18	0,16	0,21	0,19
JKSE t_t1	0,05	0,14	0,19	0,19	0,05	0,12	0,19	0,19	0,07	0,14	0,18	0,16	0,24	0,25
JKSE t_t2	0,04	0,09	0,14	0,21	0,01	0,08	0,17	0,25	0,05	0,11	0,12	0,21	0,16	0,27
KOSPI t_t1	0,15	0,27	0,34	0,27	0,17	0,30	0,25	0,24	0,15	0,25	0,44	0,32	0,45	0,35
KOSPI t_t2	0,11	0,24	0,24	0,37	0,10	0,25	0,20	0,30	0,10	0,23	0,32	0,47	0,32	0,48
IPC t_t1	1,00	0,71	0,17	0,13	0,46	0,36	0,15	0,13	0,51	0,38	0,15	0,08	0,22	0,14
IPC t_t2	0,71	1,00	0,36	0,32	0,33	0,49	0,20	0,20	0,35	0,50	0,29	0,24	0,35	0,31
AORD t_t1	0,17	0,36	1,00	0,67	0,18	0,41	0,17	0,15	0,15	0,29	0,42	0,32	0,38	0,30
AORD t_t2	0,13	0,32	0,67	1,00	0,11	0,36	0,17	0,22	0,09	0,25	0,32	0,47	0,31	0,44
S&P TSX t_t1	0,46	0,33	0,18	0,11	1,00	0,68	0,10	0,08	0,40	0,32	0,15	0,10	0,20	0,12
S&P TSX t_t2	0,36	0,49	0,41	0,36	0,68	1,00	0,17	0,16	0,28	0,41	0,32	0,30	0,35	0,32
BSE Sensex t_t1	0,15	0,20	0,17	0,17	0,10	0,17	1,00	0,69	0,10	0,15	0,18	0,18	0,25	0,22
BSE Sensex t_t2	0,13	0,20	0,15	0,22	0,08	0,16	0,69	1,00	0,12	0,17	0,17	0,23	0,20	0,28
Bovespa t_t1	0,51	0,35	0,15	0,09	0,40	0,28	0,10	0,12	1,00	0,70	0,14	0,08	0,18	0,11
Bovespa t_t2	0,38	0,50	0,29	0,25	0,32	0,41	0,15	0,17	0,70	1,00	0,26	0,23	0,28	0,27
Nikkei 225 t_t1	0,15	0,29	0,42	0,32	0,15	0,32	0,18	0,17	0,14	0,26	1,00	0,67	0,42	0,31
Nikkei 225 t_t2	0,08	0,24	0,32	0,47	0,10	0,30	0,18	0,23	0,08	0,23	0,67	1,00	0,28	0,43
HSI t_t1	0,22	0,35	0,38	0,31	0,20	0,35	0,25	0,20	0,18	0,28	0,42	0,28	1,00	0,67
HSI t_t2	0,14	0,31	0,30	0,44	0,12	0,32	0,22	0,28	0,11	0,27	0,31	0,43	0,67	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,00	0,94	0,00	0,00
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,15	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,07	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,12	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,64	0,43	0,00	0,13
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,01	0,40	0,00	0,00
JKSE t_t1	1,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,64	0,01	NA	0,00	0,00	0,00
JKSE t_t2	0,94	0,02	0,15	0,00	0,07	0,00	0,12	0,00	0,43	0,40	0,00	NA	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
KOSPI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,13	0,00	0,00	0,00	0,00	NA
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,09	0,21	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,02	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,12	0,77	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,08	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Nikkei 225 t_t2	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
HSI t_t2	0,05	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00

	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	0,00	0,00	0,01	0,05	0,00	0,00	0,05	0,02	0,00	0,00	0,00	0,04	0,00	0,05
S&P 500 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,02	0,00	0,00	0,01	0,03	0,00	0,00	0,00	0,05	0,00	0,03
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,09	0,00	0,00	0,00	0,12	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00
JKSE t_t2	0,21	0,00	0,00	0,00	0,77	0,00	0,00	0,00	0,08	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
IPC t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,01	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace, Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Higher volatility on the Energy, Precious Metals and Non-energy Commodity Market (State 2)

Spearman Correlation coefficients

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	1,00	0,62	0,59	0,39	0,59	0,42	0,58	0,37	0,66	0,35	0,16	0,06	0,27	0,19	0,75	0,45	0,17	0,08	0,75	0,38	0,34	0,22	0,78	0,46	0,09	0,11	0,22	0,18
S&P 500 t_t2	0,62	1,00	0,66	0,78	0,62	0,78	0,67	0,75	0,60	0,69	0,42	0,33	0,50	0,45	0,71	0,82	0,57	0,40	0,56	0,74	0,45	0,47	0,59	0,81	0,56	0,42	0,51	0,49
CAC 40 t_t1	0,59	0,66	1,00	0,71	0,93	0,71	0,91	0,65	0,55	0,43	0,35	0,22	0,41	0,27	0,64	0,57	0,39	0,22	0,59	0,51	0,51	0,38	0,57	0,54	0,40	0,25	0,38	0,30
CAC 40 t_t2	0,39	0,78	0,71	1,00	0,66	0,93	0,70	0,92	0,49	0,66	0,48	0,50	0,49	0,52	0,55	0,79	0,63	0,55	0,46	0,73	0,46	0,57	0,46	0,75	0,61	0,60	0,51	0,59
DAX t_t1	0,59	0,62	0,93	0,66	1,00	0,73	0,85	0,61	0,56	0,43	0,30	0,21	0,43	0,29	0,66	0,56	0,34	0,18	0,59	0,47	0,48	0,34	0,56	0,50	0,35	0,24	0,35	0,27
DAX t_t2	0,42	0,78	0,71	0,93	0,73	1,00	0,67	0,87	0,53	0,67	0,42	0,46	0,52	0,54	0,59	0,82	0,57	0,49	0,49	0,70	0,47	0,56	0,49	0,73	0,57	0,56	0,50	0,56
IBEX 35 t_t1	0,58	0,67	0,91	0,70	0,85	0,67	1,00	0,74	0,56	0,48	0,39	0,26	0,41	0,27	0,66	0,60	0,42	0,27	0,56	0,53	0,51	0,37	0,57	0,52	0,39	0,28	0,42	0,35
IBEX 35 t_t2	0,37	0,75	0,65	0,92	0,61	0,87	0,74	1,00	0,52	0,68	0,47	0,50	0,49	0,53	0,54	0,77	0,61	0,59	0,44	0,72	0,47	0,59	0,43	0,69	0,60	0,63	0,53	0,61
MERVAL t_t1	0,66	0,60	0,55	0,49	0,56	0,53	0,56	0,52	1,00	0,71	0,34	0,28	0,33	0,36	0,68	0,55	0,24	0,23	0,68	0,55	0,35	0,32	0,72	0,60	0,23	0,28	0,30	0,31
MERVAL t_t2	0,35	0,69	0,43	0,66	0,43	0,67	0,48	0,68	0,71	1,00	0,53	0,54	0,43	0,49	0,54	0,75	0,48	0,47	0,45	0,73	0,31	0,44	0,47	0,77	0,47	0,48	0,50	0,55
JKSE t_t1	0,16	0,42	0,35	0,48	0,30	0,42	0,39	0,47	0,34	0,53	1,00	0,72	0,50	0,35	0,35	0,49	0,48	0,40	0,20	0,44	0,43	0,38	0,26	0,49	0,47	0,37	0,61	0,52
JKSE t_t2	0,06	0,33	0,22	0,50	0,21	0,46	0,26	0,50	0,28	0,54	0,72	1,00	0,45	0,57	0,27	0,50	0,47	0,61	0,14	0,47	0,32	0,50	0,15	0,47	0,43	0,61	0,48	0,72
KOSPI t_t1	0,27	0,50	0,41	0,49	0,43	0,52	0,41	0,49	0,33	0,43	0,50	0,45	1,00	0,69	0,41	0,50	0,56	0,37	0,29	0,39	0,47	0,46	0,39	0,52	0,63	0,44	0,66	0,51
KOSPI t_t2	0,19	0,45	0,27	0,52	0,29	0,54	0,27	0,53	0,36	0,49	0,35	0,57	0,69	1,00	0,35	0,54	0,46	0,59	0,25	0,48	0,39	0,57	0,30	0,53	0,47	0,71	0,51	0,69
IPC t_t1	0,75	0,71	0,64	0,55	0,66	0,59	0,66	0,54	0,68	0,54	0,35	0,27	0,41	0,35	1,00	0,73	0,34	0,24	0,70	0,53	0,42	0,32	0,75	0,61	0,25	0,23	0,41	0,35
IPC t_t2	0,45	0,82	0,57	0,79	0,56	0,82	0,60	0,77	0,55	0,75	0,49	0,50	0,50	0,54	0,73	1,00	0,60	0,51	0,45	0,72	0,46	0,51	0,50	0,81	0,55	0,52	0,61	0,64
AORD t_t1	0,17	0,57	0,39	0,63	0,34	0,57	0,42	0,61	0,24	0,48	0,48	0,47	0,56	0,46	0,34	0,60	1,00	0,65	0,21	0,56	0,45	0,53	0,22	0,54	0,68	0,49	0,62	0,54
AORD t_t2	0,08	0,40	0,22	0,55	0,18	0,49	0,27	0,59	0,23	0,47	0,40	0,61	0,37	0,59	0,24	0,51	0,65	1,00	0,13	0,51	0,36	0,57	0,12	0,40	0,46	0,77	0,49	0,71
S&P TSX t_t1	0,75	0,56	0,59	0,46	0,59	0,49	0,56	0,44	0,68	0,45	0,20	0,14	0,29	0,25	0,70	0,45	0,21	0,13	1,00	0,62	0,34	0,29	0,77	0,51	0,20	0,22	0,28	0,25
S&P TSX t_t2	0,38	0,74	0,51	0,73	0,47	0,70	0,53	0,72	0,55	0,73	0,44	0,47	0,39	0,48	0,53	0,72	0,56	0,51	0,62	1,00	0,36	0,47	0,50	0,77	0,53	0,56	0,45	0,55
BSE Sensex t_t1	0,34	0,45	0,51	0,46	0,48	0,47	0,51	0,47	0,35	0,31	0,43	0,32	0,47	0,39	0,42	0,46	0,45	0,36	0,34	0,36	1,00	0,72	0,35	0,41	0,38	0,34	0,58	0,46
BSE Sensex t_t2	0,22	0,47	0,38	0,57	0,34	0,56	0,37	0,59	0,32	0,44	0,38	0,50	0,46	0,57	0,32	0,51	0,53	0,57	0,29	0,47	0,72	1,00	0,24	0,47	0,43	0,54	0,53	0,68
Bovespa t_t1	0,78	0,59	0,57	0,46	0,56	0,49	0,57	0,43	0,72	0,47	0,26	0,15	0,39	0,30	0,75	0,50	0,22	0,12	0,77	0,50	0,35	0,24	1,00	0,65	0,21	0,15	0,33	0,25
Bovespa t_t2	0,46	0,81	0,54	0,75	0,50	0,73	0,52	0,69	0,60	0,77	0,49	0,47	0,52	0,53	0,61	0,81	0,54	0,40	0,51	0,77	0,41	0,47	0,65	1,00	0,53	0,46	0,53	0,58
Nikkei 225 t_t1	0,09	0,56	0,40	0,61	0,35	0,57	0,39	0,60	0,23	0,47	0,47	0,43	0,63	0,47	0,25	0,55	0,68	0,46	0,20	0,53	0,38	0,43	0,21	0,53	1,00	0,61	0,62	0,51
Nikkei 225 t_t2	0,11	0,42	0,25	0,60	0,24	0,56	0,28	0,63	0,28	0,48	0,37	0,61	0,44	0,71	0,23	0,52	0,49	0,77	0,22	0,56	0,34	0,54	0,15	0,46	0,61	1,00	0,46	0,75
HSI t_t1	0,22	0,51	0,38	0,51	0,35	0,50	0,42	0,53	0,30	0,50	0,61	0,48	0,66	0,51	0,41	0,61	0,62	0,49	0,28	0,45	0,58	0,53	0,33	0,53	0,62	0,46	1,00	0,72
HSI t_t2	0,18	0,49	0,30	0,59	0,27	0,56	0,35	0,61	0,31	0,55	0,52	0,72	0,51	0,69	0,35	0,64	0,54	0,71	0,25	0,55	0,46	0,68	0,25	0,58	0,51	0,75	0,72	1,00

