İstanbul Bilgi University
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CEFIS WORKING PAPER SERIES
First Version: August 2017

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Barış Soybilgen, İstanbul Bilgi University

Ege Yazgan, İstanbul Bilgi University

İstanbul Bilgi Üniversitesi
LAUREATE INTERNATIONAL UNIVERSITIES

Nowcasting the New Turkish GDP

Barış Soybilgen*and Ege Yazgan†

Abstract

In this study, we predict year-over-year Turkish GDP growth rates between 2012:Q1 and 2016:Q4 with a medium-scale dataset. Our proposed model improves upon Modugno et al. (2016) and 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, information content regarding leading variables is limited. Moreover, we show that the inclusion of financial variables deteriorates the forecasting performance of the DFM, whereas credit variables improve the prediction accuracy of the DFM.

Keywords: dynamic factor model; nowcasting; gross domestic product

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 must 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 of new Turkish GDP data.

*Istanbul Bilgi University, baris.soybilgen@bilgi.edu.tr.
†Istanbul Bilgi University, ege.yazgan@bilgi.edu.tr.
[1]The accuracy of the nowcasts produced by www.nowcastturkey.com is also provided by the website and evaluated by Soybilgen and Yazgan (2016).

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 year-over-year 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. 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 dataset. Section 3 shows the results of nowcasting exercises, and section 4 concludes.

2 The dataset

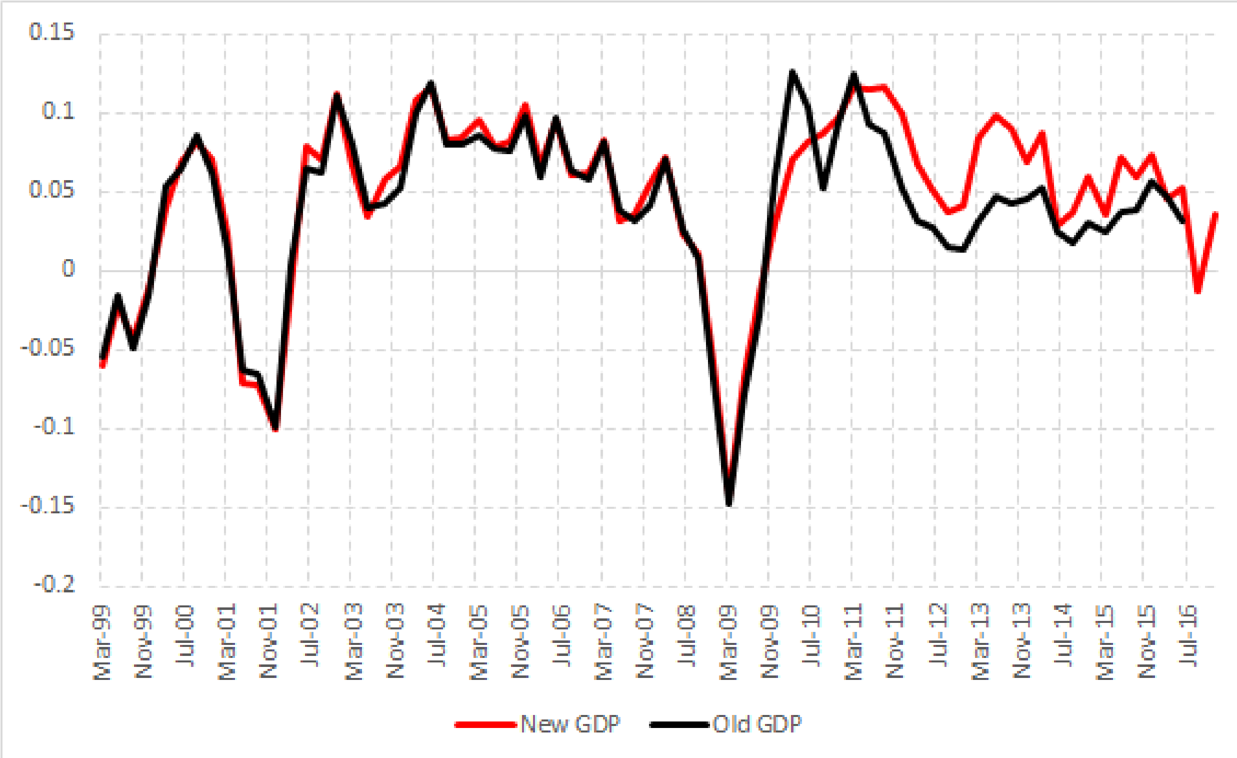
Figure 1 displays the evolution of the year-over-year real GDP growth rates of both the new and old Turkey GDP growth rates.[2] Figure 1 clearly shows that the old and new GDP growth rates have similar patterns before 2010. However, the new and old series have different structures since the beginning of 2010. The primary reason for this substantial difference since 2010 is that the old series mainly relies on sectoral surveys, whereas the new data 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 before 2010. After 2010, however, the old series continues to rely on sectoral surveys, whereas new GDP data use 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 focus on predicting year-over-year GDP growth rates instead of quarter-over-quarter GDP growth rates, because year-over-year GDP growth rates are the most closely watched economic indicator in Turkey. To obtain stationary variables, we compute log or simple yearly

