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# Evaluating the nonlinear linkage between gold prices and stock market index using Markov-Switching Bayesian VAR models

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**Abstract**

This study makes a contribution to the literature by applying the Markov-Switching Bayesian VAR models for the first time to investigate the nonlinear linkage between gold prices and stock market index. Analyses have been done in the period from 1986:04 to 2013:11. The Bayesian approach to econometrics provides a general method for combining modeller's beliefs with the evidence contained in the data. In contrast to the classical approach to estimate a set of parameters, Bayesian statistic presupposes a set of prior probabilities about the underlying parameters to be estimated. We use gold prices (USD/oz.) and S&P 500 Stock Price Index as an endogenous, the crude oil prices (Brent-$/barrel) as an exogenous variable in the analysis. We investigate the number of regime by LR test and The Markov Chain Monte Carlo (MCMC) algorithm and Sims & Zha (1998) prior distribution are employed to estimate the models.

*Keywords:* Crude oil prices, Gold prices, S&P 500, Bayesian VAR model, Sims & Zha prior distribution


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## 1. Introduction

Oil prices have acquired increasing attention of both academicians and policy makers, especially after the oil shocks in 1974, 1979, 1980, and the recent sharp increases in oil prices between 2002 and 2008. Oil plays an important role in both oil-exporting and importing countries. Recognizing that oil is the engine of economic activities, many studies have examined the impact of oil prices on different economic variables, such as gold prices, stock prices exchanges rates, growth, investment, inflation and unemployment.

In recent years, oil and gold received much attention, due to the fluctuations in their prices. Crude oil is the world's most commonly traded commodity, of which the price is the most volatile and may lead the price procession in the commodity market. Gold has a critical position among the major precious metal class, even considered the leader of the precious metal pack as increases in its prices seem to lead to parallel movements in the prices of other precious metals (Sari et al, 2010). Gold is not only an industrial commodity but also an investment asset which is commonly known as a "safe haven" to avoid the increasing risk in the financial markets. As is known, investors in both advanced

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and emerging markets often switch between oil and gold or combine them to diversify their portfolios (Soytas et al, 2009).

It is known another effect of oil prices is on stock markets through several channels. First, the price of a share being equal to its discounted future cash flow, rising oil prices can increase the interest rate to limit inflationary pressure, tighten the cost of doing business, put pressure on output prices thus decreasing profits (Jones et al., 2004). High interest rates also make bond investments more attractive than stock ones (Chittedi, 2012). All these effects generally trigger a negative relationship between oil and stock markets, which parallels the one between high oil prices and macroeconomic indicators.

The above feature descriptions of crude oil, gold and stock markets justify the economic importance of revealing the relationship between these commodities. Various researches have investigated the effects of the oil prices on gold prices and stock market indexes. But only a very few studies have considered the relationship may be nonlinear. Whereas, time series may exhibit nonlinear behaviours due to different factors like policy changes, crises, OPEC decisions, etc. Thus, if the data exhibit structural regime shifts then a model assuming constant parameters, mean and variance is likely to yield misleading results. Therefore, modelling the relation between oil prices, gold prices and stock market index within a nonlinear framework is more suitable. Also nonlinear MS-VAR model, which is used in this study, provides to examine the effects of the oil prices separately during the periods of crisis and expansion.

This study makes a second contribution to the literature by applying the Bayesian technique to the MS-VAR model for the first time to investigate the effects of the oil prices on gold prices and S&P 500. The Bayesian approach to econometrics provides a general method for combining a modeller's beliefs with the evidence contained in the data. In contrast to the classical approach to estimating a set of parameters, Bayesian statistic presupposes a set of prior probabilities about the underlying parameters to be estimated.

The paper proceeds as follows: Section 2 presents a review of previous studies on the empirical evidence of oil price changes and its effects on gold price and stock market index. Section 3 deals with methodological issues and the data used in the empirical analysis and in Section 4 the empirical evidence are presented. Section 5 concludes summary.

