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# IN SEARCH OF HEDGES AND SAFE HAVENS IN GLOBAL FINANCIAL MARKETS

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## ABSTRACT

The aim of the paper is to search for hedges and safe havens within three instrument classes: assets (represented by the S&P500 index), gold and oil prices, and dollar exchange rates. Weekly series of returns of all the instruments from the period January 1995 – June 2015 are analysed. The study is based on conditional correlations between the instruments in different market regimes obtained with the use of copula-DCC GARCH models. It is assumed that different market regimes will be identified by statistical clustering techniques; however, only conditional variances (without conditional covariances) will be taken into account. The reason for this assumption is connected with the fact that variances can be understood as market risk, and, as such, are a good indicator of market conditions. A considerable advantage of such an approach is the lack of need to determine the number of market regimes, as it is established by clustering quality measures. What is more, the methodology used in the paper makes it possible to treat the relations between instruments symmetrically. The results obtained in the study reveal that only dollar exchange rates can be treated as a (strong) hedge and a (strong) safe haven for other instruments, while gold and oil are a hedge for assets.

**Key words:** market regimes, clustering methods, copula, DCC-GARCH.

## 1. Introduction

The global financial crisis caused a dramatic decline in stock prices almost simultaneously in the stock markets worldwide. Portfolios based on public equity and other financial instruments depreciated at a rapid rate. The economic downturn, which was the result (or the symptom) of the crisis, hampered the demand for commodities. The prices of oil, other energy sources, food and most metals (excluding gold) dropped. Some experts claim that, in anticipation of

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decreases in prices, investors purchased gold, which seemed an attractive instrument during a crisis due to various reasons (a liquid instrument, a means of payment in the past).

Baur and Lucey (2010) were the first to formalize and measure the role of gold as an instrument used as a substitute for assets. They defined two categories of instruments: a hedge (a strong hedge) and a safe haven (a strong safe haven). An instrument is defined as a hedge (a strong hedge) for assets if its rates of return are uncorrelated or negatively correlated with their rates of return. An instrument is defined as a safe haven (a strong safe haven) if its returns are uncorrelated or negatively correlated with the returns of other assets in times of market stress or turmoil. Baur and Lucey (2010) study the role of the price of gold (its rate of return) with reference to stock market indexes and bonds in the USA, Great Britain and Germany. On the basis of the analyses of daily returns in the period between 30 November 1995 and 30 November 2005, they conclude that gold is a hedge for assets in the USA and Great Britain and for bonds in Germany, and a safe haven for assets in these three countries.

The aim of the paper is to investigate the possibilities of a hedge and a safe haven within three instrument classes: assets (represented by the S&P500 index), gold and oil prices, and effective dollar exchange. As it is done in studies by Joy (2011), Reboredo (2013a), and Reboredo (2013b), in this paper weekly series of returns from the period between January 1995 and June 2015 are analysed with the use of conditional correlations between instruments for different market regimes obtained from copula-DCC GARCH models. In the study it is assumed that the identification of different markets regimes will be conducted with the use of statistical clustering methods, although only conditional variances will be taken into account. The reason for such an assumption is connected with the fact that variances can be understood as market risk, thus the change (growth) of risk (variance) is a good (and classic) indicator of the condition of financial markets. One of the advantages of our approach is the lack of need to a priori determine the number of market regimes, as it is established by clustering quality measures. What is more, the methodology used in the paper allows for treating the relations between the instruments symmetrically. As a result, it is possible to establish the role of particular instruments in different market regimes. To the best of our knowledge, such an approach has not been used in the analyses of hedges and safe havens so far.

The paper is organised as follows. The second chapter reviews the subject literature devoted to identification of financial instruments which could be used as hedges and safe havens, the third chapter presents the methodology and the empirical strategy used in the paper, the fourth one presents the data and discusses the results obtained, while the fifth chapter contains the conclusions.

## 2. Literature review

Numerous papers published in recent years address the question whether gold is actually a good haven for the investment portfolio and whether there are other instruments which could play this role. Most authors adopt Baur and Lucey's (2010) definition of a hedge and a safe haven, who verify the role of gold with reference to stock market indexes and bonds in the USA, Great Britain and Germany. In subsequent papers the set of analysed instruments and research methodology have been expanded, thus they can be divided into four distinct groups.

Studies from the first group consider possibilities of using gold to hedge portfolios consisting of assets and bonds. Apart from the already mentioned work by Baur and Lucey (2010), the following papers use this approach:

(i) Baur and McDermott's (2010) paper, in which the analysis of daily, weekly and monthly rates of return in the period between 1979 and do 2009 lead to the conclusion that gold is a hedge and a safe haven for assets in European countries and in the USA, but is neither a hedge nor a safe haven for assets in developing countries and in Australia, Canada and Japan,

(ii) Beckmann, Berger and Czudaj's (2015) paper, in which it is concluded, on the basis of the analysis of monthly rates of return in the period between 1970 and 2012, that: gold is a strong hedge for assets in the euro area, Indonesia, Russia and Turkey; gold is not a hedge for assets in China and Germany; gold is a hedge for assets in the remaining economies; gold is a strong safe haven for assets in India and Great Britain and is not a hedge in the euro area, Indonesia, and Russia.

