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The Role of Economic Policy Uncertainty in Forecasting US Inflation Using a VARFIMA Model

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Abstract

We compare inflation forecasts of a vector fractionally integrated autoregressive moving average (VARFIMA) model against standard forecasting models. U.S. inflation forecasts improve when controlling for persistence and economic policy uncertainty (EPU). Importantly, the VARFIMA model, comprising of inflation and EPU, outperforms commonly used inflation forecast models.

JEL CLASSIFICATIONS: C53, E37

KEYWORDS: Inflation, long-range dependency, economic policy uncertainty

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1 Introduction

Inflation forecasts are important central bank outputs. The Federal Reserve of the United States (U.S.) produce regular inflation forecasts at various forecast horizons. From a theoretical perspective, Faust and Wright (2012) assert that the non-neutrality of monetary policy in the New-Keynesian framework has led to the importance of inflation forecasting from a policy perspective.

Many methodologies have been applied in forecasting U.S. inflation. For an excellent summary of models see Stock and Watson (2009), which compares the forecasting performance of various Phillips curve specifications, and also Faust and Wright (2012) for the performance comparison of newer methods. These methodologies range from simple linear models to large data-driven econometric models and from structural models to nonlinear specifications.

From an univariate perspective, there is widespread evidence that the US inflation rate can be best captured by a long-memory process (Barros and Gil-Alana, 2013; Caporin and Gupta, 2014). Interestingly however, the literature on U.S. inflation forecast comparisons either assume inflation to be I(1) or I(0) and then modeled as such (Lovcha and Perez-Laborda, 2013). Also inflation forecasting models that do not directly control for policy uncertainty are often misspecified, given the recent evidence that economic policy uncertainty affects in-sample behaviour of inflation (Colombo, 2013; Jones and Olson, 2013).

We address these shortcomings in a Bayesian vector autoregressive fractionally integrated (VARFIMA) model. A VARFIMA model captures the persistence of inflation. The forecasts are conditioned on an uncertainty variable by Baker et al. (2013) to model inflation . Conditioning inflation forecasts on policy uncertainty would capture the inflation or deflation effects of uncertainty. The forecasts are recursive over an out-of-sample period, the starting point of which is determined by tests of structural breaks, and would thus account for time-varying correlation with policy uncertainty. Finally we use the Diebold Mariano (1995) test to compare forecasts from alternative forecasting models.

2 Data and Methodology

We use monthly U.S. consumer price inflation data, obtained from the FRED database of the St. Louis Federal Reserve, and the uncertainty index of Baker et al. (2013), obtained from www.policyuncertainty.com, with our period covering January 1985 to June 2014. This gives us a matrix of two time series with a total of 354 observations.

To model the long and short range dependence of variables, as well the interdependency between inflation and uncertainty we propose the following VARFIMA(p,d,q) model:

$$\phi(L)D(L)[\tilde{x}_t - \tilde{\mu}] = \theta(L)\varepsilon_t \tag{1}$$

where $\tilde{x}_t$ is a vector of Gaussian time series, $\phi(L) = I - \phi_1 L - \cdots - \phi_p L^p$ and $\theta(L) = I - \theta_1 L - \cdots - \theta_p L^p$ are matrix lag polynomials for the AR and MA coefficient matrices ϕ_i, i=1,...,p, and θ_i, i=1,...,q, respectively. $\tilde{\mu}$ is the vector of the means of the time series and $D(L)$ is a diagonoal $k \times k$ matrix that contains the order of fractional integration of k time series: $D(L) = \text{diag}[(1-L)^{d_k}, \dots, (1-L)^{d_k}]$. d_i is the degree of fractional integration of the ith variable and we define $\tilde{d}$ as the vector containing d_i for $i = 1,2,\dots,k$. We assume that the errors (ε_t) are *i.i.d.*

