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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 percent 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.

Keywords: Inflation, Short-term Forecasting, Forecast Combination.

JEL classification: C52, C53, E37.

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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., 2007), and the forecasting literature displays that the forecasting experience of short-term inflation forecasting is quite 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

[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 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.

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

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

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 instead of the headline 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 very volatile sub-components of the CPI are one of the factors that are beyond the control of monetary policy. 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 CBT (2010). Accordingly, 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. With this perspective, in this paper we prefer using the CPI excluding unprocessed food and tobacco, as the price index to be projected.

Before starting the projection exercise we analyzed the stability and stationarity of our quarterly inflation series. This is important since 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 for both estimation and forecasting purposes. To this end, we conducted Bai and Perron (1998) and Quandt-Andrews[5] structural break tests which endogenously determine the possible break date.[6] Results of both tests show that there exists no structural break in the mean of inflation. Finally, the unit root test results show that quarterly inflation is stationary at 1 percent significance level.

A forecasting model with a good in-sample fit does not necessarily imply that it will have a good out-of sample performance, and therefore we apply pseudo out-of-sample forecasting exercises, which aim to replicate the experience that a forecaster faces in 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.[7] We use the training sample to estimate the forecasting models and to obtain one to four quarters ahead forecasts from these models. Extending the estimation period one period at a time, we store the forecasts at each step, which are obtained for one to four quarters ahead. This process is repeated until we reach the end of pseudo out-of-sample period.[8] In this study, the forecast performance of the models is measured with the root

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

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

[7] 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 around 2009Q3.

[8] In the first step of our forecasting practice, we use the training sample, and get forecasts starting from 2009Q4 up to 2010Q3 and we store these forecasts. 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

mean squared error (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.

The findings of this paper suggest that, the models which use multivariate predictors outperform univariate models in terms of forecasting inflation in Turkey. Compared to a benchmark random walk model, the relative performance of forecasts from these multivariate models are, on average, 30 percent better for the forecast horizon of one and two quarters. This result comes as no surprise, since multivariate models exploit larger data sets, which are likely to contain more information about inflation, compared to univariate models. 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 and slightly improves on the BVAR when RMSE weighting scheme is adopted.[9]

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 the short-term forecasting of inflation in Turkey. We now introduce each of these and discuss some empirical aspects.

2.1 UNIVARIATE MODELS (Choosing the Benchmark)

Univariate models are commonly used as benchmarks in the forecasting literature. Quite often these simple models are found hard to beat compared to large multiple-equation models such as vector autoregression and traditional structural macroeconomic models.[10] Moreover, having few independent variables, they are considered to be convenient for short data samples. The univariate modeling in this study includes the following family of models; unconditional mean, random walk, autoregression and seasonal autoregressive integrated moving average. Among them, the benchmark model is chosen on the basis of forecast errors.

2.1.1 Unconditional Mean

The first candidate benchmark model is the unconditional mean (UM), which states that the variable of interest is equal to the average of its past without any restriction or *a priori* information:

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and get forecasts for the period starting from 2010Q1 up to 2010Q4. This exercise is performed repeatedly until the estimation period covers our full sample period (2003Q1:2011Q2).

[9] Short pseudo out-of-sample period is one of the important drawbacks 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 involves 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.

[10] For a review of literature on forecasting using univariate models with the US data, see Stock and Watson (2008). For the Euro area, Hofmann (2008) shows that the random walk model cannot be outperformed significantly by any other alternative models. For emerging European countries, Arratibel et al. (2009) find that in the short term, with the exception of a few countries, it is difficult to find models that significantly outperform the benchmark random walk model.

$$\pi_{t+h} = \alpha + \varepsilon_{t+h}, \tag{1}$$

where $h = 1, \dots, 4$ is the forecast horizon, and π_{t+h} is the h-period-ahead annual inflation rate. This model suggests that the best inflation forecast for any horizon is the average of realized rates of inflation. Therefore; all forecasts are same for all horizons. UM is argued to perform well in long horizons rather than short horizons, since the series are mean-reverting in a stationary world and inflation target serves as a strong factor driving the inflation rate in the long run (Kapetanios et al. 2007).

2.1.2 Random Walk

There are two different approaches to model random walk in the literature. The first one is the iteration approach, which is used to describe the traditional random walk (RW_T):

$$\pi_{t+h} = \pi_t + \varepsilon_{t+h}, \tag{2}$$

where π_t is the annual inflation rate which equals to $((cpix_t - cpix_{t-4})/cpix_{t-4}) * 100$. Here $cpix_t$ refers to consumer price index excluding unprocessed food and tobacco products. According to the traditional random walk, the inflation forecast for any h is equal to the last realized value of annual inflation rate. In other words, the last realized value of annual inflation is iterated forward to compute future inflation conditional on information up to time t. In this study, the benchmark model is chosen as the traditional random walk since it produces lower RMSEs.

The second approach, which is also called as the "naïve" random walk, is the direct approach (RW_D). This model states that h-period-ahead inflation is forecast by the last observed h period inflation rate:

$$\pi_{t+h}^h = \pi_t^h + \varepsilon_{t+h}^h, \tag{3}$$

where π_{t+h}^h is the h-period-ahead annualized inflation rate, π_t^h is the h period seasonally adjusted annualized inflation rate and calculated as $((((cpix_t - cpix_{t-h})/cpix_{t-h}) + 1)^{4/h} - 1) * 100$.[11]

2.1.3 Autoregression (AR)

Another candidate benchmark is the AR(1) model:

$$\pi_{t+h} = \beta_0 + \beta_1 \pi_{t+h-1} + \beta_2 S_1 + \beta_3 S_2 + \beta_4 S_3 + \varepsilon_{t+h}, \tag{4}$$

where π_{t+h} is the h-period-ahead quarterly inflation rate, π_t is the quarterly inflation and calculated as $(cpix_t - cpix_{t-1})/cpix_{t-1}) * 100$. Since quarter on quarter values are used, seasonal dummies (S_i's) are introduced into the equation.

2.1.4 Seasonal ARIMA

Our last linear univariate model is the s*easonal ARIMA* (SARIMA) model. The general multiplicative form of the SARIMA can be given as:

$$\emptyset_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D cpix_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t, \tag{5}$$

[11] Unadjusted consumer price index is used throughout the paper, only exception is the direct random walk process.

where $\emptyset(B)$ and $\Phi(B)$ are the regular and seasonal AR polynomials respectively, B is the lag operator, $1-B$ is the regular and $1-B^s$ is the seasonal first difference, and $\theta(B)$ and $\Theta(B)$ are the regular and seasonal MA polynomials, respectively. s represents the number of seasons and equals to 12 as we use monthly inflation series. p (P) shows the number of autoregressive lags, d (D) is the order of integration and q (Q) refers to the number of moving average lags of the regular part (seasonal part). Finally, ε_t is a white noise sequence. A SARIMA model in the multiplicative form is commonly denoted as $(p,d,q)(P,D,Q)_s$.

After applying the model identification procedure of the Demetra+ software, the SARIMA model for $cpix_t$ is found to be$(1,1,0)(0,1,1)_{12}$, which can be shown as:

$$(1+\emptyset_1 B)(1-B)(1-B^{12})cpix_t = (1+\Theta_1 B^{12})\varepsilon_t. \tag{6}$$

Obviously, forecasts from (6) can be computed by:

$$cpix_{t+h} = (1-\emptyset_1)cpix_{t+h-1} + \emptyset_1 cpix_{t+h-2} + cpix_{t+h-12} - (1-\emptyset_1)cpix_{t+h-13} - \emptyset_1 cpix_{t+h-14} + \Theta_1 \varepsilon_{t+h-12} + \varepsilon_{t+h}. \tag{7}$$

2.2 NONLINEAR MODELS

Nonlinear models can be broadly classified into two groups according to the assumed switching behavior of the variable under consideration between different regimes. On one hand, Markov-switching models employ transition probabilities characterized by a Markov chain process, under the presumption that the regime switch is determined by an unobservable variable. Threshold models, on the other hand, assume regime changes are determined by an observable variable. Self-exciting threshold models, in particular, allow for the regime change to be determined by the past values of the series itself. Two popular examples for threshold framework are the Threshold Autoregression (TAR) model, which assumes a sharp transition between the regimes, and the Smooth Transition Autoregression (STAR) model, which implies a gradual adjustment.

A first step in nonlinear model building is linearity testing as suggested by Teräsvirta (2005). In case nonlinearity is detected, the following step would be selecting the transition framework as discussed above. However, if the null of linearity is not rejected, then it is best to avoid nonlinear modeling. As the argument goes, threshold or smooth transition frameworks, both of which imply nested linear models, suffer from identification problem under a linear data generating process, as will be discussed in a while. This may lead to inconsistent parameter estimates and therefore would produce inferior forecasts. Therefore, we first conduct unit root tests to detect the presence of a mean-reverting behavior in inflation, towards a long-run value.