The second group includes studies which investigate the role of gold as a hedge for foreign currency portfolios. The following two papers can serve as an example here:

- Joy's (2011) paper, which reveals, on the basis of weekly data of 16 exchange rates in the period between 10 January 1986 and 29 August 2008, that gold is a hedge and a weak hedge only for US dollar exchange rate (it is not a hedge for exchange rates of other currencies),
- Reboredo's (2013b) paper, which confirms, on the basis of weekly data of 8 exchange rates in the period between 7 January 2000 and 21 September 2012, the results obtained by Joy (2011) that gold is a hedge only for US dollar exchange rate.

The papers from the third group examine gold as a hedge for commodity markets. Reboredo's (2013a) paper may serve as an example here. On the basis of weekly data from the period between 7 January 2000 and 30 September 2011, this paper concluded that gold is not a hedge for oil prices, but a safe haven for them.

The fourth group comprises papers which search for other hedges than gold, e.g.:

- Hood and Malik's (2013) paper, in which daily rates of return are analysed in the period between November 1995 and November 2010, and the findings reveal that gold and VIX are a hedge and a safe haven for assets in the USA, while other precious metals are neither a hedge nor a safe haven.
- Ciner, Gurdgiev and Lucey's (2013) paper, which concludes, on the basis of daily data from the period 1990-2010, that: gold is a hedge and a safe haven for dollar exchange rates and for British pound exchange rates (since 2000); gold is a safe haven for assets and bonds in the USA; bonds are a safe haven for assets in the USA; oil is a safe haven for bonds in the USA, assets listed on the British stock exchange are a safe haven for pound exchange rate and for oil; British bonds are a safe haven for assets in Great Britain; pound exchange rate is a safe haven for assets and bonds in Great Britain and for gold.

The analysis of gold as a hedge is conducted with the use of various instruments, which allow for identifying 'normal' and 'turmoil' market regimes. In their seminal paper, Baur and Lucey (2010) use an autoregressive distributed lag model including different dummies for indicating lower quantiles of any instruments of interest. Joy (2011), Ciner, Gurdgiev and Lucey (2013) use a DCC-GARCH model, while Reboredo (2013a), and Reboredo (2013b) use the copula function and dependencies in the tails of distribution to define the relations in turmoil. Beckmann, Berger and Czudaj (2015) use two-regime threshold model (smooth transition regression), in which one regime corresponds to normal market conditions, while the other to a market in crisis.

## 3. Methodology

The aim of the empirical strategy used in the study is to investigate the possibility of using three categories of financial instruments – assets (represented by the S&P500 index), commodities (gold and oil) and US dollar rate as hedges and safe havens. It consists of two stages:

- identification of market regimes,
- the analysis of correlations between the instruments in different market regimes.

During the first stage it is assumed that market regimes will be identified with the use of statistical clustering methods of weekly periods *t* according to conditional variances of returns of all analysed instruments. This assumption is based on another assumption that variance growth is a good (and classic) indicator of financial market conditions. The market regime with the highest variance is used to identify instruments which can be treated as safe havens. Conditional variances are obtained on the basis of four-dimensional copula DCC-GARCH model.

A copula-based multivariate GARCH model used in this study allows for modelling the conditional dependence structure when standardized innovations are non-elliptically distributed. Thus, it makes it possible to model the volatility of particular financial instruments using univariate GARCH models with different standardized residual distribution. Generally, copulas allow the researcher to specify the models for the marginal distributions separately from the dependence structure that links these distributions to form a joint distribution. They offer a greater flexibility in modelling and estimating margins than in the case of using parametric multivariate distributions (see, e.g. Nelsen, 1999; Joe, 1997). Secondly, at present the copula-GARCH methodology is widely used in the analysis of financial time series (see, e.g. Patton, 2006; Serban et al., 2007; Lee and Long, 2009; Doman, 2011; Wu et al., 2012; Aloui et al., 2013; Li and Yang, 2013; Zolotko and Okhrin, 2014; and for a review Patton, 2012).

In the copula-GARCH model, multivariate joint distributions of the return vector $r_t = (r_{1,t}, ..., r_{k,t})'$, $t = 1,...,T$ conditional on the information set available at time $t-1$ ($\Omega_{t-1}$) is modelled using conditional copulas introduced by Patton (2006). This model takes the following form:

$$r_{1,t} \mid \Omega_{t-1} \sim F_{1,t}(\cdot \mid \Omega_{t-1}), ..., r_{k,t} \mid \Omega_{t-1} \sim F_{k,t}(\cdot \mid \Omega_{t-1}) \quad (1)$$

$$r_t \mid \Omega_{t-1} \sim F_t(\cdot \mid \Omega_{t-1}) \quad (2)$$

$$F_t(r_t \mid \Omega_{t-1}) = C_t\left(F_{1,t}(r_{1,t} \mid \Omega_{t-1}), ..., F_{k,t}(r_{k,t} \mid \Omega_{t-1}) \mid \Omega_{t-1}\right) \quad (3)$$

where $C_t$ denotes the copula, while $F_t$ and $F_{i,t}$ denote the joint cumulative distribution function and the cumulative distribution function of the marginal distributions at time *t*, respectively.

