TÜRKİYE CUMHURİYET MERKEZ BANKASI

Nowcasting Turkish GDP Growth with Targeted Predictors: Fill in the Blanks

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NOWCASTING TURKISH GDP GROWTH WITH TARGETED PREDICTORS: FILL IN THE BLANKS

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Abstract

This paper analyzes four dimensions of forecasting GDP growth using monthly data. Firstly, we use AR, VAR, BVAR, mean-growth and zero month-on-month change for forecasting the missing monthly data at the end of forecasting sample due to asynchronous nature of the release of the indicators. Second dimension is using a relatively large data set and testing some indicators that are not frequently used for forecasting GDP growth but due to timeliness have the potential to contribute to the forecasting performance. We analyze data from a career website, freight information from maritime transportation, capacity utilization of available plane seats, tax revenues of the central government and credit and debit card transaction volumes. Third dimension is comparing the performance of model averaging and factor models that are used to incorporate information content of large data sets to the forecasting process. Finally, we look at the forecasting performance of a core data set that is selected by a shrinkage method, namely LASSO. Our findings show that using VAR models with financial and survey indicators for forecasting missing monthly data improves short term GDP forecasting performance relative to other alternatives. We find that forecasting using targeted predictors rather than using an unscreened large data set helps to reduce forecasting errors considerably. Factor model approach performs better than forecast combination. So, using a targeted data set for factor extraction and forecasting missing monthly data with VAR performs relatively better than other specifications for producing timely and accurate nowcasts.

JEL classification: C52; C53; E20

Keywords: GDP forecasting; Bridge models; Factor models, LASSO, targeted predictors

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Özet

Bu çalışmada, model bazlı kısa dönemli milli gelir tahminlerinin performansını etkileyebilecek dört boyut incelenmektedir. İlk olarak, aylık göstergelerin eksik verilerini tahmin etmekte kullanılan yöntemin milli gelir tahmini performansına etkisi incelenmiştir. Bu çerçevede, AR, VAR, BVAR, ortalama büyüme ve aydan aya sıfır değişim ile aylık göstergelerin eksik verileri doldurulmuş, ardından milli gelir tahminleri üretilerek bu yöntemlerin tahmin performansına etkisi karşılaştırılmıştır. İkinci boyut olarak, görece geniş bir veri seti kullanmanın tahmin performansına etkisi analiz edilmektedir. Bu veri seti, zamanlı olması nedeniyle büyüme tahminlerine katkı yapabilecek ama çok sık kullanılmayan göstergeleri de içermektedir. Bu kapsamda, bir iş ilanı sitesinden veriler, deniz yolu taşımacılığı, uçak koltuklarının doluluk oranı, vergi gelirleri ile banka kartları işlemlerini takip eden bir endeks kullanılmıştır. Üçüncü boyut olarak, büyük veri setlerinin tahmin süreçlerinde kullanılmasına imkân veren tahmin birleştirmesi ve faktör modeli yaklaşımlarının sonuçları karşılaştırılmıştır. Son olarak, LASSO yöntemi ile çekirdek bir veri seti seçilmiş ve bu daha küçük veri setinin kullanılmasının filtrelenmemiş daha büyük veri seti kullanmaya göre tahmin performansına etkisi incelenmiştir. Bulgular, aylık değişkenlerin eksik verilerinin finansal ve anket göstergeleri kullanılarak VAR yöntemi ile tahmin edildikten sonra milli gelir büyümesi tahminleri üretilmesinin diğer alternatiflere göre daha az tahmin hatası yaptığını göstermiştir. Ön elemeden geçirilmemiş büyük veri seti kullanmaktansa hedefli göstergeler kullanılarak daha az sayıda gösterge ile daha iyi tahminler yapılabildiği bulunmuştur. Faktör model yaklaşımı, bireysel modellerin tahminlerinin birleştirilmesinin kullanılmasından daha iyi sonuç vermektedir. Özetle, hedef değişkenle ilişkiye göre filtrelenmiş çekirdek bir veri setinin kullanılması, bu veri setindeki aylık göstergelerin tahmin anındaki eksik verilerinin VAR ile doldurulması görece daha zamanlı ve daha isabetli milli gelir tahmini üretmeye imkân vermektedir.

JEL sınıflaması: C52; C53; E20

Anahtar Kelimeler: GSYİH, Tahmin, Köprü Denklemleri, Faktör Modelleri, LASSO

Non-technical Summary

Macroeconomic and financial data are released in an asynchronous manner. For example, survey data are timelier than the so-called hard data such as industrial production and financial indicators are even timelier. In this paper, we analyze nowcasts for Turkish GDP growth with a special emphasis on the method for forecasting the missing data for higher frequency indicators at the end of the forecasting sample. For this aim we utilize several methods ranging from a very simple method that uses only the mean growth of the indicators to the more sophisticated techniques such as using Bayesian VARS with financial and survey data.

In the paper, we use a total of 61 indicators from different areas of the economy. We use forecast combination, which is a way to pool forecasts, and factor models, which is a way to pool the information from a large number of indicators, to deal with the relatively large number of indicators. In addition to utilizing this master data set that covers a wide range of indicators we filter the master. For this aim we use LASSO approach.

Our results indicate that regarding the methods that can be used to fill the missing data, VAR with financial and survey data provides the most improvement in the forecast performance. As data accumulate for the quarter that we aim to forecast, difference of the forecasting performance from using alternative methods to fill the missing data declines. We find that using a core data set that is crafted taking into account the target variable helps at reducing short-term forecast errors considerably. Using factor models, with one or two factors, with a targeted predictor set results in competitive forecasts.

1. INTRODUCTION

Gross Domestic Product (GDP) is a key indicator for assessing the state of the economic activity. Being a major input in the decision making process, it is closely monitored by policy makers and market participants. However, GDP data are published with a certain delay. For example, for Turkish economy GDP data are published around after 60 days of the end of the quarter. While GDP data are subject to considerable publication lag, monthly indicators for the respective quarter are published on a timelier basis. Forecasting teams at the central banks and other institutions work with alternative methods and different indicators to be able to produce accurate short term forecasts and interpret the implication of data release for economic outlook.

Converting information content of the monthly indicators to reliable signals about the pace of economic activity is not a trivial task. For starters, forecasters need to solve the so-called mixed-frequency issue. This stems from the fact that GDP data are published on a quarterly basis while indicators like industrial production is published on a monthly basis. Publication lags vary across monthly indicators as well. Some indicators, like credit growth and tax revenues, are published in the first half of the following month while indicators like industrial production and foreign trade quantity indices are published with a lag of 40-45 days. So, at the end of the sample there would be different number of missing data for monthly indicators. Another key issue that can affect forecast performance is the indicator selection process. With the advent of technology, available data at the disposal of forecasters increase rapidly. As a response, researchers develop methods, such as factor models, to utilize the information content of a large number of data to monitor and forecast GDP growth. Another active research area in this domain is to test the forecasting power of new data sets such as google search trends or toll data.

In this paper we test the forecasting power of a medium data set, 61 indicators that covers a wide range of the economy tackling issues that a forecaster faces for using these indicators. Firstly, we use bridge equation approach to deal with the issue of mixed frequency. In particular, we convert monthly indicators into quarterly frequency and link those with the quarterly GDP growth using classical regression techniques. Due to asynchronous nature of data releases, in addition to the mixed-frequency issue, researchers need to engineer methods to work with ragged-edges. There are different practices in the literature from using simple AR models to more complicated Bayesian VARs. One of the issues that our paper specifically touch on is the effect of filling the missing data at the end of the sample by different methods, namely AR, VAR, BVAR, mean growth of each indicator and assuming a constant level at the latest available monthly data. Survey data and financial indicators are utilized in the VAR and BVAR models for forecasting missing data at the end of the forecasting sample. This exercise is important as the volatility of the growth rate of GDP and indicators may be different across countries. Therefore, simple AR models may be enough to capture dynamics in low-volatility economies while for economies with relatively higher volatility using the information content of financial and survey data to forecast the missing monthly data may be a better option.

Increasing availability of the data comes with the curse of dimensionality. We use model averaging and factor models to utilize the information content of the available data. For model averaging we test four approaches: (i) simple average, (ii) weighted average where weights are obtained as the inverse of the forecast errors over the last two years, (iii) trimmed mean where we discard values from two side of the distribution and (iv) the median. We estimate factors with principal component approach.

We join the recent wave of exploration of unchartered waters of data and use indicators from a wide range of blocks of the economy. In addition to industrial production, employment, sales and foreign trade data that are traditionally used to monitor developments in real activity, we use tax revenues of the central government and credit data as well. Along with these official statistics, we use indicators from private sector sources. For example, we use job application and vacancies data from a leading career website in Turkey. Logistics data may be informative as well for the strength of the economic activity. We use loading and unloading data for maritime transportation which are related to exports and imports of goods. Tourism activity is also important for Turkish economy. We use the percentage of the available plane seats occupied in a given month as an additional indicator. This indicator can be informative about the recent trends of tourism activity. Finally, we use an index that tracks the volume of transactions of credit and debit cards.

While model averaging and factor model approaches enable researchers to use very large data sets, it is still an empirical question whether more data are always better for forecasting performance. We use a shrinkage method, namely LASSO (Least Absolute Shrinkage and Selection Operator), to reduce the size of the data set by picking the most relevant variables for forecasting GDP. This approach forces coefficients of the some of the variables to zero, i.e. shrinks. Selecting a core data set by a shrinkage method is called as targeted predictors as we select the indicators based on their relation with the indicator that we want to forecast. This exercise enables us to see whether a core data set functions better than a larger data set in forecasting GDP growth.

Our results indicate that using VAR models for forecasting missing monthly data reduces the forecast error compared to the case of using other methods. Our findings support the use of targeted predictors rather than using a larger unprocessed data set. Factor models, with one or two factors, produce competitive forecasts. Indicators from domestic turnover in industry stand out in terms of contribution to the forecasting power. In addition to the indicators from industrial production, exports, employment blocks, tax revenues survive variable selection process as well.

Structure of the paper is as follows. In the next section we introduce data set, then we present the methodologies used in the paper. After discussing the forecast design, we present results and then conclude.

2. DATA

We use indicators from data groups that are classically used in the forecasting literature such as industrial production, employment, foreign trade indicators and domestic sales (Table 1, Table A1). In addition to these indicators, we use real domestic turnover in industry, credit stock and tax revenues based on the findings of Günay and Yavuz (2017) and Günay (2019). We briefly explain technicalities about indicators we use.

For industrial production, turnover in industry and foreign trade quantity indices we work with MIGS (Main Industrial Grouping) or BEC (Broad Economic Categories) classification. These classifications disaggregate headline figures into intermediate goods, consumption goods, capital goods and energy. So, indicators in BEC or MIGS level have the potential to give information about different demand components in the economy. For each of these blocks, we could have used more disaggregate data such as NACE classification. As an example, as part of the NACE classification industrial production is disaggregated into about twenty sectors such as food, textiles and chemicals. We confine our attention to broad categories but we use selected NACE classification data only for domestic turnover in industry following the findings in Günay (2019).

We use electricity production that becomes available about one week after the end of the given month. This indicator can be affected from changes in the temperature. For example, a higher than average temperature in summer will increase the demand for air conditioners which will increase electricity consumption. So, using raw data for electricity production for tracking the speed of economic activity may cause overestimation. Therefore, following Yüncüler (2016) we use electricity production adjusted for weather effect.

Table 1. Data Set

Data Block	Acronym	Number of Indicators	Publication Lag
Electricity Production	ELECT	1	5-7 Days
Plane Seat Fill Rate	PLANE	1	5-7 Days
Sea Transport	SEATR	2	5-7 Days
Vehicle Production and Sales	VEHICLE	3	5-7 Days
Kariyer.net (A career website)	CAREER	4	5-10 Days
Credit Stock (real)	CREDIT	6	5-10 Days
Central Government Spending (real)	CGS	3	15 Days
Tax Revenues (real)	TAX	6	15 Days
Credit and Debit Card Consumption Index	ETTE	2	17-22 Days
White Goods Production and Sales	WG	3	17-22 Days
Import Quantity Index	QM	7	40 Days
Export Quantity Index	QX	4	40 Days
Real Domestic Turnover	DTI	9	45-47 Days
Industrial Production	IP	6	43-47 Days
Non-Farm Employment	NFEMP	4	45 Days

Notes: Data blocks are sorted by approximate publication lags. A detailed list of the indicators are listed in Table A1.

A reading of the literature on the short term forecasting of GDP shows that testing forecasting performance of different methodologies and testing whether specific indicators contribute to the forecasting performance are two active research areas. We cite some examples from the second strand of the literature to motivate the choice of the indicators in Table 1. With the advent of techniques that can deal with mixed frequency data more effectively, researchers started to emphasize the importance of taking into account the timeliness of survey data. For example, Lahiri and Monokroussos (2013) test the marginal forecasting power of PMI for the US economy. In other cases, researchers make use of the increasing availability of data collected from internet sources. For example, Götz and Knetsch (2019) analyze google search data in the short term forecasts of German GDP growth. Smith (2016) analyze forecasting performance of google data for UK unemployment. As an another example of using novel data sets, Askitas and Zimmermann (2013) use toll data for nowcasting German economic activity. Duarte et al. (2017) use ATM/POS data for nowcasting Portuguese consumption.

