A New Model for Estimating GDP Growth in Real Time

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Abstract

This paper presents a new model developed at the Bank of Israel for nowcasting[1] quarterly GDP growth. In addition to forecasting quarterly growth, the model enables the creation of a monthly index of real activity that is presented in terms of unobserved monthly GDP growth. The index is consistent with quarterly growth forecasts in that the quarterly GDP growth forecast is obtained by adding the monthly growth forecasts. Compared with the Composite State of the Economy Index produced by the Bank of Israel, the proposed index is based on a broader panel of data, and may therefore more precisely reflect the dynamic of real economic activity at a monthly frequency.

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[1] Estimating growth that has taken place but for which the official figure has not yet been published.

1. INTRODUCTION AND SURVEY OF LITERATURE

GDP is the most important and most commonly accepted indicator of the level of aggregate economic activity. GDP data are obtained at a quarterly frequency, and with a lag of about 6 weeks from the end of the quarter. Estimating this figure in real time (nowcasting), either within or soon after the end of the quarter until the publication of the official figure, is intended to help policy makers assess economic activity and the short-term effect of policy measures. Obtaining an up-to-date macroeconomic picture is of decisive importance during crises (such as during the lockdowns that were imposed due to the COVID-19 pandemic), which feature rapid changes that create tremendous uncertainty regarding the current state of the economy.

This paper outlines a GDP growth nowcasting model that was recently developed by Ginker and Suhoy (2022). The model provides real-time estimates of GDP growth rates at monthly and quarterly frequencies. The nowcast of quarterly growth is obtained by adding up the estimates of monthly growth. A clear advantage of this method is that in addition to the quarterly forecast, it provides an indicator of aggregate economic activity at the monthly level, which is produced in easy terms of GDP growth and is consistent with the quarterly nowcast.

The proposed model belongs to the family of dynamic factor models. In their pioneering work, Stock and Watson (1989, 1991, 1993) showed that the common dynamic of a variety of economic series can be summed up in a smaller number of common factors that can be used both to describe the macroeconomic picture and for forecasting. Such models very quickly became a common tool in macroeconomic analysis and forecasting at central banks around the world (see, for instance, Banbura et al., 2013). One of the reasons for this is that they offer a simple way of dealing with a variety of application challenges. For instance, they enable a combination of series with various frequencies in the same model, as well as dealing with a variety of issues regarding missing observations.

In the United States, there are currently three well-known models that are used by Federal Reserve branches to forecast GDP growth. One of them is the model known as GDPNOW, which was developed by Higgins (2014) of the Federal Reserve Bank of Atlanta. This model uses a variety of statistical tools to forecast GDP by forecasting its components. Another model was developed by Bok et al (2017) of the Federal Reserve Bank of New York. This is a dynamic factor model for forecasting based on a broad group of monthly and quarterly series. The closest model to the methodology implemented in this work is that of Brave et al (2019) of the Federal Reserve Bank of Chicago. This is a “big data” model of dynamic factors that combines dimensionality reduction with a principal components technique that uses hundreds of series to forecast GDP growth.

The rest of this paper is as follows: Section 2 describes the data; Section 3 outlines the application challenges and structure of the model; Section 4 presents an examination of the forecasting quality on historical data; Section 5 outlines the estimated monthly GDP growth; and Section 6 concludes

2. THE DATA

The model is based on a group of 30 economic series that are used as explanatory variables. (For the full list, see Table 4 in Ginker and Suhoy, 2022.) These series include monthly, weekly, daily, and even intraday series. All of the series are entered into the model at a monthly frequency, other than the target variable, which is GDP growth and is entered into the model at a quarterly frequency. As such, the model has just two frequencies—monthly and quarterly. Series that are measured more frequently, are converted to a monthly frequency.

The group of series includes the Industrial Production Index; a number of revenue series such as trade revenue and services revenue; sales at retail chains; building starts; gasoline consumption; a number of foreign trade series; a number of series showing the demand side in the labor market; consumer confidence; series regarding taxes; fuel prices; general shares index; and a number of purchasing managers series. This broad group also includes series that the Bank has recently started to use, such as the daily volume of credit card use and intraday data on electricity consumption.