In a general case, univariate rates of return $r_{i,t}$ can be modelled by various specifications of the mean model by using the ARIMA process and various specifications of the variance model (e.g. sGARCH, fGARCH, eGARCH, gjrGARCH, apARCH, iGARCH and csGARCH). In the study, for all series of returns, the following ARIMA process is applied:

$$r_{i,t} = \mu_{i,t} + y_{i,t}, \quad (4)$$

$$\mu_{i,t} = E\left(r_{i,t} \mid \Omega_{t-1}\right), \quad \mu_{i,t} = \mu_{i0} + \sum_{j=1}^{P_i} \varphi_{ij} r_{i,t-j} + \sum_{j=1}^{Q_i} \theta_{ij} y_{i,t-j}, \quad (5)$$

$$y_{i,t} = \sqrt{h_{i,t}}\, z_{i,t}, \quad (6)$$

variance for one series is modelled with the use of a standard GARCH model (sGARCH):

$$h_{i,t} = Var(r_{i,t} \mid \Omega_{t-1}), \quad h_{i,t} = \omega_i + \sum_{j=1}^{p_i} \alpha_{ij} y_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_{ij} h_{i,t-j}, \tag{7}$$

and for the remaining three series variance is modelled with the use of an exponential GARCH model (eGARCH) (Nelson, 1991):

$$\log(h_{i,t}) = \omega_i + \sum_{j=1}^{p_i} \left( \alpha_{ij} \varepsilon_{i,t-j} + \gamma_{ij} \left( \left| \varepsilon_{i,t-j} \right| - E \left| \varepsilon_{i,t-j} \right| \right) \right) + \sum_{j=1}^{q_i} \beta_{ij} \log(h_{i,t-j}), \ \varepsilon_{i,t} = \frac{y_{i,t}}{\sqrt{h_{i,t}}}, \tag{8}$$

where $z_{i,t}$ are i.i.d. random variables which conditionally follow some distributions with the required properties (in the empirical analysis the following distributions are considered: normal distribution, skew-normal distribution, student-t, skew-student, generalized error distribution).

The dependence structure of the margins is then assumed to follow an elliptical copula with conditional correlations $R_t$. The dynamics of $R_t$ is modelled with the use of the dynamic conditional correlation model DCC($m$, $n$):

$$H_t = D_t R_t D_t, \tag{9}$$

$$D_t = diag(\sqrt{h_{1,t}}, ..., \sqrt{h_{k,t}}), \tag{10}$$

$$R_t = \left( diag(Q_t) \right)^{-1/2} Q_t \left( diag(Q_t) \right)^{-1/2}, \tag{11}$$

$$Q_t = \left( 1 - \sum_{j=1}^{m} c_j - \sum_{j=1}^{n} d_j \right) \overline{Q} + \sum_{k=1}^{m} c_j (\varepsilon_{t-j} \varepsilon'_{t-j}) + \sum_{k=1}^{n} d_j Q_{t-j}, \tag{12}$$

where conditional variances $h_{i,t}$ are modelled with the use of one-dimensional GARCH($p$,$q$) processes (7) or (8), $\varepsilon_t = D_t^{-1} y_t$ ($y_t = (y_{1,t}, ..., y_{k,t})'$) and $\overline{Q}$ is unconditional covariance matrix of standardized residuals $\varepsilon_t$. In specification (12) $c_j \ (j = 1, ..., m)$, $d_j \ (j = 1, ..., n)$ are scalars which capture the effect of previous shocks and previous dynamic correlation on the current conditional correlation respectively.

The parameters of the above copula-DCC-GARCH model are assessed using the inference function for margins (*IFM*) approach (this method is described in detail in the works by (e.g.): (Joe, 1997, pp. 299–307; Doman, 2011, pp. 35–37; Wanat, 2012, pp. 98-99)). Calculations have been done in the R package (”rmgarch” ,version 1.2-6) developed by Alexios Ghalanos.

To identify financial market regimes, statistical methods of unsupervised classification are used. The groups obtained are expected to be periods with a similar level of risk (i.e. similar conditional variance). Although the number of groups is not known a priori, it is assumed that it should be neither too small nor too large. In fact, clustering results are assessed taking into account both statistical criteria and economic interpretation of financial market regimes obtained. Clustering is conducted by means of hierarchical methods in which groups are created recursively by linking together the most similar objects (Ward's method is applied here). Other methods of division, i.e. the k-means method and the partitioning among medoids (PAM) method proposed by Kaufman and Rousseeuw (1990) are also used. In both cases, after making the initial decision about the desired number of groups, objects are allocated in such a way that the relevant criterion is met. For the k-means method the allocation of objects should minimize a within-group variance. In the PAM method the representatives of groups (medoids) are selected at each step of the analysis, and then the remaining objects are allocated to the group which includes the closest medoid. The former method is more robust to outliers than the k-means method, because it minimizes the sum of dissimilarities instead of the sum of squared Euclidean distance. In order to evaluate the optimal number of clusters in the data, we use internal validity indexes: Calinski Harabasz pseudo F statistics (Calinski and Harabasz, 1974), the average silhouette width (Kaufman and Rousseeuw, 1990), the Dunn index (Dunn, 1974), and Xie and Beni's (1991) index. The final classification of objects is, therefore, the result of the comparison of the results of respective grouping algorithms.

