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Dynamic relationships between financial conditions index and stock returns

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Abstract
Stock return predictability has been extensively considered as a stylized reality. Theories indicate that returns should change along the time, and various studies have presented evidence on this point. On the other hand, there is an optimal portfolio in each regime, and one cannot claim that a specific portfolio can minimize risk and returns in each regime. On the other hand, the financial conditions index (FCI) is an important index to specify monetary policy conditions. Regarding the importance of the issue, this research aims to present a comprehensive index, including all monetary transmission mechanisms. In this regard, it is attempted to improve the efficiency of stock return predictability in Iran's economy by incorporating an FCI and identifying relationships between FCI and stock returns using the TVP-DMA model, which can resolve shortcomings of traditional models. The study is applied research in terms of purpose. Seasonal data over the period of April 1991 to July 2019 is used. The results based on TPV, DMS, and DMA models indicate that liquidity growth rate, economic growth rate, unemployment rate, exchange rate, financial condition index, oil revenues, misery index, and budget deficit, has significantly affected factors of stock returns in 30, 50, 11, 49, 66, 54, 7, and 84 periods of 104 periods, respectively. Accordingly, budget deficit, financial condition index, oil revenues, and economic growth are the most effective factors of stock returns predictability in Iran. Further, the incorporation of flexibility in coefficients of the financial development index leads to higher forecast accuracy.

Keywords: Financial development index, Monetary conditions index, Stock returns, TVP-DMA

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Introduction

Capital market is taken into account as one of the infrastructures for economic development in developing countries and the main context to achieve the goals and favorable macroeconomic factors. A dynamic capital market in a specific process framework and mechanism leads finally to GDP growth and controlling undesirable economic factors. Since achieving economic growth and enhancing motivation to invest entails implementing fundamental and comprehensive policies, creating an appropriate context for investment seems to be necessary. Therefore, achieving these goals entails the efficient performance of stock exchanges. Dimensions of the stock exchange and its influencing mechanisms should be identified to create efficiency in this market, and this information should be released to participants in this market to enhance their awareness. The present research aims to challenge current views on stock returns predictability.

The main issue is considering constant or variable coefficients and factors influencing stock returns over time. More precisely, identification of factors affecting the capital market can significantly help investors to choose an optimal portfolio according to the market condition. However, according to the information gathered by the researcher, few studies have regarded variable uncertainties in different regimes on stock market returns within the country.

Goyal and Welch (2008) concluded according to evidence that most of the models were unstable or even incorrect and even insignificant in-sample predictors. Their evidence also indicated that the models did not help investors to use predictability when setting a portfolio. It can be concluded that although there is evidence for predictability, the evidence is so weak that investors cannot use them in practice.

One of the most important challenges researchers face is controversies about potential variables that can be incorporated into the explanatory model. However, these controversies often have led to the diversity of results. Econometrists have greatly attempted to solve this problem. For example, one of the solutions proposed is to perform a sequence of tests to add or remove variable to the model and hypothesis testing on their significance. However, these approaches do not lead to satisfactory results due to the invalidity of hypothesis testing in incorrect specifications and aggregate and consequent errors (Poirier, 1995). The Bayesian approach for the uncertainty problem is Bayesian Model Averaging (BMA) (Hoeting et al., 1999), in which the values are often estimated by a weighted average of the values of specific models. The weights depend on the extent to which data support the model used, which are measured by the posterior probability of the model. Jeffreys (1961) first founded BMA, and Leamer (1978) developed the method.

In contrast to the classical approach, in which statistical inference is used to test the significance of coefficients, the Bayesian approach bases on statistical analysis and probability distributions. The Bayesian approach is based on the Bayes theorem, which itself is based on inductive logic. In spite of the deductive logic, in which often "when a hypothesis is true, the result is also true," in the inductive logic, the trueness is probabilistic, and the correctness degree is assessed based on the number of interpretations and models in which the theorem satisfies (Gower, 1997).

In other words, a group of features is required to be able to improve the efficiency of forecasting models. For example, considering variations in volatilities over time is important because it improves the flexibility of forecasts, and estimation risk is important because the investor cannot be ensured that the forecasts have high certainty. Brenan (1998), Stambaugh (1999), and Barberis (2000) pointed out that disregarding each of these parts leads to a misleading viewpoint about the risk.

Accordingly, this research attempts to create an advantage for stock returns predictability using the time parameter. In this way, we can examine the approach that assumes volatilities are constant in regression models, and investors do not take into account volatilities and estimation risks.

Another problem that can be regarded is that whether incorporating monetary conditions indices (traditional view) and FCI (developed view) can increase stock returns predictability. In other words, whether or not localization of financial conditions indices based on specific conditions of Iran's economy can improve the results of forecasts. A great deal of discussions has been conducted about the role of other asset prices on monetary transmission mechanisms. Accordingly, in this stage, the main problem is to determine the weights of factors affecting an FCI tailored to the specific conditions of Iran's economy over time and to identify how this index influences stock returns predictability. Based on the discussions above, the research aims to deal with various problems as follows:

What are the most important factors affecting stock returns over time?

How the factors affect stock returns over time?

The highest weight of the factors affecting stock returns is related to which variable?

How much is the likelihood that the factors affect stock returns over time?

How is the impact of financial condition index on the stock returns in the case of time-varying coefficients, compared with constant coefficients?

The variety of the problems raised to the current study is due to the complex relationship between variables and numerous factors affecting stock returns predictability over time.

The rest of the paper is organized as follows. Section 2 presents theoretical foundations and a review of relevant empirical research, and Section 3 provides the methodology for estimation. The model estimation is presented in Section 4. Finally, Section 5 concludes the paper and presents policy recommendations.

