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# Nowcasting Turkish GDP and News Decomposition [*]

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**Abstract**

Real gross domestic product (GDP) data in Turkey are released with a very long delay compared with other economies, between 10 and 13 weeks after the end of the reference quarter. To infer the current state of the economy, policy makers, media, and market practitioners examine data that are more timely, that are released at higher frequencies than the GDP. In this paper, we propose an econometric model that automatically allows us to read through these more current and higher-frequency data and translate them into nowcasts for the Turkish real GDP. Our model outperforms nowcasts produced by the Central Bank of Turkey, the International Monetary Fund, and the Organisation for Economic Co-operation and Development. Moreover, our model allows us to quantify the importance of each variable in our dataset in nowcasting Turkish real GDP. In line with findings for other economies, we find that real variables play the most important role; however, contrary to the findings for other economies, we find that financial variables are as important as surveys.

*Keywords:* Dynamic factor model; Nowcasting; Gross Domestic Product; News; Developing Economy; Emerging Market.

*JEL Classification:* C33, C53, E37.

[*]The opinions in this paper are those of the authors and do not necessarily reflect the views of the Board of Governors of the Federal Reserve System.

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# 1 Introduction

Policy makers and market participants need to infer the current state of the economy to inform policy decisions and investment strategies. One of the main indicators they look at is real gross domestic product (GDP), which shows the overall health of the economy. However, real GDP is usually released with a delay with respect to the reference quarter. In particular, for the Turkish economy, GDP is released between 10 and 13 weeks after the end of the reference quarter. Compared with developed economies, Turkish GDP is released with a very long delay because early or advance estimates are not produced. For example, early estimates of U.S. and euro-area GDPs are released 4 and 6 weeks after the end of the reference quarter, respectively. Therefore, the usual practice in Turkey is to infer the current state of the economy by analyzing data released in a more timely manner than GDP, at a higher frequency. Real variables such as the industrial production index and the unemployment rate are released 6 and 10 weeks after the end of the reference month, respectively, making them more timely than GDP. Moreover, surveys such as the capacity utilization rate, the consumer confidence index, and the real sector confidence index are released a few days before the end of the reference month, and financial data such as the real effective exchange rate are released a few days after the reference month. Inferring the state of the economy by interpreting numerous variables characterized by different definitions, frequencies, and lags is a difficult task. However, we can overcome this challenge using an econometric framework that translates all sorts of data into a nowcast of GDP, summarizing scattered information into a unique index of the overall health of the Turkish economy.

In this study, following the seminal paper of Giannone et al. (2008), we use a dynamic factor model (DFM) to nowcast GDP. DFMs are natural tools for nowcasting variables such as GDP because, by capturing the co-movement among a potentially large set of variables, they allow us to exploit the more timely variables to predict the ones released with a longer delay. Indeed, these models have been successfully applied for nowcasting GDP for different countries: de Antonio Liedo (2014) for Belgium, Bragoli et al. (2015) for Brazil, Yiu and Chow (2010) and Giannone et al. (2013) for China, Arnostova et al. (2011) for the Czech Republic, Barhoumi et al. (2010) for France, Luciani et al. (2015) for Indonesia, D'Agostino et al. (2013) for Ireland, Caruso (2015) for Mexico, de Winter (2011) for the Netherlands, Matheson (2010) for New Zealand, Aastveit and Trovik (2012) for Norway, and Dahlhaus et al. (2015) for BRIC (Brazil, Russia, India and China) countries and Mexico.[1] Moreover,

[1]See Bańbura et al. (2013) for a survey of the literature on nowcasting.

the same framework has been applied to nowcast variables other than real GDP; see, among others D'Agostino et al. (2015) for the euro area trade variables and Modugno (2013) for U.S. inflation.

When using DFMs for nowcasting, one of the crucial aspects is to choose an estimation methodology that suits the needs of the task at hand: dealing with a dataset characterized by different frequencies, different time spans, and different delays. We follow the procedure proposed by Bańbura and Modugno (2014), i.e., a modified version of the expectation-maximization (EM) algorithm for maximum likelihood estimation.[2] This procedure has two important advantages over competing procedures for estimating a DFM. First, the methodology of Bańbura and Modugno (2014) can easily address mixed-frequency datasets with an arbitrary pattern of data availability, fully exploiting their information content both for the parameter estimations and for the signal extraction. Second, maximum likelihood estimation is more efficient for small samples. Turkey is a young, newly industrialized economy, so institutions have started to collect economic data only recently. As a result, our dataset is short and contains data that cover different time periods.

We nowcast both seasonally adjusted (SA) quarter-on-quarter (QoQ) GDP growth rates and non-SA (NSA) year-on-year (YoY) GDP growth rates between 2008:Q1 and 2013:Q4 with a medium-scale mixed frequency dataset including 15 variables. The dataset is constructed with publicly available time series that are followed by media, economists, and financial sector practitioners. We perform two out-of-sample exercises. In the first exercise, we nowcast the SA QoQ GDP and NSA YoY GDP. We abstract from data revisions, but we impose that our dataset replicates the data availability as it was at the time that the forecast would have been generated. This is a "pseudo real-time" exercise, and we show that in this context, the GDP nowcasts obtained with our model outperform those obtained with univariate and "partial" models.[3] In the second exercise, we nowcast NSA YoY GDP growth rates and compare our predictions with those produced by the International Monetary Fund (IMF) and available in the World Economic Outlook Database (WEOD), by the Organisation for Economic Co-operation and Development (OECD) and available in the Economic Outlook (EO), and by the Central Bank of Turkey (CBRT) collected in the survey of expec-

[2]The EM approach for maximum likelihood estimation in the case of small-scale DFMs was first proposed by Watson and Engle (1983) and Shumway and Stoffer (1982). Later, Doz et al. (2012) prove that maximum likelihood estimation is also feasible for large-scale DFMs, and Bańbura and Modugno (2014) modify the EM algorithm to account for arbitrary patterns of missing data and the serial correlation of the idiosyncratic component. Jungbacker et al. (2011) and Jungbacker and Koopman (2015) further show how the computational efficiency of the methodology can be improved.

[3]See Bańbura et al. (2013) for a definition of "partial" models.

tations (SoE), showing that our DFM outperforms professional forecasters. In order to have a fair comparison with the nowcast produced by this institutions, we construct a “partial” real-time dataset to account for the effects of data revisions on the nowcast accuracy. The dataset is a “partial” real-time one because we have vintages for the sample we analyze for only eight of the variables included in our dataset. The other series are included following the “pseudo” real-time approach.[4]

Only two studies in the literature nowcast Turkish GDP growth rates. Çağrı Akkoyun and Günay (2012) use a dynamic one-factor model with a small-scale dataset, including three real variables and one survey, to nowcast SA QoQ GDP growth rates between 2008:Q1 and 2012:Q2 and compare their model with an autoregressive (AR) model. They find that their model outperforms the benchmark model. Compared with Çağrı Akkoyun and Günay (2012), we use a more comprehensive dataset that allows us to understand which variables are informative for nowcasting Turkish GDP. We find that financial variables such as the REER and financial account, closely monitored by both policy makers and the market practitioners, are as important as surveys such as the CCI, the RSCI, and the CUR when nowcasting SA QoQ GDP growth rates. Neither of these financial or survey variables are included in Çağrı Akkoyun and Günay (2012).[5] Ermişoğlu et al. (2013) nowcast QoQ GDP growth rates for the period between 2011:Q1 and 2012:Q4 by forming bridge-type single equations that include purchasing manufacturing index (PMI) and credit data. To form bridge equations, monthly variables are converted into quarterly variables. Then, a regression or a series of regressions that includes GDP as a dependent variable and other economic indicators as explanatory variables are formed. However, as noted by Bańbura et al. (2013), “partial” models, such as bridge equations, do not allow one to interpret how new data releases revise the nowcast of the target variable for two reasons. First, single-equation models do not produce a forecast of the input variables; therefore, it is not possible to isolate the surprise component, i.e., the difference between the realization of the input variable and what the model predicted. As shown in Bańbura and Modugno (2010), it is only the surprise component, or “news,” that revises the nowcast of the target variable when new information arrives. Second, single-equation models have to be parameterized to account for the different availability of the input data and depending on the forecasting horizon for the target variable. This parametrization makes it even more difficult to interpret why the new release of an input variable revises the

[4]We do not do the same with SA real GDP given that it has been published only recently and real time vintages are not available.

[5]We do not use the purchasing managers index (PMI) used by Çağrı Akkoyun and Günay (2012) because the PMI is provided by a private company for a fee and, as a result, is not available to the larger public.

nowcast of the target variable. The methodology adopted in this paper can address these issues in a comprehensive unifying framework. In our study, we compute the "news" and find that, in line with findings for other economies, real variables play the most important role in nowcasting GDP. However, contrary to what happens for other economies, we find that financial variables play a crucial role, as important as that played by surveys, for nowcasting SA QoQ GDP growth rates.

The remainder of this paper is as follows. Section 2 explains the dataset. Section 3 presents the methodology. Section 4 shows nowcast results of SA QoQ and NSA YoY GDP growth rates. Section 5 presents nowcast results of annual GDP growth rates. Section 6 analyzes the effect of news, and Section 7 concludes.

# 2 The dataset

We construct a medium-scale dataset to nowcast Turkish GDP. The literature shows that large-scale DFMs do not necessarily lead to better forecasting performances than smaller DFMs (e.g., Boivin and Ng, 2006; Alvarez et al., 2012), and Bańbura and Modugno (2014) find that the forecasting accuracies of medium-scale DFMs are higher than those of large-scale DFMs for euro-area GDP.

Figure 1 displays the evolution of the annual real GDP growth rates of Turkey between 1990 and 2013. The figure highlights the volatile nature of Turkish growth. The hard landings in 1994, 1999, and 2001 as well as the 2008 global crisis and the rapid recovery afterward depict rather typical behavior for the Turkish economy. From the figure, it is easy to conclude that the extreme highs and lows are the rule rather than then exception.[6] In terms of international comparisons as shown by Akat and Yazgan (2013), among others, the volatility of Turkish growth is one of the highest among its emerging market peers.

