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A Bayesian VAR Approach to Short-Term Inflation Forecasting

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Abstract

In this paper, we discuss the forecasting performance of Bayesian vector autoregression (BVAR) models for inflation under alternative specifications. In particular, we consider modelling in levels or in differences; choice of tightness; estimating BVARs of different model sizes and the accuracy of conditional and unconditional forecasts. Our empirical results point out that BVAR forecasts using variables in log-difference form outperform the ones using log-levels of the data. When we evaluate forecast performance in terms of model size, the lowest forecast errors belong to the models having relatively small number of variables, though we find only small difference in forecast accuracy among models of various sizes up to two quarter ahead. Finally, the conditioning seems to help to forecast inflation. Overall, pseudo evaluation findings suggest that small to medium size BVAR models having wisely selected variables in difference form and conditioning on the future paths of some variables appear to be a good choice to forecast inflation in Turkey.

Özet

Bu çalışmada, Bayesçi vektör otoregresyon (BVAR) modellerinin enflasyon tahmin performansını alternatif model tanımlamaları altında tartışıyoruz. Özellikle, modelde değişkenleri seviye veya logaritmik fark olarak kullanmanın, hiperparametre seçiminin, farklı büyüklükteki BVAR modelleri ile koşullu ve koşulsuz tahminlerin performansını değerlendiriyoruz. Ampirik sonuçlarımız, değişkenlerin logaritmik fark olarak kullanıldığı BVAR modellerinin, log-seviye olarak kullanıldığı modellere kıyasla daha iyi tahmin performansı sergilediğine işaret etmektedir. Tahmin performansını model büyüklüğü açısından değerlendirdiğimizde, en düşük tahmin hatalarının görece az sayıda değişkene sahip modellere ait olduğu gözlenmekle birlikte, çeşitli büyüklükteki modeller arasında tahmin doğruluğu açısından iki çeyreğe kadar küçük farklar olduğu izlenmiştir. Son olarak, koşullu enflasyon tahminleri koşulsuzlara kıyasla daha düşük tahmin hatasına sahiptir. Genel olarak bulgular, enflasyonu tahmin etme içeriği gözetilerek seçilmiş ve logaritmik fark olarak tanımlanmış değişkenlere sahip olan ve modeldeki bazı değişkenlerin gelecekteki seyrine yönelik koşullama yapılan, küçük ve orta büyüklükteki BVAR modellerinin Türkiye'de enflasyonu tahmin etmek için iyi bir seçim olduğunu ileri sürmektedir.

Keywords: Inflation, Forecasting, Bayesian vector autoregression, Turkey

JEL codes: C51, C52, E37

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Non-Technical Summary

Forecasting the future course of inflation is one of the fundamental tasks in monetary policy making. However, predicting inflation is a challenging task and involves large number of specification choices. Among the possible multivariate models, Bayesian vector autoregressions have become a widely-used tools for forecasting and policy analysis. Besides, given the recent finding in the literature that BVAR models tend to produce better forecasts for Turkish inflation, this study aims to elaborate more on this predictive ability by evaluating the forecasting performance of alternative specification choices. In particular, we study some variants of BVARs such as modelling in levels or in differences; selection of hyperparameters; estimating BVARs of different model sizes and the accuracy of conditional and unconditional forecasts, and find those providing the most accurate forecasts according to out-of-sample forecast performance.

The results indicate that Bayesian VARs produce accurate point forecasts. Models handling the variables in stationary form rather than in log-levels yield better results. When we evaluate the performance in terms of model size, only a small number of variables appear to drive the majority of the fluctuations in the Turkish inflation. For instance wisely selected 7 variable BVAR model (Brent oil prices, import prices in dollars, nominal exchange rate basket, output gap, real unit labor costs, survey-based inflation expectations and CPI excluding unprocessed food and tobacco along with an exogenous variable considering the impact of tax changes on inflation) works well, though we find only small difference in forecast accuracy among models of various sizes up to two quarter ahead. Finally, the conditioning seems to help to forecast inflation. Models do a good job tracking the observed inflation when we condition on the future paths of some variables, for instance exchange rate, import and oil prices.

1. Introduction

Forecasting the future course of inflation is one of the fundamental tasks in monetary policy making. However, predicting inflation is a challenging task and involves large number of specification choices. Vector autoregression (VAR) models are popular tools for forecasting and policy analysis among the possible multivariate time series models. They are seemingly unrelated regression models, thus they do not suffer from an endogeneity problem. Yet these models might have a large number of parameters even for the models of moderate size and this may lead to a problem known as over-parameterization, resulting in inaccurate estimation of parameters. Bayesian version of VAR models (BVARs) overcome this problem by applying a shrinkage, explicitly imposing restrictions through prior distributions, which makes it possible to estimate VAR models accurately. After the approach proposed by Banbura, Giannone and Reichlin (2010), it has been feasible to estimate BVAR models with very large datasets. BVAR models have become a widely-used tools in macroeconomics. A general discussion of Bayesian VARs can be found in Koop and Korobilis (2010), Dieppe et al. (2017) and the references therein.