Our analysis contributes to the literature by testing the forecasting performance of several blocks that can potentially contribute to the nowcasting performance due to their timeliness. Firstly, we use four indicators from a leading career website *kariyer.net*. Statistics about the new vacancies, total vacancies and total applications for month *t* become available at the beginning of month *t+1*. Analysis of the data shows that application per vacancy tracks the unemployment rate successfully. Since *kariyer.net* data become available before labor market statistics, timeliness of the *kariyer.net* may help to improve nowcasts of GDP growth. This data set can be considered in the domain of Götz and Knetsch (2019) and Smith (2016) as we incorporate internet data to the short term forecasts.

Another novel data set that we test for forecasting power is statistics about the sea freight from maritime transportation. We use total loading and unloading of goods transported via maritime cargo. These indicators become available at the first week of the next month for the reference month and are expected to be informative about export and import dynamics on a timely basis. To put things into perspective, recall that export and import quantity index for month *t* would be available in the first half of the month *t+*2. Another indicator that we use regarding transportation statistics is the percentage of airplane seats filled. This indicator is expected to be informative about the tourism activity. Intuition suggests that, in the short term, higher the capacity utilization higher the tourism inflows. Swings in tourism activity may have non-negligible effect on economic activity in Turkey. So, capturing this channel on a timely basis may improve forecasting performance. This block can be considered in the same spirit as Askitas and Zimmermann (2013). Finally, we use an index called ETTE (Türkan, 2008). This index is calculated using the transaction volume in credit and debit cards and tracks the development in consumption. This block is similar to the Duarte et al. (2017).

Note that we do not use survey data such as PMI in the forecasting. The reason is that we focus on forecasting year-on-year growth. Survey data are better at giving early signals about quarter-on-quarter growth. We experimented with several survey data and we decided to use surveys for forecasting missing data of monthly indicators. So, information from surveys enter to the forecasting exercise via auxiliary models that we use for forecasting monthly variables.

All of the indicators are adjusted for seasonal and calendar effects. If the official data are available for seasonal adjusted data, such as industrial production and employment, we use official data. If seasonal adjusted data are not available, such as ETTE, we use TRAMO-SEATS approach for seasonally adjusting the indicators. Industrial production, turnover in industry, export and import quantity indices, credit stock, vehicle sales and production, white goods sales and production, kariyer.net, electricity production and maritime transportation indicators are used starting from January 2005. Tax revenues, central government statistics and plane seat utilization start from 2006, ETTE starts in April 2006.

3. METHODOLOGY

There are two issues that we need to address before using the relatively high number of monthly indicators that we consider in the paper. First issue is to do with the mixed frequency nature of the data set, as our explanatory variables are monthly while our target variable is at quarterly frequency. Second issue is the fact that in a standard OLS regression, we can use only a limited number of explanatory variables. In this paper, we use bridge equation approach to deal with the mixed frequency issue and we use model averaging and factor model approaches to deal with the curse of dimensionality stemming from the size of the data set. Increasing the size of the data set would not contribute to the forecasting performance if the additional indicators are unrelated or weakly related to the target variable that we want to forecast. In this respect, another challenge is to compile a data set that can serve well to the aim of producing accurate and robust forecasts.

a. Quarterly Target-Monthly Indicators: Dealing with Mixed Frequency

We use bridge equation approach for utilizing monthly data to forecast quarterly GDP. In the now-classical bridge equation approach, we deal with the mixed-frequency issue by converting monthly indicators into quarterly frequency. Bridge equation approach is pioneered by Klein and Sojo (1989). Another pioneering study in the domain of bridge equations is Ingenito and Trehan (1996) who forecast US GDP and early examples of bridge equations are Baffigi et al. (2004) and Diron (2008). Despite their simplicity, bridge equations are still popular both in the academic research and they are in the toolkit of policy institutions. Recent research that uses bridge equation approach either on its own or as a benchmark to compare with more sophisticated techniques are Bulligian et al. (2015), Schumacher (2016) and Götz and Knetsch (2019).

Bridge equations are especially popular at central banks who need to produce both short and medium term forecast in the design of monetary policy. For example, Anesti et al. (2017) summarize nowcasting models used at the Bank of England. They note that industry model, factor model and MIDAS are three methods that are used in practice for short term forecasting. What is called as industry model is basically bridge equations for the components of GDP. Then, forecasts for GDP are obtained as a weighted average of the supply side components. Federal Reserve Bank of Atlanta publishes nowcasts of GDP dubbed as GDPNow (Higgins, 2014). Bridge equations are used for forecasting several subcomponents. Then, authors combine these forecasts with forecasts from Bayesian VARs. For the case of Norway, Aastevit et al. (2011)

report several methods for nowcasting Norwegian GDP, one of which is the bridge equation approach. Finally, Bundesbank recently published an update about the methodologies used for forecasting (Bundesbank, 2018). Bridge equations that are used at the Bank are updated and a monthly VAR is added to the toolkit. Comparison of the three methodologies, namely bridge equation, factor model and VAR, shows that over the period of 2010Q1-2018Q1, on average bridge equation performs best.

We can express the general form of the bridge equation as in Equation 1 (Barhouimi et al.,2012 and Götz and Knetsch, 2019) where m is the number of autoregressive parameters for the dependent variable, k is the number of explanatory variables, q is the number of lags for the explanatory variables.

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q} \delta_{i,j} \, X_{j,t-i} + \varepsilon_t \tag{1}$$

Here X is a monthly variable. Depending on the timing of the forecasting, there may be missing data for X's as well. For example, in the middle of August industrial production data would be available for June while GDP data for Turkish economy would be available for the first quarter of the year. So, while for one step ahead forecast, namely Q2, one can use realizations for industrial production for all of the three months of the second quarter, for two quarter ahead forecasts, namely third quarter of the year, one needs to forecast July, August and September industrial production. After forecasting these three months, average level of the industrial production for the quarter can be obtained and annual percentage change may be calculated. Then using the coefficients of an equation that relates GDP to industrial production until the first quarter, one can produce forecasts for Q3.

b. Fill in the Blanks: Forecasting Missing Months of the Monthly Indicators

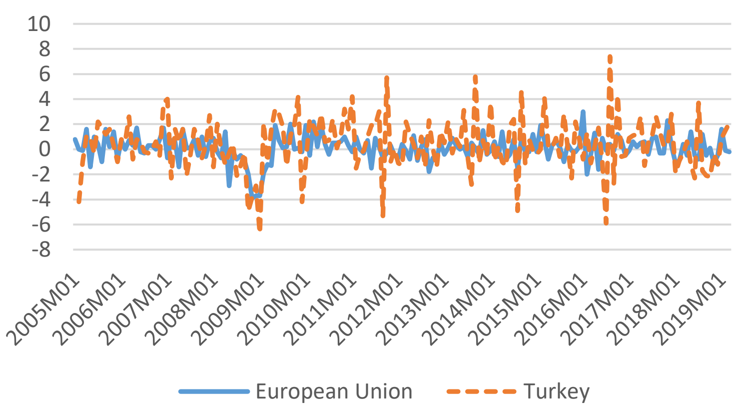
Mechanics of the bridge equation approach can be classified under two steps. First step is as discussed above where we show linking of the monthly indicator with the quarterly indicator. Depending on the timing of the forecasting exercise, there will be missing values for some months of a quarter as discussed above. If there are missing data for monthly variables, in an additional step these missing data are forecast, i.e. we fill the blanks in the data set for the forecast horizon.

As one of the earliest examples of bridge equation approach Ingenito and Trehan (1996) estimate an equation that relates the GDP growth to employment and consumption. Due to publication lags, these explanatory variables need to be forecast for producing timely forecasts as well. As a first alternative, they estimate AR models for these variables and conclude that using 6 lags produce the smallest forecast error. As another alternative, they estimate a bivariate VAR using these two variables. Then they augment this

VAR with different indicators such as industrial production, PMI, interest rates and retail sales. They did not get improvement over the simple AR model. So, they experiment with Bayesian VARs and see some improvement. In the end, they use Bayesian VARs for forecasting auxiliary variables as well.

While Ingenito and Trehan (1996) experimented with alternative methods for filing the missing values for monthly indicators, later studies frequently used simple AR models for forecasting missing values for the monthly data. For example, in a survey of mixed frequency methods Foroni and Marcellino (2013) note that it is common practice to use AR models for forecasting the missing months. For instance, Schumacher (2016) uses AR models for forecasting the missing values of the indicators. After discussing methods used in the literature for forecasting missing data and citing papers that use more sophisticated techniques, Smith (2015) notes that since there is no consensus for the method for filling the missing data he uses simple AR models.

Figure 1. Month on Month Growth Rate of Industrial Production



As can be seen from Figure 1 though month-on-month changes for Turkish industrial production have a larger range compared to EU. So, rather than fitting a simple AR model to the monthly indicators using information from other sources, such as surveys and financial indicators, may help to get better forecasts for monthly indicators.

Indeed, some papers either go beyond the use of simple AR models or discuss the possible benefits and plan to enrich the system in the further research. Barhouimi et al. (2012) use AR models for extrapolating the missing values for the monthly variables. They note though that using VAR or BVAR for this aim may be a fruitful avenue. Golinelli and Parigi (2007) use bridge equations for short term forecast of several countries. For the case of missing data in the quarter, in addition to simple AR models they use large and small dimension VAR models. Ferrara et al. (2010) take the issue even further and specifically concentrate on forecasting missing data in the bridge equations. They take the models of Diron (2008) and use a non-parametric models-k nearest neighbors and radial basis function- to fill the missing data. Drechsel and Maurin (2011) use a scheme that monthly values of the indicators are used in the regressions. For example, an equation that uses only data related to the first month of the quarter and another one up to second month of the quarter.

So, in this paper, we use five alternative methods for filling in the missing data at the end of the forecasting sample due to asynchronous publication lags: mean growth rate of the indicator, assuming zero month-on-month change which is an exercise that shows what would happen if the level of the monthly indicators stay constant at the latest available level for the rest of the forecasting period, forecasting with AR, VAR and BVAR. Except for zero growth case, we consider two types of estimation window: short and long. In the short window, we use rolling 36 month window of data. This helps use to get the most recent trends in the indicators. In the long version, we use recursively expanding window from the start of the first available observation to the information that would be available at the forecasting cycle for the respective indicator. Now, we give more detail about the methodologies that we use for filling in the missing data.

i. AR

As a first alternative, we use AR models for filling the missing data. In the literature, lag length of the AR model is in general decided by information criterion. But, fixed lag length is also considered. For example, Baffigi et al. (2004) use AR(5) while Diron (2008) use AR(6) for forecasting missing data with AR. We experimented with the information criterion and we see that in general one or two lags are chosen by these criterion. In order to be able to incorporate dynamics of the month-on-month on changes for a bit longer, in the paper we use AR(2) for one step ahead forecasts and AR(3) for two step ahead forecasts for forecasting missing values. We estimate two variants of AR models: short and long. In the long model, we estimate regressions recursively by expanding the sample size. For the short specification, we use a rolling window of 36 months. This is aimed at capturing recent trends at the forecasting step.

ii. VAR

In the VAR models we use soft data and financial indicators. If an indicator listed in Table 1 has missing data at the forecasting step, we run a VAR with spread between commercial credit interest rate and deposit rate (both in domestic currency), monthly change of exchange rate basket (0.5*Euro+0.5*Dollar), manufacturing sector confidence index and CDS. We experimented with PMI, change in the credit interest rate and production expectations from Business Tendency Survey. But, forecast performance of the auxiliary VAR models deteriorate. Regarding lag length, unlike AR models, we use information criterion for selecting the lag length. In the case of VAR, using a high number of lags may affect the estimation precision of the coefficients. In particular, we try maximum of four lags and decide the lag length with Schwarz information criterion. Similar to the AR models, for most of the cases VAR(1) is suggested by the information criterion.

iii. Bayesian VAR

For the case of forecasting the missing data with Bayesian VARs we use a similar set of explanatory variables with the VAR case. We use four lags of the indicators. Bayesian VARs are estimated using Litterman/Minesota prior (Litterman, 1986) with recursively expanding and rolling samples. Regarding hyperparameters, we use 1 for the priors of AR coefficients, 0.1 for overall tightness, 0.99 for relative cross-variable weight and 1 for lag decay.

iv. Mean growth

As an alternative for filling in the missing data, we use sample means of the indicators. This alternative would give information about what the will the growth rate be if the indicators grow in line with their historical growth rates. We calculate means of the indicators at each point of the forecast iteration with expanding window and for the last 36 months.

v. Zero monthly change

Finally, we consider a case where we hold the level of the monthly series constant and calculate year-on-year change with this assumption. As an example consider the case that we have data for industrial production until January. For forecasting the first quarter's GDP growth, we assume that February and March industrial production data stays same as the January level on a seasonally adjusted term. Then, we average the level of the values for the three months of first quarter and calculate the year-on-year change. This figure is used to calculate the forecast of the first quarter's GDP growth. While assuming that month-on-month change will be zero may seem unrealistic for the series that we work with, which exhibit high volatility for the month-on-month changes, this exercise can serve as a reference point in day to day applications. If the forecaster thinks that monthly changes will be positive, then risks on the forecasts obtained from zero month-on-month change exercise would be on the upside.