Some authors have argued that highly volatile Turkish GDP growth is mainly related to the intensity of capital inflows (e.g., Akat and Yazgan, 2013; Özatay, 2015).[7] This heavy reliance on capital flows to attain high growth is, in turn, attributed to the inadequate level of domestic savings (i.e., if domestic savings are scarce, rapid growth can only be attained

[6] Clearly this roller coaster nature of Turkish growth makes the already difficult task of forecasting more complicated than usual.

[7] See Acemoglu and Ucer (2015) for a recent history of Turkish growth emphasizing the role of structural factors.

with greater access to foreign capital). However, this is short-term gain due to the volatile nature of capital flows, leading to boom-bust cycles in the long run.[8]

By taking Turkish economic structure into account, we choose 14 publicly available economic indicators to nowcast GDP and group them as real variables, survey variables, and financial variables. Real variables used in this study are the industrial production index (IPI), automobile production, the import volume index, the export volume index, the Ercan Türkan Consumer Index, the non-agricultural unemployment rate, and the total employment excluding agriculture. The IPI, highly correlated with GDP, is often used as a proxy for GDP when monthly output data are needed for analysis (e.g., Civcir and Akçağlayan, 2010; Bildirici et al., 2011; Dedeoğlu and Kaya, 2014). Similarly, a simple method used by practitioners to predict the YoY GDP growth rate in Turkey is to use the YoY quarterly IPI with a certain amount of judgment. Automobile production is one of the most important production sectors in Turkey. It is released earlier than the IPI and is an important determinant of the IPI. Turkey's economy is generally driven by domestic demand; thus, when Turkey's economy expands, imports are also expected to increase. In this sense, imports are good predictors of both private consumption and investment expenditure. Another good predictor of private consumption expenditure is the Ercan Türkan Consumer Index that is based on credit and debit card data. Although Turkey's economy is mainly driven by domestic demand, when the current account deficit reaches unsustainable levels, policy makers curb the domestic demand (for instance, in 2012 and 2013). In these periods, growth has mainly relied on exports. Finally, we also include a time series related to labor force statistics. When the unemployment rate is increasing or total employment is stagnating, we expect the GDP to slow down.

As survey variables, we include all publicly available surveys that begin before 2008: the capacity utilization rate (CUR), the Turkish Statistical Agency's (Turkstat) consumer confidence index (CCI), the CNBC-e's CCI, and the real sector confidence index (RSCI).[9] Although financial variables are usually not informative in predicting GDP (see Bańbura et al., 2013), we select three important time series: financial accounts, the real effective

[8] The view that the Turkish economy is prone to boom-bust cycles originating from capital flows is widely shared among market professionals, some academicians, and even policy makers in Turkey and international organizations such as the IMF and World Bank (e.g., World Bank and the Ministry of Development of Turkey, 2011; IMF, 2012). However, it should be emphasized that the direction of the postulated causality from capital flows to growth may run in the reverse direction or in both direction, in the sense of both variables being affected by a set of possibly unobserved variables lurking in the background, such as increased productivity, better fundamentals, and/or macroeconomic policy stances accompanying these features.

[9] The RSCI is designed to show short-term tendencies in the manufacturing sector (see CBRT, nd)

exchange rate (REER), and TRLibor 3 Months. As explained previously, Turkey suffers from both a low savings rate and a high current account deficit. Therefore, economists are closely following developments in financial accounts. Another important piece of financial data closely followed by public and market participants is the exchange rate. As a proxy of the exchange rate, we use the real effective exchange rate. One of the reasons for this choice is that the CBRT used the REER as forward guidance for monetary policy in 2013. Finally, we include the three-month interest rate because it affects domestic demand.

We nowcast both SA QoQ and NSA YoY GDP growth rates. The NSA YoY GDP growth rate is still a very closely observed figure because market participants in Turkey have only very recently started to use seasonally adjusted data, unlike their counterparts in developed countries.

We use NSA data to nowcast NSA YoY GDP growth rates and, when available, SA data to nowcast SA QoQ GDP growth rates. If SA data are not available, we seasonally adjust those variables using Tramo-Seats.[10] SA data are usually announced together with NSA data.

Another point to discuss in our dataset is that the SA CUR and the SA RSCI begin in 2007:M01, whereas their NSA counterparts begin in 1998:M01. The CUR and the RSCI were revised in 2007 to meet the requirements of the Joint Harmonized European Union Programme of Business and Consumer Surveys. Since then, the CBRT only announces the CUR and the RSCI starting from 2007:M01. For nowcasting SA QoQ GDP growth rates, we use official SA figures. For nowcasting NSA YoY GDP growth rates, we follow the regular market practice of combining new and old surveys. First, we calculate the monthly percentage differences of the old series. Then, by using the first available data in the new survey and growth rates of the old survey, we calculate new index values for the period in which the new survey lacks data.

In order to have stationary variables, we compute yearly differences of NSA data and monthly differences of SA data. A log transformation is also applied whenever necessary. A list of variables, details about seasonal adjustment procedures, and applied transformations are shown in Appendix A.1.

[10] Official institutions in Turkey also use Tramo-Seats to seasonally adjust data series (e.g., Turkstat, 2013). We follow a simple approach and seasonally adjust all series using the automatic procedure of Tramo-Seats Rev. 941 setting RSA=4.

# 3 The methodology

We use a DFM to produce nowcasts of both SA QoQ GDP and NSA YoY GDP growth rates. By adopting a DFM, we can obtain a parsimonious representation of macroeconomic data, because a small number of dynamic factors is enough to drive a large amount of co-movements among macroeconomic data series.[11] Our DFM has the following representation:

$$x_{i,t} = \Lambda_i f_t + \epsilon_{i,t}; \quad i = 1, .., n, \tag{1}$$

$$\epsilon_{i,t} = \alpha_i \epsilon_{i,t-1} + v_{i,t}; \quad v_{i,t} \sim i.i.d.\, \mathcal{N}(0, \sigma_i^2), \tag{2}$$

where $x_{i,t}$ are our $n$ monthly observations standardized to zero mean and unit variance. $\Lambda$ is an $n$x$r$ vector containing factor loadings for monthly variables; $\epsilon_{i,t}$ are the idiosyncratic components of monthly variables that we model as an autoregressive process of order one -AR(1)- process as shown in equation 2; and $f_t$ is an $r$x1 vector of unobserved common factors.[12] $f_t$ is modeled as a stationary vector autoregression process:

$$f_t = \varphi(L) f_{t-1} + \eta_t; \quad \eta_t \sim i.i.d.\, \mathcal{N}(0, R), \tag{3}$$

where $\varphi(L)$ is an $r$x$r$ lag polynomial matrix and $\eta_t$ is an $r$x1 vector of innovations.

In order to incorporate quarterly variables into the model, we construct a partially observed monthly counterpart for each of them in which the value of the quarterly variable is assigned to the third month of the respective quarter. We assume that the "unobserved monthly" QoQ or YoY growth rate of our quarterly variables ($x_t^{UM}$) admits the same factor model representation as the monthly real variables:

$$x_{i,t}^{UM} = \Lambda_i^Q f_t + e_{i,t}^Q, \tag{4}$$

$$e_{i,t}^Q = \rho_i^Q e_{i,t-1}^Q + v_{i,t}^Q; \quad v_{i,t}^Q \sim i.i.d.\, \mathcal{N}(0, \sigma_i^2). \tag{5}$$

To link the "unobserved monthly" QoQ growth rate with its quarterly QoQ growth rate counterpart ($x^{QQ}$), we construct a partially observed monthly series and use the approxima-

[11] See Sargent and Sims (1977) and Giannone et al. (2005).

[12] Bańbura and Modugno (2014) argue that modeling the idiosyncratic component as an AR(1) process may improve the forecasts.

tion of Mariano and Murasawa (2003), imposing restrictions on the factor loadings:[13]

$$x_{i,t}^{QQ} = x_{i,t}^{UM} + 2x_{i,t-1}^{UM} + 3x_{i,t-2}^{UM} + 2x_{i,t-3}^{UM} + x_{i,t-4}^{UM}, \tag{6}$$

and to link the "unobserved monthly" YoY growth rate with its quarterly YoY growth rate counterpart ($x^{YQ}$), we follow Giannone et al. (2013):

$$\begin{aligned} x_{i,t}^{QY} &= X_{i,t}^{Q} - X_{i,t-12}^{Q} \\ &= (1 - L^{12})X_{i,t}^{Q} \\ &\approx (1 - L^{12})(1 + L + L^2)X_{i,t}^{M} \\ &= (1 + L + L^2)x_{i,t}^{UM} \\ &= x_{i,t}^{UM} + x_{i,t-1}^{UM} + x_{i,t-2}^{UM}; \end{aligned} \tag{7}$$

where $X^Q$ and $X^M$ indicate the log-level of the quarterly and the "fictional" monthly counterpart data, respectively.

A DFM can be estimated in a couple of different ways. Because Turkey is a developing economy where institutions have only recently begun to collect macroeconomic data, our dataset includes series of different sample lengths and different frequencies and has a small sample size. Therefore, we adopt the estimation techniques proposed by Bańbura and Modugno (2014) that have shown how to modify the expectations maximization algorithm for estimating factor models when data are characterized by an arbitrary pattern of availability. Moreover, because maximum likelihood estimators are more efficient in small samples, this estimation technique is a natural choice.

The number of factors in equation 1 is selected by using Bai and Ng's (2002) information criteria (BG) modified as in Doz et al. (2012) to take into account that the parameters are estimated through maximum likelihood. The number of lags in equation 3 is chosen by the Akaike information criteria (AIC).[14]

[13]See Bańbura and Modugno (2014) on how to impose restriction on the factor loadings. Camacho and Perez-Quiros (2010) argue that the aggregation proposed by Mariano and Murasawa (2003) may not be appropriate for emerging market economies. However, as shown, among others, by Bragoli et al. (2015) for Brazil, Yiu and Chow (2010) and Giannone et al. (2013) for China, Luciani et al. (2015) for Indonesia, and Caruso (2015) for Mexico, models that follow this strategy produce very accurate nowcasts.