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace*, *Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	S&P 500 t_t1	S&P 500 t_t2	CAC 40 t_t1	CAC 40 t_t2	DAX t_t1	DAX t_t2	IBEX 35 t_t1	IBEX 35 t_t2	MERVAL t_t1	MERVAL t_t2	JKSE t_t1	JKSE t_t2	KOSPI t_t1	KOSPI t_t2	IPC t_t1	IPC t_t2	AORD t_t1	AORD t_t2	S&P TSX t_t1	S&P TSX t_t2	BSE Sensex t_t1	BSE Sensex t_t2	Bovespa t_t1	Bovespa t_t2	Nikkei 225 t_t1	Nikkei 225 t_t2	HSI t_t1	HSI t_t2
S&P 500 t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,38	0,00	0,01	0,00	0,00	0,01	0,27	0,00	0,00	0,00	0,00	0,00	0,00	0,18	0,10	0,00	0,01
S&P 500 t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
CAC 40 t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
DAX t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IBEX 35 t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
MERVAL t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t1	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
JKSE t_t2	0,38	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00
KOSPI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
KOSPI t_t2	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
IPC t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t1	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
AORD t_t2	0,27	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,05	0,00	0,00	0,00	0,09	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00	0,00	0,00	0,05	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
S&P TSX t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
BSE Sensex t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Bovespa t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	0,00	0,00	0,00	0,09	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,03	0,00	0,00
Bovespa t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Nikkei 225 t_t1	0,18	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Nikkei 225 t_t2	0,10	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,03	0,00	0,00	NA	0,00	0,00
HSI t_t1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
HSI t_t2	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio and Excel, *Hmisc*, *Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace*, *Nikkei and Central Bank of Brazil Statistical Database* with the help of *Quandl.*

Appendix 5

AUC and IV's ranks

Higher volatility on the Energy Commodity Market (State 2 - I)

AUC and IV values' ranks, SSEC Index, Energy Commodity Market (State2 - I)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8_	IV_9	IV_10	IV_11_	IV_12	IV_ave	IV_rank
S&P 500 t_t2	1	1	3	8	6	2	4	1	8	3.8	2
S&P 500 t_t1	2	3	1	7	5	3	10	6	1	4.2	3
S&P TSX t_t1	3	8	5	2	3	1	1	2	3	3.1	1
MERVAL t_t2	4	2	6	5	7	10	7	4	6	5.7	5
DAX t_t1	5	11	2	3	4	6	5	11	5	5.8	6
S&P TSX t_t2	6	6	15	4	10	9	3	8	2	7.0	7
Bovespa t_t1	7	9	12	6	16	14	16	19	15	12.7	12
MERVAL t_t1	8	16	16	19	11	12	22	14	23	15.7	14
IBEX 35 t_t2	9	13	9	12	17	13	13	10	9	11.7	10
Bovespa t_t2	10	14	17	18	18	16	24	21	20	17.6	17
IBEX 35 t_t1	11	17	14	15	19	20	23	18	16	17.0	16
IPC t_t1	12	5	4	11	1	4	2	3	4	5.1	4
DAX t_t2	13	19	23	22	22	19	14	23	24	19.9	21
IPC t_t2	14	22	18	13	24	21	19	5	22	17.6	17
BSE Sensex t_t1	15	10	11	9	14	7	12	17	14	12.1	11
CAC 40 t_t1	16	20	20	20	21	26	20	12	25	20.0	23
CAC 40 t_t2	17	18	13	16	23	22	6	22	13	16.7	15
JKSE t_t1	18	4	7	10	9	11	9	7	10	9.4	9
KOSPI t_t2	19	12	10	14	20	5	8	16	11	12.8	13
KOSPI t_t1	20	26	22	24	26	23	26	27	21	23.9	25
HSI t_t1	21	23	19	21	12	18	21	20	12	18.6	19
JKSE t_t2	22	7	8	1	2	8	11	9	7	8.3	8
BSE Sensex t_t2	23	24	26	23	15	17	17	15	19	19.9	21
HSI t_t2	24	15	21	17	13	25	15	13	26	18.8	20
AORD t_t1	25	21	25	26	8	15	25	24	18	20.8	24
AORD t_t2	26	27	24	27	25	28	27	28	27	26.6	27
Nikkei 225 t_t1	27	28	28	28	27	27	28	26	28	27.4	28
Nikkei 225 t_t2	28	25	27	25	28	24	18	25	17	24.1	26

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*

Higher volatility on the Energy Commodity Market (State 2 - II)

AUC and IV values' ranks, SSEC Index, Energy Commodity Market (State2 - II)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
IBEX 35 t_t1	1	5	18	9	7	14	12	13	14	11.5	10
KOSPI t_t1	2	8	12	18	11	7	17	8	12	11.6	11
S&P TSX t_t1	3	2	14	8	5	3	6	5	6	6.1	4
IBEX 35 t_t2	4	13	6	4	6	16	2	2	4	6.6	5
HSI t_t1	5	7	4	10	16	10	10	15	13	10.6	9
AORD t_t2	6	4	1	5	1	4	1	4	1	2.6	2
S&P TSX t_t2	7	20	19	19	23	23	25	24	16	21.1	24
KOSPI t_t2	8	19	24	21	10	15	26	23	15	19.1	20
IPC t_t1	9	3	9	6	19	6	5	10	8	8.3	6
DAX t_t1	10	24	13	23	12	20	14	16	18	17.5	18
CAC 40 t_t1	11	10	2	1	2	2	3	3	3	3.3	3
JKSE t_t1	12	16	17	14	9	21	7	26	25	16.9	17
DAX t_t2	13	17	21	25	22	22	16	20	21	20.5	23
S&P 500 t_t2	14	6	10	24	8	18	13	9	17	13.1	13
JKSE t_t2	15	23	26	16	18	24	24	21	23	21.9	25
HSI t_t2	16	1	3	2	3	1	4	1	2	2.1	1
IPC t_t2	17	14	16	7	4	5	11	11	7	9.4	7
Nikkei 225 t_t2	18	25	5	28	20	8	15	18	5	15.5	15
S&P 500 t_t1	19	11	11	12	13	11	18	25	24	15.6	16
AORD t_t1	20	12	25	3	15	9	9	14	9	12.0	12
CAC 40 t_t2	21	26	28	27	28	28	27	27	27	27.3	28
BSE Sensex t_t1	22	15	27	15	24	26	19	17	10	19.1	20
MERVAL t_t1	23	27	15	20	21	19	23	19	19	20.4	22
Nikkei 225 t_t1	24	9	7	11	17	12	8	6	11	10.1	8
BSE Sensex t_t2	25	28	20	22	27	27	28	28	26	25.8	27
Bovespa t_t2	26	21	22	13	25	17	22	12	20	19.0	19
MERVAL t_t2	27	18	8	17	14	13	20	7	22	14.9	14
Bovespa t_t1	28	22	23	26	26	25	21	22	28	24.1	26

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Higher volatility on the Precious Metals Commodity Market (State 2)

AUC and IV values' ranks, SSEC Index, Precious Metals Commodity Market (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
S&P 500 t_t1	1	2	1	1	2	2	2	2	3	1,9	1
Bovespa t_t1	2	1	5	7	7	7	5	4	7	5.4	6
DAX t_t1	3	6	3	5	6	4	7	5	6	5.3	5
MERVAL t_t1	4	9	9	8	10	10	11	7	8	9.0	9

CAC 40 t_t1	5	4	8	3	1	3	1	1	1	2.8	2
IBEX 35 t_t1	6	3	4	6	4	6	4	6	5	4.8	4
S&P TSX t_t1	7	7	2	4	3	1	3	3	2	3.1	3
S&P 500 t_t2	8	5	6	2	5	9	6	8	4	5.6	7
IPC t_t1	9	8	7	10	8	8	10	9	9	8.6	8
S&P TSX t_t2	10	10	11	15	14	13	15	13	15	13.3	12
Bovespa t_t2	11	13	16	9	15	19	13	14	10	13.6	13
IBEX 35 t_t2	12	12	19	13	9	15	12	12	13	13.1	11
DAX t_t2	13	17	14	19	18	20	24	20	17	18.6	18
CAC 40 t_t2	14	14	17	14	21	12	21	17	21	17.1	15
BSE Sensex t_t1	15	11	23	16	13	11	8	10	18	13.8	14
HSI t_t1	16	20	26	28	26	25	23	28	26	25.3	26
JKSE t_t1	17	26	25	24	24	27	27	27	24	25.5	27
MERVAL t_t2	18	21	13	12	11	5	9	11	12	11.8	10
IPC t_t2	19	15	22	21	20	18	22	23	23	20.5	23
BSE Sensex t_t2	20	24	21	11	22	23	17	16	22	19.5	20
KOSPI t_t2	21	23	15	22	23	14	25	21	20	20.4	22
KOSPI t_t1	22	22	18	17	12	26	14	15	14	17.3	16
JKSE t_t2	23	16	28	26	27	24	20	25	25	23.9	25
HSI t_t2	24	25	10	25	16	17	16	24	16	18.6	18
Nikkei 225 t_t2	25	27	27	27	28	28	28	26	28	27.4	28
AORD t_t2	26	28	12	18	17	16	18	19	11	17.4	17
Nikkei 225 t_t1	27	18	20	20	19	21	19	22	19	19.8	21
AORD t_t1	28	19	24	23	25	22	26	18	27	23.0	24

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Higher volatility on the Non-energy Commodity Market (State 2)

Table 42 AUC and IV values' ranks, SSEC Index, Non-energy Commodity Market (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
IPC t_t1	1	2	8	2	6	6	8	2	10	5.5	5
Bovespa t_t1	2	7	5	3	1	4	7	11	5	5.4	4
S&P 500 t_t1	3	4	7	6	2	3	4	3	11	5.0	3
IBEX 35 t_t1	4	5	1	10	5	8	5	5	7	5.8	7
DAX t_t1	5	1	2	8	8	9	3	6	12	6.1	8
CAC 40 t_t1	6	6	3	1	3	5	6	1	2	3.4	1
S&P 500 t_t2	7	8	4	7	7	11	10	10	4	7.6	9
MERVAL t_t1	8	9	10	11	9	7	9	9	6	8.8	10
S&P TSX t_t1	9	3	9	4	4	2	1	4	3	3.8	2
S&P TSX t_t2	10	11	12	14	10	10	11	12	8	11.0	11
JKSE t_t1	11	10	13	12	13	21	15	17	16	14.6	14
MERVAL t_t2	12	13	14	9	21	16	13	8	13	13.4	13
Bovespa t_t2	13	12	6	5	11	1	2	7	1	5.6	6

HSI t_t1	14	17	23	19	19	20	24	23	15	20.0	19
BSE Sensex t_t1	15	25	24	15	16	23	23	24	23	21.6	23
IPC t_t2	16	19	17	18	18	13	25	21	18	18.6	18
IBEX 35 t_t2	17	15	15	17	15	17	18	18	20	16.9	16
DAX t_t2	18	16	18	16	17	14	17	20	14	16.5	15
CAC 40 t_t2	19	24	21	20	23	15	20	15	22	20.0	19
KOSPI t_t1	20	20	16	24	14	18	14	14	19	17.4	17
AORD t_t1	21	22	22	22	20	19	21	25	26	22.1	24
BSE Sensex t_t2	22	23	27	25	28	25	22	22	24	24.5	25
JKSE t_t2	23	26	25	26	27	22	26	26	27	25.6	26
Nikkei 225 t_t1	24	28	28	27	25	28	28	27	21	26.5	28
KOSPI t_t2	25	18	11	13	12	12	12	13	9	12.5	12
HSI t_t2	26	27	20	28	26	26	27	28	28	26.3	27
AORD t_t2	27	21	19	21	24	27	19	16	25	21.5	22
Nikkei 225 t_t2	28	14	26	23	22	24	16	19	17	20.1	21