## 2. Previous studies

Several researchers have investigated the relation between oil prices, gold prices and stock market indexes using different econometric approaches, countries and sample periods. According to Melvin and Sultan (1990)'s results, political unrest in South Africa in addition to oil price volatility is significant factors that constitute the gold spot price forecast errors. Cashin et al. (1999) test the correlations between seven commodities with the time period from April 1960 to November 1985. Empirical results from this study demonstrate that there exist significant correlation between oil and gold.

Jones and Kaul (1996) use quarterly data to test whether the reaction of international stock markets to oil shocks can be justified by current and future changes in real cash flows and changes in expected returns. Using a standard cash-flow dividend valuation model they find that the reaction of Canadian and US stock prices to oil price shocks can be completely accounted for by the impact of these shocks on real cash flows. Huang et al. (1996) use VAR approach to investigate the relationship between daily oil futures returns and daily US stock returns. They found that oil futures returns do lead some individual oil company stock returns but oil future returns do not have much impact on broad-based market indices like the S & P 500. Sadorsky (1999) show that oil prices and oil price volatility both play important roles in affecting real stock returns by using VAR model. However, the study by Ciner (2001) examines the nonlinear linkages between oil prices and the stock market. Relying on nonlinear causality tests, this study provides evidence that oil shocks affect S&P 500 stock index returns. Park and Ratti (2008) estimates the effects of oil price shocks and oil price volatility on the real stock returns of the U.S. and 13 European countries using a multivariate VAR analysis. They find that oil price shocks have a statistically significant impact on real stock returns in the same month or within one month. Nakamura and Small (2007) pointed out that both daily gold price and crude oil price data and S&P 500 are random walk series, and their first differences are independently distributed random variables or time-varying random variables. Odusami (2009) analyzed whether the nonlinear oil price effects on US stock exchange can be explained by the unexpected shocks in crude oil market. Even it is concluded that unexpected shocks have nonlinear effects. Choi and Hammoudeh (2010) applied a symmetric DCC-GARCH model and indicated increasing correlations among Brent oil, WTI oil, copper, gold and silver but decreasing correlations with the S&P500 index. Chang, McAleer, and Tansuchat (2010) based on a symmetric DCC-GARCH model investigated the conditional correlations and volatility spillovers between crude oil, FTSE100, NYSE, Dow Jones and S&P500 stock indices. Filis et. al (2011) investigates the time-varying correlation between stock market prices and oil prices for oil-importing and oil-exporting countries. A DCC-GARCH-GJR approach is employed on data from six countries; Oil-exporting: Canada, Mexico, Brazil and Oil-importing: USA, Germany, Netherlands. The results show that oil prices have negative effect in all stock markets. Also they find that the only exception is the 2008 global financial crisis where the lagged oil prices exhibit a positive correlation with stock markets. Lee and Chiou (2011) applied a univariate regime-switching GARCH model to examine the relationship between WTI oil prices and S&P500 returns. They concluded that when there are significant fluctuations in oil prices, the resultant unexpected asymmetric price changes lead to negative impacts on S&P 500 returns.

## 3. Methodology

### 3.1. Research Goal

In the study, we aim to evaluate the linkage between gold prices and stock market indexes by using Markov Switching Bayesian VAR models. We use gold prices (USD/oz.)( $GOLD$ ) and S&P 500 Stock Price Index ( $SP$ ) as an endogenous, and the crude oil prices (Brent-\$/barrel) ( $OP$ ) as an exogenous variable in the analysis. We use crude oil prices as an exogenous variable because oil prices are affected by OPEC decisions, business cycles, political developments, but not by the variable used in study. The data set comprises monthly observations over the period from 1986:04 to 2013:11. The data are obtained from the Federal Reserve Bank of St Louis Data Delivery page and World Bank's World Development Indicators. We use all the variables as a growth rate; $\Delta LGOLD$ represents $\left(\ln GOLD_t - \ln GOLD_{t-1}\right)$, $\Delta LSP$ represents $\left(\ln SP_t - \ln SP_{t-1}\right)$ and $\Delta LOP$ represents $\left(\ln OP_t - \ln OP_{t-1}\right)$. This starting date is chosen due to the fact that the spot and derivative markets for oil were established in 1986.