Under the presence of nonlinearities, it is well documented that conventional unit root tests yield low power in assessing whether the series display a stationary or unit root behavior.[12] To address this issue, we employ TAR unit root tests developed by Caner and Hansen (2001) and Exponential Smooth Transition Autoregression (ESTAR) unit root tests developed by Kapetanios et.al (2003) both of which provide more robust testing procedures when the underlying process might be subject to nonlinearities.

TAR models assume that small deviations from a long-run value are disregarded while the adjustment in response to large deviations is *immediate*. Specifically, we postulate the equation:

[12] See Hansen (1996) and Balke and Fomby (1997).

$$\Delta\pi_t = I_t\rho_1\pi_{t-1} + (1 - I_t)\rho_2\pi_{t-1} + \varepsilon_t, \tag{8}$$

where I_t is the indicator function with

$$I_t = \begin{cases} 1 \; if \; y_{t-1} < \lambda \\ 0 \; if \; y_{t-1} \geq \lambda \end{cases}. \tag{9}$$

Following Enders and Granger (1998) and Caner and Hansen (2001), which propose a self-exciting threshold framework, we choose $y_{t-1} = \pi_t - \pi_{t-m}$, where the adjustment process is determined by the previous changes in y_t, against a threshold. Caner and Hansen (2001) propose a joint test for nonlinearity and nonstationarity where the standard null hypothesis $H_0\colon \rho_1 = \rho_2 = 0$ is tested against two alternatives, including $H_{A1}\colon \rho_1 < 0, \rho_2 < 0$, which suggests overall stationarity and;

$$H_{A2}\colon \begin{cases} \rho_1 < 0 \; and \; \rho_2 = 0 \\ \rho_1 = 0 \; and \; \rho_2 < 0' \end{cases} \tag{10}$$

which implies a partial unit root case with stationarity in one of the regimes and nonstationarity in the other.[13] In economics terms, this model conjectures that when the inflation level exceeds a certain threshold, central bank actions bring it back to its long run value *immediately*.

Another way to model the aforementioned adjustment in inflation is employing ESTAR models, which assume that the adjustment is *gradual*. This framework is appealing when it takes time to see the full effect of the response of the monetary authority to deviations around the inflation target. The formal model in Kapetanios et.al (2003) can be written as:

$$\Delta\pi_t = a_1\pi_{t-1} + a_2\pi_{t-1}G[1 - exp(-\theta(\pi_{t-d} - \lambda)^2)] + \varepsilon_t. \tag{11}$$

The transition function $G(\cdot)$ includes the coefficient of the speed of adjustment θ, which determines the smoothness of the transition between regimes. Similar to Kapetanios et al. (2003), we impose a mean-zero stochastic process, setting $\lambda = 0$ and further choose $a_1 = 0$ assuming that the series display a unit root behavior when it is close to its long-run value, yet has a mean-reverting behavior when it is far away from it. Setting the delay parameter as d$= 1$, we obtain

$$\Delta\pi_t = a_2\pi_{t-1}G[1 - \exp(-\theta\pi_{t-1}^2)] + \varepsilon_t \tag{12}$$

The null hypothesis is $H_0\colon \theta = 0$ against the alternative $H_A\colon \theta > 0$. To address unidentified parameter (a_2) problem under the null, Kapetanios et al. (2003) suggest an auxiliary regression using a first order Taylor series approximation. The general model including serially correlated errors then reads:[14]

$$\Delta\pi_t = \sum_{j=1}^{p} p_j \Delta\pi_{t-j} + \gamma\pi_{t-1}^3 + \varepsilon_t. \tag{13}$$

We conduct both of the mentioned nonlinear unit root tests using data with different frequency (monthly and quarterly) due to short-data span; with and without seasonal adjustment, and with alternative lag structures (1 to 12 months and 1 to 4 quarters). In any of these cases, neither TAR nor ESTAR unit root test results suggest presence of nonlinearity.[15] Hence, we conclude that nonlinear modeling would not add any significant value to the forecasting exercise for the moment as discussed above.

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[13] The optimal threshold level λ and the lag length, m, are chosen in an endogenous manner via minimizing the residual sum of squares of the least squares estimation of (8).

[14] The asymptotic critical values for the t-statistics by employing the OLS estimation of $\gamma(\hat{\gamma})$ are given in Kapetanios et al. (2003).

[15] Results are not shown but available upon request.

2.3. DECOMPOSITION BASED MODELS

Decomposition based models for inflation forecasting mainly originates from the idea that inflation itself is a composition of two distinct parts, i.e. a permanent and a transitory part. The former refers to the underlying trend of inflation whereas the latter refers to fluctuations which will be corrected in short term and therefore do not affect the underlying trend inflation. Since these two distinct parts are not directly observable, some filtering methods are utilized to extract these components and to forecast inflation. In this study, we consider two different decomposition approaches, one working in the frequency domain (WAVE) and the other in the time domain (UC).

2.3.1 Wavelet Filter Approach

In order to separate the short term noise from the unobserved trend, different filtering methods are introduced on the frequency domain through the introduction of the Fourier series transformation.[16] This transformation enables the transition between time and frequency domain. On the frequency domain, a filter is implemented in order to remove the movements on specified frequencies. Based on this transformation, many filters have been introduced in the literature in order to approximate the ideal filter on frequency domain. Most commonly used ones are Hodrick-Prescott, Baxter-King and Christiano-Fitzgerald filters.[17] However, these filters are inflexible by construction as they are based on the assumption that a series is composed of trigonometric sine and cosine functions throughout the entire sample. This inflexibility makes these filters less successful in the detection of transitory movements and effective time periods of the frequencies. In this context, we use wavelet filter in this study which is flexible as it relies on the assumption that a series is composed of special wavelet functions that can expand or shrink.[18]

Specifically, the wavelet transformation separates a series into different components in the frequency domain by using special type of wavelet functions. The scaled versions of *father* and *mother* wavelet functions are:

$$\theta_{j,k}(t) = 2^{-\frac{j}{2}}\theta(\frac{t-2^j k}{2^j}) \tag{14}$$

and

$$\varphi_{j,k}(t) = 2^{-\frac{j}{2}}\varphi(\frac{t-2^j k}{2^j}), \tag{15}$$

and the wavelet decomposition of a time series is given as:

$$x(t) = B_j + D_j + D_{j-1} + \cdots + D_1, \tag{16}$$

where $B_j = \sum_k b_{j,k}\theta_{j,k}(t)$ and $D_j = \sum_k d_{j,k}\varphi_{j,k}(t)$, (17)

and B_j is the approximate component while D_i i=1,…,j are the orthogonal detail components. Here, the highest frequencies are denoted by D1 and D2 components, where they correspond to cycles with 2-4 periods and 4-8 periods, respectively. In other words, components D1 and D2 refer to the short term fluctuations within a time series.

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[16] The discussion of the frequency domain and the introduction of wavelet filters mainly draw from Akkoyun et al. (2011).

[17] See Hodrick and Prescott (1997), Baxter and King (1999), Christiano and Fitzgerald (2003).

[18] Gençay et al. (2002) present the advantages of the wavelet filters.

In order to forecast inflation, we first decompose price index into three unobserved parts; main trend and two parts corresponding to the short term fluctuations. This is done by applying wavelet filters to the price index excluding unprocessed food and tobacco and extracting short term fluctuations, corresponding to 2-4 and 4-8 month cycles, as D1 and D2 components. As the wavelet filters decompose a series in an additive manner, the subtraction of the D1 and D2 components from price index yields the unobserved trend component labeled as $cpix^{trend}$ (B_j). In the last step, we forecast these three components in time domain separately and then combine the forecast series back together in order to reach the price index forecasts. Once the components are available, forecasting is done by using time series techniques. In particular, each component is modeled as follows:

$$D1_{t+1} = \alpha + \sum_{i=0}^{1} \beta_i D1_{t-i} + \sum_{i=0}^{1} \theta_i \epsilon_{t-i} + \sum_{j=1}^{11} \phi_j S_j + \epsilon_{t+1}, \quad (18)$$

$$D2_{t+1} = \alpha + \sum_{i=0}^{3} \beta_i D2_{t-i} + \sum_{i=0}^{1} \theta_i \epsilon_{t-i} + \sum_{j=1}^{11} \phi_j S_j + \epsilon_{t+1}, \quad (19)$$

$$cpix_{t+1}^{trend} = \alpha + \beta cpix_t^{trend} + \sum_{i=0}^{1} \theta_i \epsilon_{t-i} + [\ln(time)]^2 + \epsilon_{t+1}, \quad (20)$$

where S_j's refer to seasonal dummies and *time* refers to linear time trend. Finally, the price index forecast for one-period-ahead is simply the summation of three components:

$$cpix_{t+1} = cpix_{t+1}^{trend} + D1_{t+1} + D2_{t+1}. \quad (21)$$

Each specification above includes AR and MA terms. In the models of short term fluctuations, D1 and D2, seasonal dummies are also included. These specifications are determined on the basis of in-sample forecasting performance. The advantage of forecasting three unobserved components separately is the fact that all components have different time series properties. D1 and D2 components are series moving around zero with different frequency lengths. Therefore, modeling them separately improves the performance of short term forecasting. On the other hand, the trend part is indeed the noise-free price index which inherently contains a time trend. Likewise, modeling the trend by itself also yields better in-sample forecasts.

