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Forecasting Monthly Inflation: A MIDAS Regression Application for Turkey

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A B S T R A C T

Forecasting the short-term price movements is especially important in terms of developing adequate monetary policies during inflationary periods. For countries such as Turkey where inflation targeting policy were adopted and relatively high inflation rates are observed, making short term forecasting using daily data will allow decision processes to react more rapidly. In Turkey, several methods are used by the Central Bank and academicians for estimating the inflation rate. However, in all these methods, covariates are used from the same frequency (mostly monthly) in modelling the inflation rate. In this study, it has been tried to develop a model which can be used in the forecasting of inflation rate by using MIDAS method which allows the series to be used in the same regression equation from different frequency. In the set regression equation, commercial credit interest rate (weekly), TL / US Dollar parity (daily), gold gram price (daily) and oil price (daily) data are used as variables which have the potential to determine the monthly producer price level (PPI) by increasing the input costs. Considering the AIC and SIC criteria, it was found that the best performing model out of four alternatives was the weighted equation according to the Almon polynomial distributed lags method. The in-sample predictive success of the model was found satisfactory.

1. Introduction

Traditional methods used in time series analysis require that the entire data set be of the same frequency. In this case, to use the series with different frequency levels in the same regression equation, it is necessary to convert the high-frequency series to the lowest frequency series. Obviously, this conversion/aggregation process will result in partial loss of information provided by the high-frequency series. An alternative mode of action is to exclude the low-frequency variable from the model, rather than transforming the high-frequency series, to avoid loss of information if the low-frequency series is in the explanatory variable position. This can be expected to cause serious exclusion deviations.

On the other hand, using short-term information provided by high-frequency series, nowcasting for low-frequency variables makes it possible to make more effective decisions, especially when forecasting is the main objective in the analysis. Regression analysis method which is developed by Ghysels *et al*. (2002) based on mixed frequency sampling data (MIDAS - Mixed Data Sampling) allows to eliminate all these drawbacks by using different frequency time series in the same regression equation. MIDAS is a reduced form parsimonious regression framework which

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does not require modelling the dynamics of each and every predictor series. By using mixed data frequency models several advantages could be gained. The inclusion of higher frequency series precludes loos of information stems from data aggregation. It is possible to update forecasts with actual data with higher frequency (Andreou and Kourtellos, 2015).

It is possible to use the MIDAS method as a suitable tool for the short-term prediction of relatively low-frequency series such as inflation, economic growth, and industrial production index. In this context, for the economies those adopted inflation targeting policy like Turkey it will be possible to determine more effective inflation and price stability policy by doing instant forecasts (nowcasting) employing high-frequency series rather than inflation forecasts obtained via using conventional single or multivariate time series analysis methods.

In this study, using high-frequency financial data, MIDAS regression analysis was conducted to determine the best forecasting model of monthly inflation rate in Turkey. In the analysis, interest rate, gold price and exchange rate as well as oil price which is a source of supply-side inflation, are included as leading financial variables. In-sample forecasting performances were examined by using obtained models tried by using different lag lengths skims like polynomial and exponential lagged Almon, step and Beta functions.

2. MIDAS Regression Analysis: Theoretical Framework

In conventional time series methods, both dependent and independent variables must be at the same frequency. This situation may cause serious problems, especially in macroeconomic analyses due to the publication of data at different time intervals and frequencies. In practice, the most common solution of using different frequency data in the same model is to reduce the high-frequency data to the frequency of the low-frequency data before proceeding with the prediction of the model (Armesto *et al.*, 2010: 521; Guliyev, 2018: 15). This is done by aggregating or averaging depending on whether the series is a stock or flow variable. However, as a result of this reduction process, both the loss of information contained in the high-frequency series may occur and the distribution properties of the original series may be differentiated (Marcellino, 1999: 129). One way to avoid loss of information is to compensate for missing observations in low-frequency series by interpolation (Foroni and Marcellino, 2013: 2). Another option is to exclude low-frequency variables from the model, which is likely to result in loss of efficiency due to variable exclusion error.

It is possible to build a model with variables of different frequency without resorting to such aggregation or interpolation. For this, a separate coefficient is assigned for each of the high-frequency variables. in this case, the number of coefficients in the regression equation may be very large.

