The impact of time-varying systemic risk on predicting the dynamics of stock return volatility in tehran stock exchange

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Abstract

Stock market volatility has received much attention in the finance literature in the last few decades. Analysts need to make correct forecasts of the price volatility as a necessary input for tasks such as risk management, allocation of portfolios, Value at Risk assessment, option pricing, and future contracts. Ignoring the effects of volatility will reduce the accuracy of stock return predictions. In this regard, the aim of the present study is to identify the dynamics of stock return to increase the accuracy of predictions. The results of time-varying parameter (TVP), dynamic model selection (DMS), dynamic model averaging (DMA) and Kalman filter output in the state-space showed that DMS with $\alpha=\beta=0.90$ outperforms other models in terms of prediction accuracy. According to this model, after the first lag of stock returns (126 periods), the oil price (58 periods), inflation rate (35 periods), interest rate (31 periods) and exchange rate (20 periods) had the highest impact on stock returns. According to the results, of 126 periods, the systemic risk indexes affected stock returns in 102 periods. As a result, it can be concluded that systemic risk plays an important role in predicting the dynamics of stock return volatility.

Macro Indicators, Kalman Filter, Stock Returns, Time-Varying Parameter, Dynamic Models

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Introduction

Due to their dynamic nature, economic and financial indicators are always changing. The factors that cause changes in financial indicators are sometimes voluntary in the form of politics and sometimes are involuntary in the form of natural phenomena. But it seems important to investigate the nature of shocks and their influence on financial markets. Previous studies indicate that the origins of economic shocks can be explained form different perspectives. Some researchers believe that inflation is the source of instability of macroeconomic variables and financial markets. However, some believe that the volatility of exchange rate, energy carrier prices and other factors such as monetary and financial shocks is the source of instability (Fischer, 2011; Fama, 1981; Daisy Li et al., 2010; Bjornland, 2009).

Various models and theories have been proposed in the academic literature to achieve an optimal investment to help investors in their decisions and assessments. It is accepted that returns on investment relates to the level of its standard deviation. On the other hand, most investment decisions are based on the relationship between the risk and return (Sharpe, 1964; Black & Scholes,1974). Consequently, an investor always considers these two factors in portfolio analysis and management. One of the key areas of economic research deals with the behavior of financial and economic variables. In addition to the direction of changes, the rate of volatility gives valuable information on the behavior of a variable and its effect. Due to uncertainty caused by the volatility of economic variables, economic models pay particular attention to decision making under uncertainty (Bollerslev et al., 1992; Jacquier et al., 2002). As a disadvantage, expected returns prediction models are not stable but are highly sensitive to different markets and conditions (Goyal & Welch, 2008).

In fact, studies have shown that although there is evidence for the predictability of expected returns prediction models, such models show a poor performance so that investors cannot use them in practice. There are several reasons for this assumption that the standard out-of-sample approach probably fails. First, the key features of stock returns are not considered in the regression model. Especially, constant volatility is strongly inconsistent with observed data, because stock returns volatility changes over time (Johannes et al., 2014).

Also, according to Johannes et al. (2014), ignoring this volatility leads to optimal portfolios solely based on the expected return (taking into consideration the constant variables over time) leading to a poor performance.

In this study we seek the causes taking into account realistic assumptions to reach stability in determining factors influencing stock returns for Tehran Stock Exchange. The goal of this work is to find out how stock return volatility affected when new data enters (changes in systemic risk macro-indicators) in Tehran Stock Exchange. The authors believe that this is the first attempt in Iran which examines the dynamic models for prediction on stock return.

The rest of the paper is organized as follows. In section 2, the theoretical backgrounds of our proposed model is presented and reviewed in brief. In section 3, the models adopted in our study with their underlying variables are introduced. Section 4, our model estimations and results are presented. Finally, section 5 contains concluding remarks and guidelines for future researches.

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Theoretical Backgrounds and Review

Dynamicity (changes over time) is the inherent nature of economic and financial phenomena. Ignoring this dynamic nature will oversimplify financial phenomena. Accordingly, the resulting models are not often realistic leading to misinterpretation of such phenomena (Belmonte & Koop, 2013). In modern portfolio theory it is assumed that a trade-off existed between the risk and expected return. Expected return changes over time with changes in risk factors and thus price action will not follow a random walk due to the changes in the expected returns of shareholders over time. Therefore, many financial experts believe that it is impossible to investigate predictability of stock prices regardless of the risks (Pesaran & Timmerman, 1995).