Background

The portfolio theory and Fisher's fundamental theory can be used to examine the relationship between the stock price index and macroeconomic factors. The portfolio theory refers to the selection of an efficient portfolio regarding effective factors. Some financial assets such as bank deposits have constant and certain and risk-free returns, and some others, such as stocks and currency, have uncertain and risky returns. Since individuals hold various combinations of cash, stocks, bank deposits, securities, gold, and currencies in their portfolios, the changes in monetary volume, exchange rate, bank interest rate, and inflation rate affect individuals' demand for maintaining each of these parts such as demand for stocks, which itself affects stock prices (Karimzadeh, 2006).

Fisher's fundamental hypothesis is used to build a theoretical framework for the relationship between the stock price index and macroeconomic variables. Fisher's fundamental equation represents the real interest rate as the differentiation of the nominal interest rate and inflation rate, as follows.

$$R_t^r = R_t^n - INF_i \qquad (1)$$

Where R_t^r represents the real interest rate, R_t^n is the nominal interest rate, and INF_i is the inflation rate. Fisher also proposed such an equation for stock returns, as follows.

$$RS_t^r = RS_t^n - INF_i \qquad (2)$$

where RS_t^r represents the real stock return and RS_t^n is the nominal stock return.(3)

Fama (1981) noted that some monetary macroeconomic variables such as liquidity and interest rate are neglected in Fisher's equation. Regarding the relationship between the money market and capital market, Fama used a money market equilibrium to prove his claim. Money market equilibrium equation is expressed for stock prices as follows:

$$LnRS_t^r = \beta_0 + \beta_1 LnY_t + \beta_2 R_t + \beta_3 LnM_t + \beta_4 P_t + U_t \qquad (4)$$

In the next section, how real and monetary variables affect stock exchange is discussed (Fama, 1981).

Financial condition index

A financial condition index indicates the state of the economy in the future that can be viewed in current financial variables (Hatzius et al., 2010). A financial condition index is a summary of current financial variables that somewhat can forecast the future state of a country's economic activities (Gonzales et al., 2013).

Deriving an FCI in each country is done via adding a specific variable. For example, in Sweden, housing prices are incorporated to create an FCI. The results indicated that housing prices had increased the forecast power of FCI for inflation, compared with traditional MCI. The same process is implemented in Swiss by adding the prices of housing and stock (Zulkhibr, 2011).

According to all economic viewpoints, except for the school of real business cycles, monetary policies affect real economic variables, at least in the short-run. Therefore, the question is that under which mechanisms and through which channels the effects of the monetary policy spread to the economy, and production and inflation are affected?

Boivin et al. (2010) divided the monetary transmission mechanism into two main types, namely, neoclassical channels, in which financial markets are perfect and non-neoclassical channels that include imperfect financial markets.

A summary of relevant research is presented as follows.

Jabeenm et al. (2019) proposed some types of FCI for Pakistan using a wide variety of financial and economic variables. They estimated an FCI using the time variable over the period 1969-2016 using seasonal data. Their model presented three versions of FCI, i.e., TVP-FAVARs, FA-TVP-VARs, and Heteroscedastic FAVAR. The results indicated that the incorporation of flexible coefficients in FCI improved the power of FCI in forecasting the stance of economic indices in Pakistan.

Kapetanios et al. (2018) attempted to formulate an FCI for the U.K. economy. They used the partial least squares approach to determine the most important variables affecting the FCI. They tried to identify how the chosen variables affect production, inflation, and capital market using the SVAR model. Their result indicated that the use of the CFI in the forecast of selected variables led to increased forecast accuracy.

Koop and Korobilis (2013), using a factor augmented vector autoregressive model with time-varying parameters, attempted to define an FCI and tried to determine effective weights in the FCI over time. Moreover, they allowed effective factors of FCI to change over time by developing the method to DMA and DMS approaches. They found that variable factors of the FCI and varying parameters led to improved forecasts.

Taheri-Bazkhaneh et al. (2018) examined dynamic relationships between financial cycles and business cycles and inflation gap in Iran's economy over the period from April 1990 to July 2016. For this purpose, an FCI was first formulated for Iran's economy. Further, using the causality test in the frequency domain, horizons available to forecast economic growth by the FCI was determined. Then, new maximal overlap discrete wavelet transforms (MODWT) and continuous wavelet transform (CWT) tools were used to inspect the research purpose and analysis in the frequency domain and time-frequency domain. The results indicated that the relationship between financial cycles and business cycles was bilateral and highly unstable in the short run and long run. In the medium run, the variable of business cycles was the leading variable, but phase transitions between the two variables in the 1990s were distinct from those in the 2000s. In the short run, there was a bilateral and unstable relationship between financial cycles and the inflation gap. Moreover, financial cycles caused inflation to keep out of its long-run trend. However, this relationship was inverted in the long run and after 2007. Regarding the results of the research, monetary policy-makers were suggested, besides smoothing output and inflation around their long-run trends, to take into account these results for the financial sector too, to be able to achieve the goals above in various horizons with lower errors.

Methodology

An applied methodology is used regarding the research purpose. Concerning the subject and purpose, the most appropriate approach in this research is the econometric method. Time series data over the period 1991-2019 was taken from Iran's Central Bank and Statistics Organization. EViews 10 and

MATLAB 2018 software packages are used. In what follows, the research variables are modeled using the Time-varying Parameter- Dynamic Model Averaging (TVP-DMA) model.

The main characteristic of the dynamic programming approach is two features. First, dynamic programming puts a specific problem into a family of control problems. Then, for each member of the problems family, the optimal value of V* functional is initially considered not the properties of the path to the optimal state of $y^*(t)$, like calculus of variations, and not the path to the optimal control of $U^*(t)$, like optimal control theory.