The Mixed-Data Sampling (MIDAS) approach developed by Ghysels *et al*. (2002) offers a different option between these two approaches. In this method, the frequency of the dependent variable must always be lower than the frequency of the independent variable (s). Thus, the MIDAS approach can use the maximum information in each observation of the high-frequency series (Guliyev, 2018: 15). Over time, different expansions of the basic MIDAS approach proposed by Ghysels *et al*. (2002) have been developed. In this context, nonlinear MIDAS (Ghysels *et al*., 2007), asymmetric MIDAS (Ghysels *et al*., 2005), smooth transition MIDAS (Galvao, 2007), Markov switching MIDAS (Guerin and Marcellino, 2011) methods can be mentioned.

As the basic starting point, let consider the following baseline model with the variables from different frequency:

$$y_t = X_t'\beta + f\left(Z_{t/m}, \theta, \lambda\right) + \varepsilon_t \tag{1}$$

where y_t is the dependent variable with a low frequency such as t. X_t is the set of regressors of low-frequency the same as y_t. $Z_{t/m}$ is the set of high-frequency variables. For example, if y_t has a yearly frequency, m is 12 for a variable with a monthly frequency. β, λ and θ are vectors of the parameter to be estimated. ε_t stands for *i.i.d.* error term as usual.

In the individual coefficient approach, high-frequency variables are included in the model as regressors. This can be demonstrated in open form as follows:

$$y_t = X_t'\beta + \sum_{r=0}^{m-1} Z'_{(t-r)/m}\theta_r + \varepsilon_t \tag{2}$$

where $Z_{(t-r)/m}$ represents the r^{th} lagged value of the high-frequency regressor *Z*. As can be seen, here a separate coefficient θ is estimated for each delayed term *m* of the *Z* regressor. In contrast, in the aggregation approach, the sum or average of the components of the high-frequency variable is taken as a regressor and a single (or common) parameter λ is estimated instead of the individual parameters.

$$y_t = X_t'\beta + \left[\sum_{r=0}^{m-1} Z_{(t-r)/m}\right]' \lambda + \varepsilon_t \tag{3}$$

Accordingly, the individual coefficients approach assigns a different weight to each high-frequency term, but this rapidly increases the number of parameters, especially in the multivariate case. On the other hand, the aggregation approach leads to lesser parameterization but imposes strict restrictions on the coefficients. Despite these two approaches, which can be seen as extreme cases, many different weighting regimes can be used in the MIDAS method.

The simplest one of these weighting regimes is the step function approach. Here the coefficients of the high-frequency variable are restricted via a step function.

$$y_t = X_t'\beta + \sum_{r=0}^{k-1} Z'_{(t-r)/m}\varphi_r + \varepsilon_t \tag{4}$$

where *k* is chosen the number of lags of high-frequency series and may be less than or greater than *m*. Although the number of parameters increases depending on the lag length of the high-frequency variable, this increase is slower than that of the individual coefficient approach.

Another approach is to employ the Almon delay function, a common method in distributed lag modelling. In the Almon approach the coefficients of the delayed/lagged terms (θ_r) are designed as polynomially varying weights. Accordingly, the baseline equation can be rewritten as follows.

$$y_t = X_t'\beta + \sum_{r=0}^{m-1} Z'_{(t-r)/m}\left[\sum_{j=0}^{p} r^j\theta_j\right] + \varepsilon_t \tag{5}$$

where *p* is the order of the Almon polynomial. An alternative way is to apply the exponential weighting proposed by Ghysels *et al.* (2005) as follows:

$$y_t = X_t'\beta + \sum_{r=0}^{m-1} Z'_{(t-r)/m}\left[\frac{exp(r\theta_1 + r^2\theta_2)}{\sum_{j=0}^{m} exp(j\theta_1 + j^2\theta_2)}\right]\lambda + \varepsilon_t \tag{6}$$

where *m* is the number of lags, λ stands for common slope coefficient across lags. Here, the responses of the dependent variable to lagged terms are monitored through MIDAS parameter θ.