### 3.2. Research Methodology: Markov Switching Bayesian VAR Models

Ever since the study of Hamilton (1989), Markov regime switching models have been utilized by researchers for modelling many macroeconomic time series which exhibits asymmetries and nonlinear behaviour (Hansen,1992; Goodwin,1993; Gray,1996; Cologni and Manera,2008). Thus the use of Markov-switching approach has become popular for determining asymmetries. Goldfeld and Quandt (1973) introduced a hidden Markov chain into a regression model in order to deal with time series data that depend on exogenous variables. Hamilton (1989) extended the model by autoregressive Markov switching models, afterwards Krolzig (1997) made an important contribution by developing MS-VAR model which is capable to characterize macroeconomic fluctuations in the presence of structural breaks or shifts. These approaches allow researchers to overcome the shortcoming of linear models to deal with the asymmetry between expansions and contractions.

Let $\mathrm{y} = \left(y_1, \ldots, y_T\right)'$ denote a time series of $T$ observations, where each $y_t$ is a $N$-variety vector for $t \in \left\{1, \ldots, T\right\}$, taking values in a sampling space $Y \subset \mathbb{R}^N$. $\mathrm{y}$ is a realization of a stochastic process $\left\{Y_t\right\}_{t=1}^{T}$. We consider a class of parametric finite Markov mixture distribution models in which the stochastic process $Y_t$ depends on the realizations, $s_t$, of a hidden discrete stochastic process $S_t$ with finite state space $\left\{1, \ldots, M\right\}$. Conditioned on the state, $s_t$, and realization of y up to time $t-1, \mathrm{y}_{t-1}, y_t$ follows an independent identical normal distribution. A conditional mean process is a Vector Autoregression (VAR) model in which an intercept, $\mu_{st}$, as well as lag polynomial matrices, $A_{st}^{(i)}$, for $i = 1, \ldots, p$, and covariance matrices, $\sum_{st}$, depend on the state $s_t = 1, \ldots, M$.

$$y_t = \mu_{st} + \sum_{i=1}^{p} A_{st}^{(i)} y_{t-i} + \varepsilon_t, \tag{1}$$

$$\varepsilon_t : i.i.N\left(0, \Sigma_{st}\right), \tag{2}$$

for $t = 1, \ldots, T$. We set the vector of initial values $\mathrm{y}_0 = \left(y_{p-1}, \ldots, y_0\right)'$ to the first $p$ observations of the available data. The $\left(M \times M\right)$ transition probabilities matrix:

In which an element, $p_{ij}$, denotes the probability of transition from state $i$ to state $j$, $p_{ij} = \Pr\left(s_{t+1} = j \middle| s_t = i\right)$. All the transition probabilities are positive, $p_{ij} > 0$ for all $i, j \in \left\{1, \ldots, M\right\}$, and the elements of each row of matrix $\mathrm{P}$ sum to one, $\sum_{j=1}^{M} p_{ij} = 1$. The parameters of the VAR process, change with time, $t$ according to discrete value hidden Markov process, $s_t$. These changes in parameter values introduce nonlinear relationships between variables.

We use complete-data likelihood function to estimate the models. Let $\theta \in \Theta \subset \mathbb{R}^k$ be a vector of size $k$, collecting parameters of the transition probabilities matrix $\mathrm{P}$ and all the state-dependent parameters of the VAR process, $\theta_{st} : \mu_{st}, A_{st}^{(i)}, \Sigma_{st},$ for $s_t = 1, \ldots, M$ where $i = 1, \ldots, p$. The complete-data likelihood function is equal to the joint sampling distribution. This distribution is considered to be a function of $\theta$ for the purpose of estimating the unknown parameter vector $\theta$. It is further decomposed into a product of a conditional distribution of $\mathrm{y}$ given $\mathrm{S}$ and $\theta$, and a conditional distribution of $\mathrm{S}$ given $\theta$:

