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Short-term inflation forecasting models for Turkey and a forecast combination analysis

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ABSTRACT

In this paper, we produce short term forecasts for the inflation in Turkey, using a large number of econometric models. In particular, we employ univariate models, decomposition based approaches (both in frequency and time domain), a Phillips curve motivated time varying parameter model, a suite of VAR and Bayesian VAR models and dynamic factor models. Our findings suggest that the models which incorporate more economic information outperform the benchmark random walk, and the relative performance of forecasts are on average 30% better for the first two quarters ahead. We further combine our forecasts by means of several weighting schemes. Results reveal that, the forecast combination leads to a reduction in forecast error compared to most of the models, although some of the individual models perform alike in certain horizons.
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1. Introduction

The primary goal of the Central Bank of Turkey (CBT) is to achieve and maintain price stability through the framework of inflation targeting policy. Accordingly, predicting the future course of inflation in a precise manner is a crucial objective to maintain this goal. To predict inflation, the CBT uses a large information set coming from expert judgments, which is derived using both nowcasting tools, and a variety of models ranging from simple traditional time series models to theoretically well-structured dynamic stochastic general equilibrium (DSGE) models. This paper aims to contribute to this information pool by providing a very rich set of short-term model-based inflation forecasts and combining these forecasts to obtain a more accurate forecast of inflation.

In the forecasting framework of the CBT, the medium term inflation projections are based on the information obtained from the short-term inflation projections (mainly one or two quarters ahead). Therefore, it is essential for the CBT to base the medium term forecasts on more accurate and well performing short-term projections, which rely on the maximum information set available. To this end, in this study, we use different modeling approaches in order to improve the performance of short term projections, and we merge the forecasts from various econometric models following the forecast combination literature to give the single best forecast.[1] Our forecasting exercise in this paper is a purely model-based mechanical one, where our results do not contain any judgmental information. In this respect, combined forecasts can be considered as a summary of the information contained in the data.[2] Therefore, they are included as an input (in addition to ones coming from other sources) to the policy makers' information set.

In this paper, we estimate series of models that are frequently employed in the forecasting studies of most central banks. We employ univariate models, vector autoregressive (VAR) models, Bayesian VARs, decomposition based approaches, unobserved component models and data intensive dynamic factor models. Our approach is similar to the Bank of England's (BoE) suite of statistical forecasting models (see Kapetanios et al., 2008), and the forecasting literature displays that the forecasting experience of short-term inflation forecasting is quite

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[1] Forecasting literature states that approaches which are solely based on empirical models are more convenient for short term projections (up to a year), as they are not very sound for getting grasp of the whole story behind the building stones of the economy, and dealing with the Lucas critique. This is one of the reasons why central banks use small or large scale structural general equilibrium models for medium term forecasting.

[2] There are also some judgment based forecasting approaches utilized at the CBT, which we refer them as judgmental forecasts. One of them (for short-term forecasting) is the disaggregated approach, in which main goods and services components of the CPI are projected separately (due to their heterogeneity) and then combined in line with their individual share in the consumer basket. In this respect, the approach we follow in this study should be considered as one side of the coin, where the other side is only composed of judgmental forecasts.

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alike at peer central banks.[3] Based on the projection process of the forecasting framework of the CBT, which can be attributed to the Quarterly Inflation Report, in this paper we estimate our models on a quarterly basis.[4] However, since inflation projections are reported on an annual base in the Quarterly Inflation Report of the CBT, in our paper all forecast error computations are reported using annual inflation rates.

In this study, we focus on the period after the 2001 financial crisis in Turkey. Following the 2001 crisis, Turkey abandoned the fixed/managed exchange rate regime and adopted the floating exchange rate regime in line with a smooth transition to inflation targeting policy. By means of these substantial changes in the policy making, the economic system in Turkey moved towards a period of rapid structural transformation, in which, the size and even the direction of the relationship between all macroeconomic variables have changed significantly. Altering price dynamics in this new phase, and the lower information content of pre-2001 period data concerning the prediction of the future, led our focus on post-2001 period.

While working with the forecasting models in this paper, we employ the CPI excluding unprocessed food and tobacco (*cpix*), instead of the headline Consumer Price Index (CPI) as the main variable of interest. This is due to the fact that the unprocessed food and tobacco prices exhibit the highest unexpected volatility within the CPI sub-components in Turkey (Öğünç, 2010). Severe volatility, which is an inherent characteristic of unprocessed food prices, and tax adjustments on tobacco cause a remarkable forecast uncertainty. Short-term forecasting practices generally claim that, it is quite problematic to model the evolution of inflation dynamics, which include these highly volatile items. Even more notably, these highly volatile sub-components of the CPI are one of the factors that are beyond the control of monetary policy. Accordingly, the topic of keeping the certain sub-components of the CPI, which have unpredictable/unexpected volatility, out of the forecasting procedures is also highlighted by the Central Bank of Republic of Turkey (2010).[5]