The number of studies focusing on forecasting inflation in Turkey in the last two decade are rather limited. Domaç (2004) concentrates on three different models; mark-up, monetary and the Phillips curve models. The findings suggest that even though the mark-up models have the best in-sample performance, the outcomes from out-of-sample forecasting reveal that the Phillips curve and the money gap models perform better than the mark-up for the early 2000s. Önder (2004) asserts that the inflation forecasts obtained from the Phillips curve for the 1987–2001 periods are found to be more accurate than the ones based on other macroeconomic variables. These two studies underline the performance of economic activity measures such as output gap. Altuğ and Çakmaklı (2016) argue that the inclusion of survey based inflation expectations in the forecast model leads additional predictive gains, particularly when inflation is volatile. A recent study by Mandalinci (2017) carries out a comprehensive comparison across emerging market economies including Turkey and find that the performances of the alternative models demonstrate noteworthy differences across both time and countries. In general, for the developed countries, models that account for time variation in the coefficients and volatilities perform better. Unobserved component stochastic volatility model proposed by Stock and Watson (2007) - which is in fact a univariate model- appears to fit the data better in Mexico and Turkey; whereas the rolling BVAR in Chile, the Philippines and Thailand; and Time-varying VAR in Indonesia and Malaysia seem to be the best performing models. Overall, the result of this study advocates the time variation in model parameters. Günay (2018) approaches the forecasting subject from the factor models angle and reaches to somewhat a broad conclusion that the performance of specifications depend on the variable at hand, the forecast horizon and the sample period.[1] The most comprehensive individual study assessing the performance of the assorted inflation forecasting models for Turkey belongs to Öğünç et al. (2013), which compare a suite of models[2] based on pseudo out-of-sample performance. They conclude that the gains are clearly evident for the VAR based models[3]. In particular, Bayesian VAR models appear to fit the Turkish data better. Likewise, as noted earlier, recently there has been a resurgence of interest in applying BVARs for forecasting macroeconomic variables both in emerging and developed economies, for instance see Koop (2013), Giannone et al. (2014), Carriero et al., (2015), Demeshev and Malakhovskaya (2015), Berg and Henzel (2015). These points indeed constitute the main motivation of the current study and accordingly we scrutinize whether the performance of BVAR models appearing to fit the Turkish data well might be further enhanced under alternative specification and model choices. In particular we evaluate which form of the variables we should use, i.e. pre-transforming the variables to render data stationary or introducing in log-levels to take into account the information in levels such as cointegration. We also consider selection of hyper parameters for respective priors, compare performance of different model sizes and discuss the accuracy of conditional and unconditional forecasts in Turkish data context.

The results indicate that the forecasting performances of Bayesian VARs are mostly satisfactory and models can be used to produce alternative scenario analysis. In a nutshell, small to medium size BVAR models having wisely selected variables in difference form and conditioning on the future paths of some variables, for instance exchange rate, import and oil prices, arise as a good choice to forecast inflation in Turkey.

The remainder of the paper is organized as follows. Section 2 describes the models and forecasting methodology in addition to the dataset; Section 3 presents the forecast evaluation results; and Section 4 concludes the study.

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[1] Note also that there are number of studies stating that Bayesian VARs do tend to forecast better than factor methods, for instance Banbura et al. (2010), Koop (2013). Likewise, Öğünç et al. (2013) put forward that the performance of factor-based models change across forecast horizons and the gains are not quantitatively noticeable most of the time compared to other competitor models in the case of Turkey.

[2] Model set consists of univariate models, time and frequency domain decomposition based approaches, time varying parameter Phillips curve model, a range of VAR and Bayesian VAR models and lastly FAVAR models.

[3] Note that Öğünç et al. (2013)'s suite of models comprise time variation in coefficients as well, throughout a TVP Phillips curve model. Even though BVAR seems to be the best individual model, TVP model shows relatively good performance as for some horizons. Therefore, given the prominent emphasis in Mandalinci (2017), it might be worthwhile to examine closely the performance of time-varying VAR models along with stochasting volatility for Turkey as a further research.

2. Models and forecasting methodology

Vector autoregressions allow us to capture dynamic interrelationships among a set of endogenous variables. A general representation of VAR(p) model can be written as:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + A_3 y_{t-3} + \cdots + A_p y_{t-p} + C x_t + \varepsilon_t, \quad \text{t=1,2,...T}$$

$$\varepsilon_t \sim N(0, \Sigma)$$

where y_t denotes the matrix containing n endogenous variables, p is the lag length, x_t is a vector of exogenous variables including the constant term and other exogenous regressors, and ε_t is vector of residuals with a variance-covariance matrix of Σ. In more compact notation, we can define the coefficients as $B = (A_1 \quad A_2 \cdots A_p \quad C)'$ and X as comprising endogenous and exogenous variables so that $Y = XB + \epsilon$. Since each equation has identical regressors, it is possible to rewrite the above model in the following vectorised form:

$$y = (I_n \otimes X)\beta + \varepsilon$$

with $y = vec(Y)$, $\beta = vec(B)$ and $\varepsilon = vec(\epsilon)$. Our aim is to estimate the coefficients of the model (B) along with the residual variance-covariance matrix Σ. Since our sample starts only from the first quarter of 2005, the estimation of these parameters with the classical approach is not straightforward. The relatively small sample size in relation to large number of variables is a challenge against precise estimation of these parameters (commonly leads to overfitting), known as dimensionality problem. To overcome this, along with its other advantages, we adopt Bayesian shrinkage approach. In the Bayesian world, every parameter is a random variable, characterized by some probability distribution. We obtain these probability distributions, explicitly the posterior distributions, by combining our prior knowledge (prior distribution) with the information in the data (likelihood function).

While working with the forecasting models in this paper, we use the CPI excluding unprocessed food and tobacco (CPI-D) (instead of the headline consumer price index) as the main variable of interest.[4] In order to produce short-term projections, we have to decide on the possible driving forces of inflation. Boivin and Ng (2006) in their factor model paper suggest that pre-selecting the variables in line with their relationship with the forecasted variable can improve the forecasting performance. Rather than relying on a large dataset, we prefer to use wisely selected set of variables having a close connection with the target variable. Andıç and Öğünç (2015) formulate a pseudo out-of-sample

[4] We prefer CPI-D inflation to headline consumer inflation because of its predictive power. The unprocessed food (roughly 40 percent of it is fresh fruits and vegetables) and tobacco prices (subject to tax changes) are highly erratic in Turkey. Note that, in addition to headline CPI projections, CBRT has also published forecasts for CPI-D in its Quarterly Inflation Report since the last quarter of 2010.