As discussed, the standard form of space-state models is as follows:

$$y_t = z_t\theta_t + \epsilon_t \quad (5)$$

$$\theta_t = \theta_{t-1} + \mu_t \quad (6)$$

where y_t is the dependent variable, $z_t = [1, x_{t-1}, y_{t-1}, \cdots, y_{t-p}]$ is a $1 \times m$ vector of estimators of the intercept and lag of the dependent variable, 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). Further, $\varepsilon_t \sim N\,(0, H_t)$ and $\mu_t \sim (0, Q_t)$ have normal distributions with zero mean and variances H_t and Q_t. These models have several advantages, of which the main advantage is enabling the user to change estimated coefficients in each time. However, they suffer the shortcoming that when the value of z_t is very large, the estimations are not reliable. Generalized models of TVP such as TVP-VAR are also affected by this problem. An appropriate development to this model has proposed by Grovin et al. (2008), in which uncertainties in the behavior of estimators were incorporated into the model, as follows.

$$y_t = \sum_{j=1}^{m} s_j\theta_{jt}z_{jt} + \varepsilon_t \quad (7)$$

where θ_{jt} and z_{jt} are the jth element of θ_t and z_t, respectively. The notable point is the inclusion of the variable $s_j \in \{0, 1\}$, a permanent variable taking values 0 or 1 for each estimator (Hoogerheide et al., 2009). Then, Raftery (2010) proposed the DMA approach that resolved all shortcomings of the previous approaches. Indeed, the method mentioned could estimate large-scale models in each moment, and it allowed changing the input variables in each time.

Bayesian inference is theoretically simple, but its calculation is somewhat impossible in dynamic models because the size of P is very large. Note that in models that there are m variables to estimate the model, each variable can be an appropriate estimator for the dependent variable. In this case, P is a $K \times K$

matrix, where $K = 2^m$. If m is not very small, the number of parameters in P is very large, and the computations are very slow and complex. Therefore, a fully Bayesian approach to dynamic models is really hard and almost impossible.

In this research, the approach proposed by Raftery et al. (2010) is used. This approach enables us to increase the forecast accuracy of estimated space-state models using the Kalman filter. (Tsionas et al.,2019)

The DMA approach introduced by Raftery et al. (2010) includes two parameters α and β called forgetting factors. For the fixed H_t and Q_t, standard filtering results can be used for recursive estimation or forecast. Kalman filtering is initiated by the following expression.

$$\theta_{t-1}|y^{t-1} \sim N\ (\hat{\theta}_{t-1}, \Sigma_{t-1|t-1}) \qquad (8)$$

In expression (17), $\hat{\theta}_{t-1}$ and $\sum_{t-1|t-1}$ are calculated via a standard manner since these values are functions of H_t and Q_t. Then, the Kalman filtering process is continued based on the following relation.

$$\theta_t|y^{t-1} \sim N\ (\hat{\theta}_{t-1}, \Sigma_{t|t-1}) \qquad (9)$$

Since $\sum_{t-1|t-1} = \sum_{t-1|t-1} + Q_t$, for simplicity, Raftery et al. (2010) replaced $\sum_{t-1|t-1} = \sum_{t-1|t-1} + Q_t$ with $\sum_{t|t-1} = \frac{1}{\beta}\sum_{t-1|t-1}$. Accordingly, $Q_t = (1 - \beta^{-1})\sum_{t-1|t-1}$ with $0 < \beta \leq 1$.

In the econometrics, the forgetting factors approach was used by Doan et al. (1980) after the TVP-sVAR method because of its limited estimation power. The name forgetting factors is due to the fact that observations of the previous j periods had the weight β^j. A value close to 1 for β represents a more gradual variation. Choosing an appropriate value for β is very important, and it is usually assumed between 90 to 99 per cent.

Note that by replacing the equation and simplicity, Q_t is not required to be estimated and simulated, and, instead, sufficient potential for estimating H_t will exist. The model estimation will be complete by constant estimators and updating function below.

$$\theta_t|y^t \sim N\ (\hat{\theta}_t, \Sigma_{t|t}) \qquad (10)$$

where

$$\hat{\theta}_t = \hat{\theta}_{t-1} + \Sigma_{t|t-1} z_t \left(H_t + z_t \Sigma_{t|t-1} \acute{z}_t\right)^{-1} \left(y_t - z_t \hat{\theta}_{t-1}\right) \qquad (11)$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1} z_t \left(H_t + z_t \Sigma_{t|t-1} \acute{z}_t\right)^{-1} z_t \Sigma_{t|t-1} \qquad (12)$$

The following relation is used to implement recursive forecast by the predictive distribution.

$$y_t|y^{t-1} \sim N\left(z_t\hat{\theta}_{t-1}, H_t + z_t \textstyle\sum_{t|t-1} \acute{z}_t\right) \tag{13}$$

In this research, the approach proposed by Raftery et al. (2010) is used in which a forgetting factor α is introduced for the state equation and different estimation models. This forgetting factor can be compared with the forgetting factor of the state equation for parameters, i.e., β. Similar to the DMA approach, the results are as follows.

$$P\ (\vartheta_{t-1}\left|y^{t-1}\right) = \textstyle\sum_{k=1}^{K} p\ (\theta_{t-1}^{(k)} \lfloor L_{t-1} = k, y^{t-1})\ Pr(L_{t-1} = k, y^{t-1}) \tag{14}$$

The expression $p\ (\theta_{t-1}^{(k)} \lfloor L_{t-1} = k, y^{t-1})$ is obtained by equation (26). For convenience, we assume $\pi_{t\lfloor s,l} = Pr\ (L_t = l|, y^s)$. Accordingly, we have $Pr(L_{t-1} = k, y^{t-1}) = \pi_{t-1\lfloor t-1,k}$.

