Economics Bulletin

Volume 38, Issue 2

Nowcasting the New Turkish GDP

Barış Soybilgen
İstanbul Bilgi University

Ege Yazgan
İstanbul Bilgi University

Abstract

In this study, we predict year-on-year and quarter-on-quarter Turkish GDP growth rates between 2012:Q1 and 2016:Q4 with a medium-scale dataset. Our proposed model outperforms both the competing dynamic factor model (DFM) and univariate benchmark models. Our results suggest that in nowcasting current GDP, all relevant information is released within the contemporaneous quarter; hence, no predictive power is added afterwards. Moreover, we show that the inclusion of construction/service sector variables and credit variables improves the prediction accuracy of the DFM.

Citation: Barış Soybilgen and Ege Yazgan, (2018) "Nowcasting the New Turkish GDP", *Economics Bulletin*, Volume 38, Issue 2, pages 1083-1089
Contact: Barış Soybilgen - baris.soybilgen@bilgi.edu.tr, Ege Yazgan - ege.yazgan@bilgi.edu.tr.
Submitted: June 05, 2017. **Published:** May 25, 2018.

1 Introduction

Turkish Gross Domestic Product (GDP) data are typically released with two quarters of delay from the beginning of the reference period. This considerable delay demands advanced flash estimates of Turkish GDP to serve policy makers and economic analysts who have to assess the current economic situation. For this purpose, Modugno et al. (2016) proposed a dynamic factor model (DFM) to nowcast real Turkish GDP growth rates. The nowcasts of Turkish GDP generated by this model have been made public at www.nowcastturkey.com and are continuously updated whenever new information becomes available, beginning from the second quarter of 2014 onward.[1] At the end of 2016, Turkish GDP was revised substantially (see Figure 1). This serious revision in GDP casts doubts on whether the DFM of Modugno et al. (2016) still accurately predicts GDP.

In this paper, we reconsider the DFM of Modugno et al. (2016) using the revised GDP series. We enrich the dataset to account for the complex dynamics underlying new Turkish GDP figures. Furthermore, we use the equal weighted averages of predictions produced by DFMs with various specifications to obtain final nowcasts instead of determining the optimal number of factors and lags using information criteria.

Using a medium-scale dataset including 19 variables, we predict non-seasonally adjusted (NSA) year-on-year (YoY) and seasonally adjusted (SA) quarter-on-quarter (QoQ) GDP growth rates between 2012:Q1 and 2016:Q4. The results show that adding commercial and consumer credit growth rates substantially increases the prediction power of the model when predicting NSA YoY GDP growth rates. Furthermore, variables related with the construction and service sector improves the performance of the DFM when nowcasting SA QoQ GDP growth rates. Using these new variables, the model performs significantly better than the model of Modugno et al. (2016).

The remainder of this paper proceeds as follows. Section 2 presents the model. Section 3 examines the dataset. Section 4 shows the results of nowcasting exercises, and section 5 concludes.

2 The model

We use a DFM to produce nowcasts of both SA QoQ and NSA YoY GDP growth rates. Our DFM has the following representation:

$$x_t = \Lambda f_t + \epsilon_t; \tag{1}$$

where $x_t = (x_{1,t}, \ldots, x_{n,t})$, $t = 1, \ldots, T$ denote n monthly series standardized to zero mean and unit variance. Λ is an nxr vector containing factor loadings for monthly variables; $\epsilon_t = (\epsilon_{i,t}, \ldots, \epsilon_{n,t})$ are the idiosyncratic components of monthly variables modeled as an

[1] The accuracy of the nowcasts produced by www.nowcastturkey.com is also provided by the website and evaluated by Soybilgen and Yazgan (2016).

autoregressive process of order one; and f_t is an rx1 vector of unobserved common factors which is modeled as a stationary vector autoregression process:

$$f_t = \varphi(L) f_{t-1} + \eta_t; \quad \eta_t \sim i.i.d. \, \mathcal{N}(0, R), \tag{2}$$

where $\varphi(L)$ is an rxr lag polynomial matrix and η_t is an rx1 vector of innovations. In order to incorporate quarterly variables into the model, we use the approximation of Mariano and Murasawa (2003) for nowcasting SA QoQ growth rates and we follow the approximation of Giannone et al. (2013) for nowcasting NSA YoY growth rates.