$$p(S,\mathrm{y}|\theta) = p(\mathrm{y}|S,\theta)\,p(S|\theta) \qquad (3)$$

The Markov process is given by:

$$p(S|\theta) = p(s_0|P)\prod_{i=1}^{M}\prod_{j=1}^{M} p_{ij}^{N_{ij}(S)} \qquad (4)$$

where $N_{ij}(S) = \#\{s_{t-1} = j, s_t = i\}$ is a number of transitions from state $i$ to state $j, \forall i, j \in \{1,\ldots,M\}$.

Classical estimation of the model consists of the maximization of the likelihood function with the EM algorithm. In this study the Bayesian inference which is based on the posterior distribution of the model parameters $\theta$ is used. The likelihood function is maintained by the choice of the prior distribution in the following form:

$$p(\theta) = \prod_{i=1}^{M} p(\theta_i)\,p(P) \qquad (5)$$

The independence of the prior distribution of the state-specific parameters for each state and the transition probabilities matrix is assumed. This allows the possibility to incorporate prior knowledge of the researcher about the state-specific parameters of the model, $\theta_{st}$, separately for each state.

The structures of the likelihood function and the prior distribution have an effect on the form of the posterior distribution that is proportional to the product of the two densities. The form of the posterior distribution is as follows:

$$p(\theta|\mathrm{y},S) \propto \prod_{i=1}^{M} p(\theta_i|\mathrm{y},\mathrm{S})\,p(P|\mathrm{y},\mathrm{S}) \qquad (6)$$

When we decompose into a posterior density of the transition probabilities matrix:

$$p(P|S) \propto \prod_{i=1}^{M} p(s_0|P)\prod_{i=1}^{M}\prod_{j=1}^{M} p_{ij}^{N_{ij}(S)}\,p(P) \qquad (7)$$

and the posterior density of the state-dependent parameters:

$$p(\theta_i|\mathrm{y},S) \propto \prod_{t:S_t=i} p(y_t|\theta_i,\mathrm{y}_{t-1},)\,p(\theta_i) \qquad (8)$$

The commonly used strategy is to simulate the posterior distribution with numerical methods. In this study The Markov Chain Monte Carlo (MCMC) algorithm and Sims & Zha (1998) prior distribution are employed to estimate the models.

In the Bayesian framework, the exact posterior distribution of the model's parameters can be easily obtained. Under the informative prior of Sims and Zha (1998), the posterior distribution of parameter $a$ has the form,

$$p(a/\mathrm{y}_t) = \pi(a_0)\,\pi(a_+/a_0), \qquad (9)$$

where $\mathrm{y}_t$ denotes the data matrix up to time T,

$$\pi(a_0) \propto |A_0|^T \exp\left(-\frac{1}{2}trace\left(A_0^{'}SA_0\right)\right), \qquad (10)$$

$$\pi(a_+|a_0) = \varphi\left((I \otimes U)a_0; I \otimes V\right),$$

and $\varphi(\mu;\Sigma)$ denotes the normal density function with mean $\mu$ and variance $\Sigma$. In equation (10), $S$, $U$ and $V$ are matrix functions of the data $\mathrm{y}_t$.

## 4. Analyses and Results

The analysis was initiated by calculating the certain statistics of the series used in the study and the results are given in Table 1.

**Table 1: Descriptive Statistics of Series**

| | *ΔLOP* | *ΔLSP* | *ΔLGOLD* |
|---|---|---|---|
| Std.Deviation | 11.68 | 3.27 | 1.14 |
| Jarque-Bera | 7.46 | 6.51 | 8.87 |
| MS-ADF (*p-value*) | -6.54<br>(0.01) | -7.28<br>(0.02) | -7.06<br>(0.00) |

According to the Jarque-Bera test statistics in the table, series are not normally distributed. MS-ADF test which is a unit root test appropriate for MS models has been applied (Hall, Psaradakis and Sola, 1999) and it is confirmed that the log-differenced series are stationary at the 5% level of significance. For the purpose of revealing the non-linear structure in the series, the approach suggested by Tsay (1989) is used and the linearity test results for different delay lengths are presented in Table 2.

