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Abstract

This paper compares several nowcast approaches that account for mixed-data frequency and "ragged-edge" problems. More specifically, it examines the relative performance of the factor-augmented MIDAS approach (Marcellino and Schumacher; 2010) in nowcasting Turkish GDP with respect to benchmark forecasts. By using 40 monthly indicators in factor extraction, several combinations of the factor-MIDAS models are estimated. Recursive pseudo-out-of sample forecasting exercise in evaluating the alternative models' performance suggests that factor-augmented MIDAS performs better than the benchmarks, especially in nowcasting. However, they do not provide much information content to forecasting a quarter ahead. Results indicate that taking into account the "ragged-edge" characteristic of the data helps improve the predictive ability of the nowcast models. Besides, dynamic factor extraction methods provide better predictions than the static factor extraction methods.

Özet

Bu çalışmada, farklı frekanslı veri ve örneklem sonunda eksik veri bulunması problemlerini hesaba katan çeşitli angörü yaklaşımları karşılaştırılmaktadır. Özel olarak, Türkiye'nin GSYİH'sini cari dönemde tahmin etmede faktörle genişletilmiş MIDAS yaklaşımının (Marcellino ve Schumacher; 2010) referans tahminlere kıyasla göreli performansı incelenmektedir. Faktör çıkarımında 40 adet aylık gösterge kullanılarak faktör-MIDAS modellerinin çeşitli kombinasyonları tahmin edilmektedir. Alternatif modellerin performansının değerlendirilmesinde yinelemeli sözde örneklem dışı tahmin çalışması, faktörle genişletilmiş MIDAS'ın, özellikle angörü yaparken, baz model tahminlerinden daha iyi performans gösterdiğine işaret etmektedir. Öte yandan, bir çeyrek sonrasını tahmin etmede çok fazla ilave bilgi içeriği sağlamamaktadırlar. Sonuçlar, verilerin "düzensiz uç" özelliğini hesaba katmanın, angörü modellerinin tahmin yeteneğini geliştirmeye yardımcı olduğunu göstermektedir. Ayrıca, dinamik faktör çıkarma yöntemleri, statik faktör çıkarma yöntemlerinden daha iyi tahminler sağlamaktadır.

JEL Classification: C52, C53, E37

Keyword: Forecasting, Mixed Frequency, Factor-MIDAS

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Non-Technical Summary

Given the publication delays in Gross Domestic Product (GDP), policymakers rely on nowcast models that account for all the available information to have a clear and early understanding of the current state of the economic activity. These models mainly use high-frequency indicators such as industrial production, international trade volumes, etc., to forecast the low-frequency variable. However, practitioners generally face problems such as mixed-data frequency and unbalanced datasets. In this study, we apply the factor-augmented MIDAS methods introduced by Marcellino and Schumacher (2010) that account for these problems in nowcasting the Turkish GDP. We estimate several combinations of the model with alternative factor estimation and MIDAS approaches. Then, we evaluate the predictive performance of the alternative models by a recursive pseudo-out-of-sample forecasting exercise. The results of the out-of-sample forecasting exercise suggest that factor-augmented MIDAS performs better than the benchmarks, especially in nowcasting. However, they do not provide much information content to forecasting a quarter ahead. The results indicate that taking into account the "ragged-edge" characteristic of the data helps improve the predictive ability of the nowcast models.

I. Introduction and Literature Review

Policymakers need to have a clear and timely understanding regarding the state of economic activity while taking their policy actions. However, they generally lack current information on the main economic activity indicator, the Gross Domestic Product (GDP), given that the realizations of the data are released with a publication lag of 2-3 months. Accordingly, accurate and on-time projections of the GDP serve as critical inputs for policymakers. In contrast to the delay for the release of quarterly GDP data, many business cycle indicators are more timely and available at higher frequencies, such as the monthly industrial production, international trade volumes, survey data like PMI (the Purchasing Managers Index), and financial data that are published more frequently. Economists benefit from the availability of higher frequency data (monthly, weekly, and even daily) as they may nowcast the GDP with more precision by increasing the frequency of the information regarding the current state of the economic activity.

Previous literature provides alternative macroeconomic modeling approaches that can incorporate all the available information in a timely manner to produce early GDP forecasts. However, due to the nature of the high-frequency data, forecasters face challenges regarding mixed-data frequency and publication lags that require tailor-made solutions. For instance, indicators released asynchronously and having different publication lags lead to irregular patterns of missing values at the end of the sample, which is called as 'ragged-edge' problem of data (Wallis, 1986). As an example of the mixed-data frequency problem, GDP is released quarterly, whereas many predictors are sampled at monthly or higher frequencies. Given that, nowcast models that account for mixed-frequency and ragged-edge data have received substantial attention in the recent period.

Among the alternative nowcast approaches, a popular and easy to implement approach to forecast lower frequency variables using higher frequency indicators is the bridge equation models that aggregate higher frequency variables to balance dimension with lower frequency target variable (Barhoumi et al. (2008)). This single equation approach relies on linear regressions in which the dependent variables are generally GDP or its components at a quarterly frequency. The explanatory variables are, however, monthly indicators, aggregated (mostly averaged) at a quarterly frequency, that have the best predictive powers to nowcast those components. One caveat of the bridge equations is that although aggregation of the variables makes the implementation of the forecasting exercise easier, the aggregation of the high-frequency variables have the risk of losing information content of the high-frequency indicators.