During the second stage of the study conditional correlations between different markets regimes obtained from the copula-DCC-GARCH method described above are analysed. In accordance with the definition adopted, the negative correlation (the lack of correlation) in the regime with 'normal volatility' signifies a strong hedge (a hedge), and the negative correlation (the lack of correlation) in the regime with considerably higher volatility signifies a strong safe haven (a safe haven).

## 4. Data and empirical results

The dataset consists of variables which represent equity, currency, gold and oil markets. Equity is represented by the S&P500 index (SP500), exchange rates are represented by the Federal Reserve Bank's Nominal Trade Weighted Effective Index (USD_B), the price of gold is represented by the gold futures contracts traded on the New York Mercantile Exchange (NYMEX) and it based in US dollars per troy ounce (GOLD), the price of crude oil is represented by contracts of crude oil futures traded on the NYMEX and it based in US dollars per barrel (WTI). The study is based on weekly data, the sample period ranges from January

1995 to June 2015 and comprises 1069 observations per variable. Weekly logarithmic rates of return are analysed, and the descriptive statistics for index returns, exchange rate returns, crude oil returns and gold returns are reported in Table 1. In the analysed period all instruments increase their values, which is visible in positive means of returns and positive medians of returns. WTI rates of return are characterised by the greatest volatility, and USD_B rates of return are characterised by the smallest volatility. Dollar exchange rate is the only instrument with positive asymmetry, while WTI and SP500 have a considerable negative asymmetry.

**Table 1.** Descriptive statistics for returns

| | S&P500 | USD_B | GOLD | WTI |
|---|---|---|---|---|
| Mean | 0.141 | 0.019 | 0.106 | 0.110 |
| Median | 0.365 | 0.001 | 0.116 | 0.244 |
| Max | 8.308 | 3.618 | 12.808 | 15.054 |
| Min | -15.279 | -2.841 | -11.827 | -19.561 |
| Std. Dev. | 1.962 | 0.563 | 1.963 | 3.800 |
| Skewness | -0.890 | 0.348 | -0.075 | -0.523 |
| Kurtosis | 8.709 | 6.277 | 7.768 | 4.980 |

*Source: Author's own calculation.*

During the first stage of the study market regimes are identified with the use of the copula-DCC GARCH model which yields conditional variances of returns of the analysed instruments. In the empirical study different variants of the ARMA-GARCH specifications are considered for individual returns. On the basis of information criteria and tests of model adequacy (the results can be obtained from the authors on request), the following models have been selected: ARMA(1,1)-eGARCH(2,2) for S&P500 and gold, ARMA(1,1)-eGARCH(1,1) for US dollar exchange rate and ARMA(1,1)-sGARCH(1,1) for oil. In all models for standardized residuals the skewed Student's t distributions (with skew and shape parameters $\xi$ and $\upsilon$ respectively) are assumed. On the other hand, Gauss and Student's t copulas have been considered in the analysis of the dynamics of dependencies between the rates of return, and, also on the basis of information criteria, Student's t with conditional correlation and constant shape parameter $\eta$ have been chosen. Table 2 presents the results of estimation, and Figure 1 the estimated conditional variances.

