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Nowcasting and monitoring real economic activity in Israel[1]

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Abstract

This paper employs an extension of the mixed-frequency collapsed dynamic factor model, introduced by Bräuning and Koopman (2014), for nowcasting Israeli GDP growth. In the proposed method, the dimension reduction is performed through a partial least squares regression that uses a proxy for the unobserved monthly GDP growth as the dependent variable. Our results show that this method allows us to improve on the accuracy of quarterly forecasts. In addition, we study the role of business surveys in real-time nowcasting. We find that including business surveys improves the accuracy of nowcasting, but only when they are used for endpoint imputation of the traditional macroeconomic indicators. In contrast, expanding the monthly panel with surveys related to some of the already included variables leads to inferior forecasting performance. Finally, the proposed model allows us to construct a monthly index of real economic activity that is consistent with the nowcast. Compared to the Composite State of the Economy Index currently published by the Bank of Israel, it utilizes a much broader data set and thus is likely to provide a more timely and precise picture of the course of economic activity.

Keywords: Nowcasting; Dynamic factor model; Partial least squares.

אמידה של פעילות כלכלית ריאלית וחיזוי טווח קצר של צמיחת התוצר בישראל

טים גינקר וטניה סוחוי

תקציר

מאמר זה מציג הרחבה של מודל פקטורי דינאמי המשלב הורדת ממד, שפותח על ידי Bräuning and Koopman (2014), לצורך חיזוי טווח קצר של צמיחת התוצר בישראל. בשיטה המוצעת, הורדת הממד נעשית בעזרת partial least squares שמשתמשת בפרוקסי לצמיחת התוצר החודשית הבלתי נצפית כמשתנה מוסבר. יישום אמפירי על נתוני ישראל מראה שהשיטה מביאה לשיפור מובהק בדיוק החיזוי של הצמיחה הרבעונית. בנוסף לכך, נבחנו היבטים שונים של שילוב נתוני סקרי המגמות בעסקים במודל. נמצא כי הוספת נתוני הסקר משפרת את דיוק החיזוי, אך רק כאשר אלה משמשים לצורך ההשלמה בקצה של האינדיקטורים המסורתיים. בנוסף לחיזוי הצמיחה הרבעונית, המודל מאפשר יצירת מדד חודשי לפעילות ריאלית שמוצג במונחי צמיחת התוצר החודשית הבלתי נצפית. המדד עקבי עם התחזית לצמיחה הרבעונית במובן שהתחזית הרבעונית לצמיחת התוצר מתקבלת מהסיכום של המדדים לצמיחה החודשית. בהשוואה למדד המשולב למצב המשק שמופק ע״י בנק ישראל, המדד המוצע מבוסס על פאנל נתונים רחב יותר ועל כן עשוי לשקף במידה מדויקת יותר את הדינמיקה של הפעילות הריאלית בתדירות החודשית.

1 Introduction

In this paper, we present a nowcasting model for Israeli GDP growth. Real-time GDP nowcasting plays an important advisory role in policymaking. Timely and accurate assessments of economic activity can facilitate the impact of policymakers' interventions and are crucial in periods of rapid change and distress, such as the COVID-19 crisis in 2020.

Since the seminal research of Stock and Watson (1989, 1991, 1993), which showed that comovement across many macroeconomic indicators can be decomposed into a few latent factors that can be used for tracking the course of economic activity, dynamic factor models have become popular in the analysis of large macroeconomic data sets in central banks and other financial institutions (Bańbura et al., 2013). In addition, dynamic factor models solve a number of important practical issues in a simple and elegant manner. More precisely, they allow us to combine monthly and quarterly series within the same framework and to deal with various types of missing observations that may arise due to different historical lengths or asynchronous data releases.

Despite the existence of appropriate estimation routines (Banbura and Modugno, 2014) direct joint modeling of quarterly GDP growth with a large panel of available monthly indicators still involves a high number of hyperparameters and hence higher forecast variance. To address this issue, Bräuning and Koopman (2014) introduced a collapsed dynamic factor model (henceforth, CDFM) that allows a large number of monthly series to be combined in a relatively parsimonious model. This is a two-step procedure, where, in the first step, the information contained in the monthly variables is decomposed into a small number of factors using principal component analysis (henceforth, PCA). In the second step, the components are modeled jointly with GDP growth in a dynamic factor model. In addition to modeling the dynamics of the extracted factors, the second step makes them more closely related to the target variable.

One known drawback of PCA arises when the dominant variation in the monthly variables is not strongly connected with the variation in the target variable, which may result in a weak correlation with the principal components extracted in the first step. Thus, while the second step of the CDFM allows further reduction of the variation in the principal components to the common factors that are more closely related to the target variable, most of the relevant information could have already been filtered out during the first step.

In this article, we employ an extension of the CDFM, aimed at increasing the amount of relevant information extracted in the first step. Factors derived from PCA are effectively weighted averages of the standardized monthly series. The idea is to adjust the weighting scheme in such a way that it would put more weight on those variables that are more strongly related to economic growth. This can be achieved by finding a suitable proxy for the unobserved monthly GDP growth and then using the partial least squares (henceforth, PLS) scores for dimension reduction instead of using the principal components. Therefore, in the first step, we use the series of monthly changes in the total revenue index as the proxy and estimate the PLS scores by regressing it on the set of monthly indicators. The choice of total revenue as a proxy can be explained as follows. By the value-added approach, a sectoral difference between the total revenue and GDP will grow with the proportion of intermediate consumption in the output. GDP in Israel is composed in such a way that roughly 60% of it is attributed to the business services sector – the sector that is characterized by a small proportion of intermediate consumption. This logic rules out some other potential proxies, such as the industrial production index that was traditionally considered a highly procyclical indicator. From an empirical perspective, at a quarterly frequency, for the sample from 2000:Q1 to 2020:Q4, log differences of the total revenue index have the highest correlation of 0.67 with GDP growth compared with only 0.17 for the industrial production index.

Our out-of-sample experiment shows that the model is able to capture nicely both the "pre-COVID-19" period of rather moderate fluctuations in GDP growth and the subsequent extreme swings that occured during the 2020 crisis. In addition to the quarterly growth nowcasts, using the same model we produce estimates of the unobserved monthly GDP growth, which can serve as a leading indicator of the current state of the economy (Brave et al., 2019). The proposed indicator is shown to be consistent with the expected monthly pattern.

Along with traditional and widely used macroeconomic series with a long history, we incorporate some newly launched data sources, such as the Business Tendency Survey (henceforth, BTS) or daily volumes of credit card purchases and electricity consumption.

In real-time applications, BTS-based indices can be used as a timely proxy for important macroeconomic variables that are typically released after a long delay. Our findings suggest that surveys can significantly increase the accuracy of nowcasting, but only when they are used for endpoint imputation of the traditional macroeconomic indicators. Different aspects of using soft data for real-time forecasting are discussed in detail in Section 4.2.

The paper is organized as follows. Section 2 presents the econometric methodology. Section 3 describes the data. Section 4 discusses our out-of-sample forecasting experiment and other practical issues related to the use of "soft" data and imputation methods in real-time applications, and Section 5 concludes.