There are various procedures to estimate a DFM. We choose the most appropriate one for our dataset. Our dataset has both short time span and numerous missing observations mainly because Turkish statistical institutions have recently begun to collect many macroeconomic indicators. Therefore, we use a modified version of the expectation maximization algorithm for maximum likelihood estimation proposed by Bańbura and Modugno (2014)[2] as this procedure is more efficient in small samples compared to the competing estimation ones such as Giannone et al. (2008) and can easily deal with arbitrary pattern of data availability.

3 The dataset

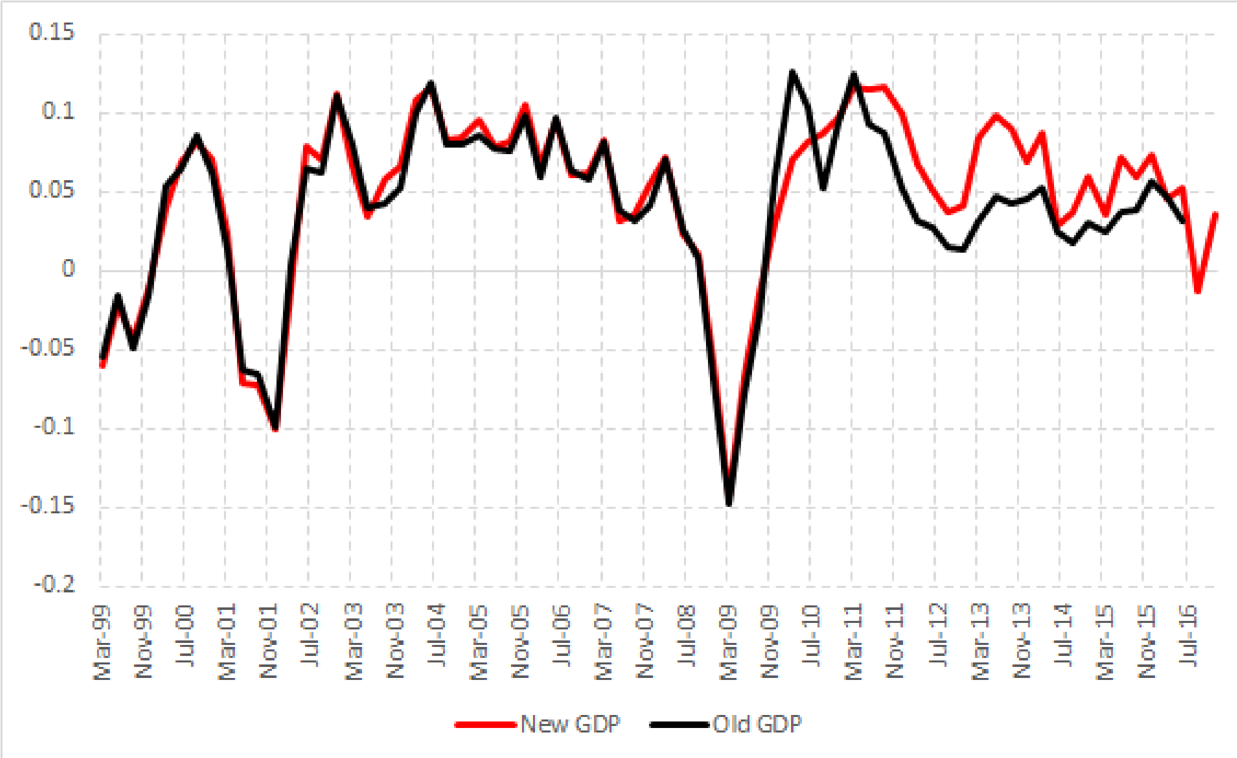
Figure 1 displays the evolution of the NSA YoY real GDP growth rates of both the new and old Turkey GDP growth rates.[3] Figure 1 clearly shows that the old and new GDP growth rates have similar patterns until the end of 2009. However, they discernibly depart from each other from then on, and acquire different features since the beginning of 2010. The primary reason for this substantial difference is claimed to be that the old series mainly rely on sectoral surveys, whereas the new figures depend on administrative data. Because administrative data are only available from the beginning of 2010, the new and old GDP series use the same sectoral surveys until 2010. After 2010, however, the old series continues to rely on sectoral surveys, whereas new GDP data employ administrative data. The Turkish statistical institute (Turkstat) suggests that the new administrative data track construction and service sectors (Co & Se) better than the old GDP series.

