Iran. Econ. Rev. Vol. 23, No. 1, 2019. pp. 209-234

Investigating the Temporary and Permanent Influential Variables on Iran Inflation Using TVP-DMA Models

Mohsen Khezri*[1], Seyed Ehsan Hosseinidoust[2],
Mohammad Kazem Naziri[3]

Received: 2017, October 30 Accepted: 2017, December 19

Abstract

Inflation forecast is one of the tools in targeting inflation by the central bank. The most important problem of previous models to forecast the inflation is that they could not provide a correct prediction over time. However, the central bank policymakers shall seek to create economic stability by ignoring the short-term and temporary changes in price and regarding steady inflation. On this basis, in the present paper, it has been aimed to provide nonlinear dynamic models to simulate the inflation in the economy of Iran using quarterly data referring to 1988-2012 as well as TVP-DMA and TVP-DMS models. These models can provide changes in input variables as well as changes in the coefficients of the model over time. Based on the results, the possibility of growth of currency in circulation, economic growth, also the growth of deposits either visual or non-visual variables, is more remarkable in modeling of inflation in economy of Iran. In addition, the predictive power of dynamic models presented in this study is more than other models.

Keywords: Dynamic Modeling, Inflation Forecasting, TVP-DMS Model.

JEL Classification: E31, E37, C11, C53.

1. Introduction

Preliminary studies in inflation forecast was mostly in the form of traditional Phillips curve that showed the relationship between

---

1. Department of Economics, Faculty of Economics and Social Science, Bu-Ali Sina University, Hamedan, Iran (Corresponding Author: m.khezri@basu.ac.ir).

2. Department of Economics, Faculty of Economics and Social Science, Bu-Ali Sina University, Hamedan, Iran (hosseinidoust@basu.ac.ir).

3. Department of Economics, Faculty of Economics and Social Science, Bu-Ali Sina University, Hamedan, Iran (Naziri_k@yahoo.co.uk).

inflation and unemployment; but, after a few decades and especially after Lucas critique, original Phillips curve was being affected greatly (King, 2008). In 1970s, stagflation happened in the economy by the incidence of crises and shocks. According to the teachings from Phillips curve, policymakers preferred the rise in inflation than in unemployment. But, as Friedman and Philips had predicted, the unemployment rate returned to the natural rate, and this time with a higher rate of inflation. Thus, the initial structural interpretation of the Phillips curve has lost its credibility. With the expiration of a period of low inflation in 1980s and early 1990s, economists studied the structural interpretation of the Phillips curve once again. From mid-1990s, assuming the neutrality of money, economists began to enter the rigidity of nominal prices into general equilibrium models. Therefore, the new curves related the actual and expected inflation not only to the unemployment rate, but the scale of the final total cost. Since the final cost in the original Phillips new Keynesian curve model stimulate the inflation, it makes the matching of data difficult; thus, Phillips new Keynesian curve model was moderated by inputting intervals in inflation (Stock and Watson, 2008).

There is no unified view of Iran's economy inflation modeling regarding the temporary and permanent variables determining inflation. Many economists believe that inflation is a monetary phenomenon. In general, studies done in the economy of Iran on structural issues, such as persistent budget deficit, inelastic supply, dependence on imported production structure, incorrect allocation of foreign exchange. Sustained increase of liquidity, and reduction in production, thus the causes of inflation in Iran can be defined in the way that temporary and permanent effects of such variables may underlie high inflation in the economy of Iran. Whereas, due to the limitations of the research method in defining the variables affecting inflation in Iran’s economy, the experimental research has always determine the variables affecting inflation assuming the permanent effects of variables. Overall, considering the Phillips curve in the past half-century review suggests the important point that relationships between variables have changed over time; according to Stock and Watson (2008) one of the problems that previous models had in prediction was that they could not correctly predict in all periods of time, and sometimes it was observed that some models could predict the estimation of recession well, and some others could predict the estimation of the boom better. Such assumption in the use of experimental results causes limitations for policymakers of the central bank, because the central bank policymakers should not react to temporary changes in the price level, and should ignore the short-term and transient changes in prices and by considering a steady inflation seek to create economic stability. in recent years, major studies conducted in the field of inflation forecast have often been in the form of time varying parameters (TVP) models, Monte Carlo Markov Chain (MCMC) (Nakajima, 2011). Such an assumption is also considered in this study, in the way that using a dynamic model averaging DMA proposed by Raftery et al. (2007) in combination with TVP model, and applying the method of Stock and Watson (1999 and 2008), the power of approved variables has been investigated through the theoretical foundations of the Phillips curve and the main variables in the domestic empirical studies that had significant impact on inflation, and non-linear impact on inflation in Iran. This paper is organized in four parts, in the second part, literature review is presented; in the third part theoretical basis of dynamic models are indicated, and the fourth part provides analysis of the results.

2. Literature Review

The first prediction of inflation was based on the Phillips curve. In 1958, using time series data in British economy, Phillips found a negative and significant relationship between unemployment and price changes in short-term. In 1960, Samuelson and Solow confirmed this rule for America's economy. The important point in Philips’s findings for policymakers is the existence of a stable relationship between inflation and unemployment. Assuming such a stable relationship enables policymakers to explain the results of their policies and carry the adjustments required. In other words, when the economic principle was expressed by the Phillips curve, providing a new theoretical topic has not been addressed; but mainly an experimental work which can explain the behavior of macroeconomic variables. This feature can be the key to the durability of the Phillips curve in macroeconomic research. Because of support from some empirical findings in different countries of the mentioned rule, the theoretical critique of the Phillips curve could not decline its position. Even issues raised by Philips (1967) and Friedman (1968) in which the volatility of existing indices have been underlined in the Phillips curve, they could not reduce the importance of the Phillips curve as long as the experimental findings have not been confirmed; however, Lucas critique (1976), which is considered an experimental criticism, has faded a considerable influence and importance of a clear rule stated by the Phillips curve. Lucas insists that the structure of a macroeconomic model consists of optimal decision rules with economic agents (people), but these optimal decisions are systematically changing in the process of decision making by policymakers. As a result, any change in policy will systematically alter the structure of macroeconomic models (Lucas, 1976). Lucas's hypothesis became a tool for economic policymakers to not to rely on the Phillips curve to predict the effects of the economic policies in future. After proposing Lucas critique, several studies using different econometric methods investigated it, and most of these studies have confirmed the lack of stability of indices. The achievement of such results may expose the application of the Phillips curve in economic analysis and its usage as a tool for policymakers to a problem. Due to the fact that in developing countries like Iran that are most vulnerable to structural changes in their economy, paying attention to these issues will be more remarkable. Estrella and Fuhrer (2003) argued that Lucas critique itself was not a theoretical result, but a warning that reveals the importance of applying parameters stability tests in macroeconomic models; therefore, econometric techniques to check the stability of parameters are essential for testing Lucas critique. These obstacles led to the original Phillips curve experiencing a lot of changes.