Another modeling framework that can deal with such a mixed frequency data structure is the Mixed-data sampling (MIDAS) model. In the MIDAS regression, a low-frequency variable is regressed on a small number of higher-frequency variables using restricted lag polynomials (Ghysels et al. (2007), Andreou et al. (2010)). Similar to the bridge equations, this approach is also a single-equation approach, but in MIDAS, the aggregation bias is avoided. Pioneering works of Clements and Galvao (2008, 2009) adopted the MIDAS methodology to predict US quarterly GDP with monthly indicators. Additionally, Kuzin et al. (2011) and Ferrara and Marsilli (2013) utilize MIDAS models to predict the Euro area and French GDP, respectively.

The data-rich environment made the factor models utilizing information from large datasets become popular in the recent forecasting literature. The main contribution of the factor models is that information content from a large data set can be represented through a few factors providing important gains in terms of degrees of freedom. These factors are used as regressors in the forecasting equation instead of using a large number of indicators as explanatory variables in the model.

There is a steadily growing literature on nowcasting Turkish GDP using factor models and, more recently MIDAS approach. Among those, Modugno et al. (2016) nowcasts Turkish GDP employing dynamic factor models with a medium-scale mixed frequency dataset that includes 15 variables. They provide evidence that real variables contribute more to nowcasting GDP than the financial variables. Similarly, using a medium-scale dataset including 19 variables, Soybilgen and Yazgan (2018) nowcast the Turkish GDP and report that the information released after the nowcast horizon does not add to the predictive power. They also show that construction and service sector variables and credit indicators contribute to the accuracy of the nowcasts. To nowcast the annual Turkish GDP, Günay (2018) employs the MIDAS approach. Using industrial production and exchange rates at the monthly frequency and quarterly GDP, he provides evidence that adding exchange rate, a proxy for financial variables, in the dataset improves the nowcast efficiency, especially in the earlier periods of nowcasting. Another study using MIDAS in nowcasting Turkish GDP, Doğan and Midiliç (2019), uses a large dataset of financial variables, specifically 204 daily financial series. They report that financial variables possess information content for the GDP and daily financial indicators lead to an increase in the nowcast performance. Recently, Günay (2020a) examines the role of the functional form of the lag polynomial in estimating Turkish GDP using the MIDAS approach. He documents that although the lag polynomial matters in the nowcasting, there is no "one size fits all" kind of functional form that can be employed in every forecast horizon, lag lengths, and series. Finally, Günay (2020b) examines some practical questions regarding the nowcasts for Turkish GDP. His results suggest that filling the missing data, especially financial and survey data, using VARs leads to an increase in the forecast performance. Besides, he provides evidence that benefitting a large number of indicators using the factor model approach has higher performance than forecast combination, a method to pool forecasts.

A summary of the literature on nowcasting Turkish GDP provides several results. First, accounting for the mixed structure of the data improves the nowcast performance. Second, against the existence of abundant economic variables, a parsimonious approach generally performs better. Third, the performance of the nowcasts may differ over time depending on the varying performances of specifications, the choice of lag polynomial, and the lag structure of the explanatory variables. Finally, financial variables generally contribute to the nowcast performance.

The combination of factor estimation and the MIDAS methods gives the Factor MIDAS (FAMIDAS) approach, as introduced by Marcellino, and Schumacher (2010). In MIDAS methodology, mainly a low-frequency target variable regressed on a set of higher-frequency indicators. In contrast, in the Factor MIDAS approach target variable regressed on estimated factors rather than a small groups of economic indicators. In other words, in the standard MIDAS approach, economic variables at a higher frequency are used as regressors, while in the Factor MIDAS approach the explanatory variables are estimated factors.

Given that factors are extracted from a balanced dataset, there are alternative factor estimation methods in the literature. Two popular approaches utilized by practitioners are static principal component analysis (PCA), which is described in Stock and Watson (2002), and dynamic principal component analysis (DPCA) introduced by Forni et al. (2005). However, as discussed above, typically, the real data structure is unbalanced due to the 'ragged-edge' problem. Therefore, factor estimation methods that take proper account of these data irregularities are required.

In this paper, we follow the methodology of the Marcellino and Schumacher (2010)[1] to estimate the factor-augmented MIDAS model that includes factor estimation with alternative methods to deal with the ragged-edge data.[2] First, to have a balanced dataset a simple realignment method offered by Altissimo et al. (2006) is employed with the dynamic principal component analysis (DPCA) factor estimator of Forni et al. (2005). Alternatively, the combination of expectation-maximization (EM) algorithm and static principal

[1] Examples for forecasting studies that estimate the factor-augmented MIDAS model following the framework of Marcellino and Schumacher (2010) are Ferrara and Marsilli (2019) for global growth, Kurz-Kim (2019) for Euro area GDP, den Reijer and Johansson (2018) for Swedish GDP, Kim and Swanson for Korean GDP, Jansen et al. (2016) for five Euro area countries, and Foroni and Marcellino (2014) for Euro area GDP.

[2] We use the Matlab codes used in Marcellino and Schumacher (2010) provided by Christian Schumacher.

component analysis (PCA) factor estimator of Stock and Watson (2002) is adopted. Finally, the two-step parametric state-space factor estimator based on the Kalman smoother of Doz et al. (2006) is utilized. After the factor extraction step, we use the estimated factors as high-frequency regressors in the alternative MIDAS models. We then compare the forecasts of these alternative MIDAS models with the benchmark estimations in nowcasting Turkish GDP.