Our dataset is mainly based on Modugno et al. (2016). However, we add four new variables to capture the dynamics in the construction and service sectors. These new variables are home sales, retail sales volume index, consumer credits, and commercial credits. In total, the dataset includes 18 public economic indicators to nowcast GDP. We group the indicators as real variables, survey variables, financial variables, service and construction sector variables, and credit variables.

We predict both NSA YoY and SA QoQ GDP growth rates. To obtain stationary variables, we compute log or simple differences of monthly data. When predicting SA QoQ

[2]Modugno et al. (2016) also adopt this estimation procedure and the DFM representation shown above.
[3]Old GDP data were discontinued in 2016:Q3.

Figure 1: Old and new NSA YoY GDP growth rates



GDP growth rates, monthly variables are seasoanlly adjusted using Tramo-Seats. A list of variables, applied transformations, and associated groups of variables are shown in Table I.

4 Predicting GDP growth rates

As mentioned above, Turkish GDP data are released with approximately 2 quarters of delay from the beginning of the reference period. As in Modugno et al. (2016), we produce our nowcasts once per month when labor force statistics are released, i.e., near the 15th day of each month. Because the delay in the publication is greater than one quarter, we also must "backcast" the previous quarter GDP in the months in which the previous quarter data are still not announced. Therefore, in the months corresponding to the first quarter of the year, we nowcast the 1st quarter GDP; in the months corresponding to the 2nd quarter, we nowcast the 2nd quarter GDP but also backcast the 1st quarter GDP because the data on the 1st quarter GDP are still not released. In the 3rd quarter, we continue in the same manner, both nowcasting and backcasting the 3rd and 2nd quarters but ceasing to backcast the 1st quarter because the data are already available.

When we estimate our DFM each month, we use all the information available at that time. Because of the different publication lags of different variables, the length (or the number of missing data) of the variables used in the estimation varies from month to month.

Table I: Description of the dataset

Group	Variables	Publication Lags	Transformation	
			Growth	Difference
Real	Industrial Production Index	2	1	0
Real	Non-Agricultural Unemployment Rate	3	0	1
Real	Total Employment excl. Agriculture	3	1	0
Real	Export Volume Index	2	1	0
Real	Import Volume Index	2	1	0
Real	Ercan Türkan Consumer Index	2	1	0
Real	Total Car Production	1	1	0
Survey	Capacity Utilization Rate	1	0	1
Survey	Turkstat Consumer Confidence Index	1	1	0
Survey	Bloomberg HT Consumer Confidence Index	1	1	0
Survey	Real Sector Confidence Index	1	1	0
Financial	Real Effective Exch. Rate by CPI	1	1	0
Financial	TRILIBOR 3-Months	1	0	1
Financial	Financial Account	2	0	1
Credit	Consumer Credits	1	1	0
Credit	Commercial Credits	1	1	0
Co & Se	Retail Sale Volume Index	2	1	0
Co & Se	Home Sales	2	1	0
GDP	Real Gross Domestic Product	5	1	0

Notes: This table shows variables, their associated groups, and their publication lags from the beginning of the reference period. Co & Se refers to the construction and service sector group. Growth refers to the growth rate of a variable, and Difference refers to the simple difference of a variable.

