Iran. Econ. Rev. Vol. 22, No. 4, 2018. pp. 867 - 886

Predicting the Country Commodity Imports Using Mixed Frequency Data Sampling (MIDAS) Model[1]

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Received: 2016, November 7 Accepted: 2017, May 8

Abstract

Predicting the amount of country imports toward assessing trade balance and its effect on the balance of payments (BOP) and finally money supply, general level of prices and the rate of economic growth is of paramount importance. Therefore, economic policymakers seriously need a model which cannot only predict the volume of imports well but also be capable of revising the initial prediction over time as soon as new data for the explanatory variables are available. To this purpose, mixed frequency data sampling model was used which allows time series variables with different annual, seasonal and even daily frequencies to be used in a single regression model. In estimating the model using the software R, annual real imports, real exports and quarterly of real GDP, real exchange rate and the volatilities of the real exchange rate in the range of 1988 to 2014 are used. Information related to 2014 is not used in preliminary estimation of relationship, so that the predictive power of the model outside of the estimated range can be tested. The proposed model predicts that real imports of goods as49948 million dollars for 2014 which is associated with an error of only41 million dollars, or about 8 percent, compared to its real amount achieved of49907 million dollars. The result suggests that the predictive power of the MIDAS model is very satisfactory.

Keywords: Imports, Models with Different Frequencies, MIDAS.
JEL Classification: F10, C53, E27.

1. Introduction

In today's world, there is no country that can meet all the needs of community without the products and services of other countries. Even

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If there is such a capacity in a country, it won't be economically viable. As a result, the issue of exchange of goods and services between countries is raised based on relative and absolute advantages. One of the criteria in evaluating the economic potential of a country is its trade balance exports and imports are considered as two main pillars of the balance. Every country provides revenues necessary to meet its import needs through export. Also, in the analysis of Macroeconomic policy-making issues, estimating imports demand function and its imports forecasting according to its effect on the trade balance and balance of payments is of paramount importance. Hence, any changes that occur in the country imports will have a significant effect on the production process, the money supply and the general level of prices.

Predicting the amount of country imports toward assessing trade balance and its effect on the balance of payments (BOP) and finally money supply, general level of prices and the rate of economic growth is of paramount importance. Forecasting the volume of imports for the end of the year help policy makers to adopt appropriate policies to improve the trade balance throughout the year. For this aim, in this paper, a mixed frequency data sampling model was used which allows time series variables with different annual, seasonal and even daily frequencies to be used in a single regression model.

In the following, section 2 will discuss theoretical foundations and research background is presented in section 3. Section four discusses the model and estimation of model coefficients. The results of the estimated model are presented in section 5 and prediction outcomes are presented in section six. Finally, the article ends with conclusions in section seven.

2. Theoretical Foundations

2.1 Import Demand Function

Import demand function is derived theoretically based on some assumptions, through maximizing the utility. Related assumptions are as follows:

1. All producers and consumers operate under perfect competition conditions, so the number of producers and consumers in the market is high and it is free to enter and leave the industry. Also, the goods are homogeneous goods and there is the possibility to be aware of the market status completely.
2. Consumers seek to maximize utility and producers seek to maximize the profit.

Given these assumptions, we can derive import demand function using the utility maximization process due to budget constraints. It is assumed that consumers are faced with the n goods, in a way that $X_{11}, X_{21}, \ldots, X_{n1}$are produced within the country and $X_{12}, X_{22}, \ldots, X_{n2}$ are produced abroad. Collective utility function is a function of the total mass of the goods produced within the country and abroad. If the price of goods produced within the country is shown by$P_{11}, P_{21}, \ldots, P_{n1}$and prices of goods produced abroad are shown as$P_{12}, P_{22}, \ldots, P_{n2}$, in this case, the total cost of the country in question due to budget is spent for the purchase of goods within the country and abroad as follows:

$$Y = P_{11}X_{11} + \cdots + P_{n1}X_{n1} + P_{12}X_{12} + \cdots + P_{n2}X_{n2} = \sum_{i=1}^{n} P_{i1} X_{i1} + \sum_{i=1}^{n} P_{i2} X_{i2} (1)$$