2 Methodology

This section describes our model specification. We start with a brief overview of the dynamic factor modeling framework. Next, following Bräuning and Koopman (2014), we specify the joint dynamics of the unobserved monthly GDP growth with the monthly indicators, as well as the refined collapsing scheme. Finally, using the approximation of Mariano and Murasawa (2003), the state space representation is extended to incorporate into the same dynamic factor framework the observed quarterly GDP growth together with the panel of monthly variables.

Let $x_t = (x_{1,t}, x_{2,t}, ..., x_{n,t})'$ with $t = 1, 2, ..., T$ be a vector of n monthly series that have been transformed to become stationary and standardized. A dynamic factor model (DFM) assumes that it is possible to decompose x_t into two unobserved orthogonal components representing common and idiosyncratic factors. The model is specified as follows:

$$x_t = \Lambda F_t + \varepsilon_t,\ \varepsilon_t \sim N(0, R), \tag{1}$$

where F_t is an $(r \times 1)$ vector of unobserved common factors, Λ is an $(n \times r)$ matrix of their loadings, and ε_t is an $(n \times 1)$ vector of the idiosyncratic components. The factors are assumed to have the following stationary VAR(p) representation:

$$F_t = \sum_{s=1}^{p} \Phi_s F_{t-s} + u_t,\ u_t \sim N(0, Q) \tag{2}$$

where Φ_s are $(r \times r)$ matrices of autoregressive coefficients. The related inference and forecast procedures can be carried out using the standard Kalman filter techniques (see, e.g., Hamilton, 1994, Ch. 13).

We start by specifying the dynamics of the unobserved monthly GDP growth, denoted by y_t. Inclusion of the quarterly and monthly variables within the same DFM framework will be discussed later in this section. We start with a benchmark assuming that the logarithm of the GDP follows a drifting random walk that gives the following dynamics of y_t:

$$y_t = \mu + \varepsilon_{y,t}, \tag{3}$$

where $\varepsilon_{y,t} \sim N(0, \sigma^2_{\varepsilon y})$, μ represents the trend component, and $\varepsilon_{y,t}$ is the error term. The performance of (3) can be further improved by augmenting the model with a set of factors derived from x_t, which yields the following representation:

$$y_t = \mu + \Lambda_{yx} F_t + \varepsilon_{y,t}.$$

In the state space form the measurement equation can be written as

$$\begin{pmatrix} y_t \\ x_t \end{pmatrix} = \begin{bmatrix} \mu \\ 0 \end{bmatrix} + \begin{bmatrix} \Lambda_{yx} \\ \Lambda \end{bmatrix} F_t + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_t \end{pmatrix} \tag{4}$$

In this formulation, it is straightforward to use a Kalman filter to treat various types of missing observations that may arise due to different historical lengths or asynchronous data releases (Durbin and Koopman, 2001).

In macroeconomic applications, the number of monthly indicators can be high relative to the number of observations, which can significantly complicate the estimation routine and introduce additional variance into the model. To overcome this difficulty, Bräuning and Koopman (2014) introduced a collapsed dynamic factor model that applies the dimension reduction transformation to the measurement equation. The idea is to use a transformed version of the measurement equation (4) pre-multiplied by the transformation matrix

$$P = \begin{bmatrix} 1 & 0 \\ 0 & A \end{bmatrix},$$

where A is an $(r \times n)$ matrix. The adjusted measurement equation therefore becomes

$$\begin{pmatrix} y_t \\ Ax_t \end{pmatrix} = \begin{bmatrix} \mu \\ 0 \end{bmatrix} + \begin{bmatrix} \Lambda_{yx} \\ A\Lambda \end{bmatrix} F_t + \begin{pmatrix} \varepsilon_{y,t} \\ A\varepsilon_t \end{pmatrix},$$

while the state equation remains unchanged. To reduce the incurred information loss, Bräuning and Koopman (2014) construct A using principal component weights. Denote by $\hat{F}_t = A_{pc}x_t$ the r principal components associated with the largest eigenvalues of the data matrix $(x_1, \ldots, x_T)'$. By writing $\hat{F}_t \approx F_t + error$, pre-multiplying (4) by $P = \begin{bmatrix} 1 & 0 \\ 0 & A_{pc} \end{bmatrix}$ gives the collapsed dynamic factor model

$$\begin{pmatrix} y_t \\ \hat{F}_t \end{pmatrix} = \begin{bmatrix} \mu \\ 0 \end{bmatrix} + \begin{bmatrix} \Lambda_{yx} \\ I_r \end{bmatrix} F_t + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_t^{pc} \end{pmatrix}, \tag{5}$$

where $\varepsilon_t^{pc} = A_{pc}(\varepsilon_t - (A'_{pc} - \Lambda)F_t)$.

Since GDP growth is observed quarterly, we need to adjust the state space representation further so that the observed GDP growth and the monthly indicators can be incorporated into the same dynamic factor system. To do so, we adopt the framework proposed by Mariano and Murasawa (2003). The idea is to express the observed quarterly GDP in terms of its partially observed monthly counterpart, which will lead to a variant of the missing observations problem that can be treated easily with the Kalman filter.

Let GDP_t^Q denote the observed quarterly level of GDP and GDP_t^M be its unobservable monthly counterpart. Thus, if GDP_t^Q is observed at the end of each quarter, we obtain that

$$\begin{cases} GDP_t^Q = GDP_t^M + GDP_{t-1}^M + GDP_{t-2}^M & t = 3, 6, 9, ... \\ NA & o.w. \end{cases}$$

Let us further define $Y_t^Q = \log(GDP_t^Q)$ and $Y_t^M = \log(GDP_t^M)$. Then, the unobserved monthly logarithmic growth rate y_t is equal to ΔY_t^M. To bridge between the observed quarterly series and the monthly data, we also define the GDP growth as a partially observed monthly series:

$$\begin{cases} y_t^Q = Y_t^Q - Y_{t-3}^Q & t = 3, 6, 9, ... \\ NA & o.w. \end{cases}$$

and apply the approximation of Mariano and Murasawa (2003):

$$y_t^Q = \frac{1}{3}y_t + \frac{2}{3}y_{t-1} + y_{t-2} + \frac{2}{3}y_{t-3} + \frac{1}{3}y_{t-4} \quad t = 3, 6, 9, ...$$

Finally, the quarterly and monthly series are modeled jointly using the suitable expansion of the state equation. For ease of exposition, let $r = p = 1$ (for a general formula see Appendix B). Then, the state space form can be written as

$$\begin{pmatrix} y_t^Q \\ \hat{F}_t \end{pmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ \varepsilon_t^{pc} \end{pmatrix}$$

$$\begin{pmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ F_t \end{pmatrix} = \begin{bmatrix} \mu \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & \Lambda_{yx}\Phi_1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \Phi_1 \end{bmatrix} \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ y_{t-5} \\ F_{t-1} \end{pmatrix} + \begin{bmatrix} 1 & \Lambda_{yx} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{pmatrix} \varepsilon_{y,t} \\ u_t \end{pmatrix}.$$

To summarize, the estimation of the CDFM consists of two steps. First, the information contained in the monthly variables is decomposed into a small number of factors through the principal component analysis. If some of the observations are missing, imputation is performed using the EM algorithm proposed by Stock and Watson (2002). In the second step, the monthly factors are modeled jointly with the quarterly GDP growth in a properly adjusted dynamic factor model.