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Higher volatility on the Energy, Precious Metals and Non-energy Commodity Market (State 2)

Table 43 AUC and IV values' ranks, SSEC Index, Energy, Precious Metals and Non-energy Commodity Markets (State2)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
IPC t_t1	1	2	1	2	3	3	1	1	1	1.8	1
S&P 500 t_t1	2	5	7	5	5	5	7	8	3	5.6	5
MERVAL t_t1	3	3	2	1	2	2	2	5	2	2.4	2
MERVAL t_t2	4	10	5	10	9	13	6	3	6	7.8	8
S&P 500 t_t2	5	11	8	12	8	11	10	13	7	10.0	9
IBEX 35 t_t1	6	1	3	4	1	4	3	6	4	3.3	3
Bovespa t_t1	7	6	9	8	6	1	8	7	9	6.8	6
S&P TSX t_t1	8	4	11	3	7	6	5	2	5	5.4	4
DAX t_t1	9	7	4	6	11	7	9	4	11	7.4	7
CAC 40 t_t1	10	12	14	9	13	15	13	19	15	13.8	13
S&P TSX t_t2	11	17	6	15	15	8	17	12	10	12.5	11
IPC t_t2	12	19	20	14	19	14	12	16	23	17.1	17
Bovespa t_t2	13	14	12	7	4	10	15	15	8	10.6	10
JKSE t_t1	14	16	17	17	18	17	20	14	22	17.6	18
BSE Sensex t_t1	15	8	18	24	10	22	11	10	18	15.1	15
IBEX 35 t_t2	16	25	10	16	12	16	14	11	14	14.8	14
DAX t_t2	17	15	13	23	14	9	19	20	12	15.6	16
CAC 40 t_t2	18	21	25	27	21	26	25	27	24	24.5	26
HSI t_t1	19	9	15	11	16	12	4	21	13	12.6	12
KOSPI t_t1	20	18	24	13	17	21	23	23	20	19.9	20
JKSE t_t2	21	23	27	28	20	25	28	24	19	24.3	25
Nikkei 225 t_t1	22	27	22	25	24	20	27	26	26	24.6	27

KOSPI t_t2	23	20	21	20	23	27	18	17	17	20.4	21
AORD t_t1	24	22	28	18	26	23	22	18	28	23.1	23
BSE Sensex t_t2	25	24	23	19	27	24	24	25	25	23.9	24
Nikkei 225 t_t2	26	28	26	26	28	28	26	28	21	26.4	28
AORD t_t2	27	26	16	22	22	19	21	22	16	20.5	22
HSI t_t2	28	13	19	21	25	18	16	9	27	18.5	19

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Lower volatility on the Energy, Precious Metals and Non-energy Commodity Market (State 1)

Table 44 AUC and IV values' ranks, SSEC Index, Energy, Precious Metals' and Non-energy Commodity Markets (State1)

Stock Market Index	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
MERVAL t_t1	1	13	18	9	7	10	2	1	12	9.0	7
S&P TSX t_t2	2	21	26	27	26	27	23	27	24	25.1	27
MERVAL t_t2	3	26	25	18	13	18	14	16	16	18.3	17
Bovespa t_t2	4	14	13	17	20	5	10	19	11	13.6	13
S&P TSX t_t1	5	23	27	16	28	25	19	26	27	23.9	26
S&P 500 t_t1	6	28	28	28	24	26	28	23	28	26.6	28
HSI t_t1	7	1	1	3	1	1	3	4	5	2.4	2
Bovespa t_t1	8	17	21	26	27	28	21	25	20	23.1	25
S&P 500 t_t2	9	7	16	25	19	6	18	11	14	14.5	14
CAC 40 t_t2	10	24	19	24	23	16	16	18	17	19.6	22
AORD t_t1	11	27	9	12	16	21	27	12	15	17.4	16
IPC t_t2	12	9	12	15	17	19	12	20	18	15.3	15
IPC t_t1	13	3	7	8	8	7	7	9	4	6.6	5
CAC 40 t_t1	14	25	17	19	14	14	17	14	26	18.3	17
KOSPI t_t1	15	5	14	14	3	4	6	5	9	7.5	6
DAX t_t2	16	20	6	4	5	2	4	3	1	5.6	4
IBEX 35 t_t1	17	22	15	13	21	23	26	13	21	19.3	19
IBEX 35 t_t2	18	18	24	20	12	24	24	22	25	21.1	24
Nikkei 225 t_t1	19	8	11	7	9	13	8	10	8	9.3	8
BSE Sensex t_t2	20	16	8	10	15	17	22	8	6	12.8	12
AORD t_t2	21	10	10	6	10	9	20	6	7	9.8	9
DAX t_t1	22	11	22	23	25	12	11	28	23	19.4	20
HSI t_t2	23	2	2	1	2	3	1	2	2	1.9	1
BSE Sensex t_t1	24	19	5	2	4	11	9	21	10	10.1	10
JKSE t_t2	25	12	20	22	18	22	15	24	22	19.4	20
KOSPI t_t2	26	15	23	21	22	20	25	15	19	20.0	23
Nikkei 225 t_t2	27	6	3	11	11	15	13	17	13	11.1	11
JKSE t_t1	28	4	4	5	6	8	5	7	3	5.3	3

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl Dataset* with the help of *Quandl*.

Appendix 6

SSEC Index and Commodity Prices

Information Value and area inder the ROC curve

Higher volatility on the Energy Commodity Market (State 2 - I)

AUC and IV values. SSEC Index. Energy Commodity Market (State2 - I)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Soybean Futures t_t2	0.57	0.09	0.10	0.10	0.09	0.10	0.11	0.11	0.15
Gold Price t_t2	0.57	0.07	0.08	0.08	0.07	0.07	0.11	0.10	0.11
Rice Futures t_t2	0.56	0.03	0.10	0.04	0.13	0.10	0.08	0.21	0.14
Gold Price t_t1	0.55	0.04	0.10	0.09	0.10	0.12	0.14	0.17	0.15
Cotton Futures t_t1	0.55	0.05	0.10	0.09	0.09	0.12	0.08	0.14	0.13
Wheat Futures t_t1	0.55	0.06	0.06	0.06	0.06	0.05	0.08	0.06	0.07
Oil Price t_t1	0.55	0.03	0.05	0.05	0.06	0.05	0.04	0.06	0.13
Sugar Futures t_t1	0.54	0.07	0.04	0.05	0.06	0.06	0.07	0.09	0.10
Sugar Futures t_t2	0.54	0.04	0.08	0.08	0.10	0.06	0.08	0.12	0.18
Wheat Futures t_t2	0.54	0.03	0.05	0.04	0.08	0.08	0.07	0.09	0.11
Rice Futures t_t1	0.53	0.02	0.03	0.05	0.04	0.06	0.05	0.07	0.06
Cotton Futures t_t2	0.52	0.07	0.06	0.10	0.06	0.08	0.09	0.13	0.14
Soybean Futures t_t1	0.52	0.05	0.01	0.04	0.08	0.11	0.12	0.07	0.09
Oil Price t_t2	0.52	0.01	0.01	0.04	0.04	0.08	0.05	0.07	0.06
Gas Price t_t1	0.52	0.02	0.04	0.03	0.08	0.09	0.06	0.04	0.08
Gas Price t_t2	0.52	0.04	0.07	0.13	0.12	0.13	0.14	0.11	0.11
Platinum Price t_t1	0.51	0.02	0.06	0.05	0.08	0.08	0.07	0.09	0.08
Platinum Price t_t2	0.51	0.03	0.04	0.11	0.06	0.09	0.05	0.13	0.12

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Energy Commodity Market (State2 - I)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Soybean Futures t_t2	1	1	1	3	6	6	5	7	3	4.0	2
Gold Price t_t2	2	2	5	8	11	13	4	9	9	7.6	8
Rice Futures t_t2	3	11	4	14	1	5	8	1	4	6.0	5
Gold Price t_t1	4	8	2	5	4	3	1	2	2	3.4	1
Cotton Futures t_t1	5	7	3	6	5	2	9	3	7	5.3	4
Wheat Futures t_t1	6	5	9	9	13	17	7	16	16	11.5	12
Oil Price t_t1	7	14	11	11	15	18	18	17	6	13.8	15
Sugar Futures t_t1	8	3	13	13	14	15	12	11	12	11.6	14
Sugar Futures t_t2	9	10	6	7	3	14	10	6	1	7.1	7
Wheat Futures t_t2	10	12	12	15	8	10	13	10	11	11.4	11

Rice Futures t_t1	11	16	16	12	18	16	17	13	17	15.6	17
Cotton Futures t_t2	12	4	8	4	12	9	6	4	5	6.5	6
Soybean Futures t_t1	13	6	18	16	9	4	3	14	13	10.4	10
Oil Price t_t2	14	18	17	17	17	11	16	15	18	16.1	18
Gas Price t_t1	15	17	14	18	10	8	14	18	14	14.1	16
Gas Price t_t2	16	9	7	1	2	1	2	8	10	5.0	3
Platinum Price t_t1	17	15	10	10	7	12	11	12	15	11.5	12
Platinum Price t_t2	18	13	15	2	16	7	15	5	8	10.1	9

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Higher volatility on the Energy Commodity Market (State 2 - II)

AUC and IV values. SSEC Index. Energy Commodity Market (State2 - II)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Sugar Futures t_t2	0.55	0.08	0.08	0.16	0.09	0.18	0.15	0.21	0.22
Gas Price t_t1	0.54	0.04	0.05	0.04	0.04	0.06	0.04	0.04	0.06
Sugar Futures t_t1	0.54	0.02	0.06	0.03	0.03	0.06	0.03	0.08	0.08
Cotton Futures t_t2	0.53	0.04	0.02	0.03	0.06	0.05	0.05	0.08	0.08
Cotton Futures t_t1	0.53	0.03	0.04	0.05	0.06	0.07	0.09	0.07	0.11
Gas Price t_t2	0.53	0.02	0.04	0.03	0.05	0.07	0.04	0.09	0.10
Soybean Futures t_t1	0.53	0.05	0.05	0.04	0.04	0.06	0.07	0.07	0.08
Soybean Futures t_t2	0.52	0.05	0.03	0.08	0.05	0.08	0.08	0.03	0.07
Wheat Futures t_t1	0.50	0.02	0.01	0.02	0.03	0.03	0.03	0.04	0.05
Wheat Futures t_t2	0.50	0.04	0.02	0.04	0.04	0.02	0.05	0.04	0.06
Oil Price t_t1	0.49	0.01	0.00	0.03	0.02	0.03	0.02	0.06	0.03
Rice Futures t_t2	0.49	0.03	0.01	0.02	0.05	0.04	0.05	0.04	0.07
Gold Price t_t2	0.49	0.04	0.04	0.06	0.03	0.05	0.06	0.08	0.09
Platinum Price t_t1	0.48	0.02	0.04	0.05	0.03	0.04	0.04	0.06	0.10
Platinum Price t_t2	0.48	0.01	0.02	0.03	0.02	0.03	0.04	0.03	0.04
Rice Futures t_t1	0.48	0.02	0.02	0.02	0.04	0.05	0.04	0.07	0.09
Oil Price t_t2	0.48	0.04	0.01	0.02	0.08	0.04	0.06	0.07	0.06
Gold Price t_t1	0.47	0.02	0.05	0.08	0.05	0.04	0.06	0.08	0.09

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Energy Commodity Market (State2 - II)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Sugar Futures t_t2	1	1	1	1	1	1	1	1	1	1.0	1
Gas Price t_t1	2	7	5	8	10	7	11	15	15	9.8	10
Sugar Futures t_t1	3	14	2	11	15	6	17	3	10	9.8	10
Cotton Futures t_t2	4	6	11	14	3	10	10	5	8	8.4	8
Cotton Futures t_t1	5	10	7	5	4	4	2	10	2	5.5	2
Gas Price t_t2	6	16	6	10	6	3	12	2	4	7.4	6
Soybean Futures t_t1	7	3	4	7	12	5	4	8	9	6.5	4