Once the components are extracted, forecasts of each component are generated using equations above for 12 months ahead of the current period. Then, summing these forecast components yields the forecast of price index for four quarters ahead, using which annual inflation rates are computed.

2.3.2 Unobserved Component Model

In this part, the price series is decomposed into two additive components, trend and cycle, using the unobserved components model (UC) utilized by Clark (1987). The model can be illustrated as:

$$cpix_t = n_t + x_t, \quad (22)$$

$$n_t = g_{t-1} + n_{t-1} + v_t, \quad v_t \sim i.i.d.\ N(0, \sigma_v^2), \quad (23)$$

$$g_t = g_{t-1} + \omega_t, \quad \omega_t \sim i.i.d.\ N(0, \sigma_\omega^2), \quad (24)$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t, \quad e_t \sim i.i.d.\ N(0, \sigma_e^2), \quad (25)$$

where $cpix_t$ is the quarterly price series, n_t is a stochastic trend component, and x_t is a stationary cyclical component. The drift term, g_t, in the stochastic trend component is modeled as a random walk.

After formulating the above model in state-space representation, we use Kalman Filter to get the dynamics of each component.[19] Coefficients of the model are estimated via maximum likelihood procedure. Obviously, forecasts from (22) can be computed by:

$$cpix_{t+h} = n_{t+h} + x_{t+h} \tag{26}$$

2.4. A PHILLIPS CURVE MOTIVATED TIME-VARYING PARAMETER MODEL

Phillips curve is a widely used canonical economic model to forecast inflation in the literature.[20] It can be broadly thought as forecasting inflation based on some measure of economic activity such as output gap or unemployment rate.

Large number of studies examined whether this approach is successful in forecasting inflation or not. While Atkeson and Ohanian (2001) argues the usefulness of the short-run Phillips curve to forecast inflation for US, Stock and Watson (2008) suggests that the performance of the curve is episodic because the slope of the short-run Phillips curve appears to change over time.[21] Considering the latter as well as the structural change Turkish economy experiencing, we estimate the Phillips curve in a time varying fashion. Specifically, we estimate an unobserved component model in which the parameters are unobserved states and evolve as random walk processes.[22] By doing so, we allow the model parameters to vary over time contrary to the standard models. This modeling approach enables us to address the theory and time series models in a coherent structure and it is especially useful for estimating relationships that are subject to change. Considering Turkey's switch to inflation targeting regime within the period at issue, it is not difficult to motivate the time-variation in the parameters.

The general form of the (TVP) model is given by:

$$\pi_t = \beta_{0,t} + \sum_i^p \beta_{1i,t}\tilde{y}_{t-i} + \sum_i^n \beta_{2i,t}\Delta pm_{t-i} + \sum_i^k \beta_{3i,t}\Delta e_{t-i} + \beta_{4,t}\Delta entax_t + \sum_i^s \beta_{5i,t}S_{i,t} + \epsilon_t, \quad \epsilon_t \sim NID(0,R), \tag{27}$$

$$\beta_{i,t} = \beta_{i,t-1} + v_{i,t} \;, \quad v_t \sim NID(0,Q), \tag{28}$$

where $\tilde{y}_t$, pm_t, e_t and $entax_t$ are the output gap, import price denominated in US dollars, exchange rate ($/TL) and average taxes on fuel oil prices, respectively. S_i is i^{th} quarterly seasonal dummy variable and $\beta_{0,t}$ is the drift term which captures the low-frequency changes in the level of inflation. As an economic activity measure, we prefer to utilize the output gap, which is recently estimated by Öğünç and Sarıkaya (2011) with a Bayesian New Keynesian perspective, rather than the original unemployment gap measure. The rest of the terms intended to capture some components of the marginal costs and seasonal variations in the pricing behavior. Lag structure of the model is

[19] See Harvey (2006) for details.

[20] See Phillips (1958), Stock and Watson (1999, 2008), Faust and Wright (2011) among many others.

[21] Önder (2004) claims that the inflation forecasts obtained from the Phillips curve for the 1987–2001 period deliver accurate results in the case of Turkey.

[22] This model is different from the unobserved component model (UC) above in the sense that the latter analyzes own dynamics of the series. Hence, we find it more appropriate to include this model in a separate section.

determined on the basis of general to specific modeling approach. The model is written in linear state space form and then estimated by exploiting the Kalman filter.

While forming the forecasts, we prefer using averages of the last 4 quarter estimates of βs to ensure some persistency. With this approach, it is possible to take into account the recent information without putting too much emphasize on the last estimate. Relaxing the conventional restriction that the parameters of the model are constant over time provides some flexibility to capture the changes in inflation dynamics.[23] In this respect, it can be argued that this approach is robust to some form of structural change, such as intercept shifts. Finally, note that βs used in forecasts are the filtered (one-sided) estimates.

2.5. VECTOR AUTOREGRESSION (VAR)

Another method that is used to forecast inflation in this study is the VAR.[24] A VAR model defines a set of endogenous variables as a function of their past and possibly a set of exogenous variables. A standard VAR with p lags is expressed as:

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \epsilon_t \qquad (29)$$

where $y_t = [y_{1,t}, \dots, y_{m,t}]'$ is the vector of variables in the model, A_0 is the $m\ x\ 1$ vector of constants and A_i is the $m\ x\ m$ matrix of coefficients of y_{t-i}.

In this study we have two particular unrestricted VAR models used to forecast inflation and we develop them at two steps. At first step, numerous VAR models are estimated using a pool of variables and their forecasts are stored. Then, the models are ranked according to their forecasting performances and top models, the ones with the lowest RMSEs, of each horizon are selected. The variables of these selected models are examined and the most repeated ones are recorded. At second step, two new VAR models are constructed using the most repeated variables of the best models, namely standard (VAR) and monetary VAR (mVAR).[25] The latter of these comprises all variables of the former and a monetary aggregate additionally. These models are fixed in the sense that they change neither at any recursive estimation nor forecasting horizon.

[23] As a matter of fact, the estimates observationally imply a change in some of the model parameters. The evolution of the sum of the coefficients of exchange rate and import prices point to a recently declining pass-through effect of external factors. In addition, we observe an increase in the coefficient of output gap with the global financial crisis, in particular after the first quarter of 2009. These observations bring to mind the possibility of a structural change in the inflation dynamics. To see whether these observations are statistically relevant, we applied Quandt-Andrews break point test to the model without time variation in the parameters. Results obtained using Hansen's (1997) p-values suggest that the possible break date of 2008Q3 is not statistically significant.

[24] See Lack (2006), Andersson et al. (2007), Bjørnland et al. (2008), Bloor (2009) and Figueiredo (2010) for similar studies.

[25] When deciding on the models, a common practice in literature is to use a time period coming before the pseudo out-of-sample period. In this way, the model estimation, selection and evaluation are all done in different sample periods. However, since we have limited number of observations we have adopted this two-stage approach in the study.

2.5.1 Building Our VAR Models

In VAR based forecasting procedure, at first stage, a pool of 22 endogenous variables is designed in order to capture the fundamental dynamics of the economy. Clearly, the variable of interest, $cpix$, is included in all models. The remaining 21 variables are grouped into five categories: real activity measures, commodity prices, exchange rates, monetary aggregates and interest rate. In addition to these, a set of exogenous variables is also added to the pool. Table 1 shows these variables by categories. Estimated VAR models consist of two to four endogenous variables and at most two exogenous variables. Each model draws its variables from these categories in such a way that two or more variables from the same category never exist at the same time in the same model. These conditions yield 2,692 VAR models.

The choice of lag order, p, is prominent in VAR modeling. However, the decision on lag selection involves a trade-off: the higher the lag order, the less precise the coefficients due to a reduction in degrees of freedom. On the other hand, the lower the lag order, the more probable that some intertemporal dynamics are omitted and the autocorrelation in the residuals are not removed (Lack, 2006). Taking into consideration the limited number of observations and the number of variables used in our VARs, different maximum number of lags are allowed in lag selection tests. At each recursion, the lag length of each model is chosen by the Akaike information criteria (AIC).

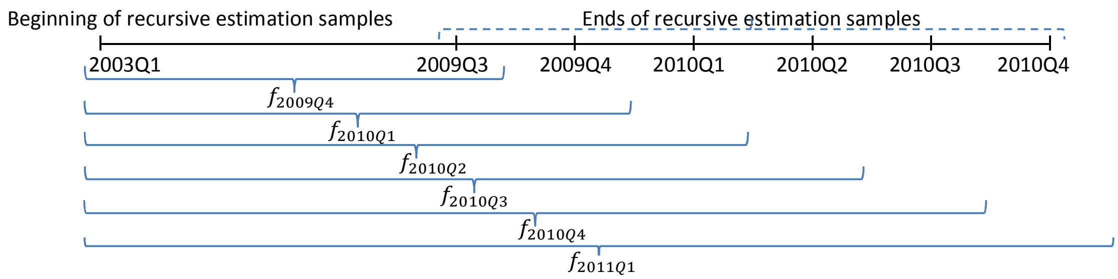
We want to note that stationary forms of the variables are used in the models. The non-stationary variables are stationarized by taking quarterly percentage change. The principle components are extracted from the series which are rendered stationary using two different approaches: percentage change and the Hodrick-Prescott filtered gaps.