Now, by maximizing the aggregate utility function and according to the budget constraint in the country and also using the technique of Lagrange, we have:

$$L = U(X_{11}, X_{12}, X_{21}, \ldots, X_{n1}, X_{n2}) + \lambda(Y - \sum_{i=1}^{n} P_{i1} X_{i1} + \sum_{i=1}^{n} P_{i2} X_{i2}) (2)$$

Using differentiation, we have:

$$\frac{\partial L}{\partial X_{i1}} = U_{1i} - \lambda P_{i1} = 0 (3)$$

$$\frac{\partial L}{\partial X_{i2}} = U_{2i} - \lambda P_{i2} = 0$$

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$$\frac{\partial L}{\partial \lambda} = Y - \sum_{i=1}^{n} P_{i1} X_{i1} + \sum_{i=1}^{n} P_{i2} X_{i2} = 0$$

By solving these equations, the demand for imports can be calculated as follows:

$$X_{i2} = X_{i2}(P_{11}, P_{12}, P_{21}, P_{22}, \dots, P_{n1}, P_{n2}, Y) \qquad i = 1,2,\dots,n(4)$$

That is, the value of imports is a function of domestic and foreign prices level and national income. Thus, according to the process of maximizing the utility function due to budget constraints in the country, import demand function can be achieved in its conventional forms.

$$M_t = M_t(Y_t, \frac{P_m}{P_d})(5)$$

$$\frac{\partial M}{\partial Y} > 0\,, \frac{\partial M}{\partial (\frac{P_m}{P_d})} < 0$$

$\frac{P_m}{P_d}$ is the relative price of imported goods to domestic products and $Y_t$is gross domestic product. In equation (5), imports is a direct function of income (i.e. increased income leads to an increase in imports) and an inverse function of relative prices (i.e. increased import prices leads to a decline in imports).

2.2 Theoretical Foundations of Mixed Frequency Data Sampling (MIDAS)

In the traditional method, for time series modeling to predict economic variables, all the variables involved in the model have not necessarily the same frequency, for example, if the dependent variable is quarterly, explanatory variables should also be quarterly. However, if there are variables in a regression equation, some annually, some quarterly or monthly, there is no possibility of estimating the coefficients of the regression unless quarterly or monthly data to be converted to annual data and then the regression coefficients to be estimated. But recently, a technique has been developed that can put variables with different frequencies in a regression and its coefficients to be estimated. Making a model accordingly has two major advantages. First, when the high-frequency variables with low-frequency variables are used in a regression, the dependent variable for the near future can be predicted more precisely. Second advantage of these models is that when new information is obtained about high-frequency variables, the previous forecasting can be revised. Models that can benefit from a combination of data with different frequencies in a regression for the first time was founded by Klein and Soju (1989) in the formulation of macro-structural econometric models.

The method which has been invented recently by Ghysels, Santa-Clara, and Valkanov (2004) and then has been developed by Ghysels, Sinko, and Valkanov (2006) is known as "Mixed Frequency Data Sampling" or is MIDAS. Before introducing the Mixed Frequency Data Sampling or MIDAS, first the notation of variables with different frequencies in the model is introduced. Suppose that $\{y_t\}_t$ and $\{x_\tau\}_\tau$ are two stationary time series with different frequencies, so that, $y_t$is dependent variable andx_τ is explanatory variable. It is the time unit used for low frequency variable. In order connect the two variables with frequencies of t and τ, s coefficient was used. The coefficient s is a fraction of the time interval between t and t-1, so that $m = 1/s$ specifies that how many the high frequency time series variables x_τ are observed in this period. Thus, t = τ.m and thus the frequency of $x_\tau$is m times greater than the frequency of$\{y_t\}_t$ per unitof time symbol $x_t^{(m)}$,means$x_\tau = x_t^{(m)}$. For example, for quarterly and monthly data, m=3, and this means that, in every season, there will be one quarterly data and three observations of monthly data. In this case, the variable which has quarterly data is low frequency variable and the variable which has monthly data, will be high frequency variable.