Due to the aforementioned limitations of the PCA procedure in extracting information from the high-frequency indicators, which can be even stronger in small markets like Israel where the number of variables is rather limited, we propose using the PLS method in the first step. PLS is a recent dimension reduction technique that unlike PCA uses an additional (possibly multidimensional) response variable in its construction and extracts orthogonal components that aim to explain both the response and the predictors. In the presence of a good proxy for the unobserved monthly GDP growth, the method has the potential to significantly improve model performance. First, the method is expected to put smaller weight on the variables with strong idiosyncratic noise. Second, it is expected to be able to extract more relevant information with a smaller number of components, thereby keeping model parsimony and reducing the variance. From a theoretical point of view, Stock and Watson (2002) showed that PCA can produce consistent estimates of F_t when both T and n tend to infinity. More recently, Groen and Kapetanios (2016) showed that PLS has a similar property. Moreover, it retains the optimality characteristics even in the weak-factor case for which it is known that PC regression becomes inconsistent. In the nowcasting literature these findings were recently utilized in the MIDAS-like framework (e.g., Kelly and Pruitt, 2015; Hepenstrick and Marcellino, 2019).

3 Data

We consider 31 economic indicators, of which only the target, GDP growth, is quarterly. An overview of the indicators including sources, available time spans, and transformations, is provided in Table 4. The monthly indicators are selected to represent a wide range of aspects of Israeli economic activity and overall are similar to what is customary in the literature (e.g., Bok et al., 2018). All the indicators are adjusted for price changes and seasonality, and are transformed to be stationary. The foreign data are presented in fixed USD prices.

In addition, in Section 4.2 we use balances of opinions from the Business Tendency Survey. This is a compulsory monthly survey conducted since 2011[1] by the Israeli Central Bureau of Statistics among $1,600$ firm managers in the manufacturing, construction, trade, hotels, and services industries, in which the managers provide an assessment (on a five-point scale, from "marked decrease" to "marked increase") of the current situation of their business and the outlook for the near future. The questionnaires are related to the companies' main parameters such as output, domestic and export sales, employment, and

[1]Even though the survey has been conducted since 2011, the data used for the current experiment have been available only since 2016 because of changes in the questionnaire format.

prices. The Business Tendency Survey is released during the second week of each month and thus these "soft-data" inputs can be used to extract the signals for the associated macroeconomic indicators that are released with much longer delays.

4 Empirical results

In this section we discuss a variety of aspects of our empirical results. First, we illustrate the advantages of the CDFM in nowcasting GDP growth. Then, we demonstrate its usefulness in monitoring the monthly changes in economic activity. Finally, we study various issues related to forecasting in real time.

Section 4.1 starts with our centerpiece, a nowcast for current-quarter GDP growth. The predictive accuracy of the DFM and CDFM is evaluated through a pseudo-real time forecasting experiment where the predictions for each quarter are calculated from the expanding set of the available data (monthly and quarterly). The smallest information set consists of the monthly data up to the first month of a quarter and has no information on the previous period's growth. Next, we consider a forecast based on two months and the previous period's growth. Finally, the biggest information set consists of full monthly data. For the CDFM, the treatment of missing data is straightforward using the EM algorithm (Stock and Watson, 2002).

Section 4.2 discusses topics related to forecasting in real time with the emphasis on the use of more timely released "soft" data.

4.1 Pseudo real-time forecasting experiment

Following the discussion in Sections 1 and 2, we estimate CDFM (henceforth, CDFM^{PLS}) using the PLS components with the total revenue index being used as a monthly proxy. Its predictive performance is then compared with the CDFM using the PCA components (henceforth, CDFM^{PC}), dynamic factor model (henceforth, DFM), and the current Bank of Israel nowcasting model (henceforth, Bridge), which is constructed as a combination of an econometric model (for more technical details see Krief, 2011) and a judgmental forecast. Both CDFM specifications contain two latent factors.

The evaluation of forecasting methods in this subsection is focused on the period before the COVID-19 crisis and it uses the monthly and quarterly data from January 2000 to December 2019. To make the nowcasts in the CDFM and DFM, for each quarter in the test sample we reestimate the model using the monthly and quarterly data from January 2000 up to one of our three variants of the information set. The initial training period is from January 2000 to January 2010, and the forecast evaluation is done for the period from 2010:Q1 to 2019:Q4. Challenges related to nowcasting in real time and during periods of distress such as 2020 will be discussed in more detail in the following subsection.

The Bridge model nowcasts are created in three steps. First, separate models are fitted through OLS to the subcomponents of the GDP using quarterly aggregates of the monthly indicators. Then, the models are combined to construct a nowcast. Finally, the nowcast is adjusted using judgment. The nowcast is performed during the second half of the last month of a quarter under consideration. Thus, its predictive accuracy is comparable only to the DFM and CDFM nowcasts that are made based on two months of data.

As was noted in Section 2, collapsing is aimed at reducing the number of parameters and hence the forecast variance. However, at the same time, it incurs a loss of information (Bräuning and Koopman, 2014). Consequently, it would be interesting to compare the predictive performance of the CDFM to that of the DFM to see whether the benefits from dimension reduction overweight the information loss. Our DFM specification is based on the same set of variables as the CDFM with the block structure proposed by Bok et al. (2018) and is fitted using the expectation maximization algorithm as described in Bańbura and Modugno (2014).

The models' out-of-sample prediction performance is compared to the benchmark AR model fitted using the Akaike information criterion (AIC). Table 1 below reports the root mean squared error (RMSE) and the mean absolute error (MAE) by the available information set as the ratios to the corresponding error metrics of the benchmark, as well as the results of the Diebold and Mariano test with correction for small samples (Harvey et al., 1997). In addition, for timeliness compatibility, Figure 1 presents a nowcast based on 2 months for each of the four models along with the most updated[2] measure of GDP growth.

[2]Available in April 2021.

Table 1: Mean squared and absolute nowcast errors

Model	By 1 month		By 2 months		By 3 months	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
$\mathrm{CDFM}^{\mathrm{PLS}}$	0.871	0.898	0.814^{**}	0.872^{*}	0.809^{**}	0.856^{**}
$\mathrm{CDFM}^{\mathrm{PC}}$	0.908	0.980	0.911	0.975	0.893	0.955
DFM	0.982	0.999	0.932	1.007	0.934	1.027
Bridge			0.876	0.925		

Note: The RMSE and the MAE for the models are reported as the ratios to the corresponding error metrics of the benchmark AR model fitted using the AIC. ** and * denote the rejection of the null hypothesis of the Diebold and Mariano (1995) test (assuming that there is no difference in forecast accuracy over the benchmark) at the 5% and the 10% level, respectively. The evaluation period is from 2010:Q1 to 2019:Q4.

Table 2: Directional forecast accuracy

Model	By 1 month	By 2 months	By 3 months
$\mathrm{CDFM}^{\mathrm{PLS}}$	74%	82%	77%
$\mathrm{CDFM}^{\mathrm{PC}}$	74%	79%	77%
DFM	77%	82%	77%
Bridge		72%	

Note: The table reports the percentage of times the models predicted correctly whether the current period growth would be higher or lower than the previous one. The naive (constant) prediction accuracy rate is 0.56 and the benchmark AR has 0.72.