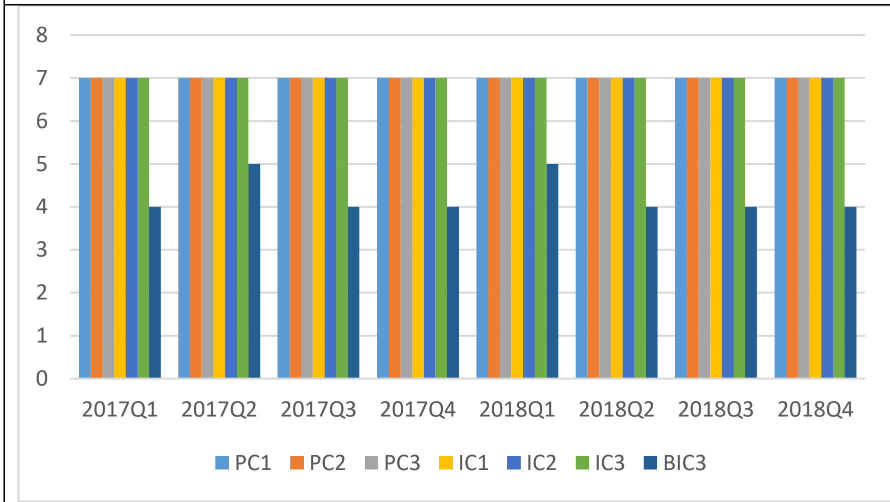
c. Large Data Set

Regarding the issue of large data, in the paper bridge equations take two forms. In the first form, we estimate bivariate equations with the indicators considered in the paper. Then, we average the forecasts of bivariate equations and use these average forecasts in the analysis. For averaging of the forecasts of the models, we consider four schemes: arithmetic average, weighted average of the forecasts where weights are the inverse of the forecast errors of the models for the previous eight quarters, trimmed mean where we discard a total of 25 percent of observations from top and bottom of forecast distribution. Finally we consider the median of forecasts.

Second form is the so-called bridging with factors or diffusion index approach (Rünstler et al. 2009 and Angelini et al. 2011). In this form, firstly we estimate factors via principal components following Stock and Watson (2002) and then we use these estimated factors in the forecasting equation. We explain more about the forecasting equation in the fourth section.

One crucial issue in the case of forecasting with factor models is to decide the number of factors that will be extracted from the data set. Several criteria are offered in the literature (Barhouimi et al. 2013). We analyze the number of factors suggested by all of the seven alternatives criteria in the Bai and Ng (2002) with a maximum of 7 factors. We see that except, BIC3, 7 factors are suggested by the alternative criteria (Figure 2). Yet, using a high number of factors in the forecasting equation may cause a deterioration in the forecasting performance due to increased parameter uncertainty. For example, Stock and Watson (2002) note that using two factors only captures most of the forecasting improvement and fine tuning models with lag length and number of factor selection with BIC criterion provides marginal improvement. In this respect, we estimate forecasting different equations that use only one factor to all of the seven factors. For instance, first equation uses only the first factor, second equation uses first and the second factor and the seventh equation includes all of the seven factors. Then we compare forecasting performance of all of these seven models. This enables us to see whether using additional factors helps to contribute to the forecasting performance or whether using a limited number of factors is better for forecasting purposes.

Figure 2. Number of Factors Suggested by Bai and Ng Criteria



Notes: Figure shows the number of factors estimated by recursively expanding the sample. For estimating the number of factors seven criteria from Bai and Ng (2002) are used. Legend in the horizontal axis shows the end of period for recursive estimation.

d. Targeted Predictors

Increasing data availability comes with curse of dimensionality. In a typical OLS regression, we cannot use more than a handful of indicators. One cure to the problem of curse of dimensionality is then estimating OLS models with a small number of variables, usually one indicator at a time, and then averaging the forecasts of these indicators. Factor model approach offers another solution as one can use a large number of series for extracting the factors of the data set. Then these factors can be used as regressors. However, there is no recipe for selecting the data set that the factors are extracted from. Moreover, it is not clear whether increasing the size of the data set contributes to the forecasting performance. For example, Rünstler et al. (2009) forecast GDP growth for several euro area countries using factor models. Number of series they use to extract changes from country to country substantially. For example, for Belgium they use 393 series while for Netherlands they use "only" 76 series. In addition to the size of the data set, composition changes also. For example, for Belgium 50 indicators from financial block is utilized while for France none.

As the use of factor model approach became more widespread, research results started to indicate that more data are not always better for factor analysis. For example, Boivin and Ng (2006) for the US and Caggiano et al. (2011) for the euro area, six euro countries and the UK find that more data is not always better. Caggiano et al. (2011) find that pre-selecting variables and reducing the data set to as low as 12 variables (for the UK) produces better forecasting performance than using more than hundred variables.

Bai and Ng (2008) offer a way out for using the large data sets in a factor model approach effectively. Consider the case of extracting factors with principal components. After compiling the data set, factors are extracted and then these factors are used in a regression for linking the target variable and the factors. However, for forecasting inflation or GDP same factors would be used from the given data set. But, it may be the case that some indicators are not relevant for forecasting GDP or inflation and hence customizing the data set may be helpful for improving forecast performance. Based on this idea, Bai and Ng (2008) define two procedures, namely hard thresholding and soft thresholding. Hard thresholding is based on the bivariate analysis of the indicators of the data set and the target variable. In the case of Bai and Ng (2008) this is done based on the t-statistics of the bivariate regressions. Variables with a t-stat over certain threshold are retained for the principal component analysis.

Another approach, which we use in the paper, is soft thresholding where one uses information from other predictors as well. Bai and Ng (2008) use LASSO, Elastic-net and LARS (Least Angle Regression) approaches for selecting the subset of the main data set. LASSO imposes a constraint on the classical OLS equation as in Equation 2 which is originally suggested by Tibshirani (1996). In LASSO some coefficients are set to zero. In Equation 3, lambda is a tuning parameter that determines the level of penalty that regulates how many coefficients are set to zero. In the end, we get a sparse data set with a few predictors compared to large data set (Bulligan et al. 2015).

$$\min_{\beta}\|Y - X\beta\| + \lambda \sum_{i=1}^{M} |\beta_i| \qquad (2)$$

There are several studies that test the effect of using targeted predictors. Schumacher (2010) tested whether targeting predictors helps to forecast German GDP growth. He compares using German data only and using German and international data together. He finds that without a preselection step, using international data does not improve the forecasting power. But, using targeted predictors is found to help to the forecasting performance. Bulligan et al. (2015) is another application that uses targeted predictors. They use LARS, LASSO, Elastic Net and Forward Selection Regressions approaches to target the variables. Since each of these thresholding approaches may suggest different subsets of indicators, they restrict attention to the pool of top 15 indicators from each thresholding method. In the end, they pick 30 variables. They find that a core data set obtained by pre-selecting variables result in lower forecast error for forecasting with diffusion indexes.

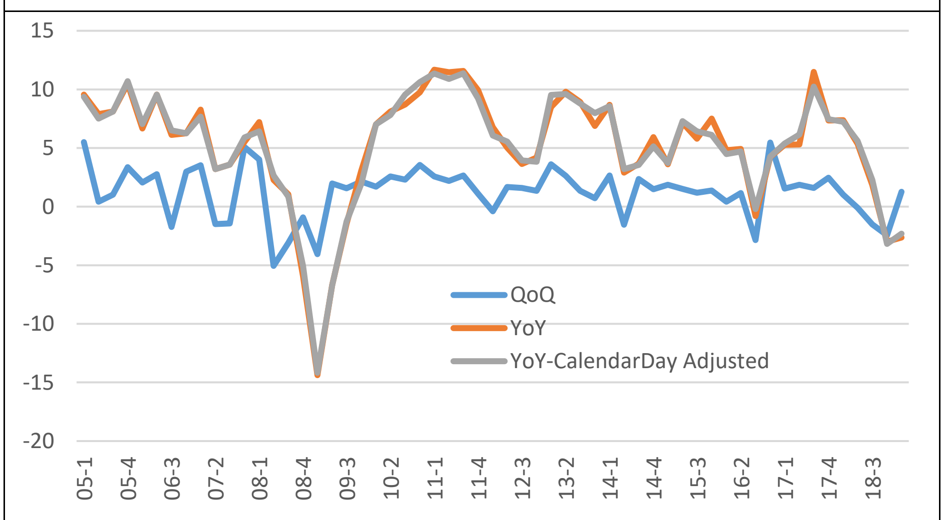
4. FORECASTING EXERCISE DESIGN

In the paper, we focus on the year-on-year GDP growth for Turkish economy. Figure 3 shows different definitions of GDP growth, namely quarter-on-quarter change with seasonally adjusted data, year-on-year changes with raw and calendar day adjusted data, respectively. GDP growth is relatively more volatile in the 2005-2008 period, in the 2009 global financial crisis period there are sharp movements in the GDP as the recovery of the Turkish economy was quite strong. Since 2010, we see cyclical movements in GDP growth.

i. Target variable

A reading of the literature shows that for advanced economies quarter-on-quarter GDP growth is in general the target to be forecast. On the other hand, for emerging countries several researchers focus on year-on-year growth. For example, Luciani et al. (2018) forecast year-on-year growth for Indonesia and Bragoli and Fosten (2018) for Indian economy. TURKSTAT publishes GDP growth both for the quarter-on-quarter and year-on-year definitions. Year-on-year growth attracts considerable attention. So, we focus on year-on-year GDP growth forecasts for one and two quarters ahead with respect to latest available data. For example, if the latest available data belongs to the third quarter of a year, we forecast fourth quarter of that year and the first quarter of the coming year.

Figure 3. GDP Growth for Turkish Economy



ii. Forecast equation

In this paper, we depart from the general representation presented for bridge equations in Equation 1 in several respects. So, we explain the structure of our forecast equation and the reasons for departing from the general form. First thing to note is that we focus on the year-on-year growth rate of GDP and its components. Lags of the dependent variable or explanatory variables are in general statistically highly insignificant and experiments over alternative forms revealed that using lags did not bring improvement to the forecasts. So, for one period ahead forecasts we focus on the simple form of the model as in Equation 3a.

For the case of two period ahead forecasting, though, augmenting the model with the previous year's growth rate, of the same quarter, helps to incorporate base effects. This is due to the fact that for two step ahead forecasts we may need to forecast up to four months of missing data. Information content of these forecasts would be limited compared to the case of one step ahead forecasts where we can incorporate realizations about the respective quarter based on the monthly data. Hence, two period ahead forecasts come with an additional term γY_{t-4} (Equation 3b).

$$One\ period\ ahead: Y_t = \alpha + \delta_j X_{j,t} + \zeta dwd + \varepsilon_t \tag{3a}$$

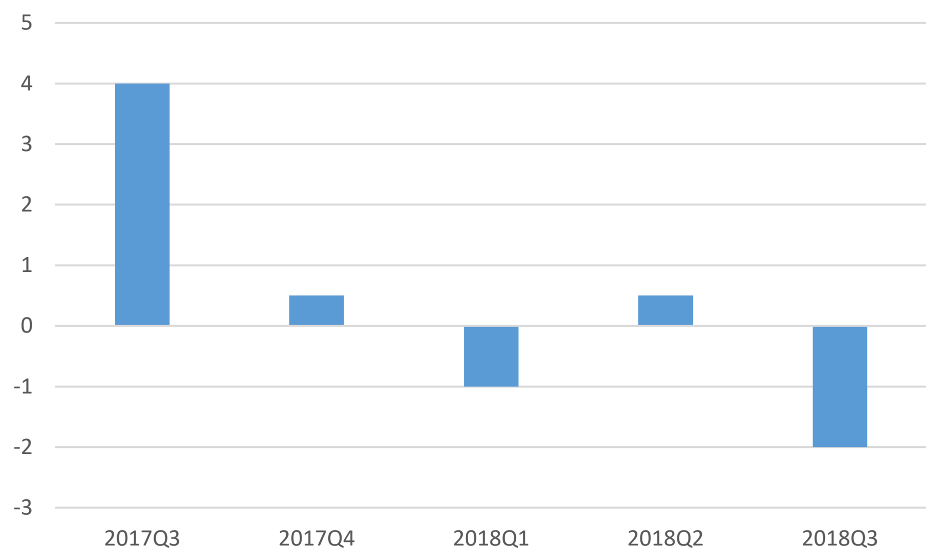
$$Two\ periods\ ahead: Y_t = \alpha + \gamma Y_{t-4} + \delta_j X_{j,t} + +\zeta dwd + \varepsilon_t \tag{3b}$$

$where\ Y_t\ is\ the\ GDP\ growth\ rate\ at\ time\ t, X_{j,t}\ are\ the\ explanatory\ indicator\ and$

$dwd\ is\ a\ term\ that\ captures\ change\ in\ the\ working\ day\ in\ a\ quarter.$

Compared to the general form given above, we have an additional term that captures the change in the working day, *dwd*. As can be seen from Figure 4, for some quarters change in the working day relative to the same quarter of the previous year can be substantial. This is due to the moving holidays in Turkey (Yüncüler, 2015). So, we augment the regression with working day effects. This is necessary from the fact that while we aim to forecast year-on-year growth rate of raw GDP series, our explanatory variables are forecast using seasonally and working day adjusted data. So, year-on-year growth rate of explanatory variables would be calendar day adjusted. This would require an adjustment for forecasting the year-on-year growth of raw GDP series. By augmenting the forecasting equation with the changes in working days, we aim to achieve this.