If we use the infinite matrix of probability transitions P with elements p_{kl}, the forecast function of the model is as follows.

$$\pi_{t\lfloor t-1,k} = \textstyle\sum_{l=1}^{K} \pi_{t-1|t-1,l}\, p_{kl} \tag{15}$$

Raftery et al. (2010) replaced the equation above by the following one.

$$\pi_{t\lfloor t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}} \tag{16}$$

Whenever $0 \leq \alpha < 1$, α will have a behavior similar to that of β. The use of α has the great advantage that it does not require the MCMC algorithm, and, further, a simple way for evaluation and comparison with updating function of Kalman filter is created. The updating function is as follows:

$$\pi_{t\lfloor t,k} = \frac{\pi_{t\lfloor t-1,k}^{\alpha} p_k\ (y_t|y^{t-1})}{\sum_{l=1}^{K} \pi_{t\lfloor t-1,l}^{\alpha} p_l\ (y_t|y^{t-1})} \tag{17}$$

where $p_l\ (y_t|y^{t-1})$ is the posterior predictive distribution for model l (normal distribution in equation (26)), which is estimated in terms of y. The recursive forecast can be obtained by weighted averaging using the weights $\pi_{t\lfloor t-1,k}$ across posterior outcomes of each model. Therefore, the point forecasts for DMA are estimated as follows.

$$E\ (y_t|y^{t-1}) = \textstyle\sum_{k=1}^{K} \pi_{t|t-1,k}\, z_t^{(k)} \hat{\theta}_{t-1}^{(k)} \tag{18}$$

In the DMS approach, a model having the highest value of $\pi_{t\lfloor t-1,k}$ in each point of time is selected. To better understand the forgetting factor α, note that this specification denotes the weight each model has at each time, as presented below.

$$\pi_{t|t-1,k} \propto \left[\pi_{t-1|t-2,k} p_k \left(y_{t-1} \middle| y^{t-2}\right)\right]^{\alpha} = \prod_{i=1}^{t-1} \left[p_k \left(y_{t-i} \middle| y^{t-i-1}\right)\right]^{\alpha^i} \quad (19)$$

Therefore, whenever the kth model has been forecasted good in past periods, it has a higher weight (the forecast is evaluated by the posterior predictive distribution $p_k\left(y_{t-i}\middle|y^{t-i-1}\right)$). The interpretation of the current period is controlled by the forgetting factor α, and, similar to β, an exponential decrease in the rate of α^i exists for observations of the previous i periods. Accordingly, if $\alpha = 0.99$, the performance of the forecast in the recent five periods has a weight equal to 80% of the current period. Also, if $\alpha = 0.95$, the performance of the forecast in the recent five periods has a weight equal to 35% of the last period. Therefore, when $\alpha = 1$, $\pi_{t\lfloor t-1,k}$ is measured strictly based on the marginal likelihood of the period $t-1$. This approach, called BMA. If $\beta = 1$, BMA uses the linear forecast model with constant coefficients over time[1]. Then, the recursive estimation of the model presented is initiated by previous values for $\pi_{0\lfloor 0,k}$ and $\theta_0^{(k)}$ $(k = 1, 2, \cdots, K)$. The only point left is how to calculate H_t. Raftery et al. (2010) assumed $H_t^{(k)} = H^{(k)}$ and proposed to use a fixed estimation instead. Nevertheless, to forecast some variables, the variance of error across time is required. Theoretically, we can use a stochastic volatilities model or ARCH for $H_t^{(k)}$. However, this approach increases the computation domain substantially. Accordingly, the present research uses an Exponentially Weighted Moving Average (EWMA) method to obtain $H_t^{(k)}$.

$$\hat{H}_t^{(k)} = \sqrt{(1-\varphi) \sum_{j=1}^{t} \varphi^{j-1} \left(y_j - z_j^{(k)} \hat{\theta}_j^{(k)}\right)^2} \quad (20)$$

EWMA estimators are often used in time-varying volatility models in financial sections. Here, φ is a discount factor. See Risk Metrics (1996) for a discussion on these models. In the Risk Metrics, the value of φ was assumed 0.97 for monthly data, 0.98 for seasonal data, and 0.94 for daily data. One of the advantages of the EWMA approach is that it is estimated by a recursive formula, which can be used to forecast volatilities. The forecast for period $t+1$ based on the information of the period t is as follows:

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[1] In this research, this approach also is used, examined, and compared as an alternative to the DMA approach.

$$\widehat{H}_{t+1|t}^{(k)} = \varphi\widehat{H}_{t|t-1}^{(k)} + (1-\varphi)\left(y_j - z_t^{(k)}\widehat{\theta}_t^{(k)}\right)^2 \tag{21}$$

In this model, the variables, based on which the dependent variable is estimated, are used in different time horizons. (22)

To examine a forecasting model or choosing the best model among different models for time-series, an indicator is required by which we decide on the acceptance or rejection of the model. Generally, the more the forecasted values ($\widehat{X}_t$) are close to their actual values (X_t), the higher the accuracy of the model is. Therefore, the quality of a model can be assessed by the forecast error ($X_t - \widehat{X}_t$). Accordingly, since one of the objectives of the present study is to compare the performance of forecasting methods, we use two criteria, namely, mean squared forecast error (MSFE) and mean absolute forecast error (MAFE), as follows.

$$MSFE = \frac{\sum_{\tau=\tau_0}^{T}[y_\tau - E\ (y_\tau|Data_{\tau-h})\ ]^2}{T-\tau_0+1} \tag{23}$$

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

where $Data_{\tau-h}$ stands for information obtained from the period $\tau - h$, h is the period of forecast, and $E\ (y_\tau|Data_{\tau-h})$ is the point forecast of y_τ[5] (Mehmet et al. 2018).

Research findings

In this section, the impact of variables affecting stock return over time is estimated. Since one of the effective factors is financial condition index, first, we attempt to identify important factors affecting this index. To measure FCI, we should derive the weights. For this purpose, the demand equation, which contains all monetary transmission mechanisms, should be estimated. Thus, according to Goodhart and Hofmann (2001) and Zulhkibr (2011) and regarding the specific conditions of Iran's economy, the aggregate demand function is expended. Accordingly, the impact of the exchange rate, inflation rate, stock returns, changes in bank deposits, housing prices, credit volume, and oil revenue index (since the country's economy depends on oil revenues) are incorporated in the model.