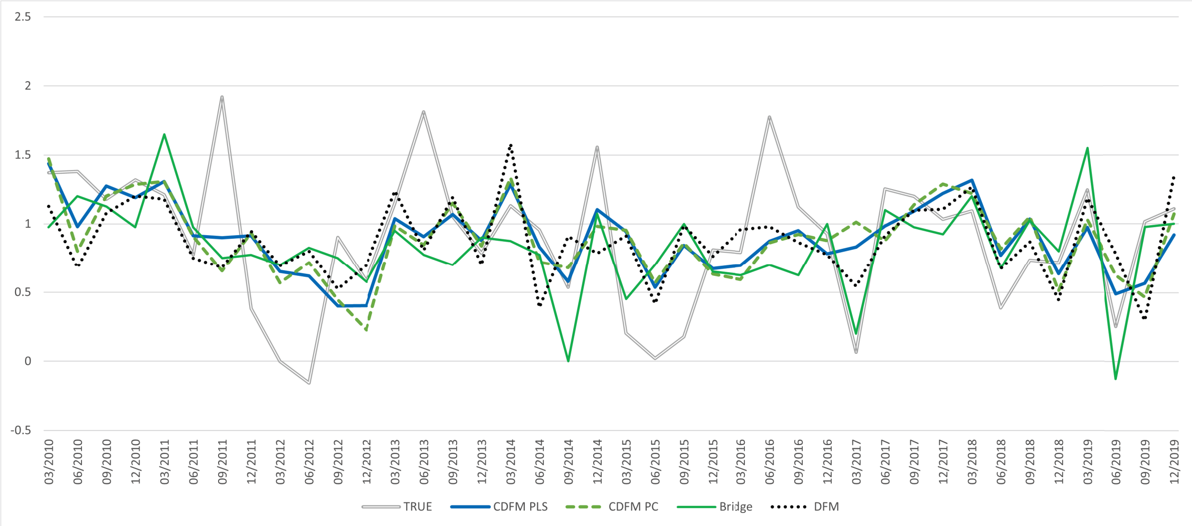

Figure 1: Quarterly GDP growth nowcasts, 2010:Q1–2019:Q4

We can generally see that in all three setups the CDFM$^{\text{PLS}}$ gives the lowest prediction error with the improvement over the benchmark ranging from 13% (when the nowcast is based on one month of data) to 19% (on the full quarterly data). The improvement is statistically significant for the setups containing 2 months of data or more. Returning to the issue of dimension reduction, it is evident that both the CDFM$^{\text{PLS}}$ and the CDFM$^{\text{PC}}$ have a smaller error than the DFM even though the improvement of the latter is not found to be statistically significant. This underlines the virtue of parsimony in forecasting models.

In addition, it would be interesting to see whether the models are able to track the directional changes in the growth level – in particular, whether the current growth would be higher than the previous one. Table 2 presents the results for the four models. It turns out that the models have similar accuracy with only a slight improvement over the benchmark.

Joint modeling of the monthly and quarterly variables in the CDFM is achieved by the expansion of the state vector in terms of the unobserved monthly GDP growth. As was demonstrated by Brave et al. (2019), these monthly growth rates can provide a valuable indication of the current state of the economy and are presented in intuitively appealing units. The associated new activity index is calculated from the smoothed values of the state corresponding to the unobserved monthly GDP growth. Several observations are in order. As can be seen from Figures 2 and 3, our activity indicator (TETA) broadly coheres with the Israeli Composite State of the Economy Index[3] (ICI) during various stages of the cycle. However, it has a much higher volatility, which partly follows from the use of a broader information set and a binding restriction on the monthly growth rates to sum up exactly to the predicted quarterly growth (or to the actual, when available).

The advantages of this higher sensitivity became apparent during 2020. As can be seen from Figure 3, during the whole period ICI continues to hover around zero and shows almost no indication of the crisis. By contrast, we observe a sharp drop in the new index, coinciding with the emergency measures enacted in March, which plunges even deeper in April. The marked improvement in May also corresponds to the easing of the lockdown restrictions. Finally, the negative values in October coincide with the second lockdown. This is in stark contrast to the ICI, which remains at almost the same level from May onward. This demonstrates the ability of our new index to give a more precise picture of the current state of the economy and to indicate earlier turning points.

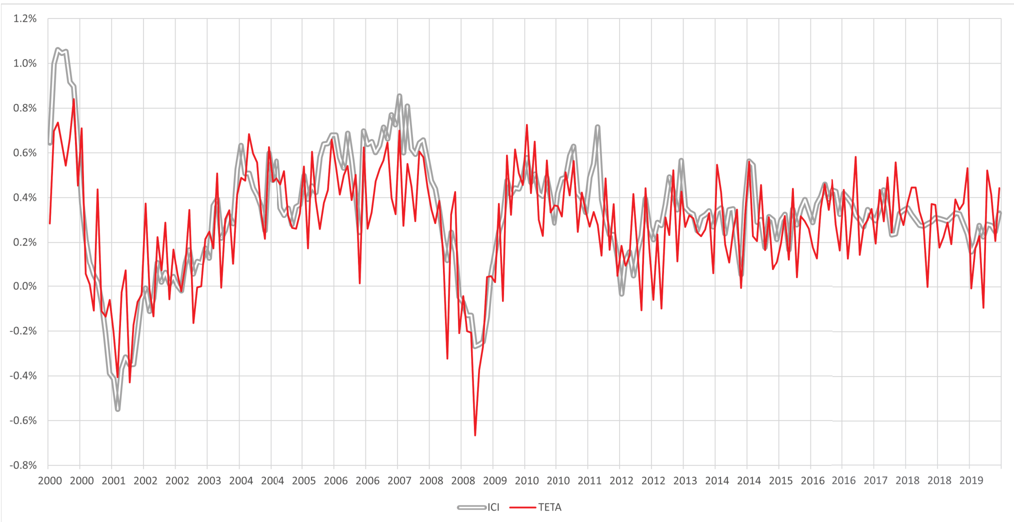

Figure 2: Monthly economic activity indices: TETA alongside ICI (2000/1–2019/12).