Figure 4. Change in the Number of Working Days in the Quarter



Case of forecasting with factors is similar to the bivariate equations (Equation 4a and 4b). We estimate seven different equations for forecasting with factors. First equation uses only one factor, second uses first two factors and the last equation uses all of the seven factors.

$$One\ period\ ahead: Y_t = \alpha + \sum_{j=1}^{k} \delta_j F_{j,t} + \zeta dwd + \varepsilon_t \qquad (4a)$$

$$Two\ periods\ ahead: Y_t = \alpha + \gamma Y_{t-4} + \sum_{j=1}^{k} \delta_j F_{j,t} + \zeta dwd + \varepsilon_t \qquad (4b)$$

$where\ F_{j,t}\ are\ the\ k\ principal\ components.$

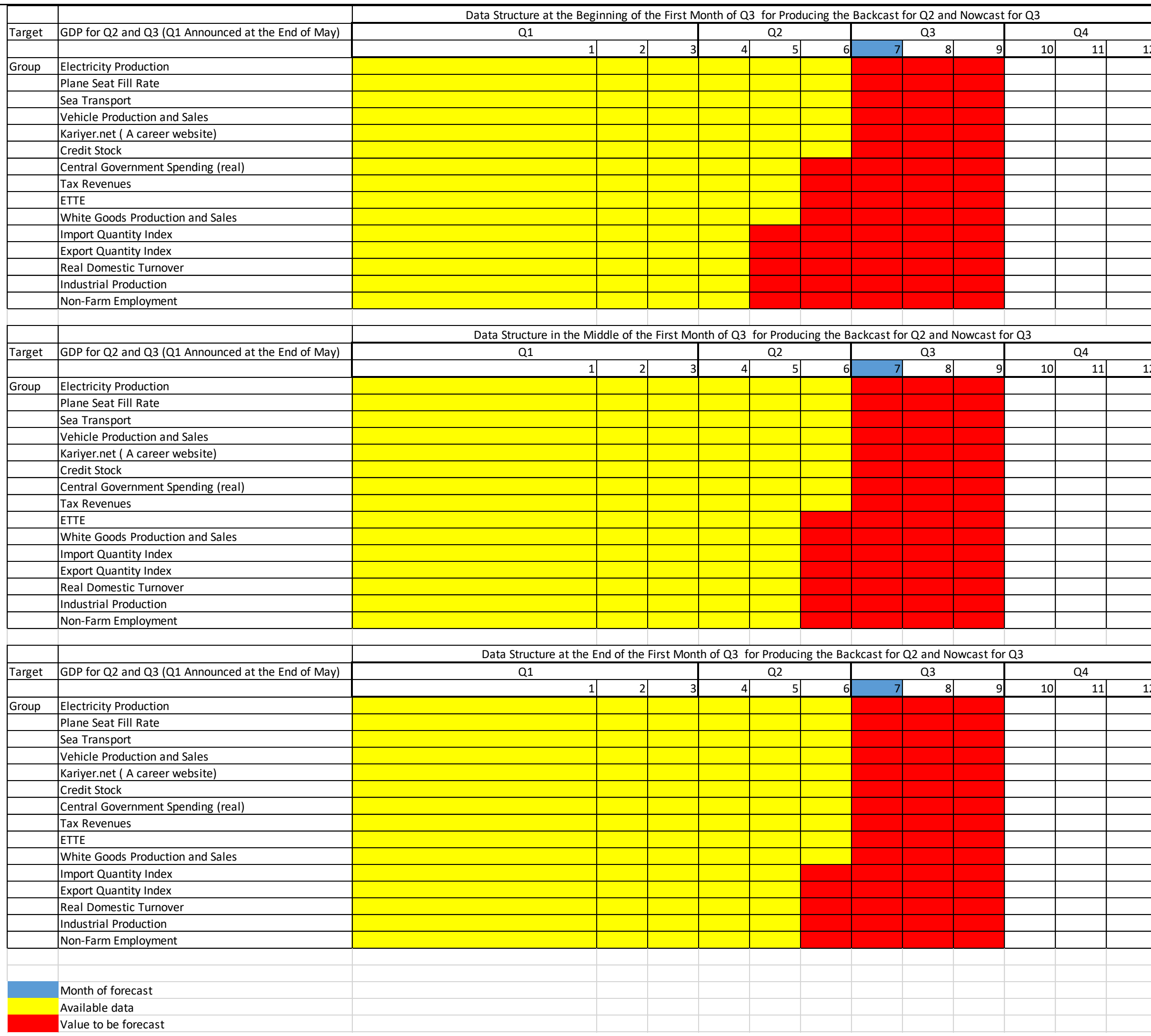
iii. Forecasting missing data

For forecasting missing data, we use AR, VAR, BVAR, mean growth and constant level cases as outlined above. After forecasting month-on-month changes for the missing monthly data, we obtain seasonally and calendar day adjusted levels of the series for the forecasting horizon. For example, if we are on the first month of the first quarter, we would know industrial production for the second month of the previous quarter. For forecasting the first quarter's GDP growth, we forecast missing data for the third month of the last quarter and the three months of the first quarter. Then using the forecasts of month-on-month changes, we obtain the level of series for the first quarter. In the literature, we see a distinction between flow and stock variables when converting these higher frequency indicators into quarterly frequency (Silvestrini and Veredas, 2008). For flow variables, such as industrial production, this is done by taking averages of the three months of the quarter while for stock variables, like credit, this is achieved by taking the last value in the quarter (Schumacher, 2016). After averaging series for flow-type indicators and using end-of-quarter level for stock type indicators we calculate the year-on-year percentage change for the first quarter. We use the growth rate of the first quarter's industrial production along with the coefficients obtained from a regression of GDP growth on industrial production until the third quarter of the previous year, which would be the latest available figure for GDP in the first month of the first quarter,. Then we produce a nowcast for the first quarter.

iv. Ragged ends

As we show in the section introducing data, indicators are published at different time of the month. So, we update forecasts three times in a month with the data that would be available at the beginning, in the middle and at the end of the month. We present the data structure by slightly changing the presentation of Figure 1 of Bulligan et al. (2015). Figure 5 shows the case for backcasting GDP growth for Q2 and nowcasting Q3 in July. At the beginning of July, data regarding June would be published for several indicators while latest industrial production data would be for April which would be published in the middle of June. Then around 15th of July, industrial production for May and tax revenues for June would be published. In general around 20th of July, ETTE and white good statistics for June would be published. So, for backcasting Q2 we would need to forecast June's industrial production even at the end of the July. In the second month of the Q3, there will be a similar pattern of publication lags. So, we adjust our sample for simulating the availability of the data and forecast missing data.

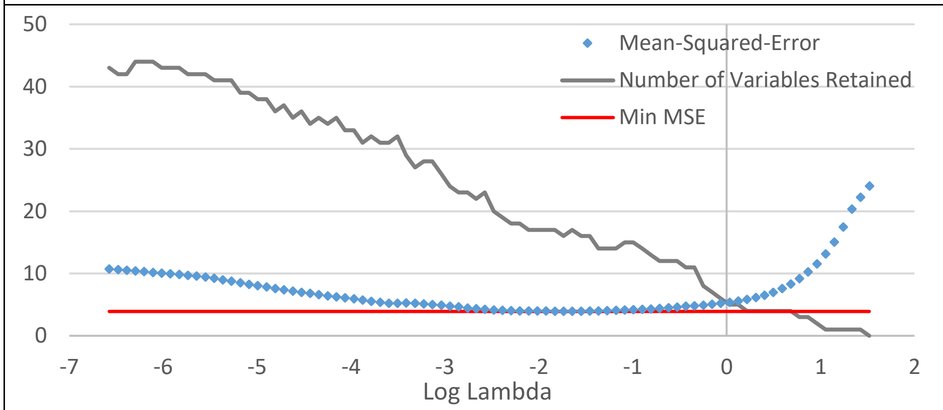
Figure 5. Timing of the Forecasting Exercise and Availability of the Data



v. Filtering the master data set

We also test whether using targeted variables helps to improve forecasting performance. We select the variables to be included in the factor extraction data set using LASSO. We use 5-fold cross validation for selecting the tuning parameter lambda. Figure 6 shows the relation between using different values for lambda and in-sample mean squared error from the cross-validation exercise. Using a small value of lambda penalizes the system only slightly and around forty variables are retained. Increasing lambda initially results in lower mean-squared-error but after a certain level of lambda, mean-squared-error starts to increase. After finding the lambda that produces the lowest mean squared error over the in-sample, following the suggestions of the applications that use LASSO, we use one standard error distance of this lambda to decide the equation that is selected by LASSO. This choice implies that we will get a relatively parsimonious core data set.

Figure 6. Mean Squared Error and Number of Variables Retained for Different Lambda Values



Variable selection using LASSO can be sensitive to the sample used and over a recursive sample it is likely that LASSO selects different variables. To circumvent this problem, we analyze the variables selected by LASSO over the 2013Q4-2018Q4. We include variables that are selected at least three times by LASSO. With this choice we end up with 12 variables. This is similar to the number of variable selected by rule SWb by Caggiano et al. (2011).

vi. Out of sample forecast design

As usually done in the literature, we test specifications using pseudo recursive out-of-sample forecasting exercise. We obtain forecasts for 2013Q1-2018Q4 taking into account the publication lags of the indicators. After obtaining backcasts and nowcasts at each round, we calculate root mean squared errors (RMSE) for each specification over the forecasting cycle. We use final vintage of data rather than a real time data set since a real time data set is not available. Note that lag length of VAR and factors are estimated at each recursion. Parameters of the bridge equation would be updated with the release of GDP data as well. As a benchmark, we estimate AR models with the lags of GDP growth only with different lag-lengths. We report the AR specifications, in terms of lag-length, with the minimum RMSE as the benchmarks for backasting and nowcasting.

5. RESULTS

We present relative RMSEs for different specifications in Tables B1 to B5. There are different dimensions of our forecasting exercise. So, we structure the presentation of our results in different sections to be able to touch on each of the following dimensions.

i. Comparing methods for filling in the missing data.

ii. Comparing model averaging and factor models for utilizing large data sets

iii. Evaluating gains from using targeted predictors.

Now we present the results under these headlines.

i. Comparing methods for filling in the blanks.

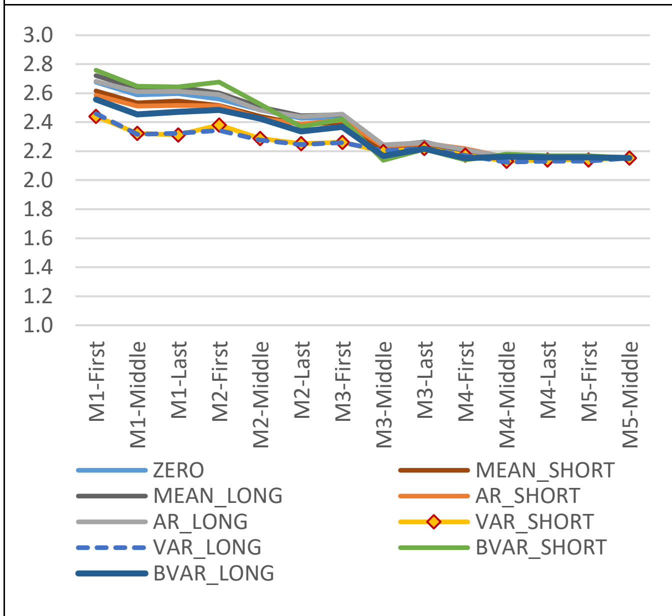
As explained above, due to asynchronous nature of data releases, we produce three forecasts for a given month: at the beginning, in the middle and at the end of the month. Regarding the timing of the forecasts relative to the publication of GDP, we produce forecasts for five months starting from the first month of the target quarter to the two months after the end of the target quarter. First three forecast, which are produced in the target quarter, are labeled as M1, M2 and M3 respectively. These would be nowcasts for the quarter. Since TURKSTAT publishes data two months after the end of the quarter, we produce forecasts after the end of the quarter as well which are so-called as backcasts. These are labeled by taking the first month of the target quarter as a reference point. So, M4 and M5 show the label for the forecasts produced one and two months after the end of the quarter. As an example, *M2-middle* in the X-axis of a graph shows the RMSE obtained for nowcasting the GDP growth with the information that would be available in the middle of the second month of the quarter. A subscript “long” means that we use recursive estimation and the sample size gets larger over time. A subscript “short” means that we use the latest 36 months of data, i.e. rolling sample, to estimate the parameters from the given method.

Figure 7 presents the minimum RMSE obtained by five methods for filling the missing data used with recursive/rolling samples. Since there are different forecast combination and factor model specifications, for clarity of presentation, we focus on results for two cases: forecast combination with inverse RMSE weights and forecasting with one factor.

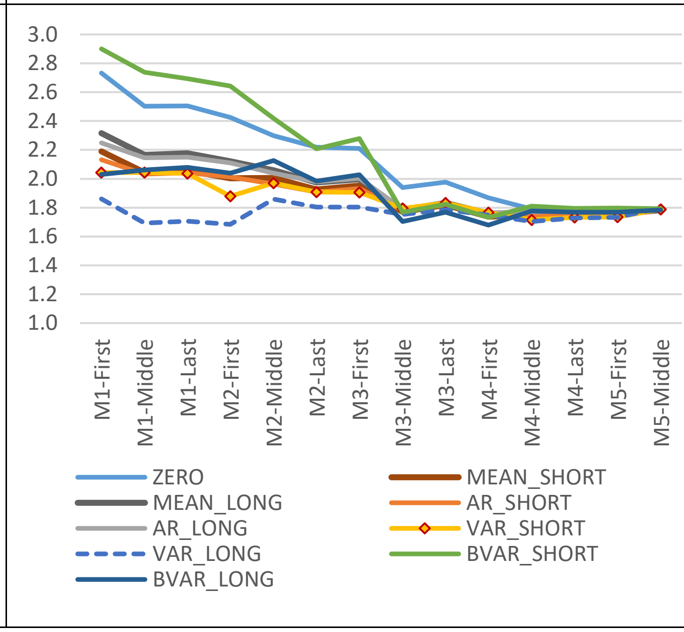
Analysis of the figures indicates that for forecasting missing monthly data using VAR estimated with expanding window results in lower RMSE compared to filling the missing data by AR models for nowcasting. For backcasting there is not a noticeable difference. Using constant level, i.e. zero month-on-month change, or using BVAR with a short sample size result in substantially worse forecast performance for nowcasting exercise. A classical finding in the nowcasting literature starting with the seminal work of Giannone et al. (2008) is that nowcasting errors decline over time with data flow. In Figure 7a we see that nowcasting errors decline over time. For the case of forecasting with one factor using VAR for filling in the missing data, results are not in line with expectation of declining nowcast errors.