**Table 2: Results of Linearity Test**

| | *d =1* | *d =2* | *d =3* | *d =4* | *d =5* | *d =6* | *d =7* | *d =8* | *d =9* | *d =10* |
|---|---|---|---|---|---|---|---|---|---|---|
| $\Delta LOP$ | 0,18 | **2,19** | 1,11 | 1,34 | 0,97 | 1,01 | 0,63 | 0,45 | 0,24 | 0,29 |
| *p-value* | 0,46 | 0,02* | 0,13 | 0,08 | 0,62 | 0,36 | 0,25 | 0,29 | 0,31 | 0,63 |
| $\Delta LSP$ | **2.18** | 0,29 | 1.01 | 2.01 | 1.45 | 0,65 | 1,14 | 0,62 | 0,45 | 0,33 |
| *p-value* | **0,02*** | 0,53 | 0,34 | 0,01 | 0,34 | 0,44 | 0,21 | 0,43 | 0,40 | 0,72 |
| $\Delta LGOLD$ | **3.29** | 0,87 | 0.97 | 1.09 | 0,66 | 0,78 | 0.45 | 0,74 | 0,34 | 0,34 |
| *p-value* | **0,01*** | 0,73 | 0,77 | 0.28 | 0,43 | 0,44 | 0,22 | 0,44 | 0,60 | 0,70 |

The probability values reported in Table 2 calculated for 10 delay show that linearity is rejected strongly in the second delay for $\Delta LOP$ and in the first delay for $\Delta LSP$ and $\Delta LGOLD$. Afterwards, LR test is made in order to determine the number of regimes of the models, which is the first stage of model selection.

**Table 3: LR Test Results**

| **LR Test** | |
|---|---|
| | $\Delta LGOLD - \Delta LSP$ |
| *Ho: Linear VAR*<br>*Ha: Two regime MS-VAR* | 14.13<br>(0.01) |
| *Ho: Two regime MS-VAR*<br>*Ha: Three regime MS-VAR* | 10.91<br>(0.03) |
| *Ho: Three regime MS-VAR*<br>*Ha: Four regime MS-VAR* | 2.43<br>(0.83) |

According to the results, it is determined that the 3-regime MS-VAR model is appropriate for the analyses. By using the Schwarz Information Criterion (SIC), the delay lengths are selected and it is decided that MSIH(3)-BVARX(2) model is appropriate for the series. We assigned a dummy variable $(DU)$ for 2008:06 in the model due to the oil prices fluctuation . MSIH(3)-BVARX(2) model, transition probabilities, regime durations and posteriors are given in Table 4.