The approach of "Mixed Frequency Data Sampling (MIDAS)", where the dependent variable usually has lower frequency, is based on two characteristics as follows: having a regression structure such as Autoregressive Distributed Lag (ARDL), as well as a weighting function (for synchronization between the low-frequency and high-frequency variables). A simple MIDAS regression with respect to a high frequency variable $x_\tau$and its lags are as follows:

$$y_t = C_0 + \beta \sum_{j=0}^{j\,max} w(j;\theta) \,.\, L^{j/m} x_t^{(m)} + u_t \qquad (6)$$

The Weighting function w (j; θ), represents a polynomial for specific weights applied a lags of x_τ. Ghysels et al. (2014) have expressed MIDAS weighting function according to Almon lag polynomial specification, exponential Almon lag polynomial, beta weighting function, which takes the general from of weighting functions as follows:

$$w(j;\theta) = \frac{\varphi(j;\theta)}{\sum_{j=1}^{j\,max} \varphi(j;\theta)} \qquad (7)$$

Depending on the type of function φ (j; θ) used in the above equation, as well as the maximum number of lags (j max), the weighting function can be different due to different frequencies and different variables. The weighting function is determined by j which shows the number of lags and a vector of parametersθ. A Weighting functions such as the above equation, create non-negative weights, and in determining the coefficient of high frequency variable and its (i.e., β), it is assumed that the sum of the weights created by this function is equal to 1.

$$\sum_{j=0}^{j\,max} w(j;\theta) \,.\, L^{j/m}(\alpha) = 1 \qquad (8)$$

As, Almon lag polynomial specification is used in this study, only this function is introduced in this section. In the Almon weighting functions, β coefficient and weights are estimated as a common parameter$\beta . w_t(j;\theta)$. With regard to the Almon equation, Almon lag polynomial specification is as follows:

$$\beta . w(j;\theta) = \sum_{j=0}^{j\,max} \sum_{p=1}^{P} \theta_p . j^p \qquad (9)$$

This weighting function creates various coefficients based on different values of the parameters θ and p, which is the Almon polynomial order. In the Fig (1) weights created by Almon lag polynomial specification is displayed with different values of parameters θ. In order to obtain the slope of the regression line β (assuming that the sum of weights being produced is not equal to 0), once all of the coefficients are estimated by ordinary least squares, following this general property of weighting functions$\sum_{j=0}^{j\,max} w(j\,;\theta)\,.\,L^{\frac{j}{m}}(\alpha) = 1$, to obtain the net weights for all lags of high frequency variable, each coefficient is divided by the sum of all coefficient weighs for all coefficients.

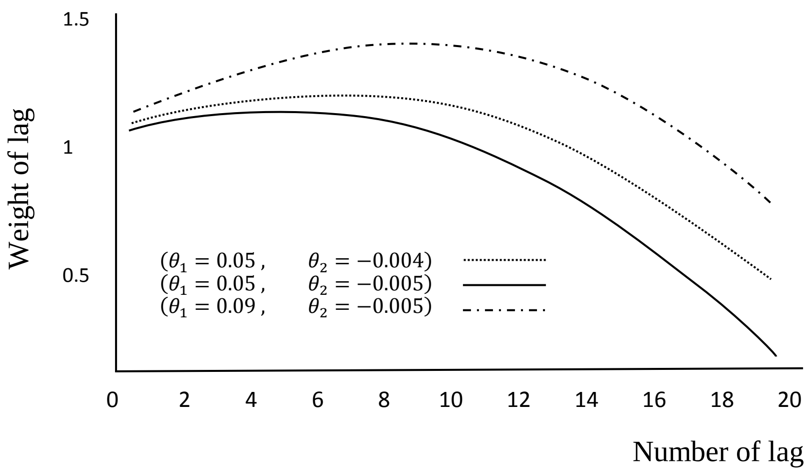

Figure 1: Different Types of Almon Function with Different Parameters

In a parametric exposition, we can consider the MIDAS model as a linear model. But by applying weights of expanded lags and imposing a parametric constraint function, it is converted from linear to nonlinear model. Therefore, according Ghysels et al. (2004), it is necessary that nonlinear estimation methods to be used to NLS estimate the MIDAS model coefficients, which minimizes the sum of squares of the disturbance term.

$$\hat{\theta} = argmin\ \theta \epsilon R \quad \left(y_t - \beta \sum_{j=0}^{j\,max} w(j;\theta).L^{j/m} x_t\right)^2 \qquad (10)$$

Here, a numerical algorithm is used for finding the value of $\hat{\theta}$ which minimizesthe term in parentheses. This algorithm by applying a replication cycle finds a proper parameter for vector θ and tries to minimize the equation $(y_t - \beta \sum_{j=0}^{j\,max} w(j;\theta).L^{j/m} x_t)^2$ (Bayat and Noferesti, 2015).