[3]https://www.boi.org.il/en/Research/Pages/ind.aspx

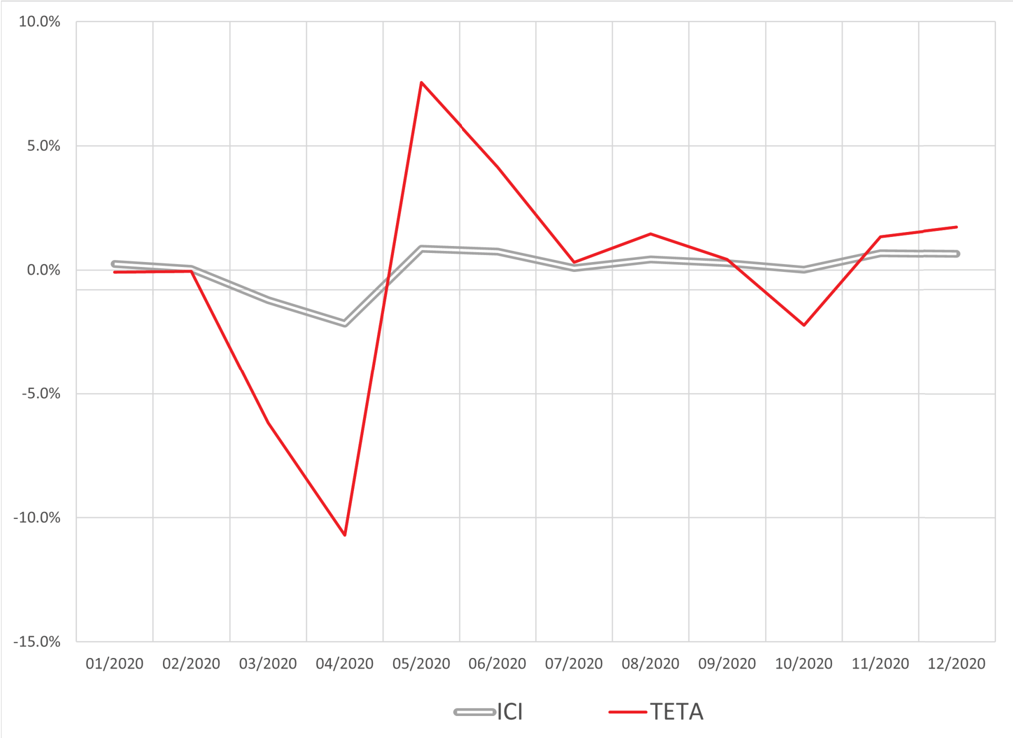

Figure 3: Monthly economic activity indices: TETA alongside ICI (2020/1–2020/12).

4.2 Real-time nowcasting and use of "soft" data

In this subsection, we discuss the issues associated with the use of soft data in real-time nowcasting. Many important monthly inputs, such as industrial production, revenue, and labor indices, are published after long delays (see Table 5 for more details on the data cycle). On the other hand, there are more timely released but potentially less accurate "soft" proxies, such as business surveys, that can be used to extract the associated signals for the aforementioned "hard" inputs earlier.

In the present application, we use the Business Tendency Survey. It is a compulsory monthly survey conducted since 2011 by the Israeli Central Bureau of Statistics among 1,600 firm managers in the manufacturing, construction, trade, hotels, and services industries, in which they provide an assessment (on a five-point scale, from "marked decrease" to "marked increase") of the current situation of their business and the outlook for the near future. The questionnaires are related to the companies' main parameters, such as output, domestic and export sales, employment, and prices. Balances of opinion from such surveys have proven useful in forecasting GDP growth (see, e.g., Pichette and Rennison, 2011; Chernis and Sekkel, 2017) and can be used either directly or for the endpoint imputation of the associated "hard" indicators.

Using survey data to forecast economic conditions has been popular at central banks; see Anesti et al. (2017), Bok et al. (2018), and Chernis and Sekkel (2017) for recent applications by central banks, and Bańbura et al. (2013) for a review of the topic. Typically, survey-based variables are added directly to the set of "traditional" monthly indicators or even used to replace them. However, it is found that the distributional properties of surveys are not homogeneous over time and that they tend to overreact in periods of high uncertainty (Anesti et al., 2017). Thus, using them directly or even together with the "traditional" indicators they are meant to proxy could make a model less stable. For instance, in the context of linear regression, it is easy to see that when the model contains both a relevant explanatory variable and its proxy (which is a mix of a signal and noise), the coefficient of the proxy variable would represent the impact of the noise. Thus, we consider a different approach where instead of training the model directly on the survey proxies, we use them only for endpoint imputation. By doing so we limit the "soft" indicators to having an impact only on the forecast uncertainty but not on the model parameters.

For this purpose, we reconstructed the data vintages at the weekly frequency and produced a sequence of forecasts based on the expanding set of information (i.e., imitating the true data cycle, starting from the second month of a reference quarter up to one month after the end of a quarter, we produced nowcasts at the weekly frequency). In the CDFM framework, BTS variables can be added directly to the monthly panel or used for external imputation of the series they are meant to proxy. To see which method is better, we evaluate the average precision of the nowcasts by comparing these to the BTS-based methods (i.e., with imputation and BTS variables being added directly) with the model without the BTS variables that serves as a benchmark. For the method using external imputation by BTS, the endpoint imputation is done using the unobserved components model (henceforth, UCM) proposed by Harvey (1990) on the log levels. For the list of the imputed series and the data cycle see Table 5.

The experiment is conducted for the period from February 2018 to January 2021 giving a total of 156 nowcasts; i.e., we make nowcasts starting from the second month up to one month after the end of a reference quarter. The choice of this period is mainly due to the short available history of the data on BTS. It is available since 2016 and the period before 2018 was used for initial training of the UCM.

Table 3 provides a breakdown of the average nowcasting error of $\mathrm{CDFM}^{\mathrm{PLS}}$ for each year by the BTS inclusion method. The bottom line summarizes the RMSE and the MAE for the overall period from 2018 to 2020 (including the COVID-19 crisis). Overall, it can be seen that using BTS imputation reduces the nowcast RMSE and MAE compared to the method without the BTS imputation. In contrast, adding the BTS variables directly increases the error compared to the benchmark without imputation. In addition, we performed the Diebold and Mariano test to verify that the difference over the benchmark method without BTS is significant. It is found that the method with imputation by BTS has a smaller error at the significance level of 1% and the method taking BTS block has a larger error at the significance level ranging between 5% and 1% depending on the error metrics. Figures 4-6 present the evolution of the nowcasts during the period from February 2018 to January 2021. It can be seen that nowcasts using BTS imputation are much smoother. In addition, the benchmark converges roughly to the same point as the model with imputation. Nevertheless, the significantly lower error rate in the case of BTS imputation underlines the usefulness of "soft" data as an early indicator.

Table 3: Error summary by BTS inclusion method

	Imputation by BTS		Without BTS		With BTS block	
Year	MAE	RMSE	MAE	RMSE	MAE	RMSE
2018	0.264	0.320	0.366	0.436	0.313	0.376
2019	0.234	0.294	0.286	0.355	0.336	0.397
2020	3.269	3.882	3.548	4.323	4.001	4.764
All	1.255***	2.225***	1.400	2.517	1.55**	2.768*

Note: The table reports the average errors by year and survey inclusion method. The nowcasts are created at a weekly frequency from February 2018 to January 2021. The bottom row provides the RMSE and MAE for the total period from 2018 to 2020. ***, ** and * denote the rejection of the null hypothesis of the Diebold and Mariano (1995) test (assuming that there is no difference in forecast accuracy over the benchmark without imputation) at the 1%, 5% and the 10% level, respectively.

