Probability Forecasts of Macro Aggregates in Turkish Economy*

Hüseyin Kaya
Bahcesehir University

M. Ege Yazgan†
Istanbul Bilgi University

January 23, 2014

Abstract

In this paper, we provide probability forecasts of key Turkish macro economic variables such as inflation and output growth. A number of probabilistic forecasts of different scenarios associated with these variables are also calculated. The probability forecasts take into account different types of uncertainties regarding the future, model and structural breaks and are derived from a core vector error correction model of the Turkish economy and its several variants. Model and window averaging are used to address uncertainties arising from estimated models and possible structural breaks. The performances of the different models and their combinations are evaluated using relevant forecast accuracy tests in different pseudo-out-of-sample settings. The results indicate that successful directional forecasts can be obtained for output growth and inflation. Both averaging over the models and estimation windows improve the level of accuracy of the forecasts. Some successful scenario forecasts associated with output growth are also presented.

JEL Classifications: C32, C53, E17

Key Words: Probability forecasts; Forecast combinations; Forecasting and structural breaks, Turkish economy

*We would like to thank the anonymous referee and the editors for very helpful comments.

†Corresponding author. E-mail:ege.yazgan@bilgi.edu.tr

1 Introduction

Forecasting is pervasive in almost all areas of economics. Given its practical importance in policy and decision making, forecasting has received considerable attention from policy makers, market professional and academics.[1]

As emphasized by Gneiting (2008), among others, forecasts ought to be probabilistic in nature. However, empirical macro study forecasts are usually presented in the form of point forecasts, and their uncertainty is characterized by forecast confidence intervals if considered. As emphasized by Garratt et al. (2003a) and Garratt et al. (2006), point forecasts are reliable only when the decision problem is linear in constraint and quadratic in the loss function (LQ form). Hence, because many decision problems in economics may not be in LQ form, probability forecasts serve useful. As discussed in Diebold and Lopez (1995) and Gneiting (2008), there are other good reasons to believe that probability forecasts can be beneficial and therefore may become increasingly prominent in economic applications. For example, in its inflation reports, the Bank of England has been issuing density forecasts of inflation and output growth, called "Fan Charts", since 1997.[2]

Despite their importance, the usage of probability forecasts in applied works is not very widespread, and point forecasts continue to be the dominant form of formulating predictions about the future values of economic variables. In this paper, we aim to contribute to the applied literature on probability forecasts by providing an application in the context of the Turkish economy.[3] To generate the probability forecasts of Turkish macro variables, following Garratt et al. (2003a), Garratt et al. (2003b), Garratt et al. (2006), Assenmacher-Wesche and Pesaran (2008),[4] this paper adopts a long-run structural modeling approach and develops a vector error correction model for the Turkish economy. We make use of some variants of this model for the purpose of model averaging and achieve better forecasting performance in combination with window averaging.

[1]The theoretical and empirical literature on forecasting is voluminous. See Elliott and Timmermann (2008) for a review.

[2]For a detailed discussion and evaluation of Bank of England's probability forecasts see Britton et al. (1998) and Clements (2004).

[3]To the best of our knowledge, this paper constitutes the first probability forecast exercise using Turkish macroeconomic data.

[4]Fair (1980) proposes a pioneering work for estimating the uncertainty of a forecast from an macroeconometric model by considering future uncertainty, parameter uncertainty, model uncertainty and uncertainty due to the exogenous-variable forecast.

Forecasts in economics are usually carried out using time series models. Model- based forecasts are subject to a number of uncertainties that make predicting the future values of the economic variables difficult. In this paper, we attempt to address some of these uncertainties by combining model and window averaging in the context of probability forecasts. We attempt to control future uncertainty, which refers to the unobserved future shocks on forecasts, using probability forecasts.

Model uncertainty, in general, arises from the fact that no model can capture all the features of the data generating process under consideration. Therefore, to account for this type of uncertainty, we use a forecast combination approach. Since the seminal work of Bates and Granger (1969), combining the forecasts of different models, rather than relying on the forecasts of individual models, has come to be perceived as an effective way of improving the accuracy of predictions regarding a certain target variable. A significant number of theoretical and empirical studies, e.g. Timmermann (2006) and Stock and Watson (2004), have been able to show the superiority of combined forecasts over single-model based predictions.

Another type of future uncertainty is related to changes in some features of the data generation process, namely structural breaks. To reduce the undesirable effects of structural breaks on forecasting performances, we introduce windows averaging and estimate the models over different estimation windows and pool forecasts from different sample periods, as suggested by Pesaran and Timmermann (2007) and Pesaran and Pick (2012). Finally, as in Assenmacher-Wesche and Pesaran (2008) and Pesaran et al. (2009), we also consider model and window averaging together to obtain a total average of the forecasts.[5]

The rest of the paper is organized as follow. Section two describes the data and their time series properties. Section three introduces a cointegrating VAR-X model for Turkey. Section four tests for the existence of the long-run relations embedded in the model and comments on the results. Section five

[5]The other types of uncertainties that are expected to affect the forecast performance are those of parameter, policy and measurement. Parameter uncertainty is concerned with the robustness of the forecast to the selection (estimation) of parameters for a given model. A method for dealing with parameter uncertainty can be easily incorporated into our framework, as we comment below. However, handling policy and measurement uncertainties (data inadequacies and measurement errors) is not as straightforward as is the case of parameter uncertainty and requires using modeling approaches different from the one used here.

explains the derivation of the probability forecasts. Section six outlines how the model uncertainty and structural breaks are taken into account while forecasting with the model. Section seven provides some of the results of the directional forecasts generated by the model and explains their evaluation within a pseudoout-of-sample framework. Section eight presents the probability forecasts of some events associated with inflation and growth for the recent period of the Turkish economy and compares them with the real outcome. Section nine concludes the paper.

