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# STUDY SYSTEMATIC RISK OF PARAMETER CHANGES PERIOD OF TIME ON DYNAMIC PREDICTION OF STOCK RETURN VOLATILITY OF US STOCK EXCHANGES

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***Abstract:*** In the current study, is used independent variable like change of Real effective exchange rate is used as a variable for shock in the domestic market, one year interest rates (monetary policy), Change in oil prices is used as a variable in external shock, Percentage change consumer retail index as a substitute inflation (public policy) and depended variable (stock return) that extracted from Central Bank and International Monetary Fund, respectively. In this study results was observed base on the time-varying-parametric model, dynamic model selection (DMS) and dynamic model averaging (DMA) with using Kalman filters. DMS model with $\alpha = \beta = 0.90$, had a better prediction accuracy with 3 months (h = 3) than the other methods. According to this model, after the first interruption, the oil price in (98 courses), inflation in (77 courses), the interest rate in (64courses) and the exchange rate in (110 courses)have had the highest effect on stock returns. Base on achieved results from (126 courses) is shown that the systemic risk indicators (changes in macro indicators) had affected on stock returns in 118 courses. Thus, systematic risk is a important factor in predicting the dynamics of stock return volatility.

***Keywords:*** Macro indicator, Kalman filter, stock returns, time-varying-parameter, dynamic model

## INTRODUCTION

The importance of economic and financial indicators means that they are dynamic and constantly changing. The factors that result in change are sometimes voluntary, and in the form of policy, but at other times they are involuntary and are in the form of natural phenomena. It appears to be important to investigate the nature of shocks and their influences on financial markets, and, from our initial research, we concluded that these shocks have different sources. Some economic experts, such as Fisher (2011), Freedman (2001), Johnston (2000), Clark (1990) and McKinnon (2002), consider inflation as the origin of macroeconomic variables and financial market instabilities, although some consider changes in exchange rates, energy prices and other factors, such as monetary and financial shocks, as the origin of instability. With regard to financial issues, different models and theories have been developed with the aim of achieving optimal investment with good returns, which give investors the power of decision-making and evaluation. Most of the decisions are based on the relationship between risk and return, and an investor always considers risk and return factors in analysis and management, thus the greater the diversion of profitability in previous years or possible profits in future periods, compared with the average profit or expected profit, the higher the share of the risk versus the value. According to theoretical foundations, shocks in macroeconomic variables are generally one of the most important factors in diversion of profitability compared with the average or expected profit. The assessment of economic and monetary variables is highly important in economic studies. In addition to these variables and the way they are changing, the level of change and fluctuations provides valuable information with regard to their differing behaviors and impacts. Uncertainty resulting from fluctuations in economic variables means that economic models pay attention to decision-making in situations of uncertainty. One problem that investors face when using expected-return forecasting models is that these models are highly sensitive to different markets and situations, and they are not at all stable. In fact, it has been shown that although there might be evidence supporting the predictability of these models, they are so unreliable that investors cannot use them. There are several reasons for this assumption that probably the standard approach outside the sample does a poor job. First, in a regression model, the most important feature of stock returns is not considered. In particular, the assumption of constant stochastic volatility is strongly at odds with the observed data because return volatility changes over time. According to Johannes (2014)[9]ignoring this variability creates optimal portfolios based solely on expected returns (considering constant variables over time), so they do a poor job. The importance of the current study is that it search the reason and cause stable the factors influencing stock returns considering more realistic theories. Our goal was to investigate how stock return volatility is affected when new data are entered (changes in macro indicators of systemic risk). In this study with using independent variable like change of Real effective exchange rate is used as a variable for shock in the domestic market, one year interest rates (monetary policy), Change in oil prices is used as a variable in external shock , Percentage change consumer retail index as a substitute inflation (public policy) and depended variable (stock return) that extracted from Central Bank and International Monetary Fund, respectively. also stock return is estimated from independent variables with AR, TVP,TVP-SV,TVP-DMS and TVP-DMA model with considering time horizon (h = 1,3,6,12) from 2006-2016.We conclude that each independent variable has a significant effect on stock returns at what period of time. Also, calculations shows which model has the best prediction at any time horizon. we obtained in h = 3 with $\alpha = \beta = 0.90$ on DMS model. finally we conclude the TVP-DMS model offered the best prediction of stock return of the US Stock Exchange over time.

## LITERATURE REVIEW

Mobility and the changing of phenomena over time is the nature of economic and financial issues. Ignoring mobility results in oversimplifying phenomena, meaning that the obtained models cannot be realistic and inaccurate interpretations will be made. One of the principles of financial theory is the exchange between risk and expected return. The expected return can change via risk factors over time, thus the price movement will not be random. Many experts in the financial field believe that it is not possible to predict stock prices without considering their risks (Timmermann and Pesaran, 1995)[18]. Different models for use in determining price and stock price changes have previously been presented, and fluctuations in financial variables, as an essential component of pricing financial assets, have been considered in many studies. The capital asset pricing model, which was developed by Sharp (1964), Linter (1965) and Musin (1966), is based on the assumptions and findings of the modern theory of Harry Markowitz's portfolio and investment, which has had remarkable effects on finance and investment. In such models, applications based on ordinary least squares regression to examine the relationship between financial variables are considered static and the evolution of this relationship over time, which alters the equation coefficients, is ignored. Several assumptions in these models state that an equation with constant coefficients can be used at different times. Inaccurate results obtained using these assumptions have created dynamic models that are more similar to the reality of the outside world. According to Stock and Watson (2009)[21], one of the most important problems in the previous predicting models was that they couldn't accurately predict over time, which led to the emergence of time-varying parametric (TVP) models and the Monte Carlo Markov Chain, which could predict huge models (with many variables) over time; the coefficient estimated in these models may change over time. The conditions mean that structural failures and cycles have been observed, whereas previous models were not able to calculate parameters in this situation. In addition, the number of variables and predictions can be very large, and an increase in the number of variables creates huge models. Whenever variable m in time t exists in the model, there will be $2m_t$ estimated models (Koop and Korobilis, 2011)[12].

Fisher's fundamental theory issued to obtain the theoretical framework for the relationship between the stock price index and macro variables. Fisher's fundamental equation states that the real interest rate is derived from the difference in the nominal interest rate and the inflation rate, so that

$$R_t^r = R_t^n + INF_t \tag{1}$$

where the real interest rate is $R_t^r$, nominal interest rate is $R_t^n$, and inflation rate is $INF_t$. Fisher also expresses such a relationship for stock returns, so that

$$RS_t^r = RS_t^n + INF_t \tag{2}$$

where the real stock return is $RS_t^r$, and the nominal stock returns is $RS_t^n$. The nominal return is equal to the rate of change in stock price, in which $RS_t^n = d(Ln(PS_t)$ and $PS_t$ is the price of stock. Regarding this equation, Fisher introduces the econometric model and states that the inflation rate affects stock returns:

$$RS_t^r = y_0 + y_1\, INF_t + U_t \tag{3}$$

Fama (1981) [5] stated that in the Fisher equation, some macro-monetary variables, such as liquidity and interest rates, have been ignored. Taking into account the relationship between the money market and the capital market, Fama uses the balance of the money market to prove his claims:

$$\frac{M_t}{P_t} = M(Y_t, R_t) \tag{4}$$

In this equation, $M_t$ is liquidity in the economy (banknotes in the hands of individuals and visually impaired deposits), $P_t$ is the general level of prices, $Y_t$ is the national income, and $R_t$ is the interest rate.Therefore, Fama claims the money demand as

$$Ln\left(\frac{M_t}{P_t}\right) = aLnY_t - bLnR_t \qquad a1, a2 > 0 \tag{5}$$

$$LnP_t = -a_1 LnY_t + a_2 LnR_t + LnM_t \tag{6}$$

We will differentiate this relationship as

$$dLnP_t = -a_1 dLnY_t + a_2 dR_t + dLnM_t \tag{7}$$

given that we have dLnPt = INFt:

$$INF_t = -a_1 dLnY_t + a_2 dLnM_t + U_t \tag{8}$$

Replacing this expression in equation (3) and rewriting it as

$$RS_t^r = \beta_0 + \beta_1 dLnY_t + \beta_2 dR_t + \beta_3 dLnM_t + U_t \tag{9}$$

results in $\beta_0 = y0$, $\beta 1 = -y1a1$, $\beta 2 = y1a2$, and $\beta 3 = y1$.

Using the relationship between nominal returns and real stock returns $(RS_t^n = RS_t^r + INF_t)$, we write the preceding equation as follows:

$$RS_t^r = \beta_0 + \beta_1 dLnY_t + \beta_2 dR_t + \beta_3 dLnM_t + \beta_4 dLnIMF + U_t \tag{10}$$

Finally, this equation for stock prices is expressed as follows:

$$LnRS_t^r = \beta_0 + \beta_1 LnY_t + \beta_2 R_t + \beta_3 LnM_t + \beta_4 P_t + U_t \tag{11}$$

Numerous studies have been conducted via the structural model and TVP methods, some of which was that carried out: Naser and Alaali (2015)[16] in their assessment entitled: 'Can the price of oil help to predict the stock in America'. have predicted S&P 500 Index indicators via dynamic model averaging (DMA), and have investigated the predictive ability of oil prices and other macro-economic and financial variables, including industrial production indices, interest rates, inflation, unemployment and financial ratios. The evidence shows that the DMA/dynamic model selection (DMS) method will significantly improve predicting compared with other predicting methods, and the performance of the DMA/DMS models increases when oil price is a predictor.

Li *et al.* (2010) [4] with using structural VAR models with short-run restrictions appropriate for Canada and the United States, they find that, in Canada, the immediate response of stock prices to a domestic contraction monetary policy shock is small and the dynamic response is brief, whereas in the United States, the immediate response of stock prices to a similar shock is relatively large and the dynamic response is relatively prolonged. so these differences are largely driven by differences in financial market openness and hence different dynamic responses of monetary policy shocks between the two countries that they model in this paper.

Zhang and Chen (2011) [3] They investigated the impact of global oil price shocks on China's stock market, using the ARJI(-ht)-EGARCH model. They separated the volatilities into expected, unexpected and negatively unexpected ones to identify how oil prices influence the stock returns. The results reveal that there are jumps varying in time in China's stock market, and that China's stock returns are correlated only with expected volatilities in world oil prices, contrary to previous research. While world oil prices have a positive effect on China's stock returns, results from this study suggest that this effect is minor.

Gupta *et al.* (2014)[6] They develop models for examining possible predictors of growth of China's foreign exchange reserves that embrace Chinese and global trade, financial and risk (uncertainty) factors. Specifically, by comparing with other alternative models, They show that the dynamic model averaging (DMA) and dynamic model selection (DMS) models outperform not only linear models (such as random walk, recursive OLS-AR(1) models, recursive OLS with all predictive variables models) but also the Bayesian model averaging (BMA) model for examining possible predictors of growth of those reserves. The DMS is the best overall across all forecast horizons. While some predictors matter more than others over the forecast horizons, there are few that stand the test of time. The US-China interest rate differential has a superior predictive power among the 13 predictors considered, followed by the nominal effective exchange rate and the interest rate spread for most of the forecast horizons. The relative predictive prowess of the oil and copper prices alternates, depending on the commodity cycles. Policy implications are also provided.

Wang *et al.,* (2010).[14] This paper uses daily data and time series method to explore the impacts of fluctuations in crude oil price, gold price, and exchange rates of the US dollar vs. various currencies on the stock price indices of the United States, Germany, Japan, Taiwan, and China respectively, as well as the long and short-term correlations among these variables. Empirical results show that there exist co-integrations among fluctuations in oil price, gold price and exchange rates of the dollar vs. various currencies, and the stock markets in Germany, Japan, Taiwan and China. This indicates that there exist long-term stable relationships among these variables. Whereas there is no co-integration relationship among these variables and the U.S. stock market indices which indicates that there is no long-term stable relationship among the oil price, gold price and exchange rate and the US stock market index. In addition, empirical results of the causal relation show that in Taiwan, for example, oil price, stock price and gold price have two-way feedback relations.

Considering to these empirical studies observes in most of studies that fluctuations in macroeconomic variables affect stock returns. Thus, investors should consider these parameters and their impact factors on the timing of an optimal portfolio. It can also be observed that the performances of variable models are better than traditional models.

## MATERIALS AND METHODS

Of the various statistical models, time-series regression models change phenomena over time, and it is usually assumed that an equation with constant coefficients is used at different times. Inaccurate findings from this unreal assumption created dynamic models, which are identical to reality. The state-space model is a method used for modeling dynamic systems; it provides structural flexibility of the parameters and allows the coefficients to vary over time. These models are known as TVP models, and are a particular type of state-space model. The system of equations of state-space models includes the observation equation and the state equation, which are estimated via a reversible algorithm (Kalman filter), such as Bayesian filtering. In Bayesian theory, the posterior probability of the density function is estimated, and this allows the calculation of the optimal state estimate with respect to each function criterion. Depending on the model of the process and measurements, there are different methods for solving Bayesian filtering. For example, if the dynamic model is linear and process and measurement noise are of a Gaussian nature, the Kalman filter is used. The methods used in the present study are introduced in the following subsections.

There are different view on the development of statistical forecasting methods. Research in empirical macroeconomics often uses time varying parameter

(TVP) models which are estimated using state-space methods such as the Kalman filter but TVP models have the potential drawback. To express clearly, so on the one hand, TVP can be developed to TVP-VAR and TVP-SV (they aim to evaluate how the transmission of a shock evolves over time and to detect possible structural breaks) but if the number of explanatory variables are large, such models can often over-fit in-sample and, thus, forecast poorly also another challenges arise due to the fact that these models potentially include a large number of variables and allow for time variation in parameters and computation time will increase with Increasing the dimension of the model size. We use dynamic model (selection and averaging) methods with TVP-SV, Because of this method involving the use of a forgetting factor which allows for computationally simple inference in TVP-SV and DMA or DMS can avoid over-parameterization.

