HOW MACROECOMIC FACTORS
INFLUENCE THE COMMODITY MARKET
IN THE FINANCIALIZATION PERIOD:
THE CASE OF S & P GSCI COMMODITY INDEX

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Abstract


In connection to the process of financialization of commodity markets which is caused by the sharp increase of money flowing into the commodity markets, the question of which factors affect commodity and commodity indices prices is discussed. In this article, the importance of chosen macroeconomic determinants to the price variability of one of the most important commodity indexes S & P GSCI by using the Boosted Trees method is quantified. The results obtained in the research show that changes in the monthly values of macroeconomic determinants reflect and can, according to the model used, explain the volatility of the monthly average index S & P GSCI Total Return to more than 75%. The most important macroeconomic determinants proved to be Nominal Effective Exchange Rate of USD or US – Short-term interest rates

Keywords: Commodity index S & P GSCI, financialization, macroeconomic determinants

1 INTRODUCTION

Investments in commodities have grown rapidly since the early 2000s. Value of total assets in commodity index funds in the United States increased from approximately $10 billion recorded in 2000 to more than $320 billion in 2012 (Lane, 2012). The increased participation of index fund investment in commodity markets contributes to the significant financialization of commodity markets which indicates the increasing role of financial motives, financial markets and financial sector entities in commodity markets (Tang, Xiong, 2010). In connection to the process of the financialization, the question arises: What factors affect the price volatility of commodity prices? There are studies which confirmed the link between macroeconomic factors (such as inflation or money supply) and stock markets, e.g. Flannery, Protopapadakis (2002). The S & P GSCI Commodity Index is one of the most popular commodity indices in the world and we argue that there are empirical relationships among the crucial macroeconomic factors that are known to influence stock markets. The aim of this article is to analyse and quantify the relationship between chosen macroeconomic determinants and price fluctuation in the S & P GSCI Commodity Index in the period from 1/2000 to 9/2013. Overestimation and underestimation of this commodity index in the given period according to the model used were analysed too.

2 LITERATURE REVIEW

Generally, the most essential indicators that affect the price of commodities are production, consumption and stocks of the commodity. Nevertheless, the investment in commodity indices cannot be based only on an analysis of individual commodities. The reason is the number of commodities involved in commodity indices and this is associated with the complexity of these factors. Another reason is a fixed methodology for creating commodity indices. However, if
the traders in commodity market want to analyse the dynamics and price volatility of commodity indices, they can work with the macroeconomic determinants. Macroeconomic factors such as economic growth, inflation or interest rates can have an impact on the price level of all commodities (Fabozzi, Fuss, Kaiser, 2008). Based on the previous study and S & P GSCI specifications, we selected the following macroeconomic factors:

**Interest Rates:** Interest rates are considered as an important determinant of commodity price fluctuation (Frankel, 2006; Akram, 2007). There are two ways how interest rates influence the commodity index performance. Firstly, direct effect in through collateralized yield and indirect effect relates, with the effect of monetary policy. Secondly, Frankel (2006) in his studies points to the inverse relationship between the real interest rates and commodities. In case of low real interest rates investors are willing to hold commodities in the storage and it leads to higher demand for storable commodities and vice versa. Moreover, investors are looking for more profitable assets then cash or bonds. Higher demand for commodities than effects its prices.

**Exchange rate of USD:** S & P GSCI is traded in US Dollars. Except for interest rates, Akram (2007) investigates also dollar exchange rates. As a result of this research he proves that the relationship between the commodity prices and interest rates is significant and a weaker dollar leads to higher commodity prices.

**Economic growth:** Geetesh Bhardwaj and Dunsby (2012) analyse correlations between commodities and equities at different levels of GDP and indicate a stronger dependence on just industrial commodities than for agricultural commodities. The fact that an economic growth influences commodity price is obvious (Bhardwaj, Dunsby, 2012). We prefer Purchasing Managers Index (PMI) on manufactory instead of GDP, because PMI provides data with monthly frequency. Moreover, The Purchasing Managers’ Index is an early signal of changes in manufacturing output and GDP.