Most studies on Phillips curve were simple and based on the rate of interrupted unemployment from the rate of inflation; but then in 2008, Stock and Watson presented the generalized Phillips curve that included inflation, unemployment, and a number of other economic variables. Stock and Watson (2008) study, done based on time series data for the United States in 1993-2008, was one of the most comprehensive studies on inflation forecast at the time. In the study, unlike previous methods, in addition to unemployment, interest rates, money supply and economic activity volume were also present. In the paper, Stock and Watson used the dynamic method of unobserved components stochastic volatility. The results of the study showed a close relationship between the volumes of recent economic activity with inflation in the future. In 2005, Primiceri used time varying parameters with structural vector autoregressive approach TVP-VAR that was the outcome of a doctoral thesis written at Princeton University, United States, and sought inflation forecast for the United States. In this study, researchers, using this model, showed that at any one time which variables could predict inflation, and in addition it could determine the trend of inflation. The main affecting factors were liquidity, unemployment, and interest rates, among which the greatest impact related to liquidity, interest rates, and unemployment, respectively. Groen et al. (2009) predicted the inflation in America's economy in the Federal Reserve New York. This study, which was published in the November 2010 report of America Federal Reserve, carried out the structural failure rate of inflation forecast with the help of Bayesian model. This study was based on empirical data conducted during 1960-2008 in the United States. Variables upon which the inflation was predicted were real GDP, liquidity, uncertainty of inflation intervals. Researchers made predictions using MCMC algorithms; moreover, Monte Carlo models as well as TVP-AR, SB-AR, and UC-SV models were also estimated. In the study, the relationship between each of the macroeconomic variables such as oil prices, real GDP, investment with inflation was determined; In addition inflation persistence probability was calculated at any period of time.

Moser and Rumler (2007), based on generalized Phillips curve presented by Stock and Watson (1999), predicted the inflation in Australia. The variables based on which prediction was made included liquidity, unemployment, industrial production, and manufactured goods exports. The main objective was to identify the best predictor of inflation in Australia, and the results showed that liquidity has been able to predict inflation better than the other variables in Australia. In another study, Cogley et al. (2005) predicted inflation for the UK using Bayesian methods. In the study, due to large number of variables and the limitations of Bayesian methods in variable models over time, they decided to make predictions by categorizing and placing the variables of the same type in a block. The model they used was TVP-BMA, in addition to inflation, GDP was predicted as well. Results showed that the main effective factors in GDP changes are industrial production and private investment, while government spending has been the main factor that characterizes inflation. In 2005, Camber and Hakes investigated the changes in the money supply on inflation and economic growth in the United States; in this study, they estimated based on statistical data, and using a panel data based on Taylor Rule. Results showed that there is a close relationship between changes in money supply and inflation rate, and the relation between liquidity changes and economic growth was lower than the relationship between changes in money supply and inflation. Jean (2011) predicted New Keynesian Phillips for Great Britain. In this study, after prediction of the new Keynesian Phillips, researchers compared his method with conventional methods based on seasonal data from 1987 to 2007. Results showed that the estimation made by Phillips curve with regard to the GDP gap can be more accurately estimated. Ball and Mazumder (2011) using generalized Phillips curve provided by Watson and Stock (1999) estimated the inflation for the United States. He introduced a new method by presenting a model based on cost parameters called Cost-Based Phelps, the considered variables of which were labor's share of the total cost, utilization rate of the capital and the marginal cost in addition to production and unemployment. Results showed that by inserting variables representing costs predictive power of inflation increased. Garratta et al. (2011) studied the relationship between inflation and GDP gaps and based on data from America, Australia, Norway, England, and New Zealand. In this study, Garratta et al. examined the relationship between inflation and GDP gap and by TVP-EWSC and TVP-RWSC methods. The main purpose of this study was to compare the two methods and compare their predictive power of inflation by these two methods. The results showed that the second method was able to predict inflation in these countries better. In 2011, Nakajima et al. examined the relationship between the number of economic variables and inflation in Japan. This study provided a general introduction of TVP models, then applied three approaches from TVP model, TVP-

AR, TVP-VAR, TVP-SVAR, and compared their predictive power. The other result of the study was sensitivity analysis of inflation reaction to changes in macroeconomic.

3. Theoretical Basis

3.1 Dynamic Models

Before investigating the above models, it is required to present the main features of these models and their role in improving the estimated results of economic modeling:

1. Given that the computational method in above models is based on Kalman filter, the estimated coefficients vary over time. In terms of structural breaks and cycle changes in time series (which is the main feature of time series in Iran's economy), the conventional methods are not enough to calculate the parameters, in this condition Kalman filter provides the possibility of modeling of the above facts with variable coefficients over time, (Stock and Watson, 2008).
2. In this type of models, the number of variables and estimators can be high. Gruen et al. used 10 estimators in their study, so that even in Factor models (Stock and Watson, 1999) the number of variables can also be more than that. Increasing number of variables creates large and bulky models. When there are m estimators in the models, selection of model's estimator may be the main challenge for modeling, and researcher can estimates 2^m different models (according to the number of different subsets of m variables). In these circumstances, in most studies, researchers use TVP Bayesian models to estimate the model (like the study by Avramov, 2002; Cremers, 2002; Koop and Potter, 2004).

In the present study, dynamic model averaging DMA proposed by Raftery et al. (2007) has been used. Raftery et al. (2007) suggested dynamic model selection DMS along with DMA that will be discussed further. Standard models of State-Space methods and in particular Kalman filter is as follows:

$$y_t = z_t \theta_t + \varepsilon_t \tag{1}$$

$$\theta_t = \theta_{t-1} + \mu_t \quad (2)$$

where y_t is inflation, $z_t = [1, x_{t-1}, y_{t-1}, \cdots, y_{t-p}]$ is a $1 \times m$ vector of the intercept estimators and variable interruption depending on model, and $\theta_t = [\varphi_{t-1}, \beta_{t-1}, \gamma_{t-1}, \cdots, \gamma_{t-p}]$is an $m \times 1$ vector of coefficients (states), $\varepsilon_t \sim N(0, H_t)$ and $\mu_t \sim N(0, Q_t)$ that have a normal distribution with zero mean and variance of H_t and Q_t respectively. This model has many advantages that the most important is that it is possible to change estimated coefficients at any moment. But the downside of it was that when z_t got larger, the estimates were not reliable. Generalized TVP models such as TVP-VAR also have the same problem. A good development in this model performed by Gruen et al. (2008) was to include the uncertainty of estimators that their model was as follows:

$$y_t = \sum_{j=1}^{m} s_j \theta_{jt} z_{jt} + \varepsilon_t \quad (3)$$

Where θ_{jt} and z_{jt}, are the j^{th} elements of θ_t and z_t. The point added to their model is the presence of $s_j \in \{0,1\}$ variable which is not able to change over time and has the only role of a permanent variable that can accept a one or a zero for each estimator (Hoogerheide et al., 2010). Then, Raftery (2010) presented DMA method that eliminates all limitations of previous methods. In fact, this method could estimate large models at any moment and provide the changes in input variables to the model at any point in time.