### 3.1. Auto Regression (AR)

Regression analysis is a statistical technique for modeling and investigating the relationships between an outcome or response variable and one or more predictor variables. The end result of a regression analysis study is often to generate a model that can be used to forecast or predict future values of the response variable, given specified values of the predictor variables.

$$Y_t = \beta_0 + \beta_1 x_{t2} + \beta_2 x_{t2} + \cdots \beta_k x_{tk} + \varepsilon_t \tag{12}$$

The unknown parameters $\beta_0$, $\beta_1$, ... , $\beta_k$ in a linear regression model are typically estimated using the method of least squares. This function is to be minimized with respect to $\beta_0$, $\beta_1$,..., $\beta_k$. Therefore the least squares estimators, say, $\hat{\beta}_0, \hat{\beta}_1, ..., \hat{\beta}_k$

$$\begin{aligned} L &= \Sigma_{i=1}^{n} \varepsilon_i^2 = \Sigma_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \cdots - \beta_k x_{ik})^2 \\ &= \Sigma_{i=1}^{n} (y_i - \beta_0 - \Sigma_{j=1}^{k} \beta_j x_{ij})^2 \end{aligned} \tag{13}$$

We now give a matrix development of the normal equations that parallels the development

$$L = \Sigma_{i=1}^{n} \varepsilon_i^2 = \varepsilon' \varepsilon = (y - X\beta)'(y - X\beta) \tag{14}$$

$$y = X\beta + \varepsilon \tag{15}$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}, \quad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}, \quad \textit{and } \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{16}$$

$$\left( \frac{\partial L}{\partial \beta} \right)_{\hat{\beta}} = -2X'y + 2(X'X)\hat{\beta} = 0 \tag{17}$$

which simplifies to

$$(X'X)\hat{\beta} = X'y \tag{18}$$

Thus the least squares estimator of $\hat{\beta}$ is

$$\hat{\beta} = (X'X)^{-1} X'y \tag{19}$$

### 3.2. The TVP Model and TVP Regression Model with Stochastic Volatility (TVP-SV)

As one of the newest techniques in econometric literature, the use of parameters with random coefficients can provide estimates of invisible variables or state variables in a system of equations. In general, dynamic systems in econometrics in a well-known general form can be presented as state-space models. The time-varying parameter (TVP) approach examines the structural instability of the model coefficients and allows for the parametric change of the model over time. In addition, one of the important advantages of this method compared to other conventional methods and time series methods (e.g., ordinary least squares) is that both examining unit root tests for time series variables and variable reliability in the level are no longer necessary. Hence, in this approach, the researcher should not be concerned about the variability of the variables and the differentiation of the time series variables. The existence of supply and demand shocks as invisible variables in these models has enabled state-space models and Kalman filter approaches to play an essential role in estimating parameters. There are two major advantages to expressing dynamic systems in state-space model. First, these models allow unobservable variables (i.e., state variables) to be placed in the system and be estimated by the system accordingly. Second, state-space models can be estimated using the Kalman filter, which is a completely reversible covariance algorithm. The Kalman filter is used to evaluate the maximum truth function, make predictions, and smooth the state variables. In econometric literature, most time series models, including linear regression models and autoregressive integrated moving average (ARIMA) models, can be expressed and estimated as special cases of state-space models. The Kalman filter method is also applicable when the coefficients of the model variables change over time, in which case, we will have TVP models. In this case, the important application of state-space models occurs with the random variables for regression, whose coefficients change over time. The TVP model, along with our stochastic volatility, can record possible changes in the fundamental structure of economics in a strong and flexible manner. In this regard, many results of studies indicate that the inclusion of stochastic volatility in the estimation of TVP significantly improves the performance of estimates.

The TVP regression model is considered as follows:

***Regression***

$$y_t = x_t'\beta + z_t'\alpha_t + \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2), \quad t = 1, \ldots, n \tag{20}$$

Time variable coefficients:

$$\alpha_t + 1 = \alpha_t + u_t, u_t \sim N(0, \Sigma), \quad t = 0, \ldots, n-1 \tag{21}$$

***Stochastic volatility***

$$\sigma_t^2 = \gamma \exp(h_t), \quad h_{t+1} = \O h_t + \eta_t, \eta_t \sim N(0, \sigma_\eta^2), \quad t = 0, \ldots, n-1 \tag{22}$$

In these equations, $y_t$ is the dependent variable matrix, $x_t$ and $z_t$ are vectors of the explanatory variables, $\beta$ is a vector of constant coefficients, $\alpha_t$ shows the time variable coefficients vector, and $h_t$ is stochastic volatility. We assume that $\alpha_0 = 0$, $u_0 \approx N(0, \Sigma_0)$, $\gamma > 0$, and $h_0 = 0$.

It is assumed that all the parameters follow the first-order random-step process, which causes permanent and temporary transmission in the parameters stochastic volatility play an important role in TVP models. Although the idea of stochastic volatility was originally presented by Black (1976) [1] there have been numerous and multiple developments in financial econometrics since then.

Even though the random variation will be complicated, the model can be estimated using the Markov Chain Monte Carlo (MCMC) method in the business inference framework. Regarding $a_t$ and $h_t$ as state variables, TVP regression forms the state-space model. Several methods are available to estimate the state-space model. For the TVP regression model, if the variance of the including disruption is assumed(variable time coefficients and constant oscillations), parameters are simply estimated by the standard Kalman filter in a linear Gaussian state-space model(West and Harrison 1997)[15]. However, if the variance is accompanied by stochastic volatility, the estimation of maximum truth is caused by the formation of the nonlinear state-space model. To check the probability function for each set of parameters until we reach the maximum, we need complex calculations and multiple filter replications. Therefore, as an alternative, we use the Bayesian model averaging (BMA) approach with the MCMC method to estimate the accurate and efficient TVP regression model. Gibbs sampling is one of the well-known methods of MCMC. To consider a vector of unknown parameters, the procedure is as follows. A initial Point is selected arbitrarily: insert and $i = 0$. According to $(\theta^i = \theta_1^i, \ldots, \theta_P^i)$, we use conditional distribution $\pi\,\pi(\theta_1^{(i+1)} \mid \theta_2^i, \ldots, \theta_P^i)$, to produce $\theta_1^{(i+1)}$, conditional distribution $\pi(\theta_2^{(i+1)} \mid \theta_1^i, \theta_3^i, \ldots, \theta_P^i)$ to produce $\theta_2^{(i+1)}$, and conditional distribution $\pi(\theta_3^{(i+1)} \mid \theta_1^i, \theta_2^i, \theta_4^i, \ldots, \theta_P^i)$ to produce $\theta_3^{(i+1)}$. To continue production $\theta_4^{(i+1)}$ and above, continue this path. insert $i = i + 1$, and go back to the second step.

To estimate the TVP regression model, there are several reasons for using the BMA inference and MCMC sampling. First, the truth function in these models is insoluble and complex because the model consists of nonlinear state equations due to stochastic volatility. Second, by using the MCMC method, not only parameters $\theta = (\beta, \Sigma, \Phi, \delta_\eta, Y)$ but also state variables $\alpha = \{\alpha_1, \cdots, \alpha_n\}$ and $h = \{h_1, \cdots, h_n\}$ are sampled simultaneously. We can deduce the variables of the state with the uncertainty of the parameter (Nakajima, 2011) [17].