methodology to choose variables that would be helpful in forecasting.[5] For this purpose, we resort to the methodology proposed by Andıç and Öğünç (2015) to select the set of predictors relevant for prediction of CPI-D inflation. The following variables come into prominence when this strategy is applied: Brent oil prices, import prices in US dollars, nominal exchange rate basket, output gap, real unit labor costs, producer prices, 12 month-ahead inflation expectations, 3 month treasury bill rate, total employment, Business Tendency Survey (BTS) total order books, real consumer credit, consumer credit and deposit rate spread, capacity utilization rate, BTS-average unit cost expectations, Bank Loans Tendency Survey (BLTS) credit standards, unemployment gap, CBOE volatility index (VIX), export quantity index and Turkey credit default swaps (CDS).[6]

Due to the existence of many predictors, we estimate seven different Bayesian VAR models ranging from small to medium size, presented in Table 1, specifically having five to twenty endogenous variables. This will allow us to comment on appropriate size of the model suitable to project Turkish inflation as well. We estimate the models with 4 lags to capture the properties of our quarterly data well. In addition, each model includes an exogenous variables titled "taxfactor", which quantifies the direct effect of various tax changes on CPI-D inflation. The model is estimated on a quarterly frequency and the sample period covers 2005Q1:2017:Q4.

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[5] This methodology uses a single-equation model as benchmark specification. Then it enlarges this single-equation model by adding candidate variables individually to the benchmark specification. It employs a pseudo out-of-sample approach and compare the forecasting performance of each variable ex-post with the benchmark model. Defining the lag structure of a variable in two different ways, the methodology determines the non-leading forecasters and leading indicators of inflation. Furthermore, this study measures forecast errors over different forecast horizons instead of over time for each horizon, which allows forecasters to evaluate the performance of the variables periodically as well.

[6] Appendix Table A.1 provides more details on the dataset.

Table 1: Variables in BVAR models

Models	M1	M2	M3	M4	M5	M6	M7
Endogenous variables							
CPI excluding unprocessed food and tobacco	*	*	*	*	*	*	*
Import prices	*	*	*	*	*	*	*
Nominal exchange rate basket	*	*	*	*	*	*	*
Output gap or log-GDP	*	*	*	*	*	*	*
Real unit labor costs	*	*	*	*	*	*	*
12 month-ahead inflation expectations		*	*	*	*	*	*
Brent oil prices			*	*	*	*	*
3 month treasury bill rate				*	*	*	*
Producer prices					*	*	*
Total employment						*	*
BTS-total orders books						*	*
Real consumer credit						*	*
Consumer credit and deposit rate spread						*	*
Capacity utilization rate						*	*
BTS- average unit cost expectations						*	*
BLTS-Credit standards							*
Unemployment gap							*
CBOE volatility index							*
Export quantity index							*
Turkey CDS							*
# of endogenous variables	5	6	7	8	9	15	20
Exogenous variables							
Constant	*	*	*	*	*	*	*
Taxfactor	*	*	*	*	*	*	*

Notes: VAR in first differences exploit output gap whereas models in log-levels use log-GDP series as a demand side measure. Each model includes a "taxfactor" variable and a constant term as exogenous variables.

Another source of ambiguity in searching the so called "true model" in forecasting the target variable is to decide on the form of the variables to utilize. Should we pre-transform the variables to render data stationary or introduce the variables in log-levels to take into account the information in levels such as the presence of error correction mechanism? To this end, we let the data speak and address this issue by estimating these distinct models under two different set of priors, first using stationary (log-difference) forms of the variables[7] with a Normal-Wishart prior distribution and second using variables in log-levels with "dummy observation prior" with the extensions of "the sum of coefficients priors", and the "dummy initial observation prior" proposed by Doan et al. (1984) and Sims (1993).[8] Under Normal-Wishart prior, we assume the following multivariate normal and inverse Wishart distributions for the prior distribution of coefficients and variance covariance matrix of Σ respectively:

$$\beta \sim N(\beta_0, \Sigma \otimes \Phi_0), \quad \Sigma \sim IW(S_0, \alpha_0)$$

For prior mean of the coefficients (β_0), we simply use the Minnesota prior by Litterman (1986). Φ_0 is a diagonal matrix and shaped with respect to hyperparameters, specifically $\lambda = (\lambda_1, \lambda_2, \lambda_3, \lambda_4)$, which controls the tightness (variance) on the prior for different coefficients. These parameters regularize the variance of the VAR coefficients and they are known as overall tightness, cross-variable specific tightness, lag decay and exogenous variable tightness correspondingly.[9] For the lag coefficients, natural conjugate prior does not differentiate between the variance of own and cross-variable lags and so we simply treat the own and cross variable lags as the same way by assuming λ_2 as 1. For the lag coefficients, variance is given by:

$$\sigma_{a_{ij}}^2 = \left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2$$

where σ_j^2 is the scaling factor which is approximated by the variance of the residuals of univariate autoregressive models. l is the lag considered by the coefficient. Variance for the exogenous coefficients (including constant terms) is defined as:

$$\sigma_c^2 = (\lambda_1 \lambda_4)^2$$

Typical values believed to be work well in the literature are $\lambda_1 = 0.1 \text{ or } 0.2$, $\lambda_3 = 1 \text{ or } 2$, $\lambda_4 = 10^2 \text{ or } 10^5$ (Robertson and Tallman (1999), Canova (2007)). There are different approaches to select these hyper parameters (λs) along with the autoregressive coefficients of the Minnesota prior; (i) choosing the ones maximizing the (log) marginal likelihood (for example, see Carriero et al. (2015)) (ii) treating these hyperparameters as random, assuming a prior distribution and then estimating them with hierarchical models (see Giannone et al. (2012)), (iii) running a forecast competition and choosing the ones maximizing forecasting performance of the model (Doan et al., 1984). We preferred the last

[7] We do not difference output gap, inflation expectations, other gap-like variables, interest rates and spreads, as they ought to be stationary conceptually.