In the following, the results of the TVP-DMA approach are presented to estimate the financial condition index. Table 1 represents the values of MAFE and MSFE obtained by the estimation of DMA and DMS.

Table 1. A comparison of different models based on the Kalman filter

Parameters Flexibility Values	*MAFE*	*MSFE*
DMA$\alpha = \beta =$ ۰/۹۹	۷/۱	۲۷۲/۷۳
DMS $\alpha = \beta =$ ۰/۹۹	۴/۸۵	۱۴۶/۱۳
DMA $\alpha = \beta =$ ۰/۹۰	۶/۱۲	۱۴۰/۴۸۹
DMS $\alpha = \beta =$ ۰/۹۰	۳/۷۱۳	۹۱/۶۸
DMA $\alpha = \beta =$ ۰/۹۵	۶/۷۶	۲۱۶/۳
DMS $\alpha = \beta =$ ۰/۹۵	۴/۳۱	۱۰۴/۰۰۴
DMA $\alpha =$ ۰/۹۹; $\beta =$ ۰/۹۰	۶/۱۱	۱۴۲/۹۵
DMS $\alpha =$ ۰/۹۹; $\beta =$ ۰/۹۰	۴/۱۷	۱۰۳/۷۳۱
DMA $\alpha =$ ۰/۹۹; $\beta = =$ ۰/۹۵	۶/۷۴	۲۰۷/۴۲۹
DMS $\alpha=$ ۰/۹۹; $\beta = =$ ۰/۹۵	۴/۴۴۶	۹۷/۸۵۹
DMA $\alpha =$ ۰/۹۰ $\beta =$ ۰/۹۹	۷/۰۷	۳۱۹/۲۸۳
DMS $\alpha =$ ۰/۹۰; $\beta =$ ۰/۹۹	۳/۳۶	۳۱/۱۹
DMA $\alpha = =$ ۰/۹۵ $\beta =$ ۰/۹۹	۷/۰۷۵	۲۹۲/۱۰۶
DMS $\alpha = =$ ۰/۹۵; $\beta =$ ۰/۹۹	۴/۵۵۷	۱۴۰/۶۷۶
DMA $\alpha =$ ۱ $\beta =$ ۰/۹۹	۷/۰۹۷	۲۶۸/۳۹۴
DMS $\alpha =$ ۱; $\beta =$ ۰/۹۹	۵/۱۷۴	۱۶۲/۲۰۷
DMA $\alpha =$ ۱ $\beta =$ ۰/۹۵	۶/۷۴	۲۰۴/۹۸
DMS $\alpha =$ ۱; $\beta =$ ۰/۹۵	۴/۵۲	۹۸/۸۸
DMA $\alpha =$ ۱ $\beta =$ ۰/۹۰	۶/۱۲	۱۴۳/۴۳
DMS $\alpha =$ ۱; $\beta =$ ۰/۹۰	۴/۸۱	۱۱۶/۰۶
DMA $\boldsymbol{\alpha} =$ ۰/۹۹; $\beta =$ ۱	۷/۱۲	۲۷۰/۲
DMS $\boldsymbol{\alpha} = =$ ۰/۹۹; $\beta =$ ۱	۴/۷۲	۱۴۲/۰۹
DMA $\boldsymbol{\alpha} =$ /۹۵ $\beta =$ ۱	۷/۰۶۵	۲۸۶/۲۸۶
DMS $\boldsymbol{\alpha} =$۰/۹۵; $\beta =$ ۱	۴/۳۵	۱۳۵/۷۰۱
DMA $\boldsymbol{\alpha} =$ /۹۰ $\beta =$ ۱	۷/۰۳	۳۰۷/۶۳۷
DMS $\boldsymbol{\alpha} =$۰/۹۰; $\beta =$ ۱	۳/۲۴	۲۸/۰۸
DMA $\boldsymbol{\alpha} =$ ۱; $\beta =$ ۱	۷/۱۲۷	۲۶۶/۷۸۹
DMS $\boldsymbol{\alpha} =$۱; $\beta =$ ۱	۴/۸۱	۱۴۳/۵۴۷
Parameters Flexibility Values	*MAFE*	*MSFE*
DMA$\alpha = \beta =$ ۰/۹۹	۷/۱	۲۷۲/۷۳
DMS $\alpha = \beta =$ ۰/۹۹	۴/۸۵	۱۴۶/۱۳
DMA $\alpha = \beta =$ ۰/۹۰	۶/۱۲	۱۴۰/۴۸۹
DMS $\alpha = \beta =$ ۰/۹۰	۳/۷۱۳	۹۱/۶۸
DMA $\alpha = \beta =$ ۰/۹۵	۶/۷۶	۲۱۶/۳
DMS $\alpha = \beta =$ ۰/۹۵	۴/۳۱	۱۰۴/۰۰۴
DMA $\alpha =$ ۰/۹۹; $\beta =$ ۰/۹۰	۶/۱۱	۱۴۲/۹۵
DMS $\alpha =$ ۰/۹۹; $\beta =$ ۰/۹۰	۴/۱۷	۱۰۳/۷۳۱
DMA $\alpha =$ ۰/۹۹; $\beta = =$ ۰/۹۵	۶/۷۴	۲۰۷/۴۲۹
DMS $\alpha=$ ۰/۹۹; $\beta = =$ ۰/۹۵	۴/۴۴۶	۹۷/۸۵۹
DMA $\alpha =$ ۰/۹۰ $\beta =$ ۰/۹۹	۷/۰۷	۳۱۹/۲۸۳
DMS $\alpha =$ ۰/۹۰; $\beta =$ ۰/۹۹	۳/۳۶	۳۱/۱۹
DMA $\alpha = =$ ۰/۹۵ $\beta =$ ۰/۹۹	۷/۰۷۵	۲۹۲/۱۰۶