In recent decades, various models have been introduced to determine prices and changes in stock prices. The volatility of financial variables as one of the main components of pricing of financial assets has been the focus of many studies. The Capital Asset Pricing Model (CAPM) is based on the assumptions and findings of the modern investment and Markowitz's portfolio theory which indeed had an undeniable effect on the field finance and investment. In CAPM, the relationship between variables in regression-based ordinary least squares is always assumed static. And, it is ignored the evolution of these relationships over time which alters the equation coefficients. In these models, it is supposed that a relationship with constant coefficients can be applied at different times. Incorrect results due to this unrealistic assumption led to dynamic models with more resemblance to the reality of the outside world (Belmonte & Koop, 2013).

According to Stock and Watson (2008), the traditional prediction models were not able to provide correct predictions over time.

Some models provided good estimates during the economic boom and some in the depression era. This led to the development of time-varying parameter (TVP) models and Markov Chain Monte Carlo Models (MCMC) that were able to predict large models (with a large number of variables) over time ((Nakajima, 2011; Mumtaz, 2010). In these models, estimated coefficients can change over time.

Due to the variation of condition, structural breaks and cyclic changes, the traditional models were not capable of calculating the parameters. Moreover, a large number of variables and estimators lead to large and bulky models. In this class of models, if there are m variables at the time interval t, there will be $2m^t$estimation models (koop & Korobilis, 2011; Korobilis, 2013). There are several studies on structural models using time-varying parameters (TVP) models.

Naser and Alaali (2015) investigated the role of oil prices and other macroeconomic and financial variables including the index of industrial production, interest rate, inflation rate, unemployment rate and financial ratios in predicting the S&P 500 index. Their empirical evidences show that the use of DMA/DMS approach leads to a significant improvement in prediction performance compared to other prediction methods. The performance of these models is improved when oil price is considered as a predictor.

Fux (2014) examined the predictability and structural modeling of stock returns. The results of this study showed that predictability of US out-of-sample stock returns over time is poor due to structural breaks and changes in the coefficients.

Based on the findings, an investor can increase the utility level up to 1.2% using DMA where instability, time-varying coefficients, and model uncertainty are taken into account compared with forecasts based on ordinary least squares.

In recent years, Bossaerts and Hillion (1999), Pastor and Stambaugh (2001), Pesaran and Timmermann (2002), Clements and Hendry (2004), Paye and Timmermann (2006), Goyal and Welch (2008) and Pettenuzo and Timmermann (2011) conducted studies on time-varying parameter and dynamic models to investigate the relationships between predictor variables and stock returns following structural breaks. Johannes, Korteweg, and Polson (2008) focused on random volatility while Dangl and Halling (2012) used time-varying variables in the state-space model to predict the S & P 500 index. Table 1 summarizes the results of various studies (proponents and opponents) on the impact of macroeconomic variables on stock returns as well as the performance of time-varying volatility models compared with traditional models.

According to Table 1, most studies show that the volatility of macroeconomic variables affects stock returns. As a result, when creating an optimal portfolio, investors should pay special attention to the influence of these indicators. In addition, time-varying models are more effective than traditional models.

Effect of microeconomic variables on stock return	
Advocates	**Opponents**
Daisy Li et al (2010), Hoogerheide et al (2010) ,Jammazi and Aloui(2009), Liu et al (2008), Buyuksalvarci(2010), Brahmasrene et al(2007)	Gay (2008), Poitras, M. (2004), Karamustafa et al (2003)
Efficiency of time-varying volatility models in comparison to traditional models	
Advocates	**Opponents**
Chan et al(2015), Gupta et al(2014), Johannes et al(2014), Nakajima(2011), Mumtaz(2010), Fux (2014), Naser and Alaali (2015), Wang et al *(*2016)	-

Table 1 Summary of the results

The Research Models and Variables

Time-series regression model is a conventional statistical model where the changes of a phenomenon are studied over time. Such techniques assume that an equation with constant coefficients can be used in different times. Inaccurate results originated from such a non-realistic assumption leaded to dynamic models which are very closer to the real world. State-space model is a method for modeling dynamic systems which models, predicts and analyzes the behavior of system in such conditions.