**Inflation:** Commodities are historically considered as an inflation hedge investment (Greer, 1978). “Commodity futures might be a better inflation hedge than stocks or bonds. Firstly because commodity futures represent a bet on commodity prices, they are directly linked to the components of inflation. Secondly because futures prices include information about foreseeable trends in commodity prices, they rise and fall with unexpected deviations from components of inflation” (Gorton, 2004).

**Money supply:** Central banks have their monetary instruments to influence the money supply, economic growth or inflation. One of these instruments is determination of nominal interest rates as discussed above. The role of actual value of monetary aggregates in the commodity markets was studied by Belke, Bordon and Hendricks (2010). They found out that global liquidity is one of the useful indicators of commodity prices movements.

**CBOE Volatility Index – VIX:** Volatility Index VIX is an appropriate indicator showing the connection between commodity and equity markets. The VIX is a measurement of the implied volatility of the S & P 500 options. The VIX measures market sentiment and is used by professional traders to measure the amount of fear and complacency in the marketplace (Connors, Alvarez, 2012). Stronger investor interest in commodities may create closer integration with conventional asset markets. Higher VIX may increase commodity returns correlation with equity returns (Silvennoinen, Thorp, 2012).

### 3.1 Analysed Macroeconomic Factors

Considering previous researches who confirmed that interest rates should be an essential indicator of commodity prices, we used more interest rates in the analysis to determinate which of these nominal interest rates is the most useful tool to predict S & P GSCI value changes. Short-term interest rates data source is OECD statistics where interest rates of individual countries in the national currencies are published. Chosen short-term interest rates are **UK interest rates, US interest rates, Japanese interest rates Chinese interest rates and an arithmetic average of these interest rates** as a global benchmark. One long-term interest rate is used, too – **CBOE Interest Rate10-Year-T-Note** whose data are available at Yahoo Finance. **Nominal Effective Exchange Rate of USD** is provided by the World Bank. Economic indicators used in the paper are **PMI on Manufacturing index** obtained from the Institute for Supply Management and **Global Industrial Production in US Dollar** from the World Bank. With regard to indicators of inflation we used **Nominal Customer Price Index** of countries included in the World Bank. Money supply can be determined by monetary aggregates. In this paper OECD member countries are used **Monetary Aggregates – broad money (M3)** index. This country set represents approximately 60 percent of the world GDP and three-quarters of world trade according the official OECD data. Last input variable
I: Abbreviations used in the research

<table>
<thead>
<tr>
<th>Description</th>
<th>Abbreviation</th>
<th>Description</th>
<th>Abbreviation</th>
</tr>
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<tbody>
<tr>
<td>S &amp; P GSCI Total Return</td>
<td>SPGSCI</td>
<td>Japan – Short-term interest rates</td>
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<tr>
<td>PMI on Manufactury</td>
<td>PMIM</td>
<td>EURO countries short-term interest rates</td>
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<td>Global Industrial Production</td>
<td>GIP</td>
<td>China – Short-term interest rates</td>
<td>ChiR</td>
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<td>CBOE Interest Rate 10-Year-Note</td>
<td>CBOEIR10</td>
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<td>IRA</td>
<td>Monetary aggregate M3 OECD countries</td>
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<td>UKIR</td>
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<td>CBOE Volatility Index – VIX</td>
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II: Descriptive statistics of the analysed data

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<td>15.86</td>
</tr>
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</table>

Source: Own calculations

is CBOE Volatility Index (VIX), data of this indicator are available at Yahoo Finance. Abbreviations of individual variables used in the research are shown in the Tab. I.

Data of all variables are analysed in the interval from January 2000 to September 2013, with monthly frequency. The index and the analysed variables developed in a rather volatile way in this period – see the following table showing the descriptive statistics.

Based on the Grubbs test, all variables include an outlier with the exception of the change indicator of Global Industrial Production (i.e. Δ GIP). In terms of the probability distribution of the data, there is a high kurtosis for almost all variables, especially with short-term interest rates [i.e. Δ IRA, Δ UKIR], then with long-term interest rates Δ CBOEIR10 and the volatility index Δ VIX. For these reasons non-parametric Boosted Trees method was selected for description of the development of the analysed index values. Moreover, the findings are not affected by the existence of outliers in the analysed sample, see below.

