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FORECASTING INFLATION USING SURVEY EXPECTATIONS AND TARGET INFLATION: EVIDENCE FOR BRAZIL AND TURKEY

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FORECASTING INFLATION USING SURVEY EXPECTATIONS AND TARGET INFLATION: EVIDENCE FOR BRAZIL AND TURKEY[†]

Abstract

In this paper, we formulate a statistical model of inflation that combines data on survey expectations and the inflation target set by central banks.. Our model produces inflation forecasts that are aligned with survey expectations, thereby integrating the predictive power of the survey expectations together with the baseline model. We further incorporate the inflation target set by the monetary authority to examine the effectiveness of monetary policy in forming inflation expectations and therefore, predicting inflation accurately. Results indicate superior predictive power of the proposed framework compared to the model without survey expectations as well as several popular benchmarks such as the backward and forward looking Phillips curves and naive forecasting rule.

JEL Classification: C32, C51, E31 and E37
Keywords: inflation forecasting, inflation targeting, state space models, survey-based expectation and term structure of inflation expectations

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1 Introduction

Understanding the expectations of economic agents is a key ingredient for predicting inflation. The importance of expectations is amplified further for many emerging markets, given their relatively recent transition to inflation targeting regimes. In this paper, we formulate a statistically coherent model of inflation that combines data on survey expectations on inflation. Our model produces inflation forecasts that are aligned with survey expectations, thereby integrating the predictive power of the survey expectations together with the statistical model. We further incorporate the inflation target set by the monetary authority to examine the effectiveness of monetary policy in forming inflation expectations and therefore, predicting inflation accurately. This model allows us to examine the deviation of inflation expectations and target inflation as a way of judging inflation targeting performance and to develop a framework for forecasting the term structure of inflation expectations.

In our empirical investigation, we focus on two key emerging economies, Brazil and Turkey. While the two countries exhibit similarities in their inflation experience in the last decade, there are certain differences which we aim to pinpoint using our framework. The inflation process in Turkey seems to behave in a more volatile manner compared to Brazil, partly because of a large seasonal component, with an unconditional mean of annual inflation rate of 8.2% (5.4% for Brazil) accompanied by a unconditional standard deviation of 9.4% (2.7% for Brazil). This difference in the structure of these two markets enables us to examine the importance of survey-based expectations in predicting inflation in different types of emerging markets. We evaluate the performance of the model with several benchmark models that have proved to be useful in predicting inflation. The results for Turkey imply that the proposed framework outperforms all benchmark models. For Brazil, the results are more ambiguous. Nevertheless, our framework for Brazil performs at least as well as the best performing benchmark models, with better predictions for some variants that involve additional information regarding global inflation and the business cycle.

In our analysis, we control for changes in trend inflation to account for the transition from high inflationary periods to lower and more stable inflation for the economies in question. Seasonal variation in the inflation data is modeled explicitly as well. Since macroeconomic data for emerging economies are often available without any seasonal adjustment, implementing a seasonal adjustment based on an arbitrary moving average filter may obscure the inference. By treating seasonality together with the other components, the model exploits further the seasonal information which is potentially correlated with the inflation level, see, for example Koopman and Lee (2009). The flexibility of this model ensures that specific patterns of inflation for emerging economies such as Brazil and Turkey during the last decade are captured adequately.

A novel feature of our framework involves integrating the monetary policy regime, i.e. inflation targeting, into our predictive model. We do so by confronting model-based inflation expectations with the formal inflation targets set by central banks. This also leads to a statistical measure of the (time-varying) discrepancy between inflation expectations and the target inflation. If the discrepancy is small, inflation targeting provides further information for predicting future inflation. Even if the discrepancy is not small but stable over time with a small variance, the implicit target inflation contributes in predicting future inflation. On the other hand, if the discrepancy is not small and stable, and thus, not binding, then the model-based inflation expectations and target inflation do not match and inflation targeting is of no use for predicting inflation.[1]

A number of papers have used survey expectations of inflation to proxy for inflation expectations in macro and monetary models. A vast majority of these studies aim to conduct inference about structural parameters in fully articulated models without making the assumption of rational expectations, see Mankiw *et al.* (2004), Klaus and Padula (2011) and Ormeno (2011) among others. Del Negro and Schorfheide (2013) examine

[1]Other papers have also examined the efficacy of inflation targeting regimes for emerging economies. Fraga *et al.* (2004) employ a small open economy model as in Batini *et al.* (2003). McCallum and Nelson (2000) examine the time path of inflation and the output gap under imperfect credibility and a Taylor rule determining the optimal interest rate to assess the inflation targeting performance of emerging economies relative to developed ones. Çiçek and Akar (2014) examine the rate of convergence of inflation expectations in Turkey to inflation targets versus actual inflation over the period 2002-2013 by controlling for the size of shocks affecting inflation.

the additional predictive gains of including survey data in dynamic stochastic general equilibrium models. Similarly, (Basturk *et al.*, 2014) use survey expectations in a New Keynesian Phillips curve, see also Roberts (1997), for enhancing the predictive performance of the model.

Our study is closest to Kozicki and Tinsley (2006), who argue that survey-based expectations often capture information about structural changes regarding the future state of the economy, shifts in the perceptions of the goals of monetary policy, or political turmoil more rapidly than the historical data. They employ a 'shifting endpoint' model (with *a priori* seasonal adjusted data) together with survey expectations focusing on extracting of term structure of inflation expectations for US. We take a different stand here, as our framework is directed towards increasing the predictive content of our baseline model where low frequency movements are modeled explicitly using a flexible approach suitable for emerging economies. The term structure of inflation expectations is then obtained as a by-product of our model. In an independent and concurrent research, Altavilla *et al.* (2013) focus on anchoring the yield curve using survey expectations. Their analysis is primarily concerned with determining, from a theoretical point of view, the conditions under which combinations of model-based forecast (using the Nelson-Siegel model of yield curve) together with survey expectations perform better than using only model-based forecasts. By contrast, our paper is oriented towards providing a predictive model of inflation together with information on survey expectations and target inflation.

The remainder of this paper is organized as follows. Section 2 presents the state space model with survey expectations and target inflations. Section 3 presents the full sample estimation results for the baseline model and illustrates quantitatively the importance of including survey expectations. Section 4 presents the out-of-sample forecasting results and a comparison with some alternative benchmark models while Section 5 elaborates on variants of our modeling framework and their forecasting performance. Section 6 provides concluding remarks.

2 Modeling the Inflation Processes for Emerging Economies

In this section, we describe a flexible model structure to approximate the inflation processes observed in emerging economies. We further integrate survey data on inflation expectations and the inflation target to enhance the information content of the model structure.

2.1 The baseline model and incorporating survey expectations

In this section, we develop a local linear trend model that accommodates many observed features of inflation for emerging economies; see Harvey (1990) or Durbin and Koopman (2012). First, we allow for changes in trend inflation by modeling the level of inflation as a random walk with a drift, where the drift itself also follows a random walk. Second, to accommodate seasonal variation in observed inflation, we explicitly model the seasonal component in the inflation process that may be correlated with the other components. Third, to capture any remaining time-dependence in inflation rates, we also allow for an AR(1) structure in the net inflation process.

Consider the following modified version of the local linear trend model for modeling inflation dynamics

$$\begin{aligned} \pi_t - \alpha_t - \gamma_t &= \phi(\pi_{t-1} - \alpha_{t-1} - \gamma_{t-1}) + \varepsilon_t \\ \alpha_t &= \alpha_{t-1} + \mu_{t-1} + \eta_{\alpha,t} \\ \mu_t &= \mu_{t-1} + \eta_{\mu,t} \\ \gamma_t &= -\textstyle\sum_{j=1}^{11} \gamma_{t-j} + \eta_{\gamma,t} \end{aligned} \tag{1}$$

In this specification, α_t denotes the trend component of inflation, μ_t denotes the slope component of the trend inflation, γ_t denotes the time-varying seasonal component in inflation while ϕ measures the backward-looking dynamics in the net inflation process.

The local linear trend model specification is flexible enough to encompass many types of popular models used frequently for capturing unobserved components of macroeconomic time series. When $\sigma^2_{\eta_\mu} = 0$, for example, the inflation process follows a random walk with a drift, μ. When $\sigma^2_{\eta_\alpha} = 0$, a deterministic trend is obtained. Additionally, when the values of

the slope become negligibly small, then the process becomes a local level model involving a random walk only for the level. On the other hand, setting only $\sigma^2_{\eta_\alpha} = 0$ but allowing $\sigma^2_{\eta_\mu}$ to be positive results in an integrated random walk process which can approximate many types of nonlinear trends including HP filter and the parameters of the HP filter can be recovered under certain re-parametrization.[2]

Given the information set that contains the observations up to and including period t, the one-period ahead forecast of the inflation would be

$$E_t^M[\pi_{t+1}] = \phi\pi_t + \alpha_{t+1|t} + \gamma_{t+1|t} - \phi\alpha_{t|t} - \phi\gamma_{t|t}, \tag{2}$$

where the superscript M stands for the "model-based expectations". Using the evolution of the unobserved components in (1), $\alpha_{t+1|t}$ can be replaced by its forecast, i.e., by $\alpha_{t|t} + \mu_{t|t}$, and $\gamma_{t+1|t}$ can be written as $-\sum_{j=1}^{11}\gamma_{t+1-j|t}$. Replacing the level and seasonality predictions, the expression for one-period ahead inflation expectation from the model is given by

$$E_t^M[\pi_{t+1}] = (1-\phi)\alpha_{t|t} + \phi\pi_t + \mu_{t|t} - (1+\phi)\gamma_{t|t} - \sum_{j=1}^{10}\gamma_{t-j|t}. \tag{3}$$