### 3.3. Dynamic Models

The standard form of state-space models, particularly Kalman filtering, is as follows:

$$y_t = z_t \theta_t + \epsilon_t \theta_t = \theta_{t-1} + \mu_t \tag{23}$$

In the equations, $y_t$ is the dependent variable of the model, $z_t = [1, x_{t-1}, y_{t-1}, ..., y_{t-p}]$ is a1 × m vector of estimation of intercept and interruption of the dependent variable, $\theta_t = [\varphi_{t-1}, \beta_{t-1}, \gamma_{t-1}, \cdots, \gamma_{t-p}]$ is a $1 \times m$ vector of coefficients (states), $\varepsilon_t \sim N(0, H_t)$ and $\mu_t \sim (0, Q_t)$ have normal distribution with zero average and the variances are $H_t$ & $Q_t$. The model has numerous benefits, the most important being that it allows the change of estimated coefficients at any moment. However, the disadvantage is that whenever $z_t$ becomes too big, the estimations are not reliable. A generalized model of TVP, such as TVP-vector autoregressive, is associated with the same problems. Hoogerheide *et al.* 2009, made some improvements, which included uncertainty of the estimators, as follows:

$$y_t = \sum_{j=1}^{m} s_j \theta_{jt} z_{jt} + \varepsilon_t \tag{24}$$

$\theta_{jt}$ and $z_{jt}$ are the $j^{th}$ component of $\theta_t$, $z_t$. Variable $s_j \in \{0, 1\}$ is added to the model, which cannot change over time. It is just a permanent variable that accepts 0 or 1 for each estimator (Hoogerheide *et al.* (2010)[7]. Raftery *et al.* (2010)[19] subsequently presented the DMA method, which resolved all limitations of the previous methods. This method could actually estimate huge models at any moment and change the input variables at any moment.

In order to describe the Dynamic Model Averaging (DMA) process, let's assume the $K$ models subset of $z_t$ variables are estimators and that $z^{(k)}$ indicates the [ $K$ models of the subset. Thus, assuming there are $K$ models of the subset at any time, the state-space model is described as follows:

$$\begin{aligned} y_t &= z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \\ \theta_{t+1}^{(k)} &= \theta_t^{(k)} + \mu_t^{(k)} \end{aligned} \tag{25}$$

$\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\mu_t^{(k)} \sim (0, Q_t^{(k)})$ and $\vartheta_t = (\theta_t^{(1)}, ..., \theta_t^{(k)}) L_t \in \{1, 2, ..., K\}$ in these equations indicate which model has the better performance. The method that estimates different models at any moment is called the DMA model (Koop and Korobilis, 2009)[13]. The differences between the DMA and DMS models in estimating a variable in time $t$ based on information $t$–1 can be considered with $L_t \in \{1, 2, \ldots, K\}$, and the DMA model includes the $Pr(L_t = k | y^{t-1})$ calculation and averaging prediction models based on the following possibility. However, DMS selects a model with $Pr(L_t = k | y^{t-1})$ highest possibility and predicts a model with maximum possibility.

To understand the nature of the above concepts, you first need to determine how the estimators arrive and exits to the model at a specific time interval.

A simple way to do this is to use the transition matrix $P$, whose elements are $p_{ij} = Pr(L_t = i | L_{t-j} = j$ with $i, j = 1, 2, \cdots, K$, which Hamilton (1989) used in the MCMC in the form of a Bayesian inference. The Bayesian inference is theoretically easy, but its calculation in dynamic models is almost impossible due to the large size of the P matrix. Consider the model in which there are m variables to estimate the model, and each of the variables can be either an appropriate estimator for the dependent variable of the model or not. In this case, $P$ is a $K \times K$ matrix in which $K = 2^m$. If m is not very small, the number of $P$ parameters will be very high, and the calculations will be slow and difficult. Therefore, with a completely Bayesian approach, dynamic models can be extremely difficult and nearly impossible. In this study, the proposed method is used by Raftery *et al.* (2010)[19]This method provides an opportunity to increase the accuracy of forecasting state-space models using the Kalman filter. The dynamic model averaging (DMA) approach presented by Raftery *et al.* (2010)[19] includes two parameters, $\alpha$ and $\beta$, which they call "missing factors." For constant values $H_t$ and $Q_t$, the standard filtering results can be used to make a recursive or predictive estimate.

The Raftery *et al.* (2010)[19] method is used, which involves the presentation of forgetting factor ? for the state equation of an estimation difference model, just as the above factor is comparable with forgetting factor $\beta$ of the state equation for parameters. Similar results when using DMA are as follows:

$$P(\vartheta_{t-1} \mid y^{t-1}) \tag{26}$$

$$= \sum_{k=1}^{K} P(\theta_{t-1}^{(k)} \mid L_{t-1}$$

$$= k, y^{t-1}) \Pr(L_{t-1}$$

$$= k, y^{t-1})$$

The relation $p(\theta_{t-1}^{(k)} \mid L_{t-1} = k, y^{t-1})$ is calculated by relation (18). To simplify assumed $\pi_{t|s,l} = \Pr(L_t = l \mid y^s)$, therefore we can say that $\Pr(L_{t-1} = k, y^{t-1}) = \pi_{t-1} \mid t-1, k$. If Matrix of Transition Probabilities $P$ is used with elements $p_{kl}$, the prediction function of the model will be as follows:

$$\pi_{t|t-1,k} = \sum_{l=1}^{K} \pi_{t-1|t-1,l}\, p_{k} \mid \tag{27}$$

Raftery *et al.* replaced it with the following equation:

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}} \tag{28}$$

If $0 \leq \alpha < 1$, its interpretation of the behavior will be similar to $\beta$. The great benefit of using ? is that using the MCMC algorithm is not required in predicting the equations of a model. Instead, a simple evaluation is performed to compare the Kalman filter update function as

$$\pi_{t|t,k} = \frac{\pi_{t|t-1,k}^{\alpha}\, p_k(y_t \mid y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l}^{\alpha}\, p_l(y_t \mid y^{t-1})}, \tag{30}$$

where $p_l(y_t \mid y^{t-1})$ is the predictive density for the model L-the normal density of relation(21)-which is calculated in terms of $y$. A recursive prediction can be accomplished by weighing averages using $\pi_{t|t-1,k}$ on the predictive results of each model; therefore, DMA points are calculated as follows:

$$E(y_t \mid y^{t-1}) = \sum_{k=1}^{K} \pi_{t|t-1,k}\, z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{31}$$

The use of the dynamic model selection (DMS) method is such that it chooses a model that has the highest value of $\pi_{t|t-1,k}$ at any point in time. To understand more about forgetting factor $\alpha$, note that this diagnosis is significant based on the weight of each model at any given time, as follows:

$$\pi_{t|t-1,k} \propto [\pi_{t-1|t-2,k}\, p_k(y_{t-1} \mid y^{t-2})]^{\alpha}$$

$$= \prod_{i=1}^{t-1} \left[ p_k(y_{t-i} \mid y^{t-i-1}) \right]^{\alpha^i} \tag{32}$$