Finally, the weighting process can also be performed via the Beta function approach introduced by Ghysels *et al.* (2003, 2004, 2006).

$$y_t = X_t'\beta + \sum_{r=0}^{m-1} Z'_{(t-r)/m}\left[\frac{\omega_r^{\theta_1-1}(1-\omega_r)^{\theta_2-1}}{\sum_{j=0}^{m} \omega_j^{\theta_1-1}(1-\omega_j)^{\theta_2-1}} + \theta_3\right]\lambda + \varepsilon_t \tag{7}$$

Slope coefficient λ is common across lags and,

$$\omega_i = \begin{cases} \delta & , \quad i = 0 \\ i/(m-1) & , \quad i = 1, 2 \ldots, m-2 \\ 1-\delta & , \quad i = m \end{cases} \tag{8}$$

where δ is a small number which is approximately equal to $2{,}22 \times e^{-16}$ in practice (IHS Markit, 2017).

3. Literature

Although the MIDAS regression approach was used primarily for the purpose of financial prediction by Ghysels *et al*. (2002) who developed the method and in the first applications (Ghysels *et al*., 2006; Chen and Ghysels, 2011;

Alper *et al*., 2012; Hoang, 2015), the method has also been used for other topics over time like growth analysis (Tay, 2006; Clements and Galvao, 2008; Schumacher and Breitung, 2008; Kuzin *et al*., 2009; Armesto *et al*., 2010; Barsoum and Stankiewicz, 2013; Leboeuf and Morel, 2014; Kingnetr *et al*., 2017; Guliyev, 2018; Yamak *et al*. 2018; Bilgin *et al*., 2018; Mikosch and Solanko, 2019; Doğan and Midiliç, 2019), private consumption (Suhoy, 2010), oil prices (Baumeister *et al*., 2014), carbon dioxide emission (Zhao *et al*., 2018), labour market (Karagedikli and Özbilgin, 2019).

One of the economic issues in which the MIDAS approach has been widely used in recent years is inflation forecasting. In a pioneering study, Kotze (2005) used daily asset prices such as interest rate, stock prices, profit rate and exchange rate for the monthly inflation forecast and found that using high-frequency series did not improve the predictive performance.

Since the oil price is one of the most important triggers of inflation it is observed that various indicators related to daily or weekly oil prices are used in the monthly inflation forecast. Ribon and Suhoy (2011) estimated the monthly inflation rate by using commodity (food and oil) series as well as some daily financial indicators and calculated the errors of the predictions obtained from different classical methods. As a result of their comparison according to two different criteria, they showed that MIDAS regression gives better predictions than alternatives. Modugno (2011), on the other hand, forecasted monthly consumer price inflation in the Eurozone by using two different oil price series – daily and weekly. Similarly, Marsilli (2017) and Salisu and Ogbonna (2017) included oil prices in their analyzes. Marsilli (2017) took the daily oil price into consideration in its inflation forecast and conducted an analysis within the framework of the expanded Phillips curve. In the analysis of the varying parameter structure, it was concluded that the Phillips curve is a convenient tool to explain the dynamics of inflation with the MIDAS approach. Salisu and Ogbonna (2017), considering the monthly inflation rate in OECD countries, state that the MIDAS regression with oil prices gives better predictions than alternative specifications.

In addition to daily financial data, Monteforte and Moretti (2012) tried to predict the euro area inflation rate by using the monthly core inflation index. Their results show that the use of daily data reduces the forecast error according to the model based on monthly data only.

One of the determinants of the results in the estimation with the MIDAS approach is to determine the lag length accurately. Especially when the effect from high-frequency explanatory variables to low-frequency dependent variable differs in the direction in the short and long term, approaches such as exponential polynomial and beta function may not be able to capture the correct form of delay function. Differently from Ghysels *et al*. (2006), Breitung and Roling (2015) propose a non-parametric MIDAS approach for the problem in question. They applied the proposed approach to the harmonized price index of the Euro area and achieved better results than parametric MIDAS.

There is ample evidence in the applied macroeconomic literature on inflation dynamics which suggest that interest rate helps in forecasting the future path of the inflation rate. Using the term structure of interest rate, Maji and Das (2016) developed a forecast model for WPI-based headline inflation rate of India in the MIDAS framework. Their results show that MIDAS performs better than traditional identical frequency models. Considering the skewed nature of inflation dynamics in India they also addressed the non-normality of errors by employing U-MIDAS model.