Iterating forward, the k-period ahead inflation expectation from the model can written as

$$E_t^M[\pi_{t+k}] = (1-\phi^k)\alpha_{t|t} + \phi^k\pi_t + k\mu_{t|t} - \phi^k\gamma_{t|t} + \gamma_{t-12+k|t}. \tag{4}$$

Following Kozicki and Tinsley (2006), we also incorporate survey expectations of inflation into the econometric model as a way of obtaining greater information about underlying inflation forecasts. Let $E_t^S[\pi_{t+\tau}]$ denote survey expectations of inflation τ-months ahead. We assume that the survey expectations should match the prediction from the econometric model (with some random error). By matching the survey expectations together with the model-based expectations, we seek to reconcile the model-based expectations with the projections obtained through expert opinion in a statistically coherent way. Using the model,

[2]See Harvey and Jaeger (1993); Harvey and Trimbur (2008); Harvey (2011); Canova (2014). Moreover, Delle Monache and Harvey (2011) show the robustness of the specification in (1) against many types of model mis-specification.

the relationship between next month's inflation prediction and survey-based expectation can be written as

$$\begin{aligned} E_t^S[\pi_{t+1}] &= E_t^M[\pi_{t+1}] + \upsilon_{1,t} \\ &= (1-\phi)\alpha_{t|t} + \phi\pi_t + \mu_{t|t} - (1+\phi)\gamma_{t|t} - \textstyle\sum_{j=1}^{10}\gamma_{t-j|t} + \upsilon_{1,t}. \end{aligned} \tag{5}$$

Similarly, the relationship between k-period ahead expectations and survey-based expectations for inflation can be combined as

$$\begin{aligned} E_t^S[\pi_{t+k}] &= \textstyle\sum_{j=1}^{k} E_t^M[\pi_{t+j}] + \upsilon_{k,t} \\ &= \textstyle\sum_{j=1}^{k}\phi^j\pi_t + \big(j - \sum_{j=1}^{k}\phi^j\big)\alpha_{t|t} + \frac{j(j+1)}{2}\mu_{t|t} - \sum_{j=1}^{k}\phi^j\gamma_{t|t} + \upsilon_{k,t}. \end{aligned} \tag{6}$$

An alternative approach to deriving information on the evolution of inflation expectations is to make use of the term structure of breakeven inflation, namely, the difference between nominal and real yields at different maturities; see, e.g, Adrian and Wu (2009). According to their approach, the difference between expected inflation and breakeven inflation is given by the inflation risk premium, which is uncovered using both the term structure of the yield curve and the term structure of their variances and covariance. However, various authors have found that using survey measures of inflation expectations to construct the term structure of inflation expectations may not be inferior to those based on breakeven inflation and may, in many cases, dominate it. Another problem with using beakeven inflation for emerging economies is the relative dearth of data on TIPS (Treasury inflation protected securities), measured over time or at different maturities.[3]

2.2 Inflation targeting

One of the key issues for central bankers in the inflation targeting regime is the extent to which agents' expectations have become anchored to the inflation target in question. In this section, we describe how to incorporate the inflation target set by central banks into

[3]See, for example, Aruoba (2014), who constructs a term structure of inflation expectations using the Nelson and Siegel (1987) model of the term structure using data on financial variables such as inflation swaps and breakeven inflation, or Gurkaynak *et al.* (2010), who estimate breakeven inflation using the yield curve for nominal off-the-run Treasury notes and bonds and the one for TIPS.

our framework.

Usually central banks set an annual inflation target for the next year at the end of each year[4], $\pi^T_{t,A}$ where the superscript T denotes the **T**arget inflation and subscript A denotes its **A**nnual frequency. Thus, the target inflation rate implies a twelve-month ahead inflation projection in December of each year. Matching target inflation together with model-based inflation projections and using our model for the month of December, we can write

$$\begin{aligned} \pi^T_{t,A} &= \delta_0 + \left(\textstyle\sum_{j=1}^{k} E_t^M[\pi_{t+j}]\right) + \upsilon_t^T, \\ &= \delta_0 + \left(\textstyle\sum_{j=1}^{12} \phi^j \pi_t + \left(12 - \sum_{j=1}^{12} \phi^k\right)\alpha_{t|t} + 78\mu_{t|t} - \sum_{k=1}^{12} \phi^k \gamma_{t|t}\right) + \upsilon_t^T. \end{aligned} \tag{7}$$

We include a constant parameter δ_0 to allow for a systematic bias when the target inflation is not met by the inflation expectations. By doing so, we are able to assess quantitatively the systematic deviation of inflation expectations implied by the model from the inflation target and to examine the predictive performance of the model with explicit use of data on the formal inflation target set by central banks. If the evolution of inflation and expectations of economic agents are in line with target inflation, then $\delta_0 = 0$. Finally, we extend the model to measure a time-varying bias by specifying a random walk process for the potential bias as follows:

$$\delta_{0,t} = \delta_{0,t-1} + \eta_{\delta,t}. \tag{8}$$

A large variance for the error term implies that the *change* in the systematic component of the deviation is unpredictable over time whereas if this variance is zero, then the systematic deviation tends to be stable over time.

[4]Central banks occasionally revise their target inflation also during the course of the year for the remaining part of the year. While our exposition is for the annual targets, we can also incorporate more frequent target inflation revisions in our model.

2.3 Statistical inference

Together with (7) and (8), the extended model can be written as

$$
\begin{aligned}
\pi_t &= \alpha_t + \gamma_t + \phi(\pi_{t-1} - \alpha_{t-1} - \gamma_{t-1}) + \varepsilon_t \\
E_t^S[\pi_{t+k}] &= \textstyle\sum_{j=1}^{k} \phi^j \pi_t + \big(j - \sum_{j=1}^{k} \phi^j\big)\alpha_t + \frac{j(j+1)}{2}\mu_t - \sum_{j=1}^{k} \phi^j \gamma_t + \upsilon_{k,t} \\
\pi_{t,A}^T &= \delta_{0,t} + \Big(\textstyle\sum_{j=1}^{12} \phi^j \pi_t + \big(12 - \sum_{j=1}^{12} \phi^k\big)\alpha_t + 78\mu_t - \sum_{k=1}^{12} \phi^k \gamma_t\Big) + \upsilon_t^T \\
\alpha_t &= \alpha_{t-1} + \mu_{t-1} + \eta_{\alpha,t} \\
\mu_t &= \mu_{t-1} + \eta_{\mu,t} \\
\gamma_t &= -\textstyle\sum_{j=1}^{11} \gamma_{t-j} + \eta_{\gamma,t} \\
\delta_{0,t} &= \delta_{0,t-1} + \eta_{\delta,t}.
\end{aligned}
\tag{9}
$$

This system can be nicely cast into a state-space framework and standard inference can be carried out using the Kalman Filter/Smoother coupled with quasi-Newton optimization methods, see (Durbin and Koopman, 2012) for details.

An added issue raised by the use of data on target inflation has to do with the measurement of the target rate on an annual basis. This implies that observations on target inflation are only available for the month of December provided there are no revisions during the course of the year. This leads to missing observations for the remaining time periods. The state state space framework also handles missing observations regarding the measurement of the inflation target at the annual frequency in a statistically optimal way, by using the evolution of the unobserved inflation components, and provides accurate and efficient (in least squares sense) predictions of **monthly** deviations of inflation expectations from target inflation. We provide the estimation details and other technical details in the Online Appendix.[5]

2.4 Model Comparison

A key aspect of our analysis is to evaluate the predictive performance of our model statistically against some alternative models that have been considered in the literature. For this

[5]The Online Appendix is available at ...

purpose, we first use the Diebold-Mariano (DM) test due to Diebold and Mariano (1995) for pairwise comparison of the competing models. The test relies on the differential of loss functions from the forecast errors of two competing models and tests the significance of this differential. In line with our estimation strategy, we use a quadratic loss function for evaluating the alternative models. Notice that the DM test can also be formulated as a regression of the loss differentials on a constant, and heteroskedasticity and autocorrelation robust (HAC) standard errors can be used. Under certain conditions involving covariance stationarity of the loss differential, the test statistic follows a standard normal distribution asymptotically. Nevertheless, finite sample approximations may be poor, as noted in Harvey *et al.* (1998) (HLN). Therefore, we use a HLN corrected version of HAC-DM test for finite samples in our pairwise forecast comparison.[6]

When the models are nested as in some of our model comparisons, the DM-test may not follow a standard distribution even asymptotically, see Clark and McCracken (2005) and McCracken (2007). In such cases, as also indicated by Clark and McCracken (2013), the critical values from standard normal distribution are not appropriate. Therefore, we use the the critical values provided in McCracken (2007) for the different cases, including the various recursive schemes that we consider.[7] In our evaluation, we use the OOS-t statistic (as it is typically referred to) and the corresponding critical values when comparing nested models.

[6]The assumption of covariance stationarity is violated asymptotically as non-stationarity is induced in loss differentials from *estimated models* as estimated parameters converge to their pseudo-true values. This is empirically verifiable, however, and our inspection of covariance stationarity of loss differentials indicates that we do not confront such problems.