Therefore, if the $k$ model is well predicted in the past, it will have a higher weight in which the prediction is measured using the predictive density $p_k(y_{t-i}) \mid y^{t-i-1})$. The interpretation of the recent period is controlled by forgetting factor $\alpha$, and, like $\beta$, there is a decrease in the $\alpha^i$ rate for the observations of the previous period. Based on this, whenever $\alpha = 0.99$, the forecast performance of the last five periods will have an equivalent weight of 80% of the weight of the last prediction period. In addition, if $\alpha = 0.95$, the prediction performance of the last five periods will have a weight of 35% of the weight of the last prediction period. Based on this, if $\alpha = 1$, then $\pi_{t|t-1,k}$, is calculated precisely on the marginal values of the $t$–1 period, which is the BMA approach. In addition, if $\beta = 1$, the BMA approach uses a conventional linear prediction model with constant coefficients over time. In the next return estimate, the proposed models are started with the previous values for $\pi_{0|0,k}$ and $\theta_0^{(k)}$ for $k = 1, 2, ..., K$. The only remaining discussion is how to calculate the value of $H_t$. Raftery *et al.* (2010)[19] proposed a simple assumption of $H_t^{(k)} = H^{(k)}$ and a displacement with a constant estimate. However, in predicting some of the variables, a variance of variable error over time is required. In theory, we can use the model of stochastic volatility -autoregressive conditionally heteroscedastic (ARCH) model for $H_t^{(k)}$ which greatly increases the computational domain of the model. Based on the model presented in this study, we use an Exponentially Weighted Moving Average (EWMA) method to calculate $H_t^{(k)}$:

$$= \sqrt{(1-\varphi)\sum_{j=1}^{t} \varphi^{j-1} (y_j - z_j^{(k)} \hat{\theta}_j^{(k)})^2} \tag{33}$$

EWMA estimates are often used in time-varying fluctuation models in financial sectors, where φ is a degradation factor. To discuss these models, refer to Risk Metrics (Morgan, J.P. (1996) Risk Metrics)[20] In Risk Metrics, the value of φ is equal to 0.97 for monthly data, 0.98 for seasonal data, and from 0.94 for daily data. One advantage of EWMA is that it can be estimated by a recursive form that can be used to predict fluctuations. The prediction of the $t + 1$ period based on information from period t can be as follows:

$$\begin{aligned} \widehat{H}_{t+1|t}^{(k)} &= \varphi \widehat{H}_{t|t-1}^{(k)} \\ &+ (1-\varphi)\left(y_j - z_t^{(k)}\hat{\theta}_t^{(k)}\right)^2 \end{aligned} \tag{34}$$

In this model, variables will be predicted as dependent variables of the model and will be used in different time horizons. If prediction of stock market yields is on horizon ofh year, the stock market returns has concept in the form of ln $\left( p_t / p_{t-h} \right)$ However, DMA has many potential benefits over other predictive methods. The greatest advantage of this method is that is eliminates the weaknesses of other methods, minimizing the number of equations and variables and predicting huge models with a large number of variables. In this case, the number of models to be estimated will be very high. The DMS and DMA methods are capable of reducing variables and subsequently models in such a way that by using equation (34), we can determine models with more weight in prediction. The advantage of this method is that if the DMA model takes more weight for some of the subsets of estimators, saving models, and low input variables, it avoids over-fitting problems in the estimation.

$$E(Size_t) = \sum_{k=1}^{K} \pi_{t|t-1,k}\, Size_{k,t}$$

Investigating the accuracy of the models

In order to investigate a predicted model, or to select the best of several different models, an indicator to help us decide whether to accept or decline the model is required. In the current study, two indicators, mean squared forecast (MSFE) and mean absolute forecast (MAFE),were used.

$$MSFE = \frac{\Sigma_{\tau=\tau_0}^{T} [y_\tau - E(y_\tau \mid Data_{\tau-h})]^2}{T - \tau_0 + 1} \tag{35}$$

$$MAFE = \frac{\Sigma_{\tau=\tau_0+1}^{T} [y_\tau - E(y_\tau \mid Data_{\tau-h})]}{T - \tau_0 + 1} \tag{36}$$

In the above equations, $\text{Data}_{\tau-h}$ is the data obtained from the $\tau - h$ period, $h$ is the time horizon forecast and $E(y_\tau \mid \text{Data}_{\tau-h})$ is the point forecast of $y^3_t$.

## 4. MODEL ESTIMATION AND RESULTS

### Variables definitions

In the present study, monthly data from 2006 to 2016 were used :

- US Stock Exchange,
- Change of Real effective exchange rate was used as a variable for shock in the domestic market
- One year interest rates (monetary policy)
- Change in oil prices were used as a variable in external shock
- Percentage change consumer retail index as a substitute inflation (public policy).
- AMEX: American Stock Exchange

The variables were obtained from the Central Bank and International Monetary Fund, respectively. The logarithm of the ratio of stock price index in each period compared with the previous period in America. The securities percentage was multiplied by 100 times the International Monetary Fund, and was considered as a return on equity in the US Stock Exchange (Aloui and Jammazi, 2009)[10].

$$Y_t = 100 \times \ln\left(\frac{AMEX_t}{AMEX_{t-1}}\right) \tag{29}$$

Constant variables (Constant) and the first flag of cash returns (ARY_1) were used in software calculations to predict and estimate the return on the cash stock exchange.

### 4.1. Model Estimation

The TVP variable coefficients obtained from estimating models with stochastic volatility are presented for the individual independent variables in Figures 1 to 4. TVP models with stochastic volatility were used, and a coefficient was calculated for each period. Figures 1 to 4 present the process of estimated coefficient for each variable (not the variable data process).

Figure 1 shows that, among states(variable in that year), first (variable in one year ago) and second(variable in second years ago) interruption, Likelihood of effectiveness of inflation on the first interruption is greater than its effect on the level and the second interruption. The Likelihood of effectiveness of inflation on stock returns on the second interruption is greater than level state. In addition, the effect of inflation on stock returns with regard to level and first interruption is greater than its effect on the second interruption in the 2006-2008 period. None of the states had any effects on stock returns in 2008-2012, also the first and second interruptions of inflation had a greater effect on stock returns compared to the level state from 2012-2016. The same is observed with regard to exchange rates, interest rates charts and oil prices, as presented in Figures 2 to 4, respectively.

Figure 2 shows that, the effect of exchange rate on stock returns with regard to level and second interruption is greater than its effect on the first interruption in the 2006-2008 period also level state of exchange rate has significant effect on stock returns from 2012-2016.

Figure 3 shows that, the effect of interest rate on stock returns with level state ,first interruption, second interruption has significant effect in all of that from 2006-2010.also the effect of interest rate on stock returns with first and second interruption has significant effect than level state from 2010-2018.Figure 4 shows that, the effect of oil price on stock returns with level state ,second interruption has significant effect than first interruption from 2006-2008. also the effect of oil price on stock returns with first interruption has significant effect from 2010-2018.