Soybean Futures t_t2	8	2	10	3	7	2	3	17	11	6.9	5
Wheat Futures t_t1	9	15	16	16	16	16	16	16	16	15.9	17
Wheat Futures t_t2	10	5	14	9	11	18	8	13	14	11.5	14
Oil Price t_t1	11	18	18	13	18	17	18	12	18	16.5	18
Rice Futures t_t2	12	9	17	18	8	13	9	14	12	12.5	15
Gold Price t_t2	13	8	9	4	13	9	6	6	7	7.8	7
Platinum Price t_t1	14	13	8	6	14	14	14	11	3	10.4	12
Platinum Price t_t2	15	17	12	12	17	15	15	18	17	15.4	16
Rice Futures t_t1	16	12	13	17	9	8	13	7	5	10.5	13
Oil Price t_t2	17	4	15	15	2	12	7	9	13	9.6	9
Gold Price t_t1	18	11	3	2	5	11	5	4	6	5.9	3

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Higher volatility on the Precious Metals Commodity Market (State 2)

AUC and IV values. SSEC Index. Precious Metals Commodity Market (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Soybean Futures t_t1	0.53	0.01	0.02	0.02	0.03	0.02	0.02	0.03	0.03
Cotton Futures t_t1	0.53	0.01	0.03	0.02	0.02	0.04	0.03	0.02	0.06
Rice Futures t_t2	0.53	0.02	0.03	0.03	0.02	0.03	0.02	0.04	0.06
Soybean Futures t_t2	0.53	0.01	0.01	0.01	0.02	0.02	0.03	0.02	0.02
Sugar Futures t_t1	0.52	0.01	0.02	0.01	0.02	0.02	0.01	0.03	0.03
Oil Price t_t1	0.52	0.01	0.01	0.01	0.01	0.02	0.02	0.03	0.02
Cotton Futures t_t1	0.52	0.01	0.01	0.02	0.01	0.02	0.03	0.04	0.02
Wheat Futures t_t1	0.52	0.00	0.01	0.01	0.02	0.02	0.03	0.03	0.02
Rice Futures t_t1	0.52	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
Sugar Futures t_t2	0.51	0.01	0.02	0.01	0.03	0.02	0.03	0.03	0.03
Wheat Futures t_t2	0.51	0.02	0.02	0.01	0.02	0.02	0.02	0.03	0.04
Gold Price t_t1	0.51	0.01	0.01	0.01	0.02	0.01	0.02	0.01	0.02
Gold Price t_t2	0.51	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
Oil Price t_t2	0.50	0.00	0.00	0.00	0.02	0.01	0.01	0.02	0.01
Platinum Price t_t1	0.50	0.02	0.00	0.03	0.03	0.03	0.03	0.04	0.04
Platinum Price t_t2	0.49	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.03
Gas Price t_t1	0.49	0.01	0.02	0.03	0.03	0.02	0.02	0.02	0.04
Gas Price t_t2	0.47	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.02

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Precious Metals Commodity Market (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Soybean Futures t_t1	1	6	5	4	4	7	7	7	8	6.0	4
Cotton Futures t_t1	2	8	1	5	12	1	1	17	2	5.9	3

Rice Futures t_t2	3	1	2	2	7	3	10	1	1	3.4	1
Soybean Futures t_t2	4	12	9	10	5	13	6	11	13	9.9	10
Sugar Futures t_t1	5	14	8	13	11	12	16	4	9	10.9	13
Oil Price t_t1	6	5	13	15	17	6	13	8	12	11.1	15
Cotton Futures t_t1	7	11	14	7	16	15	5	2	15	10.6	12
Wheat Futures t_t1	8	17	10	11	10	10	2	6	10	9.5	9
Rice Futures t_t1	9	13	15	16	18	17	17	15	18	16.1	17
Sugar Futures t_t2	10	9	3	9	3	14	4	5	6	6.6	5
Wheat Futures t_t2	11	2	4	14	8	9	8	9	4	7.3	6
Gold Price t_t1	12	16	16	17	15	18	15	18	16	16.4	18
Gold Price t_t2	13	7	12	12	13	11	12	10	11	11.0	14
Oil Price t_t2	14	18	18	18	6	16	18	16	17	15.9	16
Platinum Price t_t1	15	3	17	1	1	2	3	3	3	4.1	2
Platinum Price t_t2	16	10	6	6	14	4	9	12	7	8.5	8
Gas Price t_t1	17	15	7	3	2	5	11	13	5	7.6	7
Gas Price t_t2	18	4	11	8	9	8	14	14	14	10.3	11

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

<u>Higher volatility on the Non-energy Commodity Market (State 2)</u>

AUC and IV values. SSEC Index. Non-energy Commodity Market (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Rice Futures t_t2	0.56	0.04	0.04	0.05	0.05	0.05	0.06	0.07	0.06
Soybean Futures t_t2	0.55	0.04	0.05	0.06	0.06	0.06	0.07	0.07	0.07
Oil Price t_t1	0.55	0.03	0.05	0.03	0.04	0.04	0.04	0.04	0.05
Cotton Futures t_t2	0.55	0.03	0.04	0.04	0.04	0.06	0.04	0.05	0.06
Rice Futures t_t1	0.54	0.04	0.04	0.06	0.03	0.05	0.05	0.08	0.05
Wheat Futures t_t1	0.54	0.02	0.04	0.03	0.05	0.05	0.05	0.06	0.06
Soybean Futures t_t1	0.54	0.02	0.03	0.03	0.03	0.03	0.03	0.06	0.03
Cotton Futures t_t1	0.53	0.01	0.03	0.02	0.01	0.03	0.02	0.02	0.04
Wheat Futures t_t2	0.53	0.02	0.02	0.02	0.02	0.03	0.02	0.04	0.03
Oil Price t_t2	0.53	0.02	0.03	0.03	0.06	0.04	0.03	0.03	0.04
Sugar Futures t_t2	0.52	0.01	0.02	0.01	0.02	0.02	0.02	0.03	0.04
Gold Price t_t2	0.51	0.01	0.02	0.03	0.03	0.04	0.02	0.04	0.05
Sugar Futures t_t1	0.51	0.01	0.02	0.01	0.02	0.02	0.03	0.03	0.03
Gold Price t_t1	0.51	0.03	0.02	0.04	0.04	0.05	0.04	0.05	0.05
Platinum Price t_t1	0.49	0.03	0.05	0.04	0.05	0.06	0.06	0.06	0.08
Platinum Price t_t2	0.48	0.04	0.04	0.04	0.05	0.04	0.06	0.06	0.05
Gas Price t_t1	0.47	0.02	0.04	0.04	0.03	0.05	0.04	0.05	0.05
Gas Price t_t2	0.46	0.03	0.04	0.03	0.04	0.03	0.04	0.05	0.05

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Non-energy Commodity Market (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Rice Futures t_t2	1	2	6	3	4	5	4	2	3	3.6	3
Soybean Futures t_t2	2	3	1	1	1	1	1	3	2	1.6	1
Oil Price t_t1	3	8	3	9	9	10	7	12	7	8.1	9
Cotton Futures t_t2	4	7	10	6	7	2	11	11	4	7.3	6
Rice Futures t_t1	5	1	8	2	12	8	5	1	9	5.8	4
Wheat Futures t_t1	6	13	9	12	6	7	6	4	5	7.8	7
Soybean Futures t_t1	7	11	13	10	14	14	13	6	17	12.3	13
Cotton Futures t_t1	8	15	12	16	18	15	18	18	15	15.9	16
Wheat Futures t_t2	9	14	17	15	15	16	15	14	18	15.5	15
Oil Price t_t2	10	10	11	13	2	9	12	15	13	10.6	12
Sugar Futures t_t2	11	16	14	17	17	18	17	16	14	16.1	17
Gold Price t_t2	12	18	16	11	13	12	16	13	8	13.4	14
Sugar Futures t_t1	13	17	18	18	16	17	14	17	16	16.6	18
Gold Price t_t1	14	5	15	8	10	6	9	8	12	9.1	10
Platinum Price t_t1	15	6	2	4	3	3	2	7	1	3.5	2
Platinum Price t_t2	16	4	5	7	5	11	3	5	6	5.8	4
Gas Price t_t1	17	12	4	5	11	4	8	10	10	8.0	8
Gas Price t_t2	18	9	7	14	8	13	10	9	11	10.1	11

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Higher volatility on the Energy. Precious Metals and Non-energy Commodity Market (State 2)

AUC and IV values. SSEC Index. Energy. Precious Metals and Non-energy Commodity Markets (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Oil Price t_t1	0.61	0.27	0.20	0.25	0.27	0.26	0.38	0.35	0.30
Oil Price t_t2	0.61	0.20	0.36	0.25	0.23	0.36	0.53	0.30	0.37
Cotton Futures t_t2	0.59	0.17	0.24	0.14	0.17	0.22	0.27	0.30	0.36
Soybean Futures t_t2	0.59	0.17	0.15	0.22	0.29	0.34	0.38	0.40	0.34
Rice Futures t_t2	0.58	0.08	0.15	0.16	0.15	0.16	0.21	0.32	0.25
Wheat Futures t_t1	0.58	0.33	0.29	0.26	0.32	0.28	0.41	0.43	0.42
Cotton Futures t_t1	0.55	0.17	0.16	0.13	0.19	0.20	0.26	0.21	0.26
Wheat Futures t_t2	0.55	0.06	0.24	0.21	0.26	0.35	0.21	0.29	0.33
Soybean Futures t_t1	0.55	0.32	0.29	0.27	0.38	0.36	0.46	0.46	0.46
Sugar Futures t_t2	0.55	0.07	0.06	0.14	0.07	0.12	0.12	0.12	0.12
Platinum Price t_t2	0.54	0.13	0.06	0.08	0.28	0.13	0.16	0.13	0.37
Gold Price t_t2	0.54	0.09	0.07	0.06	0.12	0.09	0.12	0.07	0.10
Sugar Futures t_t1	0.54	0.11	0.14	0.23	0.12	0.20	0.21	0.21	0.26
Rice Futures t_t1	0.53	0.09	0.12	0.16	0.17	0.21	0.13	0.26	0.16
Platinum Price t_t1	0.52	0.05	0.09	0.07	0.09	0.09	0.07	0.21	0.17

Gas Price t_t1	0.50	0.08	0.05	0.12	0.37	0.11	0.19	0.34	0.31
Gold Price t_t1	0.49	0.02	0.11	0.12	0.16	0.13	0.16	0.11	0.22
Gas Price t_t2	0.48	0.05	0.09	0.09	0.18	0.15	0.11	0.16	0.11

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Energy. Precious Metals and Non-energy Commodity Markets (State2)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Oil Price t_t1	1	3	6	3	6	6	5	4	9	5.3	5
Oil Price t_t2	2	4	1	4	8	2	1	7	4	3.9	3
Cotton Futures t_t2	3	6	5	11	12	7	6	8	5	7.5	6
Soybean Futures t_t2	4	5	8	6	4	4	4	3	6	5.0	4
Rice Futures t_t2	5	12	9	8	14	11	9	6	12	10.1	9
Wheat Futures t_t1	6	1	2	2	3	5	3	2	2	2.5	2
Cotton Futures t_t1	7	7	7	12	9	10	7	13	11	9.5	8
Wheat Futures t_t2	8	15	4	7	7	3	8	9	7	7.5	6
Soybean Futures t_t1	9	2	3	1	1	1	2	1	1	1.5	1
Sugar Futures t_t2	10	14	17	10	18	15	15	16	16	15.1	16
Platinum Price t_t2	11	8	16	16	5	14	13	15	3	11.3	13
Gold Price t_t2	12	11	15	18	15	18	16	18	18	16.1	18
Sugar Futures t_t1	13	9	10	5	16	9	10	12	10	10.1	9
Rice Futures t_t1	14	10	11	9	11	8	14	10	15	11.0	12
Platinum Price t_t1	15	17	13	17	17	17	18	11	14	15.5	17
Gas Price t_t1	16	13	18	13	2	16	11	5	8	10.8	11
Gold Price t_t1	17	18	12	14	13	13	12	17	13	14.0	14
Gas Price t_t2	18	16	14	15	10	12	17	14	17	14.4	15

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Lower volatility on the Energy. Precious Metals and Non-energy Commodity Market (State 1)