In addition to these series, the model uses series from the Business Tendency Survey. This survey, which has been conducted since 2011 by the Central Bureau of Statistics, is an obligatory response survey that covers 1,600 company managers in the manufacturing, construction, trade, hotels, and services industries. The managers are asked to assess the current state of their business on a scale of 1 to 5, and to indicate their expectations for the near future. The survey's questions relate to the business's main parameters, such as production, sales in the domestic market and exports, employment, and prices. The survey, which is considered "soft" data and is published in the second week of each month, is used to proxy other series that come with a greater lag, such as revenue series.

3. DESCRIPTION OF THE DATA AND MODEL STRUCTURE

This section outlines the application challenges, and presents the model structure. The model overcomes a number of practical problems that do not receive a response in the traditional models that are used for forecasting, as detailed below.

First challenge – unbalanced panel data

The first challenge is in working with data panels that are not balanced. In other words, various series that make up the panel of monthly variables outlined above have different starting points, and their publication dates may be different. A possible example of this is the Industrial Production Index that is obtained at a monthly frequency since 1996 and is published with a lag of 7–8 weeks from the end of the month to which it relates, while the series of job vacancies is only available from June 2009 and is published with a lag of just 2 weeks.

The first series that are published immediately at the end of the month are, for instance, the general shares index, crude oil prices, credit card purchases, electricity consumption, and VAT receipts. Series that are published with a lag of 1–2 months are, for instance, employed persons in the labor market, gasoline consumption, and foreign trade series. The table below samples the process of information flow in February:

Table 1 – Sample of the process of information flow in February

Week number	Series that are obtained
1	Shares index, credit card purchases, electricity consumption, and VAT receipts for January
2	Business Tendency Survey, and tax revenue for January
3	Job vacancies and some foreign trade series for January
4	Purchasing Managers Indices for January and revenue series for December of the previous year

The lack of balance in the panel data poses a challenge in building the model, since the traditional forecasting models, such as the linear regression model or the bridge equation model, require a balanced panel in which the series have the same starting point and there are no missing observations at the end of the series. As a result, traditional models are limited in that the historical depth of all of the series in the model are set by the series with the shortest depth, and the date on which the forecast is obtained is set by the series with the latest publication date. The new model enables use of series with short histories, such as series from the Business Tendency Survey, which are obtained in their current format since 2016, without truncating all of the other series in the panel to the start date of the survey. As a result, the model creates a forecast with all of the information available at that time, from the second month of the forecast quarter, and is updated on a weekly basis in accordance with the flow of data.

Second challenge – over-parameterization

The second challenge is including a broad range of series in the model in order to utilize information from series that reflect various aspects of economic activity. Most macroeconomic series are available at only monthly or quarterly frequencies. This significantly limits the number of explanatory variables that can be integrated into a traditional model. For this reason, traditional models typically include only a very small number of series, due to the problem of over-parameterization. The new model includes a large number of series by summarizing them by a smaller number of factors. This broad group includes series that have recently come into use at the Bank, such as the daily volume of credit card use and electricity consumption.

Third challenge – mixed frequencies

The third challenge is in working with mixed frequencies. As part of our analysis, the target variable that we want to forecast is GDP growth measured on a quarterly basis, while the other variables are measured on a monthly basis. The traditional models know how to work only with one frequency, and they therefore convert the monthly variable into quarterly variables by adding them up over the quarter. They thus lose the monthly dynamics of the variables, which is important information. The new model maps the connection between the quarterly variable and the monthly variables directly, without needing to first add up the monthly variables over the course of a quarter.

Structure of the model

The objective of the model is to forecast GDP growth, which is the quarterly change in GDP, and to also estimate GDP growth at a monthly frequency. This estimate is currently not measured by the Central Bureau of Statistics, so we will relate to it in the model as an unobserved variable. The following is a flowchart of the model's stages.

Figure 1 – Stages of the Model

Stage 1 – Describing the link between quarterly and monthly GDP growth

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Stage 2 – Presenting the explanatory variables through a small number of factors

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Stage 3 – Describing the link between monthly GDP growth and the explanatory variables