[8] The Bayesian Estimation, Analysis and Regression (BEAR) toolbox by Dieppe et al. (2016) is used for estimation and forecasting of these models in the paper. Throughout the paper we adhere to notation of the BEAR toolbox.

[9] For further details on these hyperparameters, see Dieppe et al. (2016).

approach and came up with the following values of $\lambda_1 = 0.05,\ \lambda_3 = 2,\ \lambda_4 = 100$ for Normal-Wishart prior, which are indeed very close to the conventional values employed in the literature.[10,11] Note also that this pseudo forecasting grid search exercise results in a value of 0.1 for auto-regressive (AR) coefficients of β_0.[12]

As to the prior distribution of Σ for Normal-Wishart prior, we follow common practice (see Kadiyala and Karlsson (1997)) and set α_0 to n+2, where n is the number of endogenous variables, so we assume a loose (non-informative) prior for the degrees of freedom parameter. Prior scale parameter S_0 is determined on the basis of individual AR regressions.[13]

As mentioned above, another option would be to introduce variables in log-levels and force the dynamics to have unit root draws rather than explosive ones. More precisely, this can be done by rewriting the VAR model in the following error correction form:

$$\Delta y_t = -(I_n - A_1 - A_2 - A_3 \ldots - A_p)y_{t-1} + B_1 \Delta y_{t-1} + B_2 \Delta y_{t-2} + \cdots + B_{p-1} \Delta y_{t-(p-1)} + Cx_t + \varepsilon_t$$

If we restrict the term $(I_n - A_1 - A_2 - A_3 \ldots - A_p)$ to zero, then this means we have a VAR model in first differences. Doan et al. (1984) set a prior that shrinks this term towards zero. The hyperparameter λ_6 in the paper controls the variance of this prior. If λ_6 goes to infinity, the prior is uninformative, however when it goes to zero, this implies we approach to exact differencing case. This is called "sum-of coefficient prior" and generally implemented by means of dummy observation prior (for details of dummy observation prior see Banbura et al. (2010)). Note that in the limit the sum-of coefficient prior rules out the possibility of cointegration, hence this prior in the literature is used with additional prior known as "dummy initial observation" prior (it is also known as the single-unit-root-prior), which was proposed by Sims (1993). λ_7 parameter controls the variance of dummy initial observation prior. If λ_7 goes to infinity, the prior is diffuse, however when it goes to zero, all the

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[10] Bear in mind that Normal-Wishart prior constraints λ_2 to the value of 1. Consequently, it is generally recommended to set overall tightness parameter λ_1 to a smaller value compared to Minnesota prior to compensate the lack of extra shrinkage from λ_2. Pseudo result of 0.05 for λ_1 also appears to be reasonable from this standpoint.

[11] In selecting the hyperparameters we applied a different approach compared to forecast evaluation section. First we partly used a pre-forecast evaluation period. Second, we minimized average RMSE values for 1 to 4 quarter ahead computed from quarterly projections under full conditioning of some key variables.

[12] As mentioned, another possibility is to choose the degree of shrinkage by maximizing the log marginal likelihood of the models. If we do so, for AR coefficients we obtain values around 0.3 and 0.4 while overall tightness parameter i.e. λ_1 is found to be around 0.21-0.22. This procedure yields λ_3 and λ_4 as 1 and 100 correspondingly.

[13] Another option for prior distribution could be the use of independent Normal Wishart instead of Normal Wishart. However, this prior distribution does not have an analytical formula, hence it requires numerical methods such as Gibbs sampling to cover posterior distributions. Therefore utilizing independent Normal Wishart prior comes with a high computational burden, given that we select hyperparameters using pseudo-out of sample forecasting approach to increase forecast power.

variables are at their unconditional mean (model is stationary even though there exists unit roots in the variables so implying cointegration) or system is characterized by a number of unit roots and the variables have a common stochastic trend. [14]

We introduced these two dummy observation extensions to the above models and selected hyperparameters based on a forecasting performance. Even though they could show some variability from one model to another, we obtained the following values: $\lambda_1 = 0.05 \text{ or } 0.1$, $\lambda_3 = 2$, $\lambda_4 = 10^2$, $\lambda_6 = 0.1$, $\lambda_7 = 0.02, 0.0.4 \; or \; 0.1$.

We can construct unconditional or conditional forecasts with VAR models (Waggoner and Zha, 1999). Conditional forecasts are the forecasts obtained by conditioning the future path of the certain variables such as exchange rate or oil prices and highly useful especially for scenario analyses. Our prior assumption is that providing some paths for future evolution of some economic variables may carry information for the other variables, hence might increase the predictive power. On the other hand, some argue that by using conditional forecasts, forecasters lose some important feedbacks such as the one from inflation to these conditioning variables in the forecast period. In this regard, we compute both unconditional forecasts and conditional forecasts in the paper. In producing forecast, we condition on three variables: Brent oil prices, import prices and exchange rate basket by constructing real-time data vintages. Oil prices are derived from the financial markets' future prices at the beginning of the each forecast period. Import price data vintage rests on the CBRT's in-house projections that are vastly linked to future prices of various commodities. Finally, values of USD/TL exchange rate are based on survey expectations of agents (CBRT-Survey of Expectations)[15] and the exchange rate basket values are computed under EUR/USD parity which is fixed at the initial month of each prediction period.

3. Forecast evaluation of BVAR Models

In this section, we assess the forecasting performance of the models based on their out-of- sample forecast accuracy. We work with seven different BVAR models and two forms of the variables, which are entering the model in first log-differences and log-levels. Bear in mind that the number of lags in all the VARs is set to four. We compare the median of the forecast distributions of the rival models since our focus is on the accuracy of the point forecasts. Alternatively, one can be interested in the uncertainty around the projections as well, so might consider evaluating the models in terms of predictive likelihoods or continuous ranked probability scores.