Figure 7. RMSEs for Different Missing Data Forecasting Approaches for 2013Q1-2018Q4

a. Forecast Averaging Based on RMSE



b. Forecasts with One Factor



Notes: Figure shows the RMSE obtained by different specifications for forecasting missing data at the end of the forecasting sample and estimation window for auxiliary models. As an example, AR_Long shows forecasting missing values with AR models using a recursively expanding sample. VAR_Short shows forecasting with a VAR model with a rolling of 36-month of rolling window. Same scales are used in the Y-axes to be able to compare the forecasting performance of two methods.

ii. Comparing model averaging and factor models for utilizing large data sets

In Figure 7a and 7b we present two cases of utilizing large data. It is seen that using an equation with one factor results in lower forecast error than using forecast combination where inverse RMSE values are used as weights. In this subsection, we analyze whether a specific method for utilizing large data sets stand out in terms of forecasting performance by considering all other cases. We find that for nowcasting, using one factor in the bridge equation and forecasting missing data with a VAR estimated recursively produces lowest RMSE. However, with the release of first month's figures for industrial production and turnover, which would be in the middle of the third month of the quarter, neither factor models nor model averaging of the bivariate equations can enter the list. Rather, there is an equation using a single indicator that can produce lower RMSE than using model combination or factor models. This analysis suggests us to consider using targeted predictors as adding more indicators to the data set does not seem to improve the forecasting performance.

Table 2. Best Specifications Across Forecasting Cycles (2013Q1-2018Q4)

Time of The Forecast	**Model Averaging/Factor Model/Single Equation Models**	**Missing Data Forecasting Method**
M1-First	One Factor	VAR_LONG
M1-Middle	One Factor	VAR_LONG
M1-Last	One Factor	VAR_LONG
M2-First	One Factor	VAR_LONG
M2-Middle	One Factor	VAR_LONG
M2-Last	One Factor	VAR_LONG
M3-First	One Factor	VAR_LONG
M3-Middle	Best Single Variable Model	AR_SHORT
M3-Last	Best Single Variable Model	AR_SHORT
M4-First	Best Single Variable Model	VAR_LONG
M4-Middle	Best Single Variable Model	VAR_LONG
M4-Last	Best Single Variable Model	VAR_LONG
M5-First	Best Single Variable Model	VAR_LONG
M5-Middle	Best Single Variable Model	-

iii. Evaluating using targeted predictors.

We use LASSO for selecting the variables that will be included in the data set that the factors are extracted from. Table 3 shows selected indicators by applying LASSO recursively. We see that indicators from turnover in industry, industrial production, export quantity index, employment and taxes are selected. Turnover indicators appear relatively more frequently. Regarding the composition of the data set, indicators related to durable consumption and investment appear relatively more frequently in the list. This result can be due to the fact that these variables can capture the cyclical movement in the GDP.

Next, we compare the methods for forecasting missing data for monthly indicators with targeted predictors. We see that forecasting missing data with VARs result in lowest forecast error (Figure 8a and 8b). Forecast errors are broadly stable after *M3_Middle*. This is the period that first month's industrial production, turnover indices, foreign trade indices and employment data enters into information set.

Table 3. Selected Indicators by LASSO

Block	Indicator	Number of Times Appearing in LASSO selection for 2013Q4-2018Q4
DTI	Durable Consumption Goods	20
IP	Total Industry	19
DTI	Fabricated Metals	19
DTI	Intermediate Goods	13
QX	Consumption Goods	13
TAX	Total Tax Revenues	12
IP	Durable Consumption Goods	10
DTI	Electrical Equipment	8
TAX	Income Tax	7
DTI	Other Non-metallic Mineral	5
NFEMP	Total Non-Farm Employment	4
TAX	Imports VAT	3

Notes: See Table 1 for acronyms.

We observe that short term forecasts obtained with factor model using targeted predictors is similar to Figure 3 of Giannone et al. (2008) in the sense that as data accumulate forecast errors decline. Another point worth noting is that zero month-on-month growth assumption, i.e. holding the level of the series constant for the remainder of the forecast cycle, produces competitive forecasts. Taking these two observations along with the interpretation of Figure 7, it can be said that using targeted predictors helps to improve forecasting performance in many respects. Relatively poor performance of BVAR models, especially for the case of estimating in a short sample, shows that more work is necessary, such as using alternative priors or variable set, to fully utilize the potential benefits of BVAR.

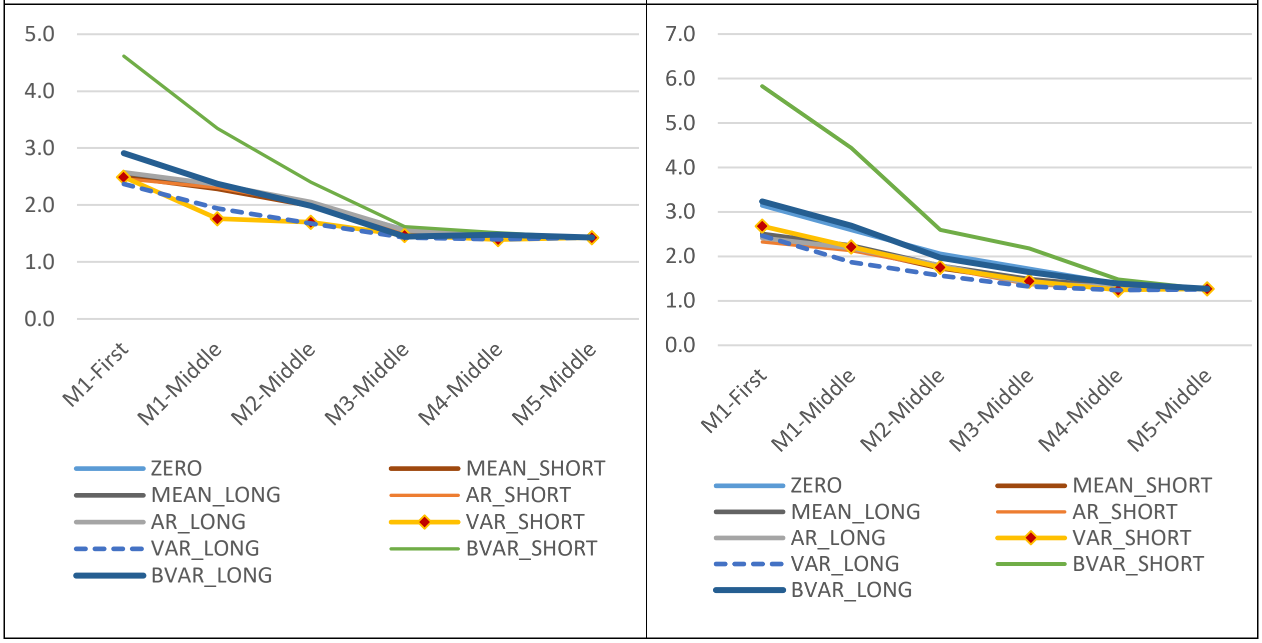
Analyzing the best performing specifications reveal that at the beginning of the forecasting cycle, median of the individual lower forecast errors than factor models (Table 4). Yet, factor models using one or two factor produces the lowest forecast error starting from the second month of the quarter. Regarding the method for filling in the blanks, again VARs stand out.

Table 4. Best Specifications with Targeted Predictors

	Model Averaging/Factor Model/Individual Models	Missing Data Forecasting Method
M1-First	Median	VAR_SHORT
M1-Middle	Median	VAR_SHORT
M2-Middle	One Factor Model	VAR_LONG
M3-Middle	One Factor Model	VAR_LONG
M4-Middle	Two Factor Model	VAR_SHORT
M5-Middle	Two Factor Model	-

Figure 8. RMSE for Missing Data Forecasting Methods for Targeted Predictors (2013Q1-2018Q4)

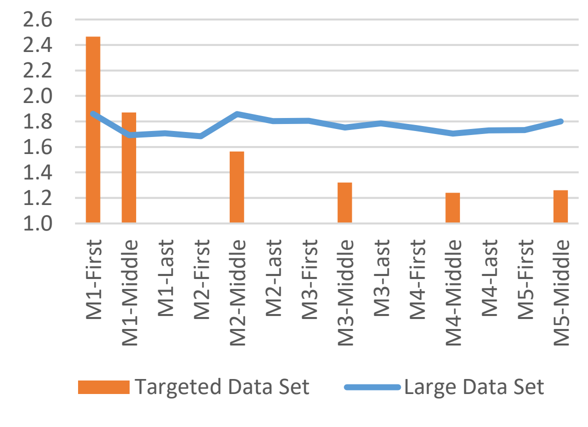
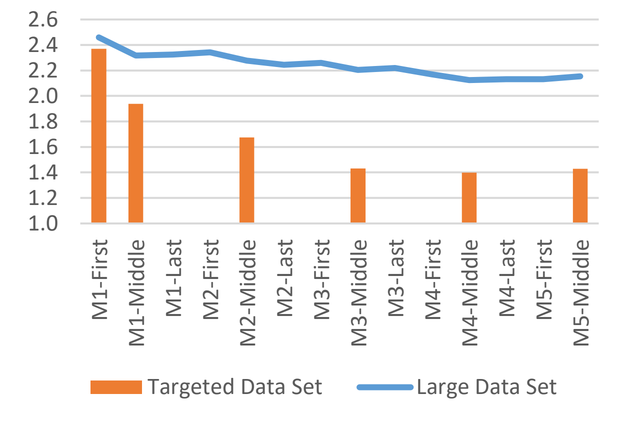
a. Forecast Averaging Based on RMSE | b. Forecasts with One Factor



Notes: Figure shows the RMSE obtained by different specifications for forecasting missing data at the end of the forecasting sample and estimation window for auxiliary models. As an example, AR_Long shows forecasting missing values with AR models using a recursively expanding sample. VAR_Short shows forecasting with a VAR model with a rolling of 36-month of rolling window.

Comparing forecasts obtained by using only these 12 indicators rather than using 61 indicators that our main data set includes would be informative about whether targeted predictors helps to decrease forecast errors. Since the targeted predictors come from blocks that are published in the middle of the month, we will not be able to update forecasts at the first and last part of the month. Table B5 presents relative performance of targeted predictors for all specifications. Here, we present two graphs to highlight the key takeaways from the table. Comparing cases for one factor model and forecast combination with RMSE weights, we see that targeted predictors produce better forecast performance than using all of the 61 indicators (Figure 9 and Figure 10).

All in all our results suggest that using targeted predictors and forecasting missing monthly data with VARs result in lower forecast error compared to other options.

Figure 9. RMSE for Forecasting Missing Data with Expanding Window VAR with One Factor Model	*Figure 10. Figure 4. RMSE for Forecasting Missing Data with Constant Window VAR with RMSE Weighted Forecast Combination*
	

6. CONCLUSION

In this paper we analyze the short-term forecasts of GDP growth of Turkish economy obtained with different specifications. We focus on the effect of forecasting missing monthly indicators with a simple auto-regressive regression, mean growth of the indicator and no change models as well as vector auto regressions, both classical and estimated with Bayesian methods. We find that for forecasting missing monthly data using VAR models brings the most improvement in the forecast performance. This is more evident for nowcasting practices. Our results indicate that factor models perform better than combination of the forecasts of individual models. Finally, we analyze whether pre-filtering the data set before conducting forecasting exercise helps. We find that using targeted predictors results in lower forecast errors compared to a data set that covers different areas of the economy. For further research, working on the composition of the data set, testing alternative shrinkage methods and looking for room for improvement in the VAR and BVAR specifications, both in terms of variables and in terms of sample size of the rolling window, can be pursued.