A further point when using the principle components in recursive regressions is the inclusion of *a priori* knowledge. The principle components involve the information inherent in the variables from which they are extracted. In other words, the components whose data start from the same period but ending at different dates are different. Therefore, it is delusive to use a principle component obtained from a group of variables ending in 2011Q1 in an estimation ending in 2009Q3 since the information after 2009Q3 will already be embedded in the principle component series. In order to include only the information known at 2009Q3 in an estimation ending at this point, the principle components are obtained from the variables ending in 2009Q3. Moving one quarter ahead, new components are derived from the same variables ending in 2009Q4. Hence, each time we move forward, new principle components are extracted from the very same variables and used in relevant recursive estimations.

2.5.2 Forecasting Using the VAR Models

At first stage, a total number of 2,692 VAR models are estimated and 2,692 inflation forecasts are obtained at each recursion in pseudo sample period for any h. Diagram 1 depicts the forecasting procedure for a VAR model for one quarter ahead.

Diagram 1
Forecasting Procedure for h = 1



f_t, t = 2009Q4,…,2011Q1, stands for the forecast of inflation rate at time t − 1. Using the sample 2003Q1: t − 1, inflation forecast for t is obtained.

Then, the RMSE of each model is calculated as:

$$RMSE_h{}^i = \sqrt{\frac{\sum_{t=2009Q3+h}^{2011Q1}(f_t - r_t)^2}{T}} \tag{30}$$

where $h = 1,\ldots,4$ quarters, i represents the model and $i = 1, \ldots, 2{,}692$, T is the out-of-sample size and equals to 6 for $h = 1$, f_t denotes the forecast and r_t is the realized value of the annual inflation rate.[26] In this way, an RMSE vector of 2,692 elements is obtained and ranked from the lowest to the highest at each horizon. Based on the RMSE calculations, top 5 models of each horizon are selected.[27]

At second stage, we have examined the variables of all top 5 models, and recorded how many times each of these variables appear in these models. In other words, we have pinned down the most-repeated variables of the top 20 models. Finally, we set up two VAR models, namely VAR and mVAR, using these repetitive variables. Five and six endogenous variables are found in the VAR and mVAR models, respectively. Specifically, the VAR model includes the output gap, commodity price index, euro/TL nominal rate, benchmark interest rate and seasonal dummies (Table 2). It is of lag length one. The mVAR model contains all of the variables in the VAR and M_3 additionally, and its lag order is one, as well. Therefore, at any time for any h, inflation forecasts are obtained from these two models.

2.6 BAYESIAN VAR (BVAR)

Bayesian vector autoregressive models were first proposed by Litterman (1980) as an alternative to standard VAR models to overcome the dimensionality problem. VAR models are useful for economic modeling since they allow for interaction of different related variables in forecasting macroeconomic variables. However, the problem of a typical VAR is the loss of degrees of freedom due to overparametrization. In VAR models, the number of parameters to be estimated increases geometrically with the number of variables and proportionally with the number of lags included. When the number of parameters is large relative to the available number of observations, the

[26] Although most of the models are estimated quarterly, forecast errors are computed by using annual inflation rates.
[27] The top models are determined in the following way: using the ranked RMSE vectors, average of the forecasts of 1 to 60 best performing models are computed at each horizon. This yields 60 combined forecasts for any h at any time. In this way, 60 RMSEs are obtained and the lowest RMSEs occurred when forecasts of the top five models of each horizon are combined.

estimates are influenced heavily by noise as opposed to signal. Hence, VARs only with relatively small number of variables are feasible in practical applications. When it comes to economic forecasting, on the other hand, it is possible that many different variables may be relevant, many more than a standard VAR can incorporate.

The BVAR approach deals with the dimensionality problem by shrinking the parameters via the imposition of priors. Banbura et al. (2008) show that with Bayesian shrinkage, it is possible to handle an unrestricted VAR with large number of variables, where the data set can even be extended to incorporate disaggregated sectoral or geographical indicators.

One of the main challenges in this approach is the selection of prior distributions. In this study, we use the procedure developed in Litterman (1986) and impose Minnesota-style priors. As described in the previous section (2.5), the standard VAR(p) has the form as in equation (29). The priors are specified to follow a multivariate normal distribution, where the means of the coefficients on first own lags are one and the coefficients on the cross lags are zero. Thus, all the equations are centered around the random walk with drift,

$$y_t = A_0 + y_{t-1} + \epsilon_t. \tag{31}$$

Additional characteristics of the Minnesota prior specification include the belief that the more recent lags should provide more reliable information than the more distant ones and that own lags of a variable influence that variable much more than the lags of other variables. According to Litterman, the standard deviation of the prior distribution for lag l of variable j in equation i is given by:

$$S(i,j,l) = \frac{[\gamma g(l) f(i,j)] s_i}{s_j}, \tag{32}$$

where

$$f(i,j) = \begin{cases} 1 \; if \; i = j \\ w \; if \; i \neq j \end{cases}, (0 \leq w \leq 1)\,,$$

and s_i is the standard error of the univariate regression on equation i. The ratio $\frac{s_i}{s_j}$ is for the correction of different magnitudes of the variables. The term γ indicates the overall tightness and is also the standard deviation on the first own lag. The prior can be tightened by reducing this value. $g(l)$ determines the tightness on lag l relative to lag one and can be type of harmonic or geometric with a decay factor (d) of one or two. It tightens the prior on increasing lags. $g(l)$ decays harmonically with $g(l) = l^{-d}$. Geometric type of $g(l)$ tends to get tight very fast. The parameter $f(i,j)$ represents the tightness of variable j in equation i relative to variable i with the relative tightness coefficient w. For deterministic variables the priors are uninformative. In the literature, overall tightness γ, lag decay factor (d) and weight parameter $f(i,j)$ are called as hyperparameters.

In the previous section, due to the dimensionality problem, VAR models only of small size (dimension 2 to 4) are estimated. In a similar way, the final two VAR models, constructed by repetitive variables are of size 5 and 6 with lag length of one. However, we can use larger scale models by employing the advantages of the BVAR approach. For the BVAR models we follow the same two steps introduced in the previous VAR section. Using a similar data set as in the VAR models we estimate two BVAR models. The first BVAR model includes the same variables as the one used for mVAR model but we allow for more lags. The second BVAR model, namely eBVAR, considers a much larger set of variables. This model extends the BVAR model by including four more variables. The summary of the VAR model specifications is shown in Table 2.

For variables in levels (first differences), the prior mean of the coefficient on the first own lag is one (zero), and the prior means of all other coefficients are set to zero.

In order to optimally pin down the hyperparameters, we follow Doan et al. (1984) and maximize out-of-sample forecasting performance of the model. We do grid search over all possible combinations of hyperparameters and lag lengths. We allow 2 to 6 lags. Overall tightness is set to range from 0.1 to 2 with increments of 0.1. The decay factor takes values of 1 and 2. Values for the weight parameter are 0.00, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 1.0. All possible combinations of hyperparameters and lag lengths yield 2400 BVAR models. Similar to the previous sections, we estimate them for the period 2003Q1:2009Q3 and construct one, two, three and 4-step-ahead forecasts. Then, the sample is extended one period and models are re-estimated. New forecasts are obtained until 2011Q2. Out of sample forecast accuracy is measured in terms of RMSE. The weighted average of 1, 2, 3 and 4-step-ahead RMSE's are calculated. We select the hyperparameters and lag length by looking at the pseudo out-of-sample forecast performances, the model having the minimum weighted average RMSE is selected as the chosen model for forecasting at all horizons.

2.7 DYNAMIC FACTOR MODEL

The last method to forecast inflation in this study is the dynamic factor model. Factor analysis is a statistical approach that can be used to analyze relationships among a large number of variables and explain these variables in terms of their common underlying dimensions. In particular, it condenses the information contained in a number of original variables into a smaller set of dimensions with a minimum loss of information.

There are two types of factor analysis. The first type is the 'common factor analysis' and it is what researchers mean when they refer to "factor analysis". This family of techniques uses an estimate of common variance among the original variables to generate the factor solution, where the solution is used to identify the structure underlying such variables and to estimate scores to measure latent factors themselves. Second approach to dimension reduction method is the principal component analysis which provides a unique solution, so that the original data can be reconstructed from results. Principal component method deals with the total variance among variables, so the solution generated will include as many factors as variables, although it is unlikely that they will all meet the criteria for retention. Besides, for the case of principal components, statistical factors do not have immediate economic interpretation. On the other hand, factor analysis has an advantage over principal component analysis such that it relies more on intuition as theory guides, as the latent factors have an underlying structure related to the theory.