Stage 1 – Describing the link between quarterly and monthly GDP growth

We label the quarterly GDP level with the variable GDP^{Q} and the monthly GDP level with the variable GDP^{M} . The first equation in the model links quarterly GDP with monthly GDP, such that the result is qual to the sum of three months of GDP in that quarter:

$$GDP^{Q} = GDP^{m\,1} + GDP^{m\,2} + GDP^{m\,3}$$

We label quarterly GDP growth, which is the change in the quarterly GDP level[2] as - Y^{Q} . For instance, second-quarter growth is the change in GDP between the first quarter and the second quarter:

$$Y^{Q\,2} = GDP^{Q\,2} - GDP^{Q\,1}$$

Using this identification, we can now describe the growth of quarterly GDP using the three monthly GDP levels in the quarter:

$$Y^{Q\,2} = GDP^{Q\,2} - GDP^{Q\,1} =$$

$$GDP_{(Q2)}{}^{m\,1} + GDP_{(Q2)}{}^{m\,2} + GDP_{(Q2)}{}^{m\,3} - GDP_{(Q1)}{}^{m\,1} - GDP_{(Q1)}{}^{m\,2} - GDP_{(Q1)}{}^{m\,3}$$

After adding and subtracting a number of expressions and a number of accounting actions, we obtain the first equation in the model:

$$\boldsymbol{Y^{Q\,2} = Y_{m3}^{Q2} + 2Y_{m2}^{Q2} + 3Y_{m1}^{Q2} + 2Y_{m3}^{Q1} + Y_{m2}^{Q1}}$$

We have now obtained an identity that describes the change in quarterly GDP as a sum of the changes in monthly GDP.

[2] More precisely, GDP growth is the percentage change in GDP that is approximately equal to the change (difference) in the natural log of GDP, and not the change in GDP presented in this paper for simplicity.

Stage 2 – Presenting the explanatory variables through a small number of factors

We label the number of explanatory variables in the model as n and in the equation $X_1^m, X_2^m, \dots, X_n^m$ the n monthly explanatory variables in the model. The explanatory variables do not directly enter the model, but are represented by a small number of factors. Each factor is essentially a weighted average of each of the variables, and the factors are differentiated from each other by weights. We label the number of factors as r and in the equation $F_1, F_2, \dots, F_r$ the r factors themselves .

Stage 3 – Describing the link between monthly GDP growth and the explanatory variables

The second equation in the model links monthly GDP growth and the factors:

$$\boldsymbol{Y^{month} = \alpha + \beta_1 F_1 + \beta_2 F_2 + \cdots + \beta_r F_r + \varepsilon}$$

The statistical meaning of this equation is that monthly GDP growth is a function of the explanatory variables presented in the model by the number of factor components plus a noise factor.

4. EVALUATION OF FORECASTING QUALITY

The model's forecasting quality was evaluated over a period preceding the COVID-19 pandemic, and used monthly and quarterly information for the period from January 2000 to December 2019. Since the new model can produce forecasts on the basis of partial monthly information during the forecast quarter, the evaluation included forecasting based on information on one month, two months, and three months in the forecast quarter. The evaluation was made using a rolling forecast for the period from the first quarter of 2010 to the fourth quarter of 2019. A rolling forecast means that in each quarter, the sample used to forecast the previous quarter (the training set) is expanded and the model is re-estimated. For instance, in order to evaluate the forecasting quality on the basis of information for up to one month in the quarter, we first adapt the model to the data from January 2000 to the first month of the first quarter of 2010, including the most recently available GDP growth figure at that point[3], and a GDP growth forecast is then made for the first quarter of 2010. We then add data for the three months of the first quarter of 2010, and add the information for the first month of the second quarter and the most recently available GDP growth figure for the quarter to the training set, and then make a forecast for the second quarter, and so forth.

The forecasting quality is evaluated according to two indices. The first is the root of the average distances squared between the forecast and the actual quarterly growth figure, according to the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where y_i is actual quarterly growth in period i and $\hat{y}_i$ is the forecast value for that period.

[3] At this stage, the most recent GDP figure is for the third quarter of 2009.

The second is the average absolute error, which is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