3.2 Boosted Trees Method

The method of Boosted Trees (BT) is a combination of the classification and regression trees method (CART) (Breiman et al., 1983), with a boosting algorithm introduced by Friedman (Friedman, 2001). Using the boosting algorithm raises the accuracy of the classification algorithm, to which it is applied by progressively reducing the error term (Braun, Mues, 2012; Breiman et al., 1983; Friedman, 2001). The resultant classification rule represents a set of many “weak” learners.

BT method enables to capture even non-linear relationship between the response variable y and a vector of explanatory \( x = [x_1, \ldots, x_n] \) through a sample of known data (learning sample) \( \{x_i, y_i\}_n \) values \( y, x \). The aim of the method is to find an approximation \( F(x) \) of a function \( F^*(x) \) which assigns to \( x \) the value of \( y \), so that minimizes the expected value of the loss function over the entire distribution of values, ie:

\[
F^* = \arg \min_{F} \mathbb{E}_{x \sim p_X} \mathbb{E}_{y \sim p_{Y|X}(y|x)} [L(y, F(x))] |x_.
\]
The method is suitable for both regression and classification (for example see Karas, Režňáková, 2013, 2014). In case of using this method for regression purposes, an average-absolute-error as a loss function (see Friedman, 2001), i.e.:

\[ L(y, \hat{F}(x)) = E_x | \hat{F}(x) - \hat{\hat{F}}(x) |. \]  \hspace{1cm} (2)

A useful feature of this method is that it allows sorting of the variables \( x_j \) according to their relative influence on the variability of \( I_j \) approximation of functions \( \hat{\hat{F}}(x) \) across the entire distribution of the input variables, this measure can be written as follows (Friedman, 2001):

\[ I_j = \left( E_x \left[ \frac{\partial \hat{\hat{F}}(x)}{\partial x_j} \right] \times \text{var}_x \left[ x_j \right] \right)^{\frac{1}{2}}. \] \hspace{1cm} (3)

### 3.2.1 Classification and Regression Trees (CART)

The basic idea behind the Trees is the division of a complex problem of feature space in a set of smaller parts known as regions \( [R] \), which is possible to describe through simpler models (for example, constants). For a two-dimensional classification problem it is possible to describe the approach of such a division using the following schemata. These schemata document the division of two-dimensional feature space in the mentioned regions using the constant \( t \).

Alternatively, the same division can be shown using trees, as in the following schema.

The central problem of the method of using trees is establishing the optimal divisional boundaries \( t \) between those regions \( R \). The boundaries are established in such a way that the demarcated regions, or the trees, fulfilled specific defined properties. This property of the regions, or the trees, is defined as a node impurity and the aim of the method is its minimalization. For classification purposes, where the output can take the value 1, 2, ..., \( K \), it is possible to describe node impurity in the following way, see (Hastie et al., 2009, p. 306). In the \( m \)-th node,

\[ \hat{p}_{\text{st}} = \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i = k). \] \hspace{1cm} (4)

Then it is necessary to define the majority of observed elements of the \( k \)-th group in the node \( m \) as:

\[ k(m) = \arg \max x_i \hat{p}_{\text{st}}. \] \hspace{1cm} (5)

Node impurity of the tree \( T \) or \( Q(T) \) can be defined using several standards, the following is used, the:

1. Misclassification error:

\[ \frac{1}{N_m} \sum_{x_i \in R_m} I(y_i \neq k(m)) = 1 - \hat{p}_{\text{st}(m)}. \] \hspace{1cm} (6)

2. Gini index:

\[ \sum_{k=1}^{K} \hat{p}_{\text{st}} \hat{p}_{\text{st}} = \sum_{k=1}^{K} \hat{p}_{\text{st}} \times (1 - \hat{p}_{\text{st}}). \] \hspace{1cm} (7)

3. Cross-entropy (deviance):

\[ -\sum_{k=1}^{K} \hat{p}_{\text{st}} \log \hat{p}_{\text{st}}. \] \hspace{1cm} (8)

Deviance as a level of node impurity was used here as part of the presented research.