On the other hand, in a more recent study, Libonatti (2018) explored inflation forecasting in the case of Argentina using an online price series. However, unlike previous studies, MIDAS specifications do not give better predictions than classical AR model. The author explains this unexpected result with the possibility that the price series used is not a suitable indicator.

4. Inflation Forecasting with MIDAS Regression Analysis

4.1. Variables and data

In this study, a series of indicators which are found to be related to inflation in the empirical economic literature are considered for the prediction of the inflation rate. These are gold price, exchange rate, oil price and interest rate. Since these variables may be related to cost-oriented inflation, inflation rate based on monthly producer price index (*PPI*) is used as inflation indicator (*INF*). Daily gram price of gold for the gold price (*AU*), daily USD/TL parity for the exchange rate (*EXC*), Brent oil price per barrel for oil price (*OIL*) and weekly interest rate applied to commercial loans are used for interest rate (*INT*).

All data were compiled from the Electronic Data Delivery System (EDDS) of the CBRT. The sampling period covers 2 January 2009 - 31 December 2018 period (10 years). All explanatory variables were considered with their logarithmic difference values, that is, financial indicators are taken into account in terms of their log-return values. In this way, it is aimed to prevent an estimation difficulty caused by the different integration levels of the series.

4.2. Results

Descriptive statistics related to the series used in the analysis are given in Table 1. As can be seen in the table, all series have a right-skewed and sharper distribution than the normal distribution. Skewness and sharpness are most noticeable in the inflation rate and exchange rate series. The Jarque - Bera statistics strongly confirm the abnormalities in the series.

Table 1. Descriptive statistics for the series

	INF	*AU*	*EXC*	*OIL*	*INT*
Mean	0,8571	0,0713	0,0516	0,0255	0,3211
Maximum	10,8820	14,2241	15,9006	10,9780	48,1264
Minimum	-2,5305	-9,0909	-7,6852	-9,2420	-32,0064
Skewness	2,9501	0,4614	2,2189	0,1779	0,7568
Kurtosis	19,9262	11,5233	42,8882	6,0027	8,6691
St. Error	1,5008	1,3438	0,9145	2,0130	7,6628
J – B statistics	1593,1482	7980,6463	174902,2251	982,8337	747,4256
(p-value)	(< 0,01)	(< 0,01)	(< 0,01)	(< 0,01)	(< 0,01)
Observation	119	2606	2606	2580	521

MIDAS regression requires series to be stationary. Although all series were expected to be stationary because of the difference type, Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) unit-root tests were also conducted for the series to determine their integration level. The results given in Table 2 indicate that all series used are stationary.

Table 2. Results of unit-root tests

	ADF		PP	
	c	*c + t*	*c*	*c + t*
INF	-6,6532 (1) [< 0,01]	-7,0065 (1) [< 0,01]	-6,0821 (2) [< 0,01]	-5,8626 (5) [< 0,01]
AU	-33,0554 (2) [< 0,01]	-33,0491 (2) [< 0,01]	-53,8300 (5) [< 0,01]	-53,8189 (5) [< 0,01]
EXC	-33,3078 (2) [< 0,01]	-33,3806 (2) [< 0,01]	-48,4180 (7) [< 0,01]	-48,4640 (6) [< 0,01]
OIL	-54,3107 (0) [< 0,01]	-54,3385 (0) [< 0,01]	-54,2650 (7) [< 0,01]	-54,3067 (6) [< 0,01]
INT	-18,5624 (2) [< 0,01]	-18,9952 (2) [< 0,01]	-39,7131 (10) [< 0,01]	-41,7807 (9) [< 0,01]

Note: The values in ( ) indicate the optimal lag length selected by SIC for the ADF test and the optimal bandwidth for the PP test. Values in [ ] are p-values. c stands for constant term, c + t stands for constant term and trend.

In this study, the MIDAS regression method was carried out separately for each explanatory variable and the predictions were obtained. Four different approaches (delay function, PDL Almon with polynomial delay, exponential PDL Almon and Beta function) were used for delay functions. In three out of the four approaches, it was concluded that exchange rate is the most appropriate indicator in terms of inflation estimation, but only in the exponential Almon approach, it was concluded in favour of the interest rate. This situation can be interpreted as producer prices in Turkey are more sensitive to the exchange rate among the four factors of inflation (Table 3-6).

