Evaluating Nowcasts of Bridge Equations with Advanced Combination Schemes for the Turkish Unemployment Rate*

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Abstract

The paper analyzes the point and density predictive performance of alternative nowcast combination schemes in the context of bridge equations for the Turkish unemployment rate. Furthermore, we also nowcast the unemployment rate by using dynamic factor models (DFMs). Our results indicate that most of the sophisticated forecast combination methods have better predictive accuracy than the simple forecast combinations, especially in higher forecast horizons, which constitutes a case for the nowcast combination puzzle. Furthermore, most of bridge equations with the advanced forecast combination schemes usually outperform DFMs which are assumed to be superior to the bridge equations. This latter result indicates that bridge equations augmented by advanced forecast combination schemes may be a viable alternative to the DFM. Finally, we show that real and labor variables play the most important role for nowcasting the Turkish unemployment rate, whereas financial variables and surveys do not seem to be beneficial. Overall, our results indicate that advanced combination schemes can increase the performance of nowcasting models.

Keywords: Nowcasting; Unemployment; Dynamic Factor Model; Forecast Combination; Density Nowcasts; Bridge Equations.

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1 Introduction

The unemployment rate is one of the key figures for a country's well-being, timely information on the unemployment rate is important for both policy makers and market participants. However, the Turkish statistical agency (Turkstat) announces labor force statistics 75 days after the end of the reference period.[1] Compared to some developed countries, this is a very long delay. For example, the unemployment rate is announced with an approximately 30-day delay in Germany and is announced much earlier in USA. Therefore, nowcasting the Turkish unemployment rate may provide valuable information to market participants and policy makers.[2]

There are a few popular approaches for nowcasting in the literature: Bridge equations (e.g., Baffigi et al., 2004; Barhoumi et al., 2012; Brunhes-Lesage and Darné, 2012; Diron, 2008; Kitchen and Monaco, 2003; Rünstler and Sédillot, 2003); mixed-data sampling (MIDAS) models (e.g., Andreou et al., 2013; Clements and Galvão, 2008; Kuzin et al., 2011; Marcellino and Schumacher, 2010; Monteforte and Moretti, 2013); and dynamic factor models (DFMs) (e.g., Dias et al., 2015; Giannone et al., 2008; Liu et al., 2012; Matheson, 2010; Modugno, 2013; Rusnák, 2016). In this study, we focus primarily on bridge equations for nowcasting the unemployment rate. Furthermore, we include a DFM among our nowcast models.

To construct bridge equations, a regression or a series of autoregressive distributed lag (ARDL) regressions that links the target variable to one or more predictors is formed. Then, predictions derived from ARDLs are combined to produce nowcasts. Even though, there are various weighting methods that focus on each individual model's in- and/or out-of-sample performance, studies that use bridge equations for nowcasting usually use equally weighted forecast combinations to combine predictions of individiual ARDLs. One of the reason for this is that numerous papers have found that the equally weighted forecast combination often outperforms estimated optimal forecast combinations in empirical applications (e.g., Clemen,

[1] One of the reasons for this long delay is that Turkstat uses a 3-month rolling window to compile labor force statistics. For example, the November 2014 unemployment rate is composed of October, November and December 2014 data.

[2] To our best knowledge, Chadwick and Sengül (2015) constitute the only study whose main focus is nowcasting the Turkish unemployment rate. Chadwick and Sengül (2015) use models with Google Insights for Search data, initial claims of unemployment and the industrial production index to nowcast the Turkish non-agricultural unemployment rate. They construct various models using different combinations of variables and select the best ones by using the Bayesian model averaging procedure and residual diagnostic tests. They show that Google data improve the forecasting accuracy of models and their constructed nowcast models have better forecasting accuracy than that of the benchmark autoregressive model.

1989; Hendry and Clements, 2004; Huang and Lee, 2010; Stock and Watson, 2004). This finding is frequently referred to as the 'forecast combination puzzle'. However, this puzzle is not a well-studied area in the nowcasting framework. In one of the notable exceptions, Kuzin et al. (2013) use a model of the inverse mean square error (MSE) of the previous four quarters of performance, the information theoretical model averaging as well as equal weights and the median to combine MIDAS and dynamic factor models. In line with the literature, Kuzin et al. (2013) find that sophisticated forecast combination methods cannot provide systematic improvements over the equally weighted forecast combination. In this study, we focus on combining individual predictions of ARDLs by using both simple and advanced forecast combination techniques to nowcast the non-agricultural (NA) unemployment rate and the total unemployment rate in Turkey. Our results show that advanced forecast combination techniques have lower root men square errors (RMSEs) than the simple ones for nowcasting both unemployment rates, especially in higher forecast horizons, which constitutes a case for the nowcast combination puzzle.

Dynamic factor models (DFMs) are also widely used for nowcasting purposes and shown by the literature that they are usually superior to the bridge equations. In this study for nowcasting Turkish unemployment rates, we use one of the most popular approaches which is the DFM of Giannone et al. (2008) estimated with the two step estimator. Our results show that bridge equations with advanced combination schemes usually outperform DFMs. This shows that bridge equations augmented by advanced forecast combination techniques may be a viable alternative to the DFM for nowcasting.

The nowcasting literature usually only focus on point nowcasts and disregard density nowcasts. There are only a few notable nowcasting studies in the literature (Aastveit et al., 2014; Aastveit et al., 2017; Mazzi et al., 2014; Carriero et al., 2015). However, Rossi and Sekhposyan (2014) point out that it is becoming more important to analyze the uncertainty around models' point predictions and central banks are increasingly interested about the uncertainty around their point forecasts of unemployment targets. Therefore, we also compute density nowcasts of models in our study and compare them by using continuous rank probability score. Our results for density nowcasts, like point nowcasts, show also that bridge equations augmented by advanced forecast combination techniques perform better than DFMs and bridge equations using equal weights.

Finally, we investigate which variables are more important for bridge equations to nowcast the Turkish unemployment rates. Our results show that real and labor variables play the most important role for nowcasting both unemployment rates, whereas financial variables and surveys do not appear to be beneficial for nowcasting unemployment rates. Furthermore, foreign demand variables seem to have small but positive impact on bridge equations' nowcasting performance.

The remainder of this paper is as follows. Section 2 introduces the dataset. Section 3 explains the methodology. Section 4 presents the design of the nowcasting exercise. Section 5 shows the results of the nowcasting exercise. Section 6 presents the impact of variables on bridge equations. Finally, Section 7 concludes.

2 The Dataset

In this study, we use a balanced dataset including monthly data between 2005:M01-2016:M04. All variables are seasonally adjusted whenever needed. If data are not obtained as seasonally adjusted (SA), we seasonally adjust them using Tramo-Seats.[3]

The target variables are the total unemployment rate and the NA unemployment rate. Both of the target unemployment variables are shown in Figure 1. Between 2005:M01 and 2016:M04, there was an approximately 2-3 percentage point difference between the unemployment rates because there is still a considerable number of people working in agriculture. However, the number of people in the agricultural sector is declining sharply due to rapid industrialization over the last decade. In 2005, 27% of employed people were working in agriculture. In 2016, this number decreased to 20%. Similar to other countries, the global economic crisis affected Turkish unemployment rates adversely, causing an increase of nearly 4-5 percentage points from 2008:M05 to 2009:M05. However, Turkey enjoyed a very rapid recovery after the crisis, and its unemployment rates fell below the pre-crisis period. In this rapid growth period, Turkey's current account deficit reached unsustainable levels, and in 2013, policy makers cooled the economy to curb the current account deficit. Since 2013, Turkey's economy has grown mildly, as seen in Figure 1.