AUC and IV values. SSEC Index. Energy. Precious Metals and Non-energy Commodity Markets (State1)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12
Rice Futures t_t2	0.54	0.02	0.02	0.02	0.03	0.03	0.05	0.05	0.05
Rice Futures t_t1	0.54	0.02	0.03	0.05	0.06	0.06	0.08	0.08	0.07
Gas Price t_t2	0.52	0.02	0.02	0.02	0.05	0.05	0.05	0.03	0.05
Wheat Futures t_t1	0.51	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
Wheat Futures t_t2	0.51	0.02	0.03	0.03	0.03	0.05	0.04	0.02	0.04
Sugar Futures t_t2	0.51	0.01	0.01	0.00	0.01	0.01	0.01	0.02	0.01
Gold Price t_t2	0.51	0.01	0.01	0.01	0.00	0.03	0.02	0.02	0.02
Gas Price t_t1	0.50	0.02	0.01	0.03	0.04	0.02	0.04	0.03	0.04
Cotton Futures t_t2	0.50	0.01	0.01	0.02	0.03	0.04	0.03	0.03	0.02
Platinum Price t_t2	0.50	0.02	0.02	0.01	0.03	0.03	0.04	0.02	0.04
Cotton Futures t_t1	0.49	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.03

Platinum Price t_t1	0.49	0.01	0.00	0.01	0.01	0.01	0.03	0.01	0.04
Soybean Futures t_t2	0.49	0.01	0.02	0.04	0.06	0.07	0.05	0.06	0.07
Sugar Futures t_t1	0.49	0.00	0.01	0.01	0.01	0.02	0.02	0.03	0.04
Gold Price t_t1	0.48	0.01	0.02	0.02	0.02	0.01	0.02	0.03	0.03
Oil Price t_t1	0.48	0.02	0.01	0.03	0.03	0.03	0.03	0.03	0.04
Soybean Futures t_t1	0.47	0.02	0.03	0.02	0.04	0.06	0.04	0.09	0.04
Oil Price t_t2	0.47	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

AUC and IV values' ranks. SSEC Index. Energy. Precious Metals' and Non-energy Commodity Markets (State1)

Commodity Price	AUC	IV_5	IV_6	IV_7	IV_8	IV_9	IV_10	IV_11	IV_12	IV_ave	IV_rank
Rice Futures t_t2	1	3	6	7	10	10	2	4	4	5.8	6
Rice Futures t_t1	2	1	1	1	2	2	1	2	2	1.5	1
Gas Price t_t2	3	6	4	6	3	4	3	6	3	4.4	3
Wheat Futures t_t1	4	11	16	12	13	16	16	18	16	14.8	17
Wheat Futures t_t2	5	2	2	5	6	5	6	12	7	5.6	5
Sugar Futures t_t2	6	16	17	18	17	18	18	15	18	17.1	18
Gold Price t_t2	7	14	13	16	18	8	15	11	17	14.0	15
Gas Price t_t1	8	9	15	3	5	12	5	7	10	8.3	8
Cotton Futures t_t2	9	17	14	11	9	6	11	10	14	11.5	11
Platinum Price t_t2	10	7	8	14	7	7	7	13	5	8.5	9
Cotton Futures t_t1	11	15	7	13	16	11	17	16	12	13.4	14
Platinum Price t_t1	12	13	18	15	15	15	10	17	9	14.0	15
Soybean Futures t_t2	13	10	5	2	1	1	4	3	1	3.4	2
Sugar Futures t_t1	14	18	12	17	14	14	12	8	11	13.3	13
Gold Price t_t1	15	12	10	10	12	17	13	5	13	11.5	11
Oil Price t_t1	16	8	11	4	8	9	9	9	6	8.0	7
Soybean Futures t_t1	17	5	3	8	4	3	8	1	8	5.0	4
Oil Price t_t2	18	4	9	9	11	13	14	14	15	11.1	10

Source: Own calculation in R Studio. *caret. Information. Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Spearman Correlation Coefficients and *p*-values - Model Based step, commodity prices

<u>Higher volatility on the Energy Commodity Market (State 2 - I)</u>

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,67	0,12	0,07	0,10	0,07	0,13	0,05	0,18	0,24	0,21	0,26	0,20	0,18	0,14	0,15	0,19	0,16
Oil Price t_t2	0,67	1,00	0,06	0,12	0,18	0,21	0,26	0,24	0,07	0,24	0,11	0,29	0,08	0,20	0,05	0,18	0,10	0,20
Gas Price t_t1	0,12	0,06	1,00	0,67	0,05	0,06	0,05	0,04	0,00	0,06	0,07	0,07	-0,02	-0,01	0,00	0,02	0,05	0,06
Gas Price t_t2	0,07	0,12	0,67	1,00	0,06	0,09	0,10	0,10	-0,05	0,03	0,11	0,11	-0,06	-0,01	-0,02	0,04	0,04	0,10
Gold Price t_t1	0,10	0,18	0,05	0,06	1,00	0,59	0,49	0,30	0,12	0,13	0,13	0,11	0,16	0,11	0,07	0,17	0,06	0,07
Gold Price t_t2	0,07	0,21	0,06	0,09	0,59	1,00	0,34	0,51	0,06	0,14	0,06	0,13	0,07	0,15	-0,01	0,10	0,04	0,10
Platinum Price t_t1	0,13	0,26	0,05	0,10	0,49	0,34	1,00	0,60	0,01	0,11	0,08	0,16	0,14	0,16	0,03	0,20	-0,01	0,13
Platinum Price t_t2	0,05	0,24	0,04	0,10	0,30	0,51	0,60	1,00	-0,02	0,07	0,09	0,14	0,07	0,15	-0,02	0,14	0,01	0,11
Wheat Futures t_t1	0,18	0,07	0,00	-0,05	0,12	0,06	0,01	-0,02	1,00	0,65	0,49	0,36	0,35	0,19	0,25	0,13	0,27	0,22
Wheat Futures t_t2	0,24	0,24	0,06	0,03	0,13	0,14	0,11	0,07	0,65	1,00	0,33	0,49	0,21	0,27	0,14	0,18	0,20	0,32
Soybean Futures t_t1	0,21	0,11	0,07	0,11	0,13	0,06	0,08	0,09	0,49	0,33	1,00	0,68	0,31	0,17	0,24	0,17	0,33	0,23
Soybean Futures t_t2	0,26	0,29	0,07	0,11	0,11	0,13	0,16	0,14	0,36	0,49	0,68	1,00	0,24	0,31	0,21	0,28	0,23	0,32
Rice Futures t_t1	0,20	0,08	-0,02	-0,06	0,16	0,07	0,14	0,07	0,35	0,21	0,31	0,24	1,00	0,67	0,09	0,01	0,20	0,12
Rice Futures t_t2	0,18	0,20	-0,01	-0,01	0,11	0,15	0,16	0,15	0,19	0,27	0,17	0,31	0,67	1,00	0,10	0,11	0,08	0,15
Sugar Futures t_t1	0,14	0,05	0,00	-0,02	0,07	-0,01	0,03	-0,02	0,25	0,14	0,24	0,21	0,09	0,10	1,00	0,67	0,20	0,14
Sugar Futures t_t2	0,15	0,18	0,02	0,04	0,17	0,10	0,20	0,14	0,13	0,18	0,17	0,28	0,01	0,11	0,67	1,00	0,10	0,17
Cotton Futures t_t1	0,19	0,10	0,05	0,04	0,06	0,04	-0,01	0,01	0,27	0,20	0,33	0,23	0,20	0,08	0,20	0,10	1,00	0,66
Cotton Futures t_t2	0,16	0,20	0,06	0,10	0,07	0,10	0,13	0,11	0,22	0,32	0,23	0,32	0,12	0,15	0,14	0,17	0,66	1,00

Source: Own calculation in R Studio, *caret, Information, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl.*

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,01	0,11	0,02	0,10	0,01	0,25	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Oil Price t_t2	0,00	NA	0,17	0,01	0,00	0,00	0,00	0,00	0,12	0,00	0,02	0,00	0,07	0,00	0,26	0,00	0,03	0,00
Gas Price t_t1	0,01	0,17	NA	0,00	0,31	0,21	0,24	0,37	0,95	0,16	0,14	0,14	0,65	0,84	0,91	0,62	0,28	0,16
Gas Price t_t2	0,11	0,01	0,00	NA	0,19	0,06	0,03	0,03	0,33	0,48	0,02	0,01	0,18	0,91	0,63	0,41	0,39	0,03
Gold Price t_t1	0,02	0,00	0,31	0,19	NA	0,00	0,00	0,00	0,01	0,00	0,01	0,01	0,00	0,02	0,14	0,00	0,17	0,15
Gold Price t_t2	0,10	0,00	0,21	0,06	0,00	NA	0,00	0,00	0,22	0,00	0,19	0,01	0,12	0,00	0,82	0,03	0,36	0,03
Platinum Price t_t1	0,01	0,00	0,24	0,03	0,00	0,00	NA	0,00	0,89	0,01	0,09	0,00	0,00	0,00	0,47	0,00	0,89	0,00
Platinum Price t_t2	0,25	0,00	0,37	0,03	0,00	0,00	0,00	NA	0,65	0,15	0,06	0,00	0,13	0,00	0,64	0,00	0,89	0,02
Wheat Futures t_t1	0,00	0,12	0,95	0,33	0,01	0,22	0,89	0,65	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
Wheat Futures t_t2	0,00	0,00	0,16	0,48	0,00	0,00	0,01	0,15	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t1	0,00	0,02	0,14	0,02	0,01	0,19	0,09	0,06	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t2	0,00	0,00	0,14	0,01	0,01	0,01	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t1	0,00	0,07	0,65	0,18	0,00	0,12	0,00	0,13	0,00	0,00	0,00	0,00	NA	0,00	0,04	0,82	0,00	0,01
Rice Futures t_t2	0,00	0,00	0,84	0,91	0,02	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,03	0,02	0,08	0,00
Sugar Futures t_t1	0,00	0,26	0,91	0,63	0,14	0,82	0,47	0,64	0,00	0,00	0,00	0,00	0,04	0,03	NA	0,00	0,00	0,00
Sugar Futures t_t2	0,00	0,00	0,62	0,41	0,00	0,03	0,00	0,00	0,01	0,00	0,00	0,00	0,82	0,02	0,00	NA	0,02	0,00
Cotton Futures t_t1	0,00	0,03	0,28	0,39	0,17	0,36	0,89	0,89	0,00	0,00	0,00	0,00	0,00	0,08	0,00	0,02	NA	0,00
Cotton Futures t_t2	0,00	0,00	0,16	0,03	0,15	0,03	0,00	0,02	0,00	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