[7]Another conventional test used in many cases including comparison of nested and non-nested models is the test proposed in Giacomini and White (2006). However, the test relies on the assumption of finite estimation window, implying essentially a rolling window scheme rather than the recursive scheme that we use.

3 Data and Full Sample Results

3.1 Data

We use data on the seasonally unadjusted consumer price index (CPI), survey expectations of inflation, and inflation targets for Brazil and Turkey. The sample period for Brazil is from November 2001 to January 2014 while for Turkey it is from August 2001 to January 2014. Figure 1 shows the data on annualized inflation, survey inflation expectations, and the inflation targets for the two countries.[8] The raw data display the seasonal variation of the actual inflation processes. These data provide some justification for our approach in terms of separately modeling the level, the slope and the seasonal component of inflation. In terms of the inflation targeting regime, Brazil moved to this regime after the currency crisis of 1999. Turkey began practicing a form of implicit inflation targeting after the severe banking and financial crisis of 2000-2001 and transited to a formal inflation targeting regime in 2006.

3.2 Full sample results

Tables 1 and 2 provide the estimation results of models for Brazil and Turkey, respectively. The results indicate that, first, the variances $\sigma^2_{\eta_\mu}$ are not significantly different from zero for both Brazil and Turkey, implying that the inflation process π_t is a random walk with drift for the two countries.[9] Second, the parameter ϕ measuring persistence in the net inflation process is estimated to be somewhat smaller for Turkey compared to Brazil.

Figures 2 and 3 show the smoothed estimates of the level, slope, the seasonality of the inflation processes for Brazil and Turkey, respectively, together with 95% confidence bands. Figure 2 for Brazil shows that both the estimated level and slope of inflation, α_t and μ_t,

[8] The raw inflation data for Brazil and Turkey are obtained from OECD main economic indicators. Survey-based measures of inflation expectations are available at different forecast horizons and sample periods for the different countries. For Brazil, we use the twelve-month ahead survey expectations compiled by the Banco Central do Brazil (BCB). Likewise, for Turkey, we use two-month and one-year ahead survey expectations compiled by the Central Bank of the Republic of Turkey (CBRT). The one-month ahead survey expectation only starts from 2006 onwards, thus we exclude these expectations from our data set. We use the monthly averages of the median daily forecasts for these countries.

[9] This is consistent with the evidence for Turkey in Altug and Uluceviz (2014).

tend to move together. The scale of the slope process is quite low with starting point close to 0. These findings mirror the findings in Table 1 which indicate that the model reduces virtually to a local level model with a negligible effect of the slope for Brazil. By contrast, Figure 3 shows that the level process α_t for Turkey is estimated to be large while the slope process, μ_t, is negative but declining in absolute value. These findings are consistent with the process of disinflation observed in Turkey between 2002-2006. Figure 3 also shows that there are significant fluctuations in the seasonal component at higher levels of inflation for Turkey, which are consistent with the positive covariance between the processes for $\eta_{\gamma,t}$ and $\eta_{\alpha,t}$ reported in Table 2.

The fourth panels of Figures 2 and 3 display the systematic deviations of model-based inflation expectations from target inflation denoted δ_{0t} for Brazil and Turkey, respectively. These figures display some salient differences between the inflation targeting experience for Brazil and Turkey. With the exception of the period of financial turbulence during the 2002-2003 period for Brazil, the systematic deviations of inflation expectations from target fluctuate around a value of zero. By contrast, expected inflation has always been above the target rate for Turkey over the entire sample period. The smoothed estimates of $\delta_{0,t}$ displayed in Figure 3 are declining in absolute value during the disinflationary period between 2002-2006 for Turkey. However, there is a tendency for inflation expectations to deviate more from the target rate during 2006 and the global financial crisis of 2008. After 2010 or 2011, the deviations of expected inflation from target inflation tend to increase for both Brazil and Turkey.[10] These findings reveal that our model can match quite closely the stylized facts of inflation for two key emerging economies.

As we discussed in the Introduction, one of the contributions of our study is to examine the role of incorporating survey expectations in a statistically coherent way for modeling and predicting inflation. Figure 4 displays the mean and 95% confidence intervals for the

[10] Tables 1 and 2 also provide some information about the anchoring of expectations for Brazil and Turkey. As a case in point, the estimated variances and covariances of the shocks to the measurement equations for the target and the survey equations are not significantly different from zero for Brazil, implying that both model- and survey-based inflation expectations are anchored to the target rate. For Turkey, however, survey-based expectations tend to differ from their model-based counterparts and to vary in similar ways with each other at both short and long horizons.

estimated systematic deviation of inflation expectations from the target level denoted by δ_{0t} for Brazil and Turkey that are calculated with and without the inclusion of the survey-based inflation expectations. One finding from this figure is that the estimated confidence intervals are much narrower when data on survey-based inflation expectations are included. Second, while the exclusion of survey expectations does not significantly alter magnitude of the estimated deviations from target inflation for Brazil, this is not the case for Turkey. Here the results of the model without use of survey expectations indicate large and positive discrepancies at the onset of the sample while the results from the model with survey data indicate negative discrepancies in line with the rest of the sample. These results suggest that survey-based expectations of inflation incorporate valuable information that allows for more precise estimates of the systematic deviation of model-based inflation expectations from target inflation in the case of an emerging economy.

4 Forecasting performance

In the previous section, we document the full-sample findings of the model augmented with survey expectations. In this section, we focus on the forecasting performance of our modeling framework. There is a wide literature that has examined the forecasting performance of alternative reduced-form models of inflation; see Stock and Watson (2007, 2008), among others. These models include autoregressive specifications, and backward and forward-looking versions of New Keynesian Phillips curves. Since the novelty of our framework is in terms of including measures of survey expectations and target inflation, considering forward-looking versions of the New Keynesian Philips curve with survey expectations among the set of alternative specifications enables us to examine the efficacy of incorporating the survey expectations in alternative modeling scenarios, including our own. This literature has demonstrated that naive models of inflation such as simple moving average specifications may dominate many structural or reduced-form specifications considered in the literature; see, for example, Atkeson and Ohanian (2001). As Mavroeidis (2010) or Cochrane (2011) have noted, this occurs because, effective monetary policy

may paradoxically make forecasting inflation difficult using such structural or reduced-form specifications. Hence, we also include a simple moving average rule among our alternatives.

We estimate and forecast recursively, using data from November 2001 for Brazil and August 2001 for Turkey to the time the forecast is made, beginning in January 2007 and extending until January 2014. We compare the h-step ahead out-of-sample forecasting performance of our model with that of several natural alternatives for forecast horizons $h = 1, \ldots, 12$. Consistent with the approach in our modeling framework, we do not implement a de-seasonalization of the data before fitting the alternative models. Instead, we choose the best model that fits the seasonal and non-seasonal components for each forecast horizon based on the Bayesian Information Criterion (BIC). Denote by $\hat{\pi}_{t+h|t}$ the forecast of inflation h periods ahead, conditional on information at date t. The alternative models that we consider in terms of their forecasting performance are (i) the state space model without survey expectations to isolate the value-added of matching the model-based forecasts with survey expectations; (ii) a naive MA model: $\hat{\pi}_{t+h|t} = \frac{1}{12}(\pi_t + \pi_{t-1} + \ldots + \pi_{t-12})$., in which case, next period's inflation forecast is equal to an average of inflation in the past twelve months, see Atkeson and Ohanian (2001); (iii) an AR(p) model: $\hat{\pi}_{t+h|t} - \pi_t = \alpha_0 + \alpha(L)\Delta\pi_t + \epsilon_t^h$, where the order of the autoregressive lag polynomial is chosen according to BIC; (iv) a backward looking Philips Curve (PC);[11] (v) a hybrid New Keynesian Philips Curve (H-NKPC) with survey expectations: $\hat{\pi}_{t+h|t} = \gamma\pi_t + (1-\gamma)\pi_t^S + \alpha_0 + \alpha(L)\Delta\pi_t + \lambda\hat{z}_t + \delta(L)\Delta z_t$.[12]

We define forecast errors at time t as $\pi_{t+h} - \hat{\pi}_{t+h|t}$, and examine the out-of-sample forecasting performance of each model according to the root mean squared error (RMSE) criterion. Mavroeidis *et al.* (2014) discuss in detail alternative estimation approaches to

[11] We use the industrial production (IP) gap as a proxy of the monthly output gap, where the IP gap is measured as the difference of the industrial production index from its long-run level extracted using the HP filter. The IP data are obtained from OECD Main Economic Indicators database.

[12] The 'hybrid' NKPC model combines both backward and forward-looking dynamics by allowing lagged inflation in the model along with forward-looking dynamics, see Galí *et al.* (2001); Galí and Gertler (1999) for details. In this equation, we have used survey data to replace the expectation of future inflation with its survey-based measure, see Roberts (1997) and Del Negro and Schorfheide (2013); Basturk *et al.* (2014), who uses survey expectations for estimating hybrid models. Fraga *et al.* (2004) make use of the private sector's inflation expectations to assess whether the Central Bank of Brazil (BCB) reacts in a forward manner to inflation expectations during the inflation targeting era. We note that the survey data capture the actual inflation expectations with some random error, which we assume to follow a normal distribution.

the New Keynesian Phillips curve, including the use of instrumental variables estimation. However, unlike the specifications that they consider, the only forward-looking variable in the models above is survey-based inflation expectations, which is likely to exhibit less endogeneity relative to the inflation process than future expectations of actual inflation that are introduced into the NKPC under the assumption of Rational Expectations. Hence, all of the alternatives discussed above are estimated using OLS. When estimating H-NKPC, we further impose the restriction that the coefficients on π_t and π_t^S sum to unity.