The forecasting performances of the variables were evaluated in terms of six different performance criteria and results are given in Table 7. When the values are inspected, it is seen that different variables exhibit better prediction performance in different models. In this regard, it can be said that exchange rate movements in terms of PDL Almon and beta function, changes in oil prices in terms of a step function and changes in interest rates in exponential Almon model give the most successful forecasts.

Table 3. PDL Almon estimates

	AU	*EXC*	*OIL*	*INT*
Constant	0,2249 (0,0769)	0,1798 (0,0638)	0,4007 (0,0039)	0,3538 (0,0122)
INF_{t-1}	0,4787 (< 0,01)	0,4116 (< 0,01)	0,5164 (< 0,01)	0,4372 (< 0,01)
PDL1	-0,0495	-0,0387	-0,0373	-0,0150
PDL2	0,0130	0,0138	0,0065	0,0542
PDL3	-0,0002	-0,0002	-0,0001	-0,0080
R^2	0,4550	0,6828	0,3259	0,3741
Log likelihood	-179,5025	**-147,5804**	-184,9426	-187,6730
Durbin-Watson	1,9252	2,2300	1,8382	1,7838
AIC	3,1271	**2,5861**	3,2748	3,2656
SIC	3,2446	**2,7035**	3,3935	3,3830
Lag length	31	41	36	6

Table 4. Step estimates

	AU	*EXC*	*OIL*	*INT*
Constant	0,6530 (< 0,01)	0,5168 (< 0,01)	0,8705 (< 0,01)	0,7829 (< 0,01)
Step 1	-0,0529	-0,1414	-0,0279	0,0491
Step 2	-0,0124	-0,1733	0,0163	0,0426
Step 3	0,1104	0,2122	-0,0292	0,0532
Step 4	-0,0139	0,1018	0,0462	0,0390
Step 5	0,0100	0,0046	0,0060	
Step 6	0,0809	0,2110	-0,0431	
Step 7	0,1940	-0,0104	0,0400	
Step 8	0,2094	0,3297	0,0142	
Step 9	0,1605	0,1619	0,0563	
Step 10	0,1106	0,1444	0,0618	
Step 11	-0,0571	0,1005	0,0423	
Step 12	0,1812	0,3105	0,0501	
Step 13	-0,0299	0,2321	0,0100	
Step 14	0,0816	0,0757	0,0421	
Step 15	0,0378	0,2246	-0,0987	
R^2	0,4017	0,6431	0,1292	0,2105
Log likelihood	-185,0096	**-154,5249**	-199,7979	-201,3726
Durbin-Watson	1,1949	1,5805	1,1181	1,1574
AIC	3,4069	**2,8902**	3,7207	3,4978
SIC	3,7827	**3,2659**	4,1005	3,6152
Lag length	41	43	43	10

As an alternative approach, Andreou *et al.* (2013) suggested that several univariate models would be estimated and then forecast combination would be used to produce a final forecast. On the other hand, a number of studies in the literature have shown that forecast averaging or forecast combining may give better prediction rather than depending on a single best forecast. The basis of this approach is to take the weighted or unweighted average of forecasts obtained from different models according to an evaluation criterion. For this purpose, the forecasts are combined by taking the average of the estimates obtained for each variable. Thus, a common forecast series that reflects the effect of all variables was tried to be obtained.

Table 5. Exponential Almon estimates

	AU	*EXC*	*OIL*	*INT*
Constant	0.8726 (< 0,01)	0.8672 (< 0,01)	0.9234 (< 0,01)	0.7182 (< 0,01)
Slope	-0,2675	0,1490	-0.1248	0,5081
ExpPDL1	105,3741	-10,9869	1,4575	0,7171
ExpPDL2	-12,2249	-3,1233	-0.3436	-0,0807
R^2	0,0439	0,0045	0,0090	0,2326
Log likelihood	-212,6697	-215,0549	-208,5939	**-199,6992**
Durbin-Watson	1,0302	1,0039	1,0042	1,1123
AIC	3,6724	3,7128	3,6341	**3,4525**
SIC	3,7663	3,8067	3,7285	**3,5465**
Lag length	44	44	40	12