Factor analysis can be made in a static or a dynamic setup and the number of studies which use dynamic factor models have increased recently.[28] The shift of focus from static factor models to

[28] Dynamic factor models were originally proposed by Geweke (1977), which opened a new page in the literature by introducing lags in factor loadings. The related literature developed new techniques for estimating these models. The time-domain approach of Stock and Watson (1989, 2002) and the frequency-domain approach of Forni and Reichlin (1998) and Forni et al. (2000) are such examples.

dynamic factor models stems from the difficulty of having empirical support for the static models, which is related to the fact that the real world is inherently dynamic and not static.

In this study, we follow the approach proposed by Giannone et al. (2008), which develops a parametric dynamic factor model cast in a state space representation and estimate the factors in two steps.[29] In the first step, we test the number of dynamic factors. Specifically, let $X_t = (x_{1,t}, x_{2,t}, \dots, x_{n,t})'$ denote the observables. We assume that X_t has the following factor model representation:

$$X_t = \mu + \Lambda F_t + \varepsilon_t, \tag{33}$$

where F_t is a $k \times 1$ vector of unobserved factors, which represents the common movements of observables and ε_t is a vector of idiosyncratic components that are assumed to have zero mean. On the other hand, the constants $\mu = (\mu_1, \mu_2, \dots, \mu_n)'$ are the unconditional means. Further, factors are modeled as a VAR process of order 1:

$$F_t = \Theta F_{t-1} + u_t, \;\; u_t \sim i.i.d.N(0, Q), \tag{34}$$

where Θ is the $k \times k$ matrix of autoregressive coefficients. Finally, we assume that the idiosyncratic component of the observables follows an AR(1) process:

$$\varepsilon_{i,t} = \alpha_i \varepsilon_{i,t-1} + \vartheta_{i,t}, \quad \vartheta_{i,t} \sim i.i.d.N(0, \sigma_i^2), \tag{35}$$

with $E[\vartheta_{i,t}\vartheta_{j,s}] = 0$ for $i \neq j$.

Using the dynamic factor illustrated above, we extract factors from six groups of different variables. Rather than using all variables in the pool at the same time, we prefer clustering them according to their relations with inflation. Hence, the clusters are inflation expectations (of households, firms, financial sector participants), economic activity measures (demand components of GDP, unemployment, industrial production, etc.), external prices (import, commodity prices), exchange rates, financial (stock prices, risk indicators) and monetary indicators (currency in circulation, non-borrowed reserves).[30] All factor estimations are done using the balanced dataset and the number of factors to be extracted within each group is decided using an information criterion developed by Bai and Ng (2007).

In the second step, we employ these factors to forecast quarterly inflation. For that, we follow two approaches, namely the linear projection of inflation based on the projected factors[31] (FM_SE) and the factor-augmented VAR (FAVAR), introduced by Bernanke and Boivin (2003).

For the linear single equation case, quarterly inflation rate is estimated as a function of projected factors:

$$\pi_{t+h} = \mu + \beta(L) f_{t+h} + \alpha(L) X_t + v_{t+h}, \tag{36}$$

where μ is a constant, f_t is estimated factor, $\beta(L)$ and $\alpha(L)$ are vectors of lag polynomials and X_t is the vector of exogenous variables (i.e. seasonal dummies in this exercise). To obtain h-step-ahead predictions for inflation, we first specify a large number of candidate models (44 models) using the

[29] Details take place in Doz et al. (2011).
[30] The details of six different data groups and the transformation of the variables can be found in Table 1.
[31] See Stock and Watson (2010).

general to specific modeling approach. Then, we apply a pseudo out-of-sample forecasting exercise and determine the best five performing models for each horizon based on the RMSEs. In the next step we have selected the most repeated three single equation models (which include the factors derived from exchange rates, economic activity measures, external prices and financial indicators) that appeared among the top 20 models and report the final forecasts as an average of the projections of these models.

For the FAVAR forecasting, we apply exactly the same procedure introduced in the VAR section. The only difference is that we use only the estimated factors as endogenous variables while exogenous variables remain the same. Based on the pseudo out-of-sample forecasting exercise and optimality calculations (see footnote 27), we determined the factors that appear most frequently in top ten performing models. Then, we build three different FAVAR models with the lag order of one by using these repetitive factors (which are the first factors of exchange rate, economic activity, external price, financial and monetary indicator groups) and inflation forecasts are formed from average of the projections of these models.

3. FORECAST COMBINATION

Having several models forecasting the same variable brings the following question: should we use a single model or is it better to combine forecasts? Timmermann (2006) argues that it is critical to identify whether or not the information sets underlying the individual forecasts are observed by the forecast user. If so, it would be appropriate to pool all the information and construct a "super" model nesting each of the individual forecasting models. Likewise, Diebold and Lopez (1996) claim that it is always optimal to combine information sets rather than forecasts if it is costless to combine the former. However, it is usually infeasible to combine the information sets in practice since they may be unobserved by the forecast user. Furthermore, Bjørnland et al. (2008) argue that usual analytical techniques may not be suitable for combined information set since the number of regressors may be large relative to the sample size. Under these conditions, the best way to exploit information from different forecasters is to combine their forecasts.

A second argument developed for forecast combination is related with structural breaks. While some models may adapt quickly and be affected only temporarily by structural changes, others may be slowly responding. Since it is generally difficult to pin down structural breaks in real time, by combining forecasts from models with different degrees of adaptability, the forecast user may have better performing forecasts compared to a single model.[27] Another reason for combining forecasts is that individual forecasting models may have misspecification biases. The true data generating process (DGP) can be more complicated and of a much higher dimension than the models ultimately used by a forecaster. If these models are subject to biases of an unknown form, then forecast combination may improve forecast accuracy by averaging out the biases.[32] Similarly, Granger and Ramanathan (1984) propose that forecast combination can yield unbiased forecasts even if the individual forecasts are biased.

The arguments made against forecast combination generally gather around deriving the combination weights. Estimation errors and nonstationarities underlying the DGP are considered to contaminate the combination weights, hence leading to less sensible forecasts.[33] However, there is

[32] See Bjørnland et al. (2008), Timmermann (2006) and the references therein.
[33] See Timmermann (2006) and the references therein.

some empirical evidence which show that forecast performance improves with forecast combination. For example, Bates and Granger (1969) show that combined forecasts of two different sets of forecasts, each having some independent information, yield improvements. Using a quarterly data set covering 1959-1999 for seven OECD countries, Stock and Watson (2004) find that forecast combination outperforms an autoregressive benchmark when forecasting output growth. Lack (2006) illustrates that the performance of VAR forecasts obtained from averaging ten different VAR models is much better than that of a single best VAR model in all forecast horizons. In their study, Kapetanios et al. (2006) find that most combination techniques beat a single benchmark model in various cases when forecasting UK inflation. Kapetanios et al. (2007), in their discussion of the BoE's suite of statistical models, show that two different models are generally preferred to combinations when forecasting UK GDP growth, while a combination method systematically outperforms the single benchmark at all horizons when forecasting inflation.

To consider whether the performance of short term forecasts of the models entertained in this study may be improved or not, we adopt forecast combination. The analysis encompasses different methods to combine forecasts and focuses on the ones with lower forecast errors. These methods are all linear combination schemes[34] and some of them assume constant weights while others use time varying weights. All the methods derive combination weights, which sum to one at each period, separately for each horizon. We consider seven alternative forecast combinations as displayed in Table 3.

Simple average, median and trimming can be considered under statistical approaches. The first of these approaches is optimal if forecast error variances are equal and the correlations between them are zero.[35] However, there are many papers finding that simple average is at least as good as more complicated schemes even when these conditions are not satisfied.[36] On the other hand, trimmed combinations may be advantageous when the data includes extreme values. By trimming, models that add marginal information are given zero weight. Hence, the forecast accuracy is improved by removing these "noisy" forecasts. How to trim and how much to trim are also important when trimming. In this study, forecasts are trimmed by 5 percent symmetrically once they are sorted from the highest to the lowest. The remaining forecasts are then equally weighted.[37]

RMSE weights and System for Averaging Model (SAM) weights are based on the forecast error performances measured by RMSE. A model with the lowest (highest) RMSE receives the highest (lowest) weight in both of these approaches. The former method uses RMSE of each model calculated for the "full" pseudo out-of sample period when assigning weights. Hence, the weights are constant within a horizon. The second approach, which is applied at the Norges Bank, computes RMSEs recursively using the pseudo out-of sample period.[38] Therefore, the weights are updated recursively within a horizon. A final forecast is computed by summing the forecasts of individual models multiplied by their weights.