2 Data Description and Time Series Properties

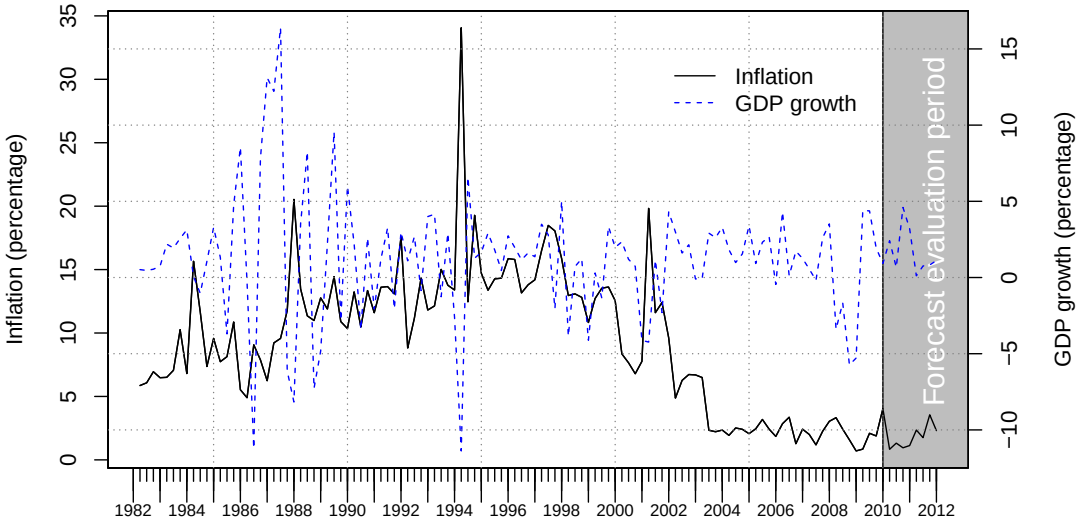
The forecasting application of this paper aims to focus primarily on two main macroeconomic aggregates, namely, output growth and inflation. Figure 1 displays the evolution of these variables over the estimation and forecasts evaluation period. The period of 1982Q1-2009Q4 is used for the estimation of the multivariate model outlined below. The remaining period of 2010Q1-2012Q1 is used to evaluate the performance of the forecasts derived from the estimated model. The figure highlights the volatile nature of Turkish growth; extreme highs and lows are the rule rather than then exception, which makes forecasting more difficult than usual.[6]

On the inflation side, the Turkish economy has been characterized by high levels of inflation and numerous stabilization attempts since the early 1980s. Turkey has succeeded in lowering inflation to single-digit levels with the implementation of a inflation targeting regime (IT), which started in January 2002. Over the period of 2002-2005, implicit inflation targeting was implemented. The plan was to reduce inflation to 35% in 2002, 20% in 2003, 12% in 2004 and 8% in 2005.[7] With the help of tight and credible fiscal policy, the outcome turned to be successful, and inflation decreased from 68% in 2001 to 7.7% in 2005. After lowering inflation from historically high

[6]The data used Figure 1 are exactly the same as we used in our estimation, i.e. they are seasonally adjusted quarterly inflation and output growth rates computed as the logarithmic difference of the seasonally adjusted output and price levels (see Appendix for detailed description the data). As is shown by Akat and Yazgan (2012), among others, yearly and year over year quarterly output growth also indicate the same pattern of volatility.

[7]Targeted inflation was formulated as December to December percentage changes in CPI.

Figure 1: Inflation and output growth



Quarterly seasonally adjusted inflation and output growth.

levels, the formal IT started to be implemented at the beginning of 2006.[8] The inflation target was set as a point target in which the end-year targets were 5% in 2006, 4% in 2007 and 2008, and 7.5% in 2009. An "uncertainty band" around the target was defined by the Central Bank of the Republic of Turkey (CBRT) and set as 2% in both directions considering uncontrollable developments such as oil prices, international liquidity conditions, taxes etc. (CBRT, 2006). In 2009, the point target was set as 6.5% for 2010, 5.5% for 2011 and 5% for 2012, with the CBRT maintaining the same 2% uncertainty band intact (see Kara (2012) for an evaluation of the recent monetary policy of Turkey).

Our model consists of 4 domestic and 3 foreign variables. The domestic variables are the Turkish output (y_t), price level (p_t), interest (r_t) and exchange rate (e_t) which is an average of the TL/Euro and TL/US Dollar exchange rates. The first two foreign variables, foreign price (p_t^*) and output (y_t^*), are constructed as the trade weighted averages of OECD countries' prices and outputs. Unlike output and price, the foreign interest rate (r_t^*) is calculated as the average of only the Euro (Euribor) and US interest rates, reflecting the fact that financial linkages can be better captured by a small

[8]For detailed information about implicit IT implementation, see Kara (2008).

number of countries dominating the Turkish financial market. All variables are expressed in logarithms. The data cover 1982Q1-2009Q4 for the estimation period but are extended to 2012Q1 for the forecast evaluation exercise. They are defined more precisely in the Appendix, where the data sources are also explained.

Because the modeling procedure described in the following sections depends on the time series properties of these variables, we apply several different unit root tests to obtain possibly robust results, and find that all the series contain a unit root in their levels.[9] In contrast, their first differences appear to be stationary. The only exception is the inflation ($\triangle p_t$), where only the unit root tests taking into account structural breaks indicate stationarity. As is well known, Perron (1987) and Perron (1997) assert that a stationary series can be spuriously detected as non-stationary in the presence of breaks.[10]

3 Cointegrating VAR-X Model

The probability forecasts are generated from a cointegrating vector autoregressive model of the Turkish Economy with exogenous foreign variables (VAR-X). The model is developed along similar lines as the cointegrating VAR-X models of the UK and Swiss economies described in Garratt et al. (2003b) and Assenmacher-Wesche and Pesaran (2008). To construct the model, we begin by assuming that the three following equilibrium relationships hold, in the long-run, for the Turkish economy;

$$p_t - p_t^* - e_t = a_{10} + a_{11}t + \varepsilon_{1,t} \tag{1}$$

$$r_t - r_t^* = a_{20} + \varepsilon_{2,t} \tag{2}$$

[9] They include 3 different ADF tests, KPSS test and Phillips-Perron test. The ADF-WS (Park and Fuller, 1995) and the ADF-GLS test (Elliott, 1996) tests are used in addition to the standard ADF test. To control structural breaks, we used Perron (1989, 1997) unit root tests. To save space, we do not report these results; however, they are available upon request.

[10] See Kaya and Yazgan (2011), among others, for statistical evidence on the apparent structural break in the Turkish inflation rate that occurred in the first month of 2002.

$$y_t - y_t^* = a_{30} + a_{31}t + \varepsilon_{3,t} \tag{3}$$

where t stands for the linear trend and $\varepsilon_{i,t+1}$, $i = 1, 2, 3$, are stationary errors capturing the deviations from long-run equilibriums implied by corresponding relations. Based on international good market arbitrage, (1) represents the Purchasing Power Parity (PPP) relationship. Although the presence of a linear trend in the PPP relation can be justified by relying on Harrod-Samuelson-Balassa effects and/or the measurement error in prices, particularly in the treatment of quality, its validity requires empirical verification. Similarly, based on the arbitrage between domestic and foreign bond holdings, (2) defines the Interest Rate Parity (IRP) relationship. Finally, based on a stochastic version of the Solow growth model, (3) represents an "Output Gap" (OG) relationship. The empirical validity of this relationship, i.e. the stationarity of the Turkish output gap, can provide evidence in favor of the long-run convergence hypothesis between the OECDs and Turkey's output levels. Similar to the PPP relation, the presence of a linear trend in the OG relation demands empirical verification in this case too. In fact, different convergence hypotheses can be formulated based on different values of a_{30} and a_{31}. In the case of $a_{30} \neq 0$ and $a_{31}, \neq 0$ corresponds to strict or rapid catching up (Li and Papell (1999)). In contrast, strict or rapid convergence can be captured by $a_{30} \neq 0$ and $a_{31} = 0$. Finally, the case of zero mean convergence of (Bernard and Durlauf, 1996) can be characterized as $a_{30} = 0$ and $a_{31} = 0$ (see Stengos and Yazgan (2013) for recent evidence on the general convergence hypothesis)