**Table 4: MSIH(3)-BVARX(2) Estimates**

| | *Regime 1* | | *Regime 2* | | *Regime 3* | |
|---|---|---|---|---|---|---|
| | $\Delta LGOLD_t$ | $\Delta LSP_t$ | $\Delta LGOLD_t$ | $\Delta LSP_t$ | $\Delta LGOLD_t$ | $\Delta LSP_t$ |
| *Constant* | 0.0069<br>(2.52)* | 0.0138<br>(2.42)* | -0.0029<br>(-2.90)* | 0.0052<br>(4.81)* | 0.0161<br>(4.26)* | 0.0054<br>(1.91) |
| $\Delta LGOLD_{t-1}$ | -0.0495<br>(-0.38) | -0.0202<br>(-0.12) | 0.0128<br>(0.18) | -0.0122<br>(-0.17) | -0.0983<br>(-0.80) | 0.0439<br>(0.48) |
| $\Delta LGOLD_{t-2}$ | 0.0038<br>(0.03) | 0.0271<br>(0.21) | -0.0289<br>(-0.43) | 0.0153<br>(0.21) | -0.0390<br>(-0.23) | 0.0111<br>(0.09) |
| $\Delta LSP_{t-1}$ | 0.0467<br>(0.62) | 0.0149<br>(0.15) | -0.0890<br>(-1.82) | 0.0494<br>(0.96) | -0.0825<br>(-1.11) | 0.0636<br>(1.15) |
| $\Delta LSP_{t-2}$ | -0.0024<br>(-0.04) | -0.0382<br>(-0.50) | -0.0083<br>(-0.17) | -0.0255<br>(-0.51) | -0.0278<br>(-0.28) | 0.0004<br>(0.00) |
| $\Delta LOP_t$ | 0.0662<br>(0.74) | 0.0372<br>(0.33) | 0.0710<br>(2.53)* | -0.0117<br>(-0.39) | 0.0536<br>(0.69) | 0.0373<br>(0.65) |
| $\Delta LOP_{t-1}$ | 0.0364<br>(0.35) | -0.0008<br>(-0.00) | 0.0105<br>(0.36) | -0.0204<br>(-0.67) | 0.0861<br>(1.07) | -0.0269<br>(-0.44) |
| $\Delta LOP_{t-2}$ | -0.0975<br>(-1.08) | 0.1253<br>(1.11) | -0.0027<br>(-0.00) | -0.0467<br>(-1.70) | -0.1137<br>(-1.52) | 0.0559<br>(1.00) |
| *DU* | 0.0030<br>(0.20) | 0.0183<br>(0.96) | -0.0225<br>(-0.71) | -0.0174<br>(-3.49)* | 0.0136<br>(1.34) | -0.0009<br>(-0.12) |

| ***Transition*** | ***Regime1*** | ***Regime2*** | ***Regime3*** | ***Prob*** | ***Durations*** | ***Data marg log*** | ***Coeff marg. posterior*** | |
|---|---|---|---|---|---|---|---|---|

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ***probabilities*** | | | | | | ***posterior*** | ***estimate*** | |
| Regime1 | 0.78 | 0.21 | 0.01 | 0.24 | 4.70 | 63.24 | 894.31 | |
| Regime2 | 0.06 | 0.85 | 0.09 | 0.56 | 6.66 | 378.44 | 3724.65 | |
| Regime3 | 0.10 | 0.19 | 0.71 | 0.18 | 3.45 | 74.66 | 1088.21 | |

LR linearity test: 91.85 Chi(10) =[0.0000] ** Chi(16)=[0.0000] **DAVIES=[0.0000] ** StdResids: Vector portmanteau(24): Chi(88)= 88.88 [0.45]
StdResids: Vector normality test : Chi(4)= 7.05 [0.13] StdResids: Vector hetero test: Chi(42)= 51.61 [0.26]

It classified that regime 1 represents growth regime; regime 2 represents pre-crises regime and regime 3 represents crises regime. As seen in Table 4, in all regimes, the effect of oil price changes on gold prices is positive in time $t$ and $t-1$, and negative in time $t-2$. But this effect on S&P index differs according to the regimes. In both growth and crisis regime, the effect of oil price changes on S&P index is positive in time $t$ and $t-2$, and negative in time $t-1$; in pre-crisis regime all effects became negative.

According to the regime probabilities shown in Table 4, it is seen that the probability of staying in the growth regime is 0.78 implying an average duration of about forth months. The probability of staying in the pre-crisis regime is 0.85 and staying in the crisis regime is 0.71. The expected duration in regimes pre-crisis and crisis is about six months and about three months, respectively As seen above, staying pre-crisis regime is higher than the other two regimes. Besides, it is seen that transition from regime 1 to regime 3 took the value of 0.01. This result made us think that there are two regimes, but the model with two regimes produced statistically insignificant results. Also MSIH(3)-BVARX(2) model has been selected from among the various models according to the posteriors. Impulse-response analyses are made after the model estimated and the graphics are as follows.