DMS α = = ۰/۹۵; β = ۰/۹۹	۴/۵۵۷	۱۴۰/۶۷۶
DMA α = ۱ β = ۰/۹۹	۷/۰۹۷	۲۶۸/۳۹۴
DMS α = ۱; β = ۰/۹۹	۵/۱۷۴	۱۶۲/۲۰۷
DMA α = ۱ β = ۰/۹۵	۶/۷۴	۲۰۴/۹۸
DMS α = ۱; β = ۰/۹۵	۴/۵۲	۹۸/۸۸
DMA α = ۱ β = ۰/۹۰	۶/۱۲	۱۴۳/۴۳
DMS α = ۱; β = ۰/۹۰	۴/۸۱	۱۱۶/۰۶
DMA **α** = ۰/۹۹; β = ۱	۷/۱۲	۲۷۰/۲
DMS **α** = = ۰/۹۹; β = ۱	۴/۷۲	۱۴۲/۰۹
DMA **α** = /۹۵ β = ۱	۷/۰۶۵	۲۸۶/۲۸۶
DMS **α** =۰/۹۵; β = ۱	۴/۳۵	۱۳۵/۷۰۱
DMA **α** = /۹۰ β = ۱	۷/۰۳	۳۰۷/۶۳۷
DMS **α** =۰/۹۰; β = ۱	۳/۲۴	۲۸/۰۸
DMA **α** = ۱; β = ۱	۷/۱۲۷	۲۶۶/۷۸۹
DMS **α** =۱; β = ۱	۴/۸۱	۱۴۳/۵۴۷

Since variations of α and β usually range between 0.90 and 1, all relevant cases have been presented in Table 1. The results in Table 1 indicate that the DMA & DMS β=۰/۹۹; α =۰ /۹۰ model, has higher accuracy. Therefore, the rest of the results are calculated based on this model.

The total impact of each variable in the whole of periods is specified by the number of periods that the target variable has affected the financial condition index. The results of the TVP-DMA model are presented in Table 2.

Table 2. Prioritization of variables affecting the aggregate demand

	Variable	Index	Number of affecting periods	Priority
١	First Lag of Exchange rate	er_1	٥١	٦
٢	Current period exchange rate	er_0	٣٨	١١
٣	Current period inflation	P_0	٥٥	٣
٤	First Lag of inflation	P_1	٣٩	١٠
٥	Current period housing	H_0	٥٣	٤
٦	First Lag of housing	H_1	٥١	٥
٧	Current period bank deposit	sr_0	٢٥	١٣
٨	First Lag of bank deposit	sr_1	٢٧	١٢
٩	Current period stock return	gy_0	٤١	٩
١٠	First Lag of istock return	gy_1	٤٤	٨
١١	Current period credit volume	DD_0	٥٦	١
١٢	First Lag of credit volume	DD_1	٥٨	٢
١٣	Current period oil revenue	TROIL_0	٢٢	١٤
١٤	First Lag of oil revenue	TROIL_1	٥٠	٧

According to the results, credit volume in the current period and the first lag, inflation rate in the current period, housing price in the current period, and credit volume in the first lag were the most effective factors of aggregate demand. The probability with which each variable affects the aggregate demand in various periods is now considered. These probabilities help policy-makers to have a true insight into how and to what extent a policy affects the aggregate demand when implementing that policy.

Finally, the FCI is measured in terms of the coefficients of the seven variables above in the current period and previous lag multiplied by the probability of the variable being effective in the target index. In other words, for example for the year 1991 the FCI is obtained as follows:

FCI 1991-1 = The share of inflation from the total coefficients in the current period of the first season in the year 1991×The probability of inflation occurring in the current period of the first season in the year 1991×Inflation in the current period of the first season in the year 1991+The share of inflation from the total coefficients in the first lag of the first season in the year 1991×The probability of inflation occurring in the first lag of the first season in the year 1991×Inflation in the first lag of the first season in the year 1991+The share of exchange rates from the total coefficients in the current period of the first season in the year 1991×The probability of exchange rates occurring in the current period of the first season in the year 1991×Exchange rates in the current period of the first season in the year 1991+The share of exchange rates from the total coefficients in the first lag of the first season in the year 1991×The probability of exchange rates occurring in the first lag of the first season in the year 1991×Exchange rates in the first lag of the first season in the year 1991+The share of housing prices from the total coefficients in the current period of the first season in the year 1991×The probability of housing prices occurring in the current period of the first season in the year 1991×Housing prices in the current period of the first season in the year 1991+The share of housing prices from the total coefficients in the first lag of the first season in the year 1991×The probability of housing prices occurring in the first lag of the first season in the year 1991×Housing prices in the first lag of the first season in the year 1991+The share of oil revenues from the total coefficients in the current period of the first season in the year 1991×The probability of oil revenues occurring in the current period of the first season in the year 1991×Oil revenues in the current period of the first season in the year 1991+The share of oil revenues from the total coefficients in the first lag of the first season in the year 1991×The probability of oil revenues occurring in the first lag of the first season in the year 1991×Oil revenues in the first lag of the first season in the year 1991+The share of stock returns from the total coefficients in the current period of the first season in the year 1991×The probability of stock returns occurring in the current period of the first season in the year 1991×Stock returns in the current period of the first season in the year 1991+The share of stock returns from the total coefficients in the first lag of the first season in the year 1991×The probability of stock returns occurring in the first lag of the first season in the year 1991×Stock returns in the first lag of the first season in the year 1991+The share of bank deposit rates from the total coefficients in the current period of the first season in the year 1991×The probability of bank deposit rates occurring in the current period of the first season in the year 1991×Bank deposit rates in the current period of the first season in the year 1991+The share of bank deposit rates from the total coefficients in the first lag of the first season in the year 1991×The probability of bank deposit rates occurring in the first lag of the first season in the year 1991×Bank deposit rates in the first lag of the first season in the year 1991+The share of credit volumes from the total coefficients in the current period of the first season in the year 1991×The probability of credit volumes occurring in the current period of the first season in the year 1991×Credit volumes in the current period of the first season in the year 1991+The share of credit volumes from the total coefficients in the first lag of the first season in the year 1991×The probability of credit volumes occurring in the first lag of the first season in the year 1991×Credit volumes in the first lag of the first season in the year 1991

A similar formula is used for subsequent seasons and years. Note that if a variable has a zero coefficient or occurrence probability, it is removed systematically from the FCI. After measuring the FCI, the impact of this variable on stock returns is examined.