We construct a stylized calendar to approximately replicate the historical data availability with respect to estimation dates. The publication lag of each variable is shown in Table I.

Because the characteristics of the new GDP data are different than the old one, particularly after 2009, we estimate our models recursively with data beginning in January 2010[4]. We evaluate the nowcast accuracy of the proposed models using the sample from 2012:Q1 to 2016:Q4 and perform sample forecasts with a recursive (expanding) estimation window. We calculate the root mean square errors (RMSEs) to evaluate nowcast accuracies. The performance of the DFM is compared with an autoregressive model (AR) with lags chosen by AIC, the sample mean of the GDP growth rate, and the DFM of Modugno et al. (2016). Kuzin et al. (2013) suggests that pooling factor models with various specifications yields robust and favorable nowcasting performance. Therefore, we use the equal weighted averages of forecasts produced by nine DFMs with factors and lags up to 3 to obtain the final prediction whereas Modugno et al. (2016) rely on information criteria to choose optimal lag and factors.

[4]Using the earlier data yield extremely poor results for the DFM of Modugno et al. (2016).

Table II and III present average RMSEs between 2012:Q1 and 2016:Q4 for successive prediction horizons from the 1st nowcast to the 2nd backcasts. The 1st nowcast refers to the nowcast accomplished in the first month of the corresponding quarter (e.g., the nowcast made in January 2012 for 2012:Q1, the nowcast made in March 2012 for 2012:Q2, etc.), and the 2nd nowcast refers to the nowcast performed in the second month of the corresponding quarter (e.g., the nowcast made in February 2012 for 2012:Q1, etc.). Similarly, the 1st backcast denotes the backcast performed in the first month of the corresponding quarter (e.g., the backcast made in April 2012 for 2012:Q1, etc.). The new DFM and old DFM refer to our DFM with the extended dataset and the DFM of Modugno et al. (2016), respectively. AR and mean refer to the univariate benchmark models.

Table II: RMSEs of NSA YoY GDP growth rates between 2012:Q1 and 2016:Q4

	New DFM	Old DFM	AR	Mean
1st Nowcast	2.72	3.48	4.00	3.32
2nd Nowcast	2.77	3.52	4.00	3.32
3rd Nowcast	2.47	2.91	3.07	3.00
1st Backcast	2.44	2.92	3.07	3.00
2nd Backcast	2.44	2.89	3.07	3.00

Note: This table reports the RMSEs of DFMs and benchmark models. New DFM and Old DFM refer to the DFM with the extended dataset and the DFM of Modugno et al. (2016), respectively. AR and Mean refer to the AR model and a sample mean of GDP growth rate, respectively.

Table III: RMSEs of SA QoQ GDP growth rates between 2012:Q1 and 2016:Q4

	New DFM	Old DFM	AR	Mean
1st Nowcast	1.64	1.75	3.44	1.73
2nd Nowcast	1.53	1.74	3.44	1.73
3rd Nowcast	1.35	1.83	1.96	1.72
1st Backcast	1.39	1.82	1.96	1.72
2nd Backcast	1.40	1.80	1.96	1.72

Note: See notes under table II.

The results in Table II and III show that the new DFM performs better than all other benchmark models at all horizons for both SA QoQ and NSA YoY GDP growth rates. On average, the RMSE of the new DFM is 22% lower than that of the old DFM in both tables. Interestingly, without the new variables the old DFM can not even outperform the sample mean of the GDP growth rate when nowcasting SA QoQ GDP growth rates. As expected, the RMSE of the new DFM decreases with each prediction horizon for NSA YoY GDP growth rates, but after the 3rd nowcast period the decline of the RMSE is very small. Furthermore, the RMSE after the 3rd nowcast period is even increasing for SA QoQ GDP growth rates. This result suggests that the majority of relevant information for predicting Turkish GDP is released up to the 3rd month of the corresponding quarter; no predictive power is added from backcasts.