These three long-run relationships of the model, (1)-(3), can be compactly written as follows

$$\boldsymbol{\varepsilon}_t = \boldsymbol{\beta}' \boldsymbol{z}_{t-1} - \mathbf{a}_1(t-1) - \boldsymbol{a_0} \tag{4}$$

where

$$\boldsymbol{z}_t = (p_t, e_t, r_t, r_t^*, y_t, y_t^*, p_t^*)'$$

$$\mathbf{a}_1 = (a_{11}, 0, a_{31})'$$

$$\mathbf{a}_0 = (a_{10}, a_{20}, a_{30})'$$

$$\boldsymbol{\varepsilon}_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \varepsilon_{3,t})'$$

and

$$\boldsymbol{\beta}' = \begin{pmatrix} 1 & -1 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 & 0 \end{pmatrix}$$

The matrix $\boldsymbol{\beta}'$ imposes all the over identifying restrictions that are necessary to correspond to the long-run relationships.

In this setting, we partition the variables where $\boldsymbol{y}_t = (p_t, e_t, r_t, y_t)$ is treated as an I(1) vector of endogenous variables and $\boldsymbol{x}_t = (y_t^*, p_t^*, r_t^*)$ is treated as an I(1) vector of weakly exogenous variables in which changes in weakly exogenous variables have a direct influence on $\boldsymbol{y}_t$ but are not affected by disequilibrium in the Turkish economy whose extent is measured by the error correction terms. This standard small open economy set-up seems to be a natural choice in the case of Turkey.

Under the assumption of weakly exogenous variables, parameters can be estimated based on the following conditional error correction model (see Pesaran et al. (2000) for example):

$$\triangle \boldsymbol{y}_t = \mathbf{a}_y - \boldsymbol{\alpha}_y[\boldsymbol{\beta}' \boldsymbol{z}_{t-1} - \mathbf{a}_1(t-1)] + \sum_{i=1}^{p-1} \boldsymbol{\Psi}_{yi} \triangle \boldsymbol{z}_{t-i} + \boldsymbol{\psi}_{yx} \triangle \boldsymbol{x}_t + \boldsymbol{v}_{yt} \qquad (5)$$

where $\boldsymbol{v}_{yt}$ is a 4×1 vector of serially uncorrelated shocks, $\boldsymbol{\alpha}_y$ is a 4×3 matrix of error correction coefficients, $\boldsymbol{\Psi}_{yi}$ are 4×7 matrices of short-run coefficients and $\boldsymbol{\psi}_{yx}$ is an 4×1 vector of coefficients that represents the impact of effects of changes in exogenous variables on $\triangle \boldsymbol{y}_t$.

Producing forecasts of endogenous variables using the conditional model requires forecasts of exogenous variables. To construct the forecasts of exogenous variables, we specify the following marginal model:

$$\triangle \boldsymbol{x}_t = \mathbf{a}_x + \sum_{i=1}^{k-1} \boldsymbol{\Psi}_{xi} \triangle \boldsymbol{x}_{\boldsymbol{t-i}} + \boldsymbol{v}_{xt} \tag{6}$$

where $\boldsymbol{\Psi}_{xi}$'s are 1×3 vectors of fixed coefficients and $\mathbf{a}_x$ is a 3×1 vector of intercepts and $\boldsymbol{v}_{xt}$ is a 3×1 vector of shocks, which are assumed to be uncorrelated with $\boldsymbol{v}_{yt}$.

Combining (5) and (6), and solving for $\triangle \boldsymbol{z}_t$, we obtain the following VECM:

$$\triangle \boldsymbol{z}_t = \mathbf{a} - \boldsymbol{\alpha}[\boldsymbol{\beta}' \boldsymbol{z}_{t-1} - \boldsymbol{a}_1(t-1)] + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \triangle \boldsymbol{z}_{t-i} + \boldsymbol{u}_t \tag{7}$$

where $\mathbf{a} = (\mathbf{a_x}, \mathbf{a}'_{\boldsymbol{y}} - \mathbf{a}'_{\boldsymbol{x}} \boldsymbol{\psi}'_{\boldsymbol{yx}})'$, $\boldsymbol{\alpha} = (\mathbf{0}, \boldsymbol{\alpha}'_{\boldsymbol{y}})'$, $\boldsymbol{\Gamma_i} = (\boldsymbol{\Psi}'_{\boldsymbol{xi}}, \boldsymbol{\Psi}'_{\boldsymbol{yi}} - \boldsymbol{\Psi}'_{\boldsymbol{xi}} \boldsymbol{\psi}'_{\boldsymbol{yx}})'$, and $\boldsymbol{u_t} = (\boldsymbol{v_{xt}}, \boldsymbol{v}'_{\boldsymbol{yt}} - \boldsymbol{v_{xt}} \boldsymbol{\psi}'_{\boldsymbol{yx}})'$ is the vector of reduced form errors assumed to be iid$(\mathbf{0}, \boldsymbol{\Sigma})$ where $\boldsymbol{\Sigma}$ is a positive definite covariance matrix.

4 Testing for Long-Run Relations

To provide evidence on the above-specified long-run relations, we test for the number of cointegration vectors (r) among the four endogenous variables of the model by employing Johansen's framework. Using model selection criteria such as AIC and SBC, we confirm that the VAR(2) model is appropriate.[11] Table 1 displays model diagnostic tests[12] and cointegration test results associated with this choice. The trace statistics provide evidence at the 10 percent significance level of the existence of three cointegration relationships.[13]

[11] Model selection criteria select VAR(1) for the marginal model.

[12] Trace correlation is a system goodness-of-fit statistic that can serve the same purpose as R^2 statistics in univariate equations. Note also that these statistics are free of the spurious fit and simultaneity biases; hence, their values are satisfactorily high. The ARCH effect seems to be present only in the interest rate equation and not system wide. Moreover, because the data are quarterly, we do not think the presence of ARCH is very likely. Autocorrelation does not appear to be a problem. However, normality is rejected in all equations and in the whole system. The rejection of normality is not an uncommon situation in similar applications (see Juselius (2006)).

[13] The trend is restricted in the long- run matrix during estimation while the intercept is left unrestricted, which seems to be the most appropriate specification given the trended nature of the data.