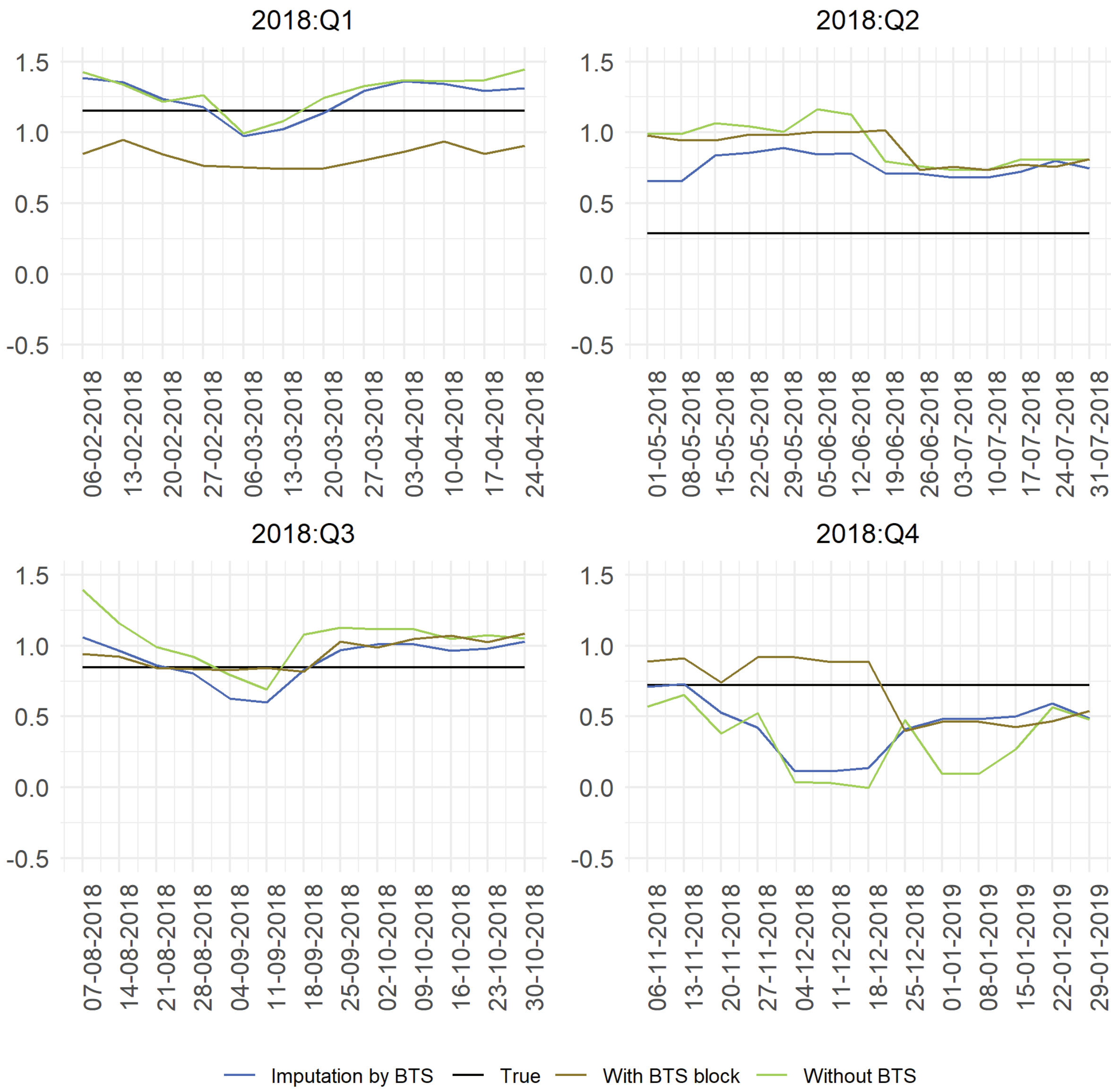

Figure 4: Real-time quarterly GDP nowcasts, 2018

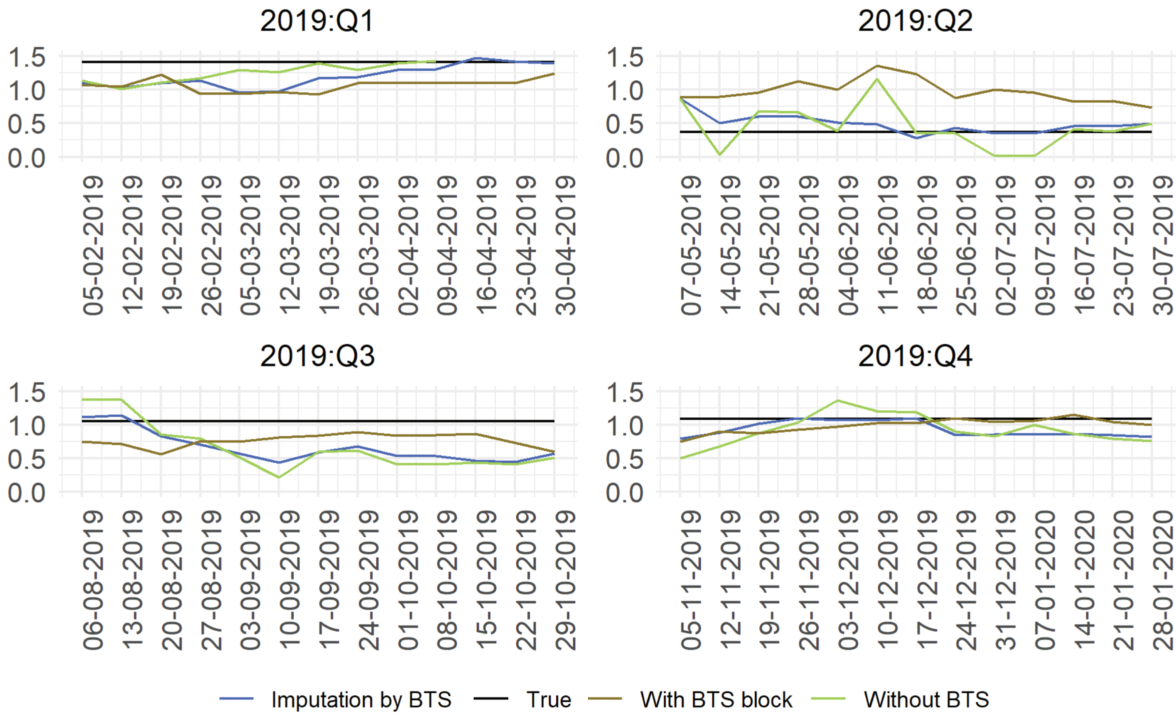

Figure 5: Real-time quarterly GDP nowcasts, 2019

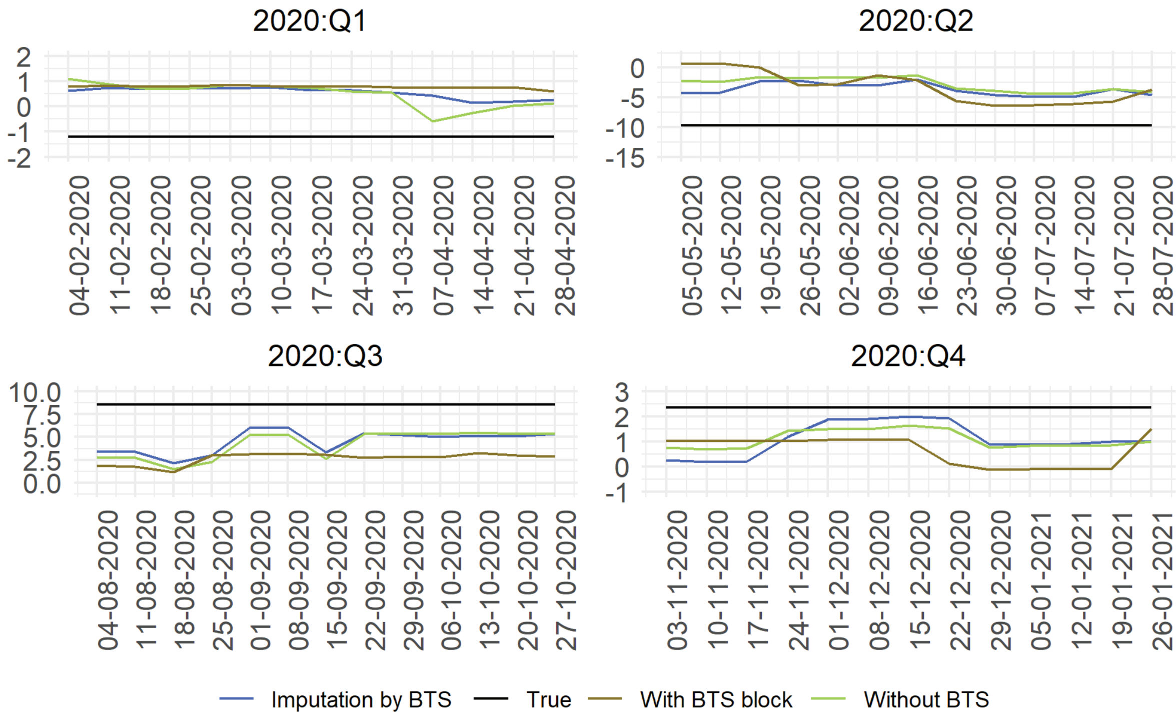

Figure 6: Real-time quarterly GDP nowcasts, 2020

4.3 Treating regulatory interventions

In this section, we discuss our treatment of the effect of vehicle import spikes on GDP growth. As can be seen from Figure 7 below, that presents the nowcasts errors based on the three types of the information sets used in Section 4.1, the errors comove strongly with the changes in vehicle imports. This happens because of the combination of national accounting rules with the ecotax regulations in Israel that result in sudden moves in the GDP that are unrelated to economic fundamentals.

As we know, GDP represents a sum of the expenditures plus the trade balance (exports minus imports). Thus, normally, an increase in imports should not lead to a significant change in GDP. However, in the case of vehicle imports in Israel, the effect is positive due to high rates of import taxes on vehicles. To understand why, consider a recently imported car. Its final price consists of the original price paid to a foreign car dealer, tariffs (approximately 90% the original price), a markup, and VAT. The final price enters the consumption (or the investment for car leasing companies) while the original price paid abroad is attributed to imports. Since the resulting final price is roughly more than twice the original price, an increase in vehicle imports surprisingly leads to an increase in GDP through its positive impact on consumption and investment. As can be seen from Figure 7 below, nowcast errors systematically have high positive spikes followed by a sharp decline. The reason behind these waves lies in the periodic updates of the vehicles ecotax regulations on emissions which lead to an increase in the price of vehicles. Since only the update date is known in advance (a couple of months before) while its breakdown is not, the resulting uncertainty causes people to massively prepone their car purchases amid the expected price increase, and we observe sudden spikes in the GDP. The resulting waves are unrelated to economic fundamentals, and thus it is harder to model their comovement with the monthly GDP growth dynamics within the CDFM by simply expanding the monthly dataset by an additional variable.