State-space models let parameters have structural instability and let coefficients be constant over time. This is one of the applications of such models. Such models are known as time-varying parameter (TVP) models which is a special state of state-space models. State-space equations system consists of two equations: observation equation and equation of state.

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The equations are estimated using recursive algorithms Kalman filter. Bayes filter is the most typical estimation method. From Bayesian theory point of view, the problem of estimation is estimating probability density function posterior. Given probability density function posterior, the optimal estimation of states can be calculated in terms of any criterion function. There are different techniques for practical solution of Bayes filter, depending on relevant process and measurement. For example, if the studied dynamic system is a linear system and process and measurement noises are of Gaussian nature, Kalman filter will be used (Nakajima, 2011; Fux 2014; Belmonte & Koop, 2013).

In the following section, we will introduce the methods adopted in this study.

TVP Regression with Stochastic Volatility

TVP model with stochastic volatility enables us to record the probable changes of the fundamental structure of economy more flexibly and more powerfully. According to many studies, combining stochastic volatilities with TVP estimation improves estimation performance significantly (Nakajima, 2011). Let us consider TVP regression model as follows:

Regression.

$$y_t = x'_t\beta + z'_t\alpha_t + \varepsilon_t \qquad \varepsilon_t \sim \mathrm{N}(0, \sigma_t^2), \quad \mathrm{t} = 1, \ldots, \mathrm{n} \tag{1}$$

Time-varying coefficients:

$$\alpha_{t+1} = \alpha_t + u_t, \quad u_t \sim \mathrm{N}(0, \textstyle\sum), \ \mathrm{t} = 1, \ldots, \mathrm{n}-1 \tag{2}$$

Stochastic volatility.

$$\sigma_t^2 = \gamma \exp(h_t), \qquad u_{t+1} = \varphi h_t + \eta_t, \quad \eta_t \sim \mathrm{N}(0, \sigma_t^2), \quad \mathrm{t} = 1, \ldots, \mathrm{n}-1 \tag{3}$$

Where y_t is a scalar of response, x_t and z_t are $(k \times 1)$ and $(p \times 1)$ vectors of covariates, respectively, β is $(k \times 1)$ vector of constant coefficients, α_t is a $(p \times 1)$ vector of Time-varying coefficients, and h_t is stochastic volatility. Stochastic volatility plays a significant role in TVP models. Although the idea of stochastic volatility was first presented by Black (1976), financial econometrics has experienced many changes (Ghysels et al, 2002; Shephard, 2005).

Dynamic Models

The standard form of state-space models, especially that of Kalman filter, is as follows:

$$y_t = z_t\theta_t + \epsilon_t \tag{4}$$

$$\theta_t = \theta_{t-1} + \mu_t \tag{5}$$

Where $y_t$the dependent variable of model is, $z_t = [1, x_{t-1}, y_{t-1}, \cdots, y_{t-p}]$ is a $1 \times m$ vector constituted of intercepts estimators and dependent variable interval and $\theta_t = [\varphi_{t-1}, \beta_{t-1}, \gamma_{t-1}, \cdots, \gamma_{t-p}]$ is a $m \times 1$ vector constituted of coefficients (states). $\varepsilon_t \sim N\ (0, H_t)$ And$\mu_t \sim\ (0, Q_t)$, which have normal distribution with zero mean, are H_t and Q_t variances, respectively.

These models have many advantages the most important of which is the possibility of varying estimated coefficients at any time. The main disadvantage of such models is that if z_t gains a high value, the estimations will not be reliable. The extended TVP model has the same problems of TVP-VAR models. This model was properly developed by Garvin et al (2008) in which the behavior uncertainties of estimators were introduced to the model as follows:

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$$y_t = \sum_{j=1}^{m} s_j \theta_{jt} z_{jt} + \varepsilon_t \quad (6)$$

Where θ_{jt} and z_{jt} are the j^{jt} element of θ_t and z_t, respectively. Their model has an additional element: the existence of $s_j \in \{0, 1\}$ variable. This variable cannot vary with time and serves as a permanent variable which can accept 1 and 0 for any estimator (Hoogerheide et al., 2009).