2.2.1 Forecasting Using MIDAS Model

As noted above, one of the advantages of modeling using MIDAS is to predict the value of the present time of dependent variable by the aid of newly published data. Considering$\beta_k = \beta.w(j;\theta)$, the following equation can be estimated:

$$y_t = C_0 + \sum_{i=1}^{p} \alpha_i\, y_{t-1} + \sum_{k=1}^{n} \sum_{j=0}^{m-1} \beta_k\, x_{t-k-j/m}^{(s)} + u_t \qquad (11)$$

Then, the following equation may be used to make predictions:

$$y_{t+1} = C_0 + \sum_{i=1}^{p} \alpha_i\, y_{t-1} + \sum_{k=1}^{n} \sum_{j=0}^{m-1} \beta_k\, x_{t-k-j/m}^{(s)} + \sum_{is=m-d+1}^{m} \gamma_s\, y_{t+1-s-1/m} + u_{t+1} \qquad (12)$$

d represents the number of high frequency periods that new data is published for them. In the above equation, the third term is related to the lag and forth term is related to the Lead. Using these equations, the future values of desired variables can be predicted and data published in high frequencies can be used to revise in predictions.

2.2.2 Evaluation of Forecasting Accuracy

Before the practical use of any econometric model, accuracy and reliability of a model should be assessed and determined to want extend it can provide reliable prediction. One of quantitative and common indicators for determining difference between value predicted and the actual value of the variable in question is Root Mean Square percentage Error, RMSPE. In this study, to assess accuracy of model forecasting, this index is used (Bayat and Noferesti, 2015).

3. Background Research

Pahlavani et al. (2007) in a study estimated the demand functions for imports and exports in the economy using ARDL method. In this study, the effects of national income, foreign exchange rates and relative prices on the demand function for imports and the effect of global income, foreign exchange rates and relative prices of export on export demand function using ARDL method is studied during 2006-2009. Based on the results, national income have had positive and significant impact and relative prices of imports and exchange rate have had negative and significant impact on import demand function of Iran. As well as, in demand function for exports, the variables of global income and exchange rates have had a positive impact and relative prices of exports have had a significant negative impact on the exports. In order to evaluate the effect of export earnings and GDP on imports, we can note to the study of Sepanlou and Ghanbari (2010). In their study, the factors affecting demand for imports of Iran were studied in terms of intermediate, capital and consumption goods. In this study, Iran's structure of foreign trade during 1971-2007 was analyzed using econometric methods with autoregressive distributed lag (ARDL). According to the study, the type and the effect of factors such as relative prices, GDP excluding oil and gas sector and the mining industry on each import functions were studied. According to the study, the type and amount of impact for the factors, such as relative prices, GDP excluding oil and gas, value added in mining industry in industry and mines on each of import functions was studied. The results indicate that the lagged variable (Imports in the previous period) was significant in all three functions, and have had the greatest impact on imports of consumer goods (confirmation of theory of consumer expectations), and the lowest impact for consumer goods, as well as revenues from oil and gas exports, as well as the added value of industry and mine sector has the greatest impact on the import of capital goods.

In order to evaluate the effects of exchange rate volatility on trade, Bahman Oskoee et al. (2014) in his study has used export data for 148 export industries and 144 import industries for South Korea during 1971-2011. They, using ARDL model, showed that a lot of industries are not affected by exchange rate fluctuations.

In line with previous studies by MIDAS, modeling and forecasting German GDP growth using MIDAS method was done by Marcelino and Schumacher (2007). The researchers used quarterly GDP data for the first quarter 1992 to third quarter 2006 and one hundred and eleven indicator of monthly price such as the price of raw materials, import and export of goods, import and export of services, domestic and foreign industrial orders, The quantity of money, consumer price index and the price index of goods and services-producing services during the period between 1992 and the first month of the eleventh month of 2006 and concluded that the predicted results were accurate and appropriate.