### 3.2.2 Boosting

Boosting is a general approach for making the final deciding rules as a set of several “weak” rules or classifiers. Among the boosting algorithms AdaBoost.M1 is one most frequently applied, see (Freund, Schapire, 1997), the principle of which will be described further. Let us consider a classification problem with a dichotomous dependent variable \( Y \), i.e. \( Y \in \{-1; 1\} \) and a vector of independent predictors \( X \) and a classifier \( G(X) \), which can only take the values -1 and 1, i.e. \( G(X) \in \{-1; 1\} \). Error rate
for the training sample is given by the relationship, see (Hastie et al., 2009, p. 337):

\[
\bar{err} = \frac{1}{N} \sum_{i=1}^{N} I[y_i \neq G(x_i)].
\]  

(9)

The basis of boosting is the gradual application of the classifier \(G(x)\) to the repeatedly modified version of data and thus gradually produce other \(M\) "weak" classifiers \(G_m(x), m = 1, 2, ..., M\). It is possible to describe the method of boosting algorithms in the following schemata, see (Hastie et al., 2009, p. 338).

The resulting classifier \(G_{\text{final}}(x)\) is then made up of the individual partial rules \(G_m(x)\), which are given the weights \(\alpha_m\). The output is standardized to attain a value of only −1 or 1, see (Hastie et al., 2009, p. 338).

\[
\alpha \sum_{m=1}^{M} \alpha_m G_m(x) = \text{sign} \left( \sum_{m=1}^{M} \alpha_m G_m(x) \right). 
\]  

(10)

The weights \(\alpha_1, \alpha_2, ..., \alpha_M\) are calculated using a boosting algorithm, representing the partial contribution of each classifier \(G_m(x)\). The modification of data in each step of the boosting algorithm is the application of the weights \(w_1, w_2, ..., w_N\) for each pair of training data \((x_i, y_i)\), where \(i = 1, 2, ..., N\). At the start of the algorithm the weights are set at the value \(w_i = 1/N\). In every other iteration \(m = 2, 3, ..., M\) the weights of individual observations are adjusted. In the \(m\)-th iteration the weights of those observations which had been wrongly classified in the previous step are increased by the classifier \(G_{m-1}(x)\), while the weights of those which were successful are lowered. By this method the wrongly classified observation is given more attention in order to increase the accuracy of the whole rule. The algorithm \(\text{AdaBoost.M1}\). can be described as follows, see (Hastie et al., 2009, p. 338–339):

1. Set the observation weights to the default value \(w_i = 1/N\), where \(i = 1, 2, ..., N\).
2. From \(m = 1\) to \(m = M\):
   a) Fit a classifier \(G_m(x)\) for the training data using the weights \(w_i\).
   b) Calculate \(\bar{err}_m = \frac{\sum_{i=1}^{N} w_i I[y_i \neq G_m(x_i)]}{\sum_{i=1}^{N} w_i}\). (11)
   c) Calculate \(\alpha_m = \log((1 - \bar{err}_m)/\bar{err}_m)\). (12)
   d) Set \(w_i \leftarrow w_i \times \exp[\alpha_m \times I(y_i \neq G_m(x_i))]\), \(i = 1, 2, ..., N\). (13)
3. Output \(G(x) = \text{sign} \left( \sum_{m=1}^{M} \alpha_m G_m(x) \right)\). (14)

A useful feature of this method is that it allows the sorting out of the variables \(x_j\) according to their relative influence \(I_j\) on the variability of the approximation function \(G(x)\) across the entire division of input predictors, this measurement can be described as follows, see (Friedman, 2001):

\[
I_j = \left( E_x \left[ \frac{\partial G(x)}{\partial x_j} \right] \times \text{var}_x \left[ x_j \right] \right)^{1/2}. 
\]  

(15)

Among the advantages of the BT method, aside from its nonparametric nature (the data need not be normally distributed), is its tolerance for outliers in the input variable space (Twala, 2010). In addition, the method can even capture non-linear relationships between the variables (Guelman, 2012).