Table 3 displays the forecasting performances of competing models for Brazil. The values in bold indicate that the naive MA model provides lower RMSE values compared to all of the competing models for all horizons except the first horizon. For the initial forecasting horizon, all of the models do equally well with very small differences between them, and rejections of equal predictive power with the naive MA specification in favor of the different models occur only at the 10% significance level. For longer horizons, the MA model performs better than the other competing models except our model in most of the cases at the 1% significance level (which is indicated by the rejection of the null hypothesis of no loss differential against a one-sided alternative of positive loss differential against the MA model.). When our model with survey expectations is considered, however, differences in the forecasting performance with the MA model are not statistically significant, the only exceptions occurring at the three-, eleven- and twelve-month ahead horizons at a significance level of 10%. This finding is related to the relatively more stable inflation process in Brazil, which makes the naive MA model relatively difficult to beat, as Atkeson and Ohanian (2001) demonstrate for the US case. On the other hand, the MA model outperforms the basic model that does not include survey expectation at all horizons except the one-year horizon with significance levels of 10% or less. Thus, we observe that the incorporation of survey expectations enhances the forecasting performance of the baseline state space model.

Table 4 displays the forecasting performances of competing models for Turkey. Clearly, the state space model that incorporates information on two-month and twelve-month ahead

inflation expectations and target inflation dominates all the other alternative specifications at all horizons when RMSE's are compared. Pairwise comparisons of the competing models with the MA model reveals that only the state space model with survey expectations performs significantly better than the MA model according to HAC-DM test. In fact for all horizons, the superior performance of our model compared to the MA model is valid at the 1% significance level for all horizons except the one-year ahead predictions. For the one year-ahead predictions, the statistical significance holds at the 5% level. When we consider the value-added of incorporating survey expectations, we observe that the state space model without survey expectations has a superior performance only up to the three-month horizon. While the test results indicate a better performance at the 1% significance level for one-month ahead forecasts, this significance drops to the 5% level for two-month ahead forecasts and only to 10% for three-month and five-month ahead forecasts. Actually the model without survey expectations performs worse than the MA model after the eight-month horizon. Evidently, the use of survey expectations at two different horizons for Turkey helps to improve the forecasting performance relative to the naive MA forecast, an autoregressive specification where the lag lengths are optimally chosen as well as backward and forward-looking Phillips curve models.

We conclude that the use of survey expectations in frameworks that are statistically coherent, as in the full state space model described by specification (9), enhances their forecasting performance whereas incorporating such expectations in simple Phillips curve-type frameworks does not. In contrast to earlier applications for developed economies, depending on the forecast horizon, the naive MA model is the second or third best performing model for Turkey, indicating the superior predictive performance of our modeling framework with survey expectations established at high levels of significance. The results for Brazil where inflation is relatively stable around the target level are more ambiguous. However, even in this case, our modeling framework performs at least as well as the best model, namely, the simple MA model, when predicting inflation.

4.1 The term structure of inflation expectations

We now use our model to generate the term structure of inflation expectations, as defined by equations (3)-(4). These provide information on expectations at different horizons that is consistent with the survey based expectations conditional on the information set only up to t. It also allows us to assess how well the state space model performs in predicting inflation at different horizons by matching it with stylized facts.

Figure 8 displays expectations of inflation for Brazil. This figure indicates that expectations of monthly inflation that include the seasonal component for Brazil are predicted to be *negative* at longer horizons in the early parts of the sample that begins in 2007, signaling the oncoming recession. In subsequent years, the term structure displays a typical declining shape, with inflation forecasts predicted to be higher at shorter horizons but declining as the horizon increases. By contrast, the estimated model for Brazil suggests increases in inflation expectations during the global financial crisis of 2009 as well as in 2011.

Figure 9 shows expectations of inflation for Turkey extracted using the forecasts from our modeling framework. According to the left panel of this figure, inflation expectations that include the seasonal component are quite volatile. This suggests that forecasting inflation adequately for Turkey may require modeling the seasonal component separately, as we have done in our analysis up to this point. The expectations of the level component inflation displayed in the right panel of Figure 9 show that inflation expectations at shorter horizons are typically high but declining as the horizon increases. An exception to this occurs during the crisis of 2008 when agents expect higher inflation at horizons to a year compared to the medium term. This may reflect agents' uncertainty about the outcome of the inflation process during the global financial crisis of 2008, which was typically unanticipated by most market participants.

5 Additional Variables

The international experience suggests that there are strong common features of inflation across countries that reflect the institutional arrangements involving central bank independence and implicit or explicit inflation targeting that have been put into practice in recent decades. Furthermore, during the sample period in question, the existence of low inflation and low interest rates in the developed economies are additional factors that may have contributed to the nature of their inflation performance. Accordingly, in this section, we first consider an augmented version of the model that allows for the first principal component of inflation rates' for the OECD countries as a measure of global inflation to affect the slope of the inflation process.[13] In this extension, the change in global inflation affects the slope of the inflation process as

$$\mu_t = \lambda\mu_{t-1} + (1-\lambda)\Delta\pi_t^G + \eta_{\alpha,t}, \tag{10}$$

with the rest of the equations in (1) for π_t, α_t, and γ_t remaining unchanged. We also need to specify a law of motion for the global inflation process. We assume that global inflation evolves as a random walk. In this case, the model-based inflation expectations at horizon k reflect the impact of changes on global inflation as follows

$$\begin{aligned} E_t^S[\pi_{t+k}] &= \textstyle\sum_{j=1}^k \phi^j \pi_t + \big(k - \sum_{j=1}^k \phi^j\big)\alpha_t + \big(\sum_{j=1}^k (k+1-j)\lambda^{j-1}\big)\mu_t \\ &+ \big(\textstyle\sum_{j=1}^k \frac{(k-1)k}{2} - (k-j)\lambda^j\big)\pi_t^G - \sum_{j=1}^k \phi^j \gamma_t + \upsilon_{k,t}, \end{aligned} \tag{11}$$

with the rest of the components of the full state space representation in (9) remaining unchanged. Notice that when $\lambda = 1$ the specification reduces to (9).

Another consideration is related to the impact of cyclical factors on inflation dynamics and hence, the inflation targeting performance of a given country. Specifically, which

[13] We conduct a specification search for inclusion of global inflation in our setting. We evaluate two models including the model explained in the main text, where global inflation is used, first, as a determinant of the level of inflation process, and second, as a determinant of the slope of inflation process in the form of changes. The version where the change in the global inflation is used as a determinant of the slope process provides the best results. We display the results regarding to these specifications in the Online Appendix.

particular phase of the business cycle a country is in at a given date - recession or boom - may affect its inflationary performance through differences in the stance of monetary policy. To elaborate this aspect, we consider a second extension of the basic model that includes measures of short-term interest rates and and the gap measure of industrial production index to proxy for the output gap at the monthly frequency directly into the measurement equation for inflation. This specification also can be viewed as a part of the reduced-form (time-varying parameter) VAR from a plain DSGE model containing only demand, supply and monetary policy equations, thus generalizing our specification in (9). The model becomes as follows

$$\pi_t - X_t\alpha_t - \gamma_t \quad = \quad \phi(\pi_{t-1} - X_{t-1}\alpha_{t-1} - \gamma_{t-1}) + \varepsilon_t. \tag{12}$$

Here $X_t = (1, y_t, i_t)'$, y_t is the output gap and i_t denotes the interest rate.[14] In the full state space model with explanatory variables, X_t is assumed to follow a random walk. In this case, the model-based inflation expectations evolve as

$$E_t^S[\pi_{t+k}] \quad = \sum_{j=1}^{k} \phi^j \pi_t + \left(k - \sum_{j=1}^{k} \phi^j\right) X_t\alpha_t - \sum_{j=1}^{k} \phi^j \gamma_t + \upsilon_{k,t}, \tag{13}$$

with the rest of the components of the full state space representation in (9) remaining unchanged.

5.1 Empirical results

A comparison of the in-sample results of the model with global inflation for both Brazil and Turkey to the initial results from the model with $\lambda = 1$, i.e. our baseline model in (9), reveals that the results are qualitatively similar. Indeed, λ is estimated as 0.99 with a very small standard errors in both cases, and hence the model virtually reduces to initial specification. We, therefore, do not display the full sample results of parameter and state estimates for the sake of brevity but refer to the Online Appendix.

[14] The interest rate is measured as the yield on one-month zero-coupon Treasury bills for Turkey. For Brazil we use the interest rate data from the IMF, IFS databases.

The parameter estimates for the model with interest rates and the output gap in the measurement equation for inflation are provided in Tables 5 and 6. These results show that the persistence parameter tends to be lower for Brazil and Turkey compared to the previous models. This is due to the fact that persistence is now partly captured by the interest rate and output gap. We also observe that the variance of the error term is substantially higher in the target inflation equation when interest rates and the output gap are added to the model for Brazil. The estimated states for the model with interest rates and the output gap are displayed in Figures 5 and 6. These figures show that the behavior of the level and slope components of the inflation process essentially reflect the time variation in the components corresponding to the output gap and the interest rates. The discrepancy measures between model-based inflation expectations and the inflation target displayed in the fourth panel of these figures further show that there is more variation in this measure relative to the baseline model.