[2] Old GDP data were discontinued in 2016:Q3.

Figure 1: Old and new year-over-year GDP growth rates



differences in monthly data. A list of variables, applied transformations, and associated groups of variables are shown in Table I.

3 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

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.

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. 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 structure of the new GDP data is different than the old one, particularly after 2010, we estimate our models recursively with data beginning in January 2010. 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. The DFM is estimated as in Modugno et al. (2016) using a modified version of an expectation maximization algorithm for maximum likelihood estimation proposed by Bańbura and Modugno (2014), which can easily address any arbitrary patterns of missing data and the serial correlation of the idiosyncratic component.

Table II presents 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 and the DFM of Modugno et al. (2016), respectively. AR and mean refer to the univariate benchmark models.

The results in Table II show that the new DFM performs better than all other benchmark models at all horizons except the 2nd nowcast period. Interestingly, the old DFM has the lowest DFM in the 2nd nowcast period. In the last prediction horizon, the RMSE of the new DFM is 23.5% lower than the old DFM. On average, the RMSE of new DFM is 14.5% lower than that of the old DFM. As expected, the RMSE of the DFM decreases with each prediction horizon, but after the 3rd nowcast period the decline of the RMSE is very small. This latter 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 II: RMSEs of year-over-year GDP growth rates between 2012:Q1 and 2016:Q4

	New DFM	Old DFM	AR	Mean
1st Nowcast	2.72	2.84	4.00	3.32
2nd Nowcast	2.77	2.75	4.00	3.32
3rd Nowcast	2.47	3.16	3.07	3.00
1st Backcast	2.44	3.12	3.07	3.00
2nd Backcast	2.44	3.19	3.07	3.00

Note: This table reports the RMSEs of DFMs and benchmark models. New DFM and Old DFM refer to our DFM 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.

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 III presents 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. Service and construction sector variables also do not appear to have a significant impact on the RMSE of the DFM. However, dropping credit variables deteriorates the performance of the DFM substantially. This latter result indicates that credit variables effectively capture the new dynamics of the new GDP series.

Table III: 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.

4 Conclusion

In this paper, we nowcast year-over-year 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 that the scope for further gains in predictive power from backcasting appears to be limited. In nowcasting current GDP growth, all relevant information is released within the contemporaneous quarter, and therefore the information content in leading variables is limited.

In addition, we analyze the impact of credit data, financial data, and service and construction sector data on nowcasting performance. The results indicate that the inclusion of financial variables deteriorates the prediction performance of the DFM, whereas credit variables improve the RMSEs of the DFM. Finally, service and construction sector variables do not appear to have an effect on nowcasting performance.

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