Figure 1

[3]Turkstat also uses Tramo-Seats to seasonally adjust data series (e.g., Turkstat, 2013), and we use the automatic procedure of Tramo-Seats Rev. 941 setting RSA=4 to seasonally adjust data.

We use a medium scale dataset[4] consisted of 20 predictors in this study[5] including labor market indicators, real variables, surveys, foreign demand and financial data. Early labor market indicators are most relevant variables for predicting the unemployment rate. We gather labor market variables from two sources: the Turkish Employment Agency (ISKUR) and the Kariyer.net which is the largest private career web site in Turkey. Kariyer.net data cover number of total vacancy, number of new vacancy, number of total applications. ISKUR data include total job seekers and regular job seekers.[6] We also include surveys which are released much earlier than real data to nowcast both unemployment rates. They are found to be beneficial in nowcasting GDP in many of studies due to their timeliness (see Angelini et al., 2011; Bańbura and Rünstler, 2011; Giannone et al., 2008; Modugno et al., 2016). Following Yüncüler et al. (2014), we also use credit data. Yüncüler et al. (2014) show that credit data, which include both consumer and commercial credit data, are relatively good leading indicators for the unemployment rate. Furthermore, we add two important financial variables into our dataset for Turkey: Borsa Istanbul 100 Index and US Dollar/Turkish Lira nominal exchange rate (USD/TRY). Our dataset also includes real variables which are good predictors of general economic activity in the economy. We choose a few important real indicators that have shorter publication lag than the unemployment rate. These are the industrial production indeces (IPI), import volume indices, total automobile production, and the Ercan Turkan consumption index that is based on credit and debit card data. Finally, we add variables regarding foreign demand such as US IPI, US imports, EU IPI, and EU imports. Further information on these variables is presented in Appendix A.

[4]Because Turkey is an emerging market economy where institutions have recently begun to collect on macroeconomic and financial indicators, it is not possible to find time series data with sufficient length for all relevant data. Therefore it is difficult to form a coherent large scale dataset in which all variables have sufficient time length. It should be emphasized that for nowcasting purposes, using a large scale dataset, instead of a small or medium scale, does not appear to be critical for a successful predictive performance. To nowcast outputs of emerging markets, many studies successfully use small or medium scale datasets (see Bragoli et al. (2015) for Brazil; Caruso (2015) for Mexico; Giannone et al. (2013) for China; Luciani et al. (2015) for Indonesia; Modugno et al. (2016) for Turkey and Dahlhaus et al. (2017) for Brazil, Russia, India and China). Furthermore, Bańbura et al. (2010) and Barhoumi et al. (2010) show that forecasting performances of medium scale datasets are as well as those of large scale datasets.

[5]For estimating bridge equations or DFMs, our dataset always contains 21 variables: 20 predictors plus the overall unemployment rate or the NA unemployment rate.

[6]This data include total job seekers minus applicants looking for a better position, retired job seekers and applicants looking for a job in a specific place.

3 The Methodology

3.1 Bridge Equations

To form bridge equations, we first build an ARDL model for each predictor. Let y_t be the monthly growth rate of the unemployment rate[7] and $x_{t,i}$ be the monthly growth rate of the predictor i. Then, we use the following ARDL model[8]:

$$y_t = c + \sum_{l=0}^{s} \gamma_l x_{t-l,i} + \varepsilon_t, \tag{1}$$

where ε_t is an error term and $i = 1, 2, \ldots, N$. The lag structure is determined by the Schwarz information criterion (SC), and the maximum lag length is 12. The parameters of equation 1 are estimated by ordinary least squares (OLS), and h steps ahead iterated out-of-sample forecasts of y_t using variable i at time t, $\hat{y}_{t+h,t,i}$, are computed as follows:

$$\hat{y}_{t+h,t,i} = \hat{c} + \sum_{l=0}^{s} \hat{\gamma}_l x_{t+h-l,i}, \tag{2}$$

where $h = 1, 2, 3, 4$ is the forecast horizon and $\hat{y}_{r,t,i} = y_t$ for $r \leqslant t$. In equation 2, some values of $x_{t+h,i}$ may be unavailable due to the publication delay.[9] Let us define z_{un} and z_i as publication lags of the unemployment rate and the predictor i, respectively. For $t + h > t + z_{un} - z_i$, $x_{t+h,i} = \hat{x}_{t+h,t,i}$, and $\hat{x}_{t+h,t,i}$ are produced by an AR model. The lag structure of the AR model is also selected by SC with a maximum lag of 12. In each period, the out-of-sample forecasts, parameters of models and lag structure are computed recursively using all the values of series from the beginning of the sample up to the latest available

[7]Unit root tests show that unemployment rates are I(1). Results for unit root tests are available upon request.

[8]We don't add AR components in equation 1 because adding AR component worsens the nowcasting accuracy of bridge equations when nowcasting the total unemployment rate. However, adding AR results don't alter the main conclusion of this paper in any way. Results for bridge equations with AR terms are presented in the Table Appendix B.1.

[9]The missing data at the end of the sample period due to the publication lag are called the 'ragged edge' problem in the literature. To overcome this problem, we follow the regular practice used in the bridge equation literature and fill the missing data at the end of the sample with forecasts obtained from an autoregressive (AR) model. More advanced multivariate techniques can also be used to fill the missing data at the end of the sample. In a GDP nowcasting exercise, Rünstler and Sédillot (2003) show that correcting the 'ragged edge' problem by multivariate and univariate models yields similar results for short forecast horizons. In this study, there are only two months of missing data at the end of the sample for real variables and one month of missing data for other variables. Therefore, we believe that more advanced solutions for the 'ragged edge' problem are not needed for our case.

data at the forecast date.[10] After growth rates of the unemployment rate's forecasts are computed, h-steps-ahead forecasts of the unemployment rate in levels by using variable i at time t, $\hat{Y}_{t+h,t,i}$ are obtained as follows:

$$\hat{Y}_{t+h,t,i} = Y_t * \prod_{i=1}^{h} \hat{y}_{t+i,t,i}, \tag{3}$$

where Y_t is the unemployment rate in levels.

In the second step, we combine the prediction of each ARDL to produce a final point nowcast as follows:

$$f_{t+h,t} = \sum_{i=1}^{n} w_{t+h,t,i} \hat{Y}_{t+h,t,i}, \tag{4}$$

where $w_{t+h,t,i}$ is the weight for the model i's h step ahead predictions calculated at time t, and $f_{t+h,t}$ shows the combination of h step ahead predictions at time t. We use several types of weights to combine nowcasts in our study. These are: simple weights, relative performance weights, Bayesian weights, rank based weights, time varying weights, and weights calculated after clustering.

3.1.1 Simple Weights

The first technique used in this study is simple averaging. In this technique, all forecasts are assigned equal weights: $w_{t+h,t,i} = 1/N$. Many empirical applications show that equally weighted forecast combinations outperform more complex ones. We also use the median forecast combination scheme.