To address this issue, similarly to Sayag et al. (2021), we adjust the CDFM nowcasts externally using the regression between the previous errors, say $e_{i,t}$ and the log difference of vehicles import say, $imv_{i,t}$,where $i \in \{1, 2, 3\}$ represents the number of known months for vehicle import and t is the time index. More specifically, similarly to the experiment in Section 4.1, $e_{i,t}$ corresponds to a nowcast error at period t that is based on the information set of i months. Accordingly, $imv_{i,t}$ represents the quarterly logarithmic growth in vehicles imports, where the current quarter amount of vehicles import is calculated solely from the data up the $i-$th month of a quarter under consideration. The corrected nowcasts are constructed as a sum of the CDFM nowcast and the prediction for $e_{i,t}$. Unfortunately, due to the very limited number of updates it is hard to assess the gain in predictive accuracy due to the correction. In addition, it is worth noting that after the correction, nowcasts become inconsistent with the estimates of the monthly GDP growth. However, this can be easily resolved by imputing the corrected nowcast back to the data set and rerunning the Kalman smoother.

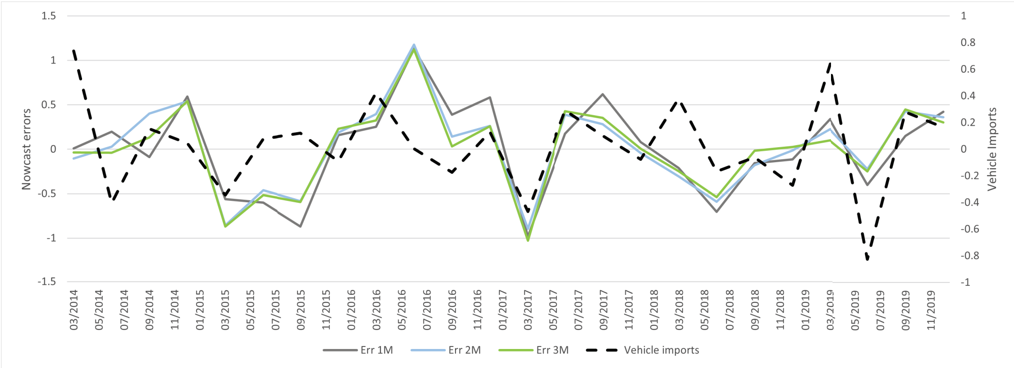

Figure 7: CDFM$^{\text{PLS}}$ nowcast errors by available information set (2014:Q1–2019:Q4).

5 Summary

In this paper, we applied an extension of the CDFM to produce the nowcasts for Israeli quarterly GDP growth. Our pseudo-real-time forecasting experiment shows that the model is able to produce nowcasts as accurately as the judgmental one (Bridge). In addition, we have shown that using a proxy for the unobserved monthly GDP growth can reduce the information loss resulting from dimension reduction and thus improve the accuracy of the forecasts. Our real-time nowcasting experiment underlines the importance of using more timely released survey-based indicators for purposes of endpoint imputation of the "hard" data. In contrast, direct expansion of the information set with the survey proxies of some of the "hard" indicators leads to inferior forecasting performance. Moreover, similarly to Brave et al. (2019), we applied the CDFM framework to produce a monthly index of economic activity. The index is shown to be able to give a more precise picture of the current state of the economy and to indicate earlier turning points.