We now proceed with examining the impact of adding interest rates and the output gap on the discrepancy measure between the model-based inflation expectations and target inflation relative to the baseline model. The left panel of Figure 7 shows that the differences between the two models are not too pronounced for Brazil. In the case of Turkey displayed in right panel of Figure 7, the discrepancy measure generated by both models moves in similar ways. However, an analysis of the behavior of the discrepancy measure for Turkey reveals evidence of cyclicality such that the discrepancy approaches to zero during times of economic distress and widens during times of economic expansion.[15] While this behavior is evident for both Turkey and Brazil, the distinction between the two models is much more evident for Turkey. In the next section, we examine the efficacy of the different variants of the state space model in terms of their out-of-sample forecasting performance.

[15] As we discuss further in the online appendix, the presence of a negative output gap and thus, a decline in economic activity during 2004 and 2006, is accompanied by a decrease in the discrepancy towards zero. On the other hand, the discrepancy widens towards values of -4% around mid-2008 where Turkey experiences an increase in economic activity according to the output gap measure.

5.2 Forecasting performance of the extended models

We display the results of the forecasting exercise in Table 7, where we exhibit the results for Turkey on the left panel and the results for Brazil on the right panel. When we consider Turkey, the RMSE values reveal very similar findings to the full-sample estimation results. The comparison of the baseline model in (9) together with the model where the change in global inflation is incorporated in the slope process indicates almost identical RMSE values for both models. Notice that the model with global inflation nests our baseline model as when $\lambda = 1$ the model reduces to the baseline model. Therefore, we proceed with the OOS-t test of Clark and McCracken (2005) and McCracken (2007) to conduct statistical pairwise comparisons. Indeed, in line with our expectations, statistically the model enhanced with global inflation does not provide additional predictive power at any conventional significance level. This indicates the inflation process in Turkey is determined mostly by domestic forces rather than global impacts.

On the contrary, the model with interest rates and the output gap functioning as explanatory variables of inflation (with time-varying parameters) has lower RMSE values in all of the cases. It seems that business cycle characteristics have a considerable impact on the inflation process for Turkey, as the addition of interest rates and the output gap enhances the forecasting power at all horizons. As in the case of the model with global inflation, this model also nests our baseline model. Indeed, when the initial values for the time-varying parameters of output gap and interest rate together with their variances of state errors are zero, the model reduces to our baseline model. Statistical evaluation validates the increase in the predictive ability of the model which includes the output gap and interest rate compared to the baseline model. In most of the cases, the OOS-t statistic indicates the superior predictive power of the extended model at conventional significance levels except some horizons including the one- and six-month ahead forecasts. Apparently, while the standard baseline model without any explanatory variables but one which includes survey-based expectations and target inflation is flexible enough to capture the salient feature of the inflation process and produces superior forecasts of inflation

relative to other benchmark models, this forecasting power can be increased further by incorporating business cycle features to the model.

The results for Brazil displayed in the right panel of Table 7 reveal interesting patterns. When we consider the effect of global inflation in the slope process of the inflation, it is more pronounced compared to Turkey in the sense that the RMSE values drop on average of 40-70 basis points at almost all horizons, with greater difference occurring at longer horizons. The exception is the 1-month ahead forecasts, where the decrease remains limited to 20 basis points. The model with interest rates and the output gap as additional explanatory variables attains similar RMSE values with slightly higher values at short horizons and slightly lower values at longer horizons. Specifically at horizons longer than seven months, the RMSE values for this model attain a minimum, indicating a further increase in the precision of inflation forecasts. Indeed, both models provide statistically significant improvement on the standard baseline model at conventional levels in most of the cases according to the results of OOS-t tests. This implies that the inflation process in Brazil is affected by both global forces and business cycle effects, where the former is more effective in the long-run while the latter is more effective in the short run.[16]

6 Conclusion

In this paper, we propose a statistical framework for predicting inflation in two key emerging economies - Brazil and Turkey - that have commonalities and differences in their experience with inflation and the inflation targeting regime. Our approach provides an efficient inflation forecasting device that incorporates expert opinion (survey based expectations) within a flexible statistical predictive model. This enables us to increase the information content used for prediction. Our model reacts to sudden changes in the inflation process that are typically observed in emerging economies such as changes in monetary policy, structural breaks or political turmoil through the use of survey expectations and other

[16] We also test the baseline model enhanced with output gap and interest rate against the MA model which produces lower RMSE values than our baseline model, albeit statistically not different than our baseline model.

exogenous factors. The state space framework allows us to incorporate information about annual target inflation into the model and to handle missing observations in a flexible and statistically coherent way. The inclusion of such information also enables us to obtain monthly deviations of the inflation expectations from target inflation as a way of measuring the stance of monetary policy and monetary credibility.

A pseudo out-of-sample forecasting exercise is used to examine the performance of our model relative to alternatives such as the forward-looking Philips curve with survey expectations or naive forecasting rule considered in the literature on inflation forecasting. Our results reveal that the inclusion of survey expectations in the model leads to superior forecasting performance compared to a version that does not. The model outperforms the benchmark models especially when inflation is volatile, displaying sudden changes as in the case of Turkey. For Brazil where inflation is more stable the performance of our modeling framework is as good as the naive forecasting rule. We also find that incorporating global factors such as global inflation into the model further improves the out-of-sample performance for Brazil while the version of the model with cyclical factors such as interest rates and the output gap yield superior forecasting performance for Turkey.

Finally, we provide an out-of-sample assessment of our model's performance in terms of the term structure of inflation that it generates. Survey-based inflation expectations at different horizons are typically not available for many emerging economies. By contrast, the approach used in this paper enables us to generate the term structure of inflation expectations for a given year. By construction, such expectations are consistent with the few available survey-based expectations. Thus, we believe that the flexible and statistically coherent approach we have analyzed in this paper provides a valuable tool for assessing the discrepancy between inflation expectations and target inflation and the behavior of inflation expectations at different horizons in addition to its superior predictive power.

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Tables and Figures

Table 1: Estimation results for Brazil: The basic state space model

	ϕ	$\sigma^2_{\eta_\alpha}$	$\sigma^2_{\eta_\mu}$	$\sigma^2_{\eta_\gamma}$	$\sigma_{\eta_\alpha,\eta_\mu}$	$\sigma_{\eta_\alpha,\eta_\gamma}$	$\sigma_{\eta_\mu,\eta_\gamma}$
Estimate	0.559	0.009	0.000	0.006	0.00009	0.007	0.00007
St. dev	(0.031)	(0.003)	(0.000)	(0.024)	(0.00004)	(0.016)	(0.0001)
	$\sigma^2_{\eta_\delta}$	$\sigma_{\eta_\delta,\eta_\alpha}$	$\sigma_{\eta_\delta,\eta_\mu}$	$\sigma_{\eta_\delta,\eta_\gamma}$			
Estimate	2.349	-0.146	-0.001	-0.118			
St. dev	(0.873)	(0.054)	(0.000)	(0.249)			
	σ^2_{ε}	$\sigma^2_{\upsilon_{12}}$	$\sigma^2_{\upsilon^T}$	$\sigma_{\varepsilon,\upsilon_{12}}$	$\sigma_{\varepsilon,\upsilon^T}$	$\sigma_{\upsilon_{12},\upsilon^T}$	
Estimate	0.672	0.554	0.295	-0.608	-0.420	0.370	
St. dev.	(0.260)	(0.446)	(0.324)	(0.306)	(0.302)	(0.308)	

Note: The table presents estimation results with standard deviations (in parentheses) of parameters of the model detailed in (9) using data on the CPI inflation rate for Brazil together with the BCB one-year ahead survey inflation expectations and the inflation target over the period from November 2001 to January 2014.

Table 2: Estimation results Turkey: The basic state space model

	ϕ	$\sigma^2_{\eta_\alpha}$	$\sigma^2_{\eta_\mu}$	$\sigma^2_{\eta_\gamma}$	$\sigma_{\eta_\alpha,\eta_\mu}$	$\sigma_{\eta_\alpha,\eta_\gamma}$	$\sigma_{\eta_\mu,\eta_\gamma}$
Estimate	0.371	0.002	0.000	0.023	-0.0001	0.005	-0.0007
St. dev	(0.034)	(0.001)	(0.000)	(0.006)	(0.00008)	(0.001)	(0.0002)
	$\sigma^2_{\eta_\delta}$	$\sigma_{\eta_\delta,\eta_\alpha}$	$\sigma_{\eta_\delta,\eta_\mu}$	$\sigma_{\eta_\delta,\eta_\gamma}$			
Estimate	0.021	-0.003	-0.00025	0.008			
St. dev	(0.016)	(0.004)	(0.00006)	(0.021)			
	σ^2_{ε}	$\sigma^2_{\upsilon_2}$	$\sigma^2_{\upsilon_{12}}$	$\sigma^2_{\upsilon^T}$	$\sigma_{\varepsilon,\upsilon_2}$	$\sigma_{\varepsilon,\upsilon_{12}}$	$\sigma_{\varepsilon,\upsilon^T}$
Estimate	0.388	0.063	0.140	1.106	-0.098	-0.231	-0.395
St. dev	(0.051)	(0.017)	(0.038)	(0.806)	(0.031)	(0.040)	(0.331)
	$\sigma_{\upsilon_2,\upsilon_{12}}$	$\sigma_{\upsilon_2,\upsilon^T}$	$\sigma_{\upsilon_{12},\upsilon^T}$				
Estimate	0.067	0.075	0.230				
St. dev	(0.024)	(0.029)	(0.190)				

Note: The table presents estimation results with standard deviations (in parentheses) of parameters of the model detailed in (9) using data on the CPI inflation rate for Turkey together with CBRT two-month and one-year ahead survey inflation expectations and the inflation target over the period from August 2001 to January 2014.