3.1.2 Relative Performance Weights

Even though an equally weighted forecast combination usually beats more advanced forecast combination schemes, Genre et al. (2013) show that sophisticated weighting techniques outperform equal weights in some cases. Next, we follow Stock and Watson (1999) and

[10] A rolling window approach can also be adopted instead of the expanding window but the nowcasting accuracy of models suffer if we adopt a rolling window approach. Therefore, we focus on the expanding window approach. Still, results for bridge equations with a rolling window scheme are presented in the Table Appendix B.2.

estimate the combination weights according to the mean square error (MSE) as follows:

$$w_{t+h,t,i} = \frac{(\mathrm{MSE}^{-1}_{t+h,t,i})^{\gamma}}{\sum_{j=1}^{N}(\mathrm{MSE}^{-1}_{t+h,t,j})^{\gamma}}, \tag{5}$$

where $\mathrm{MSE}_{t+h,t,i}$ donates the MSE of the individual model i's h-steps-ahead forecasts calculated at time t and $j = 1, \ldots, N$ is an index of all models. If $\gamma = 0$, equation 5 assigns equal weights to individual forecasts. We follow regular practice and assume $\gamma = 1$ in this study.

3.1.3 Bayesian Weights

Another popular method in the literature is the approximate Bayesian Model Averaging (BMA) strategy. We use two information criteria (ICs) to estimate Bayesian weights: the Bayesian Information Criterion (BIC or SC) and the Akaike Information Criterion (AIC). Following Hansen (2008), we compute $\mathrm{BIC}_{i,t}$ and $\mathrm{AIC}_{i,t}$ for each ARDL model i at time t as follows:

$$\mathrm{BIC}_{t,i} = T_{t,i}ln(\mathrm{RSS}_{t,i}/T_{t,i}) + n_{t,i}ln(T_{t,i}), \tag{6}$$

$$\mathrm{AIC}_{t,i} = T_{t,i}ln(\mathrm{RSS}_{t,i}/T_{t,i}) + 2n_{t,i}, \tag{7}$$

where $\mathrm{RSS}_{t,i}$ is residual sum of squares of the model i at time t and T and n donate the total sample size and number of regressors of the equation of the model i at time t. Then, we plug ICs into the following equation to compute the Bayesian weights:

$$w_{t+h,t,i} = \frac{\exp(-0.5\mathrm{IC}_{t,i})}{\sum_{j=1}^{N}\exp(-0.5\mathrm{IC}_{t,j})}. \tag{8}$$

3.1.4 Rank-based Weights

We also use rank-based methods to compute weights, following Aiolfi and Timmermann (2006) and Timmermann (2006). Let $R_{t+h,t,i}$ be the rank of the model i's h-steps-ahead forecasts at time t. $R_{t+h,t,i}$ is based on performance of forecasts up to time t calculated by the MSE. Using these ranks, weights can be calculated as follows:

$$w_{t+h,t,i} = \frac{R^{-1}_{t+h,t,i}}{\sum_{j=1}^{N}R^{-1}_{t+h,t,j}}. \tag{9}$$

Timmermann (2006) argues that this scheme is less sensitive to outliers, so the weights computed by equation 9 should be more robust than those calculated by equation 5.

3.1.5 Adaptive Weights

In the case of a structural break, it may be more advantageous to use weights that place more emphasis on recent performance of models. One way to accomplish this is to calculate the performance of models by considering only recent performance with a rolling window scheme and discarding earlier performance data. In this sense, we calculate weights in equation 5 by considering only the last one-year performance in each period. Furthermore, we use the recent best forecast combination scheme, which uses only the forecast of one individual model with the best forecasting accuracy in the last year.

Another way to calculate adaptive weights is to use an exponential discounting scheme. This scheme uses all previous data but puts less emphasis on earlier periods. Following Stock and Watson (2004), we calculate this type of scheme as follows:

$$w_{t+h,t,i} = \frac{m_{t+h,t,i}^{-1}}{\sum_{j=1}^{N} m_{t+h,t,j}^{-1}}; \quad m_{t+h,t,i} = \sum_{\tau=T_0}^{t-h} \delta^{t-h-\tau} (Y_{\tau+h} - \hat{Y}_{\tau+h,\tau,i})^2, \tag{10}$$

where $\delta = 0.9$ is the discounting factor and T_0 is the initial time.

3.1.6 Clustering

Instead of combining the forecasts of all models, discarding the forecasts of the worst models may also increase the forecasting accuracy of forecast combination methods. This may be especially true if some models produce forecasts with extreme values. Similar to Clark and McCracken (2010), we use the simpler clustering approaches of Aiolfi and Timmermann (2006) instead of their more sophisticated clustering approaches. We rank forecasts based on their past performance, as in the rank-based weighting scheme and divide forecasts into quartiles for each period. Then, we calculate the simple average of forecasts in the first quartile. Following Clark and McCracken (2010), we also estimate a regression including a constant, the simple average of forecasts in the first quartile and the simple average of forecasts in the second quartile to compute the forecasts.

Finally, we calculate weights by using least squares methods. Due to our small sample size, including all variables when estimating weights by least squares is infeasible. Therefore, we use only forecasts in the first quartile of each period in the regressions. Following Granger and Ramanathan (1984), we use three types of regressions to calculate the weights:

$$Y_{t+h} = c + \sum_{o_{t+h,t}=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} \hat{Y}_{t+h,t,o_{t+h,t}} + \varepsilon_{t+h}, \tag{11}$$

$$Y_{t+h} = \sum_{o_{t+h,t}=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} \hat{Y}_{t+h,t,o_{t+h,t}} + \varepsilon_{t+h}, \tag{12}$$

$$Y_{t+h} = \sum_{o_{t+h,t}=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} \hat{Y}_{t+h,t,o_{t+h,t}} + \varepsilon_{t+h}; \quad \sum_{i=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} = 1, \tag{13}$$

where $o_{t+h,t} = 1, 2, .., N_{q_{t+h,t}}$ is an index of the h-steps-ahead forecasts in the first quartile at time t. The first two regressions are estimated by OLS, and the last one is estimated by constrained least squares. The first regression picks up any bias in individual models with a constant, whereas the other two equations assume individual equations are unbiased. We also use one other regression that is suggested by Timmermann (2006) to compute weights:

$$Y_{t+h} = \sum_{o_{t+h,t}=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} \hat{Y}_{t+h,t,o_{t+h,t}} + \varepsilon_{t+h}; \quad \sum_{i=1}^{N_{q_{t+h,t}}} w_{t+h,t,o_{t+h,t}} = 1 \ \& \ 0 \leqslant w_{t+h,t,o_{t+h,t}} \leqslant 1. \tag{14}$$

3.2 The DFM

Finally, we use the DFM of Giannone et al. (2008) for nowcasting the unemployment rates. Consider the vector of growth rates of n monthly series $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})', t = 1, 2, \ldots, T$ which are standardized to zero mean and unit variance, and our DFM has the following representation:

$$x_t = \mu + \Lambda f_t + \epsilon_t; \quad \epsilon_t \sim \mathbb{N}(0, \Sigma_\epsilon), \tag{15}$$

where μ is constant; Λ is an nxr matrix containing factor loadings for monthly variables; $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t}, \ldots, \epsilon_{n,t})'$ are the idiosyncratic components of monthly variables; and $f_t = (f_{1,t}, f_{2,t}, \ldots, f_{r,t})'$ is an rx1 vector of unobserved common factors. f_t is modeled as a vector autoregression process:

$$f_t = \varphi(L) f_{t-1} + B\eta_t; \quad \eta_t \sim \mathbb{N}(0, I_q), \tag{16}$$

where $\varphi(L)$ is an rxr lag polynomial matrix; B is a rxq matrix of full rank q with $q \leqslant r$; and η_t is the q dimensional vector of common shocks that follows a white-noise process.