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[34] Non-linear combination methods can also be used in forecast combinations. For a discussion of such methods, see Timmermann (2006) and the references therein.
[35] See Bates and Granger (1969).
[36] For example, see Stock and Watson (2004), and Genre et al. (2010).
[37] The trimming method used in this study is similar to the one used in Stock and Watson (2004) and Genre et al. (2010). However, there can be many ways to trim forecasts. For example, Swanson and Zeng (2001) determine which forecasts to combine using the AIC or SIC criteria of the models.
[38] See Bjørnland et al. (2008).

The final combination schemes considered are Performance Based (PB) weights and Recent Best Forecaster (RBF). Both of these schemes are based on the squared forecast errors. PB weights are derived recursively by putting more emphasis on recent performance and discounting past forecast errors. Stock and Watson (2004) propose the following form for PB weights:

$$w_{it} = \frac{{m_{it}}^{-1}}{\sum_{j=1}^{n} {m_{jt}}^{-1}} \text{ and } m_{it} = \sum_{s=T_0}^{t-h} \delta^{t-h-s} (y_{s+h} - \hat{y}_{i,s+h})^2, \tag{37}$$

where δ is the discount factor and m_{it} represents the cumulative sum of discounted squared forecast errors since the start of pseudo out-of-sample (T_0). y_{s+h} is the realized value and $\hat{y}_{i,s+h}$ is the forecast of model i. The weight of model i at time t is shown by w_{it} and it is inversely proportional to model i's cumulative forecast errors. A combined forecast at a particular time is obtained by summing the weighted forecasts of each individual model, where the weights sum to one (i.e., $\sum_{j=1}^{n} w_{jt} = 1$). Clearly, to discount the historical forecast errors, δ needs to be in$[0,1)$. The closer it is to zero, the lower values assigned to more distant forecast errors in the computation of combination weights.[39] In this paper, δ is taken as 0.9, consistent with the empirical literature.[40]

RBF, on the other hand, assigns all the weight to the model which has the smallest squared forecast error in previous quarter and zero weight to the remaining models. Basically, it only uses the forecast of the recent best model for the horizon considered.[41] Alternatively, the recent best model may be determined according to the lowest mean squared forecast error over a rolling window v. Since the pseudo out- of-sample period is short, v is chosen as 1 in this study.[42]

4. FORECAST EVALUATION

The quality of the forecasts is evaluated by the relative RMSE (RRMSE), which is the ratio of the RMSE of a model or combination method to the RMSE of the benchmark. An RRMSE above (below) 1 means that the alternative approach performs worse (better) than the benchmark. The RRMSE is calculated at each forecast horizon h as follows:

$$RRMSE_h = \sqrt{\frac{\sum_{t=2009Q3+h}^{2011Q2} ({f_t}^m - r_t)^2}{\sum_{t=2009Q3+h}^{2011Q2} ({f_t}^b - r_t)^2}}, \tag{38}$$

where $h = 1, \dots, 4$ quarters, ${f_t}^m$ represents the forecast of a model or combination method, ${f_t}^b$ shows the forecast of the benchmark and r_t stands for the realized value of annual inflation rate.

[39] When $\delta = 1$, past is not discounted. This corresponds to an optimal weighting case, discussed in Bates and Granger (1969), where the individual forecast errors are uncorrelated. PB weights approach ignores correlations across forecast errors. Timmermann (2006) argues that when time series is short compared to the number of forecasts, the correlations between forecast errors can be poorly estimated. In such a situation, estimation errors in the combination weights tend to be large. Ignoring the cross correlations can be a solution to this problem.
[40] See, for example, Stock and Watson (2004) and Genre et al. (2010).
[41] Hence, RBF can be classified as a performance based weighting scheme. However, it can also be considered as a type of aggressive trimming because all models are trimmed except for the recent best.
[42] Genre et al. (2010) argue that window lengths of $v = 1$ and $v = 4$ are common in empirical analysis. When $v = 4$, the forecaster with the lowest mean squared error, which is an average of the squared errors of last 4 quarters, is chosen as the recent best.

Relatively short pseudo out-of-sample period is one of the limitations of this study. A small out-of-sample not only hampers the evaluation of the performance stability of models, but also raises doubts about the performances measured. Furthermore, the period covered by the pseudo analysis contains the effects of the global financial crisis, during which behaviors of many macroeconomic variables have changed considerably. Therefore, our findings may be specific to the sample size as well as the period studied, and subject to change as the data accumulate.

The traditional random walk is picked as the benchmark since it performs better compared to other univariate models. Although some of the univariate models either improve on or are roughly on a par with the traditional random walk, any of them neither beats it across all forecasting horizons nor has a smaller RMSE-sum of all horizons (Table 4). Furthermore, being fairly simple to be constructed, the random walk is a convenient model to compare the performances of more complicated models.

In general, performances of univariate models are not promising. They deliver relatively high forecast errors compared to other individual models. Particularly, unconditional mean displays a poor performance. As a matter of fact, Kapetanios et al. (2007) point that this model performs relatively well for longer horizons given the fact that inflation is mean-reverting in the long run and inflation targets form a natural anchor in low inflation economies. Among the univariate models only SARIMA beats the benchmark at $h = 1$. Stock and Watson (2005) suggest that with "great stability", which is defined for US inflation as straying less far from the unconditional mean than in the past, univariate models are hard to beat. However, for Turkey relatively poor performance of univariate models does not come as a surprise given that they lack information coming from macroeconomic variables that are especially important for the inflation dynamic in emerging market countries. Moreover, inflation in Turkey does not present such a stable dynamic.

Most of the entries, except for the univariate ones, in Table 4 are below 1 for the first 2 quarters ahead, suggesting that they provide better inflation forecasts relative to the benchmark. Yet, the performance of the benchmark is hard to beat for most of the individual models at 4 quarters ahead.[43] Figure 1 shows the relative performances of the individual models at $h = 1$ and $h = 2$. The gains are clearly evident for the VAR based models, which forecast 1-quarter-ahead inflation better compared to 2-quarter-ahead. Particularly, although the VAR and mVAR models outperform the benchmark by more than 45 percent at 1-step-ahead and 15 percent at 2-step-ahead, they perform relatively poor compared to the benchmark at $h = 3$ and $h = 4$. The gains under TVP model are also noticeable up to 3 quarters ahead, it improves on the benchmark by over 30 percent. In some cases, the WAVE and UC models beat the traditional random walk, however their scopes for improvement are smaller compared to other alternatives. Within the factor-based approaches, FAVAR does better than the FM_SE. However, performances of these factor-based models change across horizons and the gains are neither consistent nor quantitatively noticeable most of the time. The best forecasts are provided by the BVAR and eBVAR models.[44] They consistently outperform the benchmark at all

[43] Andersson and Löf (2007) and Kapetanios et al. (2007) show that the forecast horizon is important for assessing the forecast performances of alternative models.

[44] In the literature there are a lot of evidences showing that BVAR models with Litterman's prior outperforms the alternative models such as univariate time series models, VAR, and large scale macro-models for various macro variables (e.g., Doan et al., 1984; Kadiyala and Karlsson, 1993 and 1997; Litterman (1986) and Robertson and Tallman (1999)). Bloor and Matheson (2009) also find that the modified Litterman prior outperforms

forecasting horizons. Relative to the benchmark, they deliver a reduction in the RMSE by more than 60 percent at $h = 1$ and 30 percent at $h = 2$ and $h = 3$. Although they have similar performances up to 3 quarters ahead, the BVAR seems to have a better forecast accuracy when forecasting 4-step-ahead inflation compared to the eBVAR.

As shown in Figure 2, the best performing individual model of each horizon differs. While, the best 1-step-ahead forecasts are produced by the mVAR, other horizons are best forecast by the TVP, eBVAR and BVAR models. Yet, the performance of the BVAR is rather close to the superior models of each horizon. Therefore, the BVAR seems to be the best individual forecasting model for Turkish inflation. One point comes to mind at this point is that since the forecast evaluation period covers the effect of global financial crisis; the models that can adapt relatively faster in recursive estimation are likely to provide better out-of-sample forecasts. This could be an explanation for the relatively better performance of TVP and BVAR models.

Combining forecasts, on the other hand, improves the forecast accuracy compared to the benchmark. This is consistent with the results of Kapetanios et al. (2007) for BoE and Bjørnland et al. (2008) for Norges Bank, where they suggest that forecast combination yields a superior performance. All forecast combinations, but the RBF, have RRMSEs less than 1 for the first 3 quarters ahead. In the case of 4 quarters ahead, only some of the combination strategies improve on the benchmark and the gains are smaller compared to other horizons. Among the combination methods, the simple average, RMSE weights, SAM weights and trimmed average consistently outperform the benchmark at all forecasting horizons. Figure 3 depicts the relative forecasting performances of the combination strategies. It is notable that the forecast accuracy of the combination methods decreases as the horizon grows. The poor performance of the RBF relative to other methods is also apparent.[45] Performances of the simple average, SAM weights, trimmed average and median are quite close to each other. Specifically, the simple average provides almost 50 percent RMSE reduction at $h = 1$, and to a lesser extent at 2-4 quarters ahead.[46] The best combination scheme is the RMSE weights since it gives the lowest RRMSEs at all horizons. Specifically, the gain under the RMSE weights is more than 60 percent for one step ahead, and approximately 40 percent for other forecasting horizons.