<u>Higher volatility on the Energy Commodity Market (State 2 - II)</u>

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,65	0,07	0,05	0,05	0,06	0,09	0,07	0,05	0,04	0,06	0,06	-0,02	0,00	0,07	0,07	0,11	0,01
Oil Price t_t2	0,65	1,00	0,04	0,05	0,10	0,13	0,19	0,18	0,01	-0,01	0,03	0,06	0,01	-0,01	0,08	0,08	0,12	0,07
Gas Price t_t1	0,07	0,04	1,00	0,66	0,05	0,06	0,07	0,09	-0,07	-0,06	-0,04	0,04	-0,03	0,00	-0,06	0,02	-0,04	-0,03
Gas Price t_t2	0,05	0,05	0,66	1,00	0,04	0,07	0,06	0,12	-0,01	-0,04	0,04	0,04	-0,02	-0,01	-0,04	-0,02	-0,04	-0,06
Gold Price t_t1	0,05	0,10	0,05	0,04	1,00	0,65	0,51	0,35	-0,05	0,00	-0,09	-0,02	0,00	-0,02	0,06	0,03	0,00	0,00
Gold Price t_t2	0,06	0,13	0,06	0,07	0,65	1,00	0,40	0,50	-0,08	-0,03	-0,07	-0,06	-0,01	0,01	0,00	0,01	-0,04	0,00
Platinum Price t_t1	0,09	0,19	0,07	0,06	0,51	0,40	1,00	0,71	-0,04	-0,01	-0,02	0,09	0,02	0,03	0,00	0,01	0,03	0,09
Platinum Price t_t2	0,07	0,18	0,09	0,12	0,35	0,50	0,71	1,00	-0,05	-0,02	-0,05	0,02	0,00	0,02	0,01	0,03	0,03	0,12
Wheat Futures t_t1	0,05	0,01	-0,07	-0,01	-0,05	-0,08	-0,04	-0,05	1,00	0,66	0,33	0,17	0,11	0,06	0,08	0,03	0,10	0,04
Wheat Futures t_t2	0,04	-0,01	-0,06	-0,04	0,00	-0,03	-0,01	-0,02	0,66	1,00	0,12	0,27	0,04	0,09	0,10	0,08	0,03	0,06
Soybean Futures t_t1	0,06	0,03	-0,04	0,04	-0,09	-0,07	-0,02	-0,05	0,33	0,12	1,00	0,59	0,17	0,11	0,09	0,05	0,16	0,13
Soybean Futures t_t2	0,06	0,06	0,04	0,04	-0,02	-0,06	0,09	0,02	0,17	0,27	0,59	1,00	0,11	0,15	0,14	0,14	0,14	0,19
Rice Futures t_t1	-0,02	0,01	-0,03	-0,02	0,00	-0,01	0,02	0,00	0,11	0,04	0,17	0,11	1,00	0,69	0,04	0,07	0,08	0,03
Rice Futures t_t2	0,00	-0,01	0,00	-0,01	-0,02	0,01	0,03	0,02	0,06	0,09	0,11	0,15	0,69	1,00	0,02	0,12	0,06	0,06
Sugar Futures t_t1	0,07	0,08	-0,06	-0,04	0,06	0,00	0,00	0,01	0,08	0,10	0,09	0,14	0,04	0,02	1,00	0,68	0,14	0,12
Sugar Futures t_t2	0,07	0,08	0,02	-0,02	0,03	0,01	0,01	0,03	0,03	0,08	0,05	0,14	0,07	0,12	0,68	1,00	0,08	0,13
Cotton Futures t_t1	0,11	0,12	-0,04	-0,04	0,00	-0,04	0,03	0,03	0,10	0,03	0,16	0,14	0,08	0,06	0,14	0,08	1,00	0,66
Cotton Futures t_t2	0,01	0,07	-0,03	-0,06	0,00	0,00	0,09	0,12	0,04	0,06	0,13	0,19	0,03	0,06	0,12	0,13	0,66	1,00

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,12	0,24	0,27	0,13	0,03	0,09	0,26	0,39	0,13	0,17	0,59	1,00	0,13	0,11	0,01	0,78
Oil Price t_t2	0,00	NA	0,38	0,28	0,02	0,00	0,00	0,00	0,90	0,89	0,48	0,17	0,86	0,78	0,07	0,06	0,01	0,11
Gas Price t_t1	0,12	0,38	NA	0,00	0,24	0,14	0,10	0,03	0,11	0,14	0,39	0,39	0,42	0,95	0,15	0,65	0,41	0,52
Gas Price t_t2	0,24	0,28	0,00	NA	0,30	0,12	0,16	0,01	0,80	0,31	0,37	0,38	0,73	0,75	0,31	0,57	0,38	0,14
Gold Price t_t1	0,27	0,02	0,24	0,30	NA	0,00	0,00	0,00	0,21	0,99	0,04	0,59	0,91	0,71	0,18	0,48	0,98	0,91
Gold Price t_t2	0,13	0,00	0,14	0,12	0,00	NA	0,00	0,00	0,07	0,46	0,12	0,15	0,78	0,82	0,92	0,79	0,33	0,96
Platinum Price t_t1	0,03	0,00	0,10	0,16	0,00	0,00	NA	0,00	0,35	0,85	0,71	0,04	0,66	0,50	0,94	0,87	0,43	0,03
Platinum Price t_t2	0,09	0,00	0,03	0,01	0,00	0,00	0,00	NA	0,22	0,68	0,24	0,66	0,91	0,71	0,86	0,46	0,42	0,01
Wheat Futures t_t1	0,26	0,90	0,11	0,80	0,21	0,07	0,35	0,22	NA	0,00	0,00	0,00	0,01	0,16	0,06	0,41	0,02	0,35
Wheat Futures t_t2	0,39	0,89	0,14	0,31	0,99	0,46	0,85	0,68	0,00	NA	0,00	0,00	0,36	0,03	0,02	0,08	0,46	0,13
Soybean Futures t_t1	0,13	0,48	0,39	0,37	0,04	0,12	0,71	0,24	0,00	0,00	NA	0,00	0,00	0,01	0,03	0,24	0,00	0,00
Soybean Futures t_t2	0,17	0,17	0,39	0,38	0,59	0,15	0,04	0,66	0,00	0,00	0,00	NA	0,01	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t1	0,59	0,86	0,42	0,73	0,91	0,78	0,66	0,91	0,01	0,36	0,00	0,01	NA	0,00	0,30	0,09	0,06	0,51
Rice Futures t_t2	1,00	0,78	0,95	0,75	0,71	0,82	0,50	0,71	0,16	0,03	0,01	0,00	0,00	NA	0,60	0,01	0,16	0,17
Sugar Futures t_t1	0,13	0,07	0,15	0,31	0,18	0,92	0,94	0,86	0,06	0,02	0,03	0,00	0,30	0,60	NA	0,00	0,00	0,00
Sugar Futures t_t2	0,11	0,06	0,65	0,57	0,48	0,79	0,87	0,46	0,41	0,08	0,24	0,00	0,09	0,01	0,00	NA	0,05	0,00
Cotton Futures t_t1	0,01	0,01	0,41	0,38	0,98	0,33	0,43	0,42	0,02	0,46	0,00	0,00	0,06	0,16	0,00	0,05	NA	0,00
Cotton Futures t_t2	0,78	0,11	0,52	0,14	0,91	0,96	0,03	0,01	0,35	0,13	0,00	0,00	0,51	0,17	0,00	0,00	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

<u>Higher volatility on the Precious Metals Commodity Market (State 2)</u>

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,70	0,19	0,16	0,15	0,12	0,17	0,15	0,11	0,12	0,20	0,22	0,11	0,09	0,15	0,15	0,16	0,14
Oil Price t_t2	0,70	1,00	0,11	0,17	0,19	0,24	0,27	0,29	0,06	0,15	0,12	0,25	0,09	0,13	0,04	0,14	0,11	0,17
Gas Price t_t1	0,19	0,11	1,00	0,69	0,11	0,07	0,08	0,07	0,03	0,06	0,05	0,08	0,03	0,05	0,04	0,07	0,01	0,02
Gas Price t_t2	0,16	0,17	0,69	1,00	0,07	0,09	0,08	0,09	0,02	0,06	0,07	0,10	0,02	0,05	0,01	0,06	0,00	0,02
Gold Price t_t1	0,15	0,19	0,11	0,07	1,00	0,63	0,59	0,38	0,09	0,12	0,08	0,15	0,07	0,09	0,04	0,08	0,07	0,07
Gold Price t_t2	0,12	0,24	0,07	0,09	0,63	1,00	0,45	0,62	0,03	0,14	0,03	0,13	0,05	0,12	0,02	0,07	0,03	0,09
Platinum Price t_t1	0,17	0,27	0,08	0,08	0,59	0,45	1,00	0,65	0,09	0,17	0,08	0,21	0,08	0,13	0,04	0,14	0,08	0,13
Platinum Price t_t2	0,15	0,29	0,07	0,09	0,38	0,62	0,65	1,00	0,04	0,16	0,05	0,18	0,04	0,13	0,02	0,10	0,04	0,14
Wheat Futures t_t1	0,11	0,06	0,03	0,02	0,09	0,03	0,09	0,04	1,00	0,67	0,43	0,28	0,27	0,15	0,17	0,14	0,22	0,17
Wheat Futures t_t2	0,12	0,15	0,06	0,06	0,12	0,14	0,17	0,16	0,67	1,00	0,26	0,40	0,20	0,24	0,13	0,18	0,16	0,23
Soybean Futures t_t1	0,20	0,12	0,05	0,07	0,08	0,03	0,08	0,05	0,43	0,26	1,00	0,65	0,25	0,16	0,19	0,13	0,26	0,19
Soybean Futures t_t2	0,22	0,25	0,08	0,10	0,15	0,13	0,21	0,18	0,28	0,40	0,65	1,00	0,19	0,25	0,17	0,22	0,20	0,28
Rice Futures t_t1	0,11	0,09	0,03	0,02	0,07	0,05	0,08	0,04	0,27	0,20	0,25	0,19	1,00	0,71	0,10	0,08	0,13	0,13
Rice Futures t_t2	0,09	0,13	0,05	0,05	0,09	0,12	0,13	0,13	0,15	0,24	0,16	0,25	0,71	1,00	0,08	0,12	0,09	0,15
Sugar Futures t_t1	0,15	0,04	0,04	0,01	0,04	0,02	0,04	0,02	0,17	0,13	0,19	0,17	0,10	0,08	1,00	0,65	0,16	0,12
Sugar Futures t_t2	0,15	0,14	0,07	0,06	0,08	0,07	0,14	0,10	0,14	0,18	0,13	0,22	0,08	0,12	0,65	1,00	0,12	0,17
Cotton Futures t_t1	0,16	0,11	0,01	0,00	0,07	0,03	0,08	0,04	0,22	0,16	0,26	0,20	0,13	0,09	0,16	0,12	1,00	0,67
Cotton Futures t_t2	0,14	0,17	0,02	0,02	0,07	0,09	0,13	0,14	0,17	0,23	0,19	0,28	0,13	0,15	0,12	0,17	0,67	1,00

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Oil Price t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00
Gas Price t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,21	0,01	0,02	0,00	0,21	0,03	0,09	0,00	0,54	0,27
Gas Price t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,38	0,01	0,00	0,00	0,44	0,04	0,57	0,01	0,87	0,38
Gold Price t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00
Gold Price t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,15	0,00	0,18	0,00	0,01	0,00	0,47	0,00	0,20	0,00
Platinum Price t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,11	0,00	0,00	0,00
Platinum Price t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,07	0,00	0,02	0,00	0,05	0,00	0,46	0,00	0,08	0,00
Wheat Futures t_t1	0,00	0,00	0,21	0,38	0,00	0,15	0,00	0,07	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Wheat Futures t_t2	0,00	0,00	0,01	0,01	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t1	0,00	0,00	0,02	0,00	0,00	0,18	0,00	0,02	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t1	0,00	0,00	0,21	0,44	0,00	0,01	0,00	0,05	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t2	0,00	0,00	0,03	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Sugar Futures t_t1	0,00	0,06	0,09	0,57	0,05	0,47	0,11	0,46	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Sugar Futures t_t2	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
Cotton Futures t_t1	0,00	0,00	0,54	0,87	0,00	0,20	0,00	0,08	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
Cotton Futures t_t2	0,00	0,00	0,27	0,38	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Higher volatility on the Non-energy Commodity Market (State 2)