In order to describe the process of using DMA, it is assumed that there are K models of subset from z_t variables as estimators, and $z^{(k)}$ with $k = 1,2, \dots, K$ represents K models of the above subset, accordingly, given the K models of subset at any point in time, State-Space method is described as follows:

$$y_t = z_t^{(k)} \theta_t^{(k)} + \varepsilon_t^{(k)} \quad (4)$$

$$\theta_{t+1}^{(k)} = \theta_t^{(k)} + \mu_t^{(k)} \quad (5)$$

In this equation $\varepsilon_t^{(k)} \sim N(0, H_t^{(k)})$ and $\mu_t^{(k)} \sim N(0, Q_t^{(k)})$ with $\vartheta_t = (\theta_t^{(1)}, \cdots, \theta_t^{(k)})$ indicates that each model of K model of subsets, works better in which period of time. The method that provides the estimation of a different model at any moment is called dynamic model averaging (Koop and Korobilis, 2012). In order to describe the dynamic models of DMA and DMS in prediction of one variable at time t based on the information of $t-1$, it can be said that $L_t \in \{1,2,\ldots,K\}$, DMA model includes calculating of $Pr\ (L_t = k|y^{t-1})$ and the average of the prediction for models based on above probability; while DMS includes selection of a model with the highest probability $Pr\ (L_t = k|y^{t-1})$ and forecasting models that are most likely.

To understand the nature of these concepts, at first we need to determine how to input and output estimators to model at a particular moment. A simple way to do this is to use the transition matrix P whose elements are $p_{ij} = Pr\ (L_t = i \big| L_{t-j} = j)$ with $i,j = 1,2,\cdots,K$. Hamilton (1989) has already used it in the form of Bayesian inference Markov chain. Bayesian inference is easy theoretically but its calculation in dynamic models is almost impossible due to a large P matrix. It can be noticed that in a model with m variable to estimate the model, each variable can be a good estimator for the dependent variable or not. In this case, P is a $K \times K$ matrix where $K = 2^m$. If m is not too small, the number of P parameters will be too large, and calculations will be done slowly and with difficulty. Therefore, a fully Bayesian approach to dynamic models can be really difficult and almost impossible. In the present study, the proposed method by Raftery et al. (2007) is used. This method allows you to increase the accuracy of predictive models of space-time mode using the Kalman filter. DMA method provided by Raftery et al. (2007) includes two parameters of α and β, which are called the Forgetting Factors. In order to determine the meaning of these forgetting factors, it needs to ignore the lack of uncertainty in the standard state-space method equations (1-5) and (2-5). For H_t and Q_t constants, the standard filtering results can be used to do a recurrence estimation or prediction. Kalman filtering begins based on the following formula:

$$\theta_{t-1}|y^{t-1} \sim N\ (\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \tag{6}$$

In sentence (5), calculation of $\hat{\theta}_{t-1}$ and $\Sigma_{t-1|t-1}$ follows a standard method which is a function of H_t and Q_t, then continues in Kalman filtering process on the basis of the following equation:

$$\theta_t|y^{t-1} \sim N\ (\hat{\theta}_{t-1}, \Sigma_{t|t-1}) \tag{7}$$

Since $\Sigma_{t-1|t-1} = \Sigma_{t-1|t-1} + Q_t$, in order to simplify Raftry et al. (2007), replaced $\Sigma_{t|t-1} = \frac{1}{\beta}\Sigma_{t-1|t-1}$ with $\Sigma_{t-1|t-1} = \Sigma_{t-1|t-1} + Q_t$, accordingly with $0 < \beta \leq 1$, $Q_t = (1 - \beta^{-1}) \Sigma_{t-1|t-1}$. In econometrics, forgetting approach was used by Doan et al. in 1980, after the presentation of TVP-SVAR and due to limited computing power in its estimates. Naming of the forgetting factors is based on the concept that observation of j period in the past carries β^j in weight. The amount of β which is close to one indicates a more gradual changes of coefficients. Raftery et al. (2007) assigned the value of 0.99 to it, regarding the quarterly statistical information of last 5 years; the above value suggests that the weight of the observations in past five years has allocated 80% of the last observation. If β has a value of 95%, it suggests that the observation of past five year has accounted for 35% of weight in the last observation. Therefore, selection of β is very important which is usually considered between 95 to 99 percent. It is worth noting that by simplification (replacing the equation), there is no need to estimate and simulate Q_t, instead there will be enough potential to estimate H_t. The estimation in model will be completed with fixed estimators through updated functions as follows:

$$\theta_t|y^t \sim N\ (\hat{\theta}_t, \Sigma_{t|t}) \tag{8}$$

In which:

$$\hat{\theta}_t = \hat{\theta}_{t-1} + \Sigma_{t|t-1} z_t \left(H_t + z_t \Sigma_{t|t-1} \acute{z}_t\right)^{-1} \left(y_t - z_t \hat{\theta}_{t-1}\right) \tag{9}$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} z_t \left(H_t + z_t \Sigma_{t|t-1} \acute{z}_t\right)^{-1} z_t \Sigma_{t|t-1} \tag{10}$$

Recursive prediction acts by predictive distribution as following:

$$y_t | y^{t-1} \sim N\left(z_t \hat{\theta}_{t-1}, H_t + z_t \Sigma_{t|t-1} \acute{z}_t\right) \tag{11}$$

Raftry et.al (2007) achieved trustworthy results using the above method, and lack of need in algorithms MCMC, drastically reduced the computational domain. In models with estimator input variables in the time of equation (4) and (5), other calculations will be required in addition to the above calculations. While Kalman filter in function-based fixed estimators model is (6), (7), (8) and (9), by taking ϑ_t as a vector of all coefficients (4) and (5), in some models, the above three functions for k will be as follows:

$$\vartheta_{t-1} \Big| L_{t-1} = k, y^{t-1} \sim N\ (\hat{\theta}_{t-1}^{(k)}, \Sigma_{t-1|t-1}^{(k)}) \tag{12}$$

$$\vartheta_t \Big| L_t = k, y^{t-1} \sim N\ (\hat{\theta}_{t-1}^{(k)}, \Sigma_{t|t-1}^{(k)}) \tag{13}$$

$$\vartheta_t \Big| L_t = k, y^t \sim N\ (\hat{\theta}_t^{(k)}, \Sigma_{t|t}^{(k)}) \tag{14}$$

The value of $\hat{\theta}_t^{(k)}$ and $(\Sigma_{t|t}^{(k)})$ and $(\Sigma_{t|t-1}^{(k)})$ have been obtained by Kalman filtering and equations (9) and (10), and $\Sigma_{t|t-1} = \frac{1}{\beta} \Sigma_{t-1|t-1}$. Estimating equations provided $L_t = k$ only provides the information about $\theta_t^{(k)}$ and not the entire vector ϑ_t; hence, we have equations (12) and (13) and (14) in terms of distribution extracting $\theta_t^{(k)}$.