Recursive pseudo-out-of sample forecasting exercise in evaluating the alternative models' performance provides several important results. First, taking into account the ragged-edge data provides gains in the predictive ability of the nowcast models. Second, factor-MIDAS specifications perform better than the simple benchmark models, especially for nowcasting. However, they do not provide so much additional information in the forecast period that makes the factor-MIDAS models practical as only nowcasting tools. Third, the dynamic factor estimation method is found to demonstrate better nowcasting performance than the static factor estimation method.

The paper proceeds as follows. Section 2 briefly describes the dataset, while Section 3 provides detailed information about methodological aspects of factor estimation approaches with ragged-edge data structure and alternative MIDAS specifications. Section 4 presents the design of the forecast comparison framework and compares the empirical results of the alternative models. Finally, Section 5 summarizes and concludes.

II. Data

The dataset contains Turkish quarterly GDP growth from 2005Q2 until 2020Q1 and 40 monthly indicators from 2005M2 until 2020M5. It includes indicators from industrial production, car sales, real domestic turnover in the industry, foreign trade quantity indices, electricity production, domestic sales of white goods, transaction volume in credit and debit cards, tax revenues and government spending. Additionally, variables regarding global risk perception indicators and credit growth rates are included (Table A1).

Our approach in selecting variables for nowcasting Turkish GDP follows Günay (2020b) that we use common indicators employed in the previous forecasting literature. Specifically, we aim to include indicators from different dimensions of economic activity such as industrial production, private consumption, foreign trade, and public finance. These variables are known to have a high correlation with GDP. While composing the dataset, we have considered the parsimony principle; thus, we kept the number of variables restricted. Besides, following the previous evidence in the literature that financial variables contribute to the nowcast performance, we include the financial variables in the dataset.

The series are transformed to ensure stationarity and required seasonal adjustments are made. The dataset is final dataset and does not contain vintages of data, as they are not available for Turkey. To be able to take ragged-edge data structure into consideration, we follow the approach adopted by Banbura and Rünstler (2007). We take the data availability structure at the end of the sample and assume that such pattern remained the same for all recursions. More details about the publication scheme and a stylized example for data availability of these variables are provided in Table A2.

III. Methodology

As mentioned in the previous section, for the first time Clements and Galvao (2008, 2009) utilized MIDAS approach for macroeconomic forecasting. After that, Marcellino and Schumacher (2010) developed the factor-MIDAS approach combining MIDAS approach with factor models to forecast lower variable (GDP), via utilizing information from a large set of higher-frequency indicators.[3] To be able to account for unbalanced datasets, they utilize three alternative factor estimation methods. Moreover, to control for the effects of the alternative MIDAS specifications they use three different MIDAS approaches as basic, smoothed and unrestricted. To compare the forecast performance of Factor-MIDAS the authors take single-frequency factor model based on quarterly aggregated data as benchmark.

Following the very similar methodology of Marcellino and Schumacher (2010), in our framework consisting large data set and aiming factor forecasting; we follow the two-step procedure similar to Boivin and Ng (2005). Firstly, we estimate factors, and then construct a dynamic model for the predicted variable employing estimated factors. It should be noted that two important issues are dealt with throughout this forecasting exercise as it is done by Marcellino and Schumacher (2010). Firstly, the ragged-edge pattern exists in the data set due to different publication lags while estimating factors should be dealt with. Secondly, after factor estimation, the frequency difference between monthly estimated factors and quarterly GDP data should be addressed via alternative MIDAS models to be able to produce forecasts.

III.I. Factor Estimation with Ragged-Ends

In a general form, the static factor model representation for monthly observations can be written as follows:

$$X_{tm} = \Delta F_{tm} + \varepsilon_{tm} \quad (1)$$

[3] This section is heavily based on Marcellino and Schumacher (2010).

where $\boldsymbol{X_{tm}}$ represents $NX1$ vector of stationary variables and $\boldsymbol{F_{tm}}$ stands for the $rX1$ factor vector. Common components of each variable are defined as the factor times the NXr factor loading matrix, Δ, where $r < N$. The part of X_{tm} not explained by the factors is represented by the idiosyncratic components, ε_{tm}.

We estimate factors through two alternative approaches: static PCA as in Stock and Watson (2002) and dynamic PCA (DPCA) according to Forni et al. (2005). However, we need a balanced dataset to estimate factors via PCA or DPCA. In case of ragged edge data type due to different publication lags, we utilize three alternative ways to deal with this issue and make data balanced as Vertical Alignment (VA), EM algorithm (EM) and Kalman filter state space modelling (KFS).

i. Vertical Alignment (VA-DPCA)

Altissimo et al. (2010) propose a practical way to solve the ragged-edge problem. The main aim of the approach is the realignment of each time series and directly balancing unbalanced datasets. Assuming that the publication lag for a variable *j* is k_j months, the final available observation for the variable *j* in period T_m would be $T_m - k_j$. Altissimo et al. (2010) employ the following realignment process

$$\tilde{X}_{j,t_m} = X_{j,t_m - k_j} \tag{2}$$

for $t_m = k_j + 1, k_j + 2, \dots, T_m$. To compose a balanced dataset $\tilde{X}_{t_m}$ for $t_m = max\left(\{k_j\}_{j=1}^{N}\right) + 1, \dots., T_m)$, we apply (2) to all indicators and harmonize the series at the beginning period.