Table 3: Out-of-sample forecasting results for Brazil

Model Horizon	Model with survey	Model without survey	MA (AO)	AR	PC with IP gap	HPC with IP gap
1	0.225	0.189*	0.218	0.192*	0.191*	**0.187***
2	0.263	0.264*	**0.226**	0.247	0.355**	0.244
3	0.283*	0.287**	**0.231**	0.359***	0.418***	0.263*
4	0.284	0.307**	**0.236**	0.442***	0.478***	0.291**
5	0.278	0.331**	**0.239**	0.543***	0.560***	0.337***
6	0.270	0.332**	**0.241**	0.590***	0.617***	0.374***
7	0.270	0.340**	**0.242**	0.580***	0.611***	0.384***
8	0.275	0.317*	**0.241**	0.497***	0.540***	0.345***
9	0.284	0.301*	**0.240**	0.408***	0.501***	0.358***
10	0.296	0.294*	**0.239**	0.367***	0.515**	0.312***
11	0.304*	0.281*	**0.240**	0.361***	0.478***	0.277**
12	0.305*	0.257	**0.242**	0.369***	0.496***	0.286**

Notes: The table presents the out-of-sample forecasting performance of (i) the model detailed in (9) using information on survey expectations, denoted as model with survey; (ii) the model detailed in (9) without using information on survey expectations, denoted as model without survey; (iii) a naive MA model as suggested by Atkeson and Ohanian (AO), denoted as MA (AO) (2001); (iv) an AR(p) model, denoted as AR; (v) a backward-looking Phillips curve (PC) with the current IP gap, denoted as PC with IP gap; (vi) a hybrid New Keynesian Phillips curve (HPC) with twelve-month ahead survey expectations and the current IP gap, denoted as PC with IP gap. The different models are estimated and forecasted using a sample given initially by 2001:11-2007:1 and extending until 2014:1. Pairwise comparisons are carried out using HAC-DM test with HLN finite-sample correction. The comparisons involve the competing models against the MA model. '***' indicates significance at 1%, '**' indicates significance at 5%, '*' indicates significance at 10% against one sided alternative of the positive loss differential. A larger (smaller) RMSE with asterisk indicates statistical significance for inferior (superior) performance.

Table 4: Out-of-sample forecasting results for Turkey

Model Horizon	Model with survey	Model without survey	MA (AO)	AR	PC with IP gap	HPC with IP gap
1	**0.709*****	0.723***	0.873	0.999*	1.010*	0.838
2	**0.733*****	0.778**	0.888	1.497***	1.523***	1.019***
3	**0.726*****	0.807*	0.893	1.985***	1.977***	1.063***
4	**0.735*****	0.849	0.897	1.994***	1.989***	1.181***
5	**0.732*****	0.782*	0.892	1.726***	1.699***	1.101***
6	**0.736*****	0.843	0.899	1.523***	1.514***	1.063**
7	**0.733*****	0.868	0.896	1.534***	1.541***	1.001*
8	**0.735*****	0.895	0.881	1.779***	1.696***	1.089***
9	**0.741*****	1.018	0.880	2.124***	2.048***	1.089***
10	**0.742*****	1.003	0.876	2.130***	1.976***	1.314***
11	**0.731*****	0.966	0.855	1.552***	1.538***	1.157***
12	**0.733****	0.982	0.841	1.154***	1.062**	1.002**

Notes: See Table 3 for details.

Table 5: Estimation results for Brazil: Interest rates and output gap in the measurement equation for inflation

	ϕ	$\sigma^2_{\eta_{\alpha_1}}$	$\sigma^2_{\eta_{\alpha_2}}$	$\sigma^2_{\eta_{\alpha_3}}$	$\sigma_{\eta_{\alpha_1},\eta_{\alpha_2}}$	$\sigma_{\eta_{\alpha_1},\eta_{\alpha_3}}$	$\sigma_{\eta_{\alpha_2},\eta_{\alpha_3}}$
Estimate	0.366	0.009	0.000	0.0005	-0.0001	-0.0002	0.0000
St. dev	(0.033)	(0.002)	(0.000)	(0.0000)	(0.0000)	(0.0011)	(0.0000)
	$\sigma^2_{\eta_\gamma}$	$\sigma_{\eta_\gamma,\eta_{\alpha_1}}$	$\sigma_{\eta_\gamma,\eta_{\alpha_2}}$	$\sigma_{\eta_\gamma,\eta_{\alpha_3}}$	$\sigma_{\eta_\gamma,\eta_\delta}$		
Estimate	0.0000	-0.0002	0.000	-0.000	0.003		
St. dev	(0.0008)	(0.0000)	(0.027)	(0.000)	(0.401)		
	$\sigma^2_{\eta_\delta}$	$\sigma_{\eta_\delta,\eta_{\alpha_1}}$	$\sigma_{\eta_\delta,\eta_{\alpha_2}}$	$\sigma_{\eta_\delta,\eta_{\alpha_3}}$			
Estimate	1.628	-0.118	0.001	-0.003			
St. dev	(0.000)	(0.000)	(0.000)	(0.015)			
	σ^2_ε	$\sigma^2_{\upsilon_{12}}$	$\sigma^2_{\upsilon^T}$	$\sigma_{\varepsilon,\upsilon_{12}}$	$\sigma_{\varepsilon,\upsilon^T}$	$\sigma_{\upsilon_{12},\upsilon^T}$	
Estimate	0.609	0.010	0.575	-0080	-0.592	0.077	
St. dev	(0.151)	(0.056)	(0.175)	(0.212)	(0.142)	(0.206)	

Note: The table presents estimation results with standard deviations (in parentheses) of parameters of the state space model modified as in (13) using the CPI inflation rate for Brazil together with the BCB one-year ahead survey inflation expectations, the inflation target and data on interest rates and the IP gap over the period from November 2001 to January 2014.

Table 6: Estimation results for Turkey: Interest rates and the output gap in the measurement equation for inflation

	ϕ	$\sigma^2_{\eta_{\alpha_1}}$	$\sigma^2_{\eta_{\alpha_2}}$	$\sigma^2_{\eta_{\alpha_3}}$	$\sigma_{\eta_{\alpha_1},\eta_{\alpha_2}}$	$\sigma_{\eta_{\alpha_1},\eta_{\alpha_3}}$	$\sigma_{\eta_{\alpha_2},\eta_{\alpha_3}}$
Estimate	0.232	0.0003	0.0000	0.0007	0.0000	-0.0003	-0.0000
St. dev	(0.015)	(0.0003)	(0.0000)	(0.000)	(0.0003)	(0.0016)	(0.0088)
	$\sigma^2_{\eta_\gamma}$	$\sigma_{\eta_\gamma,\eta_{\alpha_1}}$	$\sigma_{\eta_\gamma,\eta_{\alpha_2}}$	$\sigma_{\eta_\gamma,\eta_{\alpha_3}}$	$\sigma_{\eta_\gamma,\eta_\delta}$		
Estimate	0.014	-0.001	-0.000	0.001	0.005		
St. dev	(0.000)	(0.000)	(0.004)	(0.000)	(0.190)		
	$\sigma^2_{\eta_\delta}$	$\sigma_{\eta_\delta,\eta_{\alpha_1}}$	$\sigma_{\eta_\delta,\eta_{\alpha_2}}$	$\sigma_{\eta_\delta,\eta_{\alpha_3}}$			
Estimate	0.170	0.004	0.000	-0.010			
St. dev	(0.000)	(0.001)	(0.000)	(0.049)			
	σ^2_ε	$\sigma^2_{\upsilon_2}$	$\sigma^2_{\upsilon_{12}}$	$\sigma^2_{\upsilon^T}$	$\sigma_{\varepsilon,\upsilon_2}$	$\sigma_{\varepsilon,\upsilon_{12}}$	$\sigma_{\varepsilon,\upsilon^T}$
Estimate	0.264	0.056	0.052	1.170	-0.050	-0.114	-0.302
St. dev	(0.035)	(0.014)	(0.016)	(1.999)	(0.023)	(0.021)	(0.396)
	$\sigma_{\upsilon_2,\upsilon_{12}}$	$\sigma_{\upsilon_2,\upsilon^T}$	$\sigma_{\upsilon_{12},\upsilon^T}$				
Estimate	0.033	0.253	0.178				
St. dev	(0.012)	(0.030)	(0.126)				

Note: The table presents estimation results with standard deviations (in parentheses) of parameters of the state space model modified as in (13) using data on the CPI inflation rate obtained for Turkey, the CBRT two-month and one-year ahead survey inflation expectations, the inflation target and data on interest rates and the IP gap over the period from August 2001 to January 2014.