Among other advantages of the BT method, in addition to the non-parametric assumptions, is its immunity against the presence of outliers in input variable space (see Twala, 2010). The calculations were performed with the statistical software Statistica 10.

### 3.2.3 The Analysed Model

We used the mentioned method in our research for building the following model.

The Model can be formally described as follow:

\[
\Delta S & P \ GSCI \ TR = f(\Delta IR, \Delta GPIM, ..., \Delta NEERUS), 
\]  

(16)

where \(\Delta S \& P \ GSCI\) is the change of the value of S \& P GSCI Commodity Index,
ΔIR, ΔGPIM, ..., ΔNEERUS are analysed macro-economics factors.

The difference (Δ) of analysed factors was calculated in the following way, for example the difference of S&P GSCI index (i.e. ΔS&P GSCI):

\[
\Delta S&P GSCI \text{ TR} = \sum_{d=1}^{n_M} S&P GSCI \text{ TR}_{dM} - \sum_{d=1}^{n_M} S&P GSCI \text{ TR}_{dM-1},
\]

where

\( n_M \) is the number of days in the month \( M \),

\( t \) is the time variable, defined in months, \( t = 1, 2, \ldots, 165 \),

\( S&P GSCI \text{ TR}_{dM} \) is total revenue of S&P GSCI index in the day \( d \) of month \( M \).

4 RESULTS

When using the BT method, the resulting model is derived as a set of further sub-models (in this case the trees), which are combined in a single unit. The number of the sub-models as well as the weights attributed to them is the result of an iterative calculation. The resulting model includes 81 trees.

The following table shows the achieved minimum of the loss function (see eq. 2), this value represents a goodness of fit.

Various macroeconomic determinants (independent variables) are ranked according to the degree of their contribution to the explanation of the S&P GSCI volatility (see equation 3). The most significant variable is assigned a value of the relative importance 1, i.e. 100%; other variables are assigned values according to their importance compared with the most significant variable. For the results see Tab. IV.

Tab. IV shows that the analysed macroeconomic determinants, or change of their values, affect significantly the price volatility in the commodity index S&P GSCI. According to the model, the most significant factor proved to be Nominal Effective Exchange Rate of USD, where US dollar weakening indicates an increase in S&P GSCI value. Only about one percent lower significance is for US short-term interest rates. Other indicators, which reached more than 80% of the relative significance, are World Bank Inflation Rate, CBOE Volatility Index, PMI on Manufactory, UK – Short-term interest rates, and Global Industrial Production. Lower significance was found in other short-term interest rates, as well as long-term interest rate, and the used money supply indicator.

Graph 1 below illustrates applying of the model to the analysed data set in the period 1/2000–9/2013. The black line represents the BT model value and the grey line shows real historical values of S&P GSCI monthly changes. The graph confirms the assumption that macroeconomic determinants can be successfully used to explain the price level of S&P GSCI. More precisely, changes in the value of the used set of macroeconomic determinants can explain 75.74% of S&P GSCI value changes.

Graph 2 shows the difference between the actual S&P GSCI values and the values predicted in the model for the same moments, so called residual value. These differences represent the part of the index development that was not determined by the analysed macroeconomic factors. The greatest positive difference in values that can be interpreted as an overestimation of the index was reached in the first half of 2008, followed by a sharp underestimation in the second half of 2008. Similar index overestimation was recorded also in February 2002 and underestimation in October 2004.

As far as model accuracy is concerned, the year 2008 appears to be critical. The overall accuracy of the model, measured as a percentage of the sum of squares explained, was therefore analysed in three sub-periods. In the period before the critical year 2008 (i.e. 1/2000–12/2007), the model was able to describe 91.15% of the value changes with the use of the analysed macroeconomic factors, i.e. only 8.85% values remained unexplained. In 2008, however, the model with the same variables could

### III: Achieved minimum values of the error function

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Source: author's calculation