with $\varepsilon_t \sim MV(0, \Sigma)$. It is assumed that the roots of $\phi(L)$ and $\theta(L)$ lie outside the unit circle. Furthermore the process is stationary if $-1/2 < d_i < 1/2,\ i = 1,2,\ldots,k$. If any $d_i > 1/2$ the process is not covariance stationary, but still mean reverting - it takes a long time for mean reversion. Finally, the $D(L)$ operator is defined by a binomial series (for more details see Hassler, 1994). We estimate the model using Monte Carlo Markov Chains in a Bayesian setup following Ravishanker and Ray (2002) to avoid possible over-fitting. This allows us to incorporate prior information and derive a posterior distribution that can be summarized. We use a uniform prior for $\phi(L)$, $\theta(L)$ and $\tilde{d}$, respectively and an improper prior for $\tilde{\mu}$. We assume that $\Sigma_{ii} = \sigma_i^2$ and $\Sigma_{ij} = \rho\sigma_i^2\sigma_j^2$, where ρ (measuring contemporaneous correlation) is assumed to have a uniform prior on (-1,1).

The Diebold and Mariano (1995) test modified by Harvey et al. (1997) is used to compare the forecast accuracy of the VARFIMA(p,d,q) model against alternative forecasting models, namely, the random walk (RW),. an ARIMA(2,0,0), VAR(2), and ARFIMA(2,d,0), with all models selected by the AIC. Our out-of-sample forecast starts from Sep 2005, given that the Bai and Perron (2003) tests of multiple structural breaks detected the first break on that date, based on the inflation equation in the VAR(2). We compare 1, 3, 6 and 12 quarters-ahead forecasts. Forecasts from the VARFIMA are obtained using predictive densities. The point forecasts for comparison are taken from the medians.[1]

[Insert Figure 1]

3 Results

Table 1 compares the root mean squared errors (RMSE) for 12 forecast horizons. The VARFIMA model has the lowest RMSE in the majority of the forecast horizons and performs well for short and longer forecast periods. It never did worse than second place in instances where it had a slightly higher RMSE than an alternative model.

[Insert Table 1]

Table 2 summarizes the modified DM test for h=1, 3, 6, 9, 12.[2] The table report standard errors in parenthesis. We include scores to emphasize which row models outperform column models significantly. Positive values indicate that the row model outperforms the column model, while negative values indicate the converse.

None of the models significantly outperform each other for h=1 apart from beating the RW model. The RW model is significantly outperformed by the VAR and ARFIMA models. In fact, the RW model is outperformed by all other model specifications using the DM test for h>1. The various models seem to perform equally well using the DM test, except for h=3 where the

[1] See Ravishanker and Ray (2002) for more details.

[2] We observed that the inflation density is not symmetrical and that the tails have large weights during high inflation and deflation episodes. Given this, we also used the weighted squared error forecast evaluation of van Dijk and Franses (2003), which places weights on the tails of the inflation distribution. These weights are used to penalize the forecasts. This helps us in determining which models predict better during booms and recessions. We observed that the results are more in favor of the VARFIMA model for tail, boom and recession weights. These results have been suppressed to save space, but are available upon request from the authors.

VARFIMA model statistically outperforms the ARIMA and VAR models. Note that none of the models significantly outperformed the VARFIMA model.

The advantage of using a VARFIMA model compared to other forecasting models stems from its ability to produce better forecasts. This is most likely the result of controlling for the persistence in inflation and exploiting the additional information provided by the policy uncertainty variable.

4 Conclusion

We compare the forecasting performance of a VARFIMA model against a number of traditional inflation forecasting models. Augmenting U.S. inflation data with a policy uncertainty variable improves the forecasting performance over simple univariate and multivariate specifications. Exploiting the information that inflation is a near unit root in a fractionally integrated framework further improves inflation forecasting. Our results show that the VARFIMA model has the lowest RMSE and is not statistically outperformed by other inflation forecasts specifications.

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Table 1: RMSE's

h	RW	ARMA	VAR	ARFIMA	VARFIMA	BEST MODEL
1	4.5384	3.9007	3.7744	3.9266	3.8247	VAR
2	6.0297	4.2906	4.1611	4.1004	4.0601	VARFIMA
3	6.3003	4.2925	4.2847	4.0846	4.1031	ARFIMA
4	6.0488	4.2222	4.2008	4.0324	4.0292	VARFIMA
5	6.5500	4.2188	4.2063	4.0330	4.0314	VARFIMA
6	6.5417	4.2052	4.1981	3.9977	3.9993	ARFIMA
7	6.2752	4.2127	4.2103	4.0020	4.0030	ARFIMA
8	6.3384	4.2306	4.2259	4.0180	4.0178	VARFIMA
9	6.3523	4.2408	4.2183	4.0250	4.0231	VARFIMA
10	6.1880	4.2613	4.2349	4.0449	4.0424	VARFIMA
11	6.1585	4.2832	4.2630	4.0654	4.0628	VARFIMA
12	6.8185	4.2926	4.2821	4.0729	4.0710	VARFIMA
Average	6.1783	4.2209	4.1883	4.0336	4.0223	VARFIMA