Table IV: RMSEs of year-over-year GDP growth rates between 2012:Q1 and 2016:Q4

	Full	w/o Financial	w/o Credit	w/o Co & Se
1st Nowcast	2.71	2.60	3.12	2.76
2nd Nowcast	2.77	2.69	3.06	2.78
3rd Nowcast	2.47	2.44	2.66	2.49
1st Backcast	2.44	2.40	2.57	2.44
2nd Backcast	2.43	2.34	2.51	2.43

Note: This table depicts the RMSEs of the DFM with the full dataset and the DFMs without a particular group of variables. Full, Financial, Credit and Co & Se refer to the DFM with the full dataset, the DFM without financial variables, the DFM without credit variables, and the DFM without construction and service sector variables, respectively.

Table V: RMSEs of QoQ SA GDP growth rates between 2012:Q1 and 2016:Q4

	Full	w/o Financial	w/o Credit	w/o Co & Se
1st Nowcast	1.64	1.63	1.66	1.66
2nd Nowcast	1.53	1.54	1.60	1.63
3rd Nowcast	1.35	1.40	1.45	1.58
1st Backcast	1.39	1.39	1.42	1.58
2nd Backcast	1.40	1.37	1.44	1.58

Note: See notes under table IV.

Finally, we assess the relative contribution of credit, financial, service and construction sector variables to the predictive performance of the DFM. We rerun the DFM by excluding a particular variable group to evaluate the effect of this exclusion on the prediction performance of the DFM. Table IV and V present the results of this exercise. Contrary to Modugno et al. (2016), the results suggest that the inclusion of financial variables worsens the prediction accuracy of the DFM for predicting NSA YoY growth rates. On the other hand, dropping credit variables deteriorates the performance of the DFM substantially when nowcasting NSA YoY growth rates. For SA QoQ growth rates, Co & Se variables seem to play the key role in nowcasting. These results indicate that new added variables effectively capture the new dynamics of the new GDP series.

5 Conclusion

In this paper, we nowcast SA QoQ and NSA YoY GDP growth rates between 2012:Q1 and 2016:Q4 recursively by using a DFM with a medium-scale dataset consisting of 19 variables.

We compare the predictions of this new DFM with those of the DFM of Modugno et al. (2016), the AR model, and a sample mean of GDP growth rate. The results suggest that the DFM presented in this paper clearly outperforms competing benchmark models.

The results also suggest that the majority of the relevant information is already released in the third month of the quarter and there are no further gains in predictive power from backcasting. In addition, we analyze the impact of credit data, financial data, and service and construction sector data on nowcasting performance. The results indicate that credit variables and Co & Se variables drastically improve the performance of the DFM for NSA YoY growth rates and SA QoQ growth rates, respectively.

References

Bańbura, M. and M. Modugno (2014). Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data. *Journal of Applied Econometrics 29*(1), 133–160.

Giannone, D., S. M. Agrippino, and M. Modugno (2013). Nowcasting China Real GDP. Mimeo.

Giannone, D., L. Reichlin, and D. Small (2008). Nowcasting: The Real-Time Informational Content of Macroeconomic Data. *Journal of Monetary Economics 55*(4), 665–676.

Kuzin, V., M. Marcellino, and C. Schumacher (2013). Pooling Versus Model Selection for Nowcasting GDP with Many Predictors: Empirical Evidence for Six Industrialized Countries. *Journal of Applied Econometrics 28*(3), 392–411.

Mariano, R. S. and Y. Murasawa (2003). A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series. *Journal of Applied Econometrics 18*(4), 427–443.

Modugno, M., B. Soybilgen, and E. Yazgan (2016). Nowcasting Turkish GDP and News Decomposition. *International Journal of Forecasting 32*(4), 1369–1384.

Soybilgen, B. and E. Yazgan (2016). Şimditahmin.com'un Türkiye GSYH Büyüme Oranları için Tahmin Performansı. *İktisat ve Toplum* (4), 64–71.