To estimate the DFM, we use the two-step estimator shown by Doz et al. (2011). First, the initial common factors are derived using the principal component analysis, and the parameters of the model are estimated via an OLS regression using the balanced part of the dataset. Then, the factors for the full dataset are estimated via the Kalman smoother. This procedure also allows us to obtain predictions of common factors.

After obtaining the estimates of the common factor, we use the following single equation model:

$$y_t = c + \sum_{i=1}^{r} \beta_i \hat{f}_{t,t,i} + \zeta_t, \tag{17}$$

where ζ_t is an error term and parameters are estimated by the OLS using a balanced dataset. Then h steps ahead iterated out-of-sample forecasts of the unemployment rates' growth rates at time t, $\hat{y}_{t+h,t}$, are computed as follows:

$$\hat{y}_{t+h,t} = \hat{c} + \sum_{i=1}^{r} \hat{\beta}_i \hat{f}_{t+h,t,i}, \tag{18}$$

Then these growth rates are transformed into levels, as in equation 3.

3.3 Density Nowcasts

In addition to point nowcasts, we also compute density nowcasts in this study as there is a growing interest in analyzing uncertainty around point nowcasts. To obtain density nowcasts, we apply a bootstrap procedure. Our procedure is using the stationary block bootstrap approach of Politis and Romano (1994).[11] The optimal block size is selected

[11] If the error terms are independent and identically distributed in equations 1 and 17, then we can use the residual bootstrap in our study for resampling the error term. However, many macro-econometric models exhibit autocorrelated errors. Therefore, we prefer to use block bootstrap approach that take account of autocorrelations in errors.

according to the procedure proposed by Politis and White (2004).

$b = 1, ..., B$ indicate the bootstrap iteration number and we set B as 1000. Then, the details of the bootstrap procedure is as follows:

1. For bridge equations and the DFM, estimate equation 1 and equation 17 respectively to obtain estimated parameters.

2. For bridge equations, produce $\tilde{y}_t^{(b)}$ according to $\tilde{y}_t^{(b)} = \hat{c} + \sum_{l=0}^{s} \hat{\gamma}_l x_{t-l,i} + \tilde{\varepsilon}_t^{(b)}$, where $\tilde{\varepsilon}_t^{(b)}$ is resampled from $\hat{\varepsilon}_t$. For the DFM, produce $\tilde{y}_t^{(b)}$ according to $\tilde{y}_t^{(b)} = \hat{c} + \sum_{i=1}^{r} \hat{\beta}_i \hat{f}_{t,t,i} + \tilde{\zeta}_t^{(b)}$, where $\tilde{\zeta}_t^{(b)}$ is resampled from $\hat{\zeta}_t$.

3. For bridge equations and the DFM, re-estimate equation 1 and equation 17 respectively for $\tilde{y}_t^{(b)}$ to obtain re-estimated parameters.

4. For bridge equations, obtain $\tilde{y}_{t+h,t,i}^{(b)}$ according to $\tilde{y}_{t+h,t,i}^{(b)} = \tilde{c}^{(b)} + \sum_{l=0}^{s} \tilde{\gamma}_l^{(b)} x_{t+h-l,i}$ as in equation 2. For the DFM, obtain $\tilde{y}_{t+h,t}^{(b)}$ according to $\tilde{y}_{t+h,t}^{(b)} = \tilde{c}^{(b)} + \sum_{i=1}^{r} \tilde{\beta}_i^{(b)} \hat{f}_{t+h,t,i}$ as in equation 18.

5. For bridge equations, we have one additional step. As in point nowcasts, we combine $\hat{y}_{t+h,t,i}^{(b)}$ produced by each variable i according to the combination methods mentioned in this study to get the final $\hat{y}_{t+h,t}^{(b)}$ for each combination method.

6. Repeat steps from 2 to 5 B times to obtain density nowcasts for each model.

4 The Design of the Nowcasting Exercise

As vintage data in Turkey are not published officially, we use final revised data in the estimation process. By taking into account of stylized publication lags of variables (outlined in Appendix A), we estimate our models in the mid of each month, just before the release of labor force statistics.[12] In each estimation, we replicate historical data availability and produce our nowcasts. In this way, the unemployment rate has four-month publication lags in our study. For example, when we run our models in November 2014, we lack the unemployment rates of November, October, September, and August 2014.

[12] In each estimation, we fix the publication lags of our variables according to their officially announced date of publication, even though, in some months, these publication dates show some degree of variability within the range of a couple days around the official date.

In this study, we focus only on predicting past and current values of the unemployment rate with respect to the date at which the forecasts are produced. Therefore, we forecast only 4 values of the unemployment rate in each month ($h = 1, 2, 3, 4$). For example, when we run our models in November 2014, we forecast the August 2014 unemployment rate, which is the one-step-ahead out-of-sample forecast; the September 2014 unemployment rate, which is the two-steps-ahead out-of-sample forecast; and so forth.

Because the last data in our dataset cover 2016:M04 and the maximum forecast horizon is 4, the last period that we use to estimate the regressions is 2015:M12. We begin the out-of-sample forecasting after the crisis in 2009:M03.[13] An out-of-sample training period is needed to be able to compute the forecast combination weights based on past performance. Therefore, the out-of-sample testing period for our models begins in 2010:M06.

To determine the parameters of DFMs, a parameter search across values of $r \leq 5$, $q \leq min(r, 5)$ and $p \leq 3$ is performed in the training period, and the parameters that yield the lowest average RMSE in the training are used in the actual nowcasting exercise. We also estimate AR models whose lags are chosen by SC as benchmark models. All models are estimated with a recursive (expanding) estimation window. Point nowcasting accuracies of models are evaluated using RMSEs. The Diebold and Mariano (DM) test for equal predictive accuracy test is also employed to compare the point nowcasting performance of competing models against an AR. The performance of density nowcasts are evaluated using mean value of continuous rank probability score (CRPS) for the entire sample following Panagiotelis and Smith (2008).

5 Results for the Nowcasting Exercise

Tables 1 and 2 present RMSEs and ranks of bridge equations with various forecast combination schemes and the DFM for the NA unemployment rate and the total unemployment rate, respectively. Table 3 presents CRPSs of bridge equations with various forecast combination schemes and the DFM for density nowcasts of the NA unemployment rate and the total unemployment rate, respectively.

Tables 1, 2 and 3

[13]This is the lowest level of the IPI; it increases rapidly after this point.

Several results emerge from Tables 1, 2 and 3. All bridge equations have higher point nowcasting power than AR, except for some bridge equations at $h = 1$. The improvements of the bridge equations over the benchmark model are usually substantially large at $h = 2$ or higher horizons. However, the DM tests show that bridge equations with only the clustering type weighting schemes and Bayesian model averaging outperform AR significantly for the NA unemployment rate, in some cases. For the total unemployment rate at $h = 2$ and longer horizons, bridge equations statistically outperform AR in most of the cases. Thus, the nowcasting accuracy of bridge equations is higher for the total unemployment rate. For density nowcasts, AR seems to outperform most of other bridge equations at $h = 1$. Interestingly at $h = 4$ for the NA unemployment rate, AR has higher density nowcasting accuracy than most of the competing models. In other cases, bridge equations with the advanced forecast combination techniques and the DFM generally outperform AR.