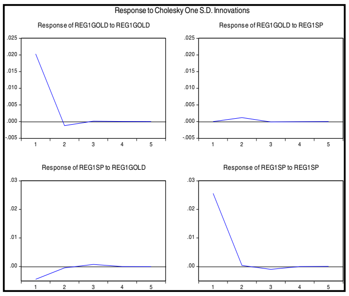


**Figure 1:** Growth Regime

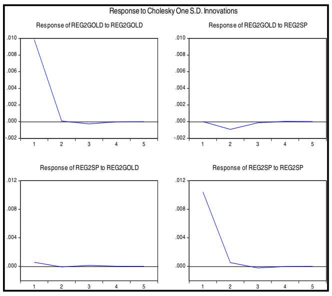


**Figure 2:** Pre-Crisis Regime

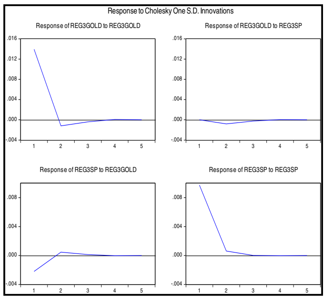


**Figure 3:** Crisis Regime

When the impulse-response graphics are examined, it is seen that the response of gold prices to S&P index shocks changes according to the regimes. In the growth regime, response of gold to S&P is positive only in the second period and its response ends the third period. In both pre-crisis and crisis regimes, response of gold prices to S&P are the same; negative response in the second period and it ends in the third period. But the response of S&P index to gold price shocks becomes different in all regimes. In the growth regime, response of S&P to gold prices is negative in the first period and its response ends the second period. In the pre-crisis regime, response of S&P to gold prices is positive in the first period and it ends in the second period, and in the crisis regime, response is negative in the first period, positive in the second period and it ends in the third period.

As a result, the finding of the study suggesting that the changes of crude oil affect the gold prices and S&P 500 and this effect differs according to regimes. This result is consistent with the finding of Ciner (2001) revealed the nonlinear linkages between oil prices and the stock market. However findings are giving conflicting results with Huang et al. (1996) use linear VAR approach to investigate the relationship between daily oil futures returns and daily US stock returns.

**Conclusion**

The aim of this study is to contribute to literature by studying the relationship between gold prices and stock market index while the crude oil prices used as an exogenous variable in the analysis. Analyses have been done in the period from 1986:04 to 2013:11 by Markov-Switching Bayesian Vector Autoregressive (MS-BVAR) model and this study makes a contribution to the literature by applying the Bayesian technique for the first time to investigate the effects of the oil prices on gold prices and S&P 500.

We investigate the number of regime by LR test, and The Markov Chain Monte Carlo (MCMC) algorithm and Sims & Zha (1998) prior are employed to estimate the models. By using of MS-BVAR analysis, it has been found that there are 3 regimes in the analysis periods. According to the regime probabilities, staying pre-crisis regime is higher than the other two regimes: growth and crisis.

After estimation of MSIH(3)-BVARX(2) model, it is seen that the changes of crude oil price affect the gold prices and S&P 500 and this effect differs according to regimes. In all regimes, oil price changes effect on gold prices is positive in time $t$ and $t-1$, and negative in time $t-2$. But oil price changes effect on S&P index are the same in both growth and crisis regime; it is positive in time $t$ and $t-2$, and negative in time $t-1$; in pre-crisis regime all effects became negative.

Besides, when the impulse-response graphics are examined, it is seen that, in the pre-crisis and crisis regime, gold prices gives declining response to S&P 500 shocks in the second period but in the growth regime this relation becomes reverse. S&P index gives different response to gold prices shocks in all regimes: in the growth regime, response of S&P to gold prices is negative in the first period; in the pre-crisis regime, response of S&P to gold prices is positive in the first period and in the crisis regime, response is negative in the first period, positive in the second period. All responses end in the third period.

Therefore these results have indicated that investors and policy makers should take into account different behaviours of in different regimes while taking decisions.

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