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APPENDIX

Table A1. Indicators Used in the Master Data Set

1	IP	Total Industry	31	TAX	Total Tax Revenues
2	IP	Intermediate	32	TAX	Domestic VAT
3	IP	Durable Consumption	33	TAX	SCT
4	IP	Nondurable Consumption	34	TAX	Imports VAT
5	IP	Energy	35	TAX	Income Tax
6	IP	Capital	36	TAX	Stamp Tax
7	DTI	Intermediate	37	CREDIT	Total Credit Growth
8	DTI	Durable Consumption	38	CREDIT	Firm
9	DTI	Nondurable Consumption	39	CREDIT	Housing
10	DTI	Capital	40	CREDIT	Vehicle
11	DTI	Other Non-metallic Mineral	41	CREDIT	Cash
12	DTI	Fabricated Metals	42	CREDIT	Credit Card
13	DTI	Electrical Equipment	43	VEHICLE	Automobiles
14	DTI	Machinery and Equipment	44	VEHICLE	Light Commercial Vehicles
15	DTI	Motor Vehicle	45	VEHICLE	Total Vehicle Production
16	QX	Exports excl. Gold	46	ELECT	Electricity Production (Adjusted for Weather Effects)
17	QX	Intermediate Goods Export excl. Gold	47	WG	Sales
18	QX	Capital	48	WG	Production
19	QX	Consumption	49	WG	Imports
20	QM	Capital	50	CAREER	New Job
21	QM	Passenger Cars	51	CAREER	Total Job
22	QM	Durable Consumption	52	CAREER	Total Application
23	QM	Semi Durable	53	CAREER	Application per Vacancy
24	QM	Nondurable Consumption	54	ETTE	Non-Food Total
25	QM	Imports excl. Gold	55	ETTE	Total (incl. Vehicles)
26	QM	Intermediate Goods Imports excl. Gold	56	CGS	Consumption
27	NFEMP	Total Non-Farm Employmeny	57	CGS	Capital
28	NFEMP	Industry	58	CGS	Current Transfers
29	NFEMP	Construction	59	SEATR	Loading
30	NFEMP	Services	60	SEATR	Unloading
			61	PLANE	Capacity Utilization

Table B1. Root Mean Squared Error Relative to the Benchmark Model for Nowcasts Obtained in the First Month of the Reference Quarter

Nowcast-M1_First	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	0.79	0.79	0.79	0.79	0.81	0.84	0.97	0.95	1.19	1.14	1.17	0.64	0.67	0.75
MEAN_SHORT	0.79	0.78	0.79	0.79	0.65	0.68	0.72	0.74	1.04	1.02	1.09	0.61	0.65	0.68
MEAN_LONG	0.82	0.81	0.83	0.82	0.69	0.72	0.78	0.78	1.08	1.04	1.06	0.64	0.65	0.68
AR_SHORT	0.78	0.77	0.80	0.80	0.63	0.66	0.71	0.73	0.84	0.96	0.99	0.56	0.63	0.66
AR_LONG	0.81	0.80	0.82	0.80	0.67	0.69	0.76	0.77	0.93	1.00	1.01	0.57	0.64	0.64
VAR_SHORT	0.75	0.72	0.75	0.73	0.61	0.74	0.98	0.98	1.18	1.24	1.17	0.55	0.63	0.64
VAR_LONG	0.74	0.73	0.76	0.77	**<u>0.55</u>**	0.59	0.66	0.66	0.85	0.90	0.93	0.55	0.60	0.63
BVAR_SHORT	0.87	0.82	0.81	0.82	0.86	1.32	1.65	1.87	2.80	3.20	3.35	0.58	0.67	0.67
BVAR_LONG	0.77	0.76	0.78	0.80	0.60	0.71	0.84	0.85	1.10	1.32	1.45	0.56	0.62	0.65
Nowcast-M1_Middle	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicato
ZERO	0.77	0.77	0.78	0.80	0.74	0.77	0.87	0.85	0.94	1.00	1.05	0.64	0.67	0.71
MEAN_SHORT	0.76	0.75	0.78	0.79	0.61	0.64	0.68	0.70	0.83	0.91	1.01	0.61	0.65	0.69
MEAN_LONG	0.79	0.78	0.81	0.82	0.64	0.67	0.74	0.74	0.87	0.94	1.00	0.64	0.65	0.68
AR_SHORT	0.76	0.75	0.78	0.77	0.60	0.63	0.68	0.70	0.78	0.89	0.97	0.56	0.63	0.66
AR_LONG	0.79	0.78	0.80	0.82	0.64	0.66	0.73	0.74	0.84	0.93	0.99	0.57	0.64	0.64
VAR_SHORT	0.71	0.69	0.68	0.65	0.61	0.63	0.87	0.92	1.57	1.74	1.41	0.55	0.63	0.63
VAR_LONG	0.70	0.69	0.71	0.70	**<u>0.50</u>**	0.53	0.58	0.59	0.75	0.85	0.92	0.55	0.60	0.63
BVAR_SHORT	0.80	0.79	0.80	0.78	0.81	0.99	1.15	1.32	2.08	2.20	2.58	0.58	0.67	0.67
BVAR_LONG	0.74	0.73	0.75	0.76	0.61	0.65	0.77	0.77	1.16	1.24	1.37	0.56	0.62	0.65
Nowcast-M1_Last	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicato
ZERO	0.77	0.77	0.78	0.80	0.74	0.77	0.86	0.84	0.93	0.96	1.00	0.64	0.67	0.71
MEAN_SHORT	0.76	0.76	0.78	0.79	0.61	0.64	0.68	0.69	0.83	0.87	0.95	0.61	0.65	0.69
MEAN_LONG	0.79	0.78	0.81	0.82	0.65	0.67	0.74	0.74	0.88	0.90	0.96	0.64	0.65	0.68
AR_SHORT	0.76	0.75	0.78	0.78	0.61	0.64	0.69	0.70	0.84	0.90	0.97	0.56	0.63	0.66
AR_LONG	0.79	0.78	0.80	0.82	0.64	0.66	0.74	0.74	0.94	0.93	0.98	0.57	0.64	0.64
VAR_SHORT	0.70	0.69	0.68	0.66	0.60	0.61	0.72	0.77	1.43	1.74	1.56	0.55	0.63	0.63
VAR_LONG	0.70	0.69	0.71	0.71	**<u>0.51</u>**	0.53	0.57	0.58	0.82	0.84	0.90	0.55	0.60	0.63
BVAR_SHORT	0.79	0.79	0.79	0.77	0.80	0.94	1.06	1.12	1.69	1.81	2.23	0.58	0.67	0.67
BVAR_LONG	0.74	0.73	0.75	0.77	0.62	0.64	0.74	0.74	1.02	1.04	1.17	0.56	0.62	0.65

Notes: Table shows RMSEs relative to the benchmark. Shading of the cells is based on the relative RMSE. Higher the relative RMSE darker is the shading of the cell. Figure that is underlined (which is also highlighted using red font) shows the specification with minimum RMSE. Zero, Mean_Short, Mean_Long, AR_Short, AR_Long, VAR_Short, VAR_Long, BVAR_Short and BVAR_Long show the methods for filling the missing monthly data. Zero means assuming zero month-on-month changes for the missing data. Mean denotes using the sample mean of monthly changes for each indicator. AR denotes the case of forecasting missing monthly data with AR models. VAR and BVAR denote the case of forecasting missing data with survey and financial data. Long and Short denote the size of the estimation window. For the case of "Long" we use recursively expanding window while for "Short" we use the latest 36 months for estimations. Simple Average, RMSE Weighted Average, Trimmed Mean, Median show the RMSE for different model averaging approaches. We estimate seven different models using one to seven factors. Last three columns show the three bridge equations using a single indicator that results in the lowest RMSE among all single indicator bridge equations.

Table B2. Root Mean Squared Error Relative to the Benchmark Model for Nowcasts Obtained in the Second and Third Month of the Reference Quarter

Nowcast-M2_First	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.76	0.76	0.77	0.79	0.72	0.74	0.85	0.84	0.94	0.98	1.03	0.61	0.65	0.71
MEAN_SHORT	0.76	0.75	0.77	0.78	0.59	0.63	0.68	0.69	0.86	0.88	0.98	0.59	0.64	0.69
MEAN_LONG	0.79	0.77	0.80	0.80	0.63	0.66	0.73	0.73	0.90	0.91	0.98	0.61	0.65	0.65
AR_SHORT	0.76	0.75	0.78	0.76	0.60	0.63	0.67	0.69	0.85	0.89	0.98	0.56	0.62	0.69
AR_LONG	0.78	0.77	0.80	0.80	0.63	0.66	0.72	0.73	0.97	0.93	1.00	0.57	0.63	0.67
VAR_SHORT	0.72	0.71	0.70	0.68	0.56	0.60	0.62	0.70	1.30	1.54	1.40	0.59	0.63	0.65
VAR_LONG	0.70	0.70	0.72	0.72	**0.50**	0.53	0.57	0.58	0.82	0.83	0.92	0.58	0.63	0.65
BVAR_SHORT	0.80	0.80	0.80	0.78	0.78	0.94	1.07	1.10	1.58	1.65	2.08	0.59	0.66	0.71
BVAR_LONG	0.75	0.74	0.76	0.77	0.61	0.64	0.74	0.74	1.00	1.02	1.17	0.58	0.65	0.69

Nowcast-M2_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.73	0.74	0.74	0.73	0.68	0.70	0.76	0.76	0.86	0.85	0.92	0.61	0.65	0.66
MEAN_SHORT	0.73	0.72	0.74	0.74	0.60	0.61	0.65	0.66	0.81	0.79	0.87	0.59	0.63	0.64
MEAN_LONG	0.75	0.74	0.76	0.75	0.61	0.63	0.68	0.68	0.83	0.81	0.88	0.61	0.64	0.65
AR_SHORT	0.73	0.72	0.74	0.73	0.58	0.60	0.64	0.65	0.80	0.82	0.92	0.56	0.62	0.65
AR_LONG	0.75	0.74	0.76	0.76	0.61	0.63	0.68	0.68	0.85	0.83	0.92	0.57	0.63	0.63
VAR_SHORT	0.68	0.68	0.69	0.68	0.58	0.59	0.63	0.64	0.75	0.74	0.90	0.59	0.63	0.64
VAR_LONG	0.68	0.68	0.70	0.70	**0.55**	0.56	0.60	0.61	0.76	0.75	0.87	0.58	0.59	0.61
BVAR_SHORT	0.74	0.75	0.73	0.73	0.72	0.76	0.84	0.84	1.05	1.00	1.23	0.59	0.66	0.71
BVAR_LONG	0.72	0.72	0.72	0.72	0.63	0.65	0.71	0.72	0.95	0.87	0.99	0.58	0.65	0.68

Nowcast-M2_Last	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.72	0.72	0.73	0.72	0.66	0.67	0.73	0.73	0.82	0.84	0.90	0.61	0.65	0.66
MEAN_SHORT	0.72	0.71	0.73	0.72	0.57	0.58	0.61	0.63	0.76	0.77	0.85	0.59	0.63	0.64
MEAN_LONG	0.73	0.73	0.75	0.74	0.59	0.60	0.65	0.65	0.79	0.80	0.86	0.61	0.64	0.65
AR_SHORT	0.72	0.71	0.74	0.73	0.57	0.58	0.62	0.64	0.81	0.81	0.91	0.56	0.62	0.65
AR_LONG	0.74	0.72	0.75	0.76	0.59	0.60	0.66	0.66	0.83	0.82	0.90	0.57	0.63	0.63
VAR_SHORT	0.68	0.67	0.69	0.68	0.57	0.57	0.60	0.61	0.71	0.73	0.86	0.59	0.63	0.64
VAR_LONG	0.68	0.67	0.69	0.70	**0.54**	0.54	0.58	0.59	0.73	0.73	0.83	0.58	0.59	0.61
BVAR_SHORT	0.70	0.70	0.70	0.70	0.66	0.65	0.73	0.73	0.98	1.03	1.10	0.59	0.66	0.71
BVAR_LONG	0.69	0.69	0.70	0.71	0.59	0.59	0.64	0.66	0.86	0.84	0.95	0.58	0.65	0.68

Nowcast-M3_First	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.85	0.85	0.86	0.85	0.77	0.79	0.87	0.87	0.98	1.00	1.09	0.73	0.78	0.79
MEAN_SHORT	0.85	0.84	0.86	0.86	0.68	0.70	0.73	0.75	0.90	0.91	1.02	0.73	0.75	0.78
MEAN_LONG	0.87	0.86	0.88	0.87	0.70	0.71	0.77	0.78	0.93	0.94	1.03	0.73	0.75	0.79
AR_SHORT	0.86	0.85	0.88	0.86	0.68	0.70	0.74	0.75	0.94	0.95	1.07	0.72	0.77	0.78
AR_LONG	0.87	0.86	0.89	0.89	0.70	0.72	0.78	0.78	0.96	0.95	1.05	0.73	0.74	0.80
VAR_SHORT	0.80	0.79	0.81	0.81	0.67	0.68	0.71	0.72	0.86	0.86	1.04	0.74	0.76	0.76
VAR_LONG	0.80	0.79	0.82	0.83	**0.63**	0.64	0.68	0.69	0.86	0.85	1.00	0.70	0.72	0.72
BVAR_SHORT	0.84	0.85	0.84	0.84	0.80	0.79	0.87	0.89	1.15	1.22	1.28	0.77	0.85	0.86
BVAR_LONG	0.82	0.83	0.84	0.83	0.71	0.71	0.77	0.79	1.01	0.98	1.11	0.75	0.81	0.84

Nowcast-M3_Middle	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.80	0.78	0.81	0.82	0.68	0.70	0.76	0.76	0.88	0.92	1.04	0.61	0.71	0.73
MEAN_SHORT	0.79	0.77	0.81	0.81	0.62	0.63	0.67	0.69	0.82	0.86	1.00	0.60	0.70	0.71
MEAN_LONG	0.80	0.78	0.82	0.83	0.63	0.64	0.69	0.70	0.84	0.88	1.00	0.61	0.69	0.73
AR_SHORT	0.80	0.78	0.82	0.84	0.62	0.64	0.67	0.68	0.81	0.84	1.00	**0.58**	0.70	0.72
AR_LONG	0.81	0.79	0.83	0.83	0.63	0.64	0.69	0.69	0.82	0.85	0.99	0.61	0.69	0.73
VAR_SHORT	0.79	0.77	0.80	0.78	0.63	0.64	0.68	0.69	0.82	0.86	0.98	0.60	0.70	0.70
VAR_LONG	0.79	0.77	0.81	0.80	0.61	0.62	0.66	0.68	0.81	0.84	0.97	0.58	0.69	0.70
BVAR_SHORT	0.76	0.75	0.78	0.80	0.62	0.65	0.73	0.75	0.96	1.05	1.18	0.75	0.76	0.76
BVAR_LONG	0.77	0.76	0.79	0.80	0.60	0.61	0.67	0.69	0.84	0.90	1.05	0.61	0.73	0.75

Nowcast-M3_Last	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.81	0.79	0.82	0.82	0.69	0.71	0.78	0.78	0.83	0.90	1.02	0.61	0.71	0.73
MEAN_SHORT	0.80	0.78	0.81	0.82	0.64	0.66	0.70	0.71	0.77	0.84	0.98	0.60	0.70	0.71
MEAN_LONG	0.81	0.79	0.82	0.83	0.64	0.66	0.72	0.72	0.79	0.86	0.98	0.61	0.69	0.73
AR_SHORT	0.81	0.79	0.82	0.84	0.64	0.65	0.70	0.70	0.77	0.83	0.98	**0.58**	0.70	0.72
AR_LONG	0.81	0.79	0.83	0.83	0.64	0.66	0.71	0.71	0.79	0.84	0.98	0.61	0.69	0.73
VAR_SHORT	0.79	0.78	0.81	0.78	0.64	0.66	0.70	0.71	0.78	0.85	0.96	0.60	0.70	0.70
VAR_LONG	0.79	0.78	0.81	0.79	0.63	0.64	0.68	0.69	0.77	0.83	0.95	0.58	0.69	0.70
BVAR_SHORT	0.78	0.78	0.79	0.81	0.64	0.67	0.75	0.76	0.93	0.97	1.14	0.75	0.76	0.76
BVAR_LONG	0.79	0.78	0.80	0.81	0.62	0.64	0.70	0.71	0.80	0.88	1.04	0.61	0.73	0.75

Notes: See notes for the Table B 1.