[14]See Appendix A.2 for details.

# 4 Nowcasting SA QoQ and NSA YoY GDP growth rates

In this section, we use the final figures as of November 2014 and ignore historical data revisions. However, every time we estimate the model and produce our nowcasts, we use only the data as they were available at that specific time by replicating historical data availability.

Turkish real GDP data are typically released with two quarters of delay from the beginning of the reference period. We produce our nowcasts once per month when labor force statistics are released, i.e., around the $15^{\text{th}}$ day of each month. Because the delay in the publication is greater than one quarter, we also need to "backcast" the previous quarter GDP in the months where the previous quarter data are still not announced. Therefore, in months corresponding to the first quarter of the year we nowcast the the first quarter GDP, and in the months corresponding to the second quarter we nowcast the second quarter GDP but also backcast the first quarter GDP because the data on the first quarter GDP are still not released. In the third quarter, we continue in the same manner and both nowcast and backcast third and second quarters but stop backcasting the first quarter because the data are already available.

As indicated previously, when we estimate our DFM each month, we use all the information that was available at that time. Because of the different publication lags of different variables, the length (or the amount of missing data) of the variables used in the estimation varies from month to month. Although the monthly variables have a rather stable structure at each month of estimation, GDP has a variable structure. The publication lags are more explicitly shown in Table 1. For example, if we assume that the DFM is estimated in April 2008, the dataset has four months of missing data for GDP, so that we can use past values of GDP with four months of missing data in our estimation. However, in May 2008 and June 2008, the dataset has five and six months of missing data for GDP, respectively, so we can use less lagged values of GDP for estimation. When the first quarter GDP data are released at the end of June, the number of months of missing data for GDP in the dataset reduces to four again. As mentioned, the number of months of missing data for monthly variables is more stable. For example, the dataset always has two months of missing data for the IPI. The number of months of missing data for a variable at the end of the sample is equal to the publication lag from the beginning of the reference period of that variable. Publication lags for all variables are shown in Appendix A.1.

## 4.1 Out of sample forecast performance evaluation

We estimate our models recursively with data starting in January 1998, given that Turkish national accounts are available since 1998:Q1. We evaluate the nowcast accuracy of the proposed models on the sample that goes from 2008:Q1 to 2013:Q4. We calculate root mean square forecast errors (RMSFEs) to evaluate nowcast accuracies. We compare the performance of the DFM with the ones of an autoregressive model, with lags chosen by AIC, with the sample mean of the GDP growth rate, and with bridge equations including all variables in the DFM.[15]

We also use White's (2000) reality check to determine whether the DFM significantly outperforms competing models. White (2000) develops a test of superior predictive ability for multiple models. The null hypothesis of the reality check is that, among competing/alternative models, no model has superior predictive ability over the benchmark model. In this exercise, we first take the DFM as benchmark and accept all other models as alternative models to show that the DFM is not inferior to other competing models. Then, we choose a rival model of the DFM with the lowest RMSFE for each nowcast horizon as the benchmark model and the DFM as an alternative model to show that the DFM has superior forecasting ability over the best rival model in each nowcast horizon.

Table 2 presents RMSFEs for successive nowcast horizons from Q(0)M01 to Q(1)M02 and average RMSFEs of all the nowcast horizons for SA QoQ and NSA YoY GDP growth rates. Figure 2 and Figure 3 also show actual and forecasted GDP growth rates for all nowcasting horizons. DFM refers to our factor model. AR and Mean refer to the univariate benchmark models, and BE refers to the bridge equations. The current quarter and the next quarter with respect to reference quarter are represented by Q(0) and Q(1), respectively. The first, second, and third months of a quarter are denoted as M01, M02, and M03, respectively. For each reference quarter, we produce forecasts from Q(0)M01 to Q(1)M02 for the reference quarter. With this method, we produce five predictions, three nowcasts (in Q(0)M01-Q(0)M03) and two backcasts (in Q(1)M01-Q(1)M02), for each reference quarter.[16] Table 3 shows p-values

[15] For bridge equations, we estimate 14 quarterly autoregressive distributed lags (ARDL) models for each predictor. Monthly predictors are transformed into quarterly variables by averaging, and when a monthly variable cannot be transformed into a quarterly variable because of the missing data at the end of the sample period, an autoregressive model is used to fill the missing data. The lag structure in ARDL models is determined by AIC. Then, predictions obtained from all ARDL models are combined by simple averaging.

[16] GDP data for the fourth and the first quarter are usually announced near the last day of March and June, respectively. GDP data for the third and the second quarter are usually announced near the $10^{\text{th}}$ of September and December, respectively (since 2013, GDP data for the first quarter have also started to be announced near the $10^{\text{th}}$ of June). According to our fixed estimation time, the middle of each month, this

for reality check tests. P-Inf tests whether the DFM is inferior to the competing models and P-Sup tests whether the DFM has superior predictive ability over the best rival model for each nowcast horizon.

Table 2 shows that factor models perform better than all other benchmark models at all horizons. For both SA QoQ GDP growth rates and NSA YoY GDP growth rates, the bridge equations have the highest forecasting accuracies among benchmark models. However, for SA QoQ GDP growth rates, the average RMSFE of the DFM is 30.8% lower than the bridge equations. For NSA YoY GDP growth rate, the average RMSFE of the DFM is 57.0% lower than that of the bridge equation model. Table 3 shows that the DFM is not worse than any alternative model. Furthermore, the DFM outperforms the best competing model in each nowcast horizon for NSA YoY GDP growth rates, whereas the DFM beats the best rival model only in early nowcast horizons for SA QoQ GDP growth rates. Finally, Figure 2 and Figure 3 show that the crisis period (2009) and the recovery period (2010) afterward are best captured by DFMs, while other competing benchmark results perform very poorly in these volatile periods.

The difference between the forecasting power of bridge equations and DFMs is especially large in early nowcast horizons, where many predictors lack data for the reference quarter. The poor performance of bridge equations, especially in early nowcast horizons, clearly shows that the joint multivariate modeling strategy in DFM is beneficial for forecasting, as shown by Angelini et al. (2010), Angelini et al. (2011) and Bańbura et al. (2013). Finally, RMSFEs of DFMs shrink with each successive forecasting horizon. In line with the literature (e.g., Giannone et al., 2008; Bańbura and Rünstler, 2011; Bańbura and Modugno, 2014), this shows that timely monthly data increase the forecasting accuracy of DFMs.

# 5 Nowcasting NSA YoY GDP

As shown in Table 2, the DFM easily beats simple forecast models chosen as benchmarks. Although using more sophisticated forecast models or alternative nowcast models as benchmarks seems to provide a more appropriate evaluation, from a policy perspective, a

procedure results in the first quarter and the fourth quarter GDP data having a six month delay and the third and the second quarter GDP data having a five month delay from the start of the reference quarter. We can also compute one additional prediction in Q(1)M03 for the first quarter and the fourth quarter GDP, but we ignore these predictions to have an equal number of nowcasts for each reference quarter. Still, results for $6^{\text{th}}$ nowcasts are shown in the note section of Table 2.

more interesting analysis can be provided by comparing the predictions of DFM with those of institutions and experts. However, it is difficult to find public SA QoQ or NSA YoY GDP forecasts for Turkey.[17]

We use forecasts of the IMF's WEOD, the OECD's EO, and the CBRT's SoE. The CBRT's SoE collects expectations of decision makers in financial and real sectors on various macroeconomic and financial variables every month. There are two questions about GDP: "Current Year Annual GDP Growth" and "Next Year Annual GDP Growth." We use the former to compare with our nowcasts. We also use forecasts of the IMF's WEOD and the OECD's EO, both updated twice per year.

We make a series of changes in the design of the previous nowcasting exercise to be able to compare our results with annual predictions. From the first month of the reference year until the end of the reference year, we predict NSA YoY GDP growth rates for every quarter of the reference year and the previous year that is not available at that specific time. Next, using actual and predicted growth rates, we calculate the annual real GDP figure (in levels) of the reference year and the annual GDP figure of the previous year if the GDP data of the previous year are not historically available at that point. Finally, we compute the annual growth rate of the reference year by using the annual calculated real GDP figure of the reference year and the annual calculated or actual (depending on the period) real GDP figure of the previous year. With this method, we obtain 12 predictions for each reference year.

As outlined previously, our exercise in this section includes backcasting, nowcasting, and forecasting NSA YoY GDP growth rates to obtain nowcasts of annual GDP growth rates.[18] Table 4 explains this process more clearly. Table 4 shows which quarter's GDP data are available at each month of the reference year. For example, in March 2008 we backcast 2007:Q4 GDP. Furthermore, we nowcast 2008:Q1 GDP and forecast GDP data of 2008:Q2, 2008:Q3, and 2008:Q4. By using this data, we compute both 2007 and 2008 annual real GDP figures to obtain the nowcast of the 2008 annual GDP growth rate. In the next month, 2007:Q4 GDP data becomes available, so as previously we backcast 2008:Q1 GDP. We nowcast 2008:Q2 GDP and forecast GDP data of 2008:Q3 and 2008:Q4. Then, we

[17]One notable exception is the CNBC-e analysts' expectation survey that contains forecasts for GDP growth rates from 2002 to present. However, there are some missing data in the survey due to disturbances in the forecast collection process from experts. In addition, the survey only includes one prediction for each quarter.

[18]We refer to this exercise as a nowcasting exercise because we predict annual GDP growth rates only during the year whose growth rate is predicted.

estimate only 2008 annual real GDP figures. By using actual 2007 real GDP and estimated 2008 real GDP figures, we obtain the nowcast of 2008 annual GDP growth rate. By using this process, we continue to nowcast the 2008 annual GDP growth rate until the end of 2008. In the first month of 2009, we begin estimating the annual GDP growth rate of 2009. We continue this procedure until the last month of 2013.