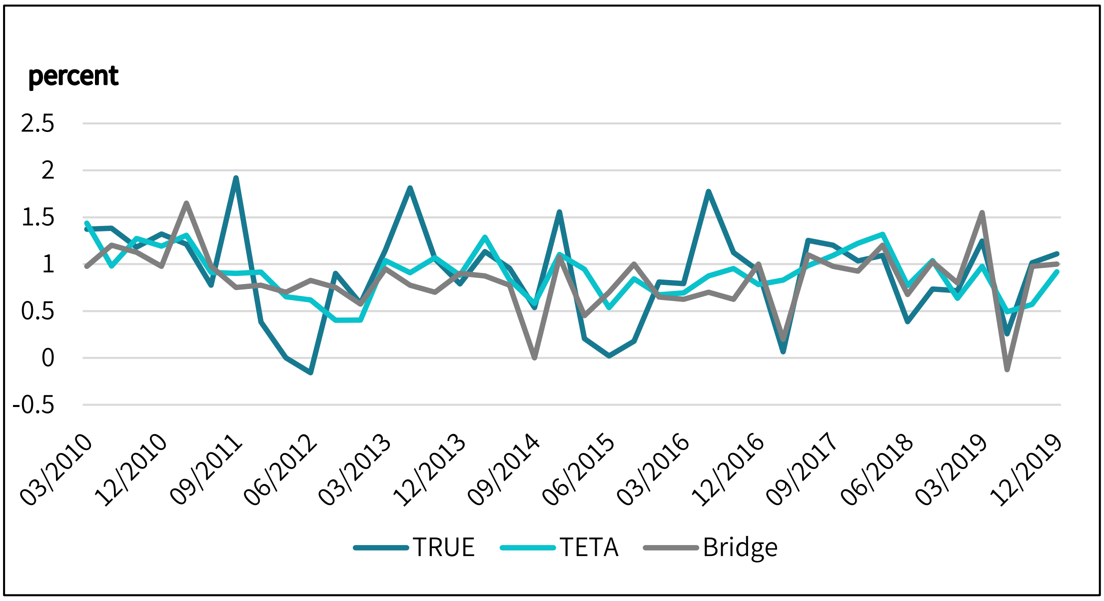
Table 2 presents the forecasting error compared with the model currently used by the Bank, which is based on a bridge equation. In addition, Figure 1 below shows the forecast of the two models (the current one—bridge; and the new one—TETA), compared with actual GDP growth. The table presents the forecasting errors on the basis of information up to the first month, the second month, and the third month of the forecast quarter. The comparison with the bridge model is only for information up to the second month of the quarter, since the model currently generates only one forecast, which is based on information on the first two months of the quarter. The forecast results from the bridge model also include a judgmental component that was made outside the model and that contributes to the forecasting quality. In contrast, the new model does not include a judgmental component.

Table 2: Average root square error and average absolute error of the new model relative to the existing model

Model	**Data up to the third month in the quarter**		**Data up to the second month in the quarter**		**Data up to the first month in the quarter**	
Type of error	Absolute	Square	Absolute	Square	Absolute	Square
New	0.856	0.809	0.872	0.814	0.898	0.871
Existing			0.925	0.876		

As we see, during the examined period, the new model predicts better than the existing model, both in terms of the average square error and in terms of the absolute error, where forecasting is based on information of up to the first two months in the forecast quarter. In addition, the new model is a better predictor than the existing model even when using just the information up to the first month of the forecast quarter.

Figure 1: The New and Existing Models and Actual GDP Growth (percent)

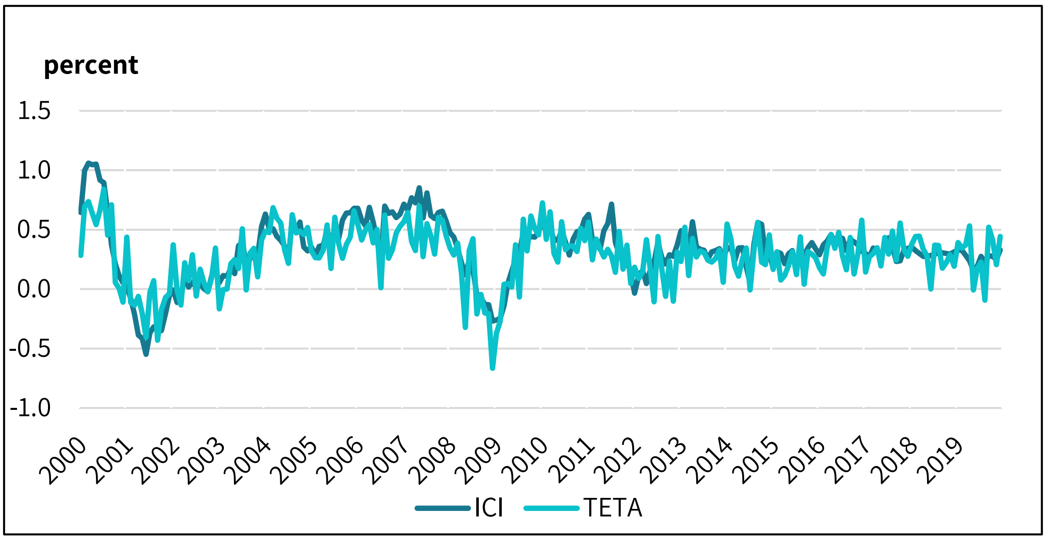


5. ESTIMATED MONTHLY GDP GROWTH

The new model maps the link between GDP growth at a quarterly frequency and GDP growth at a monthly frequency, which is included in the model as an unobserved variable. The result is the creation of an estimate of monthly GDP growth, which precisely totals quarterly GDP growth. This estimate can be used to assess economic activity at a monthly frequency.