According to the determination of the coefficient of macro indicators at various time intervals and the probability of each of these indices, we investigated the accuracy of prediction in stock returns using MAFE and MSFE, which resulted from the AR, TVP, TVP-SV, TVP-

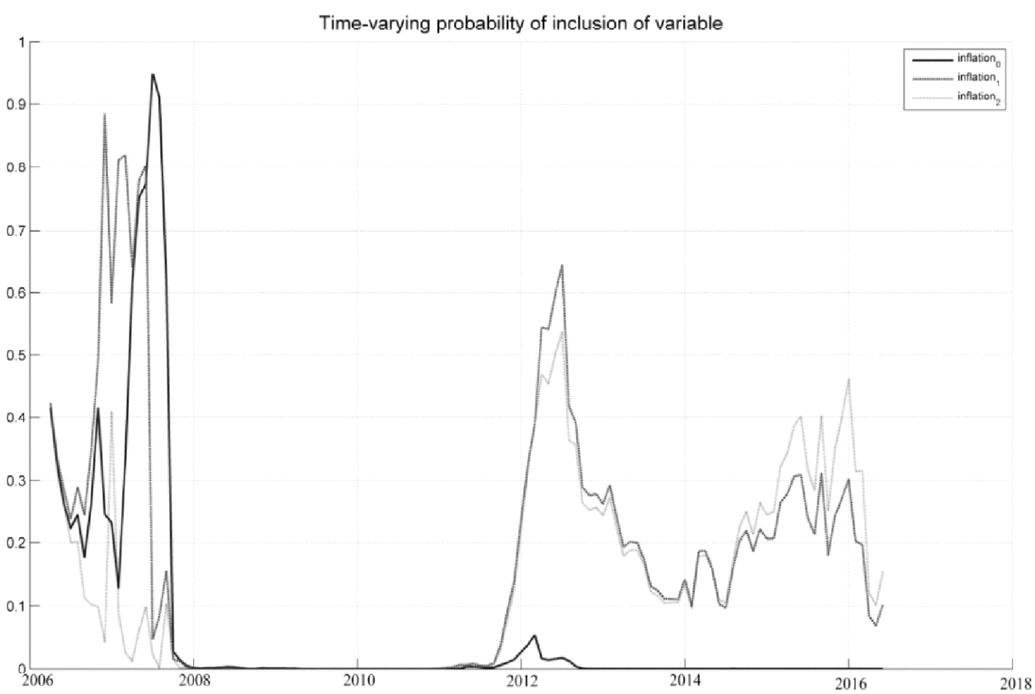


**Figure 1: The possible effect of inflation on the level, and the first and second interruptions of stock returns**

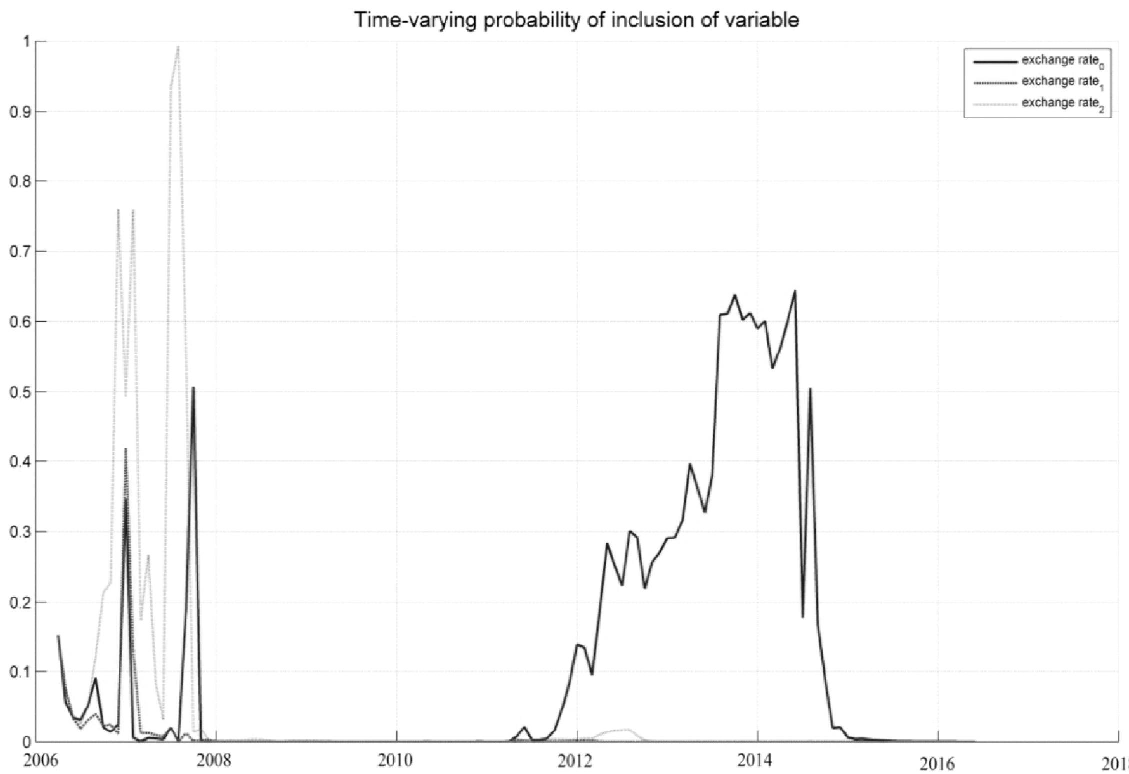


**Figure 2: The possible impact of exchange rate on level, first and second interruptions of stock returns**

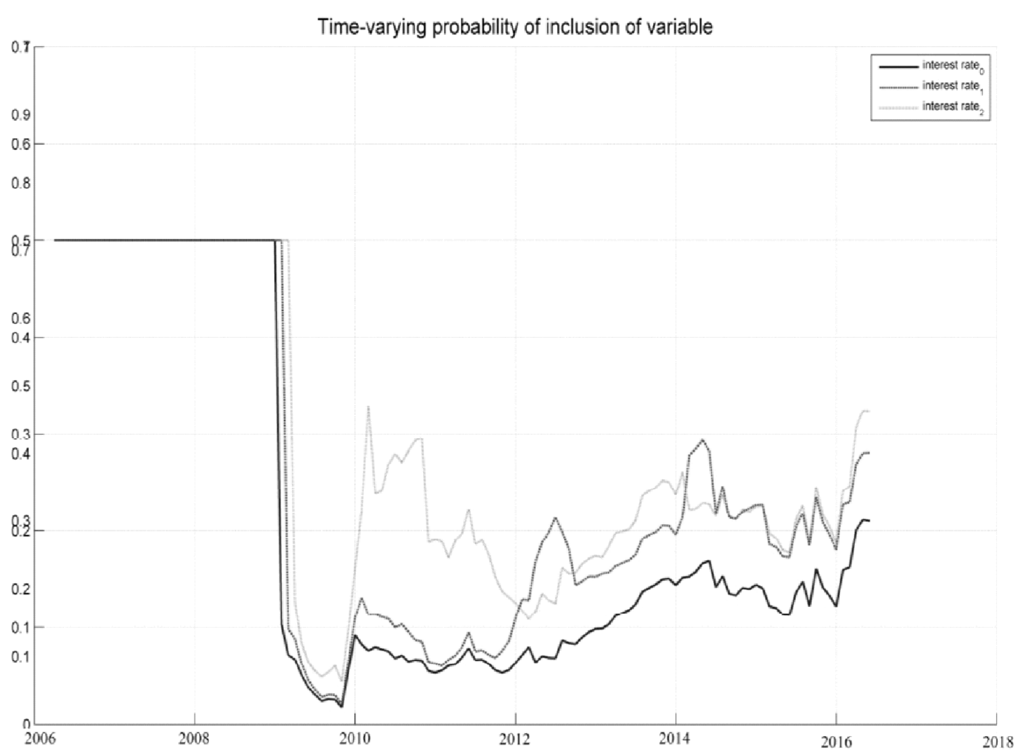


**Figure 3: The possible impact of interest rate on level, first and second interruptions of stock returns**

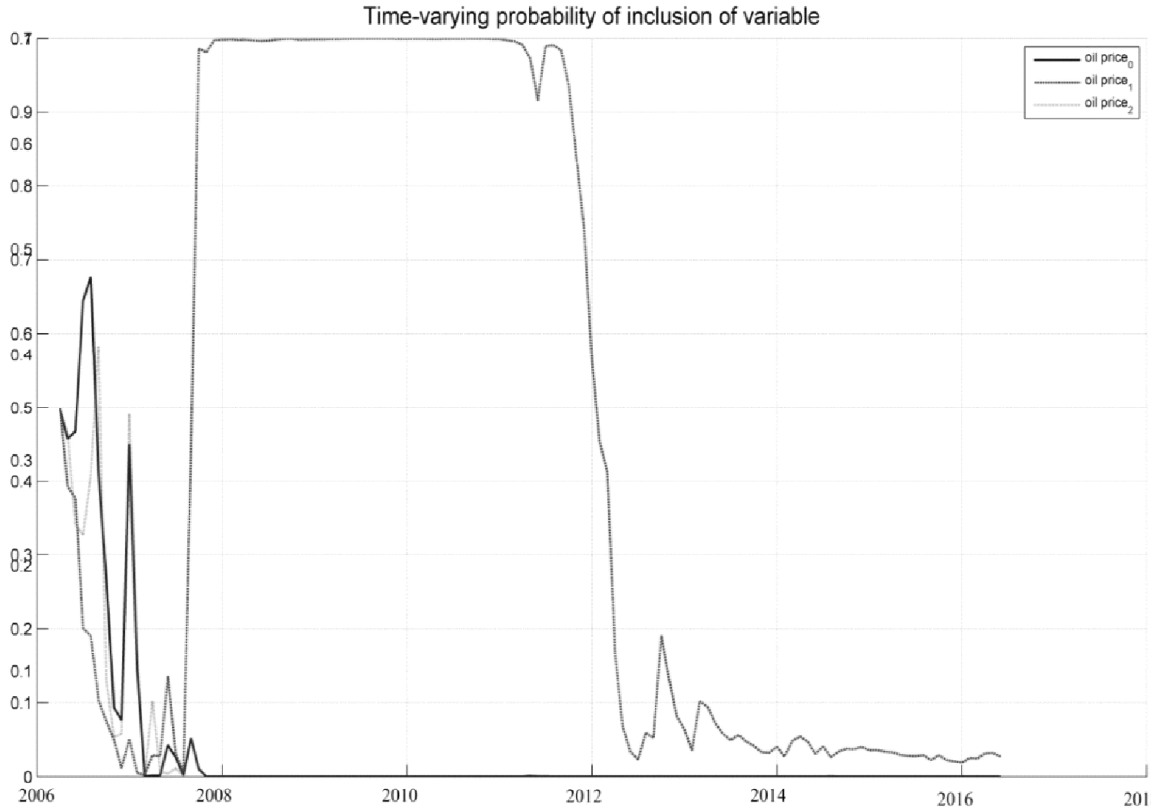


**Figure 4: The possible impact of oil price on level, first and second interruptions of stock returns**

SV-DMA and TVP-SV-DMS models. also We present iterated forecasts for horizons (h = 1, 3,6, 12) with a forecast evaluation period of 2006 through 2016. Given that the variation range of $\alpha$ and $\beta$ variations is usually between 0.90 and 1, all possible states are presented in the following tables. Like $\beta$, $\alpha$ has an exponential descending rate with the rate $a^i$ for observations of the previous period. Based on this, whenever $\alpha = 0.99$, the forecast performance of the last five periods weighs 80% of the weight of the last forecast period. In addition, if $\alpha = 0.95$, the prediction performance of the last five periods will have a weight of 35% of the weight of the last prediction period. Based on this, if $\alpha = 1$, then $\pi_{t|t-1,k}$ is calculated precisely on the marginal values of thet-1period, which is the BMA approach. If $\beta = 1$, the BMA approach uses a conventional linear prediction model with constant coefficients over time.(Koop, 2013) [11].