Su, Zhou and Wang (2013) used data for period 1, 1988 to 4 2010 related to returns of securities of stock market weekly as explanatory variable for the economic growth forecasting in Singapore, and the results indicate that MIDAS model has more power compared with regression models for high frequency data.

Bayat and Noferesti (2015) in her thesis, entitled Implementation of Mixed Frequency Data Sampling, in relation with prediction of economic growth rate concluded that, the predictive power of the model studied using MIDAS has been good. This model has predicted economic growth rate in the preliminary estimation equal to 1.8 % for 2014, and then considering the drop in oil prices has predicted this factor equainvesl to 1.5% and in the second half of 2014, and eventually after an appeal, the rate for the winter of 2013 has been predicted equivalent to 2.7%.Thus, forecasting results showed that Iran's economy in 2014 has a growth rate equal to 1.9% compared to 2013.

Noferesti and Dashtban (2017) investigate the effect of changes in population age structure on government tax revenues and forecast its evolution using MIDAS method. The specified regression model, which is estimated by using time series data within the period of 1989-2014, predicts the real amount of government's tax for 2015, which was 709,651.9 b. Rials, as 709,365.7 b. Rials, with a tiny error of almost 0.4%. This prediction is considered to be very close to the reality.

Noferesti et al. (2017) construct a model to predict the Non-Oil Export in IRAN. The model is estimated by using time series data during the years 1989 until 2014. This study is done by using MIDAS method in order to estimate the specified equation for non-oil export by the aid of R software. Results show that in the equation specified, the effect of seasonal variables such as GDP, Exchange rate, Exchange rate fluctuations on non-oil export are statistically meaningful and the nonoil export predicted for 2014 in the spring, summer, autumn and winter are as follows: 23387,53 million dollars 23706,09 million dollars, 23600.58 million dollars and23810,95 million dollars and compared to its real data which is 23864.26 million dollars, it can be convoluted that the model forecast is satisfactory.

4. Model Specification and Estimation of Model Coefficients

In order to specify a model to predict Iran's imports of goods by MIDAS, the semi-logarithmic equation is used. Semi-logarithmic models are used to estimate the non-linear functions, and are commonly used for measuring changes in the variables such as price changes, unemployment, exports and imports and alike (Derakhshan, 1995). To specify an imports model, annual data of import and export of goods at constant prices, and quarterly data, gross domestic product at constant prices, the log of real exchange rate and the logarithm of exchange rate fluctuations have been used.Annual variables related to the years 1988 to 2014, and quarterly variations related to the first quarter of 1988 to the last quarter of 2014. First, information related to quarterly variations in 1988 is not used in the estimation of equation; so that, we can test the power of model forecasting out of estimation range. Therefore, using quarterly data for the first quarter of 1988 to the fourth quarter of 2013, the equation (13) is estimated, and then imports of goods are predicted for 2014. After the first estimation of the model, information about the first quarter, second quarter, third and fourth was added to the model and the following equation will be revised at the amount expected for primary imports:

$$mfo_t = C_0 + \sum_{j=1}^{p} \alpha_j \, mfo_{t-j} + \sum_{j=1}^{q} \lambda_j \, lx_{t-j} + \beta_1 \sum_{j=1}^{j\,max} w(j;\theta).L^{j/q} lgdp_t^{(q)} + \beta_2 \sum_{j=1}^{j\,max} w(j;\theta).L^{j/q} le_t^{(q)} + \beta_3 \sum_{j=1}^{j\,max} w(j;\theta).L^{j/q} lge_t^{(q)} + u_t \quad (13)$$

In this equation, the variables are:

mfo_t: Imports of goods in Million dollar at constant prices (annual)

lx_t : Logarithm of total exports (total exports of goods and services) at constant prices (annual) in million dollar (annual)

: $lgdp_t^{(q)}$: Logarithm of GDP at constant prices per billion Rial (quarterly)

lx_t : Logarithm of total exports (total exports of goods and services) at constant price in million dollar (annual)

: $lgdp_t^{(q)}$: Logarithm of GDP at constant prices per billion Rial (quarterly)

: $le_t^{(q)}$: Logarithm of the real exchange rate (quarterly)

: $lge_t^{(q)}$: Logarithm of exchange rate volatility (quarterly)

In conjunction with estimation of the coefficients of the quarterly variables, in addition to estimating the coefficients β1, β2 and β3, weighting functions w (j; θ) should be specified and its parameters should be estimated. In this equation, among different weighting functions, Almon lag polynomial specification with better performance was selected. The weighting function has few θ parameters that will be estimated.