Second, bridge equations with the equally weighted forecast combination have somewhat high point nowcasting accuracy at $h = 1$. However, the nowcasting performance of the equally weighted forecast combination scheme quickly deteriorates at longer prediction horizons. We also perform DM tests between equally weighted averaging and other advanced forecast combination methods, as shown in Table 4. The DM tests show that it is hard for advanced forecast combination schemes to statistically beat simple averaging but some sophisticated combinations manage to outperform the equally weighted forecast combination. For density nowcasts, bridge equations with simple averaging have always one of the worst nowcasting performance among all models.

Table 4

Third, most of bridge equations with advanced forecast combination schemes usually outperform the DFM for both unemployment rates at both density and point nowcasts. This shows that bridge equations that are augmented by advanced forecast combination schemes may be a viable alternative to the DFM.

Fourth, clustering is beneficial for forecast combinations. Simple averaging with clustering has better forecasting performance than the equally weighted forecast combination at both density and point nowcasts. In addition, the best-performing combinations are forecast combinations calculated by least square weights after clustering, in most cases.

Fifth, ranking-based forecast combination schemes show slightly better point and density nowcasting accuracy than forecast combinations calculated using the relative performance weights. This is in line with Timmermann (2006)'s arguments.

Sixth, adaptive forecast combination techniques doesn't yield the desired results. On average, AW-RPW and its regular counterpart show similar results.

6 The impact of variables on bridge equations

Having tested the nowcasting accuracy of bridge equations, we now test how important a group of variables for the success of bridge equations. Variables' associated groups are shown in the Appendix A. For this exercise, we remove one group of variables from the dataset each time and calculate bridge equations without that specific group of predictors. Then, we compute relative RMSEs of these model as follows:

$$RRMSE_{i,h,j} = (\frac{RMSE_{i,h}}{RMSE_{i,h,j}} - 1) * 100, \tag{19}$$

where $RRMSE_{i,h,j}$ is the relative RMSE of model i without j^{th} group of predictors for h-step ahead nowcasts. If the relative RMSE of a model is greater (lower) than 0, it means that exclusion of variables positively (negatively) affects forecast combination schemes.

Tables 5 and 6 present relative RMSEs of bridge equations with various combinations without a specific group variables for the NA and the total unemployment rate, respectively. Gray shaded cells represent relative RMSEs greater than 0. For both unemployment rates, the exclusion of labor market and real variables worsens the nowcasting accuracy of nearly all bridge equations. As expected bridge equations with clustering are most adversely affected by the exclusion of real and labor variables as bridge equations with clustering rely only on a handful of variables. Furthermore, the exclusion of labor variables has more significant impact on clustering type combinations than the exclusion of real variables. Therefore, we can deduce that labor market variables are the most crucial variables for nowcasting the Turkish unemployment rate.

Table 5 and 6

The exclusion of financial variables and surveys increase the nowcasting accuracy of bridge equations in most of the cases. The exclusion of surveys on the nowcasting performance of models is mostly neglible. For nowcasting the NA unemployment rate, the impact of financial variables has also little effect on the nowcasting accuracy of bridge equations. However for nowcasting the total unemployment, bayesian model averaging without financial variables seem to enjoy substantial nowcasting performance improvements. Finally, foreign demand variables seem to have usually small but positive impact on models' nowcasting performance.

7 Conclusion

In this study, we construct bridge equations by using 15 different forecast combination techniques. Furthermore, we use a DFM for nowcasting. As a competing alternative model, we estimate an AR model. We calculate both density and point nowcasts for all models.

The results show that most of bridge equations with the advanced forecast combination techniques have lower RMSEs and CRPSs than those with the simple forecast combination schemes in most of the cases, especially for longer forecast horizons. In this regard, we present a case for the nowcast combination puzzle.

We point out that adaptive forecast combination techniques do not usually perform better than non-adaptive combination schemes and rank-based forecast combination schemes perform slightly better than the forecast combination calculated by using relative performance weights.

We also show that the use of clustering in the forecast combination framework greatly improves the nowcasting accuracy. In many cases, forecast combination schemes with clustering usually have better nowcasting accuracy than other forecast combination schemes.

Most of bridge equations with advanced forecast combination schemes usually outperform the DFM for both unemployment rates. This shows that bridge equations augmented by advanced forecast combination schemes may be a viable alternative to the DFM.

Finally, we show that real, labor and foreign demand variables have positive impact on the nowcasting accuracies of bridge equations, whereas financial and surveys have negative impact.

As a natural extension, this same exercise can be done with mixed data sampling models as they are also single equation models.

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Figure 1: Total and NA Unemployment Rates, 2005:M01-2016:M04

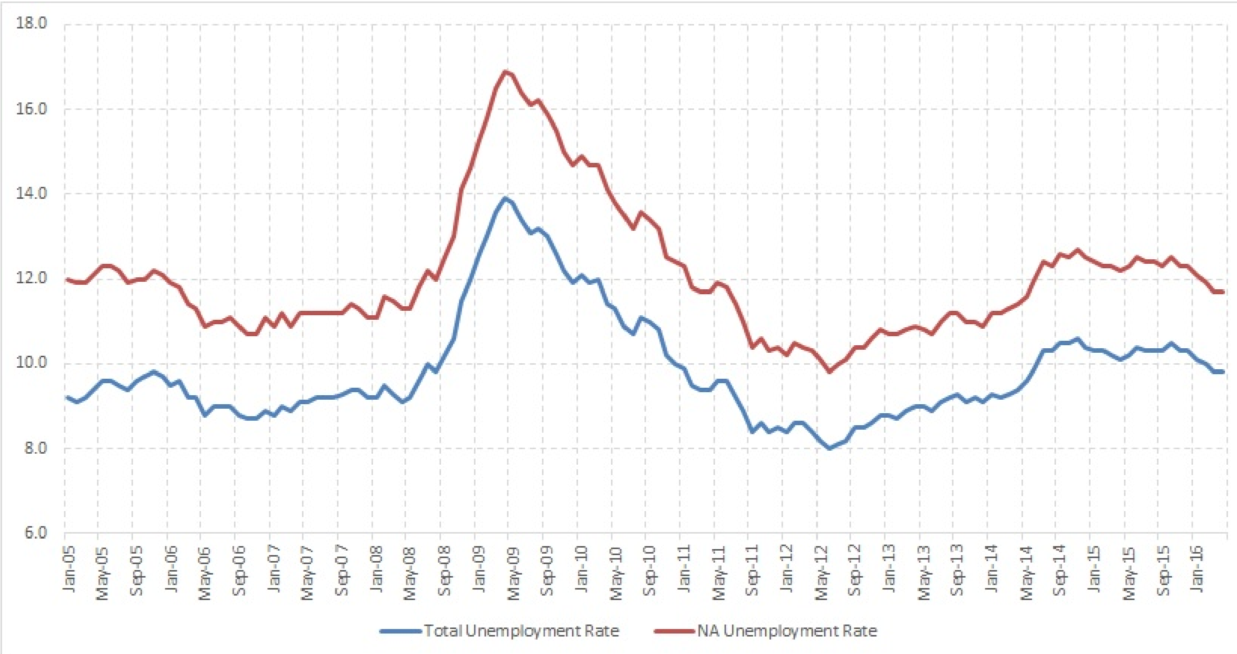

Table 1: RMSEs and ranks of bridge equations with various forecast combination schemes and the DFM for NA unemployment rate