Then, as the dataset is balanced, the two-step estimation techniques by Forni et al. (2005) can be directly used. The combination of vertical realignment and dynamic principal components factors can be called as "VA-DPCA".[4] While vertical realignment is a very convenient approach to solve ragged-edge problem, it has a limitation that the availability of data affects dynamic correlations, thus factors can change over time.

ii. Expectation Maximization (EM-PCA)

The EM algorithm to account for the missing values in the data for the estimation of factors using PCA is suggested by Stock and Watson (2002). This approach first provides an estimate of the missing observation that is generally taken as the unconditional mean. Once the dataset is balanced, PCA can be used to estimate the factors. The EM algorithm mainly includes two steps, the E-step and the M-step. The E-step updates the estimates of the

[4] Throughout the paper, we follow the terminology of Marcellino and Schumacher (2010) in denoting the methods to solve the ragged-edge problem.

missing observations using the expectation of the associate variable using estimated loadings and factors. The M-step involves re-estimating the factors and loadings using ordinary PCA and returning to the E-step until a convergence is achieved. Following the convergence, the EM algorithm generates monthly factor estimates of the missing observations. In sum, both the interpolation of missing observations and the factor estimations is handled within the factor estimation framework using the factors generated with PCA. In our study, the EM algorithm approach is denoted as "EM-PCA", in line with the denotations of Marcellino and Schumacher (2010).

iii. Kalman Filter State-Space (KFS-PCA)

Following Doz et al. (2006), the state-space approach involves a complete representation of the large factor model in state-space form. The model consists of a general factor structure and an autoregressive model for the factors. Full state-space model may be represented by the static factor representation of X_{tm} as in Equation (1) and a VAR of the factors with lag polynomial $\psi(L_m) = \Sigma_{i=1}^{p} \psi_i L_m^i$ as the following:

$$\psi(L_m) F_{tm} = A n_{tm} \tag{3}$$

where n_{tm} is an orthogonal dynamic shock.

Maximum likelihood (ML) method can be used to estimate the state space modes, especially if the dataset is small. In contrast, quasi-ML methods can be preferred if the dataset is large as in Doz et al. (2006). The estimation of factors is made using the Kalman filter. One advantage of this approach to the EM algorithm is that it explicitly takes the dynamics of the factors into account. Again, similar to the Marcellino and Schumacher (2010), we denote the state-space model Kalman filter estimator of the factors as "KFS-PCA".

III.II. Nowcasting and forecasting quarterly GDP with Factor-MIDAS

Mixed-data sampling (MIDAS) approach, previously applied by Ghysels and Valkanov (2006), Clements and Galvao (2007), and Marcellino and Schumacher (2010), is a practical tool to forecast low-frequency indicators, such as quarterly GDP, using the high-frequency indicators, namely the estimated monthly factors in our study. In this section, we briefly summarize the three MIDAS methods: basic Factor-MIDAS approach, Smoothed MIDAS and the Unrestricted MIDAS.

i. The basic Factor-MIDAS approach

Introduced by Marcellino and Schumacher (2010), Factor-MIDAS approach uses the factors estimated from high-frequency indicators as explanatory variables different from the standard MIDAS approach in which the high-frequency indicators are the explanatory variables. Assume that y_{t_q} is sampled at a quarterly frequency, such as the GDP, and X_{t_m} is sampled at a monthly frequency, we can formulate the basic Factor-MIDAS model for forecast horizon h_{q} quarters with h_{q} =$h_{\mathrm{m}}/3$ as follows:

$$y_{t_q+h_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b(L_m, \theta)\hat{f}^{(3)}_{t_m+w} + \varepsilon_{t_m+h_m} \tag{4}$$

where $b(L_m, \theta) = \sum_{k=0}^{K} c(k, \theta) L_m^k$ is the exponential Almon lag,

$c(k, \theta) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=0}^{K} \exp(\theta_1 k + \theta_2 k^2)}$ and $\theta = (\theta_1, \theta_2)$.

In this framework, $\hat{\mathrm{f}}_{\mathrm{t_{m+w}}}$ represents the monthly factors that are estimated using one of the methods discussed before. $\hat{f}^{(3)}_{t_m+w}$ includes every third observation beginning from the final one. Accordingly, one can describe this regressor as $\hat{f}^{(3)}_j = \hat{\mathrm{f}}_j\ \forall \mathrm{j} = 3 + w, 6 + w, \dots, , T_{\mathrm{m}-3} + w, T_{\mathrm{m}} + w$. The same approach is also valid for the lags of the monthly factors.

The final quarter observation of GDP is observed in month T_{m} where T_{q} =$T_{\mathrm{m}}/3$. In this respect, the up-to-date information extracted in factor estimation is employed in equation (4). Nonlinear least squares (NLS) can be used to estimate θ through regressing y_{t_m} on $\hat{f}^{(3)}_{t_{m+w-h_m}}$ and its lags. Coefficient estimations such as $\hat{\theta}_1$, $\hat{\theta}_2$, $\hat{\beta}_0$ and $\hat{\beta}_1$ are obtained from the NLS results.