Using final revised data might bias the results in favor of the DFM because institutional and professional forecasts are computed with actual real-time data. Therefore, we also construct a "partial" real-time dataset. We have vintages for GDP, the IPI, the CUR, import volume index, export volume index, the Turkstat's CCI, the RSCI, and TRLibor. Unfortunately because of a lack of vintage data for Turkey, we use final revised data of the other seven variables in this exercise. The rest of the exercise's design is the same as the previous one.

Table 5 shows RMSFEs for successive nowcast horizons and average RMSFEs of all the nowcast horizons for annual GDP growth rates. DFM refers to the model presented here. OECD, IMF and SoE refer to the OECD's EO, the IMF's WEOD, and the CBRT's SoE, respectively. Table 5 shows that, on average, the DFM performs better than the IMF, OECD, and SoE. Aside from the DFM, SoE has the best forecast accuracy as expected. However, the average RMSFE of the DFM is still 34.1% lower than that of SoE. Table 6 also shows that the DFM is not worse than any professional forecaster and outperforms the best professional forecaster in most of the nowcast horizons.

To better analyze the results, we present actual and forecasted annual GDP growth rates in Figure 4. Figure 4 clearly shows that the biggest differences between forecasts of the DFM and institutional forecasts occur in the crisis and the recovery period afterward. In 2009, Turkey contracted sharply because of the global economic crisis. Subsequently, Turkey enjoyed a very rapid economic recovery in 2010 and 2011. Institutional forecasts are conservative in these volatile periods, especially in the beginning of these periods. The DFM quickly and efficiently incorporates new information, even though there are a few significant misses in periods around the middle of the year. The results are highly interesting because Ang et al. (2007) claim that forecasts from surveys are superior to model based forecasts, and the literature shows nowcasting models perform well mostly for short forecasting horizons (Bańbura et al., 2013).

# 6 The effect of news and model re-estimation

In the previous out-of-sample forecasting evaluation, we updated GDP nowcasts each month based on the new data releases. Because our DFM produces forecasts not only for GDP but also for all the variables used in the dataset, only the news or "unexpected" component from the newly released data should revise nowcasts of GDP. In other words, the change between two consecutive nowcasts of GDP can be the result of news from all variables, i.e., is the unpredicted component of the dataset, and model re-estimation, i.e., that is the change in the model parameters as a result of newly released data.

We denote as $\Omega_{v+1}$ and $\Omega_v$ two consecutive datasets collected one month apart,[19] and $x$ as newly released data that is included in $\Omega_{v+1}$ but not in $\Omega_v$.[20] Defining the nowcast of quarterly GDP $x_t^Q$ as an orthogonal projection of itself on the available dataset, the nowcast can be shown as follows:

$$\mathbb{E}[x_t^Q \mid \Omega_{v+1}] = \mathbb{E}[x_t^Q \mid \Omega_v] - \mathbb{E}[x_t^Q \mid I_{v+1}] \tag{8}$$

where $\mathbb{E}[x_t^Q \mid \Omega_{v+1}]$ and $\mathbb{E}[x_t^Q \mid \Omega_v]$ are new and old nowcasts, respectively, and $\mathbb{E}[x_t^Q \mid I_{v+1}]$ is the revision in the two consecutive nowcasts. $I_{v+1}$ denotes news, which is the unexpected part of the release with respect to the model and is shown as $I_{v+1} = x - \mathbb{E}[x \mid \Omega_v]$. Equation 8 shows that the nowcast of GDP between successive months changes only if values of newly released variables and the DFM's predictions of those variables based on $\Omega_v$ differ. Additionally, the effect of parameter re-estimation on nowcasts with each dataset expansion is taken into account.[21]

To understand which types of news are more important with respect to all other types of news on nowcast revisions in a tractable and compact fashion, we compute the relative impact of news and model re-estimation. The relative impact metric shows, for a given horizon, how much each news or model re-estimation revises the nowcast as a percentage with respect to the sum of all the absolute contributions of news and model re-estimation. Let us define the contribution of news or a model re-estimation for the reference quarter $r$ at the nowcast horizon $h$ as $C_{i,r,h}$. We can then calculate the relative impact of news or a

[19] Any frequency can be used in principle, but we use a one month frame in this study.
[20] Here we abstract from data revisions.
[21] See Bańbura and Modugno (2010) for a more detailed explanation.

model re-estimation for the reference quarter $r$ at the nowcast horizon $h$ as follows:

$$\text{Relative Impact}_{i,r,h} = \frac{|C_{i,r,h}|}{\sum_{i=1}^{S} |C_{i,r,h}|}, \tag{9}$$

where $i = 1, \ldots, S$ is an index that contains all news and model re-estimation.

Figures 5 and 6 present relative impact of news and model re-estimation on SA QoQ and NSA YoY GDP growth rates calculated for the four consecutive nowcasts from Q(0)M02 until Q(1)M02 for each reference quarter in our evaluation period of 2008:Q1 to 2013:Q4.[22] For easier tractability, we group variables into three categories: variables relating to real economy (Real), variables obtained from surveys (Survey), and financial variables (Finance).[23] Re-estimation denotes the impact of model re-estimation (ReEst). The Y-axis shows nowcast periods. The X-axis shows reference quarters, and the Z-axis shows relative absolute impacts of news or model re-estimation as a percentage of the sum of all absolute impacts. Table 7 summarizes the information contained in Figure 5 and Figure 6.

Figures for SA QoQ GDP and NSA YoY GDP clearly show that the real variable group is the prominent factor in nowcast revisions. After the first period, the relative impact of real news account for more than 40% of all contributions. Furthermore, survey news have a significant impact on nowcast revisions in the early period because some real variables have not yet been announced at those periods. The impact of financial news is small in many periods when nowcasting NSA YoY GDP growth rates, but financial variables seem to matter more when nowcasting SA QoQ GDP growth rates. There are quite a few periods in which the relative impact of finance news reaches high levels for SA QoQ GDP nowcasts. Table 7 also shows that the average relative impact of finance news (23.57%) is higher than that of survey news (22.91%) for SA QoQ GDP growth rates. We further analyze the impact of financial variables on nowcasting by dropping financial variables from the DFM and nowcasting GDP growth rates without financial variables.[24] Table 8 shows that for SA QoQ GDP growth rates, the average RMSFE of DFM is 21.1% lower than the average RMSFE of DFM without financial variables. However, for NSA YoY GDP growth rates, the average RMSFE of DFM is only 0.9% lower than that of DFM without financial variables. Results of this nowcasting exercise are in line with the outcome of news decomposition. Results are highly interesting for SA QoQ GDP growth rates, because the literature shows

[22]Q(0)M01 is not included because nowcast revisions can only be calculated starting from Q(0)M02.
[23]See Appendix A.1. for variables' associated groups.
[24]Lag and factor structure for newly estimated DFMs are recalculated as seen in Appendix A.2.

that financial variables are not very helpful for forecasting SA QoQ GDP (e.g., Bańbura et al., 2013), and the effect of finance news on nowcast revisions for SA QoQ GDP is low (e.g., Bańbura and Modugno, 2010). Finally, the effect of re-estimation is very high during the global economic crisis because of the high volatility experienced at that time. However, the impact of model re-estimation becomes negligible after the crisis.

# 7 Conclusion

In this paper, we nowcast SA QoQ, NSA YoY, and annual GDP growth rates by using the methodology of Bańbura and Modugno (2014). In addition to efficiently handling mixed-frequency datasets with arbitrary pattern of missing data, the adopted methodology offers a comprehensive unifying solution that allows us to compute news. For nowcasting, we adopt a small-scale dataset consisting of 15 variables and recursively perform sample forecasts between 2008:Q1 and 2013:Q4.

We compare SA QoQ and NSA YoY GDP nowcast results of the DFM with those of the AR model, a sample mean of GDP growth rate, and the bridge equation model. Results show that the DFM outperforms competing benchmark models.

Furthermore, we compare annual GDP nowcasts of the DFM with those of the IMF, the OECD, and the CBRT's Survey of Expectations. We demonstrate that the DFM can even beat professional forecasters. We find that the biggest difference between institutional forecasts and forecasts of the DFM exists in volatile periods. The DFM quickly and efficiently incorporates new information, whereas professional forecasters seem to remain conservative in these periods.

Finally, we evaluate the impact of news. We find that survey news have a significant impact on nowcast revisions in earlier forecasting periods, but their impact quickly diminishes in later periods. Real variables have a high impact at all times, especially in later periods. We find that the impact of finance news on nowcast revisions is more prominent for SA QoQ GDP growth rates than NSA YoY GDP growth rates. We also analyze how helpful financial variables are in nowcasting by comparing DFMs with and without financial variables. In contrast to the literature, we find that removing financial variables from the dataset deteriorates the nowcasting accuracy of DFMs in all nowcasting horizons for SA QoQ GDP growth rates. Finally, the effect of model re-estimation is very high during the global economic crisis, but quickly fades after the crisis.

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# Tables and Figures

Table 1: The structure of missing data and available data in the dataset for GDP and the IPI between April 2008-July 2008

| Variable: GDP | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 15.1.08 | 15.2.08 | 15.3.08 | 15.4.08 | 15.5.08 | 15.6.08 | 15.7.08 |
| 15.4.08 | NA | NA | NA | NA | | | |
| 15.5.08 | NA | NA | NA | NA | NA | | |
| 15.6.08 | NA | NA | NA | NA | NA | NA | |
| 15.7.08 | A | A | A | NA | NA | NA | NA |
| Variable: IPI | | | | | | | |
| | 15.1.08 | 15.2.08 | 15.3.08 | 15.4.08 | 15.5.08 | 15.6.08 | 15.7.08 |
| 15.4.08 | A | A | NA | NA | | | |
| 15.5.08 | A | A | A | NA | NA | | |
| 15.6.08 | A | A | A | A | NA | NA | |
| 15.7.08 | A | A | A | A | A | NA | NA |

Note: This table presents an example for the calculation of publication lags for variables. The upper part shows the state of the dataset for GDP, and the lower part shows the state of the dataset for the IPI. "NA" refers to non-available data, and "A" refers to available data. Dates on the first column show the dates on which models are run. Other dates refer to positions in the dataset.