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[14] For further details see Giannone et al. (2012), Giannone et al. (2014), Dieppe et al. (2016).

[15] Simple linear interpolation methodology is employed based on current month, year-end and 12 month ahead expectations of the nominal exchange rate.

The performance of the forecasts from different models is evaluated by the root mean squared forecasting error (RMSE). For this purpose, we use each BVAR model to produce out-of-sample forecasts recursively for four horizons, namely 1 to 4 quarters. The first estimation sample for log-difference model is from 2005Q2 to 2013Q2 and the period ranging from 2013Q3 to 2017Q4 is allocated for forecast evaluation. More precisely, using data from 2005Q2 to 2013Q2, we generate the posterior predictive distributions (density forecasts) for 2013Q3-2014Q2. Then, the estimation sample size is extended one quarter while starting quarter is kept as fixed (2005Q2-2013Q3) and the models are re-estimated (thus adopting a recursive evaluation scheme). New forecasts are obtained until 2014Q3. We continue to this recursive process until the end of the sample, i.e. 2017Q4, by increasing the estimation sample by one quarter at a time and producing 4 quarter ahead forecast predictive distributions. This leads to total of 15 iterations. At this point, we have to note that our pseudo out-of-sample is relatively short due to some data constraints.[16] Consequently, the RMSE of the each model is calculated as:

$$RMSE_h^m = \sqrt{\frac{\sum_{t=T_0}^{T_1}(\pi_{t,t+h}^m - \pi_{t+h})^2}{T_1 - T_0 + 1}}$$

where $h = 1, \ldots, 4$ quarters, m is the model used to compute inflation forecast of $\pi_{t,t+h}^m$. π_{t+h} is the realized value of the annual inflation rate. Even though we estimate the models in log-difference and in levels form, we report the forecast and evaluation results using the stationary forms of the variables, more clearly by transforming the forecasted quantities into annual inflation rates. T_0 and T_1 are the start and end date of the evaluation period.

[16] Another issue that deserves discussion for forecast evaluation is the use of real-time data available to the forecaster at the time of forecasting. Even though most of variables do not suffer from data revisions such as prices, exchange rates, oil prices, expectations, interest rates, some of them particularly GDP related ones, such as output gap and real unit labor costs variables are not exempt from this problem. For those variables as well as the import prices, we have utilized the full sample data in the pseudo exercises due to lack of the real-time data set.

Table 2: Root mean squared errors

	BVAR in differences				BVAR in levels			
	Unconditional forecasts							
Model	**h=1**	**h=2**	**h=3**	**h=4**	**h=1**	**h=2**	**h=3**	**h=4**
M1	0.75	1.16	**1.54**	**2.01**	0.85	1.80	2.65	3.55
M2	0.76	1.18	1.58	2.07	**0.77**	1.54	2.16	2.87
M3	0.76	1.17	1.57	2.06	0.78	**1.49**	**2.06**	**2.73**
M4	0.76	1.18	1.59	2.08	0.78	1.55	2.21	2.95
M5	0.76	1.19	1.59	2.08	0.78	1.62	2.34	3.07
M6	**0.74**	**1.15**	1.55	2.07	-	-	-	-
M7	0.75	1.19	1.59	2.09	-	-	-	-
	Conditional forecasts							
M1	**0.53**	**0.95**	**1.24**	**1.68**	0.60	1.35	1.81	2.25
M2	**0.53**	0.96	1.25	1.69	**0.56**	**1.26**	**1.69**	**2.12**
M3	**0.53**	0.96	1.27	1.70	0.58	1.31	1.78	2.23
M4	0.54	0.99	1.31	1.74	0.59	1.34	1.85	2.34
M5	0.54	0.99	1.31	1.75	0.59	1.35	1.85	2.30
M6	**0.53**	0.98	1.29	1.72	-	-	-	-
M7	0.55	1.02	1.34	1.77	-	-	-	-
	Benchmark models							
Random walk (RW)	0.86	1.54	2.20	2.89				
SARIMA(110)(011)	0.71	1.48	2.29	3.27				

Notes: Table shows RMSEs for different BVAR combinations. RMSE calculations are based on annual inflation rates. The evaluation period is 2013Q3-2017Q4. h refers to forecast horizon and it is in quarters. RMSE values are calculated from the medians of the predictive distributions of the unconditional and conditional BVARs. The variables of each model can be found in Table 1. "BVAR in differences" refers to the models using the first difference of the variables, whereas "BVAR in levels" utilize the log-level of the variables. Lowest RMSEs within each block is shaded as light gray and bold. Model M6 and M7 include variables which are stationary by its nature such as capacity utilization ratio, survey based credit standards, interest rate spreads or tendency survey questions of total orders, average unit cost expectations. For this reason, we are not able to estimate "BVAR in levels" for these last two models.

Table 2 shows the root mean squared errors by the models including the simple benchmark model of random walk.[17] First, BVAR forecasts for consumer inflation consistently perform better than the random walk benchmark. Only exception to this is unconditional forecast of BVAR models using log-levels of the variables, which largely produces similar results to the random walk model. Second,

[17] To illustrate the effect of selection of hyperparameters on forecast accuracy, we also calculated RMSE values for model M3 (for log-differenced variables and applying conditional forecasting) based on the values of hyperparameters maximizing the marginal data density (following Carriero et al. (2015)), for further details see sensitivity analysis presented in appendix Table A.2.

markedly lower RMSE figures for conditional forecasts compared to unconditional ones for all horizons reveals that conditioning on variables as exchange rate, import and oil prices helps to lower forecast errors. Conditional forecasts are more accurate for both BVAR in levels and differences. Third, BVAR forecasts using difference of the variables outperform the ones using the log-levels of the data. In fact, the performance of the difference and level BVARs are quite similar for one quarter ahead forecasts, while the disparity among RMSE values widens starting from the second horizon in favor of the difference VARs. In this respect, smallest forecasts errors are achieved under difference BVARs using conditional information.