Results of TVP-DMA and factors affecting stock returns

In this section, the results of the TVP-DMA approach are presented. Table 3 shows the indices of the goodness-of-fit to determine the optimal model. The values of forecast log-likelihood, MAFE, and MSFE for the various DMA and DMS models are presented.

Table 3. Comparison of different models by the Kalman filter

Forecasting Method	*MAFE*	*MSFE*	*log(PL)*	Forecasting Method	*MA FE*	*MS FE*	*log(P L)*
DMA$\alpha = \beta = 0.99$	٠/١١٩	٠/٠٤٠	-٠,٢٢٦	DMA $\alpha = 1$ $\beta = 0.99$	/١٣٥ ٠	/٠٩٣ ٠	٠,٤١ -٢
DMS $\alpha = \beta = 0.99$	٠/١٢٤	٠/٠٣٥	-٠,١٨٧	DMS $\alpha = 1$; $\beta = 0.99$	/١٢١ ٠	/٠٤١ ٠	٠,٣١ -٤
DMA $\alpha = \beta = 0.90$	٠/١٣١	٠/٠٤٦	-٠,٣٥١	DMA $\alpha = 1$ $\beta = 0.95$	/١٣٤ ٠	/٠٦٣ ٠	٠,٣١ -٥
DMS $\alpha = \beta = 0.90$	٠/١٢٣	٠/٠٤١	-٠,٣٢٢	DMS $\alpha = 1$; $\beta = 0.95$	/١١٤ ٠	/٠٣٩ ٠	٠,٤١ -٢
DMA $\alpha = \beta = 0.95$	٠/١٣٢	٠/٠٤٣	-٠,٣١٠	DMA $\alpha = 1$ $\beta = 0.90$	/١٢٨ ٠	/٠٥٢ ٠	٠,٤١ -٣
DMS $\alpha = \beta = 0.95$	٠/١٤٢	٠/٠٣٧	-٠,٣٧٥	DMS $\alpha = 1$; $\beta = 0.90$	/١١٦ ٠	/٠٤٦ ٠	٠,٣٩ -٨
DMA $\alpha = 0.99$; $\beta = 0.90$	٠/١٤١	٠/٠٥١	-٠,٢٤٤	DMA $\boldsymbol{\alpha} = 0.99$ $\boldsymbol{\beta} = 1$	/١١٧ ٠	/٠٤٠ ٠	٠,١٨ -٧
DMS $\alpha = 0.99$; $\beta = 0.90$	٠/١٢٧	٠/٠٤٥	-٠,٣١٤	DMS $\boldsymbol{\alpha} = 0.99$; $\boldsymbol{\beta} = 1$	/١٠٧ ٠	/٠٣٤ ٠	٠,٣٤ -١
DMA $\alpha = 0.99$; $\beta = 0.95$	٠/١٢٩	٠/٠٤٥	-٠,٢٩١	DMA $\boldsymbol{\alpha} = 0.95$ $\boldsymbol{\beta} = 1$	/١١٧ ٠	/٠٣٨ ٠	٠,٣٢ -١
DMS $\alpha = 0.99$; $\beta = 0.95$	٠/١٠٧	٠/٠٣٩	-٠,٣٤٤	DMS $\boldsymbol{\alpha} = 0.95$; $\boldsymbol{\beta} = 1$	/١٠١ ٠	/٠٣٣ ٠	٠,٤١ -٢
DMA $\alpha = 0.90$ $\beta = 0.99$	٠/١٨٩	٠/٠٣٧	-٠,٣٢٢	DMA $\boldsymbol{\alpha} = 0.90$ $\boldsymbol{\beta} = 1$ (calculating FCI with variable coefficients in optimal model)	/٠٧٢ ٠	/٠٢٩ ٠	٠,٢٠ -٩
DMS $\alpha = 0.90$; $\beta = 0.99$	٠/٠٩٨	٠/٠٣١	-٠,٢٧٤	DMS $\boldsymbol{\alpha} =0.90$; $\boldsymbol{\beta} = 1$ (calculating FCI with variable coefficients in optimal model)	/٠٦١ ٠	/٠١٦ ٠	٠,٢١ -٤
DMA $\alpha = 0.95$ $\beta = 0.99$	٠/١٢٤	٠/٠٦١	-٠,٢١١	DMA $\boldsymbol{\alpha} = 1$; $\boldsymbol{\beta} = 1$	/١١٦ ٠	/٠٤٦ ٠	٠,٣٤ -١
DMS $\alpha = 0.95$; $\beta = 0.99$	٠/١٤٢	/٠٨١٢ ٠	-٠,٣٢٩	DMS $\boldsymbol{\alpha} =1$; $\boldsymbol{\beta} = 1$	/١١٠ ٠	/٠٣٥ ٠	٠,٣١ -٤
DMS $\boldsymbol{\alpha} =0.90$; $\boldsymbol{\beta} = 1$ (calculating FCI with variable coefficients in optimal model)	١/٧٢٣	٢/٢٥٦	-٠,٨٨٥	DMA $\boldsymbol{\alpha} = 0.90$ $\boldsymbol{\beta} = 1$ (calculating FCI with constant	/٠٩٨ ٣	/٢٣١ ١	٠,٧١ -٤

				coefficients in optimal model)			
DMS α =0, β = 0=OLS (assuming all variables affecting stock return, constant)	۲/۳۵۹	۳/۲۰۸	-۱,۳۵۱	DMA $\boldsymbol{\alpha}$ = 0; $\boldsymbol{\beta}$ = 0=OLS (calculating FCI with constant coefficients in optimal model)	/۳۰۸ ٤	/۸۱۲ ۳	۱,۷۱ -۳