All previous results were depending on $L_t = k$, and we must adopt an approach that would offer unconditional estimates. Theoretically, usually MCMC method and the P transition matrix are used; but as mentioned earlier, computing power of this method is limited and experimentally basis in a plethora of parameters, does not estimate properly. In the present study, we used Raftery et.al (2007) method which contains a forgetting factor called α for state equation in different estimating models, so the above factors is comparable with the forgetting factor in the equation of state for β parameters. The basis of using Kalman filter starts from equation (5). Similar results when using DMA are as follows:

$$P\ (\vartheta_{t-1}\left|y^{t-1}\right) = \sum_{k=1}^{K} p\ (\theta_{t-1}^{(k)} \lfloor L_{t-1} = k, y^{t-1})\ Pr(L_{t-1} = k, y^{t-1}) \quad (15)$$

Equation $p\ (\theta_{t-1}^{(k)} \lfloor L_{t-1} = k, y^{t-1})$ is calculated by the formula (12); in order to simplify, it is assumed $\pi_{t\lfloor s,l} = Pr\ (L_t = l|, y^s)$, on this basis we can say that $Pr(L_{t-1} = k, y^{t-1}) = \pi_{t-1\lfloor t-1,k}$. If we use unlimited P matrix of transition probabilities with elements p_{kl} , prediction function of the model will be as follows:

$$\pi_{t\lfloor t-1,k} = \sum_{l=1}^{K} \pi_{t-1|t-1,l}\, p_{kl} \quad (16)$$

That Raftery et.al (2007) replaced it with the following equation.

$$\pi_{t\lfloor t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}} \quad (17)$$

If $0 \leq \alpha < 1$, the interpretation will have the same manner with β. The great advantage in using α is that it may not be necessary to use MCMC algorithms in the prediction model, and instead, a simple evaluation to compare the updated Kalman filter is created, so the updated function will be as follows:

$$\pi_{t\lfloor t,k} = \frac{\pi_{t|t-1,k}^{\alpha} p_k(y_t|y^{t-1})}{\sum_{l=1}^{K} \pi_{t|t-1,l}^{\alpha} p_l(y_t|y^{t-1})} \quad (18)$$

where $p_l(y_t|y^{t-1})$ is the predictive density for model l (i.e. normal density equation (11)) which is calculated in terms of y. The recursive prediction can be applied on predictive results of each model with weighted mean using $\pi_{t\lfloor t-1,k}$. Therefore, DMA point forecast is calculated as follows:

$$E\ (y_t|y^{t-1})\ = \sum_{k=1}^{K} \pi_{t|t-1,k}\, z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{19}$$

The way DMS works is that it selects a model that has the highest amount of $\pi_{t\lfloor t-1,k}$ at any point in time. To understand the forgetting factor α better, it should be noted that the added weight in the model k in DMA model is as follows:

$$\pi_{t|t-1,k}\ \propto\ \left[\pi_{t-1|t-2,k} p_k(y_{t-1}|y^{t-2})\right]^{\alpha}\ =\ \prod_{i=1}^{t-1}\left[p_k(y_{t-i}|y^{t-i-1})\right]^{\alpha^i} \tag{20}$$

So when the k^{th} model is predicted fine in the last period, it may have more weight (where implementation of prediction is measured by predictive density $p_k\ (y_{t-i}|y^{t-i-1})$). Interpretation of the recent period is controlled by forgetting factor, α, and the same as β, we will face an exponential decline in the rate α^i for i observations of the last period. Thus, when $\alpha = 0.99$, the performance of the last five periods will possess 80% of the weight of the last period. Accordingly, when $\alpha = 1$, $\pi_{t\lfloor t-1,k}$ is exactly calculated by right-exponential marginal likelihood amounts of $t-1$ which is so-called BMA, Bayesian Approach of Averaging Model, and if $\beta = 1$, BMA uses conventional linear prediction model over time with constant coefficients. Further, the recursive estimation of the proposed model will start by previous values for $\pi_{0\lfloor 0,k}$ and $\theta_0^{(k)}$ for $k = 1,2,\cdots,K$. The only question that remains is how to calculate H_t. Raftery et al. (2007) stated a simple hypothesis by putting $H_t^{(k)} = H^{(k)}$ and replacing it with a fixed estimate, this is despite the fact that prediction of some variable do not need for variance variable over time. In theory, we could use stochastic volatility models or ARCH for $H_t^{(k)}$, which greatly increases the computational domain of the model. Accordingly, in the model presented in the book an exponentially weighted moving average (EWMA) is used to compute $H_t^{(k)}$:

$$\widehat{H}_t^{(k)}\ = \sqrt{(1-\varphi)\ \sum_{j=1}^{t} \varphi^{j-1}\ (y_j - z_j^{(k)}\hat{\theta}_j^{(k)})^{\ 2}} \tag{21}$$

EWMA estimators are often used in time variable fluctuating models in financial sectors in which φ is a decline factor. For a discussion of these models, it shall be referred to Riskmetrics (1996). In Riskmetrics, the risk of φ equal to 0.97 is used for monthly data, 0.98 for quarterly data, and 0.94 for daily data. One of the advantages of EWMA is that it can be estimated by a recursive form that can be used to predict fluctuations. According to the forecast period t, $t+1$ can be in the form below:

$$t+1\hat{H}_{t+1|t}^{(k)} = \varphi \hat{H}_{t|t-1}^{(k)} + (1-\varphi)\left(y_j - z_t^{(k)}\hat{\theta}_t^{(k)}\right)^2 \quad (22)$$

In this model, the variables upon which the dependent variable is predicted will be used in different time horizons. If expected inflation is on the horizon of *h* year, inflation is realized as $ln\ ({}^{p_t}/_{p_{t-h}})$, and in this study $h = 1{,}4\ and\ 8$. In theory, DMA has more potential benefits in prediction of independent variables of the model than other prediction models such as the possibility of changing the estimators of the model over time. The biggest advantage of this method is that some of the subsets of these estimators provide economical and low input variables that if DMA considers more weight for them, over-fitting problems in estimates could be avoided. Probabilities in DMA and DMS are more associated with economical models and just by a few estimators. If $size_{k,t}$ refers to the number of independent variable estimators in *t* for *k* model (ignoring intervals and fixed sentences), the following equation is considered to calculate the mean expected number of estimators in DMA model in *t*:

$$E(Size_t) = \sum_{k=1}^{K} \pi_{t|t-1,k} Size_{k,t} \quad (23)$$

Another purpose of the present study was to compare the performance of techniques that are used for prediction. In this study, two standard indexes of Mean Squared Forecast Error (MSFE), and the Mean Absolute Forecast Error (MAFE) are used as follows.

$$MSFE = \frac{\sum_{\tau=\tau_0}^{T}[y_\tau - E\ (y_\tau|Data_{\tau-h})\ ]^2}{T-\tau_0+1} \quad (24)$$

$$MAFE = \frac{\sum_{\tau=\tau_0+1}^{T}[y_\tau - E\ (y_\tau|Data_{\tau-h})\ ]}{T-\tau_0+1} \quad (25)$$

Where $Data_{\tau-h}$ is the information derived from the period $\tau - h$, h is the predictive time horizon, and $E\ (y_\tau|Data_{\tau-h})$ is the forecast point of y_τ. The experimental section of the study is divided into two sub-sections. The first section of this study presents the results of DMA and DMS; in the same sub-section, the events will be shown which determine which of the variables are more suitable for inflation forecast and can interpret changes of inflation better over time. The second sub-section examines the performance of DMA and DMS compared with other methods of inflation forecast. Also, it checks the sensitivity of models and results of predictions in selection of forgetting factors.