Table 3: Comparing predictive accuracy of forecasts

Harvey, Leybourne and Newbold (HLN) Test[a] (For BVAR in differences & Conditional forecasts)				
	h=1	**h=2**	**h=3**	**h=4**
M1 vs. RW	**0.030**	**0.000**	**0.000**	**0.000**
M1 vs. M2	0.843	0.700	0.700	0.634
M1 vs. M3	0.928	0.645	0.520	0.509
M1 vs. M4	0.804	0.194	**0.074**	**0.000**
M1 vs. M5	0.785	0.105	**0.008**	**0.000**
M1 vs. M6	0.752	0.232	**0.024**	**0.007**
M1 vs. M7	0.572	**0.074**	**0.008**	**0.002**

Notes: Table shows probability values for Harvey, Leybourne and Newbold (1997) forecast comparison test. Probability values reported for the null hypothesis that the forecast errors of the M1 model and the competing model are the same versus the alternative hypothesis that M1 model provides a better forecast than the rival model. Rejections of the null hypothesis at the 10 percent level are indicated in light gray and bold.

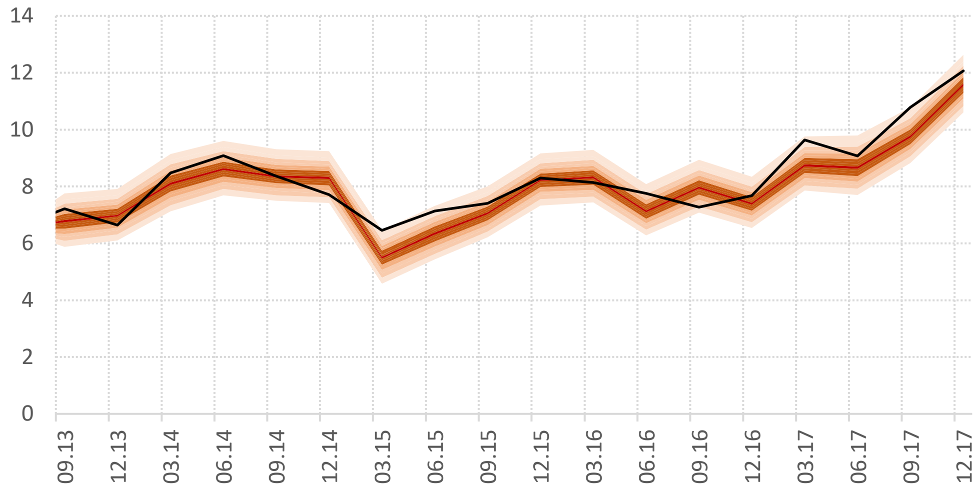
When we evaluate forecast performance in terms of model size, the lowest RMSEs for each horizon belong to the models having small number of variables. Particularly conditional forecasts of model M1 using variables in log-difference form seems to deliver the better forecasts for the consumer inflation. Table 3 provides Harvey, Leybourne, and Newbold (1997) (HLN) test of forecasting accuracy, which is the modified version of Diebold and Mariano (1995) test for small sample size, for BVAR in differences with conditional forecasts. First, Table 3 points out that M1 model provides a better forecasts than the benchmark random walk model for all horizons. Second, we do not reject the null hypothesis of equal predictive accuracy for M1, M2 and M3 for all horizons, that is to say models M1, M2 and M3 display similar forecasting performance on account of difference BVARs. Third, for the one quarter ahead forecasts, there is no statistically significant difference among all BVAR models in respect to forecast performance. This finding is also hold for the two quarter ahead forecasts except for model M7. But, as we go further, the picture changes. Specifically HLN test results indicate that forecasting performance of model M1 is somewhat better than those of M4, M5, M6 and M7 for longer horizons, namely for three and four quarter ahead. In general, as pointed out in Table 2, as the model size gets larger, forecast error slightly increases. These findings in total suggest that using a BVAR model having 5 to 7 wisely selected variables (such as M1, M2 and M3) might be adequate to forecast Turkish consumer inflation. Evidence as to the model size in the literature are rather mixed. Bloor and Matheson (2008) state that even though it is somewhat inconclusive, a 35 variable model tended to forecast better than larger or smaller models for New Zealand, whereas Demeshev and Malakhovskaya (2015) point out that a small-dimensional BVAR outperforms its high-dimensional counterpart. We argue that should the variables are selected properly by a pre-selection mechanism, it is possible to have fruitful results even with relatively small BVARs. To summarize, pseudo evaluation exercise points out that small to medium size BVAR models with educated variables in stationary form and conditioning on the future paths of selected variables appear to be a good choice to forecast inflation.

In Figure 1, we illustrate conditional BVAR distributions (trimming the upper and lower 5 percentile) of the one and two quarter ahead forecasts under model M3 (using variables in log-differences). Given the fact that the difference in forecast performance for models M1, M2 and M3 is not statistically significant for the considered sample, we go for model M3, given that oil prices and inflation expectations are crucial variables in the sense that they might enrich the possible scenario analysis concerning inflation projections. Figure 1 indicates that predictive density of the conditional forecasts for one-quarter ahead follows the observed inflation closely. Even though observed inflation is very close to upper and lower percentiles in some cases such as 2015Q1, 2017Q1 and 2017Q3, it oscillates within the forecast distribution. Another notable feature is that inflation realizations remain steadily above the median of the distribution of the conditional forecasts during 2017. When the two-quarter ahead forecasts are considered, the forecast uncertainty rises as expected. Inflation fluctuates largely within the predictive distribution except for 2015Q2, 2017Q1 and 2017Q4. Similar to the one-quarter ahead forecasts, the median of the distribution of the conditional forecasts underestimates the observed inflation in 2017.