Table 1

Given the evidence on three cointegrating relations, the exact identification of our model requires three restrictions on each of the three cointegration vectors, (on each row of $\boldsymbol{\beta}$), which in turn amounts to nine restrictions on $\boldsymbol{\beta}$ in total. However, the long-run economic theory suggests the relationships (1) to (3) in which 12 overidentifying restrictions on $\boldsymbol{\beta}$ are required. Because linear trend terms are restricted in the cointegration space, our estimation allows us to further test zero restrictions on their coefficients, which also enables us to test different convergence characterizations. This would also add three more restrictions ($a_{11} = a_{21} = a_{31} = 0$), amounting to a total of 15 over identifying restrictions. It is well documented that the LR test over-rejects overidentifying restrictions in the case; therefore, we make use of the Bartlett correction factor suggested by Johansen (2000) to overcome this problem. When the Bartlett correction is used, we find that overidentifying restrictions cannot be rejected with $\chi^2(15) = 3.06$, and the correction factor is equal to 22.04.

These results provide empirical support for the three long-run relations presented above in the case of the Turkish economy. Regarding the convergence hypothesis, the fact that the linear trend is excluded from the OG relation indicates that the rapid catching up is refuted. Hence, whether rapid or zero mean convergence prevails in the data depends on whether a_{30} is different from zero or not. We test and reject the null of $a_{30} = 0$.[14] Therefore, the evidence points to rapid convergence between Turkish and OECD outputs.

5 Derivation of Probability Forecasts

As emphasized above, future uncertainty is among the different forms of uncertainty that we aim to address. To tackle future uncertainty, we compute probability forecasts. Probability forecasts are generated via stochastic simulations of the underlying over-identified VECM model in (7). For forecasting purposes, we write (7) in its level form:

[14] To test this we use (7) (or (5)) to obtain $a_{30} = \mathrm{a}_{30}/\alpha_{30}$ from the estimated values and variance covariance matrix of a_{30} and α_{30} and perform a t test by using the delta method.

$$\boldsymbol{z}_t = \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{z}_{t-j} + \boldsymbol{b}_0 + \boldsymbol{b}_1 t + \boldsymbol{u}_t, \quad t = 1, 2, ..., T, \tag{8}$$

Let $\hat{\boldsymbol{\Phi}}_j,\ j = 1, 2, ..., p,\ \hat{\boldsymbol{b}}_0,\ \hat{\boldsymbol{b}}_1$ and $\hat{\boldsymbol{\Sigma}}$ refer to the estimators of $\boldsymbol{\Phi}_j, j = 1, 2, ..., p,\ \boldsymbol{b}_0,\ \boldsymbol{b}_1$ and $\boldsymbol{\Sigma}$ respectively. These estimators are derived using the estimated parameters of Equations (5) and (6) through the following relations; $\boldsymbol{\Phi}_1 = \boldsymbol{I} - \boldsymbol{\alpha}\boldsymbol{\beta}' + \boldsymbol{\Gamma}_1,\ \boldsymbol{\Phi}_i = \boldsymbol{\Gamma}_i + \boldsymbol{\Gamma}_{i-1},\ i = 2, 3, ..., p-1,\ \boldsymbol{\Phi}_p = -\boldsymbol{\Gamma}_{p-1}$, $\boldsymbol{b}_0 = \mathbf{a}_{\boldsymbol{y}} - \boldsymbol{\alpha}_y \boldsymbol{a}_0$, $\boldsymbol{b}_1 = \boldsymbol{\alpha}_y \boldsymbol{a}_1$ which links the parameters of the equations of (7) and (8). Then, *h-step* ahead forecast of $\boldsymbol{z}_{T+h}$, which is denoted by $\hat{\boldsymbol{z}}_{T+h}$ can be obtained iteratively by successively feeding the previous period forecasts in the following:

$$\hat{\boldsymbol{z}}_{T+h} = \sum_{j=1}^{p} \hat{\boldsymbol{\phi}}_j \hat{\boldsymbol{z}}_{T+h-j} + \hat{\boldsymbol{b}}, \quad h = 1, 2, \ldots \tag{9}$$

We obtain a simulation of the values of $\hat{\boldsymbol{z}}_{T+h}$ by the following:

$$\hat{\boldsymbol{z}}^{(i)}_{T+h} = \sum_{j=1}^{p} \hat{\boldsymbol{\phi}}_j \hat{\boldsymbol{z}}^{(i)}_{T+h-j} + \hat{\boldsymbol{b}}_0 + \hat{\boldsymbol{b}}_1 (t+h) + \boldsymbol{u}^{(i)}_{T+h}, \quad h = 1, 2, ...; i = 1, 2, ..., S \tag{10}$$

where the subscript $\hat{\boldsymbol{z}}^{(i)}_{T+h}$ represents the values of $\hat{\boldsymbol{z}}_{T+h}$ obtained in the *i-th* replication of our simulation. The $\boldsymbol{u}^{(i)}_{T+h}$ is drawn by a parametric stochastic simulation method. To obtain the simulated errors for m variables over h periods, we first generate mh draws from the standard normal distribution, denoted by $\boldsymbol{\xi}^{(i)}_{T+k}, k = 1, 2, ..., h$. Then, these are used to obtain simulated errors by $\boldsymbol{u}^{(i)}_{T+h} = \boldsymbol{P}\boldsymbol{\xi}^{(i)}_{T+h}$, where $\boldsymbol{P}^{-1}$ is the lower triangular Choleski decomposition of $\hat{\boldsymbol{\Sigma}}$ such that $\hat{\boldsymbol{\Sigma}} = \boldsymbol{P}\boldsymbol{P}'$.[15]

The probability of an event $\boldsymbol{\varphi}[\boldsymbol{z}^{(i)}_{T+1}, \boldsymbol{z}^{(i)}_{T+2}, ..., \boldsymbol{z}^{(i)}_{T+h}] < \boldsymbol{c}$, is computed as

$$\boldsymbol{\pi}(\boldsymbol{c}, \boldsymbol{h}; \boldsymbol{\varphi}(\cdot)) = \frac{1}{S} \sum_{i=1}^{S} I\{\boldsymbol{c} - \boldsymbol{\varphi}(\boldsymbol{z}^{(i)}_{T+1}, \boldsymbol{z}^{(i)}_{T+2}, ..., \boldsymbol{z}^{(i)}_{T+h})\}$$

[15]Parameter uncertainty can be captured by using bootstrap procedure in which by simulating the *R(in-sample)* values of $\boldsymbol{z}_t$, R sets of simulated in-sample values are obtained. Then, models are estimated S times to obtain the ML estimator. For each boostrap replication, S replications of the *h-step* ahead forecast can be computed in the manner described above.

where $I(\cdot)$ is an indicator function that takes a value of 1 if $\boldsymbol{c} - \boldsymbol{\varphi}[\boldsymbol{z}_{T+1}^{(i)}, \boldsymbol{z}_{T+2}^{(i)}, ..., \boldsymbol{z}_{T+h}^{(i)}] < 0$ and zero otherwise.