4. Findings

In the present study, quarterly data during 1988 to 2012 time series of the central bank is used to estimate DMA-TVP and DMS-TVP models. The variables used to predict inflation can be seen in Table1. In this table, variables' symbol are placed for brevity. Above variables include eight time-series that have been selected based on domestic past studies that have the most impact on inflation.

Table1: Model Dependent Variables and Symbols

Variable Symbol	Name of Variable
constant	Constant term
ARY_1	Inflation's lag order one
va1	Growth of goods & services exports
va2	Growth of goods & services imports
va3	Economic growth
va4	Growth of M1
va5	Growth of visible deposits
va6	Growh of invisible deposits
va7	Variations of market exchange rate (informal exchange rate)
va8	Variations of banks' deposits

After the estimate with the first interval of variables, Table2 shows the results of the best model. The mentioned model represents the best model and variable input for modeling and forecasting inflation from inflation in the economy of Iran at any given time series:

Table2: Presented Variables at any Time in Best Model

Variable Name	Period
va8_0 ARY_1 constant	1990 First
va8_0 ARY_1 constant	Second
va8_0 ARY_1 constant	Third
va8_1 va8_0 ARY_1 constant	Fourth
va8_1 va8_0 ARY_1 constant	1991 First
va8_1 va8_0 ARY_1 constant	Second
va8_1 va5_1 va8_0 ARY_1 constant	Third
va8_1 va7_1 va3_1 va8_0 ARY_1 constant	Fourth
va8_1 va7_1 va6_1 va3_1 ARY_1 constant	1992 First
va8_1 va7_1 va3_1 va5_0 ARY_1 constant	Second
va8_1 va7_1 va5_0 ARY_1 constant	Third
va7_1 va6_1 ARY_1 constant	Fourth
va7_1 va6_1 ARY_1 constant	1993 First
va7_1 va6_1 va8_0 ARY_1 constant	Second
va7_1 va6_1 va8_0 va1_0 ARY_1 constant	Third
va7_1 va6_1 va5_1 va8_0 va5_0 ARY_1 constant	Fourth
va7_1 va6_1 va8_0 va1_0 ARY_1 constant	1994 First
va8_1 va7_1 va6_1 va4_1 va3_1 va8_0 va2_0 ARY_1 constant	Second
va5_1 va4_1 va1_1 va7_0 va5_0 va4_0 ARY_1 constant	Third
va6_1 va5_1 va4_1 va2_1 va1_1 va5_0 va3_0 ARY_1 constant	Fourth
va6_1 va5_1 va7_0 va6_0 va5_0 va1_0 ARY_1 constant	1995 First
va6_1 va5_1 va1_1 va7_0 va6_0 va5_0 ARY_1 constant	Second
va5_1 va4_1 va8_0 va7_0 va6_0 va5_0 ARY_1 constant	Third
va5_1 va4_1 va8_0 va7_0 va6_0 va5_0 ARY_1 constant	Fourth
va5_1 va4_1 va8_0 va7_0 va6_0 va5_0 ARY_1 constant	1996 First
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Second
va8_1 va7_1 va6_1 va4_1 va3_1 va2_1 va7_0 va6_0 va4_0 va2_0 va1_0 ARY_1 constant	Third
va7_1 va6_1 va5_1 va4_1 va2_1 va1_1 va7_0 va6_0 va4_0 va3_0 va2_0 va1_0 ARY_1 constant	Fourth
va7_1 va6_1 va5_1 va4_1 va2_1 va1_1 va7_0 va6_0 va4_0 va3_0 va2_0 va1_0 ARY_1 constant	1997 First
va7_1 va6_1 va5_1 va4_1 va2_1 va1_1 va7_0 va6_0 va4_0 va3_0 va2_0 va1_0 ARY_1 constant	Second
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Third
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Fourth
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	1998 First
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Second
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Third
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Fourth
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	1999 First

Variable Name	Period
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Second
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Third
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Fourth
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	2000 First
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Second
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Third
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	Fourth
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	2001 First
va3_0 va1_0 ARY_1 constant	Second
va3_0 va1_0 ARY_1 constant	Third
va3_0 va1_0 ARY_1 constant	Fourth
va6_1 va5_1 va4_1 va3_1 va2_1 va1_1 va6_0 ARY_1 constant	2002 First
va3_1 va4_0 ARY_1 constant	Second
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	Third
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	Fourth
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	2003 First
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	Second
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	Third
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	Fourth
va8_1 va5_1 va3_1 va4_0 va1_0 ARY_1 constant	2004 First
va1_1 va7_0 va6_0 va4_0 va1_0 ARY_1 constant	Second
va1_1 va7_0 va6_0 va4_0 va1_0 ARY_1 constant	Third
va1_1 va7_0 va6_0 va4_0 va1_0 ARY_1 constant	Fourth
va1_1 va7_0 va6_0 va4_0 va1_0 ARY_1 constant	2005 First
va1_1 va7_0 va6_0 va4_0 va1_0 ARY_1 constant	Second
va3_1 va2_1 va4_0 va2_0 ARY_1 constant	Third
va3_1 va2_1 va4_0 va2_0 ARY_1 constant	Fourth
va3_1 va2_1 va4_0 va2_0 ARY_1 constant	2006 First
va3_1 va2_1 va4_0 va2_0 ARY_1 constant	Second
va3_1 va2_1 va4_0 va2_0 ARY_1 constant	Third
va3_1 va2_1 va4_0 ARY_1 constant	Fourth
va3_1 va2_1 va4_0 ARY_1 constant	2007 First
va3_1 va2_1 va4_0 ARY_1 constant	Second
va3_1 va2_1 va4_0 ARY_1 constant	Third
va3_1 va2_1 va4_0 ARY_1 constant	Fourth
va3_1 va2_1 va4_0 ARY_1 constant	2008 First
va3_1 va7_0 va4_0 va2_0 ARY_1 constant	Second
va3_1 va7_0 va4_0 va2_0 ARY_1 constant	Third
va8_1 va3_0 va1_0 ARY_1 constant	Fourth
va8_1 va3_0 va1_0 ARY_1 constant	2009 First

Variable Name	Period
va8_1 va3_0 va1_0 ARY_1 constant	Second
va8_1 va3_0 va1_0 ARY_1 constant	Third
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	Fourth
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	2010 First
va7_1 va2_1 va7_0 va5_0 va3_0 va1_0 ARY_1 constant	Second
va7_1 va2_1 va7_0 va5_0 va3_0 va1_0 ARY_1 constant	Third
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	Fourth
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	2011 First
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	Second
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	Third
va7_1 va6_1 va3_1 va7_0 va5_0 va3_0 va2_0 va1_0 ARY_1 constant	Fourth
va7_1 va6_1 va5_1 va3_1 va2_1 va1_1 va5_0 va3_0 va1_0 ARY_1 constant	2012 First
va8_1 va3_0 va1_0 ARY_1 constant	Second
va3_1 va2_1 va7_0 va5_0 va3_0 va1_0 ARY_1 constant	Third
va3_1 va2_1 va7_0 va5_0 va3_0 va1_0 ARY_1 constant	Fourth

In Figure1 the possibility that DMS is the best model at any point of time is presented.