The results shown in Table 4 indicate that models DMS $\boldsymbol{\alpha}$ =0.90; $\boldsymbol{\beta}$ = 1 and DMA $\boldsymbol{\alpha}$ = 0.90 $\boldsymbol{\beta}$ = 1 have the highest accuracy, and, accordingly, other results are calculated based on these models.

The penultimate row shows the estimation results without the flexibility of coefficients of the financial condition index in the optimal model. As seen in this row, compared with the case in which the flexibility is incorporated for the coefficients, the estimation error is higher. Consequently, flexible coefficients improve the results of the forecast. The last row represents the results of the case in which the coefficients of all variables affecting stock returns are not considered flexible. This row, which is equivalent to the estimates of the OLS approach, reveals that the estimation error is very high without the flexibility of the coefficients. Therefore, considering flexible coefficients for variables improves the forecasting results.

The number of periods (rows) in which a variable has been effective in stock returns should be counted. These numbers represent the overall impact of each variable in the whole period. For example, the liquidity growth rate appears in 30 periods in table 4, but the exchange rate is present in 49 periods. The results are summarized in Table 4.

Table 4. Prioritization of variables affecting stock returns

	Variable	Index	Periods of effectiveness	Priority
۱	Misery Index	unp_0	۲۱	۷
۲	Exchange Rate	er_0	٥٤	٦
۳	Liquidity Growth	m_0	۷۷	۲
٤	Economic Growth	gdp_0	٦۱	٥
٥	FCI	sr_0	۷۸	۳
٦	Oil Revenues	troil_0	٦٥	٤
۷	Unemployment Rate	un_0	۱۹	۸
۸	Budget Deficit	bd_0	۹۱	۱

According to the results, budget deficit, financial condition index, oil revenues, economic growth, exchange rates, liquidity, unemployment, and misery index have been the most important factors of stock returns in the period studied.

The probability of each variable being effective in stock returns in various periods has been considered. These probabilities help policymakers to have a true insight into how and to what extent a target policy affects stock returns.

Regarding the coefficients and occurrence probabilities of the variables affecting stock returns, an out-of-sample forecast of stock returns is carried out. Note that, in each period, each variable that has had an occurrence probability higher than 50% has been incorporated in the model in estimating the coefficient of that period. In other words, the coefficient for a target period has been calculated based on the variables affecting stock returns in that period.

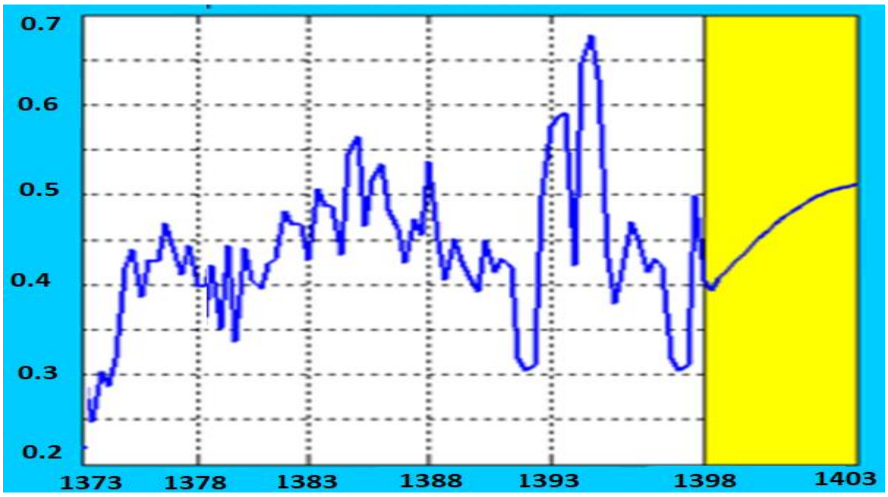

Fig1. The actual and out-of-sample predicted values using the outputs of the optimal model

According to the results, the out-of-sample forecast of stock returns indicates a positive and increasing future trend for this variable.

Conclusion and policy recommendations

The results indicate that stock returns are affected by economic growth and budget (real variables) and financial condition index and oil revenues (nominal variables) simultaneously. Accordingly, the stock returns forecast for Iran is a multidimensional and complex process, and an accurate forecast of the future trend in this market is not possible merely by implementing financial and monetary policies (demand-side policies), which only change the demand and affect nominal variables in the long run.

On the other hand, a high probability of variables being affective in stock returns in different periods indicates that various factors affect stock returns in each period. Therefore, a systemic view is required to provide a more realistic understanding of the effective factors of stock returns to improve the state of the stock market.

Regarding the implications on the positive impact of economic growth and inflation on stock returns, implementation of demand-side policies is recommended to be considered because these policies, besides increasing production and employment, reduce inflation and thus improve stock returns.

Regarding the negative impact of financial condition index on stock returns, the expansion of financial condition policies, establishment of specialized stock exchange markets, and development of financing methods for firms active in stock exchange are required to be planned.

The results indicate that the FCI can forecast future levels of stock returns with higher accuracy. Accordingly, overlooking this variable not only means missing this effective information, but also leads to a bias in analyses of the central bank and stock exchange

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