To analyze the table2, on the one hand, the results for each of the horizons (h = 1,3,6,12) can be analyzed individually.According to the local priority column, as whole it is shown, DMS methods have been better than other methods in all horizons. but on the other hand, the results of all horizons can be analyzed and compared generally.

The results is presented in table 2 that the prediction accuracy of the DMS $\alpha = \beta = 0.90$ in h = 3 is the best of all. In addition, the best model prediction results are shown with input parameters. Therefore, the DMS model offered the best prediction of stock return of the US Stock Exchange over time.

According to the TVP-SV model and its results (figure1-4) in each month, it can be mined which one of variables has an significant effect on the stock return. In table 3 is shown the variables that affected stock returns in each period. For example, in 2006-1 the interest rates and oil prices at the level has significant impact on the stock return. As another example, also it is shown that the first interruption of inflation and interest rate with first interruption has significant effect on stock return in the US Stock Exchange in 2006-8. For other periods, they can be analyzed as previously.

The results obtained from the table 3 are then presented as:

- The first lag in all period (126 courses) had a remarkable effect on stock returns.
- The interest rate and its lags in 64courses had a significant effect on stock returns.
- Inflation and its lags in 77 courses had a significant effect on stock returns.
- Oil price and its lags in 98 courses had a significant effect on stock returns.