	h=1		h=2		h=3		h=4	
	RMSE	Rank	RMSE	Rank	RMSE	Rank	RMSE	Rank
AR	0.244	17	0.362	17	0.503	17	0.583	17
Simple	0.230	11	0.343	14	0.469	14	0.563	14
Median	0.232	12	0.347	15	0.473	15	0.568	15
RPW	0.230	8	0.339	11	0.461	11	0.554	13
BMA(SC)	0.225	3	0.325	4	0.439	7	0.534	7
BMA(AIC)	0.226	5	0.326	5	0.436*	6	0.532	6
Rank	0.227	6	0.331	8	0.447	9	0.540	8
RBF	0.241	16	0.350	16	0.480	16	0.576	16
AW-RPW	0.230	10	0.340	13	0.462	13	0.551	11
AW-Exp	0.230	9	0.339	12	0.461	12	0.552	12
C-Simple	0.227	7	0.323	3	0.434*	4	0.524*	5
C-LS	0.234	13	0.321	2	0.444	8	0.540	9
LS(1)	0.235	15	0.334	9	0.435*	5	0.518	4
LS(2)	0.235	14	0.328	7	0.418**	1	0.498*	1
LS(3)	0.226	4	0.327	6	0.418**	2	0.503*	2
LS(4)	0.225	1	0.321	1	0.432*	3	0.518*	3
DFM	0.225	2	0.335	10	0.453	10	0.543	10

Note: This table shows RMSEs and ranks of bridge equations with various forecast combination schemes and the DFM for successive forecast horizons (h=1,2,3,4). For the DM test, *,** and *** indicate significance levels at the 10%, 5% and 1% levels, respectively. Rank is the rank of bridge equations with various forecast combination schemes and the DFM according to RMSEs. Abbrevations are:
Simple: simple average of individiual nowcasts.
Median: median of individiual forecasts.
RPW: forecast combination calculated by using relative performance weights according to equation 5
BMA(BIC) & BMA(AIC): forecast combination calculated by using BIC and AIC bayesian weights according to equation 8.
Rank: forecast combination calculated by using rank-based weights according to equation 9.
RBF: best model selected by using relative performance weights according to equation 5 only taking account of last one year performance.
AW-RPW: forecast combination calculated by using relative performance weights according to equation 5 only taking account of last one year performance.
AW-Exp: forecast combination calculated by exponential discounting weights according to equation 10.
C-Simple: simple average of individual nowcasts in the first quartile.
C-LS: nowcasts calculated by using a regression including constant, simple average of individual forecasts in the first quartile and simple average of individual nowcasts in the second quartile.
LS(1), LS(2), LS(3), LS(4): forecast combination calculated by least square weights according to equation 11, equation 12, equation 13, equation 14, respectively.

Table 2: RMSEs and ranks of bridge equations with various forecast combination schemes and the DFM for total unemployment rate

	h=1		h=2		h=3		h=4	
	RMSE	Rank	RMSE	Rank	RMSE	Rank	RMSE	Rank
AR	0.215	14	0.353	17	0.497	17	0.589	17
Simple	0.199	6	0.306	13	0.416**	14	0.498**	12
Median	0.200	8	0.310	15	0.418**	15	0.501**	13
RPW	0.199	3	0.303	9	0.409**	11	0.489**	11
BMA(SC)	0.201	10	0.300	7	0.402**	7	0.482*	8
BMA(AIC)	0.207	12	0.317	16	0.432	16	0.531	16
Rank	0.196	2	0.296*	4	0.399**	6	0.479**	7
RBF	0.212	13	0.307	14	0.407**	9	0.506	15
AW-RPW	0.199	5	0.304	10	0.410**	12	0.488**	9
AW-Exp	0.199	4	0.304	11	0.410**	13	0.489**	10
C-Simple	0.196	1	0.289**	2	0.386**	4	0.461**	5
C-LS	0.204	11	0.295*	3	0.408*	10	0.504*	14
LS(1)	0.218	17	0.305**	12	0.390**	5	0.459**	4
LS(2)	0.217	16	0.299*	6	0.373**	1	0.441**	1
LS(3)	0.216	15	0.297*	5	0.375**	2	0.448**	2
LS(4)	0.201	9	0.288**	1	0.383**	3	0.459**	3
DFM	0.200	7	0.302	8	0.404*	8	0.478*	6

Note: See notes under Table 1.

Table 3: CRPS of bridge equations with various forecast combination schemes and the DFM

	the NA unemployment rate				the total unemployment rate			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
AR	0.167	0.246	0.336	0.370	0.142	0.239	0.329	0.372
Simple	0.177	0.257	0.345	0.417	0.153	0.231	0.307	0.362
Median	0.176	0.254	0.340	0.410	0.152	0.229	0.303	0.357
RPW	0.177	0.254	0.341	0.412	0.153	0.229	0.304	0.358
BMA(SC)	0.165	0.232	0.305	0.373	0.145	0.217	0.281	0.336
BMA(AIC)	0.163	0.235	0.314	0.381	0.144	0.222	0.296	0.363
Rank	0.173	0.245	0.330	0.399	0.149	0.222	0.294	0.348
RBF	0.159	0.224	0.312	0.356	0.137	0.201	0.272	0.314
AW-RPW	0.177	0.255	0.341	0.408	0.153	0.230	0.304	0.355
AW-Exp	0.181	0.259	0.353	0.427	0.158	0.237	0.313	0.367
C-Simple	0.171	0.236	0.317	0.383	0.145	0.214	0.282	0.333
C-LS	0.168	0.238	0.327	0.401	0.145	0.220	0.300	0.363
LS(1)	0.158	0.228	0.310	0.374	0.140	0.208	0.275	0.330
LS(2)	0.163	0.230	0.308	0.365	0.142	0.209	0.274	0.321
LS(3)	0.155	0.224	0.305	0.367	0.135	0.202	0.270	0.322
LS(4)	0.164	0.230	0.311	0.372	0.141	0.208	0.275	0.325
DFM	0.165	0.240	0.324	0.377	0.139	0.214	0.287	0.330

Note: See notes under Table 1.

Table 4: t-statistics for the DM Test of Equal Predictive Ability against Simple Averaging

Target Variable=NA Unemployment Rate				
	h=1	h=2	h=3	h=4
RPW	1.20	2.16**	2.02**	1.78*
BMA(SC)	0.92	1.37	1.51	1.13
BMA(AIC)	0.95	1.46	1.75*	1.22
Rank	1.69*	2.23**	2.20**	1.85*
RBF	-2.05	-0.57	-0.63	-0.55
AW-RPW	1.02	1.71*	1.88*	2.30**
AW-Exp	1.34**	1.97**	1.98**	2.04**
C-Simple	1.16	2.43	2.27	1.99
C-LS	-0.34	1.30	1.47	1.39
LS(1)	-0.30	0.49	1.11	1.34
LS(2)	-0.27	1.00	1.67*	1.74*
LS(3)	0.37	1.16	1.69*	1.70*
LS(4)	1.00	2.05**	1.87*	1.75*
DFM	0.75	0.50	0.60	0.56
Target Variable=Total Unemployment Rate				
	h=1	h=2	h=3	h=4
RPW	0.44	1.80*	1.74*	1.59
BMA(SC)	-0.47	0.54	0.81	0.63
BMA(AIC)	-1.00	-0.60	-0.52	-0.70
Rank	1.30	2.22**	2.34**	1.90*
RBF	-2.36	-0.11	0.76	-0.44
AW-RPW	0.29	1.58	1.69*	1.89*
AW-Exp	0.37	1.73*	1.67*	1.65*
C-Simple	0.80	2.22**	2.15**	2.03**
C-LS	-0.51	0.99	0.72	-0.54
LS(1)	-1.67	0.09	0.88	1.25
LS(2)	-1.77	0.43	1.41	1.54
LS(3)	-1.77	0.60	1.45	1.47
LS(4)	-0.41	1.77*	1.78*	1.71*
DFM	-0.16	0.26	0.50	0.61

Note: See notes under Table 1.