6 Model Uncertainty and Structural Breaks

As is emphasized above and detailed further below, our approach for forecasting aims to address model uncertainty among other forms of uncertainty. To take model uncertainty into account, we adopt the forecast combination approach, which relies on the idea that a combination of forecasts from different models can perform better than those of the individual models constituting the combination. Therefore, we not only consider the forecasts resulting from our long-run theory-consistent specification, but also produce forecasts from the different specifications of our cointegrating VAR model to generate an average forecast. The alternative specifications include a Vector Error Correction Model (VECM) with no cointegration relationship, i.e. VAR on first differences only, and VECMs with one, two, and three exactly identified cointegration relationships, in addition to our overidentified VECM. Morevover, we consider two alternative specifications for the marginal model, namely (6) and its random walk counterpart.

Hence, a total of 10 models are considered (5 VECM models corresponding to each marginal model). To allow for the effects of model uncertainty on the forecast performance, we use weighted averages of the forecasts of these models. The weights are derived from the Bayesian Model Averaging procedure using AIC, SBC, HQ and equal weighting schemes as outlined by Garratt et al. (2003a) and Garratt et al. (2006).

Standard applications of Bayesian Model Averaging for forecasting purposes implicitly assume that all of the models under consideration are stable. However, in reality, some or all of the macroeconometric models under consideration may be subject to structural breaks, which are regarded as among the main sources of forecast failure in many cases. To take into consideration the possible structural breaks, we estimate the models over different estimation windows and pool forecasts from different sample periods, as suggested by Pesaran and Timmermann (2007) and Pesaran and Pick (2012). Like Assenmacher-Wesche and Pesaran (2008) and Pesaran et al. (2009), we also consider model and window averaging together, as mentioned below.

7 Directional Forecasts and Their Evaluations

The probability forecasts are computed for directional events of interest. We calculate the probability that r_t, and e_t rise next period, namely $Pr[\triangle r_t > 0 \mid \Im_{t-1}]$, $Pr[\triangle e_t > 0 \mid \Im_{t-1}]$ and the probability that changes in y_t, and p_t rise the next period, i.e $Pr[\triangle^2 y_t > 0 \mid \Im_{t-1}]$ and $Pr[\triangle^2 p_t > 0 \mid \Im_{t-1}]$, where $\Im_{t-1}$ denotes the information available at time t.

To evaluate the probability forecasts, we use a statistical approach in which an event forecast is realized if its probability forecast is greater than a threshold value of 0.5. We use the hit score, Kuipers score (KS) and Pesaran and Timmermann (1992) statistics (PT) for comparisons of the forecasts and realizations. The hit score is defined as follows:

$$Hit\ score = \frac{UU + DD}{(UU + UD + DU + DD)}$$

where "UU" (*upward-upward*) indicates that the forecast and realization are in the same upward direction, "DD" (*downward-downward*)indicates that they are in the same downward direction, "UD" (*upward-downward*) indicates that the forecast is in an upward direction and the realization is in a downward direction and, lastly, "DU" (*downward-upward*) indicates that the forecast is in a downward direction and the realization is in an upward direction.

KS is defined by $H - F$, where H is the proportion of ups that were correctly forecasted to occur and F is the proportion of downs that were incorrectly predicted.

$$H = \frac{UU}{(UU + DU)}, \quad F = \frac{DU}{(UU + DU)}$$

These two proportions are known as the hit rate and false alarm rate, respectively. In the case where the outcome is symmetric, in the sense that we value the ability to forecast ups and downs equally, a score statistic of zero means no accuracy, whereas high positive and negative values indicate high and low predictive power respectively. KS provides a statiscal measure of the accuracy of directional forecast; however, it does not provide a statistical test. To compensate for this shortcoming of KS, we employ PT, which provides a formal test. As shown in Granger and Pesaran (2000), PT turns out to be equivalent to a test based on KS. The PT statistic is defined by the following:

$$PT = \frac{\widehat{P} - \widehat{P^*}}{[\widehat{V}(\widehat{P}) - \widehat{V}(\widehat{P^*})]^{\frac{1}{2}}}$$

where $\widehat{P}$ is the proportion of correctly predicted upward movements, $\widehat{P^*}$ is the estimate of the probability of correctly predicting the event under the null hypothesis that forecasts and realizations are independently distributed, $\widehat{V}(\widehat{P})$ and $\widehat{V}(\widehat{P^*})$ are the consistent estimates of the variances of $\widehat{P}$ and $\widehat{P^*}$, respectively. Under the null hypothesis, PT has a standard normal distribution.

To evaluate the forecast accuracy of our models, we employ a pseudoout-of-sample methodology, estimating 10 models over different sample periods and computing one-step-ahead probability forecasts. First, we estimate the models using the data up to 2009Q4 and forecast for 2010Q1. We repeat the process recursively, moving one quarter at a time, until we obtain the forecast for 2012Q1. This procedure provides 9 1-step-ahead forecasts to be used in the evaluation of the accuracy of forecasts for the period of 2010Q1-2012Q1. To deal with structural break, we consider the estimation windows changing between 1982Q1 to 1997Q1. The first sample period is 1982Q1-2009Q4, for which 9 1-step-ahead forecasts are already produced for the period of 2010Q1-2012Q1, as described above. The sample period is then reduced by one observation, i.e. 1982Q2-2009Q4, and another set of forecasts is produced for the same period. This process is repeated until we obtain 1997Q1-2009Q4, the last sample period we consider. We obtain 60 different forecasts produced by estimation of the models over the different windows for each point in the period of 2010Q1-2012Q1.

First, we average the forecasts over different model specifications for every sample period in 2010Q1-2012Q1 using one of the averaging method mentioned above. The average forecasts obtained in this manner are denoted by *AveM*. Then, for each point in the period of 2010Q1-2012Q1, we calculate the simple average of forecasts over different estimation windows for each model. The window average forecasts are denoted by *AveW*.[16] Finally, we average the window averages over the models and denote them by *AveAve*.

Table 2 depicts the results of the directional forecasts of the overidentified long-run structural model together with those obtained under model averag-

[16]Obviously, we average 10 forecasts of the different models in the case of *AveM* and 60 forecasts for each model in the case of *AveW*.

ing (*AveM*), window averaging *AveW*[17], and both averaging procedures, i.e. *AveAve*.[18] High values of UU and DD imply that the forecasting ability of the model is high, and high values of UD and DU imply that the forecasting ability of the model is poor.