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,69	0,24	0,19	0,19	0,16	0,19	0,16	0,11	0,17	0,24	0,27	0,16	0,15	0,16	0,15	0,20	0,19
Oil Price t_t2	0,69	1,00	0,15	0,24	0,23	0,33	0,31	0,36	0,02	0,16	0,13	0,30	0,10	0,18	0,06	0,17	0,11	0,23
Gas Price t_t1	0,24	0,15	1,00	0,71	0,10	0,03	0,09	0,03	0,01	0,08	0,08	0,11	0,05	0,09	0,05	0,06	0,04	0,04
Gas Price t_t2	0,19	0,24	0,71	1,00	0,08	0,12	0,11	0,12	0,00	0,07	0,10	0,15	0,01	0,07	0,00	0,04	0,02	0,05
Gold Price t_t1	0,19	0,23	0,10	0,08	1,00	0,61	0,62	0,39	0,08	0,14	0,12	0,17	0,10	0,15	0,04	0,09	0,07	0,13
Gold Price t_t2	0,16	0,33	0,03	0,12	0,61	1,00	0,47	0,66	-0,01	0,13	0,03	0,16	0,06	0,15	0,00	0,08	0,00	0,12
Platinum Price t_t1	0,19	0,31	0,09	0,11	0,62	0,47	1,00	0,65	0,05	0,20	0,10	0,23	0,11	0,19	0,01	0,11	0,01	0,15
Platinum Price t_t2	0,16	0,36	0,03	0,12	0,39	0,66	0,65	1,00	0,00	0,18	0,09	0,23	0,07	0,19	-0,04	0,07	-0,04	0,11
Wheat Futures t_t1	0,11	0,02	0,01	0,00	0,08	-0,01	0,05	0,00	1,00	0,67	0,42	0,26	0,27	0,13	0,17	0,09	0,26	0,17
Wheat Futures t_t2	0,17	0,16	0,08	0,07	0,14	0,13	0,20	0,18	0,67	1,00	0,27	0,39	0,20	0,25	0,12	0,17	0,21	0,28
Soybean Futures t_t1	0,24	0,13	0,08	0,10	0,12	0,03	0,10	0,09	0,42	0,27	1,00	0,67	0,31	0,20	0,22	0,15	0,33	0,23
Soybean Futures t_t2	0,27	0,30	0,11	0,15	0,17	0,16	0,23	0,23	0,26	0,39	0,67	1,00	0,24	0,32	0,17	0,25	0,23	0,32
Rice Futures t_t1	0,16	0,10	0,05	0,01	0,10	0,06	0,11	0,07	0,27	0,20	0,31	0,24	1,00	0,69	0,12	0,09	0,22	0,17
Rice Futures t_t2	0,15	0,18	0,09	0,07	0,15	0,15	0,19	0,19	0,13	0,25	0,20	0,32	0,69	1,00	0,09	0,14	0,12	0,22
Sugar Futures t_t1	0,16	0,06	0,05	0,00	0,04	0,00	0,01	-0,04	0,17	0,12	0,22	0,17	0,12	0,09	1,00	0,65	0,20	0,15
Sugar Futures t_t2	0,15	0,17	0,06	0,04	0,09	0,08	0,11	0,07	0,09	0,17	0,15	0,25	0,09	0,14	0,65	1,00	0,14	0,22
Cotton Futures t_t1	0,20	0,11	0,04	0,02	0,07	0,00	0,01	-0,04	0,26	0,21	0,33	0,23	0,22	0,12	0,20	0,14	1,00	0,67
Cotton Futures t_t2	0,19	0,23	0,04	0,05	0,13	0,12	0,15	0,11	0,17	0,28	0,23	0,32	0,17	0,22	0,15	0,22	0,67	1,00

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Oil Price t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,45	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00
Gas Price t_t1	0,00	0,00	NA	0,00	0,00	0,34	0,01	0,28	0,75	0,02	0,01	0,00	0,12	0,01	0,09	0,06	0,21	0,19
Gas Price t_t2	0,00	0,00	0,00	NA	0,01	0,00	0,00	0,00	0,92	0,02	0,00	0,00	0,69	0,03	0,96	0,17	0,55	0,15
Gold Price t_t1	0,00	0,00	0,00	0,01	NA	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,24	0,00	0,03	0,00
Gold Price t_t2	0,00	0,00	0,34	0,00	0,00	NA	0,00	0,00	0,79	0,00	0,35	0,00	0,06	0,00	0,92	0,01	0,95	0,00
Platinum Price t_t1	0,00	0,00	0,01	0,00	0,00	0,00	NA	0,00	0,10	0,00	0,00	0,00	0,00	0,00	0,81	0,00	0,84	0,00
Platinum Price t_t2	0,00	0,00	0,28	0,00	0,00	0,00	0,00	NA	0,93	0,00	0,01	0,00	0,04	0,00	0,17	0,03	0,15	0,00
Wheat Futures t_t1	0,00	0,45	0,75	0,92	0,01	0,79	0,10	0,93	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,01	0,00	0,00
Wheat Futures t_t2	0,00	0,00	0,02	0,02	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t1	0,00	0,00	0,01	0,00	0,00	0,35	0,00	0,01	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t1	0,00	0,00	0,12	0,69	0,00	0,06	0,00	0,04	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t2	0,00	0,00	0,01	0,03	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Sugar Futures t_t1	0,00	0,06	0,09	0,96	0,24	0,92	0,81	0,17	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Sugar Futures t_t2	0,00	0,00	0,06	0,17	0,00	0,01	0,00	0,03	0,01	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
Cotton Futures t_t1	0,00	0,00	0,21	0,55	0,03	0,95	0,84	0,15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
Cotton Futures t_t2	0,00	0,00	0,19	0,15	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Lower volatility on the Energy, Precious Metals and Non-energy Commodity Market (State 1)

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,67	0,19	0,14	-0,01	0,02	0,02	0,05	0,01	0,05	0,03	0,03	-0,02	-0,05	0,06	0,11	0,10	0,07
Oil Price t_t2	0,67	1,00	0,18	0,20	0,07	0,08	0,08	0,12	0,07	0,09	0,05	0,06	-0,02	-0,03	0,05	0,10	0,05	0,07
Gas Price t_t1	0,19	0,18	1,00	0,67	0,08	0,06	0,07	0,04	0,03	0,06	0,03	0,03	0,03	0,02	0,03	0,04	0,05	0,06
Gas Price t_t2	0,14	0,20	0,67	1,00	0,05	0,07	0,03	0,06	0,02	0,04	0,02	0,04	0,06	0,04	0,00	0,01	0,03	0,07
Gold Price t_t1	-0,01	0,07	0,08	0,05	1,00	0,66	0,40	0,30	0,03	0,07	0,06	0,09	0,01	0,05	0,08	0,08	-0,05	0,01
Gold Price t_t2	0,02	0,08	0,06	0,07	0,66	1,00	0,32	0,44	0,04	0,09	0,02	0,09	-0,01	0,04	0,10	0,12	-0,02	0,01
Platinum Price t_t1	0,02	0,08	0,07	0,03	0,40	0,32	1,00	0,68	0,03	0,09	0,03	0,07	0,00	0,08	0,08	0,08	-0,04	0,01
Platinum Price t_t2	0,05	0,12	0,04	0,06	0,30	0,44	0,68	1,00	0,02	0,07	-0,01	0,05	-0,02	0,05	0,03	0,08	-0,03	-0,01
Wheat Futures t_t1	0,01	0,07	0,03	0,02	0,03	0,04	0,03	0,02	1,00	0,66	0,36	0,21	0,09	0,06	0,10	0,07	0,13	0,12
Wheat Futures t_t2	0,05	0,09	0,06	0,04	0,07	0,09	0,09	0,07	0,66	1,00	0,23	0,33	0,05	0,09	0,13	0,13	0,13	0,18
Soybean Futures t_t1	0,03	0,05	0,03	0,02	0,06	0,02	0,03	-0,01	0,36	0,23	1,00	0,65	0,20	0,14	0,04	0,04	0,15	0,13
Soybean Futures t_t2	0,03	0,06	0,03	0,04	0,09	0,09	0,07	0,05	0,21	0,33	0,65	1,00	0,12	0,20	0,06	0,08	0,13	0,17
Rice Futures t_t1	-0,02	-0,02	0,03	0,06	0,01	-0,01	0,00	-0,02	0,09	0,05	0,20	0,12	1,00	0,68	-0,02	-0,01	0,06	0,08
Rice Futures t_t2	-0,05	-0,03	0,02	0,04	0,05	0,04	0,08	0,05	0,06	0,09	0,14	0,20	0,68	1,00	-0,02	-0,01	0,05	0,11
Sugar Futures t_t1	0,06	0,05	0,03	0,00	0,08	0,10	0,08	0,03	0,10	0,13	0,04	0,06	-0,02	-0,02	1,00	0,65	0,04	0,01
Sugar Futures t_t2	0,11	0,10	0,04	0,01	0,08	0,12	0,08	0,08	0,07	0,13	0,04	0,08	-0,01	-0,01	0,65	1,00	0,03	0,02
Cotton Futures t_t1	0,10	0,05	0,05	0,03	-0,05	-0,02	-0,04	-0,03	0,13	0,13	0,15	0,13	0,06	0,05	0,04	0,03	1,00	0,64
Cotton Futures t_t2	0,07	0,07	0,06	0,07	0,01	0,01	0,01	-0,01	0,12	0,18	0,13	0,17	0,08	0,11	0,01	0,02	0,64	1,00

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,00	0,00	0,73	0,54	0,49	0,09	0,61	0,11	0,33	0,32	0,42	0,12	0,04	0,00	0,00	0,02
Oil Price t_t2	0,00	NA	0,00	0,00	0,01	0,01	0,01	0,00	0,01	0,00	0,06	0,03	0,46	0,38	0,09	0,00	0,07	0,01
Gas Price t_t1	0,00	0,00	NA	0,00	0,01	0,04	0,02	0,19	0,32	0,03	0,34	0,33	0,35	0,42	0,32	0,21	0,11	0,06
Gas Price t_t2	0,00	0,00	0,00	NA	0,09	0,02	0,24	0,03	0,47	0,15	0,42	0,15	0,03	0,21	0,94	0,73	0,33	0,01
Gold Price t_t1	0,73	0,01	0,01	0,09	NA	0,00	0,00	0,00	0,38	0,02	0,03	0,00	0,74	0,11	0,01	0,01	0,08	0,66
Gold Price t_t2	0,54	0,01	0,04	0,02	0,00	NA	0,00	0,00	0,13	0,00	0,51	0,00	0,66	0,16	0,00	0,00	0,50	0,79
Platinum Price t_t1	0,49	0,01	0,02	0,24	0,00	0,00	NA	0,00	0,37	0,00	0,31	0,01	0,92	0,01	0,01	0,00	0,20	0,72
Platinum Price t_t2	0,09	0,00	0,19	0,03	0,00	0,00	0,00	NA	0,57	0,01	0,83	0,07	0,47	0,09	0,30	0,01	0,28	0,72
Wheat Futures t_t1	0,61	0,01	0,32	0,47	0,38	0,13	0,37	0,57	NA	0,00	0,00	0,00	0,00	0,04	0,00	0,02	0,00	0,00
Wheat Futures t_t2	0,11	0,00	0,03	0,15	0,02	0,00	0,00	0,01	0,00	NA	0,00	0,00	0,07	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t1	0,33	0,06	0,34	0,42	0,03	0,51	0,31	0,83	0,00	0,00	NA	0,00	0,00	0,00	0,18	0,14	0,00	0,00
Soybean Futures t_t2	0,32	0,03	0,33	0,15	0,00	0,00	0,01	0,07	0,00	0,00	0,00	NA	0,00	0,00	0,03	0,01	0,00	0,00
Rice Futures t_t1	0,42	0,46	0,35	0,03	0,74	0,66	0,92	0,47	0,00	0,07	0,00	0,00	NA	0,00	0,51	0,81	0,05	0,01
Rice Futures t_t2	0,12	0,38	0,42	0,21	0,11	0,16	0,01	0,09	0,04	0,00	0,00	0,00	0,00	NA	0,40	0,74	0,06	0,00
Sugar Futures t_t1	0,04	0,09	0,32	0,94	0,01	0,00	0,01	0,30	0,00	0,00	0,18	0,03	0,51	0,40	NA	0,00	0,21	0,64
Sugar Futures t_t2	0,00	0,00	0,21	0,73	0,01	0,00	0,00	0,01	0,02	0,00	0,14	0,01	0,81	0,74	0,00	NA	0,30	0,52
Cotton Futures t_t1	0,00	0,07	0,11	0,33	0,08	0,50	0,20	0,28	0,00	0,00	0,00	0,00	0,05	0,06	0,21	0,30	NA	0,00
Cotton Futures t_t2	0,02	0,01	0,06	0,01	0,66	0,79	0,72	0,72	0,00	0,00	0,00	0,00	0,01	0,00	0,64	0,52	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Higher volatility on the Energy, precious Metals and Non-energy Commodity Market (State 2)