Table 5: Relative RMSEs of bridge equations with various forecast combination schemes calculated without a specific group of variables for the NA unemployment rate

	Without real variables				Without surveys				Without labor variables			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
Simple	-0.15	-0.80	-0.88	-0.85	-0.25	0.02	-0.01	-0.09	-0.17	-0.52	-0.51	-0.58
Median	0.45	-0.01	-0.07	-0.01	-0.23	-0.22	-0.31	-0.66	-0.91	-1.11	-0.77	-0.42
RPW	-0.17	-1.04	-1.17	-1.10	-0.24	0.05	0.04	-0.02	-0.08	-0.38	-0.37	-0.61
BMA(SC)	0.35	-0.13	-0.46	-0.48	0.00	0.01	0.01	0.00	0.01	-0.07	-0.08	-0.10
BMA(AIC)	0.32	-0.51	-1.14	-0.70	0.02	0.08	0.07	0.05	0.01	-0.01	-0.01	-0.02
Rank	-0.17	-0.75	-1.67	-1.41	0.10	0.02	0.04	-0.01	-0.08	-0.73	-0.73	-0.89
RBF	-0.65	0.42	-0.22	-0.57	-0.32	0.00	0.00	0.00	-0.02	-0.60	-0.33	-2.61
AW-RPW	-0.09	-0.63	-0.61	-0.40	-0.23	0.08	0.11	0.11	-0.09	-0.58	-0.57	-0.81
AW-Exp	-0.08	-0.78	-0.84	-0.75	-0.24	0.07	0.08	0.08	-0.07	-0.45	-0.42	-0.59
C-Simple	-0.39	-1.19	-1.35	-1.14	-0.66	0.49	0.57	0.40	-0.18	-1.58	-1.96	-3.24
C-LS	1.65	-1.72	-1.49	-2.12	-1.87	0.22	1.62	1.75	-1.01	-1.49	-0.80	-3.14
LS(1)	-0.03	0.42	-1.32	-3.13	-0.05	0.52	2.31	0.33	-0.02	-2.04	-1.93	-11.64
LS(2)	-0.02	-0.26	-2.22	-1.43	0.10	0.85	-0.13	-0.13	0.06	-1.98	-6.51	-7.43
LS(3)	0.63	-0.09	-3.99	-2.64	-0.52	-0.39	-0.27	-0.10	1.76	0.43	-7.21	-7.98
LS(4)	0.10	-1.50	-0.99	-0.48	0.03	0.01	0.17	0.03	-0.01	-1.79	-4.51	-5.51

	Without foreign demand variables				Without financial variables			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
Simple	-0.36	-0.44	-0.52	-0.46	-0.25	0.02	-0.01	-0.09
Median	0.01	-0.42	-0.50	-1.18	-0.23	-0.22	-0.31	-0.66
RPW	-0.46	-0.46	-0.56	-0.48	-0.24	0.05	0.04	-0.02
BMA(SC)	-2.85	0.99	1.84	1.34	0.00	0.01	0.01	0.00
BMA(AIC)	-3.12	0.93	1.14	0.53	0.02	0.08	0.07	0.05
Rank	-1.82	-0.04	-0.73	-0.51	0.10	0.02	0.04	-0.01
RBF	1.67	4.42	2.95	0.71	-0.32	0.00	0.00	0.00
AW-RPW	-0.51	-0.67	-1.06	-1.21	-0.23	0.08	0.11	0.11
AW-Exp	-0.51	-0.61	-0.81	-0.92	-0.24	0.07	0.08	0.08
C-Simple	-0.74	-0.75	-0.98	0.01	-0.66	0.49	0.57	0.40
C-LS	-4.22	-1.02	6.93	5.12	-1.87	0.22	1.62	1.75
LS(1)	-1.12	3.41	-0.09	-0.58	-0.05	0.52	2.31	0.33
LS(2)	-1.00	4.84	-0.28	-0.67	0.10	0.85	-0.13	-0.13
LS(3)	-1.77	4.72	-0.75	-1.21	-0.52	-0.39	-0.27	-0.10
LS(4)	-1.61	-0.15	-1.17	-0.34	0.03	0.01	0.17	0.03

Note: See notes under Table 1.

Table 6: Relative RMSEs of bridge equations with various forecast combination schemes calculated without a specific group of variables for the total unemployment rate

	Without real variables				Without surveys				Without labor variables			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
Simple	-0.04	-0.38	-0.41	-0.31	-0.17	0.01	-0.09	-0.20	-0.21	-0.40	-0.34	-0.39
Median	0.18	0.09	0.19	0.48	-0.16	-0.36	-0.10	-0.29	-0.84	-0.32	-0.46	-0.19
RPW	-0.15	-0.67	-0.78	-0.63	-0.19	0.02	-0.05	-0.18	-0.15	-0.30	-0.19	-0.34
BMA(SC)	-0.69	-0.33	-0.49	-0.14	0.01	0.05	0.05	0.02	-0.03	-0.12	-0.10	-0.13
BMA(AIC)	-1.19	-0.15	-0.21	0.51	0.08	0.19	0.26	0.11	0.00	-0.01	-0.01	-0.01
Rank	-0.26	-1.14	-1.57	-1.23	-0.05	0.08	0.28	0.60	-0.28	-0.63	-0.76	-0.93
RBF	0.03	-0.80	-2.22	-0.28	0.04	0.00	-0.22	-0.14	-0.01	0.29	-0.25	-0.23
AW-RPW	-0.06	-0.36	-0.36	-0.14	-0.16	0.07	0.01	-0.07	-0.15	-0.42	-0.32	-0.57
AW-Exp	-0.05	-0.45	-0.53	-0.40	-0.16	0.04	-0.04	-0.10	-0.15	-0.36	-0.25	-0.40
C-Simple	-0.84	-1.34	-1.54	-1.09	-0.44	0.43	0.58	0.29	-0.29	-1.28	-3.47	-5.27
C-LS	-0.52	-1.61	-0.82	-1.66	-0.99	-0.08	1.71	1.72	-0.73	-2.09	-2.59	1.31
LS(1)	1.72	0.83	-0.12	-2.80	0.38	1.01	2.27	1.25	2.87	-1.39	-2.09	-12.70
LS(2)	1.73	0.12	-2.18	-1.41	0.45	2.63	0.06	0.15	4.70	-1.15	-7.16	-11.30
LS(3)	4.34	-0.45	-4.53	-3.10	0.70	1.82	0.56	0.39	4.98	1.46	-5.04	-7.40
LS(4)	-0.47	-2.08	-2.04	-0.87	-0.06	0.92	0.68	0.43	0.16	-1.29	-2.97	-5.15