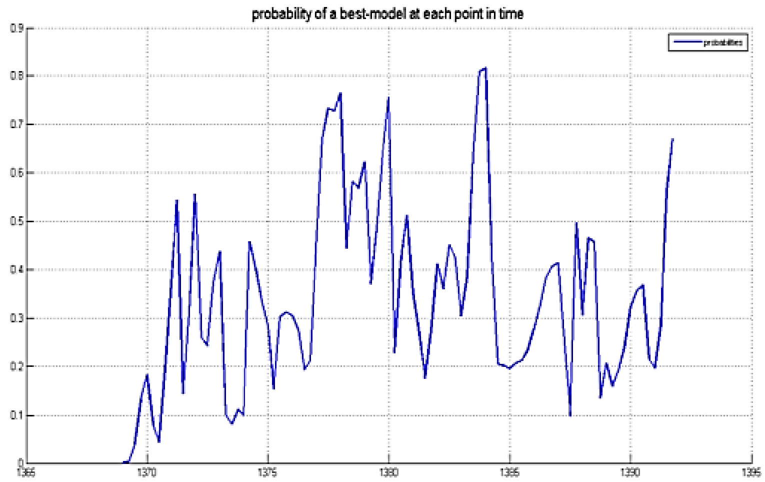

Figure1: Possibility of the Best Model

As shown in Figure.1, the possibility of the best model is not high in all-time series, thus selection of a model based on the highest possible input variables at any point in time will not lead to accurate results; therefore it looks suitable that the contribution of each variables to be specified in modeling of inflation at all time-series.

Given that after the estimate of DMA model, it is possible to determine probable input of independent variables (and intervals) in a simulated inflation is Iran. Figure (2) to (9) shows the possibility of any of the independent variables in the model when it is estimated with the forecast horizon 1 (h = 1).

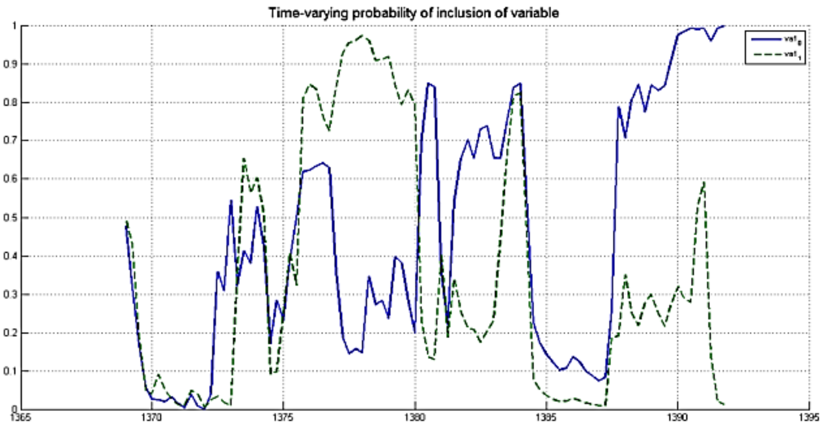

Figure 2: Possibility of Export Growth in the Model with Prediction Horizon of 1

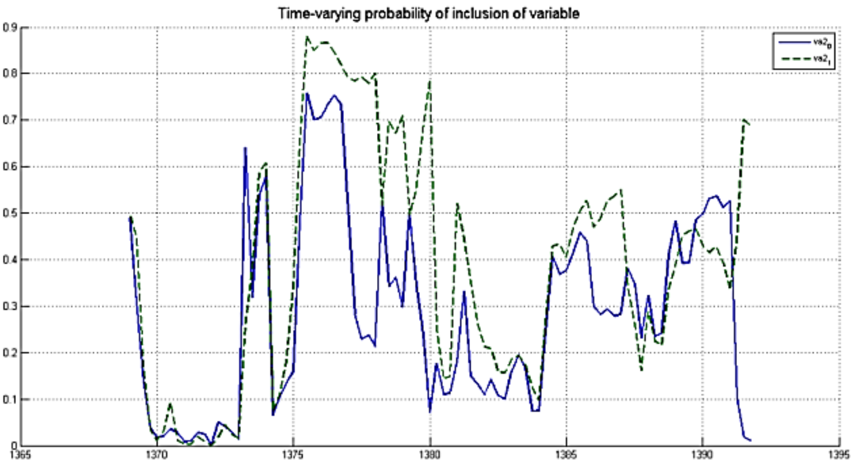

Figure 3: Possibility of Import Growth Variable in the Model with Prediction horizon of 1

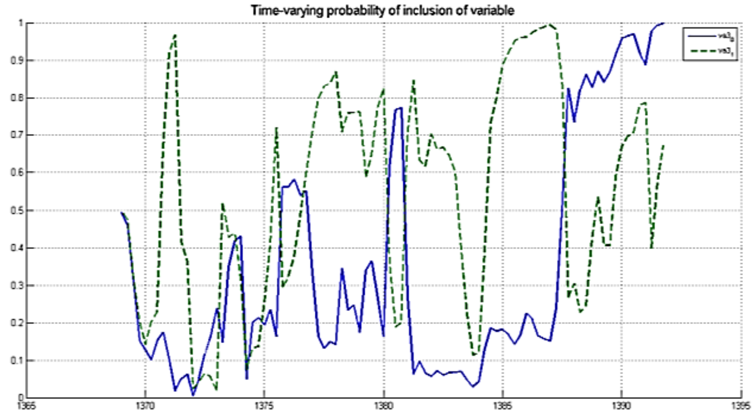

Figure 4: Possibility of Economic Growth Variable in the Model whit Prediction Horizon of 1

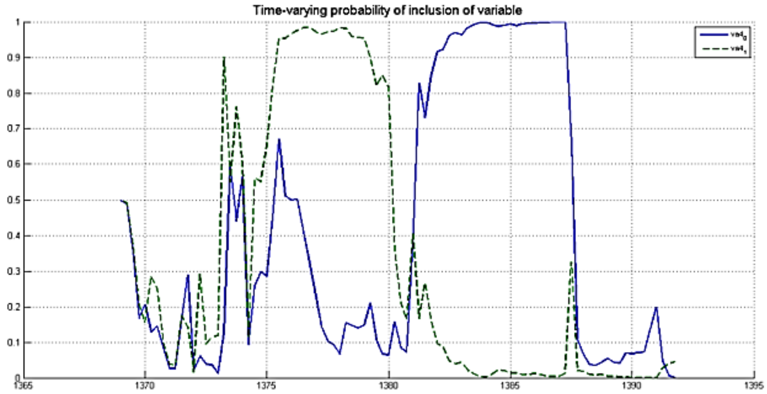

Figure 5: Possibility of M1 Growth in the Model with Prediction horizon of 1

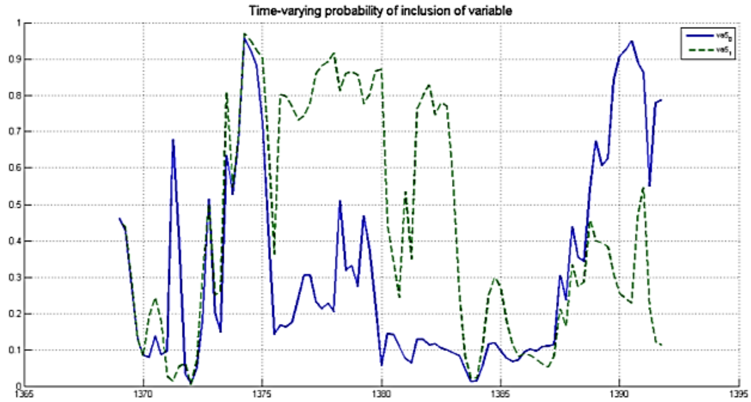

Figure 6: Possibility of Visible Deposit Growth in the Model with Prediction Horizon of 1