Overall, results indicate that the very best forecasts are produced by the BVAR and the RMSE weights. Figures 4 and 5 display the inflation forecasts and their corresponding realizations. Both approaches produce more accurate forecasts when forecasting 1-quarter-ahead inflation compared to 2-quarter-ahead. Besides, 1-quarter-ahead forecasts of these are strikingly close to the realizations. However, as shown in Figure 6, the BVAR has a tendency to underpredict inflation once all horizons are taken into account. In brief, though both approaches improve on the benchmark, the gain under the forecast combination is a bit stronger relative to the BVAR since RMSE weighted method yields a smaller RMSE-sum of all quarters.

univariate and VAR benchmarks and produces comparable forecast accuracy to the judgmentally-adjusted forecasts produced internally at the Reserve Bank of New Zealand.

[45] Consistent with this result, Timmermann (2006) and the references therein find that choosing the previous best models is “not a good idea” since they usually become the worst models in the future or vice versa.

[46] The competitive performance of the simple average comes as no surprise. For example, a similar finding has been shown in Stock and Watson (2004) and Genre et al. (2010). Also, while all individual forecasts are only equally weighted in Lack (2006), simple averaging is one of the two main combinations of interest in Kapetanios et al. (2007) since both of these studies acknowledge that the simple average works well in practice.

5. CONCLUDING REMARKS

This study produces short term forecasts for Turkish inflation by using a large number of econometric models. Testing the presence of nonlinearity and finding out its absence, we conclude that nonlinear modeling would not add any significant value when forecasting Turkish inflation. Hence, we proceed with the set of models which include univariate models, decomposition based models, a Phillips curve motivated time varying parameter model, a suite of VAR and Bayesian VAR models and dynamic factor models. Furthermore, several weighting methods are implemented to combine individual model forecasts.

It should be noted that due to relatively short pseudo out-of-sample period, the findings of the study might be subject to change as the data accumulates. But the initial evaluation of the forecasts illustrates that individual models incorporating more economic information performs better than the benchmark random walk model at least up to two quarters ahead. This finding comes as no surprise since these models exploit larger data sets, which are likely to involve more information about inflation compared to a data set used by any single equation model. The gains are clearly evident for the VAR based models. In particular, Bayesian VAR models appear to fit the data well. They consistently outperform the benchmark at all forecasting horizons. Although the best performing individual model of each horizon differs, the performance of BVAR is rather close to the superior models of each horizon. Despite the favorable gains under individual models, there is a scope for improvement from combination strategies. Forecast combination in general leads to a reduction in forecast error compared to individual models and slightly improves on the BVAR when RMSE weighting scheme is adopted.

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Table 1: Variables in VAR and Dynamic Factor Models

Variables in Unrestricted VAR Models Estimated at First Stage

Category	Variables
Real activity measures	Output gap, three different principle components of the GDP components
Commodity prices	Import price index, Goldman Sachs commodity price index, and a principle component of these two
Exchange rates	Euro/TL, USD/TL nominal rates, and a principle component of these two
Monetary aggregates	M_2, M_3, currency in circulation, currency issued and principle components of these
Interest rate	Benchmark interest rate
Exogenous variables	Seasonal dummies, tax on fuel oil prices

Variables in Dynamic Factor Models

Category	Variables
Inflation expectations	12 month ahead CPI inflation expectation (Survey of Expectations), 12 month ahead CPI inflation expectation of consumers (Consumer Tendency Survey), 12 month ahead CPI inflation expectation of financial sector participants (CNBC-e Survey)
Real activity measures	Output gap, capacity utilization rate (sa), industrial production (sa), unemployment rate (sa), employment excluding agriculture (sa), GDP (sa), private consumption (sa), government consumption (sa), private investment (sa), change in stocks (sa), total final domestic demand (sa), export (sa), import (sa), output gap of OECD region, CNBC-e consumption index (sa), consumer confidence index
External prices	Import price index, Goldman Sachs commodity price index, Goldman Sachs wheat price index, FAO food price index, Crude oil prices per barrel (Brent), gold prices (Bloomberg, sa), import price index of food manufacturing industry
Exchange rates	Euro/TL, USD/TL nominal rates, and CPI based real effective exchange rate index (CBT)
Financial indicators	ISE national 100 index, MSCI EM equity index, S&P500, EMBI+ composite total return, EMBI+ Turkey total return, EMBI+ sovereign spread (all EM), EMBI+ Turkey sovereign spread, 5 year CDS rate of Turkey, VIX index
Monetary indicators	Currency in circulation (sa), nonborrowed reserves, net liquid assets of banking sector, benchmark interest rate, weighted average interest rates for deposits (in TL) up to 3 months

Note: "sa" refers to seasonally adjusted series

Table 2: Variables in VAR models

Endogenous variables	VAR models			
	Unrestricted		Bayesian	
	VAR	**mVAR**	**BVAR**	**eBVAR**
Output gap	*	*	*	*
Goldman Sachs commodity price index	*	*	*	*
Euro/TL nominal exchange rate	*	*	*	*
Benchmark interest rate	*	*	*	*
M_3		*	*	*
Wage				*
Total Credits				*
ISE National 100 Index				*
EMBI+ Turkey				*
Exogenous variables				
Constant	*	*	*	*
Seasonal dummies	*	*		
Lags	1	1	4	4

Table 3: Forecast Combination Methods by Type of Weights

Method	
Constant Weights	**Time Varying Weights**
Simple Average	Median
Trimmed Average	System for Averaging Models (SAM) Weights
RMSE Weights	Performance Based (PB) Weights
	Recent Best Forecaster (RBF)

Table 4: RMSEs Relative to the Traditional Random Walk Benchmark

	Forecast Horizon			
	h=1	**h=2**	**h=3**	**h=4**
Individual Model Forecasts				
RW_T[1]	1.00	1.00	1.00	1.00
RW_D	2.07	1.18	1.20	**0.96**
UM	3.59	2.35	2.50	3.24
AR	1.10	1.37	1.90	2.91
SARIMA	**0.76**	**0.99**	1.27	1.38
VAR	**0.53**	**0.82**	1.02	1.17
mVAR	**0.24**	**0.69**	1.17	1.79
BVAR	**0.30**	**0.60**	**0.61**	**0.58**
eBVAR	**0.36**	**0.66**	**0.60**	**0.85**
TVP	**0.61**	**0.54**	**0.67**	1.11
WAVE	**0.88**	**0.72**	1.08	1.04
UC	**0.93**	1.04	1.00	**0.90**
FM_SE	1.24	**0.75**	1.20	1.19
FAVAR	**0.93**	**0.58**	**0.98**	1.74
Forecast Combination				
Simple Average	**0.53**	**0.61**	**0.69**	**0.88**
Median	**0.43**	**0.63**	**0.83**	1.01
RMSE Weights	**0.34**	**0.54**	**0.55**	**0.62**
SAM Weights	**0.43**	**0.71**	**0.81**	**0.96**
PB Weights(δ=0.9)	**0.39**	**0.94**	**0.95**	1.29
RBF	**0.37**	1.39	1.23	1.77
Trimmed Average	**0.47**	**0.61**	**0.69**	**0.85**

Notes: The abbreviations of the individual forecasting models are used as follows: RW_T: Traditional Random Walk, RW_D: Direct Random Walk, UM: Unconditional Mean, AR: Autoregressive Model, SARIMA: Seasonal ARIMA, VAR: Vector Autoregressive Model, mVAR: Monetary VAR, BVAR: Bayesian Vector Autoregressive Model, eBVAR: Extended BVAR, TVP: Phillips Curve Motivated Time Varying Parameter Model, WAVE: Wavelet Filter Approach, UC: Unobserved Component Model, FM_SE: Factor Model Single Equation, FAVAR: Factor-augmented Vector Autoregression Model.

[1] The entries are the RMSE of the alternative model or combination method relative to the RMSE of the traditional random walk. Figures in bold represent RRMSEs smaller than one. Best performing models/methods of each horizon are shaded in grey.

