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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.

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 fore-

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[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.

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cast combination often outperforms estimated optimal forecast combinations in empirical applications (e.g., Clemen, 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, 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 Fig. 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 Fig. 1.

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.

3. The methodology

3.1. Bridge equations

To form bridge equations, we first build an ARDL model for each

[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.

[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.