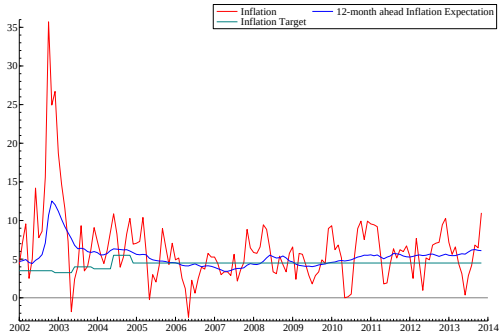
Table 7: Out-of-sample forecasting results: Comparison with extended models

	Turkey			**Brazil**		
Model Horizon	Baseline model (BM)	BM with global inflation	BM with additional variables	Baseline model (BM)	BM with global inflation	BM with additional variables
1	0.709	0.711	**0.703**	0.225	**0.205***	0.416
2	0.733	0.735	**0.694*****	0.263	0.223***	**0.218****
3	0.726	0.729	**0.706****	0.283	0.245**	**0.232****
4	0.735	0.737	**0.697*****	0.284	**0.231*****	0.236**
5	0.732	0.735	**0.701****	0.278	0.246**	**0.238****
6	0.736	0.739	**0.723**	0.270	0.237**	**0.236***
7	0.733	0.736	**0.718****	0.270	**0.219*****	0.233**
8	0.735	0.738	**0.718***	0.275	0.232***	**0.227****
9	0.741	0.744	**0.709*****	0.284	**0.226*****	0.232**
10	0.742	0.746	**0.714*****	0.296	**0.231*****	0.236**
11	0.731	0.736	**0.698*****	0.304	**0.236*****	0.244**
12	0.733	0.735	**0.682*****	0.305	**0.233****	0.246**

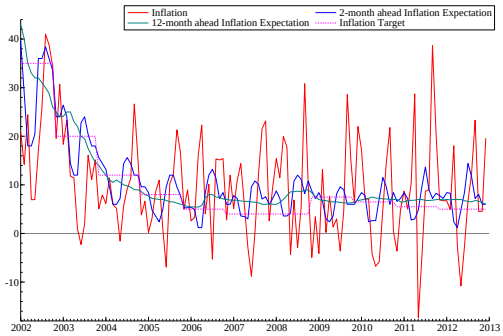
Notes: The table presents the out-of-sample forecasting performance of (i) baseline model (BM) detailed in (9) using information on survey expectations, Baseline Model (BM); (ii) the specification with the change of global inflation in the slope process of inflation detailed in (10), denoted as BM with global inflation; and (iii) the specification with output gap and interest rate in the inflation process detailed in (12), denoted as BM with additional variables. The different models are estimated and forecasted using a sample given initially by 2001:8-2007:1 for Turkey (2001:11-2007:1 for Brazil) and extending until 2014:1. Pairwise comparisons are carried out using OOS-t test, see Clark and McCracken (2005); McCracken (2007) for details. The comparisons involve the competing models against the baseline model. '***' indicates significance at 1%, '**' indicates significance at 5%, '*' indicates significance at 10% with the critical values provided in McCracken (2007) for the recursive scheme. A larger (smaller) RMSE with asterisk indicates statistical significance for inferior (superior) performance.

Figure 1: Sample Characteristics

(i) Brazil

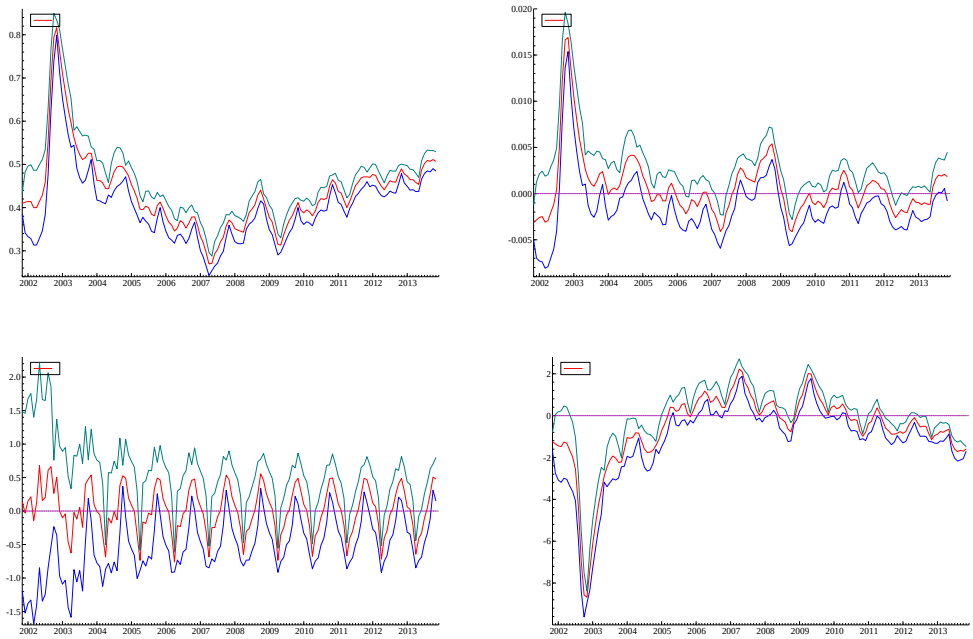


(ii) Turkey



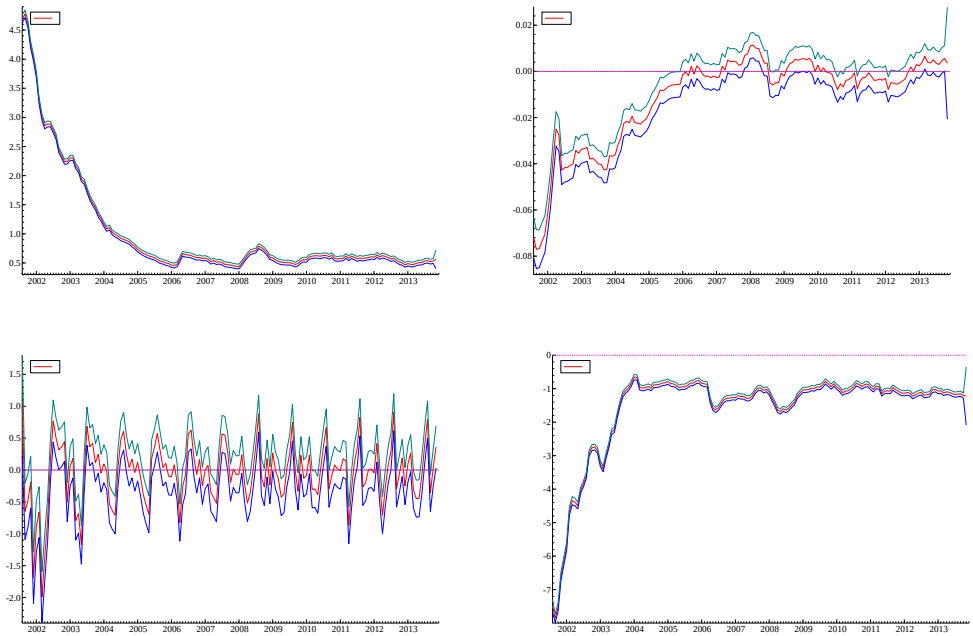
Note: For Brazil, the graph shows the CPI inflation for Brazil together with one-year ahead survey expectations and the inflation targets over the period November 2001-January 2014. For Turkey, the graph shows the CPI inflation for Turkey together with two-month and one-year ahead survey expectations and the inflation targets for the period August 2001-January 2014.

Figure 2: Estimated Components of Inflation for Brazil



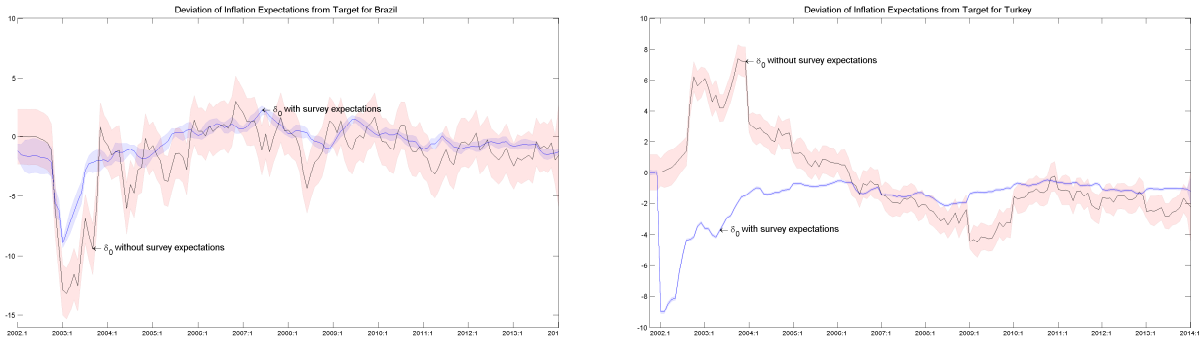
Note: The graphs show the inflation level, slope, and seasonality obtained from the model in (9) using consumer price index in Brazil together with survey expectations of one-year ahead inflation and the estimated deviations from target inflation over the period from November 2001-January 2014 for Brazil.