**Table 2.** Copula-DCC–GARCH model estimation results

| | SP500 | USD_B | GOLD | WTI |
|---|---|---|---|---|
| GARCH Model | eGARCH(2,2) | eGARCH(1,1) | eGARCH(2,2) | sGARCH(1,1) |
| Mean Model | ARMA(1,1) | ARMA(1,1) | ARMA(1,1) | ARMA(11) |
| Distribution | Skewed Student's | Skewed Student's | Skewed Student's | Skewed Student's |
| Parameters of univariate models | | | | |
| $\mu$ | 0.12185 (0.00991) | 0.02937 (0.16007) | 0.04532 (0.41810) | 0.09392 (0.44854) |
| $\varphi_1$ | -0.17052 (0.01358) | 0.20266 (0.11964) | -0.11796 (0.08054) | 0.10080 (0.69841) |
| $\theta_1$ | 0.32150 (0.00000) | 0.08406 (0.53949) | 0.34913 (0.00000) | 0.09081 (0.72951) |
| $\omega$ | 0.05288 (0.00037) | -0.05176 (0.00700) | 0.04854 (0.02876) | 0.24883 (0.05896) |
| $\alpha_1$ | -0.31312 (0.00000) | 0.04231 (0.03079) | 0.08058 (0.01535) | 0.07009 (0.00001) |
| $\alpha_2$ | 0.13897 (0.00375) | - | -0.01038 (0.76281) | - |
| $\beta_1$ | 1.00000 (0.00000) | 0.96169 (0.00000) | 0.13882 (0.00000) | 0.91452 (0.00000) |
| $\beta_2$ | -0.05326 (0.00163) | - | 0.81050 (0.00000) | - |
| $\gamma_1$ | 0.13848 (0.07462) | 0.20927 (0.00000) | 0.26303 (0.00000) | - |
| $\gamma_2$ | 0.04129 (0.60239) | - | 0.14724 (0.00549) | - |
| $\xi$ (skew ) | 0.73460 (0.00000) | 1.08361 (0.00000) | 0.94755 (0.00000) | 0.86033 (0.00000) |
| $\upsilon$ (shape) | 18.48111 (0.04565) | 15.36894 (0.03426) | 7.50841 (0.00000) | 9.46780 (0.00005) |
| Copula-DCC parameters | | | | |
| Distribution | Four-dimensional t-Student | | | |
| DCC Order | DCC(1.1) | | | |
| | Parametry | | | |
| $c_1$ | 0.021553 (0.00069) | | | |
| $d_1$ | 0.970817 (0.00000) | | | |
| $\eta$ (mshape) | 15.096596 (0.00001) | | | |

Probability values (p-values) are in parentheses.

*Source: Author's own calculation.*

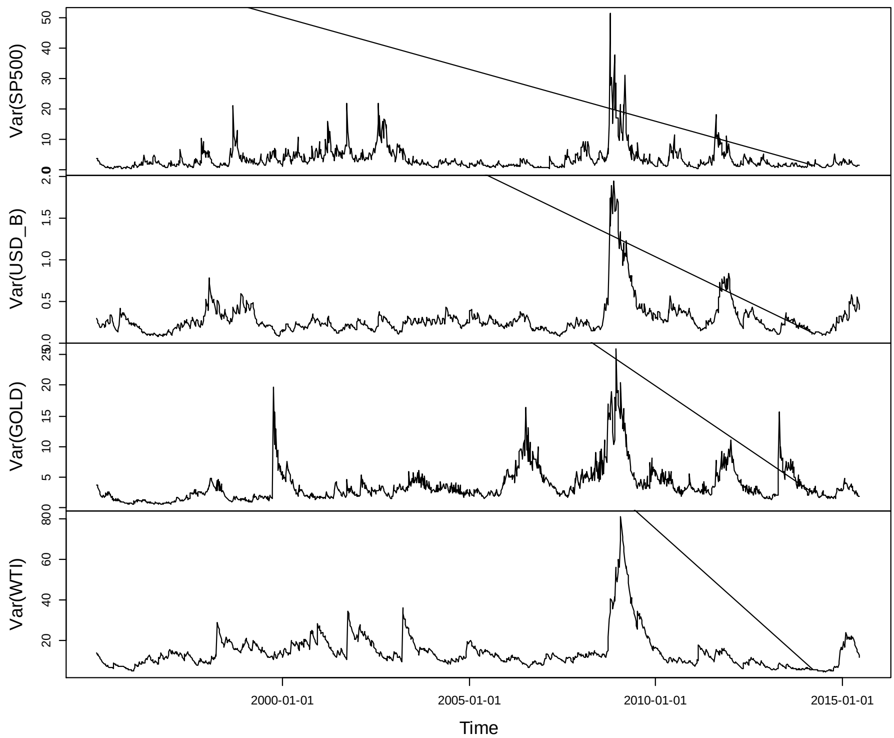


**Figure 1.** Conditional variances.

During the second stage conditional variances obtained with the use of Copula-DCC–GARCH model are clustered. Precisely, the moments of time characterised by four-dimensional vectors of conditional variances obtained for particular instruments are clustered. This procedure is supposed to indicate the periods in which financial markets are characterised by similar levels of risk.

Clustering is conducted with the use of three methods: Ward's method, the k-means method and the partitioning among medoids (PAM). The assessment of the quality of clustering is presented in Table 3, and index validation clustering is calculated with the assumption that the number of groups in not smaller than 2 and not larger than 6. The majority of measures, regardless of the clustering method applied, reveal that the division into two clusters is optimal (the highest values of the Silhouette and Dunn index, the lowest value of the Xie-Beni index). The Silhouette index clearly indicates that the best division is obtained for the k-means method (the average silhouette width 0.7782 for 2 clusters, and 0.4741 for three clusters). The Calinski Harabasz index indicates that the optimal division consists of three clusters when Ward's method and the k-means method are used, and of four clusters when PAM is used. The Dunn index and Xie-Beni index indicate the division into five groups when PAM is used. Taking into consideration a possibility of multi-faceted interpretation of clustering results obtained with the use of the Silhouette index, that is a possibility of assessing the objects (here moments) which belong to a given group (regime), it has been decided that in further analysis clusters which have been obtained by the k-means methods will be used. The division into two and three groups is analysed in this case[4]. After comparing the elements of clusters created for the division into two and three groups, it turns out that all elements from a less numerous (consisting of 29 elements) group obtained after the division into two clusters constitute a single cluster obtained after the division into three clusters. What is interesting is that this cluster includes only the periods at the beginning of 2009, that is the moment of the collapse of the commodity market. The more numerous group (obtained after the division into two clusters) is divided into two separate groups.