Table 2

The overall hit scores of all 4 modelling procedures range between 0.611 and 0.750, and their PT statistics are significant, indicating that the null of the independency of the forecasts and realizations is either rejected at the 10 or 5 percentage significance level. The overall hit ratio equal to 0.750 of the *AveAve* forecasts indicates that 27 out of the 36 directional changes (9 each of 4 variables) are correctly predicted between 2010Q1-2012Q1. The results suggest that all the averaging procedures considered here significantly improve the forecasting performance over the overidentified model.[19] Window averaging produces the least improvement over the overidentified model, and the highest improvement is provided by combining both the window and model averaging procedures in the *AveAve* forecasts.

The change in growth is the most accurately predicted variable among the 4 endogenous variable of our model, with hit ratios varying between 0.788 to 1. In the *AveAve* forecasts, the direction of change is correctly predicted in all of the 9 quarters between 2010Q1-2012Q1. The overidentified model and *AveW* forecasts are accurate in 8 of these 9 cases, with a hit ratio of 0.889, and the *AveM* forecasts produce the lowest hit ratio, with 7 correct forecasts.

The hit ratios of the forecasts of the change in the inflation lie between 0.555 and 0.778. Only in the best forecaster of *AveW* are 7 out of 9 cases predicted with success. Given that an apparent structural break in inflation

[17]We perform window averaging with the overidentified model.

[18]In the forecast evaluation, we compare our forecast seasonally adjusted with the seasonally adjusted actual figures following the common practice in the forecast literature. An alternative approach would be to evaluate the success of these seasonally adjusted forecasts by first deseasonalizing them by the estimated additive seasonal adjustment factors of X12-ARIMA and comparing these values with actual figures. In our application, this alternative procedure yields similar results.

[19]To save some space, we report the results with Marginal Equation (6) when the overidentified model is concerned in the averaging procedures results with either HQ weights (*AveAve*) or equal weights (*AveM*) because these two schemes provide the best results. Even if we choose one of these schemes, the results remain qualitatively the same. The complete results are available upon request.

occurred in 2002 (see footnote 10), it is not surprising that window averaging performs the best. In the case of the interest rate, its changes are most accurately forecasted by *AveAve*, like the case of growth. Consistent with the forecasting literature,the exchange rate remains the most poorly predicted variable, with hit ratios between 0.444 and 0.666. Model averaging provides the best forecasts, with 6 correct predictions out of 9. The fact that model averaging improves the forecasts may indicate that an important source of uncertainty leading to incorrect predictions in exchange rates may be alleviated by considering different models.

8 Probability Forecast of Events for Inflation and Growth

The above forecast evaluation exercise reveals that the models and their combinations over different estimation windows generally forecast the change in output growth and inflation more accurately compared to the changes in the interest and exchange rate, the latter of which has the poorest results.

Relying on this property of our VECMs, in this section, we consider another application of probability forecasting and present probability forecasts of selected events for inflation and output growth for the period of 2010Q1-2012Q1. Then, we evaluate their performance by comparing them with their realized values. This time, we use a four-quarter moving average (MA) of inflation and output growth, where annualized quarterly inflation and output growth rates are measured as $400[(p_{t+h} - p_{t+h-1})]$ and $400[(y_{t+h} - y_{t+h-1})]$.

As mentioned in Section 3, the inflation targets set by the CBRT are December-to-December annual increases in price level. The targets are set with an associated 2% uncertainty band around them. Table 3 provides the 4-quarter moving average of the inflation targets and their uncertainty bands for the period of 2010Q1-2012Q1, for which we aim to produce forecasts. The quarterly targets assume equally distributed inflations for each quarter corresponding to their annual targets, which seems plausible given the deseasonalized nature of our data.

Table 3

Table 3 also provides 4-quarter MAs of actual, quarter-over-quarter, an-

nualized rates of inflation and output growth.[20] According to Table 3, the CBRT is successful in keeping the actual inflation within the band when the Turkish economy registered a strong growth performance between 2010Q1-2011Q3. In the last 2 quarters, however, when the growth slowed, inflation moved above the upper band of the targets. With this background information in mind, we consider the following events:[21]

- E1: A single event of inflation in which the inflation target of the CBRT is met. The attainment of the target is defined as the four-quarter moving average of inflation between the four-quarter moving average of the uncertainty band provided in Table 3.
- E2: A single event of recession, in which quarterly output growth is negative for two consecutive quarters.
- E3: A single event of weak growth, in which the four-quarter moving average of output growth is less than 4 percent.
- E4: A single event of strong growth, in which the four-quarter moving average of output growth is greater than 7 percent.

Conditional on the information available at the end of 2009Q4, we calculate the probability forecasts of the above events at $h = 1, 2, 3, ...9$ forecast horizons via stochastic simulations, as described above.[22] We report the probability forecasts for these events in Table 4 below.

Table 4

The emboldened entries indicate the correctly predicted events obtained using the calculated probabilities reported in the tables.[23] According to the

[20]Notice that actual inflation figures at the 4th quarters are different from the December-to-December annual targets for the corresponding year because they are calculated using a period average CPI index, consistently to our data, constructed according to the annual targets. The details of the computation is available upon request.

[21]It is also possible to define some joint events and calculate their associated probabilities.

[22]Note also that unlike the directional forecasts where we only calculate and evaluate 1-step ahead forecasts, in the event probabilities, we use forecasts up to a 9-step horizon calculated iteratively by feeding the previous period forecasts, as described in Equations (9) and (10).

[23]The decision is based on a 0.5 threshold, as above.

tables, the event E2 is successfully predicted across all models in all periods. By contrast, the event E3 is predicted correctly with the *AveAve* model in all periods except 2011Q4. The remaining 2 events can be predicted correctly only between 2 to 4 cases out of 9. Overall, while the models are successful in terms of not disseminating false signals of recession or weak growth, they are not successful in terms of correctly predicting strong growth or events associated with inflation targets. We observe the same property in the directional forecasts of the change in growth and inflation such that the hit rates of all the models associated with the growth forecasts are generally better than those of the inflation forecasts. That directional forecasts provide significantly better results compared to event forecasts is noticeable. Given the fact that directional forecasts are 1 step ahead ands event forecasts are 1 to 9 steps ahead, the success of directional events is not surprising. is not surprising.

9 Conclusion

In this paper, we presented probability forecasts of the directional events related to a number of macro aggregates based on a cointegrating VAR-X model of Turkey. The directional forecasts of output and inflation are found to be quite successful except for the period of the 2008 crisis, for which their performance deteriorated to a certain extent. The probability forecasts of certain events associated with output and inflation are also illustrated and compared with the actual outcomes for a recent period of the Turkish economy. This exercise proved successful too, at least for the events defined on the output. Our results indicated that averaging over models and estimation windows helps increase the forecast accuracy.