Figure 3: Estimated Components of Inflation for Turkey



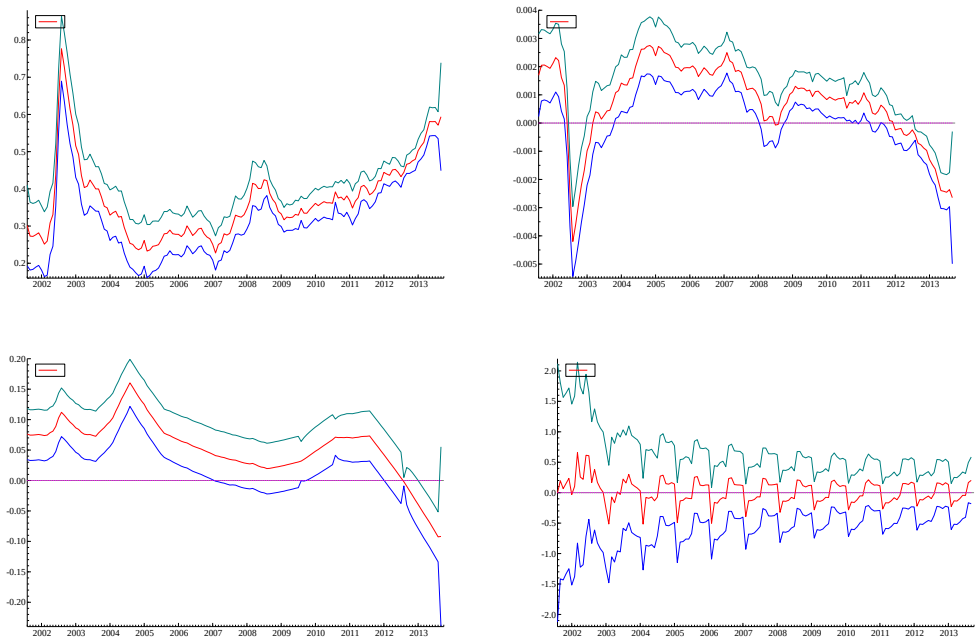
Note: The graphs show the inflation level, slope, and seasonality obtained from the full state space model in (9) using consumer price index in Turkey together with CBRT survey expectations of two-month and one-year ahead inflation and the estimated deviations from target inflation over the period from August 2001-January 2014 for Turkey.

Figure 4: Systematic Component of the Deviations of Inflation from Target for Brazil and Turkey: Comparison of baseline model with and without survey expectations



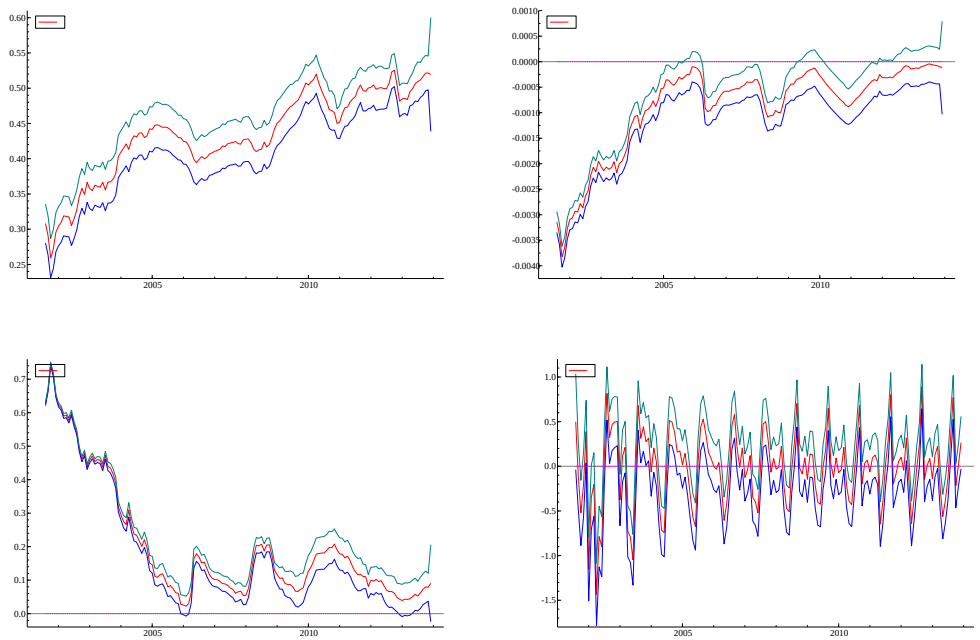
Note: The graphs show the estimate of the systematic component of inflation expectations from the target calculated with and without the use of survey expectations in the full space model in (9)

Figure 5: Estimated Components of Inflation for Brazil: Interest rates and IP gap in the measurement equation for inflation



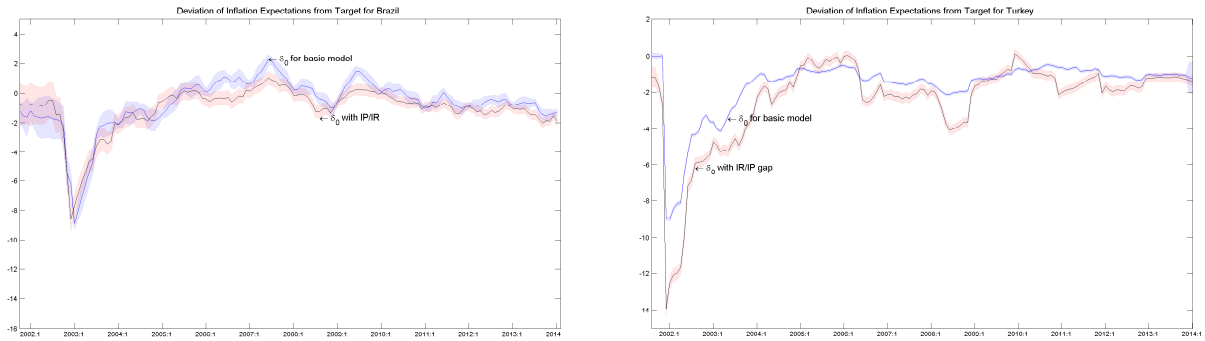
Note: The graphs show from left to right and from top to bottom the evolution of time varying intercept, the coefficient of the IP gap, the coefficient of interest rates, and seasonality component in Brazil based on the state space model modified as in (13) estimated using the period November 2001-January 2014.

Figure 6: Estimated Components of Inflation for Turkey: Interest rates and IP gap in the measurement equation for inflation



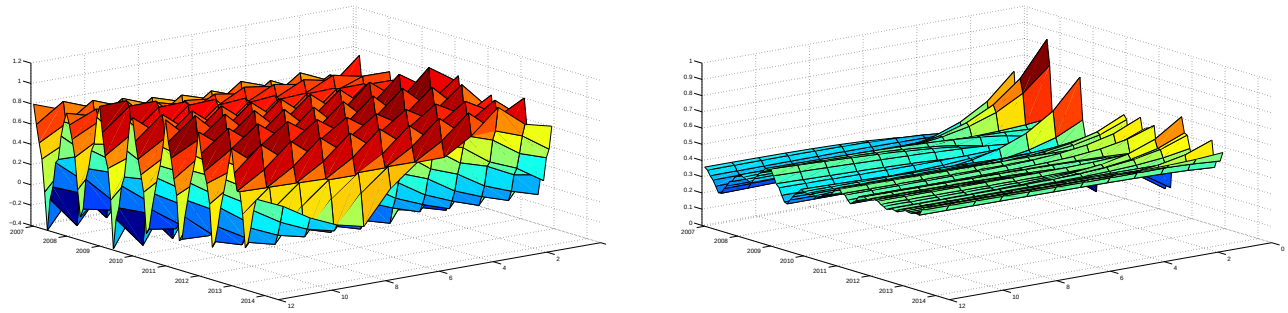
Note: The graphs show from left to right and from top to bottom the evolution of time varying intercept, the coefficient of IP gap, the coefficient of interest rates, and seasonality component in Turkey based on the state space model modified as in (13) estimated using the period August 2001-January 2014.

Figure 7: Systematic Component of the Deviations of Inflation from Target for Brazil and Turkey: Comparison of baseline model and model with interest rate and output gap



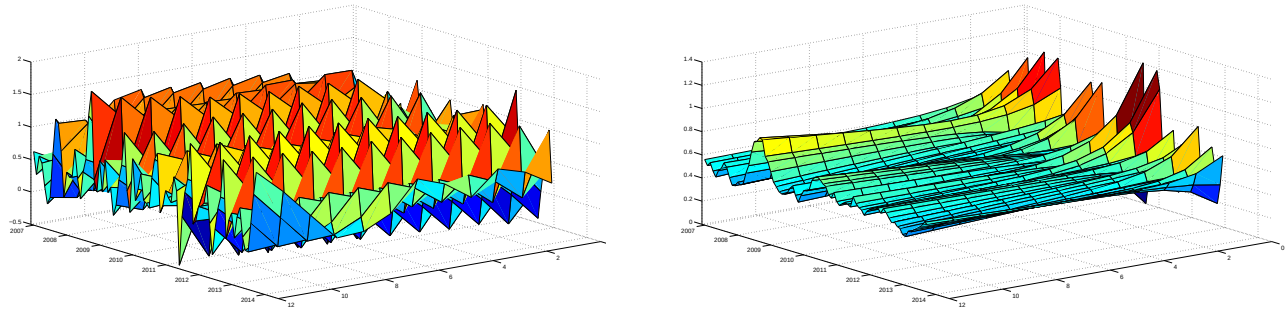
Note: The graphs show the discrepancy between the model-based expectations and the target inflation for the basic model and for the model modified as in (13) for the period November 2001-January 2014 for Brazil (August 2001-January 2014 for Turkey).

Figure 8: Term Structure of Expectations of Inflation and Its Level for Brazil



Note: The graphs show the expectations of monthly inflation and its level based on the full state space model in (9) for the period January 2007-January 2014

Figure 9: Term Structure of Expectations of Inflation and Its Level for Turkey



Note: The graphs show the expectations of monthly inflation and its level based on the full state space model in (9) for the period January 2007-January 2014.