	Without foreign demand variables				Without financial variables			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
Simple	-0.35	-0.41	-0.51	-0.51	0.67	1.23	1.48	1.40
Median	-0.16	-0.29	-0.58	-1.06	0.18	0.56	0.10	-0.50
RPW	-0.37	-0.37	-0.54	-0.50	0.87	1.62	1.95	1.98
BMA(SC)	-1.40	-2.47	-4.04	-5.81	4.36	5.15	5.85	5.09
BMA(AIC)	-0.28	0.95	0.32	0.24	7.37	10.39	13.43	15.24
Rank	-1.18	-0.22	-0.69	-0.61	0.60	1.77	1.92	2.69
RBF	3.76	2.11	1.72	-3.78	-0.43	-2.16	-1.34	1.83
AW-RPW	-0.45	-0.42	-0.67	-0.89	0.71	0.96	1.19	1.16
AW-Exp	-0.45	-0.46	-0.66	-0.76	0.81	1.30	1.53	1.43
C-Simple	-1.07	-1.69	-1.02	-0.61	2.25	3.18	3.13	3.00
C-LS	-4.72	-1.25	6.32	6.68	2.81	2.99	4.29	5.15
LS(1)	0.33	3.78	0.05	-1.32	4.86	-0.55	-5.02	-1.12
LS(2)	0.25	4.00	-0.36	-0.25	5.34	-0.36	-2.48	-3.12
LS(3)	0.13	2.10	-0.52	-0.79	10.86	1.62	-3.17	-3.69
LS(4)	0.24	0.11	-0.68	-0.18	5.69	-0.90	-0.64	-1.16

Note: See notes under Table 1.

Appendix A: Description of the Dataset

Table Appendix A.1: Description of the Dataset

Variables	Source	SA by	Publication lag	Group
Total Job Seekers	ISKUR	Authors	1	Labor
Regular Job Seekers	ISKUR	Authors	1	Labor
New Vacancy	Kariyer.net	Authors	1	Labor
Total Vacancy	Kariyer.net	Authors	1	Labor
Total Application	Kariyer.net	Authors	1	Labor
Industrial Production Index	Turkstat	Turkstat	2	Real
Automobile Production	AMS	Authors	1	Real
Import Volume Index	Turkstat	Turkstat	2	Real
Ercan Turkan Consumption Index	Turkstat	Turkstat	2	Real
Capacity Utilization Rate	CBRT	CBRT	1	Survey
Real Sector Confidence Index	CBRT	CBRT	1	Survey
Consumer Confidence Index	Turkstat	Authors	1	Survey
Consumer Credit	CBRT	Authors	1	Financial
Commercial Credit	CBRT	Authors	1	Financial
USD/TRY	TDM	NA	1	Financial
Borsa Istanbul 100 Index	TDM	NA	1	Financial
US IPI	FED	FED	1	Foreign
US Imports	US Census	US Census	2	Foreign
EU IPI	EuroStat	EuroStat	2	Foreign
EU Imports	EuroStat	EuroStat	2	Foreign
Unemployment Rate	Turkstat	Turkstat	4	Target
NA Unemployment Rate	Turkstat	Turkstat	4	Target

Note: This table shows variables, their associated groups, their publication lags, and institutions or people by which variables are produced and seasonally adjusted (SA). USD/TRY and Borsa Istanbul 100 Index aren't seasonally adjusted. Turkstat refers to the Turkish Statistical Institute. CBRT refers to the Central Bank of Republic of Turkey. AMS refers to the Automotive Manufacturers Association. ISKUR refers to the Turkish Employment Agency. TDM refers to the Turkish Data Manager. Eurostat refers to the Statistical Office of the European Communities. FED refers to the Board of Governors of the Federal Reserve System.

Appendix B: Additional Results

Table Appendix B.1: RMSEs of bridge equations including AR terms with various forecast combination schemes and the DFM

	the NA unemployment rate				the total unemployment rate			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
AR	0.24	0.36	0.50	0.58	0.22	0.35	0.50	0.59
Simple	0.23	0.33	0.46	0.54	0.20	0.32	0.44	0.50
Median	0.23	0.33	0.46	0.55	0.21	0.33	0.44	0.50
RPW	0.23	0.33	0.45	0.53	0.20	0.32	0.42	0.49
BMA(SC)	0.23	0.32	0.44	0.51	0.20	0.31	0.41	0.47
BMA(AIC)	0.25	0.35	0.46	0.52	0.20	0.31	0.42	0.48
Rank	0.22	0.32	0.44	0.52	0.20	0.31	0.41	0.48
RBF	0.23	0.33	0.49	0.57	0.22	0.32	0.43	0.49
AW-RPW	0.23	0.33	0.46	0.54	0.20	0.32	0.43	0.49
AW-Exp	0.23	0.33	0.46	0.54	0.20	0.32	0.43	0.49
C-Simple	0.23	0.32	0.44	0.52	0.21	0.30	0.40	0.47
C-LS	0.24	0.32	0.46	0.58	0.22	0.32	0.45	0.56
LS(1)	0.23	0.32	0.45	0.54	0.22	0.32	0.41	0.49
LS(2)	0.23	0.31	0.43	0.50	0.22	0.31	0.39	0.46
LS(3)	0.22	0.31	0.43	0.51	0.21	0.30	0.39	0.47
LS(4)	0.22	0.31	0.43	0.51	0.21	0.30	0.39	0.46
DFM	0.23	0.34	0.45	0.54	0.20	0.30	0.40	0.48

Note: See notes under Table 1.

Table Appendix B.2: RMSEs of bridge equations with various forecast combination schemes and the DFM using rolling window.

	the NA unemployment rate				the total unemployment rate			
	h=1	h=2	h=3	h=4	h=1	h=2	h=3	h=4
AR	0.26	0.39	0.53	0.62	0.22	0.34	0.49	0.58
Simple	0.24	0.37	0.51	0.64	0.20	0.32	0.44	0.54
Median	0.24	0.38	0.52	0.65	0.21	0.33	0.46	0.56
RPW	0.24	0.37	0.51	0.63	0.20	0.32	0.43	0.53
BMA(SC)	0.25	0.38	0.51	0.62	0.24	0.34	0.49	0.60
BMA(AIC)	0.27	0.40	0.53	0.66	0.25	0.35	0.50	0.62
Rank	0.23	0.36	0.49	0.62	0.20	0.31	0.42	0.53
RBF	0.26	0.38	0.50	0.62	0.20	0.32	0.43	0.54
AW-RPW	0.24	0.37	0.51	0.63	0.20	0.32	0.44	0.54
AW-Exp	0.24	0.37	0.51	0.63	0.20	0.32	0.43	0.53
C-Simple	0.23	0.35	0.48	0.59	0.19	0.30	0.41	0.51
C-LS	0.24	0.35	0.50	0.63	0.20	0.31	0.43	0.53
LS(1)	0.25	0.37	0.47	0.58	0.21	0.31	0.44	0.50
LS(2)	0.25	0.37	0.46	0.56	0.21	0.31	0.41	0.50
LS(3)	0.24	0.36	0.46	0.57	0.20	0.30	0.41	0.50
LS(4)	0.23	0.35	0.47	0.57	0.20	0.30	0.41	0.50
DFM	0.23	0.35	0.47	0.56	0.20	0.30	0.41	0.49

Note: See notes under Table 1.