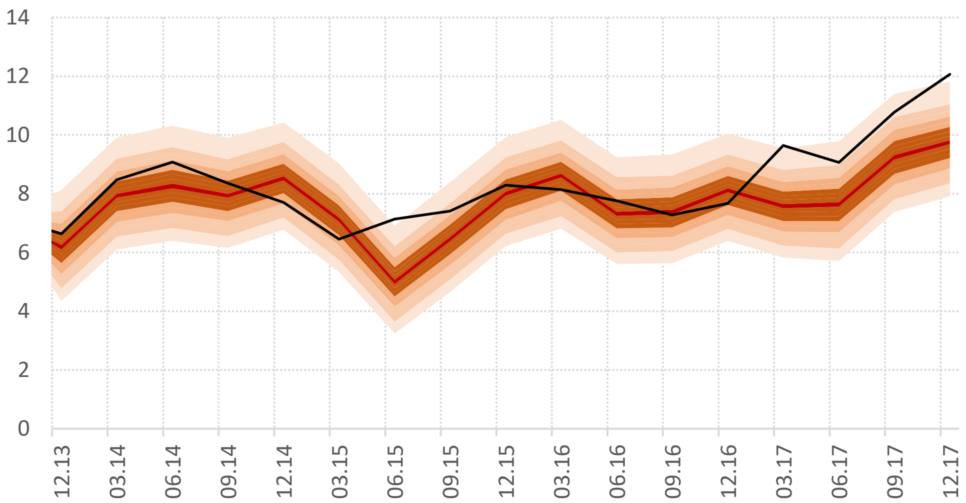
Figure 1: BVAR predictive density of the conditional inflation forecasts for model M3

(black solid line=realized inflation)

(a) One-quarter ahead forecasts



(b) Two quarter ahead forecasts



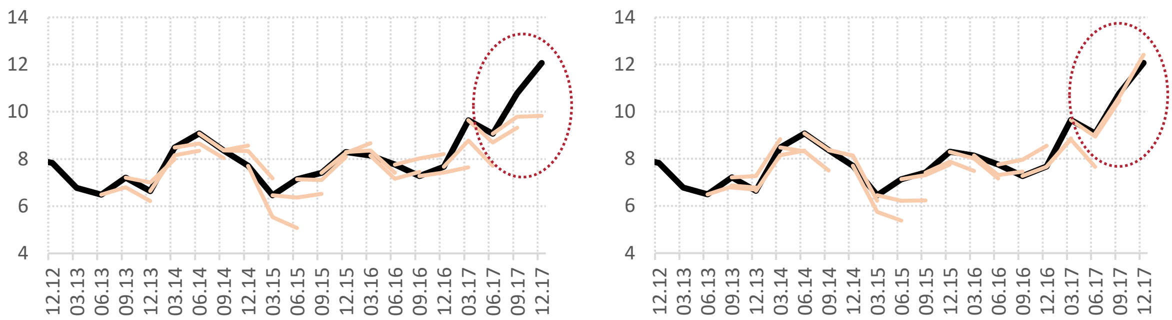
Notes: Black solid line represents the realized annual inflation. The figure displays the conditional distribution (trimming the upper and lower 5 percentiles) of forecasts recursively for model M3 under two different horizons. Forecast period runs from 2013Q3 to 2017Q4. Number of recursive periods for one and two quarter ahead forecasts are 18 and 17 correspondingly.

Understanding the recent forecast errors

The underestimation of median forecasts in 2017 could be due to the conditioning variables. Since Turkish lira depreciated considerably in 2017, similarly import prices including the Brent oil prices picked up higher than implied by the oil futures and the economic activity recovered faster than the expectations. In this context, to determine the source of this underperformance of the model, we applied a simple exercise and produced forecasts from model M3 under full conditioning of exchange rate, import and Brent oil prices, in other words we pretended as if we had knowledge of the true values of these three variables at the start of forecast round. Consequently Figure 2 presents the median of the distribution of the conditional forecasts for model M3 when (a) we condition the exchange rate, import and oil prices as we did in the entire article (based on survey of expectations and futures correspondingly) and (b) we condition these three variables to their actual future values. This simple exercise points out that model does a good job tracking the observed inflation when we condition the variables at hand properly.

Figure 2: Two-quarter ahead median conditional inflation forecasts for model M3
(black solid line=realized inflation)

(a) Conditioning exchange rate, import and oil prices to expectations and futures | **(b) Conditioning exchange rate, import and oil prices to their actual future information**



Notes: Black solid line represents the realized annual inflation. Forecast period runs from 2013Q3 to 2017Q4. The figure displays the median of the conditional distribution of forecasts recursively for model M3 (variables are in log-differences) under two different conditioning for exchange rate, import and Brent oil prices.

Exercise presented in Figure 2 and Table 4 reveal that accurately conditioning on the variables is particularly important for after one quarter ahead. Besides, as an extreme hypothetical example, we also condition all the model variables to their actual future values (full conditioning) to comprehend the limits of the model (see the last row in Table 4). It is possible to reduce the 4-quarter ahead forecast error by half for model M3 if the forecaster can predict the future course of variables correctly. Overall, this simple exercise suggests that there is a room to improve forecast performance of the models by setting the exogenous future paths of the certain variables namely exchange rate, import and oil prices more accurately, specifically for the second quarter and afterwards.