Clements and Galvao (2008) incorporate an autoregressive (AR) term into the baseline MIDAS specification. By accounting the dynamic structure more properly, this extension may help handle the possible autocorrelation in the idiosyncratic components. MIDAS models with autoregressive (AR) terms, is in the following form:

$$y_{t_m+h_m} = \beta_0 + \lambda y_{t_m} + \sum_{i=1}^{r} \beta_{1,i} b_i(L_m, \theta_i)(1 - \lambda L_m^3)\hat{f}^{(3)}_{i,t_{m+w}} + \varepsilon_{t_m+h_m} \tag{5}$$

where NLS can be used to estimate the AR coefficient λ with all the other variables.

ii. Smoothed MIDAS

A second mixed-frequency approach is the one Altissimo et al. (2006) use to develop the New Eurocoin Index that is a real time economic activity indicator for the Euro area. In essence, this approach involves projecting the smoothed GDP on monthly factors. h_{m} step forecasts in the smoothed MIDAS approach can be presented as:

$$y_{t_m+h_m|T_m+w} = \hat{\mu} + G\hat{F}_{t_{m+w}} \tag{6}$$

$$G = \tilde{\Sigma}_{yF(hm-w)}\ x\ \hat{\Sigma}_F^{-1} \tag{7}$$

where $\hat{\mu}$ represents the sample mean of the GDP growth, given the factors have zero-mean. G stands for a projection coefficient matrix. The estimated sample covariance of the factors is indicated by $\hat{\Sigma}_F$ whereas the k monthly lagged cross-covariances between the factors and GDP growth is represented by $\tilde{\Sigma}_{yF(k)}$. It can also be noticed that smoothed MIDAS can be deduced from the basic MIDAS model presented in Equation (4) using a different lag structure. In line with Marcellino and Schumacher (2010), we denote this MIDAS approach as "MIDAS- smooth".

iii. Unrestricted MIDAS

An alternative method to the basic MIDAS model that involves a polynomial distributed lag function is the unrestricted MIDAS model that relies on an unrestricted lag polynomial of order k, $(L_m) = \sum_{j=0}^{k} D_j\, L_m^j$, as the following:

$$y_{t_m+h_m} = \beta_0 + D(L_m)\hat{f}_{t_{m+w}}^{(3)} + \varepsilon_{t_m+h_m} \tag{8}$$

The parameters of the model can be estimated using the OLS. In practice, lag specification can be chosen following Bayesian Information criteria and a fixed scheme with k=0. The unrestricted MIDAS with k=0, one of the simplest forms of MIDAS, can be used as a benchmark against the other alternative MIDAS models presented before. Following the notations of Marcellino and Schumacher (2010), we denote the unrestricted MIDAS with k = 0 as 'MIDAS-U0', and with estimated lag order by BIC as "MIDAS-U".

IV. Empirical Results

We conduct recursive pseudo-out-of-sample forecasting exercise to evaluate the forecast performance of the alternative models. The estimation sample is between 2005Q2 to 2014Q4 and recursively expanded over time. We obtain nowcasts and short-term forecasts for 2014Q4-2020Q1 for a total of 22 quarters via taking into account related monthly information sets. We present six projections (three nowcast and three forecast) for each GDP observation of the evaluation period based on available information set. In particular, for the initial evaluation period 2014Q4, we want to compute nowcasts in December 2014, November, and October, while the one quarter ahead forecasts are computed from September 2014 backwards.

Following Marcellino and Schumacher (2010), to compare the nowcasts with the realizations of GDP growth, we use the relative mean-squared error (MSE) to GDP variance, where the variance is computed over the evaluation period. If the values of the relative MSE to GDP variance is less than one, it implies that the forecast of a model for the chosen forecast period have some leading information content for GDP. It should be noted that this relative statistic can also be interpreted as a benchmark corresponding MSE of the out-of-sample mean of GDP as a naive forecast (Marcellino and Schumacher (2010)).

We compare MSEs relative to the GDP growth variance for alternative specifications. In terms of monthly horizons, horizons 1 to 3 refer to the nowcasts while 4 to 6 addressing forecasts for 1 quarter ahead. For example, horizon 1 is the nowcast made in the third month of the current quarter, whereas horizon 2 is the nowcast made in the second month of the current quarter and goes on.

Within this framework, we present empirical findings for nowcasting and forecasting of Turkish GDP. First of all, we give a comparison of the performances of alternative factor estimation methods in the next subsection. Then, a comparison of the predictive power of alternative Factor MIDAS specifications is presented. Next, the related subsection compares the monthly nowcast models with quarterly benchmark factor models. The final subsection evaluates the performances of the static and dynamic factor estimation methods.

IV.I. Comparison of factor estimation methods

As the relative MSEs of most of the combinations of factor estimation and projection methods have values less than one, the model projections have information content for the nowcast (Table 1). We first observe that there is not a clear pattern of declining MSEs over the forecast horizon. The findings seems puzzling given that the information content expands each month with new data releases. Marcellino and Schumacher (2010) also report similar findings and explain the results with relatively short sample and the higher uncertainty associated with it.