Raftery et al. (2010) introduced DMA method and eliminated all restrictions of previous methods. This method could estimate large models at any instant and made it possible to change the input variables of model at any time.

In order to explain DMA process, let us assume that there are k sub-set models of z_t variables of estimators where $z^{(k)} (k = 1,2, \cdots, K)$ indicates 6 sub-set models. Based on this assumption, given k sub-set models at any time, state-space model is described as follows:

$$y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \quad (7)$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + \mu_t^{(k)} \quad (8)$$

Where $\varepsilon_t^{(k)} \sim N\,(0, H_t^{(k)})$ and $\mu_t^{(k)} \sim (0, Q_t^{(k)})$. $\vartheta_t = (\theta_t^{(1)}, \cdots, \theta_t^{(k)})$ $L_t \in \{1,2, \ldots, K\}$ stands for the model, out of the K sub-set models, which best fits with a given time. That method which makes it possible to estimate a different model at a given instant is called dynamic averaging model (Coop & Kroublis, 2011).

Regarding the differences of DMA and DMS dynamic models in forecasting a variable at time t based on data of time $t-1$, it can be argued that given $L_t \in \{1,2, \ldots, K\}$, DMA calculates $Pr\,(L_t = k | y^{t-1})$ and determines the average of the models predictions based on the above probability; while DMS selects a model with the highest possible probability of $Pr\,(L_t = k | y^{t-1})$ and forecasts the model with the maximum probability.

Evaluation of the Accuracy of Estimation Models

In order to evaluate a prediction model or to select the best fit model out of different available models for given time series, we need an index by which we can make decision about the acceptance or rejection of prediction model. This study adopts mean squared forecast error (MEFE) and mean absolute forecast error (MAFE) indices as follows:

$$MSFE = \frac{\sum_{\tau=\tau_0}^{T} [y_\tau - E\,(y_\tau | Data_{\tau-h})\,]^2}{T-\tau_0+1} \quad (9)$$

$$MAFE = \frac{\sum_{\tau=\tau_0+1}^{T} [y_\tau - E\,(y_\tau | Data_{\tau-h})\,]}{T-\tau_0+1} \quad (10)$$

Where $Data_{\tau-h}$ is data derived from period $\tau - h$ and h is forecasting time horizon and $E\,(y_\tau | Data_{\tau-h})$ is the point forecast of y_τ.

Our Model Estimations and Results

This study employed 1382-1392 data (with monthly intervals) for the variables of Tehran Stock Exchange return, non-official exchange rate change as the variable of internal market shock, interest rate (monetary policy), oil price change as the variable of foreign shock and inflation (general policy).

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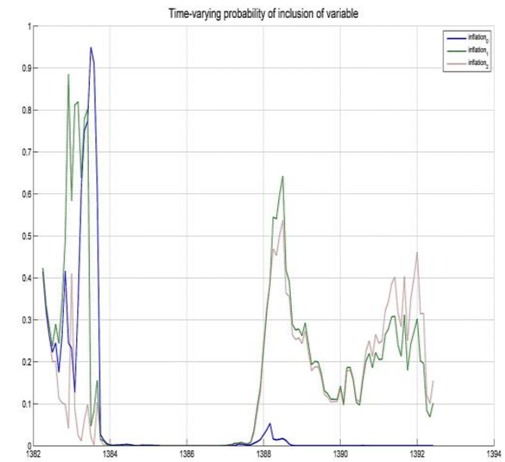
These variables were extracted form Iranian Central Bank official website and International Monetary Fund data, respectively. Tehran Stock Exchange Index at a given period to the previous period was multiplied by 100 and was considered as the return of Tehran Stock Exchange via the below calculation:

$$Y_t = 100 \times ln\,(\frac{TEPIX_t}{TEPIX_{t-1}})$$

The variables used in computer-based calculations to forecast and estimate the return of Tehran Stock Exchange are extracted as below:

stock return –
Inflation –
Non-official exchange rate change –
Interest rate –
Oil price change –

Figures 1 to 4 show the time-varying coefficients obtained from TVP model with the Stochastic Volatility of individual independent variables. In traditional regression models, only one point coefficient is calculated for each variable. In nonlinear models such as regime change models, depending on the number of regimes which is generally two or three regimes, two or three coefficients are calculated for each variable. TVP models with Stochastic volatility are used in the following figures. In this method, a coefficient is calculated for each time period. As a result, the number of model coefficients is equal to the number of time periods. The following figures show the estimated coefficients for each variable (not data trends).