**Table 3.** Validation indices for data partitions.

| Validation criterion | Number of clusters | | | | |
|---|---|---|---|---|---|
| | 2 | 3 | 4 | 5 | 6 |
| | | | Ward's method | | |
| Silhouette | **0.4144** | 0.4132 | 0.2420 | 0.2468 | 0.2760 |
| Calinski Harabasz index | 525.5172 | **1128.4202** | 891.4865 | 888.8947 | 845.2170 |
| Dunn index | 0.0074 | **0.0092** | 0.0070 | 0.0070 | 0.0070 |
| Xie-Beni index | **247.1301** | 118.3295 | 181.6336 | 146.8908 | 128.1764 |
| | | | k-means | | |
| Silhuette | **0.7782** | 0.4741 | 0.3431 | 0.3232 | 0.3574 |
| Calinski Harabasz index | 1112.4198 | **1205.3381** | 1101.2847 | 933.7506 | 919.3722 |
| Dunn index | **0.0229** | 0.0065 | 0.0027 | 0.0050 | 0.0050 |
| Xie-Beni index | **28.9347** | 227.7294 | 1026.4980 | 274.5502 | 232.5727 |
| | | | PAM | | |
| Silhuette | **0.4637** | 0.2568 | 0.3236 | 0.3285 | 0.2934 |
| Calinski Harabasz index | 609.9561 | 463.9710 | **1075.3220** | 962.8447 | 909.4470 |
| Dunn index | 0.0038 | 0.0042 | 0.0049 | **0.0051** | 0.0034 |
| Xie-Beni index | 938.7358 | 684.6099 | 317.8286 | **261.2086** | 505.2739 |

Source: *Own calculations performed with the use of the 'clusterSim' package developed by M. Walesiak and A. Dudek (the Silhouette and Calinski Harabasz index) and the 'clusterCrit' package developed by Bernard Desgraupes (the Dunn and Xie-Beni index).*

Note: numbers in bold indicate the optimal number of groups with reference to a given criterion.

[4] The division into 3 groups is attractive as it offers a possibility of a sensible economic interpretation. Market regimes identified in the study could be described as: regimes of a low, moderate and high volatility.

In further analysis it is assumed that different market regimes correspond to different classes. Conditional variances in different market regimes are demonstrated in Figure 4. It reveals that the first regime, which occurs only during the greatest turbulences in global markets at the beginning of 2009, is characterised by a high volatility (a high risk level), the second regime – by a heightened volatility (a moderate risk level[5]) and the third regime – by a low volatility of instruments (a low risk level). Additional information on the clustering quality from Figure 2 leads to the conclusion that cohesion and separation are quite similar for the three clusters considered. What is more, if period *t* belongs to the first regime, its neighbour belongs to the second regime, and if period *t* belongs to the second regime, its neighbour belongs to the first regime. During a crisis regimes with moderate and high risks are neighbours, while regimes with low and high risks are never neighbours. These results strongly support the decision to apply the definition of a safe haven to the third regime and the definition of a hedge to the first and second regimes.

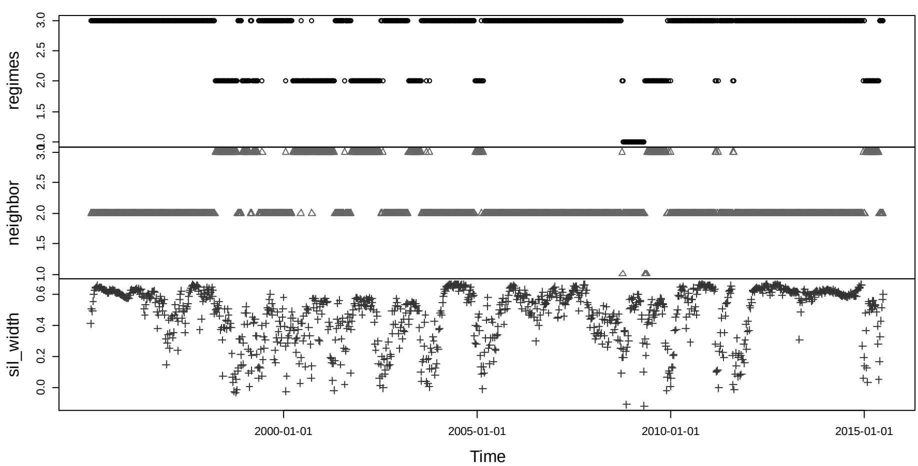


**Figure 2.** Market regimes

During the second stage of the study conditional correlations between instruments in the whole period between January 1995 and June 2015 and in different market regimes are analysed. It should be mentioned here that the results of testing for parameter constancy indicate strong evidence against the assumption of constant conditional correlations: the test, developed by Engle and Sheppard (2001), uses a $\chi^2$-statistic to test the null of $R_t = R$. The resulting test statistics, 50.022 (p-value =0.0000), is highly significant, rejecting the null hypothesis of constant conditional correlations. Fig. 5 demonstrates the dynamic conditional

[5] The only exception is gold for which conditional variances in the first and in the second regime seem to be similar.

correlations between instruments. Generally, negative correlations between US dollar exchange rate and other instruments and positive correlations between gold and oil can be observed. Correlations between the S&P500 index and commodities (gold, oil) in certain periods are positive and in other periods are negative.