Table 6. Beta function estimates

	AU	*EXC*	*OIL*	*INT*
Constant	0,5984 (< 0,01)	0,5272 (< 0,01)	0,8978 (< 0,01)	0,8438 (< 0,01)
Slope	3,5092	5,6054	0,8443	0,5036
Beta1	1,2379	1,7413	0,9999	-3,9032
Beta2	1,0053	1,0467	0,9999	2,7787
Beta3	-0,0143	-0,0086	-0,0238	-3,5601
R^2	0,2604	0,5320	0,0507	0,1722
Log likelihood	-197,5200	**-170,5243**	-204,7987	219,9317
Durbin-Watson	1,0859	1,4300	1,0280	1,1393
AIC	3,4325	**2,9750**	3,6172	3,5453
SIC	3,5499	**3,0924**	3,7359	3,6627
Lag length	42	42	42	12

Table 7. Comparison of the forecasting performance of the models

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
F1	1,2172	0,8269	427,7222	98,8693	0,4276	3,9435
F2	0,8773	0,6617	361,0216	97,6004	0,2736	3,6944
F3	1,3876	0,8840	402,1591	95,1114	0,4993	2,8824
F4	1,3254	0,9341	504,2835	107,0184	0,4722	4,5421
Mean_F	0,9694	0,6333	382,2576	85,6379	0,3399	3,8215
FF1	na	2,30E+259	9,40E+261	197,6285	na	na
FF2	1,4265	0,9479	450,1141	112,1821	0,4560	5,5955
FF3	1,5075	0,9069	441,7679	98,8682	0,5579	2,5042
FF4	1,3670	0,9283	448,1523	101,5030	0,5001	4,2728
Mean_FF	na	2,30E+258	9,50E+260	197,1611	na	na
FFF1	1,4671	0,9131	371,4349	97,1575	0,5563	2,2761
FFF2	1,4971	0,9054	367,4990	92,6632	0,5787	2,4941
FFF3	1,4389	0,8932	368,5648	91,8939	0,5467	3,0094
FFF4	1,3144	0,9374	498,1949	106,6610	0,4618	4,9219
Mean_FFF	1,3223	0,8384	411,9390	92,0678	0,5007	3,4828
FFFF1	1,3448	0,9029	410,5039	100,9797	0,4786	4,0566
FFFF2	1,1323	0,8004	474,1150	104,1300	0,3737	3,3458
FFFF3	1,4285	0,8574	423,3818	90,7697	0,5372	2,0860
FFFF4	1,3652	0,9466	519,5857	107,1320	0,4904	4,3064
Mean_FFFF	1,2071	0,7586	431,4114	88,2311	0,4425	3,7648

Note: F, PDL Almon; FF, step; FFF, exponential Almon; FFFF is a Beta function prediction. 1, the price of gold; 2, exchange rate; 3, the price of oil; 4, denotes the estimated model for the interest rate. *Mean_* denotes the predictive means obtained by the MSE-Rank method developed by Aiolfi and Timmermann (2006) for four different models.

When the values given in the table are analysed, it is seen that the forecasts averages do not perform better than the individual forecasts. Accordingly, it can be said that combining the forecasts does not provide a significant gain in terms of the success of the forecasting.

5. Conclusion

The short-term inflation forecast is particularly important for the economic management of countries with high and volatile inflation rates. As a country which adopted the inflation targeting policy since 2006, for Turkey price stability and disinflation subjects remain on the government's agenda. After high inflation periods in the 80s and 90s, the fact that the single-digit inflation rate, which has been kept in single digits since the beginning of 2000s, has exceeded 10% again in recent years, makes the prediction of reliable short-term inflation even more valuable.

In this study, the effect of a number of high-frequency indicators on monthly inflation forecast performance was investigated via the MIDAS regression approach. In the analysis taking into consideration the period of January 2009 - December 2018, obtained results show that producer prices inflation in Turkey is more sensitive to the exchange rate among the four factors (gold price, exchange rate, oil prices and interest rate). Moreover, exchange rate changes are also prominent in terms of forecast performance. Based on these findings, it can be said that the daily exchange rate movements can be utilized for short-term forecast of inflation rate in Turkey.