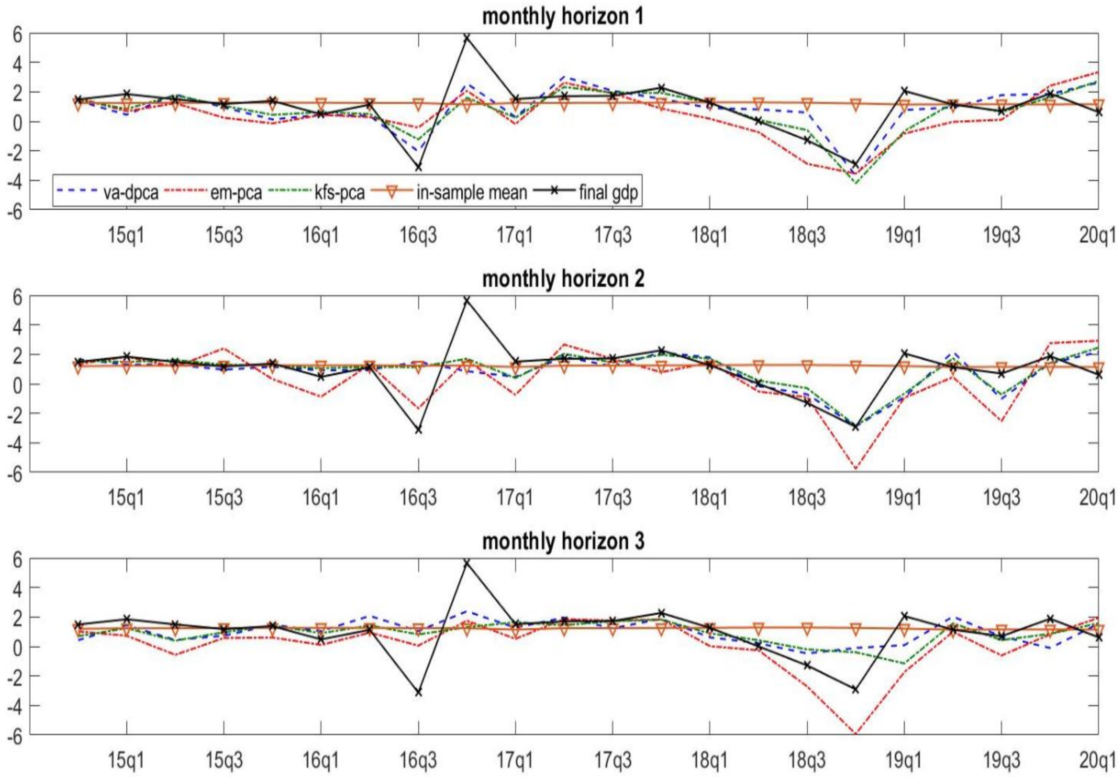
Comparing the forecast performance of factor estimation methods for the one-quarter, the results are not clear as some relative MSEs are larger than one for some horizons and smaller for others. This indicates that the methods employed here can be regarded as suited mainly for nowcasting.

Table 1. Comparison of Nowcast and Forecast Results for Different Factor Estimation Methods
(Mean-squared error (MSE) relative to GDP variance)

		Nowcast			Forecast		
		Current Quarter			1 Quarter Ahead		
	Monthly Horizon	***1***	***2***	***3***	***4***	***5***	***6***
MIDAS-basic	**VA-DPCA**	0.46	0.93	0.76	1.42	1.03	1.06
	EM_PCA	0.80	0.98	0.97	0.96	1.42	0.99
	KFS_PCA	0.58	0.75	0.86	1.13	1.09	0.99
MIDAS-U	**VA-DPCA**	0.52	0.75	0.71	1.49	1.04	1.07
	EM_PCA	0.58	1.02	0.75	1.21	1.50	1.00
	KFS_PCA	0.64	0.87	0.69	0.92	1.06	1.02
MIDAS-Smooth	**VA-DPCA**	0.78	1.02	0.85	1.47	1.00	1.05
	EM_PCA	1.16	0.67	0.75	0.75	1.30	1.07
	KFS_PCA	0.98	0.78	0.98	0.95	1.06	1.02
MIDAS-U0	**VA-DPCA**	0.68	1.14	0.70	1.32	1.02	1.05
	EM_PCA	1.11	0.71	0.78	0.81	1.36	0.99
	KFS_PCA	1.00	0.65	1.05	0.91	1.07	1.02

In the rankings of nowcast performance, there are no systematic differences in nowcasting performance between factor estimation by VA-DPCA and KFS-PCA, as the relative MSE rankings change depending on the nowcast and forecast horizons. On the other hand, EM-PCA factors show relatively poor performance compared to others. The results in Figure 1 show that the factor models perform clearly better than the simple benchmark. Therefore, in line with the similar MSE findings before and the findings of Marcellino and Schumacher (2010), we find no clear indications of dramatic differences between the nowcast accuracy of the three-factor models over time.

Figure 1. Nowcasts with MIDAS-U0 and Different Factor Estimation Methods



Note: The figure shows nowcasts for the different factor estimation methods and the in-sample mean as a benchmark.

IV.II. Comparison of MIDAS projection types

We now compare the different MIDAS projections for each factor estimation method. Similar to the findings of Marcellino and Schumacher (2010) for German GDP and recently Ferrara and Marsilli (2019) for global growth and Kim and Swanson (2018) for Korean GDP, our results suggest that factor MIDAS models can improve the forecast performance with respect to the benchmark forecasts. Results also indicate that the differences between the MIDAS approaches are not big as all approaches lead to nowcasts that have information content for current GDP growth, and some combinations of EM_PCA and KFS_PCA factor estimations with MIDAS projection also have some predictive ability for the next quarter (Table 2).