Figure 1: Relative RMSEs of Individual Models at h=1 and 2

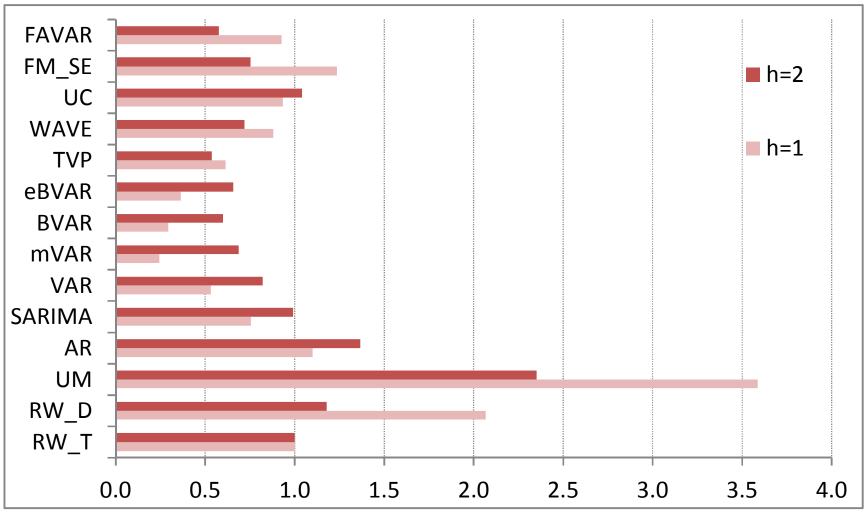


Figure 2: RRMSEs of Best Performing Individual Models For Each Horizon

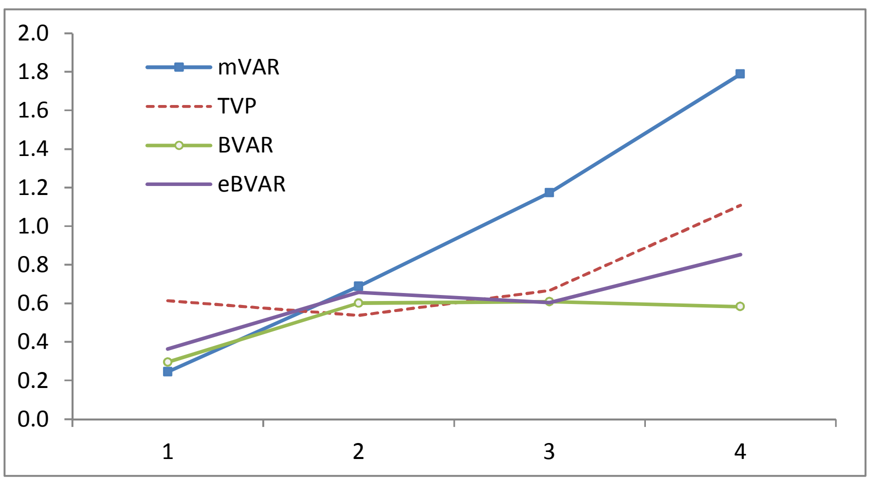


Figure 3: Relative Forecasting Performance of the Combination Strategies

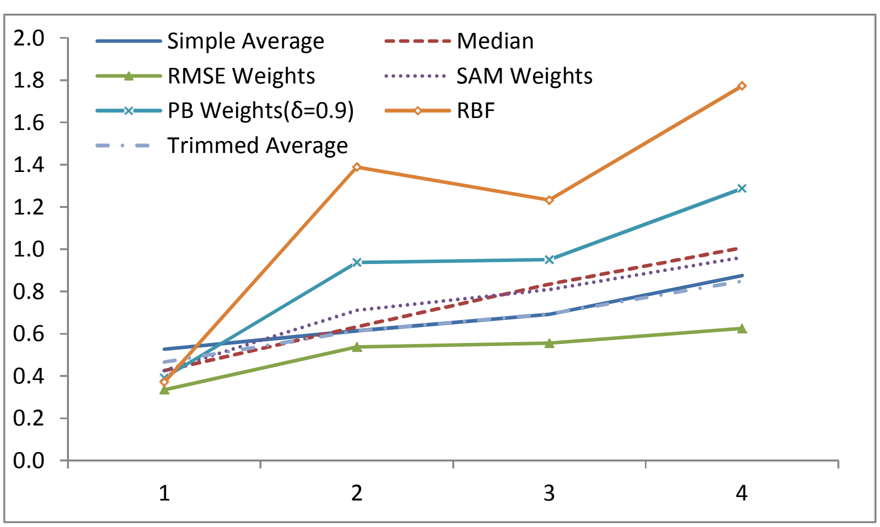
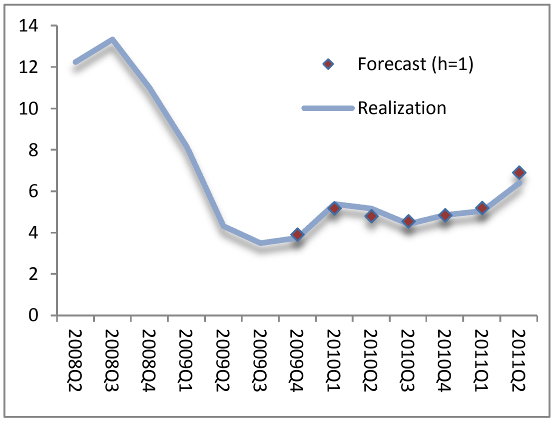


Figure 4: Forecasts and Realizations for h=1

a) BVAR



b) RMSE Weighted Combination Method

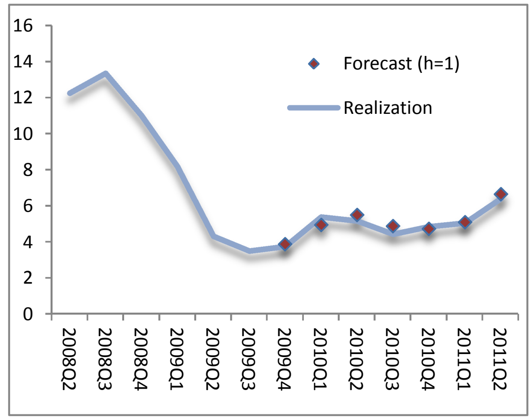
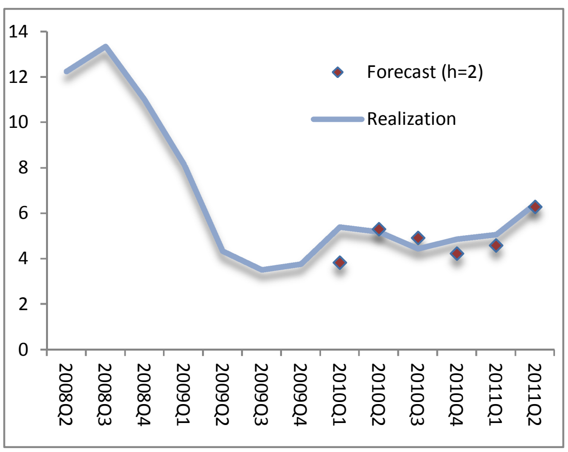


Figure 5: Forecasts and Realizations for h=2

a) BVAR



b) RMSE Weighted Combination Method

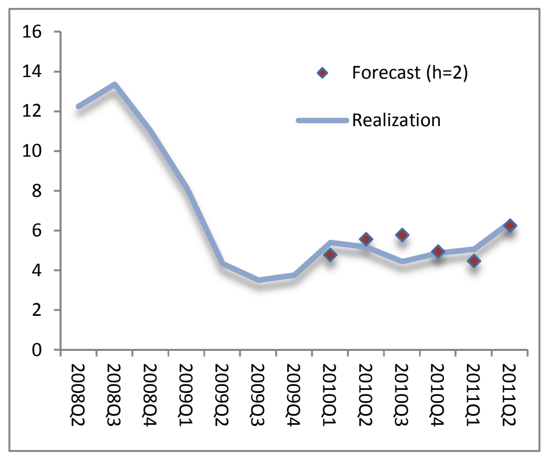
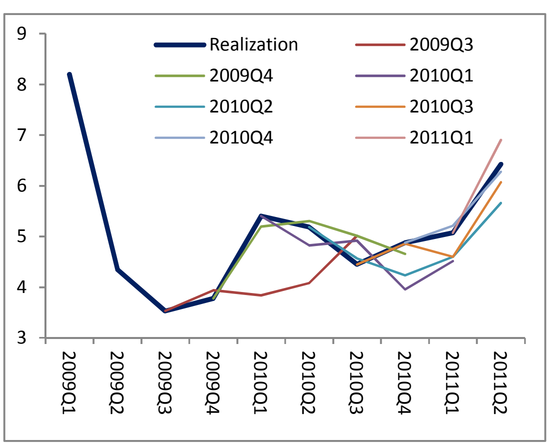
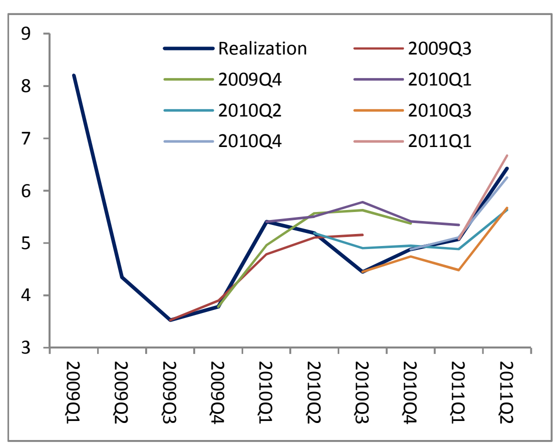


Figure 6: Realization and Forecasts

a) BVAR



b) RMSE Weighted Combination Method



Note: Figure graphs BVAR forecasts at different times. Dates in the legends refer to the end date of each recursive sample.

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