Overall, the probability forecasting approach adopted in this paper can be deemed a promising forecasting tool. In particular, the events described in the previous section can increase in number in several interesting directions depending on the characteristic of the period for which they are formed. Following this line of research by extending the basic model and considering others for combined forecasts can be useful in terms of increasing the forecast accuracy. In this paper, for the purpose of combining forecasts, we only considered simple variants of our overidentified model. Although this approach was in line with the applied forecast combination literature, in which combinations from significantly different models are not usually taken into account,

including forecasts from different models, especially non-linear models, may be helpful in improving the forecast performance. Another interesting future research area may be to develop similar sectoral models with linkages to the aggregate economy to produce forecasts at the sectoral level and combine them to create aggregates.

References

Akat, A. and M. E. Yazgan (2012). Observations on turkeys recent economic performance. *Atlantic Economic Journal 40 (4)*.

Assenmacher-Wesche, K. and M. H. Pesaran (2008). Forecasting the swiss economy using vecx* models: An exercise in forecast combination across modelsand observation windows. *National Institute Economic Review 203*, 91–108.

Bates, J. and C. Granger (1969). The combination of forecasts. *Operations Research Quarterly 20*, 451–468.

Bernard, A. and S. Durlauf (1996). Interpreting tests of the convergence hypothesis. *Journal of Econometrics 71*, 161–173.

Britton, E., P. Fisher, and J. Whitley (1998). The inflation report projections: Understanding the fan chart. *Bank of England Quarterly Bulletin 38*(1), 30.

CBRT (2006). *The booklet of Inflation Targeting (in Turkish)*. Central Bank of Republic of Turkey.

Clements, M. P. (2004). Evaluating the bank of england density forecasts of inflation. *Economic Journal 114*(498), 844–866.

Dees, S., F. di Mauro, M. H. Pesaran, and L. V. Smith (2007). Exploring the international linkages of the euro area: A global var analysis. *Journal of Applied Econometrics 22*, 1–38.

Diebold, F. X. and J. A. Lopez (1995). Forecast evaluation and combination. Research Paper 9525, Federal Reserve Bank of New York.

Elliott, G. and A. Timmermann (2008). Economic forecasting. *Journal of Economic Literature 46*(1), 3–56.

Fair, R. C. (1980). Estimating the expected predictive accuracy of econometric models. *International Economic Review 21*(2), 355–78.

Garratt, A., K. C. Lee, M. H. Pesaran, and Y. Shin (2003a). Forecast uncertainties in macroeconomic modeling: An application to the u.k. economy. *Journal of the American Statistical Association 98*(2), 829–838.

Garratt, A., K. C. Lee, M. H. Pesaran, and Y. Shin (2003b). A long run structural macroeconometric model of the uk. *Economic Journal 113*(1), 412–455.

Garratt, A., K. C. Lee, M. H. Pesaran, and Y. Shin (2006). *Global and National Macroeconometric Modelling: A Long-Run Structural Approach*. Oxford University Press.

Gneiting, T. (2008). Editorial: Probabilistic forecasting. *Journal Of The Royal Statistical Society Series A 171*(2), 319–321.

Granger, C. and M. Pesaran (2000). Economic and statistical measures of forecast accuracy. *Journal of Forecasting 19*, 537–560.

Johansen, S. (2000). A small sample correction of the test for cointegrating rank in the vector autoregressive model. *Econometric Theory 16*, 740–778.

Juselius, K. (2006). *The Cointegrated VAR Model:Methodology and Applications*. Oxford University Press.

Kara, A. H. (2008). Turkish experience with implicit inflation targeting. *Central Bank Review 8*(1), 1–16.

Kara, A. H. (2012). Monetary policy after the global crisis. *Atlantic Economic Journ 40(4)*.

Kaya, H. and M. E. Yazgan (2011). Has inflation targeting increased predictive power of term structure about future inflation: Further evidence from turkish market. *Applied Financial Economics 21(20)*, 1539–1547.

Li, Q. and D. Papell (1999). Convergence of international output: time series evidence for 16 oecd countries. *International Review of Economics and Finance 8*, 267–280.

MacKinnon, J. G., A. A. Haug, and L. Michelis (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics 14*, 563–77.

Perron, P. (1987). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica 57*, 1361–1401.

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics, 80, 80*, 355–385.

Pesaran, M., T. Schuermann, and L. Vanessa Smith (2009). Forecasting economic and financial variables with global vars. *International Journal of Forecasting 25*, 642–675.

Pesaran, M. and A. Timmermann (1992). A simple nonparametric test of predictive performance. *Journal of Business and Economic Statistics 10*, 461–465.

Pesaran, M. and A. Timmermann (2007). Selection of estimation window in the presence of breaks. *Journal of Econometrics 137*, 134–61.

Pesaran, M., S. Y., and R. Smith (2000). Structural analysis of vector error correction models with i(1) variables. *Journal of Econometrics 97*, 293–343.

Pesaran, M. H. and A. Pick (2012). Forecast combination across estimation windows. *Journal of Business Economics and Statistics 29*, 307–318.

Stengos, T. and M. E. Yazgan (2013). Persistence in convergence. *Macroeconomic Dynamics Forthcoming*.

Stock, J. and M. Watson (2004). Combination forecasts of output growth in a seven country data set. *Journal of Forecasting 23*, 405–430.

Timmermann, A. (2006). Forecast combinations. *In: G. Elliot, C. W. J. Granger, and A. Timmermann (eds), Handbook of Economic Forecasting 1*, 135–196. Elsevier.

Tables

Table 1: Cointegration and model statistics

(a) Cointegration test

r	Trace Statistics	P-Value
0	97.653	0.000
1	52.776	0.004
2	27.483	0.031
3	9.052	0.177

(b) Diagnostic tests

Univariate Statistics			
Variable	ARCH(2)	Normality	R^2
$\triangle e_t$	01.370 [0.504]	52.271 [0.000]	0.392
$\triangle y_t$	00.823 [0.663]	30.627 [0.000]	0.359
$\triangle r_t$	10.515 [0.005]	64.802 [0.000]	0.325
$\triangle p_t$	3.316 [0.191]	38.740 [0.000]	0.750
Multivariate Statistics			
Trace Correlation		0.429	
Autocorrelation LM(2)		010.265 [0.852]	
Normality		155.729 [0.000]	
ARCH LM(2)		181.149 [0.826]	

Notes: For trace statistics and their p-values, see MacKinnon et al. (1999). The values in squared parentheses are the p-values of the associated test statistics. Trace Correlation is a multivariate R^2 statistic. See (Juselius, 2006, Chapter 4.) for explanations of these statistics.