Table 2: RMSFEs for SA QoQ and NSA YoY GDP growth rates, 2008:Q1-2013:Q4

| | SA QoQ GDP | | | | NSA YoY GDP | | | |
|---|---|---|---|---|---|---|---|---|
| | DFM | BE | AR | Mean | DFM | BE | AR | Mean |
| Q(0)M01 | 2.29 | 3.07 | 3.02 | 3.81 | 2.76 | 7.83 | 6.40 | 7.05 |
| Q(0)M02 | 1.99 | 3.21 | 3.02 | 3.81 | 2.56 | 6.89 | 6.40 | 7.05 |
| Q(0)M03 | 1.62 | 2.93 | 2.87 | 3.32 | 2.09 | 4.35 | 5.70 | 5.89 |
| Q(1)M01 | 1.60 | 1.93 | 2.74 | 2.91 | 1.76 | 3.30 | 4.11 | 4.32 |
| Q(1)M02 | 1.52 | 1.87 | 2.74 | 2.91 | 1.77 | 3.14 | 4.11 | 4.32 |
| Average | 1.80 | 2.60 | 2.87 | 3.35 | 2.19 | 5.10 | 5.34 | 5.72 |

Note: This table reports RMSFEs of DFMs and benchmark models for SA QoQ and NSA YoY GDP growth rates. DFM refers to our factor model. AR, Mean, and BE refer to the AR model, a sample mean of GDP growth rate, and the bridge equation model, respectively. Average shows average RMSFEs of all nowcast horizons. Q(1)M03 results for SA QoQ GDP growth rates: DFM (1.66), BE (1.81), AR (3.02), RW (2.34). Q(1)M03 results for NSA YoY GDP growth rates: DFM (2.17), BE (2.43), AR (5.14), RW (5.19).

Table 3: White's reality check test p-values for SA QoQ and NSA YoY GDP growth rates, 2008:Q1-2013:Q4

| | SA QoQ GDP | | NSA YoY GDP | |
|---|---|---|---|---|
| | P-Inf | P-Sup | P-Inf | P-Sup |
| Q(0)M01 | 0.83 | 0.07 | 0.99 | 0.00 |
| Q(0)M02 | 0.93 | 0.00 | 0.99 | 0.00 |
| Q(0)M03 | 0.95 | 0.00 | 0.97 | 0.00 |
| Q(1)M01 | 0.75 | 0.21 | 0.96 | 0.00 |
| Q(1)M02 | 0.76 | 0.20 | 0.95 | 0.00 |

Note: This table reports p-values for White's reality check test both for SA QoQ and NSA YoY GDP growth rates. Columns under P-Inf shows p-values when the DFM is the benchmark and other models are the alternative. Columns under P-Sup shows p-values when the DFM is the alternative and the best model according to RMSFE for each horizon is the benchmark.

Table 4: The availability of quarterly GDP data for each month

| | Previous Year | Reference Year | | | |
|---|---|---|---|---|---|
| | Q4 | Q1 | Q2 | Q3 | Q4 |
| M01 | NA | NA | NA | NA | NA |
| M02 | NA | NA | NA | NA | NA |
| M03 | NA | NA | NA | NA | NA |
| M04 | A | NA | NA | NA | NA |
| M05 | A | NA | NA | NA | NA |
| M06 | A | NA* | NA | NA | NA |
| M07 | A | A | NA | NA | NA |
| M08 | A | A | NA | NA | NA |
| M09 | A | A | A | NA | NA |
| M10 | A | A | A | NA | NA |
| M11 | A | A | A | NA | NA |
| M12 | A | A | A | A | NA |

Note: This table shows the availability of GDP data for each month in the reference year. M01, ..., M12 denote first month, ..., twelfth month of a reference year. "NA" refers to unavailable data, "A" refers to available data.
* Since 2013, GDP data for the first quarter are announced around the $10^{\text{th}}$ of June instead of at the end of the June.

Table 5: RMSFEs for annual GDP growth rates, 2008-2013

| | DFM | OECD | IMF | SoE |
|---|---|---|---|---|
| M01 | 2.18 | 4.38 | 4.62 | 3.90 |
| M02 | 2.13 | 4.38 | 4.62 | 3.51 |
| M03 | 2.03 | 4.38 | 4.62 | 3.30 |
| M04 | 1.46 | 4.38 | 4.28 | 2.88 |
| M05 | 2.48 | 4.38 | 2.50 | 2.59 |
| M06 | 2.76 | 3.04 | 2.50 | 2.40 |
| M07 | 2.08 | 1.76 | 2.50 | 2.24 |
| M08 | 1.89 | 1.76 | 2.50 | 2.21 |
| M09 | 0.75 | 1.76 | 2.50 | 2.21 |
| M10 | 0.62 | 1.76 | 1.55 | 1.81 |
| M11 | 0.67 | 1.76 | 1.55 | 1.58 |
| M12 | 0.66 | 1.20 | 1.55 | 1.23 |
| Average | 1.64 | 2.91 | 2.94 | 2.49 |

Note: This table reports RMSFEs of the DFM, institutions, and the survey for annual GDP growth rates for "partial" real-time dataset. DFM refers to our factor model. OECD, IMF, and SoE refer to the OECD's EO, the IMF's WEOD, and the CBRT's SoE, respectively. Average shows average RMSFEs of all nowcast horizons. M01, ..., M12 denote first month, ..., twelfth month of a reference year.

Table 6: White's reality check test p-values for annual GDP growth rates, 2008-2013

| | P-Inf | P-Sup |
|---|---|---|
| M01 | 0.98 | 0.00 |
| M02 | 0.98 | 0.00 |
| M03 | 0.99 | 0.00 |
| M04 | 1.00 | 0.00 |
| M05 | 0.78 | 0.42 |
| M06 | 0.38 | 0.81 |
| M07 | 0.27 | 0.85 |
| M08 | 0.40 | 0.73 |
| M09 | 1.00 | 0.00 |
| M10 | 1.00 | 0.00 |
| M11 | 1.00 | 0.00 |
| M12 | 1.00 | 0.00 |

Note: This table reports p-values for White's reality check test both for annual growth rates. Columns under P-Inf shows p-values when the DFM is the benchmark and professional forecasters are the alternative. Columns under P-Sup shows p-values when the DFM is the alternative and the best professional forecaster according to RMSFE for each horizon is the benchmark. M01, ..., M12 denote first month, ..., twelfth month of a reference year.

Table 7: Average relative impact of news and model re-estimation, 2008:Q1-2013:Q4

| | **SA QoQ GDP** | | | | **NSA YoY GDP** | | | |
|---|---|---|---|---|---|---|---|---|
| | Finance | Real | ReEst | Survey | Finance | Real | ReEst | Survey |
| Q(0)M02 | 23.34 | 32.50 | 3.57 | 40.59 | 14.27 | 37.58 | 4.75 | 43.41 |
| Q(0)M03 | 15.05 | 48.76 | 9.33 | 26.86 | 11.49 | 47.24 | 7.68 | 33.58 |
| Q(1)M01 | 31.94 | 43.57 | 10.23 | 14.26 | 14.83 | 52.26 | 11.01 | 21.90 |
| Q(1)M02 | 23.93 | 49.24 | 16.89 | 9.94 | 27.88 | 50.60 | 12.40 | 9.12 |
| Average | 23.57 | 43.52 | 10.01 | 22.91 | 17.12 | 46.92 | 8.96 | 27.00 |

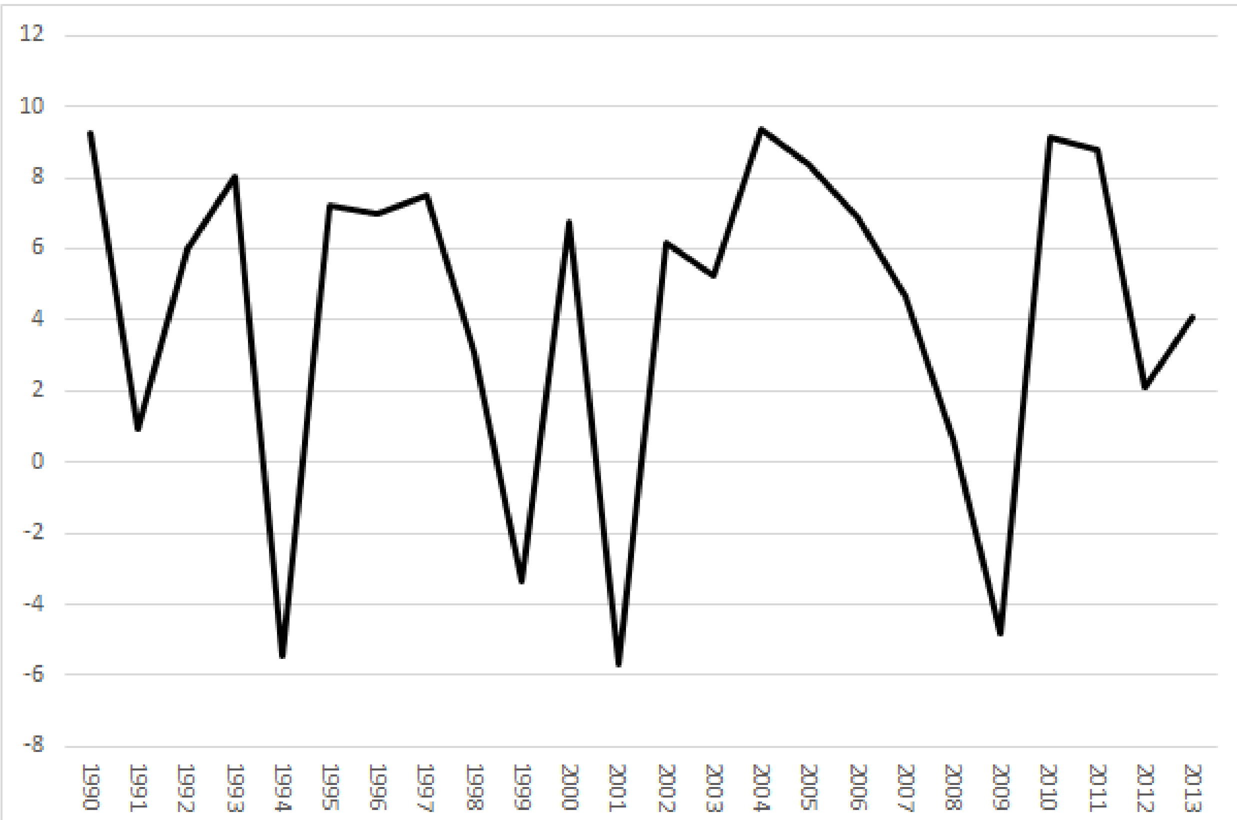
Note: This table shows the average relative impact of news and model re-estimation over all reference quarters. "Average" is the average of relative impact of news and model re-estimation over all reference quarters and nowcast periods.