Table 2. Comparison of Nowcast and Forecast Results from Different MIDAS Projections
(Mean-squared error (MSE) relative to GDP variance)

		Nowcast			Forecast		
		Current Quarter			1 Quarter Ahead		
	Monthly Horizon	***1***	***2***	***3***	***4***	***5***	***6***
VA-DPCA	**MIDAS-basic**	0.46	0.93	0.76	1.42	1.03	1.06
	MIDAS-U	0.52	0.75	0.71	1.49	1.04	1.07
	MIDAS-Smooth	0.78	1.02	0.85	1.47	1.00	1.05
	MIDAS-U0	0.68	1.14	0.70	1.32	1.02	1.05
EM_PCA	**MIDAS-basic**	0.80	0.98	0.97	0.96	1.42	0.99
	MIDAS-U	0.58	1.02	0.75	1.21	1.50	1.00
	MIDAS-Smooth	1.16	0.67	0.75	0.75	1.30	1.07
	MIDAS-U0	1.11	0.71	0.78	0.81	1.36	0.99
KFS_PCA	**MIDAS-basic**	0.58	0.75	0.86	1.13	1.09	0.99
	MIDAS-U	0.64	0.87	0.69	0.92	1.06	1.02
	MIDAS-Smooth	0.98	0.78	0.98	0.95	1.06	1.02
	MIDAS-U0	1.00	0.65	1.05	0.91	1.07	1.02

Comparing the methods, we see that the difference between MIDAS-basic based on exponential lags and MIDAS-U is not clear-cut, as none of them outperforms the other across all factor estimation methods and horizons. However, these two methods perform relatively better than other MIDAS specifications. Our findings are in line with that of the Marcellino and Schumacher (2010) that the basic, or the most parsimonious, MIDAS models perform better than the other MIDAS specifications.

In Table 3, the MIDAS-AR is compared with the basic MIDAS specification without AR terms. The results in Table 3 show that considering AR terms does not improve the nowcast and forecast performances systematically, as in Marcellino and Schumacher (2010) for nowcasting German GDP, Kim and Swanson (2018) for nowcasting Korean GDP. For different horizons and different factor estimation methods, the ranking between MIDAS-AR and MIDAS-basic changes.

Table 3. Comparison of MIDAS-AR and MIDAS-basic
(Mean-squared error (MSE) relative to GDP variance)

		Nowcast			Forecast		
		Current Quarter			1 Quarter Ahead		
	Monthly Horizon	***1***	***2***	***3***	***4***	***5***	***6***
VA-DPCA	**MIDAS-AR**	0.47	0.93	0.85	1.36	1.11	1.10
	MIDAS-basic	0.46	0.93	0.76	1.42	1.03	1.06
EM_PCA	**MIDAS-AR**	0.88	1.12	1.04	1.00	1.40	1.08
	MIDAS-basic	0.80	0.98	0.97	0.96	1.42	0.99
KFS_PCA	**MIDAS-AR**	0.52	0.88	0.85	1.15	1.07	1.09
	MIDAS-basic	0.58	0.75	0.86	1.13	1.09	0.99

IV.III. Comparison of mixed frequency and single frequency factor models

Alternatively, to obtain a balanced sample of data the standard techniques of factor forecasting with single-frequency data can be employed. As GDP data published on a quarterly basis, we will also compare the mixed-frequency factor models with the quarterly factor models.

Table 4. Comparison of Mixed-frequency Models with Quarterly Factor and Benchmark Models
(Mean-squared error (MSE) relative to GDP variance)

		Nowcast			Forecast		
		Current Quarter			1 Quarter Ahead		
	Monthly Horizon	***1***	***2***	***3***	***4***	***5***	***6***
MIDAS-basic	**VA-DPCA**	0.46	0.93	0.76	1.42	1.03	1.06
	EM-PCA	0.80	0.98	0.97	0.96	1.42	0.99
	KFS-PCA	0.58	0.75	0.86	1.13	1.09	0.99
Quarterly Factor Models	**PCA-BIC, r=1**	1.10	1.03	1.03	1.03	1.02	1.02
	PCA-BIC, r=2	1.00	1.04	1.04	1.04	1.04	1.04
	PCA-BIC	1.10	1.03	1.03	1.03	1.02	1.02
Benchmarks	**AR**	1.13	1.06	1.06	1.06	1.09	1.09
	In-sample mean	1.03	1.03	1.03	1.03	1.03	1.03

*The first two specifications of quarterly factor model are based on a fixed number of factors and the number of lags is chosen by BIC, while PCA-BIC selects the number of factors as well as the lag orders using BIC as in Stock and Watson (2002).

As representatives of the nowcast models, we present results based on MIDAS-basic and the three different ragged-edge factor estimation methods. In the empirical nowcast comparison, the simple benchmarks show poor performance, as can be seen from the bottom rows of Table 4. Both the AR model and the in-sample mean have relative MSEs larger than one.

Thus, according to these results, taking into account ragged-edge information as in the nowcast models with monthly indicators can improve the current estimate of GDP growth. As the use of time-aggregated data implies a loss of information at the end of the sample, the results imply that the nowcast methods employed here can to some extent exploit this information. In summary, we can confirm that in general it is advisable to employ the ragged-edge data together with the different factor estimation techniques especially for nowcasting.

IV.IV. Comparison of static and dynamic factor models

In general, there is no consensus in the literature concerning the appropriate factor estimation method to be employed for forecasting (Marcellino & Schumacher (2010)). In the previous subsections, dynamic principal component analysis was employed to estimate the factors together with the vertical alignment methodology which is denoted as VA-DPCA. To see the effects of the static factor methodology against dynamic approach, we compare the existing figures using VA-DPCA with those resulting from static PCA and vertical realignment of the data, which can be denoted as VA-PCA.