Appendix A: Data description

Table 4: Monthly variables list

Explanatory Variable	Data Source	Data start	Seas. adj.	Fixed price	Transformation
Total Revenue	Index, CBS	2000-01	✓	NIS	log-dif
Industrial Production - total	Index, CBS	2000-01	✓	NIS	log-dif
Revenue in Trade	Index, CBS	2000-01	✓	NIS	log-dif
Revenue in Services	Index, CBS	2000-01	✓	NIS	log-dif
Revenue in business and private services (a)	Index, CBS	2000-01	✓	NIS	log-dif
Revenue in food and accommodation services	Index, CBS	2000-01	✓	NIS	log-dif
Sales Value in Chain Stores	Index, CBS	2000-01	✓	NIS	log-dif
Credit cards purchases (a)	CBS/Shva	2002-01 /2016-01	✓	NIS	log-dif
Building starts	CBS	2000-01	✓		log-dif
Benzine consumption	Ministry of Energy, Fuel Dep.	2000-01	✓	NIS	log-dif
Imports of consumer goods	CBS	2000-01	✓	$	log-dif
Imports of production inputs	CBS	2000-01	✓	$	log-dif
Imports of capital goods	CBS	2000-01	✓	$	log-dif
Exports of goods	CBS	2000-01	✓	$	log-dif
Exports of business and tourist services	CBS	2009-01	✓	$	log-dif
Exports of services	BOI system	2000-01	✓	$	log-dif
Imports of services	BOI system	2000-01	✓	$	log-dif
Employment excluding absent workers	CBS	2000-01	✓		log-dif
Employee posts in the private sector	CBS	2000-01	✓		log-dif
Total (real) wages per employment posts (c)	CBS	2000-01	✓	NIS	log-dif
Job openings	CBS	2009-06	✓		log-dif
PMI of Israel	Bank-Hapoalim	2000-01	✓		
PMI of USA	Bloomberg	2000-01			
Electricity consumption (06:00-11:00), adjusted for weather conditions (b)	BOI model	2002-01	✓		log-dif
Taxes: VAT net (c)	Ministry of Finance	2000-01	✓		log-dif
Taxes: indirect (c)	Ministry of Finance	2000-01	✓		lag(1), log-dif
Taxes: health (c)	National Insurance	2000-01	✓		log-dif
Consumer confidence	Bank-Hapoalim	2002-02			
Cushing oil price	Bloomberg	2000-01			log-dif
TA General shares index	TASE	2000-01			log-dif

Notes: a - Adjusted for CPI; b - Based on on-line hourly data from Israel Electric Company and Israel Meteorological Service; c - Adjusted for CPI and legislation changes.

Table 5: Data release timeline

Explanatory Variable \ Day of month	< 7	$7 - 14$	$15 - 22$	> 22
Total Revenue	-2	E (2)	E (2)	E (1)
Industrial Production - total	-2	E (2)	E (2)	E (1)
Revenue in Trade	-2	E (2)	E (2)	E (1)
Revenue in Services	-2	E (2)	E (2)	E (1)
Revenue in business and private services	-2	E (2)	E (2)	E (1)
Revenue in food and accommodation services	-2	E (2)	E (2)	E (1)
Sales Value in Chain Stores	-1	E (1)	E (1)	E (1)
Credit cards purchases value	✓	✓	✓	✓
Building starts	-5	E (4)	E (4)	E (4)
Benzine consumption	-1	-1	-1	-1
Imports of consumer goods	-1	-1	-1	✓
Imports of production inputs	-1	-1	✓	✓
Imports of capital goods	-1	-1	✓	✓
Exports of goods	-1	-1	✓	✓
Exports of business and tourist services	-2	-2	-2	E (2)
Exports of services	-1	-1	-1	✓
Imports of services	-1	-1	-1	✓
Employment excluding absent workers	-1	E (1)	E (1)	E (1)
Employment posts in the private sector	-2	E (2)	E (2)	E (2)
Total (real) wages per employment posts	-2	E (2)	E (2)	E (2)
Job openings	-1	-1	-1	✓
PMI of Israel	-1	-1	-1	✓
PMI of USA	-1	-1	✓	✓
Electricity consumption (06:00-11:00), adjusted for weather conditions	✓	✓	✓	✓
Taxes: VAT, net	✓	✓	✓	✓
Taxes: indirect	-1	✓	✓	✓
Consumer confidence	-1	-1	✓	✓
Taxes: health	-1	✓	✓	✓
Cushing oil price	✓	✓	✓	✓
TA General shares index	✓	✓	✓	✓

Notes: ✓- denotes full availability of the predictor for the target month. -1, -2 etc - denote missing observations with a delay of 1 or 2 months, respectively. E (1), E (2) denote missing observations of 1 and two months that are imputed using BTS as described in Section 4.2.

Appendix B

Here we give a general formula of the mixed frequency state space representation in Section 2. Let $\Lambda_{yx} = [\Lambda_1, \Lambda_2, ..., \Lambda_r]$ be a $(1 \times r)$ matrix of the factor coefficients. We define the state space as follows:

Measurment equation

$$\begin{pmatrix} y_t^Q \\ \hat{F}_t \end{pmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & \mathbf{0}_{(1\times r)} & \mathbf{0}_{(1\times r(p-1))} \\ \mathbf{0}_{(r\times 1)} & \mathbf{0}_{(r\times 1)} & \mathbf{0}_{(r\times 1)} & \mathbf{0}_{(r\times 1)} & \mathbf{0}_{(r\times 1)} & I_r & \mathbf{0}_{((r\times(p-1))} \end{bmatrix} \begin{pmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ F_t \\ F_{t-1} \\ \vdots \\ F_{t-p+1} \end{pmatrix} + \begin{pmatrix} 0 \\ \varepsilon_t^{pc} \end{pmatrix}$$

State equation

$$\begin{pmatrix} y_t \\ y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ F_t \\ F_{t-1} \\ \vdots \\ F_{t-p+1} \end{pmatrix} = \begin{pmatrix} \mu \\ 0 \\ 0 \\ 0 \\ 0 \\ \mathbf{0}_{(r\times 1)} \\ \mathbf{0}_{(r\times 1)} \\ \vdots \\ \mathbf{0}_{(r\times 1)} \end{pmatrix} + \begin{bmatrix} T_{11} & T_{12} \\ T_{21} & T_{22} \end{bmatrix} \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ y_{t-3} \\ y_{t-4} \\ y_{t-5} \\ F_{t-1} \\ F_{t-2} \\ \vdots \\ F_{t-p} \end{pmatrix} + \begin{bmatrix} 1 & \Lambda_{yx} \\ \mathbf{0}_{(4\times 1)} & \mathbf{0}_{(4\times r)} \\ \mathbf{0}_{(r\times 1)} & I_r \end{bmatrix} \begin{pmatrix} \varepsilon_{y,t} \\ u_t \end{pmatrix}.$$

For ease of exposition, subcomponents of the state transition matrix are defined separately as

$$T_{11} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \; T_{12} = \begin{bmatrix} \Lambda_{yx}\Phi_1 & \Lambda_{yx}\Phi_2 & \cdots & \Lambda_{yx}\Phi_p \\ \mathbf{0}_{(4\times r)} & \mathbf{0}_{(4\times r)} & \cdots & \mathbf{0}_{(4\times r)} \end{bmatrix}$$

$$T_{21} = \mathbf{0}_{(rp\times 5)}, \; T_{22} = \begin{bmatrix} & \Phi & \\ I_{p-1}\otimes I_r & & \mathbf{0}_{(r(p-1)\times r)} \end{bmatrix},$$

where Φ is an $r \times pr$ matrix of the autoregressive coefficients

$$\Phi = \begin{bmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_p \end{bmatrix}.$$

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