Graphic 1 The probability of the impact of inflation in the level and first and second lags on stock returns

As can be seen in Graph 1, of the three modes of level, first and second lags, the impact of inflation rate in the first lag is greater than the level and second lag. Furthermore, the impact of inflation on stock returns in the second lag is greater than in level.

The impact of inflation on stock returns in the level and first lag from 2003 to 2005 is greater than the second lag. In the period from 2005 to 2009, none of the levels have a significant impact on stock returns.

In the period from 2009 to 2013, the first and second lags have a more significant impact on stock returns than the level. A similar analysis can be provided for interest rate, oil price, and exchange rate.

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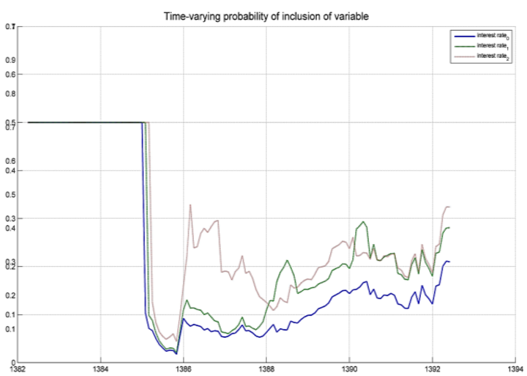
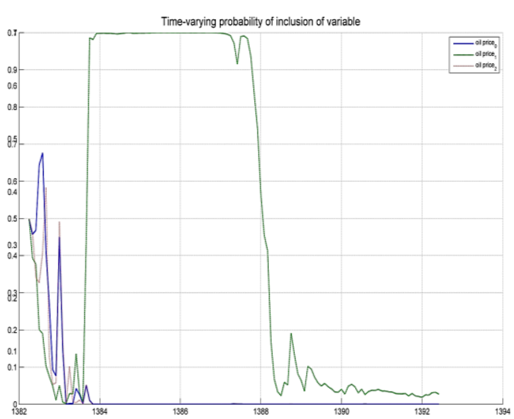
Graphic 2 The probability of the impact of exchange rate in the level and first and second lags on stock returns



Graphic 3 The probability of the impact of interest rate in the level and first and second lags on stock returns



Graphic 4 The probability of the impact of oil price in the level and the first and second lags on stock returns

According to the coefficients of macro-indicators at different time intervals and their probabilities, the accuracy of stock returns predictions is investigated using MAFE and MSFE estimated by DMA, DMS and TVP in the 1 and 4 anticipation horizons.

According to Table 2, DMS with α=β= 0.90 shows the highest prediction accuracy compared to other methods. Table 4 shows the results of the best estimation model with the input parameters, α=β=0.90. The above model with time-varying input variables provides the best prediction of stock returns in the Tehran Stock Exchange.

MSFE	MAFE	Prediction method
h = 1		
DMA $\boldsymbol{\alpha = \beta = 0.99}$	7.87	98.11
DMS $\boldsymbol{\alpha = \beta = 0.99}$	7.03	72.66
DMA $\boldsymbol{\alpha = \beta = 0.90}$	6.68	73.87
DMS $\boldsymbol{\alpha = \beta = 0.90}$	6.13	50.64
DMA $\boldsymbol{\alpha = 0.99;\ \beta = 0.90}$	6.67	71.08
DMS $\boldsymbol{\alpha = 0.99;\ \beta = 0.90}$	5.90	56.25
DMA $\boldsymbol{\alpha = 0.90;\ \beta = 0.99}$	6.22	71.25
DMS $\boldsymbol{\alpha = 0.90;\ \beta = 0.99}$	4.88	44.91
TVP-SV	7.86	101.31
h = 4		
DMA $\boldsymbol{\alpha = \beta = 0.99}$	114.08	8.68
DMS $\boldsymbol{\alpha = \beta = 0.99}$	106.02	7.93
DMA $\boldsymbol{\alpha = \beta = 0.90}$	62.34	7.04
DMS $\boldsymbol{\alpha = \beta = 0.90}$	39.87	4.77
DMA $\boldsymbol{\alpha = 0.99;\ \beta = 0.90}$	62.11	6.86
DMS $\boldsymbol{\alpha = 0.99;\ \beta = 0.90}$	53.65	5.96
DMA $\boldsymbol{\alpha = 0.90;\ \beta = 0.99}$	85.19	7.89
DMS $\boldsymbol{\alpha = 0.90;\ \beta = 0.99}$	47.68	5.73
TVP-SV	128.02	9.05