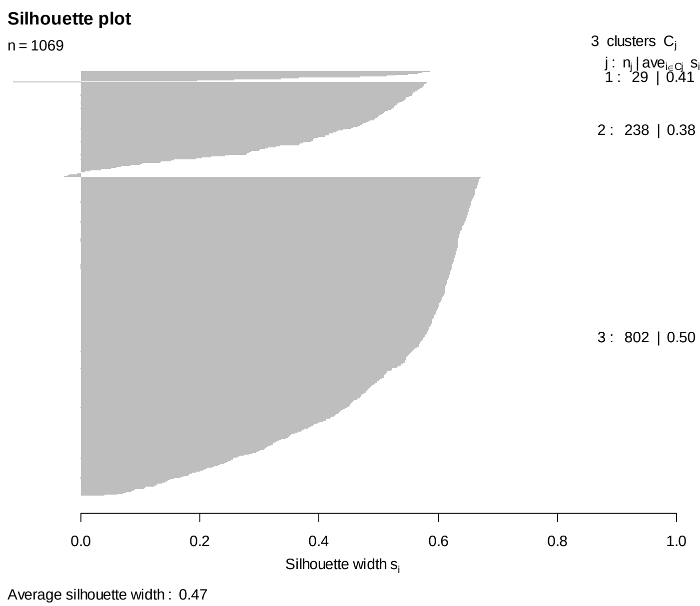


**Figure 3.** Silhouette plot

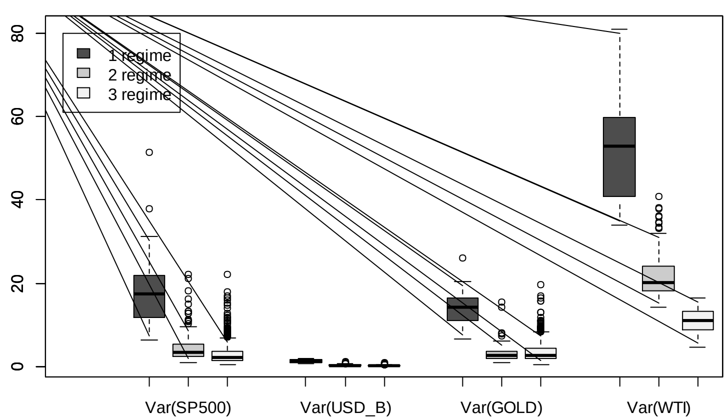


**Figure 4.** Distribution of variance in different regimes

The analysis of correlations in different market regimes allows for identification of the instruments which can serve as a hedge and a safe haven for other financial instruments. It has been assumed that the definition of a safe haven refers to the first regime, characterised by the highest volatility (the greatest risk), and the definition of a hedge refers to two other regimes (the second and third regime). The distribution of correlations in different regimes is demonstrated in Figure 6, and, on its basis, it can be concluded that:

1. Correlations between instruments are not the same in all market regimes.
2. Differences in correlations in the first regime are much smaller than in the remaining two regimes, which means that in the turmoil periods, relations are more stable than in other two regimes (correlations remain at a similar level).
3. The greatest differences between correlations for particular pairs can be found in the first regime.
4. The level of correlation in the first regime considerably differs from the level in the second and third regimes.
5. Correlations in the first regime do not change the sign in comparison with the second and third regimes and are considerably stronger, except for correlations between the S&P500 index and gold.
6. The level of correlation is similar between particular instruments in the second and third regime, that is the ones with a moderate and low risk levels respectively.

Taking into consideration definitions of a hedge and a safe haven adopted in this study, the following conclusions can be drawn:

(i) Dollar exchange rate is negatively correlated with other instruments in all market regimes, throughout the majority of the analysed period, thus it can be treated as a (strong) hedge and a (strong) safe haven for the remaining instruments.

- Oil is weakly correlated with the S&P500 index in the second and third regimes, so it can be a hedge for assets.
- Gold is weakly correlated with the S&P500 index in all regimes, so it can be treated as a hedge and a safe haven for assets.
- Oil is only a hedge for assets in 'normal' conditions.
- Both commodities (gold and oil) are weakly correlated with assets in the regimes with low and moderate volatility. However, only gold remains uncorrelated with assets in the regime with the highest volatility. It means that gold and oil are a hedge for assets, but only gold is a safe haven for assets.