Statistical data in this study are in form of, quarterly and annual time series, which time series database of Iran's central bank and economic indicators have been used to gather them. Imports of goods data has been in terms of current dollars which are converted to constant prices using America's wholesale price index.

4.1 Estimation of the Real Exchange Rate Uncertainty Variable Using the GARCH Model

In recent years, many studies have been conducted on the modeling and prediction of variability, especially in the stock market, exchange rates and inflation. Variability is one of the most important issues in economic and financial studies. Variability is often defined as the standard deviation or variance, which has a certain concept in any subject (Souri, 2014). For this purpose, to show the real exchange rate uncertainty, the variance of the real exchange rate is used. This variance is modeled using the GARCH (1,0) model as follows. The first equation is the average real exchange rate equation and the second equation is the variance of the real exchange rate.

$$1)\ e_t = \beta_0 e_{t-1} + \varepsilon_t$$
$$2)\ h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \qquad (14)$$

In this equation, h_t is the conditional variance in short term. The results of estimation of GARCH model (1,0) for the real exchange rate is shown using quarterly data from the 1988 to 2014 using Eviews8 software.

Table 1: Results of the Real Exchange Rate Uncertainty Variable Estimation Using the GARCH Model

	Estimate	Std. Error	tvalue	Pr(> |t|)
β_0	0.97	0.00	998.86	0.00
Variance				
α_0	18.63	3.99	4.65	0.00
α_1	4.25	0.35	11.82	0.00
		DW= 2.147 R^2=0.88		

Source: Research findings

All coefficients of α_0 and α_1 are significant at the level of 5%. Therefore, mean and variance equation of the GARCH (1,0) model can be written as follows:

$$e_t = 0.976efr_{t-1} + \varepsilon_t (15)$$
$$h_t = 18.63 + 4.250\varepsilon_{t-1}^2$$

As stated, ht is conditional variance and variable which is used as a proxy for the real exchange rate uncertainty variable.

5. The Results of the Estimated Model

First it is necessary that before the model coefficients estimation, the parameters are tested in terms of reliability. The results obtained based on Dickey-Fuller test are shown in Table 2.

Table 2: Results of the Reliability of Variables Related to the Import of Goods

	Prob	t-value	std-Error	Variables
I(1)	0.2320	-3.6032	-2.7355	MFO
I(0)	0.0185	-1.9550	-2.7355	DMFO
I(1)	0.8077	-3.4540	-1.5443	LGDP

I(0)	0.0001	-3.4540	-5.3120	DLGDP
I(1)	0.4223	-3.4523	-2.3143	LE
I(0)	0.0000	-4.0469	-10.3023	DLE
I(0)	0.0000	-3.4527	-5.7368	LGE
I(1)	0.7837	-3.5950	-1.5528	LX
I(0)	0.0053	-3.6032	-4.6628	DLX

Source: Research findings

To estimate the proposed model, software package Midas in the R, prepared by Ghysels, Kvedaras and Zemlys (2014) and the variables of the first quarter of 1988 to fourth quarter 2013 (without entering the seasonal variations in 2014) have been used. The results of the model coefficients estimation are reported in Table 3.

$$\begin{aligned} mfo_t &= (-7749) + (-0.6259) * y_{t-1} + (9474) * lx_t \\ &+ \sum_{j=4}^{10} (-4183.193) * w\big(7; (41920, -10630)\big). L^{j/q} lgdp_t^{(q)} \\ &+ \sum_{j=4}^{6} (-3590.18) * w\big(3; (21240,10020)\big). L^{j/q} le_t^{(q)} + \sum_{j=4}^{9} (-648.7781) \\ &* w\big(6; (-1447,1120, -170.2)\big). L^{j/q} lge_t^{(q)} + \varepsilon_t \end{aligned} \quad (16)$$

In equation explained, imports of goods variable depends on an annual lag and seasonal seven lags of GDP, six lags of explanatory variable log real exchange rate as well as three lags of the real exchange rate.