In fact, the results obtained are not surprising considering the existing literature on inflation dynamics in Turkey. It is known that the inflation rate in many countries shows a high sensitivity to the exchange rate. The validity of this phenomenon in Turkey, which is called the exchange rate pass-through to inflation effect, has been demonstrated in recent years with many empirical studies. The intensity of imported consumer goods, the densely use of imported inputs in production sectors and the indexation channel increase the effect of exchange rate fluctuations on inflation. For this reason, it is important to follow the exchange rate movements well in terms of both the better inflation forecasts and controlling effectively the inflation rate. It can also be concluded that exchange rate interventions should have a predominant place in inflation rate policies.

References

[1] Aiolfi, M. and Timmermann, A. Persistence in forecasting performance and conditional combination strategies, Journal of Econometrics, 135 (1-2) (2006) 31-53

[2] Alper, C. E., Fendoğlu, S. and Saltoğlu, B. MIDAS volatility forecast performance under market stress: Evidence from emerging stock markets, Economics Letters, 117 (2012) 528-532

[3] Andreou, E., Ghysels, E. and Kourtellos, A. Should macroeconomic forecasters use daily financial data and how?, Journal of Business and Economic Statistics, 3 (2013) 240–251.

[4] Andreou, E. and Kourtellos, A. The state and the future of Cyprus macroeconomic forecasting, Cyprus Economic Policy Review, 9 (1) (2015) 73-90.

[5] Armesto, M., Engememann, K. and Owyang, M. T. Forecasting with mixed frequencies. Federal Reserve Bank of St.Louis Review, 92 (2010) 521-536.

[6] Barsoum, F. and Stankiewicz, S. Forecasting GDP Growth Using Mixed-Frequency Models with Switching Regimes, University of Konstanz, Working Paper, No. 2013-10 (2013)

[7] Baumeister, C., Guérin, P. and Kilian, L. Do High-Frequency Financial Data Help Forecast Oil Prices? The MIDAS Touch, Bank of Canada, Working Paper, No. 2014-11 (2014)

[6] Bilgin, D., Jankovic, D. and Lam, A. MIDAS regression using inflation and unemployment to predict GDP, Mimeo. (2018)

[7] Breitung, J. and Roling, C. Forecasting inflation rates using daily data: A non-parametric MIDAS approach, Journal of Forecasting, 34 (2015) 588-603.

[8] Chen, X. and Ghysels, E. News –good or bad– and its impact on predicting future volatility, Review of Financial Studies, 24 (1) (2011) 46-81.

[9] Clements, M. P. and Galvao, A. B. Macroeconomic forecasting with mixed-frequency data: forecasting output growth in the United States, Journal of Business and Economic Statistics, 26 (2008) 546-54.

[10] Doğan, M. Ş. and Midiliç, M. Forecasting Turkish real GDP growth in a data-rich environment, Empirical Economics, 56 (1), (2019) 367-395.

[11] Foroni, C. and Marcellino, M. A Survey of Econometric Methods for Mixed-frequency Data, Norges Bank, Working Paper, 2013-06. (2013)

[12] Galvao, A. B. Change in Predictive Ability with Mixed Frequency Data, Queen Mary University, Working Paper, No. 595. (2007)

[13] Ghysels, E., Santa-Clara, P. and Valkanov, R. The MIDAS touch: mixed data sampling regressions, Draft paper. (2002)

[14] Ghysels, E., Santa-Clara, P. and Valkanov, R. Predicting volatility: getting the most out of return data sampled at different frequencies, Working paper, UNC and UCLA. (2003)

[15] Ghysels, E., Santa-Clara, P. and Valkanov, R. There is a risk-return trade-off after all, Journal of Financial Economics, 76 (2005) 509-548.

[16] Ghysels, E., Santa-Clara, P. and Valkanov, R. Predicting volatility: Getting the most out of return data sampled at different frequencies, Journal of Econometrics, 131 (2006) 59-95.

[17] Ghysels, E., Sinko, A. and Valkanov, R. MIDAS regressions: Further results and new directions, Econometric Reviews, 26 (2007) 53-90.