Table B3. Root Mean Squared Error Relative to the Benchmark Model for Backcasts Obtained One and Two Months After End of the Reference Quarter

Backcast-M4_First	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.80	0.77	0.81	0.80	0.65	0.69	0.75	0.79	0.80	0.88	0.84	0.60	0.64	0.68
MEAN_SHORT	0.80	0.76	0.81	0.80	0.61	0.64	0.67	0.70	0.69	0.73	0.71	0.59	0.62	0.65
MEAN_LONG	0.80	0.77	0.81	0.80	0.62	0.65	0.69	0.72	0.71	0.76	0.74	0.60	0.62	0.67
AR_SHORT	0.81	0.78	0.82	0.80	0.62	0.66	0.68	0.70	0.68	0.74	0.68	0.59	0.60	0.66
AR_LONG	0.81	0.77	0.82	0.81	0.62	0.66	0.68	0.70	0.70	0.78	0.73	0.60	0.62	0.66
VAR_SHORT	0.79	0.76	0.80	0.77	0.62	0.66	0.68	0.69	0.68	0.76	0.69	0.59	0.63	0.66
VAR_LONG	0.79	0.76	0.80	0.79	0.61	0.67	0.69	0.76	0.84	0.98	0.91	0.57	0.61	0.64
BVAR_SHORT	0.77	0.75	0.78	0.79	0.61	0.66	0.72	0.76	0.86	0.94	0.93	0.69	0.70	0.74
BVAR_LONG	0.78	0.75	0.79	0.80	0.59	0.62	0.67	0.70	0.69	0.75	0.78	0.61	0.67	0.70

Backcast-M4_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.80	0.76	0.81	0.80	0.63	0.65	0.69	0.71	0.69	0.78	0.71	0.58	0.62	0.64
MEAN_SHORT	0.80	0.75	0.81	0.79	0.61	0.64	0.68	0.70	0.69	0.74	0.68	0.58	0.62	0.63
MEAN_LONG	0.80	0.76	0.81	0.80	0.61	0.64	0.68	0.70	0.69	0.75	0.69	0.58	0.63	0.64
AR_SHORT	0.79	0.76	0.80	0.79	0.61	0.64	0.67	0.69	0.66	0.74	0.68	0.58	0.62	0.63
AR_LONG	0.80	0.76	0.81	0.79	0.62	0.64	0.67	0.69	0.68	0.80	0.72	0.58	0.61	0.64
VAR_SHORT	0.79	0.75	0.80	0.79	0.60	0.63	0.64	0.66	0.64	0.72	0.66	0.57	0.59	0.61
VAR_LONG	0.79	0.74	0.80	0.79	0.60	0.61	0.63	0.66	0.67	0.75	0.82	0.56	0.60	0.61
BVAR_SHORT	0.81	0.76	0.82	0.82	0.63	0.66	0.69	0.70	0.69	0.80	0.81	0.62	0.66	0.68
BVAR_LONG	0.80	0.76	0.81	0.80	0.62	0.65	0.69	0.71	0.70	0.76	0.70	0.60	0.65	0.66

Backcast-M4_Last	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.80	0.76	0.81	0.80	0.63	0.66	0.69	0.71	0.69	0.78	0.71	0.58	0.62	0.64
MEAN_SHORT	0.80	0.75	0.81	0.80	0.61	0.64	0.68	0.70	0.69	0.74	0.69	0.58	0.62	0.63
MEAN_LONG	0.80	0.76	0.81	0.80	0.62	0.64	0.68	0.70	0.69	0.75	0.70	0.58	0.63	0.64
AR_SHORT	0.80	0.76	0.81	0.79	0.61	0.64	0.67	0.69	0.67	0.75	0.69	0.58	0.62	0.63
AR_LONG	0.80	0.76	0.81	0.80	0.62	0.65	0.67	0.69	0.68	0.83	0.75	0.58	0.61	0.64
VAR_SHORT	0.79	0.75	0.80	0.79	0.61	0.64	0.65	0.67	0.64	0.73	0.67	0.57	0.59	0.61
VAR_LONG	0.79	0.75	0.80	0.79	0.61	0.63	0.64	0.65	0.68	0.75	0.79	0.56	0.60	0.61
BVAR_SHORT	0.80	0.76	0.82	0.82	0.63	0.65	0.68	0.69	0.67	0.77	0.75	0.62	0.66	0.68
BVAR_LONG	0.80	0.76	0.81	0.80	0.62	0.65	0.69	0.71	0.70	0.75	0.70	0.60	0.65	0.66

Backcast-M5_First	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.80	0.76	0.81	0.80	0.63	0.66	0.69	0.71	0.69	0.78	0.71	0.58	0.62	0.64
MEAN_SHORT	0.80	0.75	0.81	0.80	0.61	0.64	0.68	0.70	0.69	0.74	0.69	0.58	0.62	0.63
MEAN_LONG	0.80	0.76	0.81	0.80	0.62	0.64	0.68	0.70	0.69	0.75	0.70	0.58	0.63	0.64
AR_SHORT	0.80	0.76	0.81	0.79	0.61	0.64	0.67	0.69	0.67	0.75	0.69	0.58	0.62	0.63
AR_LONG	0.80	0.76	0.81	0.80	0.62	0.65	0.67	0.69	0.68	0.80	0.73	0.58	0.61	0.64
VAR_SHORT	0.79	0.75	0.80	0.79	0.61	0.64	0.65	0.67	0.64	0.73	0.66	0.57	0.59	0.61
VAR_LONG	0.79	0.75	0.80	0.79	0.61	0.63	0.65	0.66	0.70	0.76	0.75	0.56	0.60	0.61
BVAR_SHORT	0.80	0.76	0.82	0.82	0.63	0.65	0.69	0.70	0.67	0.77	0.75	0.62	0.66	0.68
BVAR_LONG	0.80	0.76	0.81	0.80	0.62	0.65	0.69	0.71	0.70	0.75	0.70	0.60	0.65	0.66

Backcast-M5_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.80	0.75	0.81	0.80	0.63	0.65	0.67	0.68	0.66	0.75	0.69	0.56	0.59	0.61
MEAN_SHORT	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.70	0.69	0.75	0.69	0.56	0.59	0.61
MEAN_LONG	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.70	0.69	0.75	0.69	0.56	0.59	0.61
AR_SHORT	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.69	0.67	0.75	0.69	0.56	0.59	0.61
AR_LONG	0.80	0.75	0.81	0.80	0.63	0.65	0.67	0.68	0.67	0.75	0.69	0.56	0.59	0.61
VAR_SHORT	0.80	0.75	0.81	0.80	0.63	0.65	0.67	0.69	0.67	0.75	0.69	0.56	0.59	0.61
VAR_LONG	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.69	0.68	0.76	0.71	0.56	0.59	0.61
BVAR_SHORT	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.69	0.67	0.74	0.69	0.56	0.59	0.61
BVAR_LONG	0.80	0.75	0.81	0.80	0.63	0.65	0.68	0.70	0.69	0.75	0.69	0.56	0.59	0.61

Notes: See notes for the Table B 1.

Table B4. Targeted Predictors: Root Mean Squared Error Relative to the Benchmark Model for Nowcasts and Backcasts

Nowcast-M1_First	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.76	0.76	0.76	0.79	0.93	0.92	0.98	0.97	0.98	0.97	1.02	0.84	0.85	0.88
MEAN_SHORT	0.74	0.74	0.73	0.75	0.74	0.76	0.78	0.77	0.80	0.79	0.79	0.82	0.86	0.89
MEAN_LONG	0.75	0.76	0.75	0.76	0.74	0.77	0.80	0.79	0.82	0.80	0.81	0.84	0.86	0.93
AR_SHORT	0.73	0.73	0.73	0.74	0.69	0.71	0.72	0.71	0.74	0.74	0.75	0.80	0.83	0.84
AR_LONG	0.75	0.76	0.75	0.72	0.72	0.74	0.77	0.76	0.78	0.78	0.79	0.83	0.83	0.86
VAR_SHORT	0.75	0.74	0.69	**0.66**	0.80	0.92	0.95	0.89	0.89	0.88	0.97	0.80	0.84	0.89
VAR_LONG	0.73	0.70	0.72	0.72	0.73	0.70	0.73	0.72	0.74	0.74	0.75	0.74	0.78	0.83
BVAR_SHORT	1.37	1.37	1.25	1.31	1.73	1.85	1.93	1.99	1.98	1.97	2.12	1.53	1.59	1.77
BVAR_LONG	0.88	0.86	0.80	0.81	0.96	0.98	1.03	1.02	1.07	0.99	1.07	0.99	1.00	1.09

Nowcast-M1_Middle	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.69	0.69	0.69	0.69	0.77	0.78	0.82	0.83	0.86	0.86	0.90	0.75	0.76	0.82
MEAN_SHORT	0.68	0.68	0.68	0.69	0.65	0.68	0.69	0.70	0.74	0.74	0.77	0.69	0.77	0.79
MEAN_LONG	0.71	0.70	0.71	0.70	0.67	0.70	0.72	0.73	0.77	0.77	0.79	0.72	0.78	0.82
AR_SHORT	0.69	0.69	0.69	0.69	0.63	0.66	0.66	0.66	0.69	0.70	0.72	0.74	0.77	0.79
AR_LONG	0.71	0.70	0.71	0.71	0.65	0.68	0.70	0.70	0.73	0.73	0.75	0.72	0.78	0.82
VAR_SHORT	0.55	0.52	0.51	**0.51**	0.66	0.72	0.73	0.75	0.79	0.78	0.82	0.63	0.68	0.70
VAR_LONG	0.60	0.58	0.59	0.62	0.56	0.58	0.62	0.60	0.62	0.61	0.63	0.65	0.66	0.67
BVAR_SHORT	1.02	0.99	1.00	1.01	1.32	1.50	1.55	1.56	1.60	1.57	1.57	1.12	1.14	1.25
BVAR_LONG	0.72	0.70	0.72	0.71	0.80	0.88	0.91	0.94	0.95	0.95	0.96	0.76	0.87	0.95

Nowcast-M2_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.58	0.60	0.58	0.60	0.61	0.63	0.67	0.67	0.68	0.67	0.70	0.66	0.67	0.72
MEAN_SHORT	0.58	0.59	0.57	0.59	0.51	0.54	0.56	0.57	0.58	0.58	0.59	0.63	0.66	0.70
MEAN_LONG	0.60	0.61	0.59	0.60	0.53	0.56	0.58	0.59	0.60	0.60	0.61	0.64	0.67	0.71
AR_SHORT	0.60	0.60	0.60	0.64	0.52	0.54	0.57	0.57	0.59	0.59	0.61	0.65	0.66	0.71
AR_LONG	0.61	0.61	0.61	0.64	0.53	0.56	0.58	0.59	0.60	0.60	0.62	0.63	0.68	0.72
VAR_SHORT	0.51	0.50	0.49	0.48	0.52	0.57	0.58	0.61	0.59	0.59	0.59	0.63	0.64	0.65
VAR_LONG	0.49	0.50	0.49	0.49	**0.46**	0.50	0.53	0.53	0.52	0.53	0.53	0.59	0.61	0.61
BVAR_SHORT	0.67	0.71	0.61	0.65	0.77	0.77	0.80	0.85	0.87	0.86	0.84	0.91	0.92	0.94
BVAR_LONG	0.56	0.59	0.55	0.54	0.58	0.60	0.62	0.64	0.64	0.64	0.62	0.73	0.77	0.77