Table 5. Comparison of Static PCA and Dynamic PCA
(Mean-squared error (MSE) relative to GDP variance)

		Nowcast			Forecast		
		Current Quarter			1 Quarter Ahead		
	Monthly Horizon	***1***	***2***	***3***	***4***	***5***	***6***
MIDAS-basic	**VA-DPCA**	0.460	0.933	0.761	1.419	1.029	1.056
	VA_PCA	0.476	0.956	0.812	1.470	1.028	1.058
MIDAS-U	**VA-DPCA**	0.516	0.747	0.713	1.488	1.037	1.073
	VA_PCA	0.541	0.771	1.027	1.559	1.053	1.076
MIDAS-Smooth	**VA-DPCA**	0.780	1.021	0.850	1.468	1.000	1.052
	VA_PCA	0.805	1.034	0.889	1.507	0.983	1.055
MIDAS-U0	**VA-DPCA**	0.680	1.139	0.696	1.325	1.018	1.047
	VA_PCA	0.706	1.157	0.749	1.360	1.032	1.050
Relative MSE: DPCA/PCA	**MIDAS-basic**	0.970	0.980	0.940	0.970	1.000	1.000
	MIDAS-U	0.950	0.970	0.690	0.950	0.980	1.000
	MIDAS-Smooth	0.970	0.990	0.960	0.970	1.020	1.000
	MIDAS-U0	0.960	0.980	0.930	0.970	0.990	1.000

Table 5 shows that the information content of the nowcasts and forecasts improves if the factors are estimated by DPCA instead of PCA. Moreover, Table 5 shows relative MSE defined as the MSE obtained from using DPCA factors divided by the MSE obtained from using static PCA factors for forecasting as well. The results show systematic advantages over the horizons between the dynamic and static factor estimation methods.

V. Conclusion

Given the publication delays in GDP, policymakers rely on nowcast models that account for all the available information to have a clear and early understanding of the current state of the economic activity. These models mainly use high-frequency indicators such as industrial production, international trade volumes, etc. to forecast the low-frequency variable, which is the GDP in our analysis. However, practitioners generally face problems such as the mixed-data frequency and the ragged-edge data. In this study, we apply the recent factor-augmented MIDAS methods, introduced by Marcellino, and Schumacher (2010), that accounts for these problems in nowcasting the Turkish GDP. We estimate several combinations of the model with alternative factor estimation and MIDAS approaches. Then, we evaluate the predictive performance of the alternative models by a recursive pseudo-out-of-sample forecasting exercise.

The results of our study can be summarized as follows. First, we do not observe a clear pattern of declining MSEs over the forecast horizon. Second, factor-augmented MIDAS models provide better predictive performance than the naive benchmark model. However, the performance gains are only valid for the nowcasting. Alternative combinations of the factor-augmented MIDAS model fails to add information content for a quarter-ahead forecast. Thus, the approach is more practical as a nowcasting tool in the Turkish case. Third, taking into account the indicators' ragged edge characteristics can improve the nowcasts of the GDP. Results suggest that there is no significant difference between the three methods to deal with the ragged-edge data problem, namely Vertical Alignment (VA), Expectation maximization (EM) and the Kalman Smoothing (KFS). In this way, there is no suggestive evidence that there are apparent differences between their forecast ability of three alternative factor extraction methods. Fourth, regarding the relative performance of four different MIDAS methods, we do not observe significant differences between the MIDAS-U and MIDAS-basic. In comparison, both of the two methods have better predictive ability than MIDAS-Smooth and MIDAS-U0. Fifth, adding an autoregressive term in the

MIDAS-basic does not improve the performance. Finally, using dynamic factor estimation methods systematically provides better performance than using static factor estimation methods.

A key policy implication of these findings is that both ragged-edge data and the mixed-data frequency should be taken into account while nowcasting the GDP. This increases the predictive ability of the nowcasts that helps policymakers to monitor the current state of the economy accurately. Besides, factor-augmented MIDAS appears to be a competitive method that may be included in the toolbox of the forecasters interested in nowcasting Turkish GDP.

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APPENDICES

Table A1: Indicators Used for Factor Extraction in Utilized Data Set

Sub-Dimensions	Description of Utilized Data	Conversion Method
Industrial Production	Total Intermediate Durable Consumption Nondurable Consumption Energy Capital	Log difference is taken.
Car Sales	Total	Log difference is taken.
Import Quantity Index	Total Capital Durable Consumption Semidurable Consumption Nondurable Consumption Intermediate Intermediate Goods (excluding gold)	Log difference is taken.
Export Quantity Index	Total Capital Durable Consumption Semidurable Consumption Nondurable Consumption Intermediate Intermediate Goods (excluding gold)	Log difference is taken.
Electricity	Electricity Production	Log difference is taken.
White Goods	Domestic Sales	Log difference is taken.
Real Domestic Turnover in the Industry	Total Capital Durable Consumption Semidurable Consumption Nondurable Consumption Intermediate Intermediate Goods (excluding gold)	Log difference is taken.
ETTE	Total	Log difference is taken.
Tax Revenues	Total	Log difference is taken.
Government Spending	Total	Log difference is taken.
Financial and Credit	VIX CDS Total Credit Growth Firm Credit Growth (Adjusted for Exchange Rate) Consumer-Housing Credit Growth Consumer- Vehicle Credit Growth	For VIX and CDS, level is taken. For credit growth indicators, log difference is taken.

Table A2: Example Data Scheme of Utilized Data Set

	Data Structure at the end of June		
	April	May	June
Industrial Production			
Car Sales			
Import Quantity Index			
Export Quantity Index			
Electricity			
White Goods			
Real Domestic Turnover in the Industry			
ETTE			
Tax Revenue			
Government Spending			
Financial and Credit			

	Available Data
	Imputed Data
*Last available GDP Q1	

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