The findings of this paper suggest that, the models which use multivariate predictors outperform univariate models in forecasting inflation in Turkey. Compared to a benchmark random walk model, the relative performance of forecasts from these multivariate models is, on average, 30% better for the forecast horizon of one and two quarters. These models which exploit larger data sets and contain more information about inflation can better capture the relatively unstable inflation dynamics in an emerging market economy in contrast to advanced ones, which experienced "great stability" period. Second, although the best performing individual model of each horizon differs, the performance of BVAR is rather close to the superior models of each horizon. Finally, our results show that forecast combination in general leads to a reduction in forecast error compared to individual models, which is consistent with the results of Kapetanios et al. (2008) for BoE and Bjørnland et al. (2008) for Norges Bank, and forecast combination slightly improves on the BVAR when root mean squared error (RMSE) weighting scheme is adopted.[6]

The plan for the remainder of the paper is as follows. We briefly summarize the building blocks of the forecasting models in the next section. In Section 3 we explain the forecast combination procedure we utilized in our short-term forecasting practice and in Section 4 we present our results. Finally, Section 5 concludes the paper.

2. Models

We use several types of models for forecasting the short-term inflation for Turkey. We briefly introduce each of these models, but before that we first discuss some empirical aspects.

An analysis on the stability and stationarity of our quarterly inflation series precedes the estimation process. Our sample includes the period of global crisis and thus it is likely to observe a break in the mean, which should be taken into account both for estimation and forecasting purposes. To this end, we conduct Bai and Perron (1998) and Quandt-Andrews[7] structural break tests which endogenously determine the possible break date. Results of both tests show that there exists no structural break in the mean of inflation.[8] Finally, the Augmented Dickey–Fuller unit root test results show that non-stationarity is rejected at 1% significance level for quarterly inflation.

A forecasting model with a good in-sample fit does not necessarily imply a good out-of sample performance. Therefore, we apply pseudo out-of-sample forecasting exercises, which aim to replicate the experience that a forecaster encounters during a forecasting practice. To this end, we divide our sample period (2003Q1:2011Q2) into two parts. The first period is the training sample, which includes all data up to 2009Q3, and the second period is the forecasting sample, which includes the remaining data from 2009Q4 to 2011Q2.[9] We use the training sample to estimate the models. Then, throughout the forecasting sample, one to four quarters ahead forecasts are obtained from these models. Extending the estimation period one period at a time, we collect the forecasts at each step, which are obtained for one to four quarters ahead. This process is repeated until the end of pseudo out-of-sample period.[10] The forecast performance of the models is measured with the RMSE, which is calculated separately for each forecast horizon. Based on the forecast errors, we derive the forecast combination weights and compute the results for forecast combination in line with these weights.

Another empirical aspect that deserves some discussion is the use of real-time data or estimates to assess the forecasting power of alternative models accurately. Any forecasting exercise should be built on the real-time data that is available to the forecaster at the time of forecasting. Most of the data exploited in our study, including the CPI, do not suffer from data revision. However, our study is not fully exempt from this problem due to revisions in GDP, of which the real-time data set is not available at the moment. Another feature of real-time analysis in forecasting is related with the estimation or filtering of unobserved variables, which should be based on one-sided estimation. Correspondingly, we employ one-sided (filtered) estimates where appropriate, such as in the estimation of TVP coefficients. However, for the output gap data, we make use of full sample (two-sided) estimates due to lack of real-time estimates for the output gap figure.

[3] See, for example, Bjørnland et al. (2008) for Norges Bank, and Andersson and Löf (2007) for Riksbank.

[4] Seasonal ARIMA and wavelet filter approach are the only exceptions, which are estimated on a monthly base.

[5] The CBT started to publish forecasts of the CPI inflation excluding unprocessed food and tobacco in its Quarterly Inflation Report starting from the last quarter of 2010.

[6] Short pseudo out-of-sample period is a prominent drawback of this study and the results of pseudo analysis may be limited to the period studied, which is an unusual period in itself, since it includes the effects of global financial crisis. Therefore, relative performance of the models used in this study might change as the real-time records accumulate over time.

[7] See Andrews (1993) and Andrews and Ploberger (1994).

[8] The results of structural break tests are available upon request. We use Hansen's (1997) asymptotic p-values for Quandt-Andrews test to make sure that the results are not affected from the finite sample problem.

[9] The end period of the training sample is chosen as 2009Q3 to include the possible implications of the financial crises in the models so that they will provide better out-of-sample forecasts. In addition, to have a reasonable number of out-of-sample forecasts it was necessary to end the training period at 2009Q3.

[10] In the first step of our forecasting practice, we get forecasts starting from 2009Q4 up to 2010Q3. Moving one period forward in the next step, we re-estimate all the models including one more data period, and we use the data until the fourth quarter of 2009 and get forecasts for the period starting from 2010Q1 up to 2010Q4. This exercise is performed repeatedly until the end of the pseudo out of sample period.

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