Table 3: Results of Estimation of the Imports of Goods Coefficients Using Midas Software Package

	Estimate	**Std. Error**	**t value**	**Pr(> |t|)**	**sig level**
$Intercept$	-7.749e+03	4.420e+04	-0.175	0.863344	
mfo	-6.25e-01	1.477e-01	4.239	0.000826	***
lx	9.474e+03	4.282e+03	2.212	0.044065	*
$lgdp_1$	4.192e+04	1.125e+04	3.727	0.002255	**
$lgdp_2$	-1.063e+04	2.783e+03	-3.820	0.001876	**
le_1	-2.124e+04	6.003e+03	-3.538	0.003280	**
le_2	1.002e+04	5.783e+03	3.600	0.002898	**
lge_1	-1.447e+03	5.794e+02	-2.498	0.025552	*
lge_2	1.120e+03	3.492e+02	3.207	0.006326	**
lge_3	-1.702e+02	4.547e+01	-3.742	0.002188	**

: 0 ‘*’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1** $\boldsymbol{Singnif.codes}$

$\boldsymbol{R^2 = 0.9771}$ $\boldsymbol{R^2 adj = 0.9607}$ $\boldsymbol{Durbin\ Watson = 1.801589}$

$\boldsymbol{Shapiro - Wilk\ normality\ test = 0.9812 (p = 0.9175)}$ $\boldsymbol{hAh = 4.2121 (p = 0.8969)}$

Source: Research findings

The test statistic $hAhtest$ value is equal to 0.8969, which shows that the constraints imposed on model coefficients specified, statistically are highly significant and sufficient. Coefficient of determination was estimated as $R^2 = 0.9771$ for the model that indicates that the explanatory power of the model is very high. According to Durbin-Watson statistics quantity and normality test of Shapiro-Wilk, the terms in the model don't have serial correlation and have normal distribution.

6. Forecasting

The equation explained for import of goods is estimated using data of the first quarter 1988 to fourth quarter of 2013. Based on the estimated equation (16), the first prediction has been made on a sample for 2014 using quarterly data available by the end of the last quarter of 2013 as follows:

The value predicted, $\widehat{mfo}_{t+1\,,MIDAS} = \ 49537.27$

The value of imports of goods in 2014, $mfo_{t+1} = 49907.20859$

The predictions are displayed in figure 2.

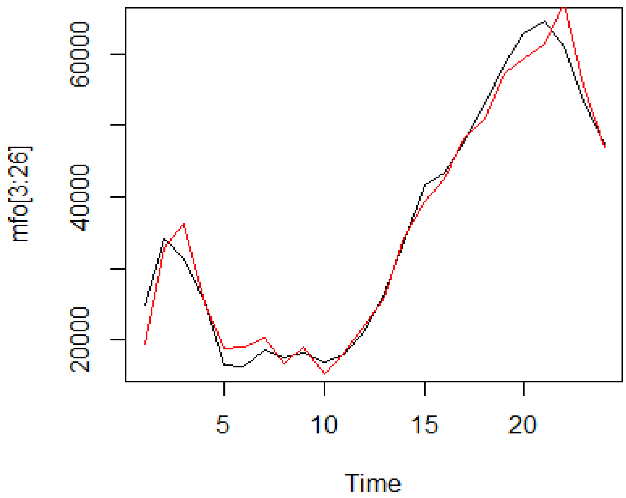

Figure 2: The Actual and Simulated Values by the Import of Goods Equation for 2014

Figure 2 shows the simulated values by the equations and the actual values for imports of goods. The red lines indicate the simulated values, and the black lines represent actual values, which can confirm that estimatedR^2 higher than what is expected level in the equations.