### IV: Importance of chosen macroeconomic determinants

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<th>Relative Importance</th>
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<td>ΔCBOEIR10</td>
<td>76</td>
</tr>
<tr>
<td>ΔUSIR</td>
<td>99</td>
<td>ΔIRA</td>
<td>74</td>
</tr>
<tr>
<td>ΔWBIR</td>
<td>90</td>
<td>ΔMAM3</td>
<td>74</td>
</tr>
<tr>
<td>ΔVIX</td>
<td>86</td>
<td>ΔEUIR</td>
<td>73</td>
</tr>
<tr>
<td>ΔPMIM</td>
<td>82</td>
<td>ΔCHIR</td>
<td>69</td>
</tr>
<tr>
<td>ΔUKIR</td>
<td>81</td>
<td>ΔJIR</td>
<td>54</td>
</tr>
<tr>
<td>ΔGIP</td>
<td>81</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: author's calculation
be used to explain only 65.26% of values, i.e. 34.74% of the value changes remained unexplained. This is approximately 3.9 times more if compared to the analysed period 1/2000–12/2007. After 2008, the model accuracy reached 74.57%.

5 DISCUSSION

The analysis implies that the macroeconomic determinants can explain S & P GSCI volatility with a relatively high accuracy. The process of selection of individual macroeconomic indicators was based on previous studies which support the idea that macroeconomic factors may influence the volatility of commodity prices. The most significant factors are therefore the following:

- **Importance of the US dollar:** The US dollar was confirmed to be the most significant currency used in global commodity exchange for commodities trading and settlement. This can be documented by the fact that fluctuations of the US dollar against other major currencies affect commodity prices (the higher the US dollar, the lower their prices are and vice versa).

- **US short-term interest rates:** The importance of this factor is partially connected with the above mentioned importance of USD. It proves that the choice of short-term reference interest rates is related to a short-term speculation, and moreover, that its development has a significant impact on an on-exchange trading in commodities. We agree with the Frankel's (2006) explanation that investors are looking for more profitable assets in the situation when short-term interest rates are low, and due to the increased demand commodity prices are higher. Especially in the period of the financialization of commodity markets when there are many non-commercial investors and opportunities to invest in the commodity assets. Lower interest rates also enhance investor’s (incl. speculators’) expectations of faster economic growth and therefore the anticipated increase in the demand for commodities susceptible of industrial usage, as well as the increase in their prices.
World inflation: The impact of the “world inflation” factor on the commodity price dynamics can be seen as anticipated and valid in the long term.

Volatility Index – VIX: Proved significance of the volatility index related to possibly the most important US stock market index S&P 500 is connected with the investors’ sentiment. Significance of this factor is supported by the hypothesis of a closer integration of the analysed commodity index with the stock market during the period of financialization of commodity markets (Tang, Xiong, 2010; Silvennoinen, Thorp, 2012).

Purchasing Managers Index: Its importance (or relatively high correlation) accents expectations of the professionals in the corporate sector regarding future economic development (which is quite different from the volatility index representing subjective opinions of speculators). When using the analysed macroeconomic variables, the model could not explain sharp changes in the index in 2008, as well as minor changes in 2002 and 2005. In other words, in these moments the model failed to describe the occurred index dynamics using the analysed fundamental factors. The most likely explanation seems to be the influence of a factor that is external for the model, or a factor that is not fundamental for it. According to the literature (see Demirer, Lee, Lien, 2013; UNCTA, 2011), so called herd behaviour is more likely in the period of financialization of commodity markets. In this context, a significant increase of the index in the first half of 2008 is explained as a creation of a speculative bubble (e.g. see Gilbert, 2010). As a result of the analysis of the model accuracy, it was found that up to 34.74% of the value changes could be caused by this speculative bubble.

SUMMARY
The article analyses relationship between the chosen macroeconomic determinants movements and S&P GSCI Commodity Index price volatility in the financialization period. For this purpose, a Boosted Trees model was used in the research. It was proved that changes in the value of the used set of macroeconomic determinants can explain 75.74% of S&P GSCI value changes in the interval from January 2000 to September 2013. According to the model, the most significant factor is Nominal Effective Exchange Rate of USD or US short-term interest rates. The ex-post analysis of the model accuracy also proved that up to 34.74% of the value changes in 2008 cannot be explained by the analysed macroeconomic factors, but other factors of a different character.

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