Nowcast-M3_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.55	0.55	0.56	0.57	0.60	0.62	0.66	0.66	0.68	0.68	0.72	0.61	0.71	0.74
MEAN_SHORT	0.53	0.52	0.54	0.54	0.51	0.53	0.56	0.56	0.59	0.59	0.63	0.60	0.70	0.72
MEAN_LONG	0.54	0.54	0.55	0.55	0.52	0.55	0.58	0.58	0.60	0.61	0.64	0.61	0.69	0.73
AR_SHORT	0.55	0.54	0.55	0.55	0.48	0.50	0.54	0.54	0.56	0.57	0.60	0.58	0.70	0.74
AR_LONG	0.55	0.55	0.56	0.56	0.49	0.51	0.56	0.55	0.58	0.58	0.61	0.61	0.69	0.73
VAR_SHORT	0.51	0.51	0.51	0.55	0.51	0.53	0.57	0.56	0.58	0.59	0.62	0.60	0.70	0.70
VAR_LONG	0.50	0.50	0.51	0.50	**0.46**	0.49	0.53	0.52	0.54	0.54	0.57	0.58	0.69	0.70
BVAR_SHORT	0.58	0.57	0.57	0.64	0.76	0.79	0.83	0.84	0.85	0.86	0.91	0.75	0.84	0.92
BVAR_LONG	0.51	0.51	0.52	0.54	0.58	0.60	0.64	0.64	0.65	0.66	0.70	0.61	0.77	0.78

Backcast-M4_Middle	Simple Average	RMSE Weighted	Trimmed Mean	Median	First Factor	First Two Factors	First Three	First Four Factors	First Five Factors	First Six Factors	First Seven	Best Single Indicator Bridge	Second Best Single Indicator	Third Best Single Indicator
ZERO	0.54	0.51	0.55	0.54	0.48	0.48	0.51	0.54	0.56	0.57	0.57	0.58	0.62	0.64
MEAN_SHORT	0.54	0.51	0.55	0.54	0.46	0.45	0.49	0.52	0.54	0.55	0.55	0.58	0.62	0.63
MEAN_LONG	0.55	0.51	0.55	0.54	0.46	0.46	0.49	0.52	0.54	0.55	0.55	0.58	0.63	0.64
AR_SHORT	0.54	0.52	0.55	0.54	0.45	0.44	0.48	0.50	0.52	0.52	0.53	0.58	0.62	0.64
AR_LONG	0.54	0.52	0.55	0.54	0.46	0.45	0.48	0.52	0.54	0.54	0.55	0.58	0.61	0.64
VAR_SHORT	0.52	0.49	0.53	0.52	0.44	**0.43**	0.46	0.49	0.51	0.51	0.52	0.57	0.59	0.61
VAR_LONG	0.52	0.49	0.53	0.52	0.43	0.44	0.48	0.51	0.51	0.51	0.51	0.56	0.60	0.61
BVAR_SHORT	0.57	0.53	0.57	0.58	0.52	0.51	0.57	0.60	0.61	0.61	0.61	0.62	0.66	0.70
BVAR_LONG	0.56	0.52	0.56	0.56	0.49	0.48	0.52	0.55	0.56	0.57	0.56	0.60	0.65	0.66

Backcast-M5_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicator Bridge Equation
ZERO	0.53	0.50	0.53	0.55	0.45	**0.44**	0.47	0.50	0.51	0.51	0.51	0.56	0.61	0.65
MEAN_SHORT	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.49	0.50	0.51	0.51	0.56	0.61	0.65
MEAN_LONG	0.53	0.50	0.53	0.55	0.45	0.44	0.47	0.50	0.51	0.51	0.51	0.56	0.61	0.65
AR_SHORT	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.50	0.51	0.51	0.51	0.56	0.61	0.65
AR_LONG	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.49	0.51	0.51	0.51	0.56	0.61	0.65
VAR_SHORT	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.50	0.51	0.51	0.51	0.56	0.61	0.65
VAR_LONG	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.48	0.49	0.51	0.50	0.56	0.61	0.65
BVAR_SHORT	0.53	0.50	0.53	0.55	0.44	0.44	0.47	0.49	0.50	0.51	0.51	0.56	0.61	0.65
BVAR_LONG	0.53	0.50	0.53	0.55	0.45	0.44	0.47	0.50	0.51	0.51	0.51	0.56	0.61	0.65

Notes: See notes for the Table B 1.

Table B5. Relative RMSE for the Case of Using All of the 61 Indicators Relative to the RMSE for 12 Variables Selected by LASSO

Nowcast-M1_First	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.04	1.05	1.04	1.01	0.87	0.91	0.99	0.99	1.21	1.18	1.15	0.76	0.78	0.84
MEAN_SHORT	1.06	1.05	1.08	1.05	0.88	0.90	0.93	0.97	1.31	1.30	1.38	0.74	0.75	0.76
MEAN_LONG	1.09	1.06	1.10	1.09	0.92	0.93	0.97	1.00	1.33	1.30	1.31	0.76	0.76	0.73
AR_SHORT	1.06	1.05	1.09	1.09	0.92	0.93	0.98	1.03	1.14	1.31	1.32	0.71	0.76	0.79
AR_LONG	1.07	1.04	1.09	1.11	0.93	0.93	0.99	1.01	1.19	1.27	1.28	0.69	0.76	0.74
VAR_SHORT	0.99	0.98	1.08	1.11	0.76	0.80	1.03	1.09	1.32	1.41	1.20	0.69	0.75	0.72
VAR_LONG	1.02	1.04	1.06	1.06	0.75	0.85	0.90	0.92	1.14	1.22	1.25	0.75	0.77	0.76
BVAR_SHORT	0.64	0.60	0.65	0.62	0.50	0.71	0.86	0.94	1.42	1.62	1.58	0.38	0.42	0.38
BVAR_LONG	0.87	0.88	0.97	0.98	0.63	0.72	0.81	0.83	1.03	1.33	1.36	0.56	0.62	0.60
Nowcast-M1_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.11	1.12	1.13	1.15	0.96	0.99	1.06	1.02	1.10	1.15	1.16	0.85	0.88	0.87
MEAN_SHORT	1.11	1.11	1.13	1.15	0.94	0.94	0.99	0.99	1.13	1.22	1.31	0.88	0.84	0.87
MEAN_LONG	1.12	1.12	1.14	1.17	0.96	0.95	1.02	1.01	1.14	1.22	1.27	0.89	0.84	0.83
AR_SHORT	1.10	1.09	1.12	1.12	0.96	0.97	1.03	1.06	1.13	1.28	1.35	0.76	0.82	0.83
AR_LONG	1.11	1.11	1.12	1.15	0.98	0.97	1.04	1.05	1.15	1.27	1.33	0.79	0.81	0.78
VAR_SHORT	1.28	1.32	1.32	1.29	0.92	0.88	1.19	1.22	1.98	2.23	1.73	0.88	0.93	0.90
VAR_LONG	1.17	1.19	1.20	1.13	0.90	0.90	0.93	0.97	1.22	1.40	1.46	0.85	0.91	0.93
BVAR_SHORT	0.78	0.79	0.80	0.77	0.62	0.66	0.74	0.84	1.31	1.40	1.65	0.52	0.59	0.54
BVAR_LONG	1.03	1.03	1.05	1.07	0.77	0.74	0.84	0.82	1.21	1.31	1.43	0.74	0.72	0.69
Nowcast-M2_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.26	1.23	1.27	1.21	1.12	1.11	1.14	1.13	1.27	1.26	1.32	0.92	0.98	0.92
MEAN_SHORT	1.26	1.23	1.29	1.25	1.16	1.14	1.16	1.15	1.39	1.36	1.49	0.94	0.96	0.91
MEAN_LONG	1.26	1.23	1.28	1.26	1.15	1.13	1.16	1.15	1.37	1.36	1.45	0.95	0.95	0.91
AR_SHORT	1.22	1.20	1.25	1.15	1.12	1.11	1.13	1.15	1.35	1.38	1.52	0.86	0.95	0.92
AR_LONG	1.23	1.21	1.24	1.18	1.14	1.12	1.16	1.16	1.41	1.39	1.49	0.90	0.93	0.88
VAR_SHORT	1.35	1.35	1.42	1.41	1.12	1.04	1.09	1.05	1.26	1.26	1.52	0.94	0.98	0.98
VAR_LONG	1.40	1.36	1.44	1.42	1.19	1.13	1.13	1.14	1.46	1.42	1.63	0.98	0.97	1.00
BVAR_SHORT	1.10	1.05	1.19	1.13	0.93	0.99	1.06	0.98	1.20	1.16	1.47	0.65	0.72	0.75
BVAR_LONG	1.28	1.22	1.32	1.32	1.08	1.08	1.15	1.12	1.49	1.36	1.59	0.80	0.85	0.89
Nowcast-M3_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.45	1.43	1.46	1.44	1.13	1.12	1.15	1.16	1.30	1.35	1.43	1.00	1.00	0.99
MEAN_SHORT	1.49	1.47	1.51	1.50	1.22	1.19	1.19	1.22	1.40	1.45	1.59	1.00	1.00	1.00
MEAN_LONG	1.48	1.45	1.49	1.51	1.20	1.18	1.19	1.22	1.39	1.45	1.56	1.00	1.00	1.00
AR_SHORT	1.46	1.45	1.50	1.51	1.31	1.27	1.24	1.27	1.44	1.47	1.66	1.00	1.00	0.98
AR_LONG	1.47	1.44	1.48	1.48	1.28	1.25	1.23	1.25	1.42	1.45	1.62	1.00	1.00	1.00
VAR_SHORT	1.53	1.50	1.56	1.43	1.24	1.20	1.19	1.23	1.41	1.45	1.57	1.00	1.00	1.00
VAR_LONG	1.57	1.54	1.59	1.59	1.33	1.26	1.26	1.30	1.51	1.55	1.69	1.00	1.00	1.00
BVAR_SHORT	1.32	1.32	1.37	1.26	0.81	0.82	0.89	0.90	1.13	1.22	1.30	1.00	0.90	0.83
BVAR_LONG	1.50	1.50	1.53	1.48	1.03	1.03	1.05	1.08	1.29	1.37	1.51	1.00	0.95	0.96
Backcast-M4_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.46	1.47	1.47	1.47	1.30	1.38	1.34	1.31	1.22	1.38	1.24	1.00	1.00	1.00
MEAN_SHORT	1.47	1.48	1.48	1.48	1.33	1.41	1.37	1.33	1.26	1.35	1.25	1.00	1.00	1.00
MEAN_LONG	1.46	1.47	1.47	1.48	1.33	1.39	1.38	1.35	1.29	1.36	1.27	1.00	1.00	1.00
AR_SHORT	1.47	1.46	1.47	1.45	1.36	1.44	1.41	1.38	1.28	1.42	1.28	1.00	1.00	0.99
AR_LONG	1.47	1.47	1.47	1.47	1.35	1.43	1.38	1.33	1.27	1.46	1.31	1.00	1.00	1.00
VAR_SHORT	1.52	1.53	1.51	1.52	1.38	1.48	1.41	1.34	1.26	1.42	1.27	1.00	1.00	1.00
VAR_LONG	1.51	1.52	1.51	1.51	1.37	1.39	1.31	1.29	1.31	1.48	1.61	1.00	1.00	1.00
BVAR_SHORT	1.41	1.44	1.44	1.42	1.23	1.30	1.20	1.17	1.13	1.32	1.32	1.00	1.00	0.97
BVAR_LONG	1.44	1.46	1.46	1.43	1.28	1.34	1.33	1.30	1.25	1.33	1.24	1.00	1.00	1.00
Backcast-M5_Middle	Simple Average	RMSE Weighted Average	Trimmed Mean	Median	First Factor	First Two Factors	First Three Factors	First Four Factors	First Five Factors	First Six Factors	First Seven Factors	Best Single Indicator Bridge Equation	Second Best Single Indicator Bridge Equation	Third Best Single Indicato Bridge Equatio
ZERO	1.50	1.51	1.51	1.47	1.41	1.48	1.44	1.38	1.31	1.47	1.34	1.00	0.97	0.93
MEAN_SHORT	1.50	1.51	1.51	1.47	1.41	1.47	1.45	1.42	1.37	1.47	1.36	1.00	0.97	0.93
MEAN_LONG	1.50	1.51	1.51	1.47	1.40	1.46	1.46	1.41	1.37	1.47	1.36	1.00	0.97	0.93
AR_SHORT	1.50	1.51	1.51	1.47	1.41	1.48	1.44	1.39	1.33	1.48	1.36	1.00	0.97	0.93
AR_LONG	1.50	1.51	1.51	1.47	1.42	1.48	1.43	1.39	1.32	1.49	1.36	1.00	0.97	0.93
VAR_SHORT	1.50	1.51	1.51	1.47	1.41	1.47	1.44	1.38	1.31	1.47	1.35	1.00	0.97	0.93
VAR_LONG	1.50	1.51	1.51	1.47	1.43	1.46	1.45	1.42	1.38	1.51	1.42	1.00	0.97	0.93
BVAR_SHORT	1.50	1.51	1.51	1.47	1.42	1.47	1.44	1.40	1.34	1.46	1.36	1.00	0.97	0.93
BVAR_LONG	1.50	1.51	1.51	1.47	1.40	1.46	1.46	1.41	1.37	1.47	1.36	1.00	0.97	0.93

Notes: Grey shaded cells show cases of relative RMSE greater than 1. A figure greater than 1 indicates that RMSE using targeted predictors is lower than the case of using all of the indicators in Table 1. See also notes for the Table B 1.

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