Table 2: Diebold-Mariano Tests

	RW	ARMA	VAR	ARFIMA	VARFIMA	plus	minus
			h=1				
RW		-1.59 (0.11)	-2.14 (0.03)	-1.84 (0.07)	-1.39 (0.17)	0	2
ARMA	1.59 (0.11)		-0.34 (0.74)	-0.37 (0.71)	0.78 (0.43)	0	0
VAR	2.14 (0.03)	0.34 (0.74)		-0.07 (0.94)	0.43 (0.66)	1	0
ARFIMA	1.84 (0.07)	0.37 (0.71)	0.07 (0.94)		0.47 (0.64)	1	0
VARFIMA	1.39 (0.17)	-0.78 (0.43)	-0.43 (0.66)	-0.47 (0.64)		0	0
			h=3				
RW		-2.28 (0.02)	-2.22 (0.03)	-2.32 (0.02)	-2.34 (0.02)	0	4
ARMA	2.28 (0.02)		0.33 (0.74)	-1.53 (0.13)	-1.70 (0.09)	1	1
VAR	2.22 (0.03)	-0.33 (0.74)		-2.44 (0.01)	-2.59 (0.01)	1	2
ARFIMA	2.32 (0.02)	1.53 (0.13)	2.44 (0.01)		-1.42 (0.16)	2	0
VARFIMA	2.34 (0.02)	1.70 (0.09)	2.59 (0.01)	1.42 (0.16)		3	0
			h=6				
RW		-1.94 (0.05)	-1.94 (0.05)	-2.00 (0.05)	-2.00 (0.05)	0	4
ARMA	1.94 (0.05)		-0.21 (0.83)	-1.32 (0.19)	-1.33 (0.18)	1	0
VAR	1.94 (0.05)	0.21 (0.83)		-1.27 (0.21)	-1.27 (0.20)	1	0
ARFIMA	2.00 (0.05)	1.32 (0.19)	1.27 (0.21)		-0.97 (0.33)	1	0
VARFIMA	2.00 (0.05)	1.33 (0.18)	1.27 (0.20)	0.97 (0.33)		1	0
			h=9				
RW		-1.94 (0.05)	-1.97 (0.05)	-2.13 (0.03)	-2.13 (0.03)	0	4
ARMA	1.94 (0.05)		-1.44 (0.15)	-1.32 (0.19)	-1.32 (0.19)	1	0
VAR	1.97 (0.05)	1.44 (0.15)		-1.20 (0.23)	-1.20 (0.23)	1	0
ARFIMA	2.13 (0.03)	1.32 (0.19)	1.20 (0.23)		0.95 (0.34)	1	0
VARFIMA	2.13 (0.03)	1.32 (0.19)	1.20 (0.23)	-0.95 (0.34)		1	0
			h=12				
RW		-2.03 (0.04)	-2.03 (0.04)	-2.11 (0.03)	-2.11 (0.03)	0	4
ARMA	2.03 (0.04)		-0.86 (0.39)	-1.26 (0.21)	-1.26 (0.21)	1	0
VAR	2.03 (0.04)	0.86 (0.39)		-1.22 (0.22)	-1.22 (0.22)	1	0
ARFIMA	2.11 (0.03)	1.26 (0.21)	1.22 (0.22)		0.74 (0.46)	1	0
VARFIMA	2.11 (0.03)	1.26 (0.21)	1.22 (0.22)	-0.74 (0.46)		1	0

Notes: Numbers in brackets represent the two-sided p-value for the modified DM test. A positive sign indicates that the forecast error of the row model is smaller than the column model. The last two columns indicate the number of times the row model significantly outperforms the column model (+), or is outperformed (-).