Spearman Correlation coefficients

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	1,00	0,71	0,25	0,18	0,17	0,14	0,24	0,18	0,32	0,35	0,42	0,44	0,31	0,29	0,27	0,30	0,38	0,35
Oil Price t_t2	0,71	1,00	0,16	0,24	0,15	0,29	0,35	0,36	0,14	0,39	0,22	0,48	0,17	0,32	0,08	0,28	0,17	0,37
Gas Price t_t1	0,25	0,16	1,00	0,71	0,04	0,06	0,13	0,12	-0,02	0,11	0,10	0,07	-0,03	0,00	-0,05	0,06	0,04	0,07
Gas Price t_t2	0,18	0,24	0,71	1,00	-0,01	0,14	0,13	0,18	-0,03	0,12	0,10	0,12	-0,05	0,01	-0,07	0,03	0,01	0,12
Gold Price t_t1	0,17	0,15	0,04	-0,01	1,00	0,57	0,57	0,34	0,19	0,19	0,15	0,12	0,25	0,11	0,11	0,23	0,06	0,03
Gold Price t_t2	0,14	0,29	0,06	0,14	0,57	1,00	0,40	0,61	0,07	0,21	0,00	0,11	0,10	0,14	0,00	0,15	-0,07	0,09
Platinum Price t_t1	0,24	0,35	0,13	0,13	0,57	0,40	1,00	0,63	0,11	0,29	0,09	0,24	0,24	0,27	0,05	0,23	0,02	0,21
Platinum Price t_t2	0,18	0,36	0,12	0,18	0,34	0,61	0,63	1,00	0,01	0,17	0,05	0,18	0,10	0,22	-0,05	0,10	-0,04	0,17
Wheat Futures t_t1	0,32	0,14	-0,02	-0,03	0,19	0,07	0,11	0,01	1,00	0,64	0,53	0,34	0,36	0,15	0,33	0,20	0,39	0,29
Wheat Futures t_t2	0,35	0,39	0,11	0,12	0,19	0,21	0,29	0,17	0,64	1,00	0,30	0,49	0,20	0,23	0,18	0,33	0,28	0,45
Soybean Futures t_t1	0,42	0,22	0,10	0,10	0,15	0,00	0,09	0,05	0,53	0,30	1,00	0,66	0,40	0,24	0,34	0,23	0,50	0,36
Soybean Futures t_t2	0,44	0,48	0,07	0,12	0,12	0,11	0,24	0,18	0,34	0,49	0,66	1,00	0,30	0,38	0,29	0,42	0,35	0,49
Rice Futures t_t1	0,31	0,17	-0,03	-0,05	0,25	0,10	0,24	0,10	0,36	0,20	0,40	0,30	1,00	0,70	0,22	0,11	0,29	0,19
Rice Futures t_t2	0,29	0,32	0,00	0,01	0,11	0,14	0,27	0,22	0,15	0,23	0,24	0,38	0,70	1,00	0,21	0,22	0,15	0,26
Sugar Futures t_t1	0,27	0,08	-0,05	-0,07	0,11	0,00	0,05	-0,05	0,33	0,18	0,34	0,29	0,22	0,21	1,00	0,69	0,29	0,22
Sugar Futures t_t2	0,30	0,28	0,06	0,03	0,23	0,15	0,23	0,10	0,20	0,33	0,23	0,42	0,11	0,22	0,69	1,00	0,19	0,31
Cotton Futures t_t1	0,38	0,17	0,04	0,01	0,06	-0,07	0,02	-0,04	0,39	0,28	0,50	0,35	0,29	0,15	0,29	0,19	1,00	0,63
Cotton Futures t_t2	0,35	0,37	0,07	0,12	0,03	0,09	0,21	0,17	0,29	0,45	0,36	0,49	0,19	0,26	0,22	0,31	0,63	1,00

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

Spearman Correlation, *p*-values

	Oil Price t_t1	Oil Price t_t2	Gas Price t_t1	Gas Price t_t2	Gold Price t_t1	Gold Price t_t2	Platinum Price t_t1	Platinum Price t_t2	Wheat Futures t_t1	Wheat Futures t_t2	Soybean Futures t_t1	Soybean Futures t_t2	Rice Futures t_t1	Rice Futures t_t2	Sugar Futures t_t1	Sugar Futures t_t2	Cotton Futures t_t1	Cotton Futures t_t2
Oil Price t_t1	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Oil Price t_t2	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,06	0,00	0,00	0,00
Gas Price t_t1	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,21	0,01	0,02	0,00	0,21	0,03	0,09	0,00	0,54	0,27
Gas Price t_t2	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,38	0,01	0,00	0,00	0,44	0,04	0,57	0,01	0,87	0,38
Gold Price t_t1	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,05	0,00	0,00	0,00
Gold Price t_t2	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,15	0,00	0,18	0,00	0,01	0,00	0,47	0,00	0,20	0,00
Platinum Price t_t1	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,11	0,00	0,00	0,00
Platinum Price t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,07	0,00	0,02	0,00	0,05	0,00	0,46	0,00	0,08	0,00
Wheat Futures t_t1	0,00	0,00	0,21	0,38	0,00	0,15	0,00	0,07	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Wheat Futures t_t2	0,00	0,00	0,01	0,01	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t1	0,00	0,00	0,02	0,00	0,00	0,18	0,00	0,02	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Soybean Futures t_t2	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t1	0,00	0,00	0,21	0,44	0,00	0,01	0,00	0,05	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00	0,00
Rice Futures t_t2	0,00	0,00	0,03	0,04	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00	0,00
Sugar Futures t_t1	0,00	0,06	0,09	0,57	0,05	0,47	0,11	0,46	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00	0,00
Sugar Futures t_t2	0,00	0,00	0,00	0,01	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00	0,00
Cotton Futures t_t1	0,00	0,00	0,54	0,87	0,00	0,20	0,00	0,08	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA	0,00
Cotton Futures t_t2	0,00	0,00	0,27	0,38	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	NA

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl CHRIS Database* with the help of *Quandl*.

SSEC Index and Commodity Prices - Stochastic Gradient Boosting Approach

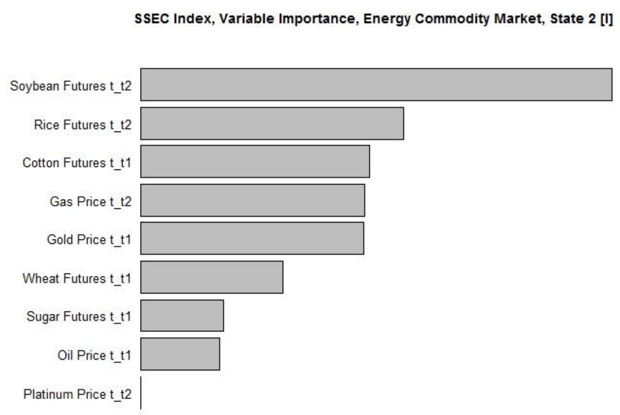
Higher volatility on the Energy Commodity Market (State 2 - I)

AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Energy Commodity Market (State2 - I)

Tuning Parameters	***Value***
n.trees	150
interaction depth	1
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.5757

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Energy Commodity Market (State2 - I).



Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

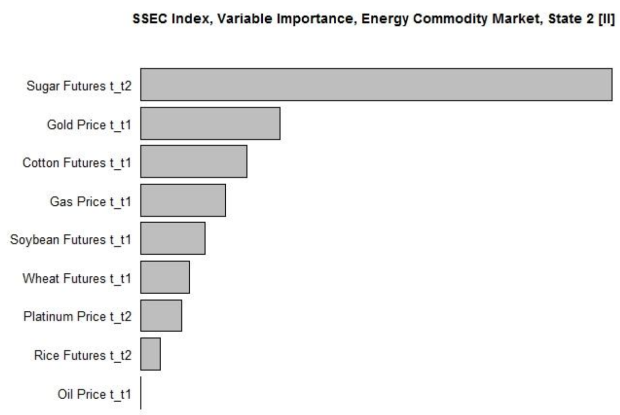
Higher volatility on the Energy Commodity Market (State 2 - II)

AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Energy Commodity Market (State2 - II)

Tuning Parameters	***Value***
n.trees	150
interaction depth	4
shrinkage	0.001
n.minobsinnode	10
AUC *test set*	0.5875

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Energy Commodity Market (State2 - II).



Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

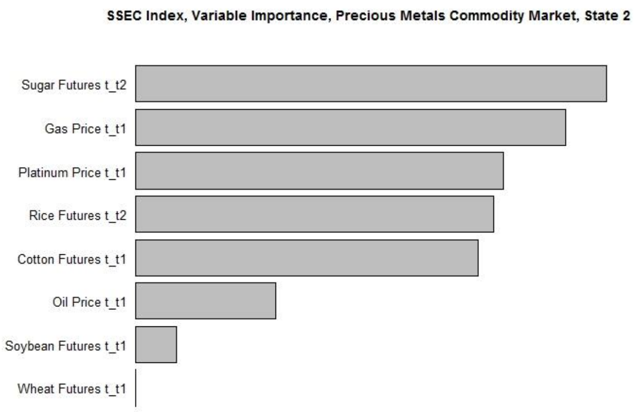
Higher volatility on the Precious Metals Commodity Market (State 2)

AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Precious Metals Commodity Market (State2)

Tuning Parameters	***Value***
n.trees	500
interaction depth	2
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.5296

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Precious Metals Commodity Market (State2).



Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

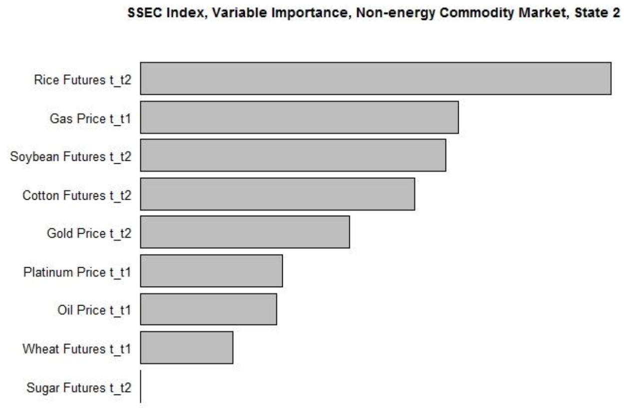
Higher volatility on the Non-energy Commodity Market (State 2)

AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Non-energy Commodity Market (State2)

Tuning Parameters	***Value***
n.trees	50
interaction depth	4
shrinkage	0.01
n.minobsinnode	10
AUC *test set*	0.5321

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Non-energy Commodity Market (State2).



Own calculation in R Studio, *caret*, *gbm* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl*.

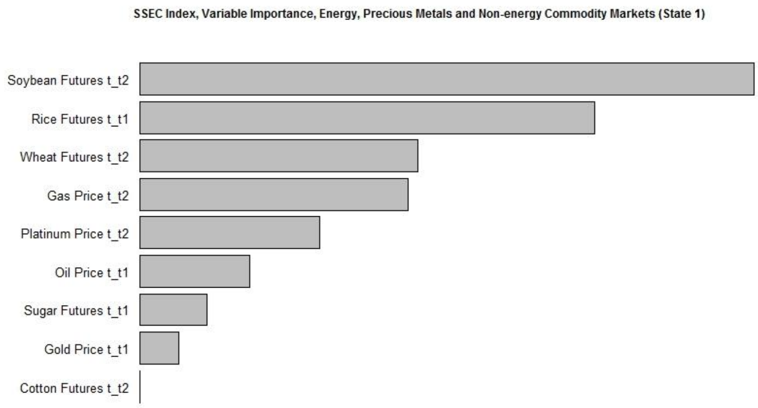
Lower volatility on the Energy, precious Metals and Non-energy Commodity Market (State 1)

AUC and Tuning Parameters' values - SSEC Index and Commodity Prices, Energy, Precious Metals and Non-energy Commodity Markets (State1)

Tuning Parameters	***Value***
n.trees	150
interaction depth	4
shrinkage	0.001
n.minobsinnode	10
AUC *test set*	0.5299

Source: Own calculation in R Studio, *caret, gbm, pROC, Quandl* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*

Variable importance based on the Stochastic Gradient Boosting model - SSEC Index and Commodity Prices, Energy, Precious Metals and Non-energy Commodity Markets (State1)



Own calculation in R Studio, *caret, gbm* packages. Data source: the time series data have been retrieved from *Quandl YFinace and CHRIS Database* with the help of *Quandl.*