**Table 2**
**A comparison of the different models based on Kalman filtering (Source: *Calculations of the researcher*)**

*h = 1*

| *Method of predicting* | *MAFE* | *MSFE* | *General Prioritize* | *LocalPrioritize* |
|---|---|---|---|---|
| DMA $\alpha = \beta = 0.99$ | 7.85 | 79.11 | 20 | 9 |
| DMS $\alpha = \beta = 0.99$ | 7.05 | 57.66 | 14 | 7 |
| DMA $\alpha = \beta = 0.90$ | 6.71 | 50.87 | 11 | 6 |
| DMS $\alpha = \beta = 0.90$ | 6.17 | 43.64 | 7 | 3 |
| DMA $\alpha = 0.99$; $\beta = 0.90$ | 6.69 | 49.08 | 10 | 5 |
| DMS $\alpha = 0.99$; $\beta = 0.90$ | 5.92 | 36.25 | 5 | 2 |
| DMA $\alpha = 0.90 \beta = 0.99$ | 6.19 | 45.25 | 8 | 4 |
| DMS $\alpha = 0.90; \beta = 0.99$ | 4.95 | 20.91 | 2 | 1 |
| AR(1) | 11.07 | 134.95 | 37 | 11 |
| TVP | 8.14 | 87.39 | 23 | 10 |
| TVP-SV | 7.86 | 67.31 | 19 | 8 |

h = 3

| Method of predicting | MAFE | MSFE | General Prioritize | LocalPrioritize |
|---|---|---|---|---|
| DMA $\alpha = \beta = 0.99$ | 8.66 | 102.23 | 28 | 8 |
| DMS $\alpha = \beta = 0.99$ | 7.77 | 65.12 | 18 | 6 |
| DMA $\alpha = \beta = 0.90$ | 6.91 | 55.37 | 13 | 5 |
| DMS $\alpha = \beta = 0.90$ | 4.08 | 17.11 | 1 | 1 |
| DMA $\alpha = 0.99; \beta = 0.90$ | 6.84 | 52.17 | 12 | 4 |
| DMS $\alpha = 0.99$; $\beta = 0.90$ | 5.82 | 32.45 | 4 | 3 |
| DMA $\alpha = 0.90 \beta = 0.99$ | 7.91 | 84.32 | 21 | 7 |
| DMS $\alpha = 0.90; \beta = 0.99$ | 5.67 | 24.78 | 3 | 2 |
| AR(3) | 16.21 | 167.73 | 42 | 11 |
| TVP | 9.21 | 110.09 | 31 | 10 |
| TVP-SV | 9.05 | 107.02 | 30 | 9 |

h = 6

| Method of predicting | MAFE | MSFE | General Prioritize | LocalPrioritize |
|---|---|---|---|---|
| DMA $\alpha = \beta = 0.99$ | 12.32 | 145.21 | 40 | 9 |
| DMS $\alpha = \beta = 0.99$ | 9.02 | 106.14 | 29 | 7 |
| DMA $\alpha = \beta = 0.90$ | 8.11 | 85.34 | 22 | 5 |
| DMS $\alpha = \beta = 0.90$ | 6.12 | 40.21 | 6 | 1 |
| DMA $\alpha = 0.99; \beta = 0.90$ | 8.21 | 90.11 | 25 | 6 |
| DMS $\alpha = 0.99$; $\beta = 0.90$ | 7.04 | 60.65 | 15 | 3 |
| DMA $\alpha = 0.90 \beta = 0.99$ | 7.09 | 61.19 | 16 | 4 |
| DMS $\alpha = 0.90; \beta = 0.99$ | 6.24 | 27.68 | 9 | 2 |
| AR(6) | 17.37 | 173.73 | 43 | 11 |
| TVP | 11.05 | 131.09 | 36 | 8 |
| TVP-SV | 14.79 | 159.02 | 41 | 10 |

h = 12

| Method of predicting | MAFE | MSFE | General Prioritize | LocalPrioritize |
|---|---|---|---|---|
| DMA $\alpha = \beta = 0.99$ | 10.45 | 126.08 | 34 | 7 |
| DMS $\alpha = \beta = 0.99$ | 10.88 | 130.02 | 35 | 8 |
| DMA $\alpha = \beta = 0.90$ | 8.39 | 99.34 | 26 | 3 |
| DMS $\alpha = \beta = 0.90$ | 8.45 | 101.87 | 27 | 4 |
| DMA $\alpha = 0.99; \beta = 0.90$ | 7.33 | 62.11 | 17 | 1 |
| DMS $\alpha = 0.99$; $\beta = 0.90$ | 8.16 | 88.71 | 24 | 2 |
| DMA $\alpha = 0.90 \beta = 0.99$ | 10.44 | 117.13 | 33 | 6 |
| DMS $\alpha = 0.90; \beta = 0.99$ | 10.13 | 114.71 | 32 | 5 |
| AR(12) | 23.18 | 183.12 | 44 | 11 |
| TVP | 12.09 | 140.16 | 39 | 10 |
| TVP-SV | 11.13 | 137.02 | 38 | 9 |

**Table 3**
**Available variables at any time in BEST MODEL[2,3]**

| *Period* | *Name of available variables at any time in best model* | | | | |
|---|---|---|---|---|---|
| 2006-1 | constant | ARY_1 | interest rate_0 | oil price_0 | |
| 2006-2 | constant | ARY_1 | interest rate_0 | oil price_0 | |
| 2006-3 | constant | ARY_1 | oil price_0 | | |
| 2006-4 | constant | ARY_1 | interest rate_0 | oil price_0 | |
| 2006-5 | constant | ARY_1 | interest rate_0 | oil price_0 | |
| 2006-6 | constant | ARY_1 | oil price_2 | | |
| 2006-7 | constant | ARY_1 | interest rate_1 | | |
| 2006-8 | constant | ARY_1 | inflation_0 | interest rate_1 | |
| 2006-9 | constant | ARY_1 | interest rate_0 | inflation_1 | exchange rate_2 |
| 2006-10 | constant | ARY_1 | interest rate_0 | inflation_1 | exchange rate_1 |
| 2006-11 | constant | ARY_1 | interest rate_0 | inflation_1 | |
| 2006-12 | constant | ARY_1 | inflation_1 | interest rate_1 | |
| 2015-12 | constant | ARY_1 | inflation_2 | | |
| 2016-1 | constant | ARY_1 | oil price_0 | interest rate_0 | |
| 2016-2 | constant | ARY_1 | oil price_0 | interest rate_0 | |
| 2016-3 | constant | ARY_1 | inflation_1 | | |
| 2016-4 | constant | ARY_1 | inflation_1 | oil price_0 | |
| 2016-5 | constant | ARY_1 | inflation_2 | oil price_1 | |
| 2016-6 | constant | ARY_1 | inflation_1 | oil price_1 | |

- The exchange rate in 110 courses had a significant effect on stock returns.

It can ultimately be observed that, after the first interruption, oil price, inflation, interest rate and exchange rate had the greatest impact on stock return in the periods studied. According to the findings, 118 of 126 courses of systematic risk factors had an effect on stock returns. Thus, systematic risk is an important factor in stock return volatility.

## CONCLUSION

The results of the present study show that systematic risks have different impacts on stock returns in different periods. Therefore, combined DM

A and DMS methods and TVP models showed that particular systematic risks make an impact on stock returns and the possibility of these risks occurring depends on the possibility of occurring which mainly results from their repetitions.

Variables with different intensities (different coefficients) are influential on stock returns in different periods. Therefore, oil price variables and inflation variables have a greater effect on stock returns compared with interest rate and exchange rate. The findings of the current study are consistent with the findings of Nasser (2015)[16], Chan *et al.* (2015)[2], Johannes *et al.* (2014)[9], Nakajima (2011)[17], Groen *et al.* 2013 [8] .

The findings of the present study show that different variables have different impacts on stock returns over time. Thus, the use of models that have the ability to separate a policies change into different risk levels to predict stock returns is suggested. Therefore, it is recommended that policy-makers and stakeholders active in financial markets use general policies for improving conditions in financial markets at any time, and use suitable instruments to make policies on each government depending on what factors are the most important with regard to affecting stock returns at that time.

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