Table 2: Directional Forecasts: 2010Q1-2012Q1

		Overidentified model					*AveM*				
Variable	Threshold	UD	DD	DU	UU	Hit rate	UD	DD	DU	UU	Hit rate
e_t	$\triangle e_t > 0$	4	1	0	4	0.555	2	3	1	3	0.666
y_t	$\triangle^2 y_t > 0$	0	4	1	4	0.889	1	3	1	4	0.778
r_t	$\triangle r_t > 0$	5	0	0	4	0.444	2	3	0	4	0.778
p_t	$\triangle^2 p_t > 0$	4	0	0	5	0.555	3	1	0	5	0.666
		Hit rate: 0.611, PT :1.820*, KS: 0.400					Hit rate: 0.722, PT :2.870**, KS: 0.500				

		AveW Overidentified model					*AveAve*				
Variable	Threshold	UD	DD	DU	UU	Hit rate	UD	DD	DU	UU	Hit rate
e_t	$\triangle e_t > 0$	4	1	0	4	0.555	4	1	1	3	0.444
y_t	$\triangle^2 y_t > 0$	0	4	1	4	0.889	0	4	0	5	1.000
r_t	$\triangle r_t > 0$	5	0	0	4	0.444	0	5	1	3	0.889
p_t	$\triangle^2 p_t > 0$	2	2	0	5	0.778	3	1	0	5	0.666
		Hit rate: 0.667, PT :2.439*, KS: 0.482					Hit rate: 0.750, PT :3.167**, KS: 0.542				

Notes: ** and * indicate statistical significance at the 5 and 10 percent levels, respectively.

Table 3: Inflation Target and Actual Growth and Inflation.

period	Uncertainty upper limit	Uncertainty lower limit	Inflation target	Actual inflation	Actual growth
2010Q1	9.005	5.005	7.005	8.862	11.622
2010Q2	8.769	4.769	6.769	8.848	9.642
2010Q3	8.541	4.541	6.541	8.072	5.930
2010Q4	8.320	4.320	6.320	7.138	8.598
2011Q1	8.086	4.086	6.086	4.232	10.871
2011Q2	7.848	3.848	5.848	5.750	8.566
2011Q3	7.617	3.617	5.617	6.181	8.662
2011Q4	7.392	3.392	5.392	8.786	4.890
2012Q1	7.237	3.237	5.237	9.962	2.804

Table 4: Event probabilities.

	Overidentified				*AveM*			
period	E1	E2	E3	E4	E1	E2	E3	E4
2010Q1	0.062	**0.000**	0.431	0.261	0.249	**0.000**	**0.360**	0.344
2010Q2	0.049	**0.179**	**0.155**	**0.684**	0.189	**0.125**	**0.096**	**0.798**
2010Q3	0.026	**0.374**	0.580	**0.263**	0.177	**0.174**	**0.274**	0.577
2010Q4	0.023	**0.469**	0.867	0.061	0.222	**0.206**	**0.462**	0.403
2011Q1	0.097	**0.455**	0.906	0.046	0.281	**0.207**	**0.495**	0.380
2011Q2	0.071	**0.393**	0.926	0.038	0.283	**0.176**	0.508	0.362
2011Q3	0.094	**0.379**	0.885	0.065	0.299	**0.188**	**0.492**	0.388
2011Q4	**0.092**	**0.375**	0.832	**0.087**	**0.303**	**0.197**	**0.480**	**0.397**
2012Q1	**0.108**	**0.322**	**0.807**	**0.117**	**0.307**	**0.178**	0.477	**0.405**

	AveW overidentified				*AveAve*			
period	E1	E2	E3	E4	E1	E2	E3	E4
2010Q1	0.282	**0.000**	**0.447**	0.189	0.381	**0.000**	**0.457**	0.195
2010Q2	0.152	**0.155**	**0.098**	**0.777**	0.310	**0.127**	**0.064**	**0.823**
2010Q3	0.115	**0.160**	**0.310**	**0.475**	0.355	**0.100**	**0.202**	0.604
2010Q4	0.116	**0.193**	0.594	0.228	0.477	**0.105**	**0.402**	0.403
2011Q1	0.116	**0.226**	0.624	0.217	**0.578**	**0.130**	**0.382**	0.444
2011Q2	0.118	**0.219**	0.661	0.184	**0.645**	**0.130**	**0.405**	0.418
2011Q3	0.120	**0.247**	0.697	0.166	**0.681**	**0.158**	**0.453**	0.386
2011Q4	**0.119**	**0.268**	0.712	**0.161**	0.702	**0.174**	0.485	**0.352**
2012Q1	**0.121**	**0.248**	**0.723**	**0.157**	0.712	**0.156**	**0.499**	**0.341**

Notes: Emboldened items refer to the correctly predicted events.

Appendix: Data and Sources

- y_t: The logarithm of domestic output is measured by the Real GDP Volume, which is obtained from the International Financial Statistics (IFS). The quarterly series for the period of 1980-1986 were interpolated from yearly figures using the methodology described in Dees et al. (2007). y_t are seasonally adjusted by using the X12 method.

- p_t: The logarithm of the domestic price level is measured by CPI, which is obtained from the IFS as the period averaged values. p_t is seasonally adjusted by using the X12 method.

- e_t: The logarithm of the exchange rate is measured by the average of the period averages of TL/US Dollar and TL/Euro exchange rates, which are obtained from the IFS. For the construction of the Euro exchange rate for the period before 2000, TL/German Mark exchange rate series are converted to the Euro by using the Euro conversion rate.

- r_t: The domestic interest rate is measured by the annualized deposit rate, R_t, which is calculated as $0.25ln\left(1+\frac{R_t}{100}\right)$ and obtained from the IFS. Because there are missing data in the three-month Treasury Bill rates, we use the discount rate.

- y_t^*: Foreign output is constructed as the trade-weighted average of OECD countries' GDPs, which is calculated as $y_t^* = ln\left(\sum_{i=1}^{n} w_{it}Y_{it}\right)$, where Y_{it} is the real GDP of country i, n is the number of OECD countries and w_{it} is the trade shares of country i in Turkey's total trade with the OECD. Trade is calculated as the sum of its imports and exports. The bilateral trade data are gathered from the Direction of Trade Statistics. GDP Volume series are obtained from the IFS. Y_{it} are seasonally adjusted by using the X12 method when necessary.

- p_t^*: Foreign price is constructed as the trade-weighted average of OECD countries' CPIs, $p_t^* = ln\left(\sum_{i=1}^{n} w_{it}P_{it}\right)$, where P_{it} is the CPI of country i. CPI series are obtained from the IFS as the period averages. For the period before German unification in 1990 Q4, the West German CPI is used to obtain a common index. P_{it} are seasonally adjusted by using the X12 method when necessary.

- r_t^*: The foreign interest rate is measured by the average annualized three-month USA Treasury Bill and Euribor rates. The period before 2000 of the Euribor series is completed by using the three-month German Treasury Bill rate, which is calculated as $0.25ln\left(1+\frac{R_t^*}{100}\right)$, where R_t^* are the average values of foreign rates, which are obtained from the IFS and http:/www.euribor.org.