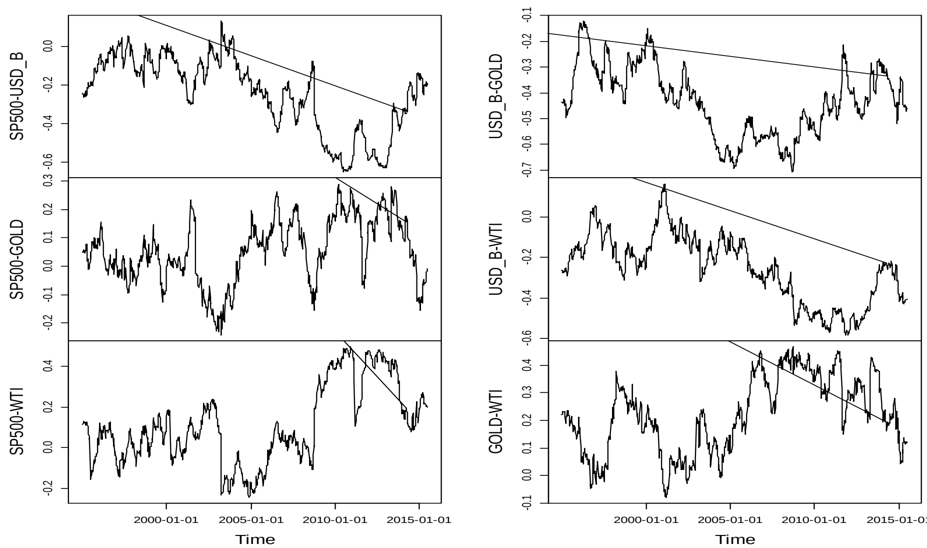


**Figure 5.** Dynamic conditional correlations

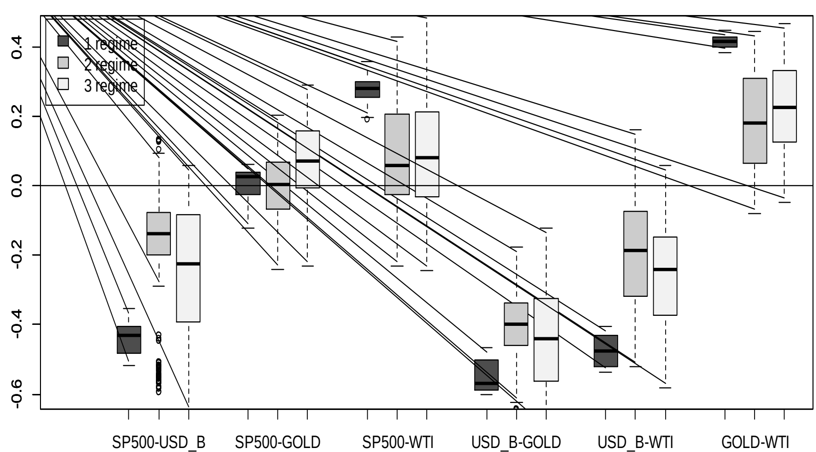


**Figure 6.** Distribution of correlation in different market regimes

## 5. Conclusions

The aim of the study was to identify instruments which can serve as a hedge and a safe haven for other financial instruments. Three classes of instruments were taken into consideration: US dollar exchange rate, the S&P500 index, and the prices of two commodities, gold and oil. The empirical strategy applied in the study consisted of two steps: in the first one market regimes were identified and in the second one correlations between instruments in different market regimes were analysed. Market regimes were identified by analysing the risk (volatility) of the instruments. Both statistical criteria of clustering and a possibility of a sensible economic interpretation indicate three different market regimes in the analysed period: a regime of low volatility of instruments, a regime of heightened volatility of instruments and a regime of the highest volatility of financial instruments (which occurred only in the period of the greatest turbulences in global markets at the beginning of 2009). In the second step it was decided that the definition of a safe haven would refer to the regime with the highest volatility, and the definition of a hedge would refer to the two remaining regimes. This allowed for differentiating mutual correlations between instruments in market regimes with low and moderate volatility, which had not been done in the subject literature before. The distribution of correlations obtained for different market regimes justifies drawing the following conclusions.

Firstly, correlations between instruments are not the same in all market regimes. The greatest differences are observed when comparing correlations in the regime with the highest volatility and in two remaining regimes. Mutual correlations in the regimes with low and moderate volatility are similar. What is interesting is that in the period of the highest volatility correlations are usually (with the exception of the pair S&P500-GOLD) higher (per module), but have the same sign as in the two remaining market regimes. Secondly, only dollar exchange rate is negatively correlated with other instruments, thus it can be treated as a (strong) hedge and as a (strong) safe haven for other instruments. Thirdly, both commodities (gold and oil) are weakly correlated with assets in the regimes of low and moderate volatility. However, only gold remains uncorrelated with assets in the regime with the highest volatility. Similar results for gold were obtained by Baur and Lucey (2010) and Baur and McDermott (2010).

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