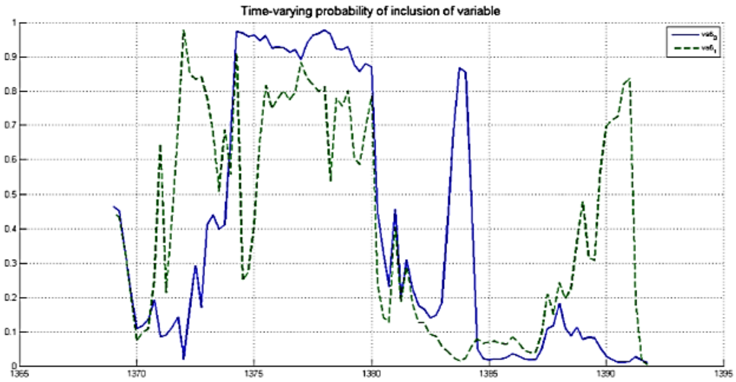

Figure 7: Possibility of Invisible Deposits Growth in the Model with Prediction Horizon of 1

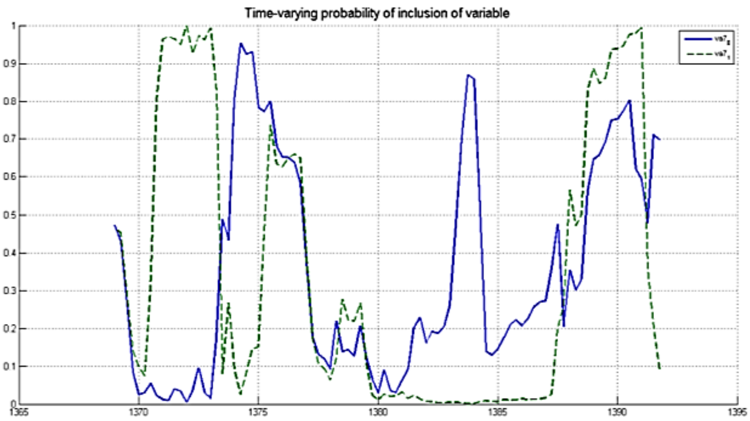

Figure 8: Possibility of Informal Exchange Rate in the Model with Prediction Horizon of 1

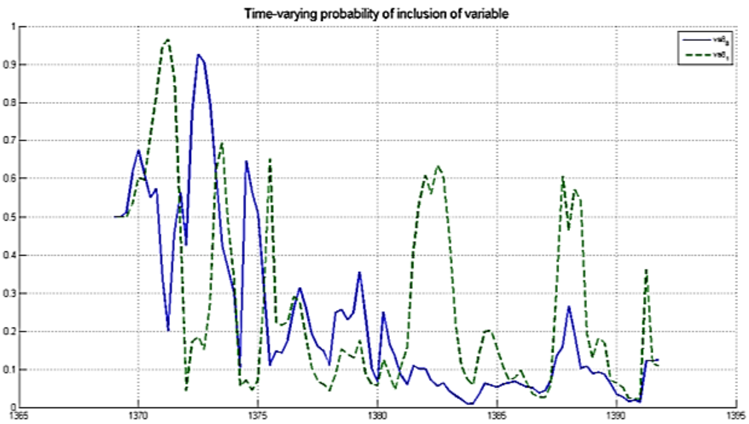

Figure 9: Possibility of Bank Deposits Rate in the Model with Prediction Horizon of 1

According to Figures (2) to (9) the possibility of currency in circulation growth, economic growth, growth in visual and non-visual deposits in modeling of inflation in the economy is more:

The true and expected value of inflation in the forecast horizon h = 1 and h = 4 with $\alpha = \lambda = 0.99$ can be seen in Figures (10) and (11):

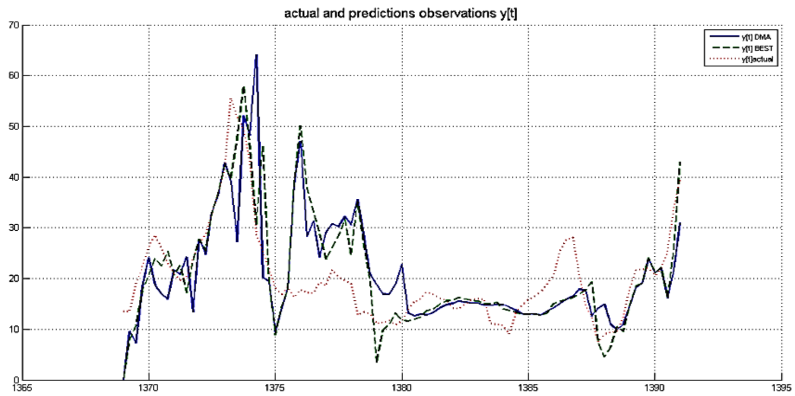

Figure 10: The true and expected value of inflation in the forecast horizon h = 1 with $\alpha = \lambda = 0.99$

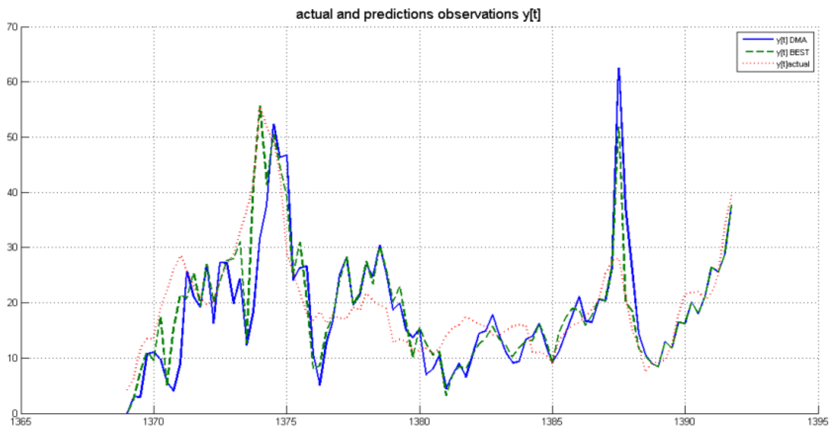

Figure 11: The true and expected value of inflation in the forecast horizon h = 4 with $\alpha = \lambda = 0.99$

In Table (3) the value of MSFE and MAFE in different models of DMA, DMS, TVP-BMA, BMA and TVP in the forecast horizon 1 and 4 are offered:

Table 3: Comparison of Models

Prediction Method	MAFE	MSFE
	h = 1	
DMA $\alpha = \lambda = 0.99$	3.969	28.87
DMS $\alpha = \lambda = 0.99$	3.15	21.16
DMA $\alpha = \lambda = 0.95$	3.45	22.33
DMS $\alpha = \lambda = 0.95$	2.51	12.93
DMA $\alpha = 0.99$; $\lambda = 0.95$	3.63	24.2
DMS $\alpha = 0.99$; $\lambda = 0.95$	2.86	15.88
DMA $\alpha = 0.95$; $\lambda = 0.99$	3.65	25.48
DMS $\alpha = 0.95$; $\lambda = 0.99$	2.65	13.36
TVP- BMA ($\lambda = 1$)	4.04	30.36
BMA (DMA with $\alpha = \lambda = 1$)	4.19	32.9
TVP	6.3	42.11
	h = 4	
DMA $\alpha = \lambda = 0.99$	6.52	77.78
DMS $\alpha = \lambda = 0.99$	5.05	46.18
DMA $\alpha = \lambda = 0.95$	5.90	72.58
DMS $\alpha = \lambda = 0.95$	4.56	49.64
DMA $\alpha = 0.99$; $\lambda = 0.95$	6.37	77.32
DMS $\alpha = 0.99$; $\lambda = 0.95$	5.26	55.74
DMA $\alpha = 0.95$; $\lambda = 0.99$	6.09	72.59
DMS $\alpha = 0.95$; $\lambda = 0.99$	4.32	40.26
TVP- BMA ($\lambda = 1$)	6.81	82.86
BMA (DMA with $\alpha = \lambda = 1$)	7.14	94.22
TVP	6.2	45.16

Source: Research Findings

The results suggested that dynamic models act more accurate in inflation forecast in Iran; hence, MAFE and MSFE in different models of DMA, DMS that are fully dynamic are higher than TVP-BMA, BMA and TVP. The results clearly indicated that the mere changes in variable coefficients in TVP model could not lead to inflation simulating, and dynamic assumption of input variables to the model is an important factor in increasing the accuracy of inflation modeling in Iran’s economy. The results of the estimation of DMS model represents the input variables change over time, and the importance of taking into account the dynamic models in the modeling of inflation, rather than using constant inputs to the model.

5. Conclusion

Inflation forecast is one of the tools in targeting inflation by the central bank. The most important problem that previous models had in forecasting was that were they could not correctly predict over time. However, the central bank policymakers should ignore the short-term and transient changes in prices and seek to create economic stability by estimating constant inflation. Accordingly, in this study, it has been tried to present nonlinear dynamic models for simulation of inflation in Iran’s economy using TVP-DMA and TVP-DMS models. These models can provide the changes in input variables over time as well as changes in the coefficients of variables over time. The results of DMS estimation model represented the input variables have change over time, and the importance of taking into account the dynamic models in the modeling of inflation, rather than using constant input variable.

The results of DMA estimation model indicated that the possibility of currency in circulation growth, economic growth, growth in visual and non-visual deposits in modeling of inflation in the economy is more. The results suggested that dynamic models act more accurate in inflation forecast in Iran; hence, MAFE and MSFE in different models of DMA, DMS that are fully dynamic are higher than TVP-BMA, BMA and TVP. The results maintained that the mere changes in variable coefficients in TVP model would not lead to inflation simulating, and dynamic assumption of input variables to the model is an important factor in increasing the accuracy of inflation modeling in Iran’s economy. As mentioned before, studied variables include eight time-series that have been selected based on domestic past studies that had the most impact on inflation. In further studies, by entering more variables into the model, it may be possible to investigate the effects of a time variable in other variables determining inflation in Iran’s economy.

References

Ball, L., & Mazumder, S. (2011). Inflation Dynamics and the Great Recession. *Brookings Papers on Economic Activity*, *42*(1), 337-405.

Cogley, T., Morozov, S., & Sargent, T. (2005). Bayesian Fan Charts for U.K inflation: Forecasting and Sources of Uncertainty in an Evolving Monetary System. *Journal of Economic Dynamics and Control*, *29*, 1893-1925.

Cremers, K. (2002). Stock Return Predictability: A Bayesian Model Selection Perspective. *Review of Financial Studies*, *15*, 1223-1249.

Friedman, M. (1968). The Role of Monetary Policy. *American Economic Review*, *58*, 1-17.

Garratta, A., Mitchellb, J., Vahey, S. V., & Wakerly, E. C. (2011). Real-time Inflation Forecast Densities from Ensemble Phillips Curves. *North American Journal of Economics and Finance*, *22*, 78-88.

Groen, J., Paap, R., & Ravazzolo, F. (2009). Real-time Inflation Forecasting in a Changing World. *Erasmus University Rotterdam, Econometric Institute Report*, Retrieved from https://www.econstor.eu/bitstream/10419/60913/1/622767062.pdf.

Hamilton, J. (1989) A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica*, *57*, 357-384.

Hoogerheide, L., Kleijn, R., Ravazzolo, F., van Dijk, H., & Verbeek, M. (2010). Forecast Accuracy and Economic Gains from Bayesian Model Averaging using Time-Varying Weights. *Journal of Forecasting*, *29*(1-2), 251-269.

Kalman, R. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, *82* (Series D), 35-45.

King, R. G. (2008). The Phillips Curve and U. S. Macroeconomic Policy: Snapshots, 1958-1996. *Economic Quarterly*, *94*(4), 311-359.

Koop, G., & Korobilis, D. (2012). Forecasting Inflation Using Dynamic Model Averaging. *International Economic Revie*w, *53*, 867-886.

Koop, G., & Potter, S. (2004). Forecasting in Dynamic Factor Models using Bayesian Model Averaging. *The Econometrics Journal*, *7*, 550-565.

Lucas, R. Jr. (1976). Econometric Policy Evaluation: A Critique. *Carnegie-Rochester Conference Series on Public Policy*, *Elsevi*er, *1*(1), 19-46.

Moser, S., & Rumler, F. (2007). Forecasting Austrian Inflation. *Economic Modeling*, *24*, 470-480.

Nakajima, J., Munehisa, K., & Toshiaki, W. (2011). Bayesian Analysis of Time-varying Parameter Vector Autoregressive Model for the Japanese Economy and Monetary Policy. *Journal of the Japanese and International Economies, 25*(3), 225-245.

Primiceri, G. (2005). Time Varying Structural Vector Auto regressions and Monetary Policy. *Review of Economic Studies*, *72*, 821-852.

Raftery, A., Karny, M., & Ettler, P. (2010). Online Prediction under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill. *Technimetrics*, *52*, 52-66.

Raftery, A., Karny, M., Andrysek, J., & Ettler, P. (2007). Online Prediction under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill. *University of Washington, Technical Report 525*, Retrieved from https://www.tandfonline.com/doi/abs/10.1198/TECH.2009.08104.

Stock, J., & Watson, M. (2008). Why Has U. S. Inflation Become Harder to Forecast? *Journal of Monetary Credit and Banking*, *39*, 3-33.

---------- (1999). Forecasting Inflation. *Journal of Monetary Economics*, *44*, 293-335.