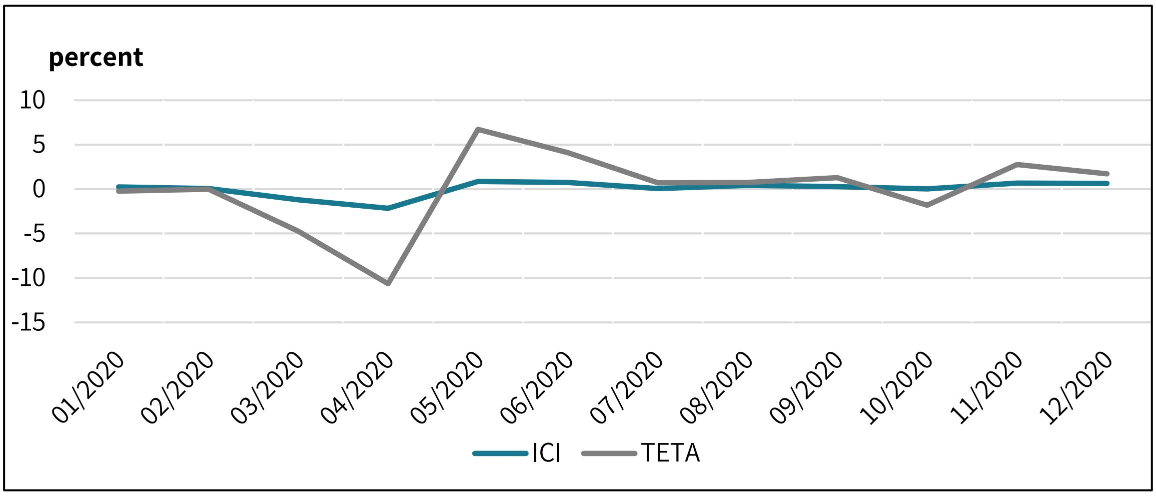
Figure 2 shows the estimate of GDP growth with a monthly frequency (TETA) and the Composite State of the Economy Index (ICI), which is the monthly estimate of economic activity currently published by the Bank of Israel.

Figure 2: Estimated Monthly GDP Growth, New Model and Composite State of the Economy Index (percent)



We can see that the estimate of the new model is more volatile than the Composite State of the Economy Index. This volatility is partly due to the difference in the structures of the two models. While the Composite Index is intended to present "smoothed" growth, the new model's structure forces monthly growth to precisely total quarterly growth. In addition, the new model includes a broader panel of economic indicators. The advantage of this volatility was prominent in 2020, at the height of the COVID-19 crisis, when the Composite Index was close to zero for most of the period, while the new estimate was more in line with the timing and intensity of the economic events that took place during the period. The outbreak of the pandemic led to a strong economic crisis, mainly due to the healthcare measures intended to slow the spread of the virus, including various restrictions on the public. These policy responses partly included closure to incoming tourism, restrictions on gatherings, restrictions in the education system and the transition to remote learning, and three economy-wide lockdowns. The figure shows the sharp decline in March, which intensified in April due to the severe restrictions and the first lockdown. The increase in May shows the economy's exit from the first lockdown. The slowdown in July is consistent with the start of the second wave of the pandemic and the tightening of restrictions, and the decline observed in October marks the second lockdown.

Figure 3: Estimated Monthly GDP Growth, New Model and Composite State of the Economy Index, 2020 (percent)



6. CONCLUSION

This paper outlines a nowcasting model that the Bank of Israel has developed for assessing GDP. Relative to the existing model, the new model improves the forecast quality with regarding to the forecast timing and to its precision. The new estimate of monthly GDP growth provides a picture of the intraquarter dynamic, which is more consistent with the economic story that took place in 2020. The Bank of Israel is currently developing and expanding its macroeconomic forecasting models by using nontraditional information, such as textual information, payments data, and data that can be accessed on the Internet through webscraping methods.

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