Table 8: RMSFEs for DFMs with and without financial variables, 2008:Q1-2013:Q4

| | Full Dataset | | Partial Dataset | |
|---|---|---|---|---|
| | SA | NSA | SA | NSA |
| Q(0)M01 | 2.29 | 2.76 | 2.46 | 2.68 |
| Q(0)M02 | 1.99 | 2.56 | 2.47 | 2.63 |
| Q(0)M03 | 1.62 | 2.09 | 2.29 | 2.28 |
| Q(1)M01 | 1.60 | 1.76 | 2.09 | 1.74 |
| Q(1)M02 | 1.52 | 1.77 | 2.11 | 1.72 |
| Average | 1.80 | 2.19 | 2.28 | 2.21 |

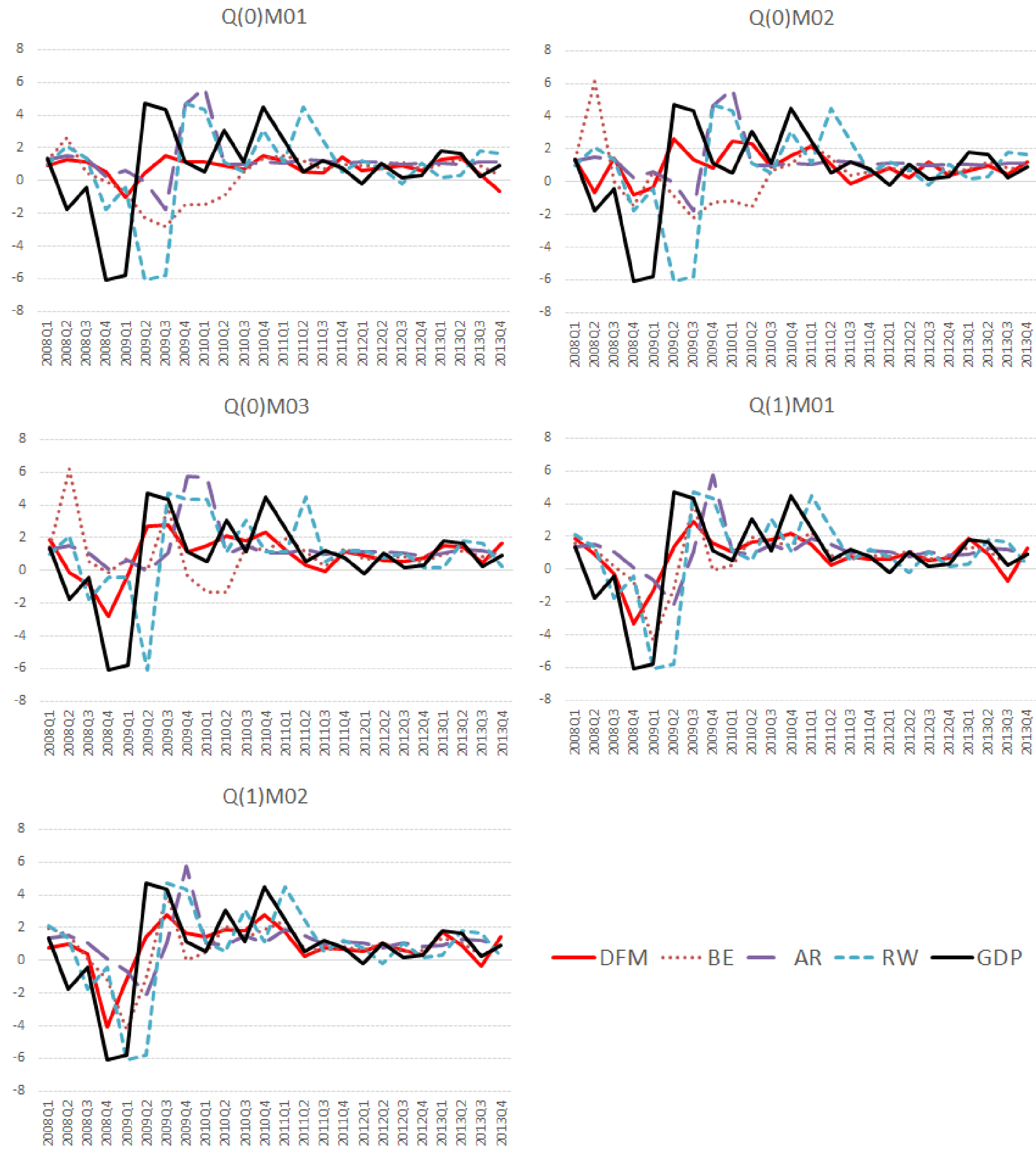
Note: This table reports RMSFEs of DFMs for the full and partial dataset. The partial dataset doesn't include financial variables. SA refers to SA QoQ GDP growth rates and NSA refers to NSA YoY GDP growth rates. Average shows average RMSFEs of all nowcast horizons. Q(1)M03 results for full dataset: SA (1.66), NSA (2.17). Q(1)M03 results for partial dataset: SA (2.48), NSA (2.08).

Figure 1: Annual GDP growth rates, 1990-2013



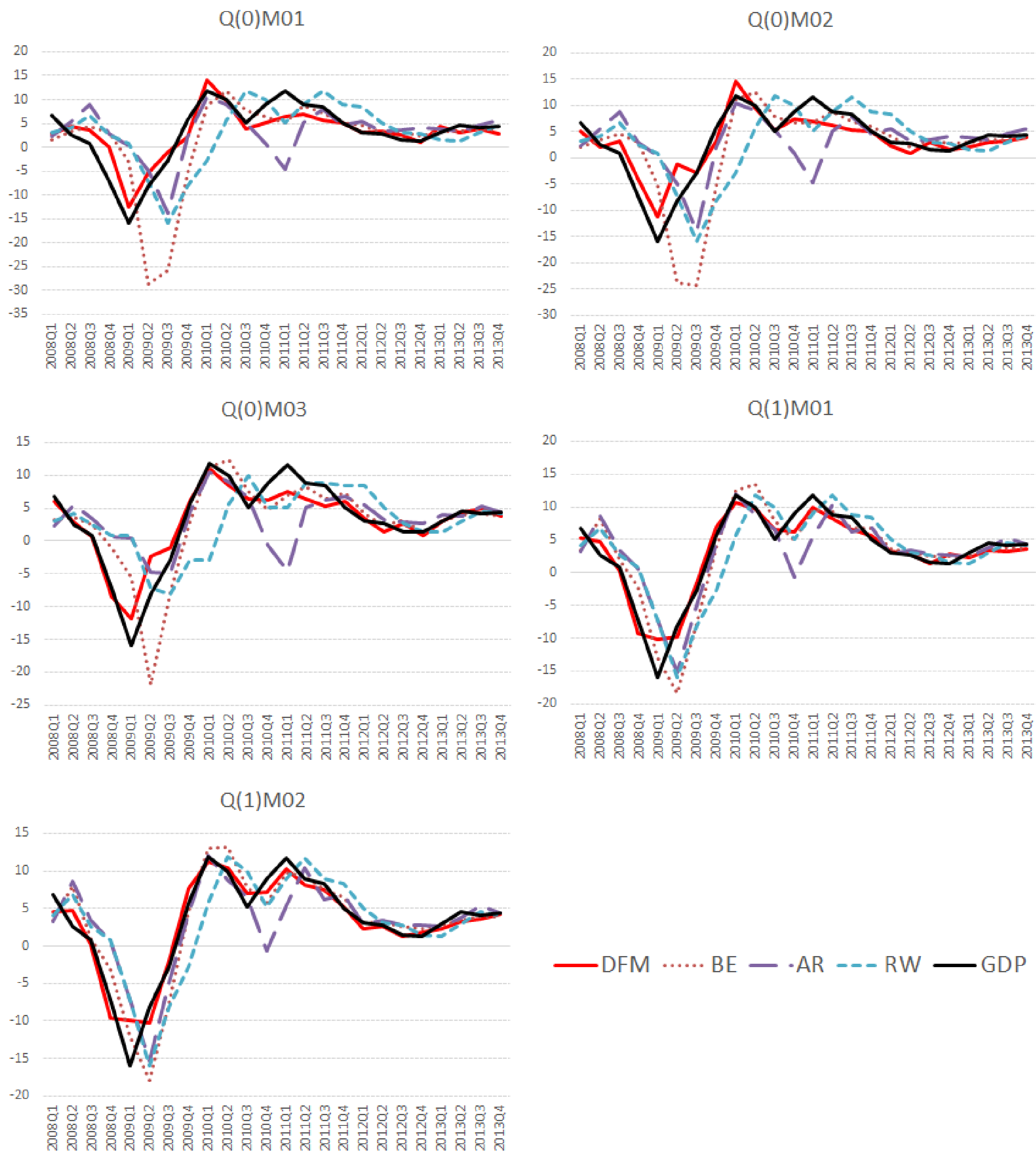

Note: This figure shows annual GDP growth rates from 1990 and 2013.