Table 4: Role of conditioning: root mean squared error for model M3 (Variables are in log-differences)

	Conditional forecasts			
	h=1	**h=2**	**h=3**	**h=4**
M3 (Conditioning exchange rate, import and oil prices to expectations and financial futures)	0.53	0.96	1.27	1.70
M3 (Conditioning exchange rate, import and oil prices to their actual future information)	0.53	0.84	1.14	1.50
M3 (Under full conditioning, conditioning all the model variables to their actuals)	0.45	0.68	0.76	0.81

Notes: Table shows RMSEs calculated from the medians of the predictive distributions for model M3 under different conditionings. Models utilize the log-difference form of the variables with a normal-inverted Wishart prior. RMSE calculations are based on annual inflation rates and the evaluation period is 2013Q2-2017Q4. h refers to forecast horizon and it is in quarters.

4. Conclusion

There is growing literature that VARs with Bayesian shrinkage produce reasonable point and density forecasts. Accordingly, we aim to forecast quarterly Turkish inflation using Bayesian VARs. However, there are various different options to implement such a model and alternative specification choices may influence the final predictive ability. We study some variants of BVARs such as modelling in levels or in differences; selection of hyperparameters; estimating BVARs of different model sizes and the accuracy of conditional and unconditional forecasts, and find those providing the most accurate forecasts according to out-of-sample forecast performance.

BVAR forecasts using variables in log-difference form outperform the ones using log-levels of the data. In terms of model size, with a pre-selecting the variables based on the methodology proposed by Andıç and Öğünç (2015), the lowest forecast errors belong to the models having relatively small number of variables, for instance knowledgeably selected 7 variable BVAR model (Brent oil prices, import prices in dollars, nominal exchange rate basket, output gap, real unit labor costs, survey-based inflation expectations and CPI excluding unprocessed food and tobacco along with an exogenous variable considering the impact of tax changes on inflation) works well, though we find only small difference in forecast accuracy among models of various sizes up to two quarter ahead forecast horizon. The conditioning decidedly helps to lower forecast error. Models do a good job tracking the observed inflation when we condition on some key variables properly. Overall, small to medium size BVAR models having wisely selected variables in difference form with a normal-inverted Wishart prior and conditioning on the future paths of certain exogenous variables such as exchange rate, import and oil prices seem to be a good choice to forecast inflation in Turkey.

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Appendix:

Table A.1: Description of the dataset

Series	Description	Source
CPI excluding unprocessed food and tobacco	CPI-D price index (2003=100), seasonally adjusted	TURKSTAT
Import prices	Import unit value index (2010=100)	TURKSTAT
Nominal exchange rate basket	0.5*US dollar/TL+0.5*Euro/TL	CBRT
Output gap	Average of different output gap estimates (Multivariate Bayesian estimate, modified HP estimate, estimate based on survey indicators, Kalman filter estimate based on disaggregated GDP components)	CBRT In-house estimate
Gross domestic product	Chain linked volume index (2009=100), seasonally adjusted	TURKSTAT
Real unit labor costs	Non-farm real unit labor cost indicator, seasonally adjusted	CBRT
12 month-ahead inflation expectations	Survey of expectations, 12 month-ahead inflation expectations	CBRT
Brent oil prices	Brent crude oil prices, $ per barrel	Bloomberg
3 month treasury bill rate	3 month treasury nominal interest rate	Bloomberg
Producer prices	Domestic producer price index, (2003=100)	TURKSTAT
Taxfactor	This variable quantifies the direct effect of tax changes of certain sub-items (these sub-items are the ones subject to frequent tax changes, such as fuel-oil, automobiles, white goods, furniture, mobile phones) on CPI-D inflation. The calculations assume that the tax changes will be reflected into the prices one-to-one.	CBRT In-house estimate
Total employment	Household Labour Force Survey, seasonally adjusted	TURKSTAT
BTS-total orders books	Business Tendency Survey, Q2-current overall order books, balance statistics, seasonally adjusted	CBRT
Real consumer credit	Total consumer credit stock deflated by consumer prices, seasonally adjusted	CBRT
Consumer credit and deposit rate spread	Nominal interest rate spread between TL consumer credit and TL deposit rates	CBRT
Capacity utilization rate	Business Tendency Survey, capacity utilization rate of the manufacturing industry, seasonally adjusted, deviation from historical average	CBRT
BTS- average unit cost expectations	Business Tendency Survey, Q25-average unit cost expectations over the next 3 months, balance, seasonally adjusted	CBRT
BLTS-Credit standards	Bank Loan Tendency Survey, Credit standards for commercial loans, realized net change, %	CBRT
Unemployment gap	HP filter based unemployment gap measure	Author’s calculation

CBOE volatility index	The Chicago Board Options Exchange volatility index (VIX)	Bloomberg
Export quantity index	Non-gold export quantity index, (2010=100), seasonally adjusted	TURKSTAT, CBRT
Turkey CDS	Turkey 5-year credit default swaps	Bloomberg

Table A.2: Some sensitivity checks: root mean squared errors for model M3 under alternative choices

	Conditional forecasts (Variables are in log-differences)			
	h=1	**h=2**	**h=3**	**h=4**
Baseline, Lag 4, forecast competition for λs (ar=0.1, $\lambda_1 = 0.05$, $\lambda_3 = 2$, $\lambda_4 = 100$)	0.53	0.96	1.27	1.70
Lag 4, λs maximizing marginal likelihood (ar=0.3, $\lambda_1 = 0.22$, $\lambda_3 = 1$, $\lambda_4 = 100$)	0.58	1.22	1.75	2.37
Baseline, Lag 2, forecast competition for λs	0.53	0.98	1.31	1.75

Notes: Table shows RMSEs calculated from the medians of the predictive distributions for model M3 under different hyperparameter choices (forecast completion vs the ones maximizing the log-likelihood) and lag structures (lag 4 vs lag 2 as an example). Models use the log-difference form of the variables with a normal-inverted Wishart prior. RMSE calculations are based on annual inflation rates and the evaluation period is 2013Q2-2017Q4. h refers to forecast horizon and it is in quarters.

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