In addition, quarterly data from the first quarter of 1988 to the first quarter of 2014, and then quarters of II, III and IV in 2014 were used for forecasting. Results of forecasting for2014in the field of imports of goods are as Table 4:

Table 4: Comparison of Actual and Simulated Values of Imports of Goods Based on the Entire Quarters of 2014

Achieved values	The predicted values	Imports of goods forecasting in 2014
49907.20	49179.13	Using the first quarter of 1393
49907.20	49438.54	Used data from the first quarter and second quarter 1393
49907.20	49884.08	Used data from the first quarter, second quarter and third quarter of 1393
49907.20	49948.72	Using the first quarter, second quarter, third quarter and fourth quarter 1393

According to Table 4, as can be seen by entering the data for the fourth quarter of quarterly variations used in the equation, the predicted value is very close to the actual amount. Comparison of the value of imports of goods predicted of 49948.72 million dollars with the actual amount of 49907.20 million dollars showed that the model forecasting is made accurately.

7. Conclusion

Forecasting imports of goods is very important regarding the estimation of trade balance, and its effect on the balance of payments and the supply of money, prices and economic growth rate. Given that, the imports of goods variable is released at low frequency and maximum as quarterly with relatively long intervals, so, in this study, it was a model provided for forecasting these variables. Using combined data of time series with different frequencies modeling that is known as MIDAS, a model was provided to predict and estimate the imports of goods. The explanatory variables with quarter and annual frequency were used to predict the imports of goods. The explanatory variables are: total exports logarithm on an annual basis, log of quarterly GDP at constant prices, log of the real exchange rate and log of quarterly fluctuations in exchange rate. The study scope included the first quarter of 1988 to the last quarter of 2014.First, information related to quarterly variations in 1988 is not used in the estimation of equation, so that, we can test the power of model forecasting out of estimation range. After the first estimation of imports of goods, information relating to the first quarter, then the second to fourth quarter, is added to the models, the amount of primary imports of goods forecasting was revised. Finally, the model of real imports of goods for 2014 equal to 49948 million dollars predict that the annual value reported is equal to 49907.20 million dollars which indicate that the model forecasting has been accurate. MIDAS method, which derives the weighted data, is preferable to a simple method to predict the imports, so, this flexible approach, which derives data's weight economically, can be used as an applied method in future studies.

References

Bahmani-Oskooee, M., Hengerty, S. W., & Zhang, R. (2014). The Effects of Exchange Rate Volatility on Korean flows: Industry Level Estimates. *Economic Paper, 33*(1), 76-97.

Bayat, M., & Noferesti, M. (2015). *Applied Econometric of Time Series: Mixed Frequency Data Sampling*. Tehran: Noor-e-Elm Publication.

Derakhshan, M. (1995). *Econometrics; Single Equations with Classical Assumptions*. Tehran: Samt Publishing.

Ghysels, E., Kvedaras, V., & Zemlys, M. (2014). Mixed Frequency Data Sampling Regression Models: the Package Midas. *Journal of Statistical Software*, *10*, 18-25.

Klein, L. R., & Sojo, E. (1989). *Combinations of High and Low Frequency Data in Macroeconomic Models*. Retrieved from https://link.springer.com/chapter/10.1007/978-94-009-0463-7_1.

Noferest, M., & Dashtban, S. (2017). Effect of Changes in Age Structure of the Population on Government Tax Revenues and Predicting its Changes: An Approach of Mixed Frequency Data Sampling (MIDAS). *Journal of Economic Research*, *22*(6), 59-75.

Noferesti, M., Varahrami, V., & Javaherdehi, S. (2017). Seasonal Variations and Prediction Revision of Annual Non-oil Export: A Mixed Data Sampling (MIDAS) Approach. *Journal of Economic and Modeling*, *8*(29), 67-88.

Sayadi, F., & Moghadasi, R. (2015). The Effect of Energy Prices on the Price of Grain Using Regression Models with Complex Data. *Research Journal of Applied Economics studies in Iran*, *15*, 149-160.

Sepanlou, H., & Ghanbari, A. (2010). The Factors Affecting the Demand for Imports in Terms of 223 Goods, Capital and Consumer. *Journal of Business Research*, *57*, 209-210.

Souri, A. (2014). *Econometrics; along with Eviews 8 Application & Stata 12*. Tehran: Publishing Culturology.

Tsui, A. K., Xu, C. Y., & Zhang, Z. Y. (2013). Forecasting Singapore Economic Growth with Mixed-Frequency Data. *20th International Congress on Modeling and Simulation*, Retrieved from http://ro.ecu.edu.au/cgi/viewcontent.cgi?article=1339&context=ecuworks2013.