Figure 2: Actual and forecasted SA QoQ GDP growth rates for successive nowcast horizons, 2008:Q1-2013:Q4



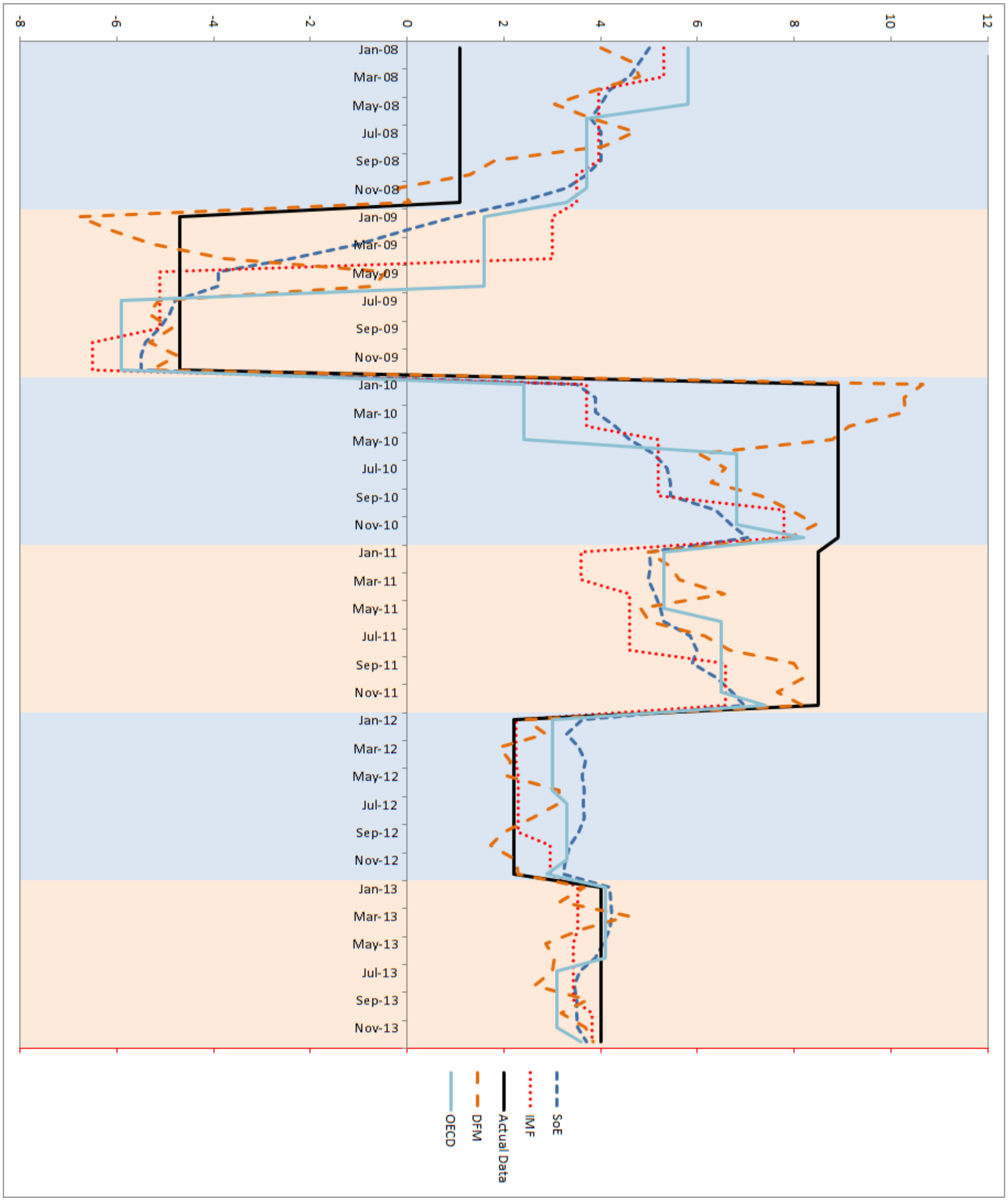

Note: These five panels show actual and forecasted SA QoQ GDP growth rates between Q(0)M01 and Q(1)M02. DFM refers to our factor model. AR, Mean, and BE refer to the AR model, a sample mean of GDP growth rate, and the bridge equation model, respectively. Legend is shown in the lower left hand side of the page.

Figure 3: Actual and forecasted NSA YoY GDP growth rates for successive nowcast horizons, 2008:Q1-2013:Q4



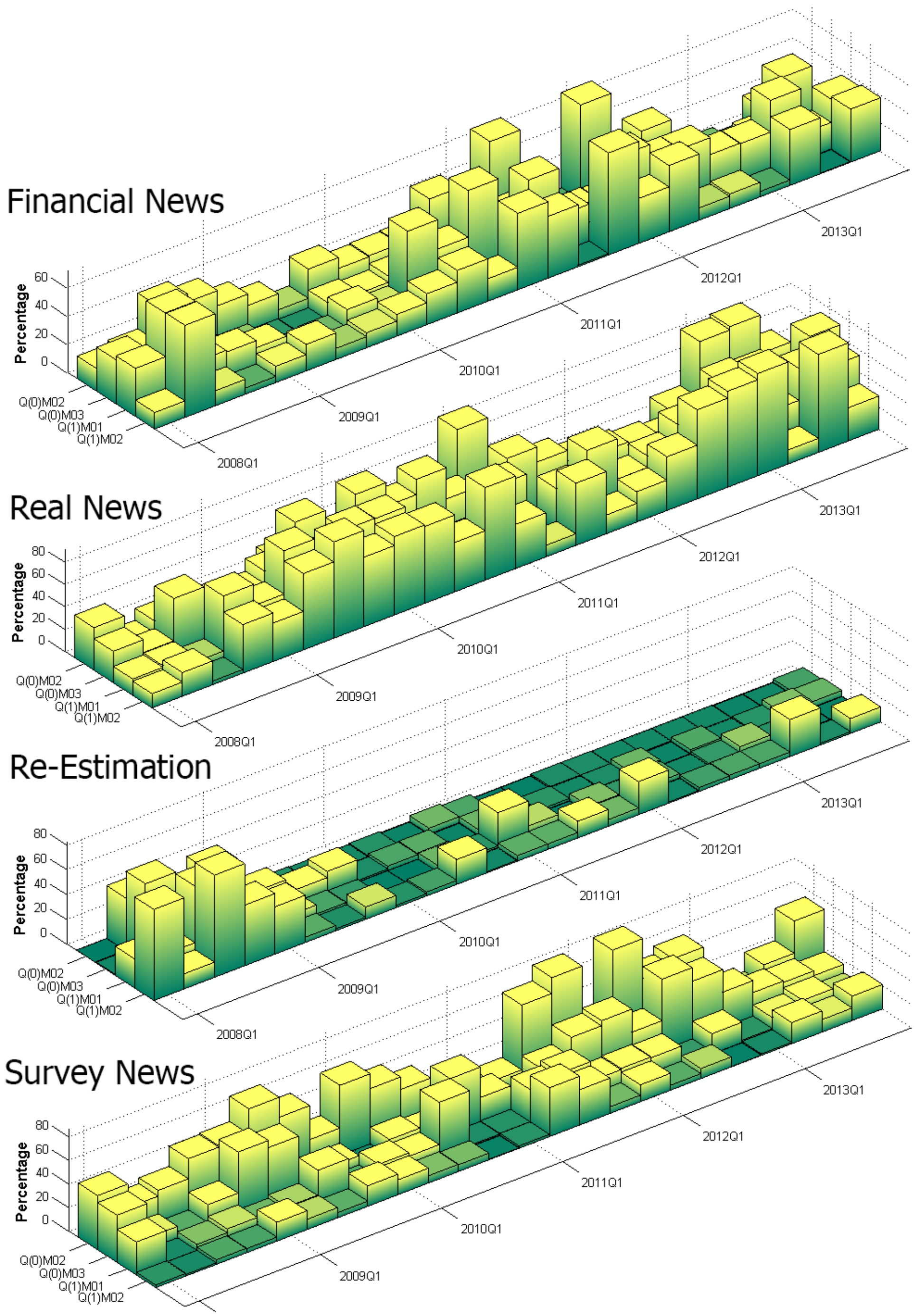

Note: These five panels show actual and forecasted NSA YoY GDP growth rates between Q(0)M01 and Q(1)M02. DFM refers to our factor model. AR, Mean, and BE refer to the AR model, a sample mean of GDP growth rate, and the bridge equation model, respectively. Legend is shown in the lower right hand side of the page.