Table 2 Comparison of Different Models based on the Kalman Filter

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Table 3 shows variables affecting stock returns in different time periods. For example, in the period 2003-3, the first lag of stock returns and interest rate affect stock returns. In the period 2003-10, the first lag of stock returns, inflation rate and interest rate in the current period had the highest impact on stock returns in the Tehran Stock Exchange. Such analyses can be provided for all other periods.

		Time periods			Variables
2003-3	constant	ARY_1	interest rate_0	-	-
2003-4	constant	ARY_1	interest rate_0	-	-
2003-5	constant	ARY_1	oil price_0	-	-
2003-6	constant	ARY_1	interest rate_0	oil price_0	-
2003-7	constant	ARY_1	interest rate_0	oil price_0	-
2003-8	constant	ARY_1	oil price_2	-	-
2003-9	constant	ARY_1	interest rate_0	-	-
2003-10	constant	ARY_1	inflation_0	interest rate_0	-
2003-11	constant	ARY_1	interest rate_0	inflation_1	exchange rate_2
2003-12	constant	ARY_1	interest rate_0	inflation_1	exchange rate_2
2004-1	constant	ARY_1	interest rate_0	inflation_1	exchange rate_2
2004-2	constant	ARY_1	inflation_1	interest rate_1	-
2013-2	constant	ARY_1	inflation_2	-	-
2013-3	constant	ARY_1	-	-	-
2013-4	constant	ARY_1	-	-	-
2013-5	constant	ARY_1	-	-	-
2013-6	constant	ARY_1	-	-	-
2013-7	constant	ARY_1	-	-	-

Note: The indexes 0 and 1 respectively refer to the variable level and the first lag.

Table 3 Variables at Different Time Periods in the Best_Model[1]

Below, the results of the above table are summarized:

The first lag of stock returns in all time periods (126 periods) had a significant impact on stock returns.

Interest rate and its lags had a significant impact on stock returns in 31 time periods.

Inflation rate and its lags had a significant impact on stock returns in 35 time periods.

Oil price and its lags had a significant impact on stock returns in 58 time periods.

Exchange rate had a significant impact on stock returns in 20 time periods.

In general, after the first lag of stock returns, oil prices, inflation rate, interest rate and exchange rate had the highest impact on stock returns during the study period. Based on the results of 126 periods, systemic risk factors had a significant impact on stock returns in 102 periods. As a result, it can be concluded that systemic risk plays an important factor in stock returns volatility.

Conclusion and Results

The results clearly indicated this fact that the systematic risks at different time intervals have different effects on stock returns. Combining DMA and DMS with TVP models, it was shown that certain systemic risks affect stock returns in each period and the likelihood of this type of risks is dependent on their probabilities mainly due to the repeating nature of this type of risks. The results showed that variables with different intensities (different coefficients) affect stock returns at various time intervals. Accordingly, the impact of oil prices and inflation rate on stock return is greater than interest rate and exchange rate. The results of the present study are consistent with those of Naser and Alaali (2015), Chan *et al.* (2015), Johannes et al. (2014), Fux (2014), Nakajima (2011) and Wang et al. *(*2016).

[1] In order to be concise, only the results of the first and last year are provided

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According to the research findings, given that different variables at different time intervals have different effects on stock returns, the use of models to separate the regime changes in different risk levels is recommended to predict stock returns. As a result, policy-makers and those involved in financial markets are suggested not to use the general policies at all times to improve financial markets. They are also recommended to set policies in every regime depending on the most important factors affecting stock returns using appropriate tools.

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