[18] Guerin, P. and Marcellino, M. Markov-switching MIDAS Models, CEPR Discussion Papers, 8234. (2011)

[19] Guliyev, H. Karma Frekanslı Verilerde MIDAS Regresyon Modellerinin Uygulanması: Türkiye'nin Ekonomik Büyüme Tahmini, Master Thesis, Akdeniz University – ISS, Antalya. (2018)

[20] Hoang, D. H. The Effects of Macroeconomic Variables on Asian Stock Market Volatility: A GARCH MIDAS Approach, Master Thesis, Lund University, Sweeden. (2015)

[21] IHS Markit, Eviews 2010 User's Guide II. (2017)

[22] Karamelikli, Ö. and Özbilgin, M. Mixed in New Zealand: Nowcasting Labour Markets with MIDAS, Reserve Bank of New Zealand, Analytical Note, No. AN2019/04. (2019)

[23] Kingnetr, N., Tungtrakul, T. and Sriboonchitta, S. Forecasting GDP growth in Thailand with different leading indicators using MIDAS regression models, in Robustness in Econometrics, Ed.: V. Kreinovich et al., Springer International Publishing. (2017)

[24] Kotze, K. L. Forecasting inflation with high frequency asset price data, University of Stellenbosch, Working Paper. (2005)

[25] Kuzin, V., Marcellino, M. and Schumacher, C. MIDAS versus mixed-frequency VAR: Nowcasting GDP in the euro area, Discussion Paper No. 07/2009, Deutsche Bundesbank. (2009)

[26] Lebouef, M. and Morel, L. Forecasting Short-term Real GDP Growth in the Euro Area and Japan Using Unrestricted MIDAS Regression, Bank of Canada, Working Paper, No. 2014-3. (2014)

[27] Libonatti, L. MIDAS Modeling for Core Inflation Forecasting, IDB Working Paper Series, No. IDB-WP-897. (2018)

[28] Maji, B. and Das, A. Forecasting Inflation with Mixed Frequency Data in India, Calcutta Statistical Association Bulletin, 68 (1-2) (2016) 92-110.

[29] Marcellino, M. Some consequences of temporal aggregation in empirical analysis. Journal of Business & Economic Statistics, 17 (1999) 129-136.

[30] Marsilli, C. Nowcasting US inflation using a MIDAS augmented Phillips curve, International Journal of Computational Economics and Econometrics, 7 (2017) 64-77.

[31] Mikosch, H. and Solanko, L. Forecasting quarterly Russian GDP growth with mixed-frequency data, Russian Journal of Money and Finance, 78 (2019) 19-35.

[32] Modugno, M. Nowcasting Inflation Using High Frequency Data, European Central Bank, Working Paper Series, No. 1324. (2011)

[33] Monteforte, L. and Moretti, G. Real-time forecasts of inflation: The role of financial variables, Journal of Forecasting, 32 (2012) 51-61.

[34] Ribon, S. and Suhoy, T. Forecasting Short-run Inflation Using Mixed Frequency Data (MIDAS), Bank of Israel, Occasional Paper, 2011.02. (2011)

[35] Salisu, A. A. and Ogbonna, A. E. Improving the predictive ability of oil for inflation: An ADL-MIDAS Approach, Centre for Econometric and Allied Research, University of Ibadan Working Papers Series, CWPS 0025. (2017)

[36] Schumacher, C. and Breitung, J. Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data, International Journal of Forecasting, 24 (2008) 386–398.

[37] Suhoy, T. Monthly Assessments of Private Consumption, Bank of Israel, Discussion Paper, No. 2010-09. (2010)

[38] Tay, A. S. Mixing Frequencies: Stock Returns as a Predictor of Real Output Growth, Singapur Management University, Working Paper, No. 34-2006. (2006)

[39] Yamak, N., Samut, S. and Koçak, S. Farklı frekanslı seriler altında ekonomik büyüme oranının tahmini, Ekonomi Bilimleri Dergisi, 10 (2018) 34-49.

[40] Zhao, X., Han, M., Ding, L. and Calin, A. C. Forecasting carbon dioxide emissions based on a hybrid of mixed data sampling regression model and back propagation neural network in the USA, Environmental Sciences and Pollution Research, 25 (2018) 2899-2910.