Figure 4: Actual and forecasted annual GDP growth rates, 2008-2013



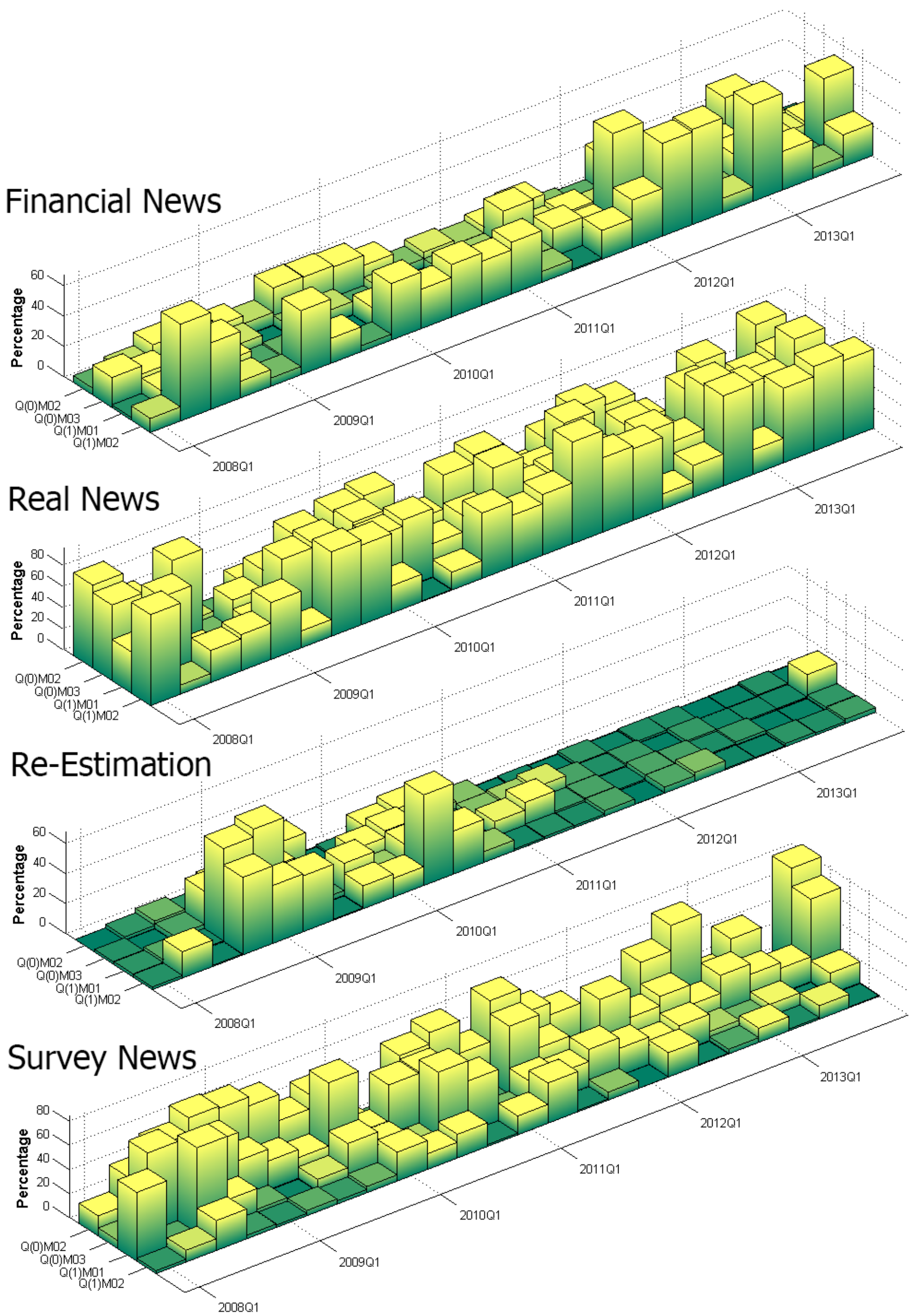

Note: This figure shows actual and forecasted annual GDP growth rates. DFM refers to our factor model. OECD, IMF, and SoE refer to the OECD's EO, the IMF's WEOD, and the CBRT's SoE, respectively.

Figure 5: Relative impact of news and model re-estimation for SA QoQ GDP growth rates, 2008Q1-2013Q4




Note: This figure shows the relative impact of news and model re-estimation for SA QoQ GDP growth rates. The Z axis shows percentages. The X axis shows reference quarters (2008:Q1-2013:Q4). The Y axis shows nowcast periods.

Figure 6: Relative impact of news and model re-estimation for NSA YoY GDP growth rates, 2008:Q1-2013:Q4




Note: This figure shows the relative impact of news and model re-estimation for NSA YoY GDP growth rates. The Z axis shows percentages. The X axis shows reference quarters (2008:Q1-2013:Q4). The Y axis shows nowcast periods.

# Appendix A.1: Description of Dataset

Table Appendix A.1: Description of Dataset

| Group | Variables | Publication Lags | Transformation Log | Transformation Difference[§] | Released by | SA by[¶] | Starting Date |
|---|---|---|---|---|---|---|---|
| Real | Industrial Production Index | 2 | 1 | 1 | Turkstat | Turkstat | 2005M01 |
| Survey | Capacity Utilization Rate | 1 | 0 | 1 | CBRT | CBRT | 2007M01, 1998M01[†] |
| Real | Export Volume Index | 2 | 1 | 1 | Turkstat | Turkstat | 1998M01 |
| Real | Import Volume Index | 2 | 1 | 1 | Turkstat | Turkstat | 1998M01 |
| Real | Ercan Türkan Consumer Index | 2 | 1 | 1 | Ercan Türkan | TDM | 2006M04 |
| Real | Total Car Production | 1 | 1 | 1 | AMS | Authors | 1999M01 |
| Survey | Turkstat Consumer Confidence Index | 1 | 1 | 1 | Turkstat | Authors | 2004M01 |
| Survey | CNBC-E Consumer Confidence Index | 1 | 1 | 1 | CNBC-E | Authors | 2002M01 |
| Survey | Real Sector Confidence Index | 1 | 1 | 1 | CBRT | CBRT | 2007M01, 1998M01[†] |
| Real | Non-Agricultural Unemployment Rate | 3 | 0 | 1 | Turkstat | Turkstat | 2005M01 |
| Real | Total Employment excl. Agriculture | 3 | 1 | 1 | Turkstat | Turkstat | 2005M01 |
| Financial | Real Effective Exch. Rate by CPI | 1 | 1 | 1 | CBRT | NSA | 2003M01 |
| Financial | TRLIBOR 3-Months | 1 | 0 | 1 | BAT | NSA | 2002M08 |
| Financial | Financial Account | 2 | 0 | 1 | CBRT | Authors | 1998M01 |
| Real | Real Gross Domestic Product | 5, 6[‡] | 1 | 1 | Turkstat | Turkstat | 1998Q1 |

Notes: This table shows variables, their associated groups, their publication lags from the start of the reference period, applied transformations, institutions and people by which variables are released and seasonally adjusted, and their starting date. Turkstat refers to the Turkish Statistical Institute. CBRT refers to the Central Bank of Republic of Turkey. AMS refers to the Automotive Manufacturers Association. BAT refers to the Banks Association of Turkey. TDM refers to the Turkish Data Manager.

[§] We use yearly differences for NSA data and monthly differences for SA data.

[¶] Only applicable for SA data

[†] 1998M01 is the starting date for NSA data, 2007M01 is the starting date for SA data.

[‡] GDP data for the fourth quarter and GDP data for the first quarter except the first quarter of 2013 have a maximum six months announcement lag. Others have maximum five months announcement delay. For more information for publication lags, see Section 4.

## Appendix A.2: Factor and Lag Selection

Bai and Ng (2002) propose information criteria to determine the number of factors in an approximate factor model with a balanced dataset. The original information criteria are for principal components. We use the modified information criteria for the maximum likelihood estimation. In addition to notations already defined in Section 3, $T$ and $n$ refer to the number of observations and variables in the dataset, respectively. Then, the modified information criteria is as follows:

$$\mathrm{IC}(r) = \ln(V(r,f)) + r\ln(g(n,T))/g(n,T) \tag{10}$$

where $g(n,T) = min(\sqrt{T}, n/\ln(n))$ and $V(r,f) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(x_{it} - \Lambda_i f_t)^2$.

We test up to five factors and try to find the number of factors that minimize $\mathrm{IC}(r)$. Our dataset is highly unbalanced, so we reorganize it to make it balance. To make sure that our test results are robust, we use three different reorganized datasets. First, we use part of an estimation period (January 1998 to December 2007) in which all variables have available data. This reorganization yields 8 observations for the SA dataset and 6 observations for the NSA dataset. Second, we remove some variables with short data span to make the first one longer. We remove three variables from SA dataset, which yields 32 observations. We remove 1 observation from NSA dataset and our number of observations expand to 21. Third, we use part of a whole period (January 1998 to March 2014) in which all variables have available data. This yield 83 observations for the SA dataset and 81 observations for the NSA dataset. Results for both SA and NSA datasets are shown in Table A.2. Results for all datasets indicate one factor. Therefore, we use one factor in equation 1.

We determine the number of lags equation 3 by using AIC. We estimate one factor (as shown by BG) for the estimation period and then choose the number of lags that minimize AIC. The maximum number of lags tested is five. AIC chooses three lags for the SA full dataset, two lags for the SA dataset without financial variables, and four lags for both NSA datasets.

Table Appendix A.2: Bai and NG criteria for determining number of factors

| | SA Dataset | | | NSA Dataset | | |
|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 1st | 2nd | 3rd |
| 1 | -6.26 | -6.61 | -5.91 | -3.63 | -4.32 | -4.38 |
| | (-15.67) | (-15.33) | (-14.75) | (-11.23) | (-10.67) | (-10.58) |
| 2 | -5.93 | -6.30 | -5.62 | -3.27 | -3.99 | -4.07 |
| | (-14.98) | (-14.60) | (-14.27) | (-10.26) | (-10.05) | (-9.96) |
| 3 | -5.63 | -6.01 | -5.35 | -2.88 | -3.65 | -3.77 |
| | (-14.37) | (-14.05) | (-13.79) | (-9.76) | (-9.61) | (-9.51) |
| 4 | -4.77 | -5.35 | -4.82 | -2.51 | -3.33 | -3.38 |
| | (-13.99) | (-13.58) | (-13.38) | (-9.47) | (-9.16) | (-9.10) |
| 5 | -4.44 | -5.83 | -4.38 | -2.26 | -3.04 | -3.17 |
| | (-13.12) | (-12.71) | (-12.81) | (-8.52) | (-8.55) | (-8.49) |
| **T** | **8** | **32** | **83** | **6** | **21** | **81** |
| **n** | **14 (11)** | **11 (8)** | **14 (11)** | **14 (11)** | **13 (10)** | **14 (11)** |

Notes: This table shows Bai and NG information criteria values for both SA and NSA datasets with and without financial variables. Numbers without parentheses are the results for the full dataset, and numbers with parentheses are the results for the dataset without financial variables. First column shows the number of factors tested in corresponding rows. $T$ is the number of observations in datasets. $n$ denotes number of variables in datasets.